BANK STRESS TESTS:
IMPLICATIONS ON ACCOUNTING DISCRETION, TRANSPARENCY AND MARKET DISCIPLINE

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DECLARATION

I hereby declare that this thesis has not been and will not be, submitted in whole or in part to another University for the award of any other degree.

Signature: ....

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Summary

Since 2009, regulators worldwide have conducted large-scale stress tests to reveal systemically important banks' soundness to financial markets. Regulators aim to enforce market discipline that penalises excessive risk-taking and requires banks to operate more responsibly leading to financial stability. In this thesis, I contribute to this current debate by empirically analysing the implications of bank stress tests on three important aspects, namely accounting discretion, transparency and market discipline.

First, based on a unique accounting dataset of stress-tested and untested European banks, I reveal that the accounting information of stress-tested banks is affected by stress tests. In particular, stress tests incentivise bank managers to exercise accounting discretion over loan loss provisions to manage both capital and earnings. The results suggest that stress tests exacerbate discretionary behaviour with the purpose of passing stress tests and conveying a sound picture of the bank's financial condition to regulators and market participants.

Second, examining a unique textual dataset of stress-tested European banks, I find that stress tests incentivise banks to enrich their textual narratives utilising certain stress test terms that I call 'stress test sentiment'. This effect may specifically apply to newly than regularly stress-tested banks. Importantly, banks seem to compensate an increased stress test sentiment using a more positive disclosure tone; this may obfuscate market players, as market measures indicate lower information asymmetry and more analyst coverage.

Third, based on a dataset of European and U.S. stress-tested banks, I show that stress tests do promote market discipline in both positive and negative directions as well as in short- and long-term event windows. In Europe, bank fundamentals are improved in terms of reduced bank risk-taking and funding structure, whilst the U.S. results are inconclusive. However, stress tests also tend to exacerbate negative performance of weaker institutions, due to market discipline, which could unintentionally compromise financial stability.

In summary, this thesis provides novel results on stress tests that might be of interest to policymakers and regulators. I conclude that stress tests are an important addition that increases regulatory awareness and can enhance financial stability. However, I also show that stress tests may lead to unintended drawbacks on bank accounting practice and market discipline. Therefore, stress tests must be paired with a carefully executed disclosure policy to be a more effective regulatory tool.

Table of Contents

List of Tables

List of Figures

Abbreviations

AIC	Akaike Information Criterion
BCBS	Basel Committee of Banking Supervision
BIS	Bank for International Settlements
BvD	Bureau van Dijk
CAPM	Capital Asset Pricing Model
CCAR	Comprehensive Capital Analysis and Review
CEBS	Committee of European Banking Supervisors
CRD IV	Capital Requirements Directive IV
CRR	Capital Requirements Regulation
C4F	Carhart (1997) Four-Factors Model
CTIME	Calendar-Time Portfolio
DFAST	Dodd-Frank Stress Test
DiD	Difference-in-Difference
EBA	European Banking Authority
ECB	European Central Bank
EFTA	European Free Trade Association
EMU	European Monetary Union
EU	European Union
FF3F	Fama and French (1993) Three-Factors Model
GKM	Gaussian Kernel Matching
IAS	International Accounting Standards
IFRS	International Financial Reporting Standards
IMF	International Monetary Fund
IRH	Incomplete Revelation Hypothesis
M&As	Mergers and Acquisitions
MRM	Market Return Model
PSM	Propensity Score Matching
SCAP	Supervisory Capital Assessment Program
SIFI	Systemically Important Financial Institution
SREP	Supervisory Review and Evaluation Process
SSM	Single Supervisory Mechanism
U.S.	United States of America

Chapter 1 – Introduction

1.1. Background and main objectives of regulatory stress tests

The 2008 financial crisis has unravelled severe problems. Most issues are connected to inadequate bank liquidity and capital; this has led to bank instabilities, failures, bailouts and forced mergers and, in turn, created uncertainty within financial markets. This uncertainty has affected the entire economy, as banks play an important role of intermediation that stimulates economic growth and wellbeing. Consequently, policy makers and regulators have been forced to take drastic measures to mitigate this uncertainty and regain the investor's trust to stabilise the economic system (Wheeler, 2019; Acharya and Steffen, 2015; Papanikolaou and Wolff, 2014; Flannery et al., 2013).

The authorities learnt that financial instability is mainly linked to large financial institutions because a failure of such institutions causes major shocks in the economy and leads to severe meltdowns. For example, large European banks, such as Dexia, Hypo Real Estate, Allied Irish Bank, Bank of Ireland and Anglo Irish Bank, to name a few, needed emergency financial support to withstand the crisis; this was even though they were complying with regulatory requirements (see, Braouezec and Wagalath, 2018 for a detailed case study). Before the financial crisis, the general belief was that the economic system would be sound if individual banks retained adequate liquidity and capital. However, in turmoil, the situation is different from normal economic times. Banks could infect one another and hit the markets when they are most vulnerable; this is called systemic risk that plays a major role in shaping current financial regulation. For instance, the Basel Committee of Banking Supervision (BCBS) defines a systemically important financial institution (SIFI) as an institution that has a specific size, complexity, is highly interconnected, hard to substitute and globally active (BCBS, 2018). Financial institutions that fulfil these criteria are seen to be too-big-to-fail because a failure would lead to a chain reaction that could lead to bankruptcy of other, related institutions, and ultimately to the failure of the economic system (Demirgüç-Kunt and Huizinga, 2013; Allen and Gale, 2000).

During the financial crisis, regulators and policy makers were most concerned about systemic risk. The dogma that a bank is safe if it fulfils adequate regulatory requirements no longer held. Consequently, regulators needed a tool to regain the trust of market players. Amongst other amendments to regulatory requirements and policies, regulators in the United States of America (U.S.) and Europe have resorted to large-scale stress tests as a standard tool to provide new valuable information and to win back the market's trust. Stress tests were first applied before the financial crisis as an internal self-exercise for the bank. In 2009, financial regulators adopted this method to provide market participants with additional information that separates sound from unsound banks (Borio et al., 2014; Schuermann, 2014).

In the U.S., stress tests were implemented as a regulatory device with the 2009 Supervisory Capital Assessment Program (SCAP). It tested the 19 largest U.S. financial institutions on capital adequacy criteria. The assessment found that half the banks did not fulfil the capital requirements, and that banks needed to raise more capital over the succeeding six months. This regulatory intervention successfully restored trust of the markets and helped to stabilise the economy. As stress tests were a success, in the Dodd-Frank act that was finalised in July 2010, politicians implemented stress tests as a yearly exercise. Therefore, the Federal Reserve conducts Dodd-Frank Stress Tests (DFAST) and Comprehensive Capital Analysis and Reviews (CCAR) to test resilience against adverse financial shocks during tranquil times, which should maintain the market's trust.[1]

In Europe, the Committee of European Banking Supervisors (CEBS) and the succeeding European Banking Authority (EBA) conducted stress tests in 2009, 2010 and 2011 with similar intention. However, stress tests could not contribute as much to gain back control of the financial sector because banks were not obliged to raise capital ratios questioning the regulator's reliability and authority (Schuermann, 2014). In 2014 and 2015, the European Central Bank (ECB) assessed European SIFIs within the European Monetary Union (EMU) member states as part of the induction of the Single Supervisory Mechanism (SSM). Recently, stress tests have become a supporting part of Pillar 2 (supervisory review) of the Basel Accord.[2] In 2016 and 2018, the EBA has used the stress test results for the Supervisory Review and Evaluation Process (SREP). This enables regulators and supervisors to understand particular needs of banks and to detect problems early. Thus, Pillar 2 complements Pillar 1 (capital requirements) and Pillar 3 (market

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[1] Detailed information on U.S. stress tests may be accessed on the Federal Reserve website: https://www.federalreserve.gov/supervisionreg/dfa-stress-tests.htm.

[2] The Basel Accord, that constitutes regulatory requirements for financial institutions, is currently based on the recently finalised Basel III framework. Basel III comprises of three pillars (capital requirements, supervisory review and market discipline). The European Parliament has adopted Basel III within the Capital Requirements Directive IV (CRD IV) and the Capital Requirements Regulation (CRR). Details about the Basel III framework may be accessed on the Bank for International Settlements (BIS) website: https://www.bis.org/bcbs/basel3.htm.

discipline) that aim to increase bank soundness with more quality and quantity of bank capital, as well as well-informed markets that penalise extensive bank risk-taking.[3]

Analysing the stress test exercises in Europe and the U.S., Borio et al. (2014) and Schuermann (2014) conclude that stress tests may be an effective crisis management tool, but cannot be used as an early warning device. Conceptually, both studies claim that the success of stress tests in enhancing financial stability depends on the level of credibility and the coherence in the implementation of the stress tests. In fact, both are essentially easier to achieve during a crisis than in normal economic times. Specifically, regulators usually apply a one-size-fits-all approach, although some banks might be more affected by the chosen scenario than others. However, selecting a scenario that accommodates all banks is more difficult in normal times than during financial distress; this is because regulators are required to rely on information about past crises. Therefore, they propose that these challenges might be resolved through regulators' individual judgement or by exercising a dual approach that combines top-down with bottom-up criteria. Although this dual approach helped in the U.S. to learn about idiosyncratic risks of participating banks, it is very difficult to implement in a balanced way.

On the other hand, owing to these technical weaknesses, regulators might not be able to implement credible scenarios and signal the soundness of the financial system during normal economic times, which seems to be more a part of the problem than the solution. Borio et al. (2014) argue that no stress test conducted prior to the financial crisis of 2008 was able to detect the risks that banks held in their exposures. Even if regulators were able to predict this risk correctly, markets might not have taken them seriously, owing to the sentiment and experiences prior to the crisis. Consequently, this signal of soundness encouraged all stakeholders with an incorrect perception of safety to continue with their high risk-taking practices.

In support of the above analysis, there is a growing theoretical literature that develops a stress test disclosure theory, debating issues around disclosing detailed (i.e., bank-specific) or aggregated (i.e., summarised) stress test information. The main argument is that the positive impact of detailed stress test disclosures appears to be vital during times of financial distress, whereas researchers cast doubt on their benefits during normal

[3] Detailed information on European stress tests may be accessed on the EBA and ECB websites: https://eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing; https://www.bankingsupervision.europa.eu/banking/tasks/comprehensive_assessment/html/index.en.html.

economic times. Bouvard et al. (2015) illustrate that during financial crises more transparency reduces bank-specific uncertainty among market participants, which contributes to financial stability. However, during relatively calm economic periods, detailed regulatory information might not fully convince market players, therefore backfire by increasing uncertainty and harming the market's trust. Similarly, Goldstein and Leitner (2018) and Goldstein and Sapra (2013) conclude that stress test disclosures may increase market discipline, in particular, when regulators provide both the underlying methodology and the results. However, detailed stress test disclosures might come at a cost of reduced risk sharing by investors, and a decline in analyst information production. Further, investors might follow the regulators information instead of their own analyst's resources, and bank managers might undertake unfavourable short-term decisions that assist in passing stress tests. Moreover, Prescott (2008) argues that banks might not be willing to share as much information with regulators if they knew that this information is going to be disclosed.

Some empirical studies have shed light on bank and market behaviour around stress test announcements. On the one hand, European and U.S. event studies indicate that markets react on stress test disclosures as these reports add new and valuable information (Carboni et al., 2017; Morgan et al., 2014; Petrella and Resti, 2013). However, not all studies find significant market responses as stress test results might correspond with market expectation (Sahin and de Haan, 2016). Also, the impact of regular stress test information appears to decrease over time (Flannery et al., 2017). On the other hand, in European studies on bank behaviour, Bischof and Daske (2013) report that stress test participants voluntarily disclose information to mitigate bad stress test signals, while Gropp et al. (2019) show that stress tests incentivise banks to manage capital. In the U.S., researchers document that stress tests influence bank behaviour with respect to lending activities (Acharya et al., 2018) and increase lobbying expenses to pass stress tests (Cornett et al., 2019). In contrast, Flannery et al. (2017) cannot confirm strong empirical evidence for Goldstein and Sapra's (2013) proposition that that stress tests affect analyst information production and short-term investment decisions.

Motivated by the growing regulatory importance of bank stress tests, I examine the following key research question. Do stress tests fulfil the goal of mitigating information asymmetry that stimulate market discipline or do stress tests have unintended (potential negative) consequences for financial stability? The main objective of this thesis is to contribute to knowledge by shedding ample light on the cost and benefits of stress tests that might be useful for regulators and policymakers (Bouvard et al., 2015; Goldstein and Sapra, 2013). In particular, I am interested in the implications of stress tests on bank behaviour, and whether bank managers adjust their accounting practices to mitigate any 'bad' regulatory market signals (Gropp et al., 2019; Flannery et al., 2017; Bischof and Daske, 2013). This thesis, therefore, provides a novel link from stress tests to three particular aspects that are widely established in the accounting and finance literature. I analyse the implications of bank stress tests on accounting discretion (Chapter 2), transparency and opacity (Chapter 3), and market discipline (Chapter 4).

In the following Sections 1.2, 1.3 and 1.4, I present for each underlying empirical chapter (i.e., study) the key research questions, methodologies, main findings and individual contributions to the relevant literature.

1.2. Bank stress tests: An active treatment or a placebo?

Banks and their accounting practices are seen as highly opaque (Flannery et al., 2013; Morgan, 2002). There is an extant literature on bank accounting discretion and manipulation that highlights that banks exercise discretion over loan loss provisioning to manage their capital and earnings. Banks usually aim to report consistent earnings growth because investors prefer such a development. Further, banks manage capital because it is a costly funding resource (Bushman and Williams, 2012; Huizinga and Laeven, 2012; Laeven and Majnoni, 2003).

Consequently, the first empirical chapter of this thesis (Chapter 2) is a study that links bank stress tests and accounting discretion. I view stress tests as a regulatory treatment that might incentivise banks to exercise accounting discretion to pass stress tests and to signal financial strength to regulators and markets. In this context, I examine the subsequent research questions. What is the effect of stress tests on the participating bank's accounting quality? In particular, do stress tests incentivise participating banks to exercise discretion over loan loss provisioning? Do banks with lower capital levels exercise more accounting discretion?

To evaluate the research questions, I gather a unique dataset of stress-tested and untested banks from 27 European countries. The accounting data comprises various variables such as asset quality and capital adequacy over a period 2005-2015, which is supplemented by hand-collected figures. I resort to propensity score matching (PSM), combined with a difference-in-difference (DiD) approach to estimate participation indicators and treatment effects on stress-tested banks. Further, relying on fixed effects regressions, I assess stress-tested bank's earnings and capital management behaviour, including institutional variables and individual capital levels.

I find a significant treatment effect of stress tests on the quality of the relevant accounting data. In particular, this study shows that banks subject to stress tests report different accounting figures in terms of asset quality and capital adequacy, compared to untested banks. While tested banks report more pro-cyclical loan loss provisions in 2010 and 2011, the overall capital adequacy of stress-tested banks was lower and increased after the 2014 stress tests. Second, stress-tested banks have stronger incentives to delay loan loss provisions to strengthen their capital adequacy ratios, which signal resilience and soundness to regulators and market players. In 2010 and 2011, stress tests motivate banks to manage capital and earnings, whilst in 2014 stress tests mitigate discretionary behaviour. Further, low-capitalised stress test participants delay loan loss provisions to boost capital, whereas medium- and high-capitalised banks increase loan loss provisions to smooth income and optimise capital, respectively. Third, I document that a more reliable institutional environment may mitigate the degree of earnings management during stress test periods. Overall, the results suggest that stress tests convey, on certain occasions, a 'placebo' image to regulators and markets, but can also be an 'active' treatment.

The contribution to the literature is threefold. First, this study is one of the first to empirically link stress tests and accounting discretion. I shed light on an implicit stress test mechanism that incentivises bank managers to exercise discretionary accounting (Wheeler, 2019; Bushman and Williams, 2012; Gebhardt and Novotny-Farkas, 2011; Beatty and Liao, 2011). Second, I contribute to the debate on the cost and benefits of stress test disclosures. The results illustrate discretion over loan loss provisions to manage earnings and capital; this is rather a cost and unintended consequence from stress tests when the results are disclosed in detail (Flannery et al., 2017; Bouvard et al., 2015; Bischof and Daske, 2013; Goldstein and Sapra, 2013). Third, my analysis relies on a unique stress test and propensity-score-matched control sample. To increase data quality, I hand-collect missing figures from annual and interim bank reports to supplement the dataset.

1.3. Transparency versus opacity: Are bank stress tests worthwhile?

Transparency reduces the informational gaps amongst economic agents and is generally accepted to promote bank performance and decreases the cost of capital. The more transparent the operation of a bank is, the more accurately outsiders can assess its value; this leads to better-informed investment decisions (Bushman et al., 2004). BCBS (1998, p. 15) defines transparency as "public disclosure of reliable and timely information that enables users of that information to make an accurate assessment of a bank's financial condition and performance, its business activities, and the risks related to those activities." Further, BCBS (1998) emphasises that more transparent disclosure is high-quality disclosure.

In the second empirical chapter of this thesis (Chapter 3), I scrutinise a bank's textual disclosures and accounting figures to assess if bank managers influence the transparency mechanism by amending their bank reports following stress test disclosures. Transparency from stress test results can provide useful information that enables markets to assess the soundness of banks. In turn, however, this may come at a cost that could lead to certain market inefficiencies (Goldstein and Leitner, 2018; Bouvard et al., 2015; Goldstein and Sapra, 2013). Further, because the outcome of the stress tests is made public, the incentives of banks to cooperate with authorities and disclose high-quality information may be lowered (Prescott, 2008). Consequently, to be subject to stress testing can incentivise bank managers to adjust their information disclosure strategies to offset the effect of negative stress test results or to enhance that of positive results (Cornett et al., 2019; Gropp et al., 2019; Acharya et al., 2018; Flannery et al., 2017; Bischof and Daske, 2013). In this context, I propose the following research questions. What is the impact of stress tests on participating banks' transparency? Does stress test language affect the sentiment and tone of participating banks' textual disclosures? Are the sentiment and tone measured in participating banks' share prices?

To address the research questions, I compose a unique dataset of stress-tested banks from 25 European countries that comprises quarterly accounting, textual and market data over the period 2005-2017. The empirical analysis is divided into a quantitative and qualitative approach. On the one hand, I establish a transparency index that measures the quantity of accounting figures within bank reports and, therefore, the level of transparency of these reports. On the other hand, I hand-collect stress test disclosures and bank reports to analyse the stress test language within the narratives of these bank reports.

In particular, I establish a word list from these stress test disclosures that, first, measures the sentiment that comes from specific words within those regulatory disclosures and, second, shows how bank reports are influenced by stress test words. I also measure the tone in bank reports to estimate if bank managers apply a more positive tone during stress test periods to mitigate negative stress test outcomes.

The study shows that stress-tested banks adjust their bank reports during stress test periods. First, I find terms and language within bank reports that is related to stress test sentiment. It is evident that the relative number of stress test words increases considerably over time, while new participants apply more stress test words compared to their regularly tested peers. Second, the stress test disclosure sentiment appears to incentivise stress test participants to change their disclosure tone towards more positive (or less negative) language. Third, I report that market measures show less information asymmetry when banks use a more positive disclosure tone. In particular, the results suggest that a more positive disclosure tone is related to a lower bid-ask spread and more analyst coverage, indicating a strengthened level of transparency. This is an indication that market participants might be obfuscated when banks use a more positive tone in their textual disclosures.

This study contributes to the literature in several ways. First, I link the stress test with the growing textual analysis literature (Henry and Leone, 2016; Loughran and McDonald, 2016). On the one hand, I establish a unique stress test word list based on frequently used words in stress test disclosures, and search for those words in the hand-collected interim and annual reports of European financial institutions. On the other hand, I connect widely established corporate word lists by Loughran and McDonald (2011a) to measure disclosure tone. Second, I provide a novel perspective on bank textual reporting behaviour with regards to stress test disclosures (Flannery et al., 2017; Bischof and Daske, 2013). Third, I expand the literature on bank transparency and opacity by examining the implications of stress test disclosures (Jones et al., 2012; Morgan, 2002).

1.4. Market discipline and financial stability: Are bank stress tests meeting expectations?

Disclosure of stress test results can provide markets with useful information about the soundness of banks and can, in turn, enhance market discipline in financial industries. The concept of market discipline relies on market monitoring and its influence on bank management (Danisewicz et al., 2018; Flannery, 2001). In principle, stress test information mitigates information asymmetry between bank managers and investors. Once investors are better-informed, they will identify risky activities and then penalise bank manager's excessive risk-taking. This may, in turn, incentivise bank managers to take more prudent decisions that can boost the level of trust in the banking system and ensure its stability (Cornett et al., 2019; Acharya et al., 2018; Flannery et al., 2017; Bischof and Daske, 2013).

In the third empirical chapter of my thesis (Chapter 4), I explore specifically the key purpose of stress tests, which is enabling markets to discipline bank risk-taking. The stress test literature provides some results on its benefits but has not yet concluded on the impact of stress tests on market discipline (Acharya et al., 2018). Since market discipline is the third pillar of the recently finalised Basel III Accord, I examine the following research questions that shed ample light on this crucial regulatory effect. Do stress tests contribute to market discipline and safeguard financial stability? What is the disciplining effect of new stress test information? What is the impact of stress test information on banks' risk-taking and funding structure?

To address the research questions, I analyse a European and U.S. sample of banks and stress test observations. My empirical analysis is twofold. First, I implement an event study approach that measures the market reactions from stress test information on bank shares. I employ various estimates that illustrate the short- and long-term effect of stress tests. In particular, I resort to the capital asset pricing model (CAPM), the Fama and French (1993) three-factors model (FF3F), and the Carhart (1997) four-factors model (C4F) to estimate the short-term cumulative abnormal return (*CAR*) and buy and hold abnormal return (*BHAR*). Further, I follow a calendar-time portfolio (CTIME) approach that shows the long-term bank performance following stress test exercises and whether stress-tested banks over-or under-perform the markets. Second, I measure the time-series effect of stress tests by applying various bank fundamentals on information asymmetry, bank risk-taking and funding structure. The purpose of this analysis is to estimate if the impact from stress tests is transferred into the investor's influence.

In this study, I document that the disciplining effect is mixed across both the European and U.S. markets as the assessments are intrinsically different from each other. In Europe, the results indicate some significant and positive market responses (e.g., the exercise in 2011), while, in the U.S., I recognise disciplining market reactions that are mainly negative (e.g., the assessments in 2013, 2016, 2017 and 2018). Further, for the majority of stress tests in both jurisdictions, I find, on average no significant abnormal return around the days of the result announcement; this implies that stress test results correspond with market expectations. However, the results also show that stress test events may push abnormal returns towards negative and positive directions. For instance, when a bank reports an overall downward trend, additional negative stress test information further exacerbates this downward trend, and *vice versa*. This holds true specifically for the U.S. 2009 SCAP (positive) and the 2011 (positive), and 2014 (negative) European assessments, whilst the negative market reactions are more persistent than the positive responses. This consequence may harm financial stability as weaker institutions are punished more. On certain occasions, the positive or negative momentum even transfers into long-term 'alphas', indicating that bank stocks over- or under-perform compared to the market portfolio.

Furthermore, I report that, supporting prior event study results, information asymmetry reduces significantly during earlier stress test periods in Europe (in 2010-11) and in the U.S. (in 2009-13). However, this finding deteriorates during more recent stress test periods. Further, the results show that analyst coverage rises for European first-time participants in 2010-11, while analyst estimates dispersion increases. Therefore, lower information asymmetry contributes to market liquidity, while some uncertainty remains among analysts. In contrast, similar to prior U.S. studies, stress tests do not substantially change U.S. analyst behaviour as the analysis provides inconclusive evidence on analyst coverage or earnings forecasts (Flannery et al., 2017). On the other hand, in both jurisdictions, stress-tested banks significantly reduce risk-taking during stress test periods as capital adequacy, insolvency risk and credit risk improves. Further, the markets reward European banks, indicated by a favourable cost and structure of funding. In particular, first-time participants in 2010-11 are affected, which implies the growing confidence of the markets and a potential learning curve of those banks. In contrast, the results are more profound in Europe than in the U.S. as I cannot find influence on U.S. banks leverage, credit risk and credit portfolio quality, nor on the funding structure.

This chapter contributes to the literature by linking stress tests and market discipline, which has not yet been fully investigated (Acharya et al., 2018). Importantly, I shed light on the influence mechanism of stress tests on market discipline and extend the related literature (Danisewicz et al., 2018; Nier and Baumann, 2006). In particular, I implement the analysis from two perspectives. First, I examine the direct impact of stress tests on market discipline as reflected in the market's sentiment (Flannery et al., 2017; Morgan et al., 2014; Petrella and Resti, 2013). I contribute to this literature by adding a complete picture of the short- and long-term disciplining effect of stress tests on participating banks' abnormal returns. Second, I expand empirical research that explores bank behaviour by showing the implications of stress tests on bank fundamentals that are connected to market discipline (Cornett et al., 2019; Gropp et al., 2019; Bischof and Daske, 2013).

The remainder of my thesis is structured as follows. Chapters 2, 3 and 4 constitute the three studies that I conduct as discussed above. In particular, Chapter 2 examines the impact of bank stress tests on discretionary behaviour. Chapter 3 scrutinises the implications of bank stress tests on quantitative and qualitative transparency. Chapter 4 explores the contribution of bank stress tests to market discipline. Ultimately, Chapter 5 concludes the thesis.

Chapter 2 – Bank stress tests: An active treatment or a placebo?

2.1. Introduction

It is widely accepted that banks play a special role in the economy. The healthy and unwavering operation of the banking sector greatly contributes to the stability of the financial system and to that of the overall economy. After the outbreak of the global financial crisis in mid-to-late 2007, supervisors and regulators had to regain the trust of market participants, the public and all the other economic players in the financial services industry. Towards this, authorities in Europe, the U.S., and elsewhere decided, amongst other actions, to conduct regular stress tests to assess the resilience of Systemically Important Financial Institutions (SIFI) to adverse macroeconomic conditions (Flannery et al., 2017; Bouvard et al., 2015; Bischof and Daske, 2013).

Stress tests simulate an adverse exogenous shock to measure the exposure of banks to common risk factors. Authorities evaluate the relevant outcome with respect to the capital adequacy and the liquidity level of banks (Borio et al., 2014). Prior to the crisis, banks conducted stress tests mainly as internal self-assessment exercises. In 2009, regulators launched large-scale stress tests of SIFIs to supply markets with specialised information on the resilience of those institutions as stand-alone accounting figures were not deemed as being sufficient to mirror banks' solvency (Schuermann, 2014). For instance, several large European banks, such as Dexia, Hypo Real Estate, Allied Irish Bank, Bank of Ireland and Anglo Irish Bank, to name a few, needed urgent financial support to withstand the consequences of the crisis, although they were complying with the regulatory requirements (Braouezec and Wagalath, 2018).

Stress tests have nowadays turned to be one of the most important tools at the hands of regulatory and supervisory authorities. Such a tool can produce several benefits to the financial system and to the economy as a whole. Carboni et al. (2017), Candelon and Sy (2015), Morgan, et al. (2014), Quijano (2014), and Petrella and Resti (2013) show that stress tests significantly reduce the informational asymmetries amongst the economic agents thereby contributing to the transparency and the stability of financial system. However, transparency is costly (e.g., Di Maggio and Pagano, 2017) and the accounting information that is utilised by regulators in carrying out stress tests can be opaque (e.g., Flannery et al., 2017; Jones et al., 2012; Morgan, 2002). Along these lines, Bouvard et al. (2015) and Goldstein and Sapra (2013) have lately developed the stress test disclosure theory, which argues that mandatory stress test disclosures may incentivise discretion to bank managers to curb the signalling effect of ‘bad news’ on market participants (Bouvard et al., 2015; Goldstein and Sapra, 2013). This theory can be linked to the well-established literature on accounting discretion (e.g., Beatty and Liao, 2014; Bushman and Williams, 2012; Gebhardt and Novotny-Farkas, 2011), according to which bank managers resort to loan loss provisions to smooth income and manage capital.

In practice, the outcome of stress tests in Europe suggests that the bank participants can be successful in both signalling soundness to authorities and also in mitigating the impact of stress test disclosures. Comparing the U.S. with the European stress test exercises conducted in the midst of the crisis, Schuermann (2014) concludes that the latter ones were lacking credibility because authorities claimed additional capital of only €3.5bn (for 7 out of the 91 banks) in 2010 and €2.5bn (for 8 out of the 90 banks) in 2011, even though the actual needs of banks later proved to be much larger. In this context, two independent assessments that were carried out by the International Monetary Fund (IMF) revealed large capital gaps in the accounts of some Irish and Spanish banks, which yet had passed all prior assessments undertaken by national authorities. On the other hand, the U.S. regulators required the amount of $75bn as additional capital requirements for more than half the participating banks. Acharya and Steffen (2014) focus on the banks that participated in the European Central Bank (ECB)’s 2014 assessment predicting larger capital shortfalls than those officially reported. Finally, in the stress test conducted by the European Banking Authority (EBA) in July 2016, almost all the assessed banks except two, i.e., Banca Monte dei Paschi di Siena and Allied Irish Bank, were found to be sufficiently sound.

Motivated by the regular and extensive stress tests conducted lately and also by their growing impact on the economy, this study empirically examines the quality of accounting information that authorities utilise in carrying out stress tests and how this affects the outcome of the tests as perceived by market participants and other economic agents. I view stress tests as a regulatory treatment and assume that tested banks have incentives to signal financial strength to regulators and markets. In this context, I address the following research questions. What is the effect of stress tests on the quality of the accounting figures that banks report? Further, do stress tests provide banks with incentives to exercise accounting discretion? If yes, what is the profile of banks, which are engaged in discretion? Do the tested banks exercise more accounting discretion compared to their untested peers? And, lastly, does a stronger institutional environment decreases the incentives of banks to resort to discretion in the context of stress tests?

I construct a unique dataset of tested and untested banks from 27 European countries, which relies upon hand-collected accounting data on asset quality, capital adequacy and earnings. Data are of a half-yearly frequency and cover the period 2005-2015. I conduct a Propensity Score Matching (PSM) analysis, which is paired with a Difference-in-Difference (DiD) approach to estimate the average treatment effect of bank stress test participation. I also resort to a fixed effects regression model to link stress tests with possible accounting discretion controlling for the impact of the institutional environment.

The contribution of this study to the literature is threefold. While the disclosure of stress test outcomes has been found to be useful for market participants, the implications of the information quality of the accounting data used in bank stress tests have not yet been explored. Therefore, I contribute to the strand of literature that analyses the costs and benefits of stress tests (Flannery et al., 2017; Bouvard et al., 2015; Bischof and Daske, 2013; Goldstein and Sapra, 2013). Second, I examine stress tests through the lenses of an implicit, underlying incentives mechanism for bank managers and executives to exercise accounting discretion. In that sense, I enhance the current literature (e.g., Beatty and Liao, 2011; Bushman and Williams, 2012; Gebhardt and Novotny-Farkas, 2011) by considering stress tests as a novel motivation for banks to apply discretion in the relevant figures they report on their books. Third, the empirical analysis relies on a unique dataset, which consists of all the available banks that participated in the European stress tests both prior to and after the onset of the global financial crisis. Secondary accounting data are widely complemented by hand-collected raw data, therefore creating an all-inclusive dataset that allows me to shed ample light on the research questions.

I document a vigorous treatment effect of stress tests on the quality of the relevant accounting figures of the participating banks. In particular, the results show that stress tests reveal both the weaknesses and the strengths of tested banks in terms of asset quality and capital adequacy. The potency of this treatment effect is found to vary significantly between different stress test exercises. More concretely, the 2010 and 2011 assessments highlight a pro-cyclical loan loss provisioning behaviour of tested banks and illustrate an increase in backward-looking non-performing loans. The strength of these findings is largely enhanced when the 2014 stress test is considered. Furthermore, tested banks are found to disclose lower regulatory capital ratios compared to untested banks, which demonstrates the difficulty of the former banks to be recapitalised. In contrast, the assessments that occurred in 2010 and 2011 show no significant difference in the capital adequacy between the tested and the untested banks, but significantly higher capital in 2014. Stress tests were moderate in terms of additional capital requirements for banks, compared to the relatively stricter 2014 exercises. In summary, the results suggest that bank accounting figures are indeed influenced by stress tests, revealing managers' incentives to mitigate regulatory interventions.

Focusing on accounting discretion practices, I find that tested banks are more likely to manage capital and earnings compared to untested banks. During stress test periods, the former banks delay discretionary loan loss provisions to boost capital adequacy. In this context, low-capitalised institutions are more motivated to do so, while high- and medium-capitalised institutions increase loan loss provisions to either optimise capital or to smooth income. I provide evidence of excess capital management and income smoothing for the banks that were stress-tested for the first time in 2010 and 2011, while the discretionary behaviour of the first-time participants in the 2014 exercise is found to be milder. I, further, report that a more resilient institutional environment constraints banks' incentive to resort to earnings management during stress test periods but has no effect on their incentives to manage their capital. Overall, the results suggest that stress tests may exacerbate banks' discretionary behaviour in order to convey a sounder picture of their operations to regulators and market participants. On certain occasions, the outcome of stress tests is considered as being a 'placebo' treatment rather that an 'active' treatment. In earlier stress tests (i.e., those conducted in 2010 and 2011) a placebo treatment prevails, while the 2014 test is closer to an active treatment mainly due to the enhancement of the authorities' learning curve, which can discipline banks more effectively.

I run various robustness checks to ensure the validity of my findings. First, I apply different probit model specifications and matching algorithms in the context of the PSM analysis to eliminate any inconsistencies due to the possible bias emerging either from covariates imbalance or matching inequality. Further, I test the robustness of the DiD approach by accounting for alternative covariates as well as for a set of additional control and environmental variables. I also incorporate banks outside the common support area in the sample to address potential hidden bias, in the context of the DiD and the fixed effects regression analyses. Moreover, I safeguard the robustness of the latter analysis by removing banks from non-EU countries as well as those with multiple stress test participation from the sample that may spoil the results. In addition, I account for banks that use local (and not international) accounting standards and for those banks which are involved in Mergers and Acquisitions (M&As) or have gone bankrupt. Overall, the robustness checks provide strong support to the findings of the baseline analysis.

The remainder of this chapter is as follows. Section 2.2 reviews the relevant studies and presents the main arguments and limitations of the extant literature. Section 2.3 develops the hypotheses I test in the empirical analysis based on the relevant research questions. Section 2.4 presents the data collection process and describes the econometric models and techniques I employ in the analysis. Section 2.5 reports and discusses the empirical results and sheds the spotlight on the relevant policy and business implications. Section 2.6 is devoted to robustness checks and Section 2.7 concludes the chapter.

2.2. Theoretical framework and related literature

This study lies upon two pillars, which are rather controversial in the banking literature. First, the literature has increasingly evaluated stress tests from different angles and concludes that the effect of stress tests on financial stability may be positive or negative. During the 2008 financial crisis, stress tests have become a very important tool for enhancing financial stability by playing a fundamental role in informing market participants about banks' solvency and rebuilding market trust. However, during normal economic conditions, stress tests and the disclosure of their outcomes can produce negative market reactions. Second, it is well-documented that bank managers exercise discretion over their loan loss provisions (*LLP*), which have been highlighted as being the key discretionary tool to manage both earnings and capital. While accounting discretion that reduces information asymmetry is positive, short-sighted accounting practice is on the negative side of *LLP*.[4] In this study, I argue that stress tests may not convey reliable information to markets and may be utilised by bank managers to signal soundness as bank accounting information can be influenced by discretionary behaviour.

[4] The literature consists of other streams that evaluate stress test methodologies (e.g., Gross and Población, 2015; Acharya et al., 2014; Buncic and Melecky, 2013) and misreporting (i.e., accounting fraud, cooking the books, etc.) combined with enforcement actions (e.g., Silvers, 2016; Peterson, 2012; Erickson et al., 2006), which I do not present here as they are not closely linked to my study.

2.2.1. Stress tests, transparency, and financial stability

Several event studies illustrate that the disclosure of stress test results leads to a reduction in bank opacity. Focusing on the reaction of the U.S. (Candelon and Sy, 2015; Morgan et al., 2014; Quijano, 2014) and European (Carboni et al., 2017; Petrella and Resti, 2013) markets to stress tests, the literature rejects the irrelevance hypothesis that markets ignore stress test results. Evidence is indeed provided for significant market reactions shown through abnormal share or bond price variations of tested banks before and after the disclosure of the stress test results. These studies conclude that the observed outcome of stress tests cannot be predicted and, hence, can provide novel and valuable information that mitigates informational asymmetries in the market. In contrast, Flannery et al. (2017) argue that the positive influence of regularly conducting stress tests on the U.S. market has decreased over time. Similarly, Sahin and de Haan (2016) display that the European markets did not react to EBA's 2014 stress test because market players were expecting those results. According to their view, the benefits of stress tests are linked to the authority's increased learning curve through the in-depth investigation of the participating institutions.

Borio et al. (2014) and Schuermann (2014) conclude that stress tests are an effective crisis management tool, but cannot be used as an early warning mechanism. Both studies find that the success of stress tests in enhancing financial stability depends on the level of credibility of scenario analysis and the coherence in the implementation of the tests. In fact, these two aims are essentially easier to be achieved during a crisis than in normal times because selecting a single scenario for all banks is less difficult in the case of a financially distressed environment compared to normal economic conditions where multiple scenarios need to be shaped and examined. This is to say; regulators may not be able to develop credible scenarios to signal the level of soundness of the financial system when the economy grows.

The increase in transparency through the disclosure of stress test results can be beneficial during times of distress, but harmful during normal economic and financial conditions. Based on a theoretical model, Bouvard et al. (2015) illustrate that the enhancement of transparency in a crisis period can reduce uncertainty among banks and contribute to financial stability. In contrast, increased transparency in normal times undermines market trust and is likely to lead to a run on weak banks. Furthermore, the authorities might waive negative information concerning individual banks to avoid adverse market reactions.

Along these lines, Goldstein and Sapra (2013) propose that during crises detailed information should be published to give markets the opportunity to determine with the additional information which banks are sound or unsound. For instance, detailed results were provided after EBA's 2011 stress test and the Irish exercise, which increased credibility in the markets during times of uncertainty (Schuermann, 2014). However, Goldstein and Sapra (2013) further suggest that during normal times the regulators should provide no disclosure or only aggregated results and should be mindful with the type of disclosure to avoid over-reactions from the markets and participating banks. In particular, stress test disclosures might motivate banks to make inefficient short-term decisions to pass stress tests, while failing to accommodate the potential adverse long-term effects of those decisions. Although Flannery et al. (2017) cannot find evidence in the U.S., this conceptual view is partly confirmed in the European context. Bischof and Daske (2013) analyse the effects of CEBS's 2010 and EBA's 2011 stress tests and the following capital exercise in 2012 on participating banks' disclosure behaviour. Their empirical results indicate that tested banks increased their voluntary disclosure of sovereign risk exposure in response to the mandatory stress test results. Consequently, banks do not underestimate the signalling effect that stress test disclosures can convey to the markets.

2.2.2. Quality of accounting information and loan loss provisioning

Banks typically use provisions to build reserves against loan losses to cover expected losses, whereas capital should absorb unexpected losses. However, owing to discretionary accounting choices, banks may understate or delay current *LLP* in the presence of low profitability, and *vice versa*. This behaviour might overshadow future bank performance because it hides the actual level of the loan portfolio risk and, hence, the required capital buffers. In case of a delayed loan loss recognition, capital needs to cover both the expected and unexpected losses (Bushman and Williams, 2015; Beatty and Liao, 2011; Laeven and Majnoni, 2003). In the following subsections, I focus on income smoothing and capital management as the main motives for discretion. As regulators evaluate bank soundness using earnings and capital adequacy measures within stress test exercises, both incentives to resort to discretionary *LLP* might be exacerbated by stress test participation.

2.2.2.1. Income smoothing

First, income smoothing, also known as earnings management, indicates that investors prefer and reward steady earnings increases (Barth et al., 1999; DeAngelo et al., 1996). Many studies document that managers influence bank performance by making specific accounting choices, such as discretion over *LLP*, to become more attractive to investors. For instance, the extent of income smoothing through *LLP* depends on banks' profitability and loan portfolio structure (Liu and Ryan, 2006), economic cycles (Laeven and Majnoni, 2003) and dispersed ownership (Beatty et al., 2002; Beatty and Harris, 1999). The latter studies argue that private banks have less motivation to smooth income as their investors suffer less under information asymmetry and are more long-term orientated. Thus, private bank owners do not penalise unstable earnings as much as public banks' shareholders. In another study, Nichols et al. (2009) show that public banks recognise timelier loan losses to manage earnings to decrease information asymmetry.

From a regulatory accounting perspective, Fonseca and González (2008) compare a global sample and argue that stricter rules on accounting disclosures, bank activities and regulation can reduce income smoothing incentives. This view is partly supported by Gebhardt and Novotny-Farkas (2011), who find European evidence for income smoothing through discretionary *LLP* and further illustrate that mandatory International Financial Reporting Standards (IFRS) adoption and stronger rules in International Reporting Standards (IAS) 39 decrease banks' ability to exercise discretion over *LLP* to manage earnings. In contrast, they argue that stricter accounting regimes cannot completely eliminate discretionary behaviour. For instance, part of their findings suggests that, after IFRS adoption, *LLP* were less timely. This result is consistent with Pérez et al. (2008), who analyse Spanish banks and display that stricter *LLP* rules do not discourage managers from income smoothing practices.

Furthermore, specific accounting practices can be observed from the risk-taking and discipline perspective, which enables investors and supervisors to monitor banks. For instance, Bushman and Williams (2012) conclude that banks' discretion over *LLP* may have a positive or negative impact on discipline of bank risk-taking. When bank managers exercise discretion to decrease perceived risk, it curbs market discipline, but discretion that reduces information asymmetry through forward-looking disclosures should strengthen market discipline. Considering the financial crisis, other research shows that *LLP* can be triggered by bank competition (Bushman et al., 2016) and can negatively influence the financial strength of individual banks and exacerbate systemic risk (Bushman and Williams, 2015). Overall, managing earnings propose more soundness to markets and regulators. Hence, I posit that banks participating in stress tests might be particularly interested in applying income smoothing.

2.2.2.2. Capital management

Second, capital management refers to banks' motivation to optimise their capital efficiently to meet regulatory capital requirements and buffers. Analysing distinct capital regimes, many studies consistently find evidence for capital management using the discretionary portion of *LLP* (Ahmed et al., 1999; Beatty et al., 1995; Collins et al., 1995; Moyer, 1990). In particular, low-capitalised banks during the post-Basel I period delayed their *LLP* in response to the regulatory change to avoid non-compliance with capital requirements (Kim and Kross, 1998).

Examining the 2008 financial crisis, Allen et al. (2011) and Thakor (2012) document the positive impact of capital on survival likelihood. Their models predict that capital attenuates banks' motivation to invest in risky and innovative products and decreases moral hazard. Focused on financial distress, Berger and Bouwman (2013) conclude that the likelihood of bankruptcy before and during a crisis is lower for small banks that hold more capital. However, the impact of capital on medium and large banks depends on the banks' situation and is only ensured during crises. Consequently, the recent banking regulation amendments in Basel III (Pillar 1) require that banks raise capital standards supplemented by leverage and liquidity ratios. This implies that banks hold more common equity (Tier 1 capital) and additional capital buffers to cover distinct risks of counterparties, securities and trading books. Further, under Basel III, *LLP* decrease Tier 1 capital by reducing retained earnings. However, loan loss reserves (*LLR*), up to a maximum of 1.25% of credit risk-weighted assets, may be added back to Tier 2 capital and boost total regulatory capital (Ng and Roychowdhury, 2014; BCBS, 2011).[5]

Due to the continuously increasing focus on regulatory capital requirements, banks seem to have a higher need to optimise their capital adequacy ratios. Towards this, empirical evidence on the financial crisis shows that banks managed capital requirements intensively towards their goals. Huizinga and Laeven (2012) argue that banks with

[5] Details on Basel III may be accessed on the Bank for International Settlements (BIS)'s website: https://www.bis.org/bcbs/basel3.htm.

relatively high amounts of mortgage-backed securities contracts had significantly lower *LLP* in their accounts in 2008 to manage their capital ratios. In another study, Beatty and Liao (2011) illustrate that delayed recognition of expected loan losses were widely used in the financial crisis to optimise capital which led to increased pro-cyclicality and exacerbated the credit crunch. Further, Bierey and Schmidt (2017) argue that in the sovereign debt crisis banks delayed write-offs on Greek government bonds to strengthen capital and to receive higher governmental support. Hence, those studies support my view that stress tests might enhance capital management activities as those exercises focus on capital adequacy to signal soundness.

2.3. Hypotheses

2.3.1. Stress test signal and accounting quality

The results of stress tests, provided by the banking regulators, are supposed to supplement the available information in the market to sketch out banks' strengths and weaknesses (Schuermann, 2014). With this additional information the authorities aim to enhance transparency that enables market participants to discipline bank risk-taking towards financial stability. Despite banking regulators and investors have not necessarily the same interests, both groups share the common goal of avoiding severe financial distress and business disruptions (Schaeck, et al., 2012). On certain occasions, regulators would not mind banks being less transparent and having lower accounting quality for investors if this opacity assists banks to build larger reserves or to utilise more equity finance than shareholders might permit under better transparency. For instance, bank opacity may benefit liquidity and risk sharing purposes (Dang et al., 2017; Bushman, 2014). However, the importance and the purpose of stress test information, produced and published by the authorities may be justified for two main reasons. First, stress test reports disclose bank-specific regulatory information to restore and maintain the market's trust during crises and normal economic times, respectively (Bouvard et al., 2015; Borio et al., 2014). For this higher public interest of financial stability, regulators make an exception and publish regulatory information that would be kept confidential under normal circumstances (Feldberg and Metrick, 2019; Bushman, 2014).

Along these lines, the disclosure theory (see, e.g., Bagnoli and Watts, 2007; Einhorn, 2005; Dye, 1990) distinguishes between two types of disclosure. First, the mandatory disclosure that refers to the information that is required to be disclosed in line with the regulatory framework; and, second, the voluntary disclosure that is reflected in the additional piece of information that banks optionally disclose. The disclosure of stress test results is mandatory and is likely to be costly for banks in case it conveys a ‘bad’ signal to the market. In such a case, banks would prefer the relevant information not to be disclosed. This is, however, not feasible due to the mandatory character of stress tests and, hence, banks have incentives to shape a disclosure strategy that aims to offset the ‘bad’ stress test signal through a responsive voluntary disclosure.

Analysing European stress tests, Bischof and Daske (2013) find that the tested banks increased their voluntary disclosure of sovereign risk exposures in response to the stress test results. In addition to this, it is rational for bank managers to attempt to mitigate a possibly bad signal in anticipation of stress tests. Goldstein and Sapra (2013) conclude that stress tests can provide banks with incentives to take short-term investment decisions that may contribute to a positive outcome, notwithstanding the potentially negative long-term consequences of these decisions. Such a signalling game cultivates an environment in which market players can be misguided like in the years preceding the 2008 financial crisis (Bouvard et al., 2015). In my analysis, I focus on both tested and untested banks and use a set of key regulatory variables to examine if the accounting information that regulators utilise in the conduct of stress tests is influenced by banks’ incentives to hedge the stress test signals. I therefore formulate the following two hypotheses:

H1. *The quality of accounting figures is enhanced for the stress-tested banks.*

H2. *Stress tests provide banks with incentives to exercise accounting discretion.*

2.3.2. Stress test participation and discretionary behaviour

The literature documents that banks widely use loan loss provisions as the principal discretion channel to manage their earnings and capital (Bushman and Williams, 2012; Huizinga and Laeven, 2012; Beatty and Liao, 2011). Further, Bierey and Schmidt (2017) suggest that banks may overstate capital to avoid regulatory enforcements. On the other hand, according to Basel III, there is a regulatory demand for increased quality of capital buffers. Moreover, stress test disclosures, such as the EBA’s 2016 results, recognise that the amount (and change) of credit losses from non-performing loans (the so-called Credit Risk driver) is the main contributor in scenarios reducing capital adequacy ratios and earnings figures (EBA, 2016). Hence, the stress test participants are likely to exercise more discretion over loan loss provisions than non-participants to mitigate the Credit Risk driver and to smooth the impact on their capital adequacy and earnings, which could produce a poor signal through regulatory stress test disclosures. It is thus important to shed the spotlight on the stress test participation and examine whether the tested banks exercise more discretion over loan loss provisions compared to their untested peers.

H3. *Tested banks exercise more accounting discretion compared to their untested peers.*

In addition, the literature accounts for the impact of the institutional environment on the level of accounting discretion. A robust environment is considered to impose limitations on banks' discretionary practices (Bierey and Schmidt, 2017; Bushman and Williams, 2012; Gebhardt and Novotny-Farkas, 2011). Moreover, the theory suggests that corruption can have severe consequences on the operation and the growth of a business (Shleifer and Vishny, 1993). Beck et al. (2006) link the regulatory framework with the level of corruption in banking. Therefore, I test the influence of the institutional environment on banks' discretionary behaviour in terms of supervisory power, capital regulation requirements, and corruption.

H4. *A stronger institutional environment leads to a decrease in accounting discretion.*

2.3.3. Low capital levels and discretionary behaviour

As earlier indicated, a key determinant of the individual performance of banks in the light of stress tests is the level of capital adequacy. Kim and Kross (1998) argue that the relatively low-capitalised banks are more prone to regulatory intervention and, hence, they have stronger incentives to exercise accounting discretion to manage their capital upwards. In this vein, Bierey and Schmidt (2017) show that financially distressed banks are those that manage their level of capital in order to avoid an intervention from regulatory authorities. Candelon and Sy (2015) and Goldstein and Sapra (2013) document that banks with relatively low capital are anxious about the outcome of stress tests and therefore aim to strengthen their capital adequacy ratios. Consequently, my last hypothesis tests whether the treatment banks resort to accounting discretion to a higher degree compared to the untested institutions with the purpose to demonstrate an enhanced performance in stress tests.

H5. *Treatment banks with lower capital buffers exercise more accounting discretion.*

2.4. Empirical analysis

In this section, I illustrate the construction of the stress test samples and data as well as the empirical models that I employ in my analysis. The description of variables and the relevant data sources are provided in Table 2.1.

[Please refer to Table 2.1 here]

2.4.1. Sample selection

The Committee of European Banking Supervisors (CEBS) undertook the first stress tests in Europe in 2009 and 2010. A year later, its responsibilities were handed over to EBA, which conducted a series of stress tests in 2011, 2014 and 2016. In a similar vein, the ECB comprehensively assessed all the SIFIs in the Eurozone in 2014 and 2015. I construct the sample of treatment banks based on the stress test exercises that were conducted by CEBS, EBA, and ECB over the period 2010-2016. The names of the banks that participated in the CEBS's 2009 exercise were not specified and this justifies why it is not included in my dataset.[6]

As shown in Table 2.2, Panel A, the initial sample of the entire population of treatment banks (*TREATALL*) consists of 187 institutions from 25 European economies. I identify the treatment banks based on the regulatory stress test reports (EBA, 2011, 2014, 2016; ECB, 2014, 2015; CEBS, 2010) and I select those banks on Bureau van Dijk (BvD) Bankscope.[7] Following Bischof and Daske (2013) and Carboni et al. (2017), I take a broad perspective considering the European Union (EU) and the European Free Trade Association (EFTA) economies. I begin with the 28 EU member states which are, however, reduced to 24 states, as there were no stress-tested banks in Bulgaria, Romania, Croatia and the Czech Republic. I then proceed to include Norway in my sample, which is the only EFTA member state that contributes to the stress test observations.

[Please refer to Table 2.2 here]

A total of 98 banks were assessed for the first time in the 2010-11 stress tests, while 77 banks were first assessed in the 2014 test. Only a small number of sample banks (12

[6] The relevant press release of the CEBS does not provide the names of the stress-tested banks; it simply states that "22 major European cross-border banking groups" were tested. For further details on this, see: http://www.eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing/2009.

[7] Apart from Deutsche Bank Malta, I identify all banks on BvD Bankscope by name, as shown in stress test disclosures.

banks) were first assessed in a subsequent stress test exercise, meaning that the most systemically important banks were those assessed in the first three stress test exercises. I therefore use two dummy variables, i.e., *TREAT1011* and *TREAT14* to capture the first-time participants. I group the first-time participants in the 2010-11 stress tests together because the two tests were carried out one after the other within a very short period of time. In addition, the banks that were stress-tested in 2010 were (almost) the same with those tested in 2011 as shown in Table 2.2 (Panel A).

As regards the geographical structure and density of participation in stress tests (as shown in Table 2.2, Panel A), the majority of the stress-tested banks are from France, Germany, Italy and Spain, which are the four largest European (and Eurozone) economies with the biggest banking sectors. It is worth to note that the EBA and ECB select their samples based on their supervisory responsibilities. The EBA examines SIFIs from the entire EU and the ECB reviews banks from EMU economies. Consequently, ECB's comprehensive assessments in 2014 and 2015 consider large subsidiaries from non-EMU countries (e.g., HSBC France). Owing to the disparity of selection approaches, the treatment sample consists of 171 parent banks and 16 subsidiaries. The treatment sample comprises a variety of commercial banks, savings banks, cooperative banks and bank holding companies (according to BvD Bankscope classification). I exclude 36 banks due to a lack of data availability and/or inconsistency (e.g., from M&As and bankruptcies) that could not be manually corrected; see Table 2.2, Panel B for more information.[8] This sample construction process leads me to a total treatment sample (*TREATALL*) of 151 banks, including subsamples of 86 and 60 first-time participants in 2010-11 (*TREAT1011*) and 2014 (*TREAT14*), respectively. The remaining 5 banks, not included in the sub-samples (i.e., 151-86-60=5), participated in a later stress test exercise for the first time.

As I describe in Section 2.4.5.1, the PSM approach requires to construct a suitable benchmark portfolio of untested banks. Following the European authorities' geographic sample structure, the sample of treatment banks covers the 69.5% of the entire European market size (EU and EFTA) based on total (year-end 2015) consolidated assets. Thus, the benchmark portfolio is congregated from the pool of the remaining 30.5% of total assets. I further adjust the benchmark portfolio and include only banks that have the same business classification as the treatment sample (i.e., mainly commercial banks, savings

[8] As I aim to analyse a complete treatment sample, I do not generally exclude banks due to bankruptcies, consolidations or M&As. Thus, banks with sufficient data quality remain in the sample. I run a robustness check including an additional covariate for banks' activity status (*ACTIVE*) and receive similar results.

banks and cooperative banks). As data availability for most inactive banks is inconsistent, I select only banks that are classified as 'active' on BvD Bankscope. Further, I carefully analyse banking groups and their subsidiaries and remove banks that are clearly not independent to avoid having an inflated benchmark portfolio.[9] Overall, the control group consists of 367 banks from 27 countries as described in Table 2.2, Panel A. The groups of control banks for *TREAT1011* (432 banks) and *TREAT14* (372 banks) are augmented by 65 and 5 banks, respectively. These banks participated in a stress test conducted at some later point in time. I follow the PSM literature that suggests to adjust control groups as appropriate (Flannery et al., 2017; Casu et al., 2013; Caliendo and Kopeinig, 2008).

2.4.2. Data construction

I first refer to the BvD Bankscope to collect the accounting data that I need to construct the variables. The data period covers the years from 2005 to 2015. To confirm the validity and consistency of my data, I utilise three additional mainstream databases: Bloomberg, Thomson Reuters Worldscope and SNL Financial. Due to some gaps and inconsistencies I identify in some data series, I follow Gebhardt and Novotny-Farkas (2011) and Hamadi et al. (2016) to supplement the available data by hand-collecting any missing or erratic figures. Towards this, I resort to the individual banks' financial statements that I obtain from their official websites, or from Bloomberg's corporate filings archive. Hand-collection enables me to construct a much more complete dataset by enriching the number of observations and enhancing the reliability of my data series.

Due to the different reporting policies in some sample economies, the reporting frequency varies. To ensure consistency, I require a bank to provide accounting data at least on a half-year basis. Since most of the banks are systemically important both at the European level (Global-SIFIs) and also at their home countries (Domestic-SIFIs) as dictated by the EBA Guidelines and the Basel Committee recommendations for SIFIs (Castro and Ferrari, 2014), they all meet this reporting requirement.

[9] I follow BvD Bankscope definitions by using the criteria 'Status' ('active') and 'BvD Independence Indicator' (A, U, -) to identify inactive and subsidiaries, respectively. I manually cross-check the extracted data to eliminate errors. Moreover, as Lichtenstein has no significant banking sector, no bank could hold those criteria and, hence, where automatically excluded.

2.4.3. Key variables

I rely on the regulatory stress test reports (EBA, 2011, 2014, 2016; ECB, 2014, 2015; CEBS, 2010) in combination with the stress test literature (Acharya et al., 2018; Carboni et al., 2017; Flannery et al., 2017; Bischof and Daske, 2013) to identify all the accounting variables on bank performance and risk-taking, which are linked to stress tests. In the PSM analysis, I measure asset quality using loan loss provisions (*LLP*) as a forward-looking measure, and non-performing loans (*NPL*) as a backward-looking measure; capital adequacy is captured by the Tier 1 regulatory capital ratio (*T1R*); the credit risk profile of banks is reflected in the risk-weighted assets (*RWA*).

Further, I refer to the accounting discretion literature (Hamadi et al., 2016; Beatty and Liao, 2014; Bushman and Williams, 2012; Gebhardt and Novotny-Farkas, 2011) and utilise *LLP* as the dependent variable in my fixed-effects regression model, controlling for *NPL*, the growth in outstanding loans (*ΔLOAN*) and the change in non-performing loans (*ΔNPL*) to isolate the discretionary component of *LLP*. In addition, I capture capital management by referring to *T1R*, while I measure income smoothing using the earnings before provisions and taxes (*EBPT*). To mitigate estimation problems arising from possible outliers, I follow the banking literature (Gropp et al., 2014; Beatty and Liao, 2011) and winsorise all variables at the 1 and 99 percentiles.

2.4.4. Descriptive statistics and correlation tests

Table 2.3 reports the descriptive statistics of the bank-specific variables for the groups of treated and untreated (control) banks (Panel A and Panel B, respectively). On average there are some differences and similarities between treatment and benchmark banks that I need to address in my PSM analysis to find adequate matches. I test the statistical significance of those variables by t-statistics (see also, Table 2.5, Panel B). First, based on the natural logarithm of total assets (*SIZE*), treatment banks report 11.1, whilst benchmark banks account 6.4. Thus, treatment banks are on average larger than their untreated counterparts. However, the minimum, maximum and standard deviation indicate similar distributions among both samples. As EBA and ECB overview banks from distinct economies, where relatively small banks count as SIFIs, the treatment samples also account for smaller banks.

[Please refer to Table 2.3 here]

Second, the average portion of traditional assets, such as outstanding loans (*LOAN*), yields on average 58.8% for treated banks, which is lower compared to untested banks (78.4%). In contrast, treatment banks' asset composition has a higher average portion of non-traditional earning assets (*OEA*) than benchmark banks. The relevant means are equal to 36.20% and 20.00%, respectively. This implies that treatment banks' business models appear to be riskier compared to untested banks' business models. Further, the general loan quality, measured by a higher portion of loan loss reserves (*LLR*), appears to be lower for treatment (2.4%) compared to their counterparts (1.2%). Third, benchmark banks have higher bank capital (*CAP*), regulatory capital adequacy (*T1R*) and deposits and short-term funding (*DSFR*), indicating stricter compliance with capital and liquidity requirements. Fourth, from an income statement perspective, return on assets (*ROA*) indicate that both samples have on average similar profitability.

[Please refer to Table 2.4 here]

Table 2.4 provides the Pearson pairwise correlation coefficients for the variables I use in the PSM analysis (Panel A), and for those used in the fixed-effects regression analysis (Panel B). Panel A shows that it is only outstanding loans (*LOAN*) and other earnings assets (*OEA*) which are strongly correlated (-85.80%) at the 1% level of significance. For this reason, I discard *LOAN* from the PSM baseline analysis. Panel B reveals a moderate positive correlation between loan loss provisions (*LLP*) and loan loss reserves (*LLR*) as well as non-performing loans (*NPL*), which accounts for the non-discretionary portion of loan loss provisions and is confirmed by the literature (Bushman and Williams, 2012, 2015). I also report a highly significant positive correlation between *LLR* and *NPL* (87.80%), which is consistent with the accounting discretion literature (Beatty and Liao, 2014; Gebhardt and Novotny-Farkas, 2011). To avoid possible multicollinearity, I exclude *LLR* from the fixed effects regression analysis. Further, a statistically significant positive correlation of 41.50% is observed between *LLP* and earnings (*EBPT*), which is also in line with the accounting discretion literature (Hamadi et al., 2016; Kim and Kross, 1998).

2.4.5. Empirical models

To test the hypotheses, I conduct a PSM analysis paired with a DiD and a fixed effects regression analysis.

2.4.5.1. The PSM analysis

PSM, which can be traced back to the Roy-Rubin model (Rubin, 1973; Roy, 1951), has been widely employed in social sciences (e.g., Lechner, 1999; Taylor et al., 1999; Heckman and Robb, 1985), but also in the accounting and finance literature (see, Shipman et al., 2017). In banking, PSM has been utilised to measure the treatment effect of public guarantees on bank risk-taking (Gropp et al., 2014), to account for securitised and non-securitised bank activities (Casu et al., 2013), and to control for corrupted and non-corrupted environments (Smith, 2016). Caliendo and Kopeinig (2008) argue that PSM can be applied in any empirical framework that aims to observe a treatment by identifying two entity groups: one that receives the treatment, and a second one which does not. In this analysis, stress test participation specifies the groups of banks: treated versus untreated (control) banks. The treatment sample is selected by resorting to stress test disclosures, which represents about 70% of the population of stress-tested banks, while the control sample is matched by using control variables based on regulatory criteria and the related literature. In what follows, I show how I apply PSM in this study.[10]

PSM is implemented in three steps: first, I estimate the propensity scores; I then match the treated with the untreated banks; and, finally, I measure the average treatment effect of stress tests on treated banks. I repeat this process three times to receive matched control banks for the three distinct stress test participation samples (i.e., *TREATALL*, *TREAT1011*, and *TREAT14*) as discussed in Section 2.4.1. To calculate propensity scores, I run a probit model based on the common support option:

$$P\left(X_{iT_0j}\right) = Pr\ (TREAT = 1|X_{iT_0j}) \tag{2.1}$$

where, $P\left(X_{iT_0j}\right)$ is the propensity score for sample bank i at country j that is estimated over the pre-treatment period T_0. This equals to the probability of a bank to be a member of the treatment group (*TREAT* = 1, which stands for one of the three stress test participation samples (i.e., *TREATALL*, *TREAT1011*, and *TREAT14*) that is conditional on the covariates vector X_{iT_0j}. Covariates must be estimated prior to the treatment so that they are not influenced by the treatment itself (independence condition). Thus, covariates are measured for each sample bank over the pre-treatment period T_0 that varies for each of the three samples. Following Gropp et al. (2019), I employ extended periods (including

[10] A detailed theoretical framework of the PSM approach is provided on pages 222-225 of the APPENDIX.

three semesters or more) prior to the treatment event to average out confounding events such as contemporaneous changes in fiscal and monetary policy, or market overreactions during the twin (financial and fiscal) European crises. For the total stress test participation (*TREATALL*), T_0 extends from the second semester of 2005 (2005S2) to the second semester of 2008 (2008S2); T_0 covers the period 2008S2-2009S2 for the first-time participation in 2010-11 (*TREAT1011*); and, finally, T_0 spans from 2012S2-2013S2, for the first-time participation in 2014 (*TREAT14*).

As described in the PSM framework (see, APPENDIX), the selection of the model covariates hinges upon certain stress test criteria (i.e., relevant bank characteristics) that regulators use to decide which bank should participate in stress tests or be left out. Banks are selected by the authorities to participate in stress tests based on their size in relation to national economic strength, which is a crucial determinant of systemic importance (Carboni et al., 2017; Bischof and Daske, 2013). Thus, I control for bank size by referring to the natural logarithm of total assets (*SIZE*) and economic strength measured by the nominal Gross Domestic Product (*GDP*). Further, I account for the non-traditional banking activities captured by other earning assets (*OEA*); credit portfolio quality measured by loan loss reserves (*LLR*); liquidity risk captured by the deposits and short-term funding ratio (*DSFR*); the equity-to-assets ratio reflected by bank capital (*CAP*); and profitability measured by returns on assets (*ROA*).[11]

After the estimation of the propensity scores for the treatment and control samples, I proceed to select the matching algorithm from the group of widely used algorithms (e.g., ‘Kernel’, ‘Nearest-neighbour’, ‘Radius’, etc.). According to Caliendo and Kopeinig (2008), the choice of the matching estimator depends on the data structure, which is characterised by a trade-off between bias and efficiency. Gaussian Kernel Matching (GKM)[12] is a non-parametric matching estimator that performs matching on estimated Kernel weights of all sample banks within the common support area. It depends on the

[11] Following the suggestion of an anonymous reviewer that regulators may select banks to participate in stress tests based on the level of their loan loss provisions, I also incorporate *LLP* in Equation 2.1. However, I find that *LLP* is non-significant, indicating that provisions are not a crucial factor in the decision of regulators to select the stress test banks. Moreover, excluding Swiss banks from my control samples does not significantly affect the baseline results. All results are available upon request.

[12] Another popular matching method is that of Nearest-neighbour, which considers the closest control matches of each treatment bank based on the estimated propensity scores. While the Nearest-neighbour estimator may reduce bias, it uses significantly fewer control observations which comes at the cost of decreased precision (Smith and Todd, 2005; Dehejia and Wahba, 2002). After testing several matching estimators, I find that GKM is the most appropriate one for my dataset (see also the robustness section).

distances between the propensity scores of treatment and control banks. Suitable control matches receive a higher weight than non-suitable ones. It further allows to employ Kernel weights in the fixed effects regression analysis that I describe in the following Section 2.4.5.2. To reduce possible matching bias, I employ the so-called 'trimming' that enables to smooth the high densities of propensity scores, while the bandwidth parameter allows a tolerance level of Kernel weights (Smith and Todd, 2005). Ultimately, this process yields, respectively, matched treatment and control groups of 132 versus 122 (*TREATALL*), 71 versus 108 (*TREAT1011*), and 55 versus 87 (*TREAT14*) European banks (see, Section 2.5.1 and Tables 2.5 and 2.6 on the PSM and DiD results).

Then, conditional on the estimated propensity scores $P(X_{iT_0j})$ obtained by Equation 2.1, the treatment effect of stress tests on tested banks (τ_i) that I estimate in the context of *H1* may be written as follows:

$$\tau_i = E\left(\Delta y_{i(T_1T_2)j}(1)\middle|TREAT = 1, P(X_{iT_0j})\right) - E\left(\Delta y_{i(T_1T_2)j}(0)\middle|TREAT = 0, P(X_{iT_0j})\right) \quad (2.2)$$

where $E\left(\Delta y_{i(T_1T_2)j}(1)\middle|TREAT = 1, P(X_{iT_0j})\right)$ stands for the mean difference in the outcome of treated banks and $E\left(\Delta y_{i(T_1T_2)j}(0)\middle|TREAT = 0, P(X_{iT_0j})\right)$ is the mean difference in the outcome of untreated banks within the common support area and accounting for Kernel-weighted propensity scores. *TREAT* is the parameter that stands for total stress test participation (*TREATALL*), first-time participation in 2010-11 (*TREAT1011*) and 2014 (*TREAT14*) as defined in Equation 2.1. $\Delta y_{i(T_1T_2)j}$ denotes the weighted average change in the outcome variables (y) of each bank i over the post-treatment period T_2 that follows stress tests, minus the pre-treatment period T_1 that precedes the exercise. These outcome periods (T_1, T_2) vary for each of the three stress test samples. For the total stress test participation sample (*TREATALL*) the pre-treatment period T_1 exceeds from 2005S2-2008S2 and the post-treatment period T_2 covers 2009S2-2015S2 (*BAST*). For the first-time participants in 2010-11 (*TREAT1011*) and 2014 (*TREAT14*) the outcome periods (T_1, T_2) comprise four half-year periods before and after the particular exercise; i.e. the pre-treatment periods T_1 span respectively from 2008S1-2009S2 and 2012S1-2013S2, while the post-treatment periods T_2 extends respectively from 2010S1-2011S2 and 2014S1-2015S2 (*BAST1011*, *BAST14*).

Eventually, (τ_i) yields the average difference, or DiD, of the two individual differences in the outcome variables of the treatment over the control group. In other words, the average stress test effect on participating banks is predicted as the difference between the stress-tested banks after stress test participation and that of the banks that had *ex ante* the probability of stress test participation but were not selected. The outcome variables (*y*) measure this average treatment effect of regulatory stress tests that are asset quality (*LLP* and *NPL*), capital adequacy (*T1R*), and credit risk exposure (*RWA*).

2.4.5.2. Fixed effects models

In the second part of my analysis, I test *H2* and introduce stress tests as a particular incentive for banks to resort to accounting discretion practices. Further, I suspect stress-tested banks to exercise more accounting discretion than their untested counterparts (*H3*). Accordingly, I follow the extant accounting discretion literature (i.e., Bushman and Williams, 2012; Fonseca and González, 2008; Gebhardt and Novotny-Farkas, 2011) and build the subsequent fixed effects models that I pair with prior PSM and DiD analysis to capture the effects of stress test participation on banks' discretionary behaviour.

Based on the literature and the stress test reports, the main measures of discretionary accounting practices on *LLP* are capital management (*T1R*) and income smoothing (*EBPT*). To analyse the impact of stress test exercises (i.e., stress test participation and periods), I allow for interactions between the main independent variables, i.e. capital management (*T1R*) and income smoothing (*EBPT*), and two dummy variables that constitute stress test participation as well as pre- and post-treatment periods. Stress test participation is measured using the three distinct treatment samples that I develop in Section 2.4.5.1 (i.e., *TREATALL*, *TREAT1011*, and *TREAT14*). These time-invariant dummy variables take the value one for receiving the stress test treatment and zero otherwise. It should be noted that I use Kernel weights that I receive from the PSM analysis to enhance comparability of the treatment and control groups. Suitable control matches receive a higher weight than non-suitable ones.

Similar to Section 2.4.5.1, the pre-and post-treatment periods, that isolate the stress test effect, are estimated differently for total stress test participation (*TREATALL*) and the first-time participation in 2010-11 (*TREAT1011*) and 2014 (*TREAT14*). For total stress test participation (*TREATALL*), I create a dummy variable that measures 'hot' and 'cold' stress test periods (*STHC*), taking the value of one for 'hot' stress test periods (i.e., 2009S1-2011S2 and 2014S1-2015S2) and zero for 'cold' (i.e., 2005S2-2008S2 and 2012S1-2013S2). For first-time participation in 2010-11 (*TREAT1011*) and 2014

(*TREAT14*), I employ dummy variables that estimate the exact outcome period that is four half-year periods before and after stress tests (*BAST1011* and *BAST14*). The variables take the value of one for the post-treatment periods after the 2010-11 and 2014 stress tests (i.e., 2010S1-2011S2 and 2014S1-2015S2, respectively) and zero for the pre-treatment periods before the 2010-11 and 2014 stress tests (i.e., 2008S1-2009S2 or 2012S1-2013S2, respectively). The outcome periods are consistent with the periods T_1 and T_2 in Section 2.4.5.1 as well as the 'hot' and 'cold' stress test periods, and *vice versa*. The cut-off point that separates between the periods before and after the treatment is the first half-year bank report (semester S1), as the stress test results are released during the time when banks typically produce and release these reports (Bischof and Daske, 2013). I expect the stress test impact to be particularly strong during the post-treatment periods T_2 that happen 'after' the stress test exercises.

Accordingly, I run the following model that is based on the total treatment participation (*TREATALL*), the Kernel-weighted control sample and 'hot' and 'cold' stress test periods (*STHC*):

$$\begin{aligned} LLP_{itj} = {} & \gamma_0 + \gamma_1 NPL_{it-1j} + \gamma_2 \Delta NPL_{itj} + \gamma_3 \Delta LOAN_{itj} + \gamma_4 T1R_{it-1j} + \gamma_5 EBPT_{itj} + \\ & \gamma_6 STHC + \gamma_7 TREATALL * STHC + \gamma_8 TREATALL * T1R_{it-1j} + \gamma_9 STHC * \\ & T1R_{it-1j} + \gamma_{10} TREATALL * STHC * T1R_{it-1j} + \gamma_{11} TREATALL * EBPT_{itj} + \\ & \gamma_{12} STHC * EBPT_{itj} + \gamma_{13} TREATALL * STHC * EBPT_{itj} + \gamma_{14} SIZE_{it-1j} + \\ & \gamma_{15} \Delta GDP_{tj} + \gamma_{16} \Delta UNEM_{tj} + \gamma_{17} HPI_{tj} + \gamma_{18} IRATE_{tj} + \alpha_i + \delta_t + \\ & \varepsilon_{itj} \end{aligned} \quad (2.3_{\text{A}})$$

To analyse the distinctive implications of the particular stress tests in 2010-11, I amend Equation 2.3_{A} and run the subsequent modification based on the sample of first-time participants in 2010-11 (*TREAT1011*), the Kernel-weighted control sample and the equivalent outcome periods (*BAST1011*):

$$\begin{aligned} LLP_{itj} = {} & \gamma_0 + \gamma_1 NPL_{it-1j} + \gamma_2 \Delta NPL_{itj} + \gamma_3 \Delta LOAN_{itj} + \gamma_4 T1R_{it-1j} + \gamma_5 EBPT_{itj} + \\ & \gamma_6 BAST1011 + \gamma_7 TREAT1011 * BAST1011 + \gamma_8 TREAT1011 * T1R_{it-1j} + \\ & \gamma_9 BAST1011 * T1R_{it-1j} + \gamma_{10} TREAT1011 * BAST1011 * T1R_{it-1j} + \\ & \gamma_{11} TREAT1011 * EBPT_{itj} + \gamma_{12} BAST1011 * EBPT_{itj} + \gamma_{13} TREAT1011 * \\ & BAST1011 * EBPT_{itj} + \gamma_{14} SIZE_{it-1j} + \gamma_{15} \Delta GDP_{tj} + \gamma_{16} \Delta UNEM_{tj} + \\ & \gamma_{17} HPI_{tj} + \gamma_{18} IRATE_{tj} + \alpha_i + \delta_t + \varepsilon_{itj} \end{aligned} \quad (2.3_{\text{B}})$$

Similarly, to estimate the stress test in 2014, I amend Equation 2.3A and run the following modification based on the sample of first-time participants in 2014 (*TREAT14*), the Kernel-weighted control sample and the equivalent outcome periods (*BAST14*):

$$LLP_{itj} = \gamma_0 + \gamma_1 NPL_{it-1j} + \gamma_2 \Delta NPL_{itj} + \gamma_3 \Delta LOAN_{itj} + \gamma_4 T1R_{it-1j} + \gamma_5 EBPT_{itj} + \gamma_6 BAST14 + \gamma_7 TREAT14 * BAST14 + \gamma_8 TREAT14 * T1R_{it-1j} + \gamma_9 BAST14 * T1R_{it-1j} + \gamma_{10} TREAT14 * BAST14 * T1R_{it-1j} + \gamma_{11} TREAT14 * EBPT_{itj} + \gamma_{12} BAST14 * EBPT_{itj} + \gamma_{13} TREAT14 * BAST14 * EBPT_{itj} + \gamma_{14} SIZE_{it-1j} + \gamma_{15} \Delta GDP_{tj} + \gamma_{16} \Delta UNEM_{tj} + \gamma_{17} HPI_{tj} + \gamma_{18} IRATE_{tj} + \alpha_i + \delta_t + \varepsilon_{itj} \quad (2.3_C)$$

where, in all Equations 2.3A, 2.3B and 2.3C, for bank *i*, time *t* and country *j*, *LLP* is current loan loss provisions scaled by lagged total assets, *NPL* and *ΔNPL* stand for the lagged level and current change in non-performing loans divided by lagged total assets, respectively, and *ΔLOAN* is the contemporary change in outstanding loans scaled by lagged total assets. These variables are included to adjust for the non-discretionary component of *LLP* as they measure the beginning degree and current shift of banks' asset quality and credit risk (*NPL, ΔNPL*) as well as the current response of banks to reduce risk exposures (*ΔLOAN*). Thus, I control for the mechanism that current *LLP* are mainly determined by the lagged level and current change in banks' asset quality and depend to some extent on the quality of the performing loan portfolio. I do not include *LLR* in the model as this variable is mechanically related to *LLP* and highly correlated with *NPL* (see, Table 2.4) and causes multicollinearity (Gebhardt and Novotny-Farkas, 2011).[13]

Further, I include, respectively, the lagged Tier 1 capital ratio (*T1R*) and current earnings before provisions and taxes scaled by lagged total assets (*EBPT*) to measure income smoothing and capital management. Based on the extant literature on accounting discretion, I observe capital management and/or income smoothing when one or both main independent variables (i.e., *T1R, EBPT*) explain the variation of the dependent variable, i.e. the current loan loss provisions. I lag the independent accounting variables to the necessary extent to reduce the risk that the independent and dependent variables might be jointly determined and cause bias (Beatty and Liao, 2014; Bushman and Williams, 2012).

[13] For more *LLP* model analyses, I refer to Gebhardt and Novotny-Farkas (2011) and Beatty and Liao (2014).

In the outcome of the interaction variables of capital management (*T1R*) and income smoothing (*EBPT*) with stress test participation (i.e., *TREATALL, TREAT1011,* and *TREAT14*) and stress test periods (i.e., *STHC, BAST1011, BAST14*), I expect to see the impact of stress tests on banks' capital management and income smoothing behaviour. Thus, the interaction terms are the variables of interest that show if stress-tested banks, compared to their Kernel-weighted counterparts, are incentivised to increase (positive coefficients) or decrease (negative coefficients) the current portion of discretionary *LLP* to manage capital and/or to smooth income. Moreover, to disentangle the consequences of stress test participation on discretionary practices over *LLP*, the setting creates various challenges due to potentially confounding bank-specific and macro-prudential responses to the financial and sovereign debt crisis. Therefore, I use bank size assessed by the lagged natural logarithm of total assets (*SIZE*) to control for differences within, and most importantly, across treatment and control groups.

I consider contemporaneous fiscal and monetary policy changes as well as market instabilities such as illiquidity, constrained capital and higher volatility (Bonner and Eijffinger, 2016). In particular, I utilise the country's macroeconomic fundamentals using economic growth (*ΔGDP*), unemployment growth (*ΔUNEM*), price level in the housing market (*HPI*), and sovereign debt risk (*IRATE*). These variables control for the economic cycles of the stress test periods that might affect bank's discretionary behaviour (Hamadi et al., 2016; Vallascas and Hagendorff, 2013; Bushman and Williams, 2012). Further, after statistical testing (i.e., the Hausman test), I employ bank-specific fixed effects (α) and half-year fixed effects (δ) to account respectively for time-invariant unobserved heterogeneity and time-variant common shocks that may not be covered by the PSM-obtained Kernel weights and/or the various bank- and country-specific control variables employed in my analysis (e.g., Hagendorff et al., 2018; Hamadi et al., 2016). It may be noted that the applied statistical software Stata omits overlapping time and fixed effects dummies to avoid multicollinearity. In addition, I cluster the standard errors at the bank level to shield my analysis from being biased by heteroskedasticity and autocorrelation (Acharya et al., 2018). Finally, I include the residual (ε).

Next, in the context of *H4*, I account for contemporaneous responses of banking regulation and supervision along with the level of corruption to test if a stronger institutional environment leads to a decrease in discretionary behaviour over *LLP*. Inspired by Gebhardt and Novotny-Farkas (2011) and Bushman and Williams (2012), I subsequently expand the baseline model in Equation 2.3_A that is based on the total treatment participation (*TREATALL*), the Kernel-weighted control sample and 'hot' and 'cold' stress test periods (*STHC*):

$$\begin{aligned} LLP_{itj} = {} & \gamma_0 + \gamma_1 NPL_{it-1j} + \gamma_2 \Delta NPL_{itj} + \gamma_3 \Delta LOAN_{itj} + \gamma_4 T1R_{it-1j} + \gamma_5 EBPT_{itj} + \\ & \gamma_6 STHC + \gamma_7 TREATALL * STHC + \gamma_8 TREATALL * T1R_{it-1j} + \gamma_9 STHC * \\ & T1R_{it-1j} + \gamma_{10} TREATALL * STHC * T1R_{it-1j} + \gamma_{11} TREATALL * EBPT_{itj} + \\ & \gamma_{12} STHC * EBPT_{itj} + \gamma_{13} TREATALL * STHC * EBPT_{itj} + \gamma_{14} INSTVAR + \\ & \gamma_{15} TREATALL * INSTVAR + \gamma_{16} STHC * INSTVAR + \gamma_{17} TREATALL * STHC * \\ & INSTVAR + \gamma_{18} INSTVAR * T1R_{it-1j} + \gamma_{19} TREATALL * INSTVAR * T1R_{it-1j} + \\ & \gamma_{20} STHC * INSTVAR * T1R_{it-1j} + \gamma_{21} TREATALL * STHC * INSTVAR * \\ & T1R_{it-1j} + \gamma_{22} INSTVAR * EBPT_{it-1j} + \gamma_{23} TREATALL * INSTVAR * EBPT_{it-1j} + \\ & \gamma_{24} STHC * INSTVAR * EBPT_{it-1j} + \gamma_{25} TREATALL * STHC * INSTVAR * \\ & EBPT_{it-1j} + \gamma_{26} SIZE_{it-1j} + \gamma_{27} \Delta GDP_{tj} + \gamma_{28} \Delta UNEM_{tj} + \gamma_{29} HPI_{tj} + \\ & \gamma_{30} IRATE_{tj} + \alpha_i + \delta_t + \varepsilon_{itj} \end{aligned} \tag{2.4}$$

where, all other variables equally defined as in Equation 2.3_A, the parameter *INSTVAR* stands for one of the three institutional variables *SUPERV*, *CAPREG* and *CORRUPT*. I apply two indices capturing, respectively, the country's bank supervisory strength (*SUPERV*) and regulatory capital stringency (*CAPREG*) obtained from a 2012 World Bank survey (Cihák et al., 2012; Barth et al., 2001), and the country's corruption level (*CORRUPT*) assessed by Transparency International's Corruption Perceptions Index. I separately add the three institutional variables to the interaction term of the main independent variables, i.e. capital management (*T1R*) and income smoothing (*EBPT*), the total treatment participation sample (*TREATALL*), and 'hot' and 'cold' stress test periods (*STHC*) that I employ in Equation 2.3_A. Thus, the extended interaction term constitutes the variable of interest that shows if a robust regulatory environment imposes limitations on stress-tested banks' discretionary behaviour. As Table 2.3, Panel C illustrates the strength of bank supervisors (*SUPERV*) and the regulatory capital stringency (*CAPREG*) differs across European countries that might aid country-specific discretion and forbearance (Wheeler, 2019). Furthermore, I expect new insights by implementing the country's corruption level (*CORRUPT*). For instance, banks operating in countries with more corruption might be more prone in exercising accounting discretion.

Further, following Kim and Kross (1998) and Bushman and Williams (2012), I consider differences in bank capital levels to test if stress-tested banks with lower capital buffers are more inclined in discretionary behaviour (*H5*). Thus, I divide the total stress test participation sample (*TREATALL*) and the Kernel-weighted control banks into three subsamples that I use to separately run the baseline model on discretionary *LLP* displayed by Equation 2.3_A. I distinguish between banks with high (*CAPH*: *CAP* > 10%), medium (*CAPM*: 7% ≤ *CAP* ≤ 10%) and low (*CAPL*: *CAP* < 7%) bank capital, as in Bushman and Williams (2012). According to the extant literature, low-capitalised banks might have more incentives to optimise capital to meet regulatory requirements and to avoid regulatory intervention. In this context, stress tests might provide additional motivation for banks with low capital buffers to exercise accounting discretion.

2.5. Results

This section provides empirical evidence on the treatment effect of stress tests and discusses the accounting discretion behaviour of treatment banks compared to control banks in the different settings established in Sections 2.3 and 2.4.

2.5.1. The treatment effect of stress tests

First, I provide the results of the PSM probit models, which estimate the determinants of banks' probability of being stress-tested and produce propensity scores for subsequent matching procedures (Equation 2.1).[14] Table 2.5, Panel A, illustrates, with a pseudo-R^2 of 0.692 (Model 1), 0.625 (Model 2) and 0.462 (Model 3) indicating a high goodness of fit, that bank size (*SIZE*) is the sole consistent statistically significant predictor for stress test participation. There is mixed significance of the other covariates namely country's economic strength (*GDP*), non-traditional banking activities (*OEA*), asset quality (*NPL*), liquidity risk (*DSFR*), bank capital (*CAP*) and profitability (*ROA*).

[Please refer to Table 2.5 and Figures 2.1, 2.2 and 2.3 here]

According to EBA's methodology notes for distinct stress tests, regulators focus on banks' size relative to the home country and the European market to select stress test participants as this is an important measure for systemic relevance. Interestingly, the results suggest that regulators further appear to consider a wider range of bank-specific characteristics. For instance, in Model 1, the overall selection case, profitability (*ROA*),

[14] I use widely established Stata modules such as 'psmatch2' (Sianesi and Leuven, 2003) in my analysis.

asset quality (*LLR*) and bank capital (*CAP*) are significantly associated with stress test participation. These measures might be used by regulators as they play a fundamental role in banks' performance, risk aversion and ability to meet long-term commitments (Schuermann, 2014). In contrast, the selection process for the assessments in 2010-11 (Model 2) integrates the country's economic strength (*GDP*) and non-traditional activities (*OEA*), whilst in 2014 (Model 3) liquidity and bank capital are of great importance for the regulators' selection process. The latter result suggests that banks with a higher bank capital and liquidity base are more likely to be stress-tested, which is an indicator for regulators learning curve as they might be able to partly see through banks' capital and liquidity management (Bierey and Schmidt, 2017).

Second, Table 2.5, Panels B, C and D report the matching equality by comparing the means of the covariates before and after running the GKM algorithm. Accordingly, the bias has been minimised for all covariates. Before matching, the means of almost all variables are significantly diverse, while the difference in means of all variables after matching is insignificant. Moreover, the pseudo-R^2 is reduced to a minimum of 0.009 (Panel B), 0.027 (Panel C) and 0.012 (Panel D) for the matched samples. Figures 2.1, 2.2 and 2.3 show that the density of the Kernel weighted propensity scores between the matched treatment and control samples is very similar compared to the unmatched cases. Therefore, the GKM method works well in eliminating significant differences between the treatment and control groups. Importantly, the Kernel matching procedure has removed any meaningful differences along observables from the two groups of banks during the pre-treatment periods, which ensures that the parallel trend assumption has been satisfied. Consequently, this explained PSM process leads to the final samples that I use in the subsequent DiD and fixed effects analyses. As I adopt the common support option, treatment and control banks with particularly high or low propensity scores are automatically removed. This yields a total European matched sample of 132 treatment and 122 control banks (*TREATALL*), including matched samples of first-time participants of 71 treated to 108 controls in 2010-11 (*TREAT1011*), and 55 treated to 87 controls in 2014 (*TREAT14*).

[Please refer to Table 2.6 and Figures 2.4, 2.5, and 2.6 here]

Third, Table 2.6 and Figures 2.4, 2.5 and 2.6 provide the PSM and DiD analysis and empirical evidence on the average treatment effect of stress tests (Equation 2.2). To test *H1*, I compare the GKM-matched samples of European treatment and control banks before and after treatment. I conduct my analysis on the following outcome variables, which measure forward- and backward-looking asset quality (*LLP*, *NPL*), capital adequacy (*T1R*) and credit risk (*RWA*). The examination is divided into three parts, where Panel A presents the total stress test participation effect of all treatment banks over the entire sample period 2005-2015. Panels B and C examine the stress test effect separately four half-year periods before and after the 2010-11 and the 2014 treatments, respectively (as defined in Section 2.4.5.1).

In terms of asset quality (*LLP, NPL*), I do not observe a statistically significant average treatment effect (DiD) for total stress test participation (Panel A). However, the single differences for asset quality (*LLP, NPL*) indicate that treatment and control banks report more *NPL* (increase of 0.71% and 0.45%) for the treatment over the pre-treatment period that are statistically significant, while only the control banks show more *LLP* (increase of 0.17%) for the same periods. This may also be explained by Figure 2.4 illustrating that treatment banks had made exhaustive *LLP* during the financial crisis suggesting pro-cyclicality of such activities (Wheeler, 2019; Vallascas and Hagendorff, 2013; Bushman and Williams, 2012; Beatty and Liao, 2011; Laeven and Majnoni, 2003). Regarding the individual assessment of first-time participants in 2010-11, I document a statistically significant average treatment effect (DiD) showing that treatment banks report lower *LLP* (-0.13%) and increased *NPL* (0.35%). This average treatment effect partly continues for the first-time participants of the 2014 exercise, as I find a significant increase in *NPL* (0.55%), but not in *LLP*. As regulators comprehensively assess the asset quality of tested banks, this result shows that stress tests reveal weaknesses in the loan portfolio quality of treated banks in terms of backward-looking classification of *NPL*.

Interestingly, the results for capital adequacy vary intensely between the three examination periods. While I measure an average treatment effect (DiD) on capital adequacy (*T1R*) for total stress test participation that is negative and significant (-1.15%), the average treatment effect (DiD) in 2010-11 is insignificant and in 2014 positive and significant (2.00%). On average, treatment banks seem not to re-capitalise as stringent compared to untreated banks after the financial crisis. Only recently, as suggested by the positive and significant treatment effect in 2014 (2.00%), stress-tested banks show a learning curve and increase their capital levels. This development is supported by the negative single differences for the treatment over the control groups which are significant for all treatment and pre-treatment periods except for the treatment period in 2014. On the other hand, with regards to credit risk (*RWA*), I document a statistically significant average treatment effect (DiD) for the 2010-11 assessments (-3.53%) but not for total stress test participation and the 2014 exercise. Further, all single differences of the treatment and control groups that compare the treatment over the pre-treatment periods are negative and statistically significant at the 1% level. This indicates that stress-tested banks and their counterparts decreased their risk exposures substantially.

Thus, stress test exercises do not appear to improve capital adequacy of treatment banks on all occasions, while banks might shrink risk exposure than increase their capital base (Gropp et al., 2019). In particular, the 2010-11 stress tests appeared to be rather mild regarding additional capital requirements (Schuermann, 2014), which seem to be benefited by the reduction in credit risk (Braouezec and Wagalath, 2018; Beltratti and Paladino, 2016). In contrast, the 2014 stress test focused more on capital adequacy and banks were required to increase capital when a capital shortfall was disclosed (Sahin and de Haan, 2016). In addition, the ongoing process of implementing Basel III considerably raises the capital base, which is captured in the PSM and DiD approach, as it affects both treated and untreated banks similarly. Stress tests might further motivate both treatment and control banks to capitalise positively as markets might penalise weak banks owing to the fear of future regulatory enforcement actions (Carboni et al., 2017). Overall, I can constitute that, in support of *H1*, the 2014 stress test enhanced treatment banks' accounting figures and, thus, contributed to safety and soundness of the banking system, whilst the 2010-11 exercises did not trigger those positive bank reactions.

2.5.2. The effect of stress test participation on discretionary behaviour

Table 2.7 illustrates the results of the fixed effects baseline model, which estimates stress test effects on banks' capital and income smoothing through *LLP* and therefore introduces stress tests as a novel accounting discretion motive (as hypothesised in *H2* and *H3*). In Model 1, I run Equation 2.3_A on the entire matched treatment and control sample of 265 European banks, whereas, based on Equation 2.3_B and Equation 2.3_C, in Models 2 and 3, I estimate stress test effects on first-time participants' discretionary behaviour before and after the 2010-11 and 2014 treatments, respectively. Most importantly, my findings provide support for *H2* and *H3* and indicate capital management of stress test participants compared to the control banks. In particular, I report capital management related to the total stress test participation and CEBS/EBA's 2010-11 exercises, as the interaction terms *TREATALL*STHC*T1R* in Model 1 and *TREAT1011*BAST1011*T1R* in Model 2 are statistically significant. Further, I find increased and reduced income smoothing activities of first-time participants in 2010-11 and 2014, respectively, as the interaction terms *TREAT1011*BAST1011*EBPT* and *TREAT14*BAST14*EBPT* are statistically significant. The latter result indicates the impact of stress tests on banks' discretionary behaviour that may be positive or negative depending on the individual exercise.

[Please refer to Table 2.7 here]

Consistent with *H2* and *H3*, the results show that current *LLP* decreases with *T1R*, suggesting that treatment banks, in contrast to untreated banks, delay more loan losses to manage their capital adequacy. In economic terms, if *T1R* increases by 1%, current *LLP* of treated banks decrease by -3.10% compared to untreated banks, on average and *ceteris paribus* (see interaction term *TREATALL*STHC*T1R* in Model 1). According to Basel III, higher *LLP* increases *LLR*, which reduce retained earnings and Tier 1 capital. As stress-tested banks are exposed to regulatory intervention to raise capital adequacy in t–1, this appears to have an impact on future banks' discretionary behaviour. Banks delay current loan losses to reduce pressure on earnings figures, to recover from regulatory re-capitalisation and to prepare for potential forthcoming interventions. Further, in Model 2, the interaction term *TREAT1011*BAST1011*T1R* is significant at the 1% confidence level, while the equivalent term in Model 3 (*TREAT14*BAST14*T1R*) is insignificant. Therefore, in support of *H2* and *H3*, the stress test effect in 2010-11 appears to incentivise first-time participants to boost capital by delaying *LLP*, unlike during the 2014 stress test period. Regarding the CEBS/EBAs' treatments in 2010-11, if *T1R* increases by 1%, current *LLP* of first-time participants decrease after the stress test by -7.19% compared to untreated banks, on average and *ceteris paribus*.

On the other hand, in Models 2 and 3, the interaction terms *TREAT1011*BAST1011*EBPT* and *TREAT14*BAST14*EBPT* illustrate respectively that stress tests significantly exacerbate or mitigate income smoothing by first-time participants. In particular, conform to *H2* and *H3*, after the 2010-11 stress tests, first-time participants seem to influence their earnings by applying discretionary *LLP*, while, in opposition of *H2* and *H3*, the effect on 2014 first-time participants is negative. If *EBPT* increase by 1%, current *LLP* of treatment banks increase by 20.07% after the 2010-11 stress tests in contrast to untreated banks, on average and *ceteris paribus*. This effect on *LLP* after the EBA/ECB's 2014 assessments yields -29.84%. Both results, on capital and earnings management, support my PSM and DiD analysis as regulatory intervention focused on capital adequacy and asset quality in 2014, which mitigated discretion, implying that stress tests in 2010-11 might be influenced by such accounting practices. Moreover, the outcome supports Schuermann (2014), who conclude that the 2010-11 stress test experiences lacked sufficient reliability. In contrast, ECB's assessment in 2014 was much more credible, indicating a regulatory learning curve (Sahin and de Haan, 2016).

In addition, my results support earlier findings of the existing literature such as Bushman and Williams (2012), Gebhardt and Novotny-Farkas (2011) and Fonseca and González (2008), who report evidence of income smoothing in different settings. For instance, Table 2.7 reports that *LLP* increase with *NPL* and the change in *NPL*, which is the non-discretionary component of *LLP* (Hamadi et al., 2016). Moreover, the change in loans (*ΔLOAN*) is negatively related with *LLP*, which supports Laeven and Majnoni (2003), who argue that less timely *LLP* in combination with an economic downturn affect credit quality negatively.

[Please refer to Table 2.8 here]

Fifth, Table 2.8 presents the results for the first modification of the baseline model (Equation 2.4, *H4*) by separately including institutional variables as suggested by Gebhardt and Novotny-Farkas (2011). Model 1 reports the results of including the local supervisory power (*SUPERV*), Model 2 considers the stringency of capital requirements (*CAPREG*) and Model 3 incorporates the country's corruption level (*CORRUPT*). As hypothesised by *H4*, the results illustrate that the institutional environment is significantly related to the manager's choice to exercise discretionary *LLP*. My findings indicate that stress tests in combination with more bank supervisory strength significantly relates to both capital and earnings management, while stricter capital regulation and corruption influences capital or earnings, respectively.

In particular, in Models 1 and 3, the interaction variables that connect stress test participation and earnings with the supervisor's strength (*TREATALL*STHC*SUPERV*EBPT*) and the corruption level (*TREATALL*STHC*CORRUPT*EBPT*) are negative and significant at the 1% confidence level. In support of *H4*, this implies that in countries where supervisors have more strength and corruption is lower, if earnings increase by 1%, *LLP* decrease respectively by -19.14% and -0.74% compared to the control banks, on average and *ceteris paribus*. Therefore, I conclude that stronger supervisors may mitigate income smoothing of stress-tested banks, whilst a lower corruption level may be a contributing factor, but the absolute impact is minimal and therefore statistically but not economically significant. Surprisingly, in Models 1 and 2, the interaction terms that combine stress test participation and capital management with supervisor's strength (*TREATALL*STHC*SUPERV*T1R*) and capital stringency (*TREATALL*STHC*CAPREG*T1R*) are negative and significant at the 1% and 10% confidence levels, respectively. If *T1R* increase by 1%, *LLP* decrease respectively by -3.75% and -3.56%. Thus, in opposition to *H4*, unlike income smoothing, stricter banking supervisory and capital regulation regimes do not necessarily mitigate the bank manager's incentives to delay *LLP* and to boost earnings during stress test periods. This indicates that the total effect of stress tests on the capital management of treated banks remains strong, even within stricter regimes.

[Please refer to Table 2.9 here]

Sixth, I examine whether high-, medium- or low-capitalised treatment banks are more driven to exercise discretionary behaviour (*H5*). I follow Bushman and William's (2012) definition and run Equation 2.3_A separately for treatment banks reporting high (Model 1: *CAP* > 10%), medium (Model 2: 7% ≤ *CAP* ≤ 10%) and low (Model 3: *CAP* < 7%) capital levels. In Table 2.9, Model 3, as the interaction term *TREATALL*STHC*T1R* is significant at the 10% confidence level, I find consistent with *H5* that that low-capitalised treatment banks apply more discretionary practices. In economic terms, if *T1R* increases by 1%, current *LLP* decrease by -5.31%, on average and *ceteris paribus*. There is also an overall tendency of low-capitalised banks to exercise capital management (*T1R*). This result suggests that especially weakly capitalised banks boost their capital adequacy figures by delaying *LLP* in particular during stress test periods owing to the fear of additional bad market reactions and regulatory interventions (Bierey and Schmidt, 2017; Kim and Kross, 1998).

On the other hand, in Model 1, the same interaction term turns positive at the 10% confidence level, indicating that highly capitalised banks increase *LLP* to optimise capital adequacy (4.07%). In Table 2.9, Model 2, the relationship between *LLP* and the interaction terms *TREATALL*EBPT* (i.e., 30.85%) and *TREATALL*STHC*EBPT* (i.e., 32.77%) is positive and significant at the 1% and 5% confidence levels, which indicates that medium-capitalised treatment banks apply accounting discretion to smooth income compared to untreated peers. In comparison with earlier findings in Table 2.7, Model 1, this suggests that high- and low-capitalised treatment banks may drive capital management practices in both directions, while medium-capitalised treatment banks rather smooth income.

2.6. Robustness analysis

In this section, I test the robustness of my findings and the validity of the econometric analysis. Main results are displayed in Tables 2.10 and 2.11 and additional robustness is reflected in the APPENDIX (Tables A.1 to A.8).

2.6.1. Unconfoundedness and common support control

As earlier mentioned, it is essential that the PSM and DiD analyses meet the unconfoundedness and common support assumptions. The model covariates are required to have an important influence on the participation choice and the treatment outcome to be in the right balance (i.e., neither over-, nor under-parameterised) and independent of the outcome. To ensure that these conditions hold true and, hence, minimise any confoundedness emerging from covariate imbalance, I run an alternative probit model using the leave-one-out strategy. In Table 2.10, Panel A, I display the alternative robustness model that is based on the full set of covariates including the Loan-to-Deposit ratio (*LTDR*) as an additional covariate that measures liquidity risk. As banks were highly exposed to liquidity risk during the 2008 financial crisis, regulators might focus on selecting banks that report weak liquidity reserves. However, the results do not show that liquidity risk is a significant selection criterion. Further, I find that my results with respect to the probability of banks participating in stress tests, shown in Table 2.10, Panel A, are overall unaffected.

[Please refer to Table 2.10 here]

Next, to ensure that the PSM and DiD approach (Equation 2.2) is resilient against remaining differences of the treatment and control banks after matching and hidden bias from the PSM probit model, I control for additional confounding covariates in the model. In Table 2.10, Panel B, I include a set of dummy variables to isolate different sample banks as I test if those banks are inherently different and alter my conclusions. In particular, although I believe that Swiss and Norwegian banks operate under comparable regulatory environments, I separate banks from countries outside the EU (*EU*) because the different regulatory regimes might cause inherently different accounting behaviour compared to EU banks. Further, as mandatory IFRS was introduced in 2005, most of the sample bank observations are based on IFRS. To address sensitivities from distinct accounting standards, I consider those banks that still use local GAAP (*GAAP*). Similarly, I acknowledge listed banks (*PUBLIC*), which might be more affected by market responses than their private counterparts. Moreover, I control for some banks which are under stricter supervision than other treatment banks, as the parent and subsidiaries are considered in stress tests (*MULTIPLE*) as well as stress test reports revealed a capital shortage (*SHORT*). As multiple stress test participation and capital inadequacy of banks might intensify pressure, those banks might have more incentives to exercise discretion. In addition, I control for inactive banks (*ACTIVE*) and follow related studies (e.g., Beatty and Liao, 2011) that separately analyse banks involved in M&As and bankruptcies as those banks might be influenced by special survival circumstances. The results displayed in Table 2.10, Panel B, appear to be similar in all distinct settings.

[Please refer to Table 2.11 here]

In Table 2.11, I ensure the robustness of the fixed effects baseline models in Equations 2.3_A, 2.3_B and 2.3_C. In particular, Lechner (2008) argues that the information excluded due to the common support option might result in biased treatment effects. Therefore, I run the fixed effects regressions including all treatment banks outside the common support area. I incorporate 11 and 15 treatment banks that were not within common support for the samples of total stress test participation (*TREATALL*) and first-time participants in 2010-11 (*TREAT1011*), respectively. As the 'trimming' function does not exclude any treatment bank from the sample of first-time participants in 2014 (*TREAT14*), I test my results discarding the four largest treatment banks. From this analysis, I retrieve consistent results, compared to my baseline analysis, as the coefficients vary slightly but conform regarding the operator and the statistical significance of the main capital and earnings management variables.

2.6.2. Additional robustness checks

In addition to the main robustness checks in Section 2.6.1, I run several testings, displayed in the APPENDIX (Tables A.1 to A.8), to further support my baseline results.

First, in Table A.1, Panel A, I repeat the leave-one-out strategy and run another alternative probit model to test covariance imbalance. In particular, I exchange asset composition measures (*OEA* with *LOAN*). Further, in Panel B, I rerun the baseline probit model based on the matched sample within common support (i.e., double PSM) to detect any significant remaining differences after matching. [15]

Second, based on the baseline samples, I employ various matching algorithms, where the choice is a trade-off between reducing bias and variance (Caliendo and Kopeinig, 2008). Those tests are crucial as I aim to optimise matching equality that reduces the difference between treatment and control banks by retaining as many sample banks as possible. In particular, I examine results from Nearest-neighbour matching with and without 'Caliper', replacement or oversampling, 'Radius', 'Kernel' (i.e., 'Epanechnikov' 'Biweight', etc.) and 'Mahalanobis'. The results appear to be different depending on the exact combination of covariate and algorithm variations. Nevertheless, in Table A.1, Panels C, D and E, I present Radius and Nearest-neighbour matching, which are similar in achieving equality of means of treatment and control banks after matching.

Third, in Table A.2, I repeat the common support robustness check and include treatment banks that were automatically excluded by the PSM algorithm as the estimated propensity scores were not in the common support area. This test ensures that leaving out the information outside this common support area does not significantly screw the results (Lechner, 2008). Moreover, the DiD results are insensitive to the addition of *NPL* in the PSM probit model. I conclude that the significant difference of *LLP* between treatment and control banks seems to be truly attributed to the treatment effect. On the other hand, I do not explicitly consider exogenous macroeconomic changes, such as the financial or sovereign debt crisis, as PSM addresses individual differences between treatment and control groups. Hence, PSM assumes that both groups similarly suffer from those external influences.[16]

Fourth, in Tables A.3, A.4 and A.5 I exclude a different set of sample banks as those banks are inherently different and might alter my conclusions. In particular, similar to the robustness check in Section 2.6.1, I rerun the baseline models of Equations 2.3_{A}, 2.3_{B} and

[15] I also attempted to introduce the Herfindahl-Hirschman Index, listing status, bank specialisation, non-performing loans, relative size (Total assets/*GDP*). However, I discard those variables, as they do not achieve a balanced property of the propensity score or produce too biased matching results. The relevant results are all available upon request.

[16] I gratefully thank an anonymous reviewer for valuable comments on the treatment effect results.

2.3C removing banks from non-EU countries (*EU*), banks with multiple stress test participation (*MULTIPLE*), banks using local GAAP (*GAAP*) and inactive banks (*ACTIVE*). Further, to fully rule out the influence of macroeconomic fluctuations that may confound the findings of the fixed effects regressions, I include an interaction term between the treatment groups and the unemployment rate. In Table A.6, the results of all models illustrate that the coefficients of the interaction terms are positive, indicating pro-cyclicality of *LLPs*, that are, however, statistically insignificant. Lastly, in Table A.7 and Figure A.1, I provide the marginal effects of the interaction terms of the baseline regressions, while Table A.8 shows additional testings on multicollinearity by excluding time fixed effects. From all those distinct settings, the results are consistent as the coefficients are marginally different but match my baseline analysis regarding the operator and the statistical significance of the main variables and interaction terms of interest that reflect capital and income smoothing.

2.7. Concluding remarks

The benefits of stress tests in Europe and the U.S. have been determined through event and conceptional studies that report markets' reaction to stress test disclosures. Owing to the complexity of regulatory exercises, recent studies such as those by Carboni et al. (2017) and Flannery et al. (2017) have expanded the literature by using different information measures and event study designs. Instead, my work advances prior research by empirically connecting treatment banks' accounting information quality and stress test disclosures. In particular, using a unique sample and dataset from 27 European countries, I employ PSM and various fixed effects models to measure the treatment effect of stress tests and the implications of these exercises on tested banks' discretionary behaviour. I document that tested banks are highly influenced by stress tests, which provides incentives for these banks to apply discretionary loan loss provisions to manage capital and earnings.

First, this study shows that banks subject to stress tests report different accounting figures in terms of asset quality and capital adequacy, compared to untested banks. While tested banks report more pro-cyclical loan loss provisions in 2010-11, overall capital adequacy of tested banks was lower and increased after the 2014 stress tests. Second, tested banks have stronger incentives to delay loan loss provisions to strengthen and boost their capital adequacy ratios; this signals resilience and soundness to regulators and market players. In particular, in 2010-11, stress tests motivate banks to manage capital and earnings, whilst in 2014 stress tests mitigate discretionary behaviour. Further, specifically low-capitalised stress test participants delay loan loss provisions to boost capital, whereas medium- and high-capitalised banks increase loan loss provisions to smooth income and optimise capital, respectively. Third, I document that a more reliable institutional environment mitigates the degree of earnings management, whilst capital management remains the same during stress test periods. Overall, my results suggest that stress tests convey, on several occasions, a ‘placebo’ image to regulators and markets, but can also be an ‘active’ treatment.

This study is the first that links the quality of accounting information with stress test disclosures in such a comprehensive manner and has distinct political and business implications. Undoubtedly besides their intrinsic limitations, stress tests are a useful regulatory tool during crises to distinguish banks by their quality (Borio et al., 2014; Schuermann, 2014). Furthermore, comprehensive assessments provide unique opportunities for regulators to gain in-depth insights to improve the supervision of SIFIs (Carboni et al., 2017; Sahin and de Haan, 2016). However, my findings indicate that stress-tested banks use *LLP* to manage capital and earnings to signal soundness. I conclude that stress tests might exacerbate market pressure particularly on weaker institutions as they expose bank-specific information in calm economic times; this might lead to financial instability. Therefore, this study empirically advances previous research on stress tests that suggested to amend mandatory stress test disclosures towards aggregated information, particularly in normal economic times, as this policy would reduce pressure and banks’ signalling incentives (Bouvard et al., 2015; Goldstein and Sapra, 2013).

Table 2.1 Variable definitions and data sources

Abbreviations	Variables	Description	Data sources
SIZE	Bank size	Natural logarithm of total assets	BvD Bankscope, Bank reports
CAP	Bank capital	Total equity capital divided by total assets	BvD Bankscope, Bank reports
LOAN	Traditional banking activities	Outstanding loans scaled by lagged total assets	BvD Bankscope, Bank reports
ΔLOAN	Loan growth	Change in outstanding loans scaled by lagged total assets	BvD Bankscope, Bank reports
NPL	(Backward-looking) asset quality	Non-performing or impaired loans scaled by lagged total assets	BvD Bankscope, Bank reports
ΔNPL	Change in (backward-looking) asset quality	Change in non-performing or impaired loans scaled by lagged total assets	BvD Bankscope, Bank reports
LLP	(Forward-looking) asset quality	Loan loss provisions for non-performing or impaired loans scaled by lagged total assets	BvD Bankscope, Bank reports
LLR	Credit portfolio quality	Loan loss reserves for non-performing or impaired loans scaled by lagged total assets	BvD Bankscope, Bank reports
DSFR	Liquidity risk	Deposit ratio: deposits and short-term funding divided by total assets	BvD Bankscope, Bank reports
LTDR	Liquidity risk	Loan-To-Deposit ratio: outstanding loans divided by deposits and short-term funding	BvD Bankscope, Bank reports
OEA	Non-traditional banking activities	Other earning assets scaled by lagged total assets	BvD Bankscope, Bank reports
EBPT	Income smoothing	Earnings before provisions and taxes scaled by lagged total assets	BvD Bankscope, Bank reports
ROA	Profitability	Return on assets: earnings before taxes scaled by total assets	BvD Bankscope, Bank reports
T1R	Capital adequacy and capital management	Regulatory Tier 1 capital divided by risk-weighted assets	BvD Bankscope, Bank reports
RWA	Credit risk	Risk-weighted assets scaled by lagged total assets	BvD Bankscope, Bank reports
TREATALL	Stress test participation	Dummy variable that takes the value of 1 for stress-tested banks and 0 otherwise	BvD Bankscope, Bank reports
TREAT1011	First-time participation in the 2010-11 stress tests	Dummy variable that captures the first-time participants in the 2010-11 stress tests	EBA and ECB stress test disclosures
TREAT14	First-time participation in the 2014 stress test	Dummy variable that captures the first-time participants in the 2014 stress test	EBA and ECB stress test disclosures
STHC	‘Hot’ vs. ‘cold’ stress test periods	Dummy variable with a value of 1 for 'hot' (2009S1-2011S2 and 2014S1-2015S2) and 0 for 'cold' (2005S2-2008S2 and 2012S1-2013S2) stress test periods	EBA and ECB stress test disclosures
BAST	Treatment vs non-treatment overall stress test periods	Dummy variable that takes the value 1 for the overall treatment period (2009S1-2015S2) and 0 for the overall pre-treatment period (2005S2-2008S2)	EBA and ECB stress test disclosures
BAST1011	Treatment vs non-treatment 2010-11 stress test periods	Dummy variable that takes the value 1 for the 2010-11 treatment period (2010S1-2011S2) and 0 for the 2010-11 pre-treatment period (2008S2-2009S2)	EBA and ECB stress test disclosures
BAST14	Treatment vs non-treatment 2014 stress test periods	Dummy variable that takes the value 1 for the 2014 treatment period (2014S1-2015S2) and 0 for the 2014 pre-treatment period (2012S2-2013S2)	EBA and ECB stress test disclosures
GDP	Economic strength	Nominal Gross Domestic Product in Trillion Euros	OECD, Bloomberg
ΔGDP	Economic growth	Change in Gross Domestic Product in Euros	OECD, Bloomberg

Table 2.1 continued

ΔUNEM	Unemployment growth	Change in unemployment rate	OECD, Bloomberg
HPI	Price level in the housing market	House price index (available at: http://www.bis.org/statistics/pp.htm)	BIS Residential Property Price database
IRATE	Sovereign debt risk	The difference between short- and long-term interest rates in government bond markets	OECD
SUPERV	Bank supervisory strength	A composite index indicating the power of national supervisors following Bushman and Williams (2012)	World Bank
CAPREG	Regulatory capital stringency	A composite index indicating the stringency of capital regulation following Bushman and Williams (2012)	World Bank
CORRUPT	Corruption level	The Corruption Perceptions Index (available at: https://www.transparency.org)	Transparency International
EU	EU membership	Dummy variable that takes the value of 1 for the banks which are headquartered in an EU member state and 0 otherwise	BvD Bankscope
GAAP	Accounting standards	Dummy variable that takes the value of 1 if a bank follows GAAP and 0 if a bank follows IFRS	BvD Bankscope
ACTIVE	Bank status	Dummy variable that takes the value of 1 for a bank is active as a going concern entity, and 0 otherwise	BvD Bankscope
PUBLIC	Listed banks	Dummy variable that takes the value of 1 if a bank is listed on the exchange market, and 0 otherwise	BvD Bankscope
SHORT	Capital shortage	Dummy variable that takes the value of 1 if a bank does not meet the regulatory capital requirements, and 0 otherwise	EBA and ECB stress test disclosures
MULTIPLE	Multiple stress test participation	Dummy variable that takes the value of 1 if both the parent bank and its subsidiaries have participated in a stress test exercise and 0 if only the parent bank has participated in a stress test	EBA and ECB stress test disclosures

Table 2.2 European stress tests and sample construction

Panel A: Geographical structure of sample banks

	Stress test participation CEBS/EBA[a]				Stress test participation ECB		Total treatment sample	First-time participants	First-time participants	Benchmark portfolio
	2010	2011	2014	2016	2014	2015	(*TREATALL*)	2010-11 (*TREAT1011*)	2014 (*TREAT14*)	
Austria	2	3	6	2	6	2	10	4	3	2
Belgium	2	2	5	2	6	1	7	2	4	0
Cyprus	2	2	3	0	4	0	5	2	3	0
Denmark	3	4	4	3	0	0	4	4	0	41
Estonia	0	0	0	0	3	0	3	0	3	0
Finland	1	1	1	1	3	1	4	1	2	3
France	4	4	11	6	13	1	15	4	9	7
Germany	14	12	24	9	25	0	27	14	13	3
Greece	6	6	4	0	4	4	6	6	0	1
Hungary	2	1	1	1	0	0	2	2	0	2
Iceland	0	0	0	0	0	0	0	0	0	2
Ireland	2	3	3	2	5	0	5	3	2	0
Italy	5	5	15	5	15	0	15	5	10	18
Latvia	0	0	1	0	3	0	3	0	3	1
Lithuania	0	0	0	0	3	0	3	0	3	1
Luxembourg	2	1	2	0	6	1	8	2	5	0
Malta	1	1	1	0	3	1	4	1	2	0
Netherlands	4	4	6	4	7	0	7	4	3	2
Norway	0	1	1	1	0	0	1	1	0	92
Poland	1	1	6	1	0	0	6	1	5	1
Portugal	4	4	3	0	3	1	5	4	0	3
Slovakia	0	0	0	0	3	0	3	0	3	0
Slovenia	1	2	3	0	3	1	4	2	1	1
Spain	27	25	15	6	15	0	32	28	3	2
Sweden	4	4	4	4	0	0	4	4	0	36
Switzerland	0	0	0	0	0	0	0	0	0	128
United Kingdom	4	4	4	4	0	0	4	4	0	21
Total sample	**91**	**90**	**123**	**51**	**130**	**13**	**187**	**98**	**77**	**367**

Table 2.2 continued

Panel B: PSM samples of banks						
	TREATALL	Control	*TREAT1011*	Control	*TREAT14*	Control
Initial sample of banks	187		98		77	
Excluded banks due to financial reporting inconsistencies	27		3		17	
Excluded banks due to lack of data caused by M&As	8		8		0	
Excluded banks due to lack of data caused by bankruptcies	1		1		0	
Sample of banks used in the PSM estimation	**151**	**367**	**86**	**432**[b]	**60**	**372**[b]
Excluded banks as no propensity score estimated due to data constraints	8	27	0	42	5	27
Samples of banks with estimated propensity scores	**143**	**340**	**86**	**390**	**55**	**345**
Excluded banks that are not in the common support area	11	218	15	282	0	258
Final PSM samples	**132**	**122**	**71**	**108**	**55**	**87**

This table presents the European stress test participation and sample construction. Panel A reports the number of treated and untreated (control) banks for each sample European (i.e., EU and EFTA) country. For the former group of banks, participation in either the CEBS/EBA, or the ECB stress tests over the period 2010-2016 is considered. *TREATALL* reflects the entire population of treatment banks; it covers the 69.5% of the entire European banking market based on total year-end 2015 consolidated assets. The benchmark portfolio as described in the last column is congregated from the pool of banks with the remaining 30.5% of total assets. I use two dummy variables (*TREAT1011* and *TREAT14*) to capture the first-time participants in the 2010-11 and the 2014 stress tests, respectively. Panel B describes the filtering criteria I apply to my samples of banks in the conduct of the PSM analysis. I exclude banks due to financial reporting inconsistencies, and also due to the lack of data caused either by M&As, or bankruptcies. To obtain the final PSM samples, I exclude banks for which no propensity scores are produced due to data constraints as well as banks that do not fall into the common support area.

[a]The stress tests in 2009 and 2010 were conducted by CEBS. The names of the participating banks of the CEBS stress test in 2009 were not published.

[b]The untreated (control) groups for *TREAT1011* and *TREAT14* are augmented by 65 (i.e., 367 + 65 = 432) banks and 5 (i.e., 367 + 5 = 372) banks, respectively. These banks participated in a stress test exercise at some later point in time.

Table 2.3 Descriptive statistics

Panel A: Treated banks						
	Obs.	Mean	SD	Min.	Max.	Median
SIZE	2827	11.102	1.641	4.860	14.254	11.058
CAP	2552	0.073	0.065	0.006	0.480	0.062
LOAN	2527	0.588	0.188	0.057	1.084	0.610
ΔLOAN	2526	0.012	0.052	-0.135	0.241	0.006
NPL	2034	0.044	0.049	0.000	0.244	0.027
ΔNPL	1740	0.003	0.010	-0.025	0.046	0.001
LLP	2494	0.004	0.007	-0.002	0.042	0.002
LLR	2259	0.024	0.026	0.000	0.132	0.016
DSFR	2534	0.637	0.236	0.027	1.427	0.624
LTDR	2522	1.187	1.375	0.045	14.251	0.930
OEA	2544	0.362	0.191	0.016	0.936	0.324
EBPT	2539	0.008	0.007	-0.006	0.051	0.007
ROA	2551	0.004	0.009	-0.026	0.043	0.003
T1R	2512	0.119	0.053	0.059	0.394	0.109
RWA	2237	0.503	0.209	0.079	1.026	0.502
Panel B: Control banks						
	Obs.	Mean	SD	Min.	Max.	Median
SIZE	6747	6.429	1.623	3.682	13.706	6.062
CAP	5684	0.090	0.076	0.006	0.480	0.078
LOAN	5660	0.784	0.211	0.057	1.084	0.842
ΔLOAN	5655	0.028	0.057	-0.135	0.241	0.022
NPL	3291	0.020	0.034	0.000	0.244	0.010
ΔNPL	1841	0.001	0.007	-0.025	0.046	0.000
LLP	5341	0.003	0.006	-0.002	0.042	0.001
LLR	3436	0.012	0.019	0.000	0.132	0.006
DSFR	5608	0.785	0.204	0.027	1.427	0.824
LTDR	5599	1.305	1.691	0.045	14.251	1.056
OEA	5679	0.200	0.171	0.016	0.936	0.143
EBPT	5693	0.008	0.008	-0.006	0.051	0.006
ROA	5694	0.005	0.008	-0.026	0.043	0.004
T1R	1974	0.168	0.054	0.059	0.394	0.162
RWA	2042	0.581	0.166	0.079	1.026	0.574

Table 2.3 continued

Panel C: Means of country-specific variables

Country	*ΔGDP*	*ΔUNEM*	*HPI*	*IRATE*	*SUPERV*	*CAPREG*	*CORRUPT*
Austria	0.012	0.004	134.371	1.285	15	7	32.261
Belgium	0.012	0.003	100.283	1.530	18	6	33.342
Cyprus	0.009	0.057	88.776	N/A	20	7	27.840
Denmark	0.008	0.026	105.086	0.758	17	7	40.471
Estonia	0.013	0.020	131.205	N/A	17	6	29.853
Finland	0.009	0.009	102.319	1.143	13	8	39.838
France	0.011	0.008	100.529	1.305	19	9	31.148
Germany	0.014	-0.043	104.981	0.867	15	8	35.119
Greece	-0.005	0.051	84.985	7.324	15	9	18.242
Hungary	0.010	-0.005	99.733	0.601	20	7	23.472
Iceland	0.016	0.032	247.133	-1.287	20	8	35.812
Ireland	0.027	0.048	93.219	2.996	17	8	32.365
Italy	0.004	0.024	96.070	2.438	17	9	19.191
Latvia	0.012	0.026	129.046	1.406	18	7	23.009
Lithuania	0.020	0.034	342.657	2.369	18	7	24.881
Luxembourg	0.021	0.019	104.290	1.120	19	8	35.977
Malta	0.038	-0.015	176.490	N/A	19	10	24.923
Netherlands	0.011	0.012	96.348	1.146	20	9	37.571
Norway	0.013	0.007	146.129	0.381	15	7	38.099
Poland	0.026	-0.038	97.476	0.927	15	9	25.808
Portugal	0.006	0.018	95.954	3.785	17	7	25.057
Slovakia	0.024	-0.014	98.790	2.011	14	9	21.288
Slovenia	0.011	0.015	97.200	2.440	19	8	26.440
Spain	0.009	0.050	83.467	2.386	16	9	27.041
Sweden	0.016	-0.001	101.429	1.214	15	7	39.343
Switzerland	0.015	0.012	388.255	0.948	14	8	38.205
United Kingdom	0.012	0.003	92.200	1.119	16	8	34.388
Country mean	0.014	0.013	131.053	1.676	16.963	7.852	30.407
Country median	0.012	0.012	100.529	1.250	17	8	31.148

This table reports the descriptive statistics (i.e., observation, mean, standard deviation, minimum maximum and median) of the bank-specific accounting variables for the group of treated (Panel A) and that of untreated (Panel B) banks, winsorised at the 1 and 99 percentiles. These variables are: Bank size measured by natural logarithm of total assets (*SIZE*), bank capital captured by total equity capital (*CAP*), traditional banking activities and its growth shown by (change in) outstanding loans (*LOAN*, *ΔLOAN*), (backward-looking) asset quality assessed by (change in) non-performing loans (*NPL*, *ΔNPL*), (forward-looking) asset quality captured by loan loss provisions (*LLP*), credit portfolio quality shown by loan loss reserves (*LLR*), liquidity risk measured by deposit ratio and Loan-To-Deposit ratio (*DSFR*, *LTDR*), non-traditional banking activities shown by other earning assets (*OEA*), income smoothing captured by earnings before provisions and taxes (*EBPT*), profitability estimated by and return on assets (*ROA*), capital adequacy/capital management measured by regulatory Tier 1 capital ratio (*T1R*), and credit risk assessed by risk-weighted assets (*RWA*). The means of the country-specific control variables are reported in Panel C. These variables are: Economic growth (*ΔGDP*), unemployment growth (*ΔUNEM*), price level in the housing market (*HPI*), sovereign debt risk (*IRATE*), bank supervisory strength (*SUPERV*), regulatory capital stringency (*CAPREG*), and corruption level (*CORRUPT*). The description of variables and the relevant data sources are provided in Table 2.1.

Table 2.4 Correlation coefficients

Panel A: PSM analysis								
Variables	*SIZE*	*GDP*	*OEA*	*LOAN*	*LLR*	*DSFR*	*CAP*	*ROA*
SIZE	1.000							
GDP	0.519***	1.000						
	(0.000)							
OEA	0.450***	0.336***	1.000					
	(0.000)	(0.000)						
LOAN	-0.492***	-0.333***	-0.858***	1.000				
	(0.000)	(0.000)	(0.000)					
LLR	0.099***	-0.049***	0.013	-0.132***	1.000			
	(0.000)	(0.000)	(0.314)	(0.000)				
DSFR	-0.492***	-0.316***	-0.258***	0.392***	0.084***	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
CAP	-0.187***	-0.003	0.185***	-0.196***	0.120***	0.020*	1.000	
	(0.000)	(0.799)	(0.000)	(0.000)	(0.000)	(0.077)		
ROA	-0.104***	-0.041***	0.054***	0.007	-0.260***	-0.025**	0.459***	1.000
	(0.000)	(0.000)	(0.000)	(0.550)	(0.000)	(0.023)	(0.000)	

Table 2.4 continued

Panel B: Fixed effects model												
Variables	*LLP*	*LLR*	NPL_{t-1}	ΔNPL	$\Delta LOAN$	$T1R_{t-1}$	*EBPT*	$SIZE_{t-1}$	ΔGDP	$\Delta UNEM$	*HPI*	*IRATE*
LLP	1.000											
LLR	0.658***	1.000										
	(0.000)											
NPL_{t-1}	0.530***	0.878***	1.000									
	(0.000)	(0.000)										
ΔNPL	0.376***	0.273***	0.093***	1.000								
	(0.000)	(0.000)	(0.000)									
$\Delta LOAN$	-0.162***	-0.138***	-0.206***	0.105***	1.000							
	(0.000)	(0.000)	(0.000)	(0.000)								
$T1R_{t-1}$	-0.175***	-0.125***	-0.120***	-0.153***	0.004	1.000						
	(0.000)	(0.000)	(0.000)	(0.000)	(0.791)							
EBPT	0.415***	0.221***	0.197***	0.065***	0.008	0.069***	1.000					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.451)	(0.000)						
$SIZE_{t-1}$	0.062***	0.099***	0.161***	0.047***	-0.171***	-0.472***	-0.064***	1.000				
	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)					
ΔGDP	-0.039***	0.012	0.032**	-0.069***	0.020*	0.159***	-0.039***	0.001	1.000			
	(0.001)	(0.367)	(0.027)	(0.000)	(0.067)	(0.000)	(0.000)	(0.959)				
$\Delta UNEM$	0.145***	-0.069***	-0.056***	0.181***	-0.157***	-0.053***	0.008	-0.015	0.115***	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.452)	(0.159)	(0.000)			
HPI	-0.184***	-0.290***	-0.270***	-0.066***	0.219***	0.237***	-0.251***	-0.392***	0.058***	0.029***	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)		
IRATE	0.326***	0.398***	0.372***	0.230***	-0.112***	-0.134***	-0.030***	0.215***	-0.023**	0.115***	-0.148***	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.000)	(0.023)	(0.000)	(0.000)	

This Table reports the Pearson pairwise correlation coefficients and p-values for the variables I use in the PSM analysis (Panel A), and for those used in the fixed-effects regression analysis (Panel B). Panel A relies on the following variables: Bank size measured by natural logarithm of total assets (*SIZE*), economic strength estimated by nominal Gross Domestic Product (*GDP*), (non-)traditional banking activities assessed by other earning assets and outstanding loans (*OEA, LOAN*), asset quality predicted by loan loss reserves (*LLR*), liquidity risk captured by deposit ratio (*DSFR*) bank capital measured by total equity capital (*CAP*) and profitability predicted by return on assets (*ROA*). Panel B relies on the following variables, winsorised at the 1 and 99 percentiles: (Forward-looking) asset quality captured by loan loss provisions (*LLP*), credit portfolio quality shown by loan loss reserves (*LLR*), (backward-looking) asset quality assessed by (change in) non-performing loans (NPL_{t-1}, ΔNPL), loan growth shown by change in outstanding loans ($\Delta LOAN$), income smoothing captured by earnings before provisions and taxes (*EBPT*), capital adequacy/capital management measured by lagged regulatory Tier 1 capital ratio ($T1R_{t-1}$), bank size measured by lagged natural logarithm of total assets ($SIZE_{t-1}$), and country-specific macroeconomic fundamentals captured by economic growth (ΔGDP), unemployment growth ($\Delta UNEM$), price level in the housing market (*HPI*), and sovereign debt risk (*IRATE*). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of variables and the relevant data sources are provided in Table 2.1.

Table 2.5 PSM analysis of stress test participation predictors and matching equality

Panel A: Determinants of banks' probability to participate in stress tests

	(1)	(2)	(3)
Covariates	*TREATALL*	*TREAT1011*	*TREAT14*
$SIZE_{itj}$	0.6764***	0.7875***	0.5994***
	(0.0759)	(0.0955)	(0.0877)
GDP_{tj}	-0.2487	-0.4662***	-0.0260
	(0.1568)	(0.1644)	(0.1661)
OEA_{itj}	0.0673	-1.1845*	0.6998
	(0.5494)	(0.6526)	(0.5578)
LLR_{itj}	52.5814***	-3.0506	1.4683
	(16.5449)	(4.8819)	(2.0216)
$DSFR_{itj}$	0.6308	0.9969	1.5434***
	(0.5722)	(0.6984)	(0.5938)
CAP_{itj}	-9.5260**	0.9899	6.0888***
	(4.3287)	(4.0417)	(2.0246)
ROA_{itj}	43.3069***	10.1317	-1.3432
	(15.6988)	(9.1826)	(4.5948)
Constant	-6.7455***	-8.4602***	-7.8283***
	(0.9141)	(1.3941)	(1.0311)
Observations	483	476	400
Pseudo R^2	0.692	0.625	0.462
Log likelihood	-90.28	-84.27	-86.10

Panel B: t-Test before and after matching for equality of means of covariates including all treatment banks

	Unmatched samples			Matched samples		
Covariates	*TREATALL*	Control banks	Difference in means	*TREATALL*	Control banks	Difference in means
$SIZE_{itj}$	10.9440	6.0875	4.8565***	10.7470	10.7230	0.0240
GDP_{tj}	0.9741	0.4431	0.5310***	0.9464	0.9032	0.0432
OEA_{itj}	0.3692	0.1829	0.1863***	0.3505	0.3811	-0.0306
LLR_{itj}	0.0133	0.0076	0.0057***	0.0133	0.0122	0.0011
$DSFR_{itj}$	0.5889	0.7314	-0.1425***	0.5974	0.5997	-0.0023
CAP_{itj}	0.0609	0.0943	-0.0334***	0.0636	0.0636	0.0000
ROA_{itj}	0.0067	0.0079	-0.0012	0.0069	0.0079	-0.0010
Observations	143	340	483	132	122	254
Pseudo-R^2		0.692			0.009	

Panel C: t-Test before and after matching for equality of means of covariates for first-time participants in 2010-11

	Unmatched samples			Matched samples		
Covariates	*TREAT1011*	Control banks	Difference in means	*TREAT1011*	Control banks	Difference in means
$SIZE_{itj}$	11.8420	6.7965	5.0455***	11.7870	11.7910	-0.0040
GDP_{tj}	0.9177	0.4960	0.4217***	0.9177	0.8479	0.0698
OEA_{itj}	0.3477	0.2101	0.1376***	0.3477	0.4035	-0.0558
LLR_{itj}	0.0145	0.0119	0.0026	0.0145	0.0087	0.0058
$DSFR_{itj}$	0.5916	0.7199	-0.1283***	0.5916	0.5587	0.0329
CAP_{itj}	0.0546	0.0855	-0.0309***	0.0546	0.0472	0.0074
ROA_{itj}	0.0029	0.0039	-0.0010	0.0029	0.0030	-0.0001
Observations	86	390	476	71	108	179
Pseudo-R^2		0.625			0.027	

Table 2.5 continued

Panel D: t-Test before and after matching for equality of means of covariates for first-time participants in 2014						
	Unmatched samples			Matched samples		
Covariates	*TREAT14*	Control banks	Difference in means	*TREAT14*	Control banks	Difference in means
$SIZE_{itj}$	10.1250	6.5702	3.5548***	10.0510	10.0030	0.0480
GDP_{tj}	1.0157	0.4724	0.5433***	0.9849	1.0272	-0.0423
OEA_{itj}	0.3515	0.2064	0.1451***	0.3453	0.3495	-0.0042
LLR_{itj}	0.0273	0.0156	0.0117*	0.0273	0.0441	-0.0168
$DSFR_{itj}$	0.6331	0.7358	-0.1027***	0.6444	0.6270	0.0174
CAP_{itj}	0.0772	0.0899	-0.0127	0.0819	0.0868	-0.0049
ROA_{itj}	0.0015	0.0042	-0.0027	0.0015	0.0015	0.0000
Observations	55	345	400	55	87	142
Pseudo-R^2		0.462			0.012	

This table reports the PSM results based on Equation 2.1. Panel A shows the estimates of the bank's propensity of being stress-tested for the samples of total stress test participation (*TREATALL*), first-time participation in 2010-11 (*TREAT1011*) and 2014 (*TREAT14*). Panels B, C and D illustrate the mean comparison of bank-specific covariates for treated and untreated (control) banks, before and after Gaussian Kernel Matching (GKM). The difference in means is calculated as the difference between treated and untreated banks' means. The two rows below the covariates illustrate the number of observations and Pseudo-R^2 before and after matching. I include the following covariates in my analysis: Bank size measured by natural logarithm of total assets ($SIZE_{itj}$), countries' economic strength estimated by nominal Gross Domestic Product (GDP_{tj}), non-traditional banking activities assessed by other earning assets (OEA_{itj}), asset quality predicted by loan loss reserves (LLR_{itj}), liquidity risk captured by deposit ratio ($DSFR_{itj}$), bank capital measured by equity divided by total assets (CAP_{itj}), and profitability predicted by return on assets (ROA_{itj}). The covariates are obtained as an average value from 2005S2-2008S2 (*TREATALL*), from 2008S2-2009S2 (*TREAT1011*) and from 2012S2-2013S2 (*TREAT14*). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Standard errors of the coefficients in Panel A are clustered at bank level. The description of the variables and the relevant data sources are provided in Table 2.1.

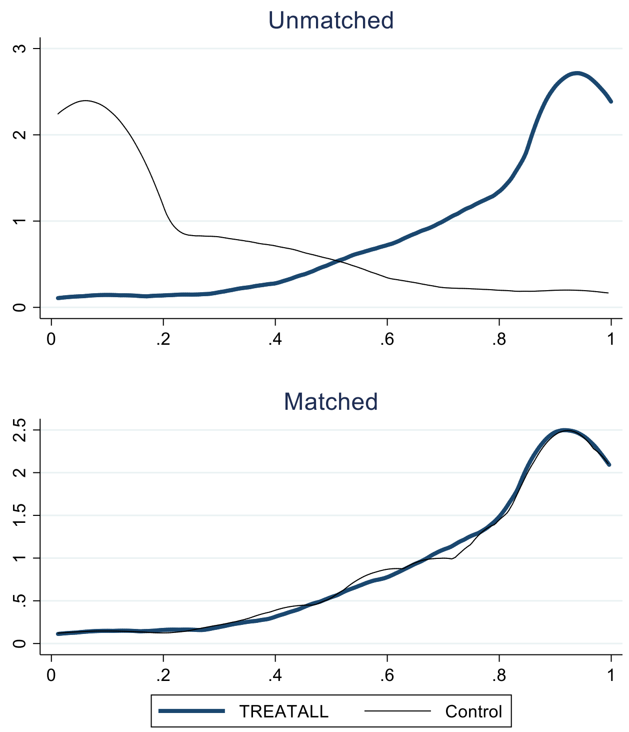

Figure 2.1 Matching equality of *TREATALL*
This figure plots the density of estimated propensity scores for the sample of total stress test participation (*TREATALL*) compared to control banks before and after matching.

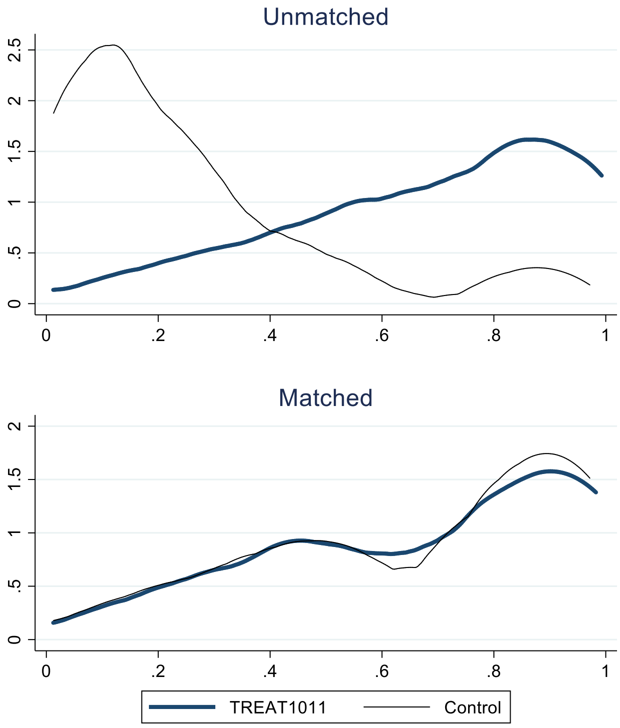

Figure 2.2 Matching equality of *TREAT1011*
This figure plots the density of estimated propensity scores for the sample of first-time participants in 2010-11 (*TREAT1011*) compared to control banks before and after matching.

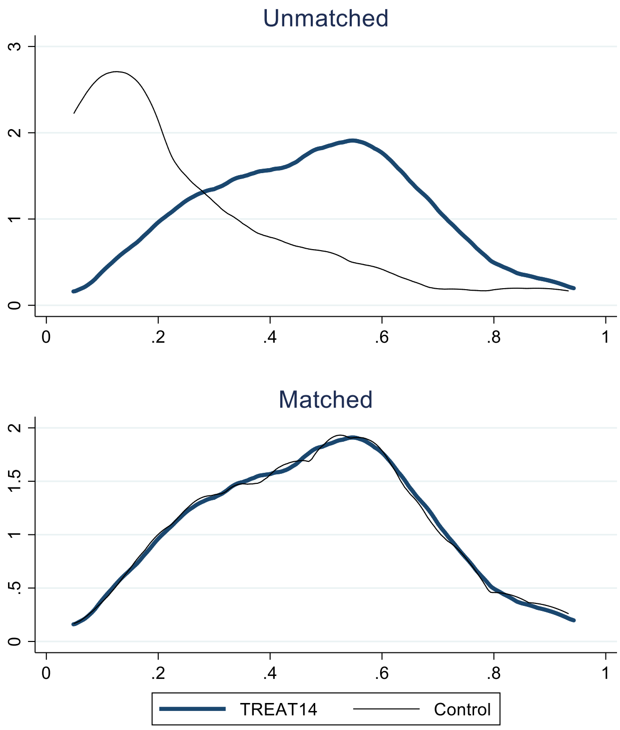

Figure 2.3 Matching equality of *TREAT14*
The figure plots the density of estimated propensity scores for the sample of first-time participants in 2014 (*TREAT14*) compared to control banks before and after matching.

Table 2.6 PSM/DiD analysis of the average treatment effect of stress tests

Panel A: Total stress test participation effect						
	Asset quality (*LLP*)			Asset quality (*NPL*)		
	TREATALL	Control	Diff (T–C)	*TREATALL*	Control	Diff (T–C)
Treatment period (T_2)	0.0040	0.0050	-0.0010*	0.0366	0.0374	-0.0008
Pre-treatment period (T_1)	0.0037	0.0033	0.0004	0.0295	0.0329	-0.0034
Diff ($\Delta y_{i(T_1T_2)j}$)	0.0003	0.0017**		0.0071***	0.0045*	
DiD ($\tau_{i(T_1,T_2)j}$)			**-0.0014**			**0.0026**
Observations		3,223			2,749	
Adjusted R-squared		0.7648			0.9002	
	Capital adequacy (*T1R*)			Credit Risk (*RWA*)		
	TREATALL	Control	Diff (T–C)	*TREATALL*	Control	Diff (T–C)
Treatment period (T_2)	0.1290	0.1519	-0.0229***	0.4525	0.4132	0.0394
Pre-treatment period (T_1)	0.0612	0.0726	-0.0114***	0.6490	0.6120	0.0370
Diff ($\Delta y_{i(T_1T_2)j}$)	0.0678***	0.0793***		-0.1965***	-0.1988***	
DiD ($\tau_{i(T_1,T_2)j}$)			**-0.0115****			**0.0023**
Observations		2,440			2,650	
Adjusted R-squared		0.4414			0.6023	
Panel B: 2010-11 EBA first-time stress test participation effect						
	Asset quality (*LLP*)			Asset quality (*NPL*)		
	TREAT1011	Control	Diff (T–C)	*TREAT1011*	Control	Diff (T–C)
Treatment period (T_2)	0.0039	0.0043	-0.0004	0.0284	0.0270	0.0014
Pre-treatment period (T_1)	0.0035	0.0026	0.0009	0.0215	0.0236	-0.0021
Diff ($\Delta y_{i(T_1T_2)j}$)	0.0004	0.0017***		0.0069***	0.0034***	
DiD ($\tau_{i(T_1,T_2)j}$)			**-0.0013****			**0.0035****
Observations		1,051			897	
Adjusted R-squared		0.6747			0.8693	
	Capital adequacy (*T1R*)			Credit Risk (*RWA*)		
	TREAT1011	Control	Diff (T–C)	*TREAT1011*	Control	Diff (T–C)
Treatment period (T_2)	0.1247	0.1389	-0.0142**	0.3794	0.3910	-0.0116
Pre-treatment period (T_1)	0.0811	0.0966	-0.0155***	0.5279	0.5042	0.0237
Diff ($\Delta y_{i(T_1T_2)j}$)	0.0436***	0.0424***		-0.1485***	-0.1132***	
DiD ($\tau_{i(T_1,T_2)j}$)			**0.0013**			**-0.0353***
Observations		871			915	
Adjusted R-squared		0.4549			0.6800	
Panel C: 2014 EBA/ECB first-time stress test participation effect						
	Asset quality (*LLP*)			Asset quality (*NPL*)		
	TREAT14	Control	Diff (T–C)	*TREAT14*	Control	Diff (T–C)
Treatment period (T_2)	0.0043	0.0037	0.0006	0.0412	0.0418	-0.0005
Pre-treatment period (T_1)	0.0028	0.0027	0.0001	0.0397	0.0458	-0.0061
Diff ($\Delta y_{i(T_1T_2)j}$)	0.0015***	0.0010		0.0015	-0.0040	
DiD ($\tau_{i(T_1,T_2)j}$)			**0.0005**			**0.0055***
Observations		880			751	
Adjusted R-squared		0.5811			0.8921	
	Capital adequacy (*T1R*)			Credit Risk (*RWA*)		
	TREAT14	Control	Diff (T–C)	*TREAT14*	Control	Diff (T–C)
Treatment period (T_2)	0.1580	0.1653	-0.0073	0.4559	0.4085	0.0474
Pre-treatment period (T_1)	0.1145	0.1418	-0.0273**	0.5733	0.5095	0.0638*
Diff ($\Delta y_{i(T_1T_2)j}$)	0.0434***	0.0235**		-0.1174***	-0.1010***	
DiD ($\tau_{i(T_1,T_2)j}$)			**0.0200****			**-0.0164**
Observations		626			720	
Adjusted R-squared		0.3697			0.5757	

This table reports the average treatment effect of stress tests based on Equation 2.2. Panel A illustrates the total stress test participation effect (*TREATALL*). Panel B estimates the effect of the 2010-11 treatments (*TREAT1011*). Panel C analyses the effect of the 2014 EBA/ECB treatments (*TREAT14*). I apply a DiD design using Gaussian Kernel probability weights, covariates obtained from my prior PSM analysis and control for half-year time effects. I include the following outcome variables in my analysis: Forward- and backward-looking asset quality measured by loan loss provisions (*LLP*) and non-performing loans (*NPL*), capital adequacy captured by lagged regulatory Tier 1 capital ratio ($T1R_{t-1}$), and credit risk assessed by risk-weighted assets (*RWA*). $\tau_{i(T_1,T_2)j}$ yields the average double difference, or DiD, between the difference of the outcome variables before and after the treatment ($\Delta y_{i(T_1,T_2)j}$) and the difference of the treatment (*TREAT, TREAT1011*, and *TREAT14*) over the control group. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 2.1.

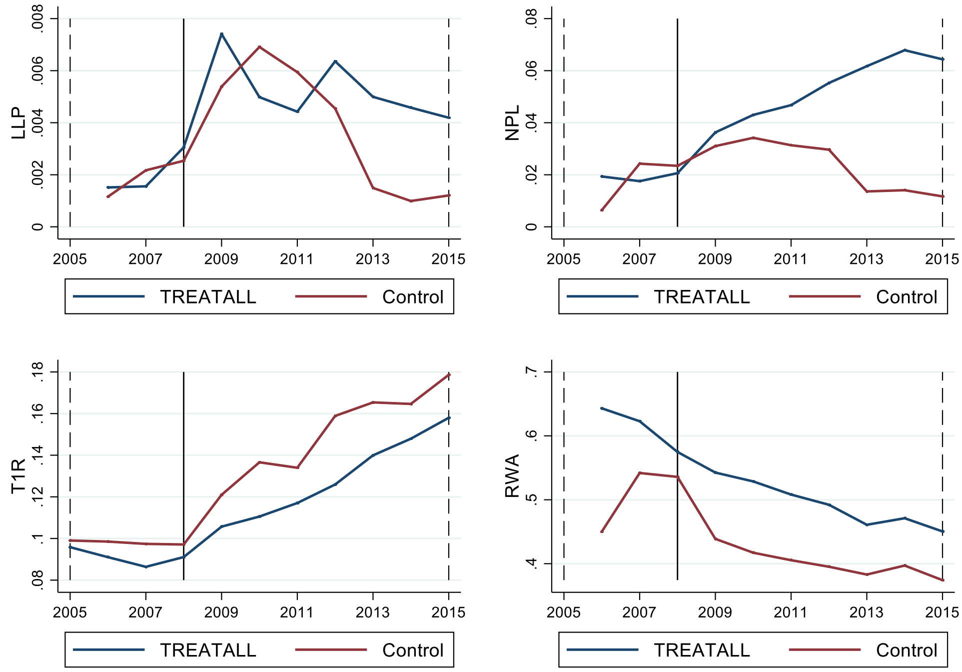

Figure 2.4 Total stress test participation
The graphs plot Gaussian Kernel weighted means of outcome variables for the sample of total stress test participation (*TREATALL*) and matched control banks. Dashed lines indicate the observed period, while the solid line marks the treatment separating pre- and post-treatment periods. I include the following variables in my analysis: Forward-looking and backward-looking asset quality measured by loan loss provisions (*LLP*) and non-performing loans (*NPL*), capital adequacy captured by regulatory Tier 1 capital ratio (*T1R*), and credit risk assessed by risk-weighted assets (*RWA*).

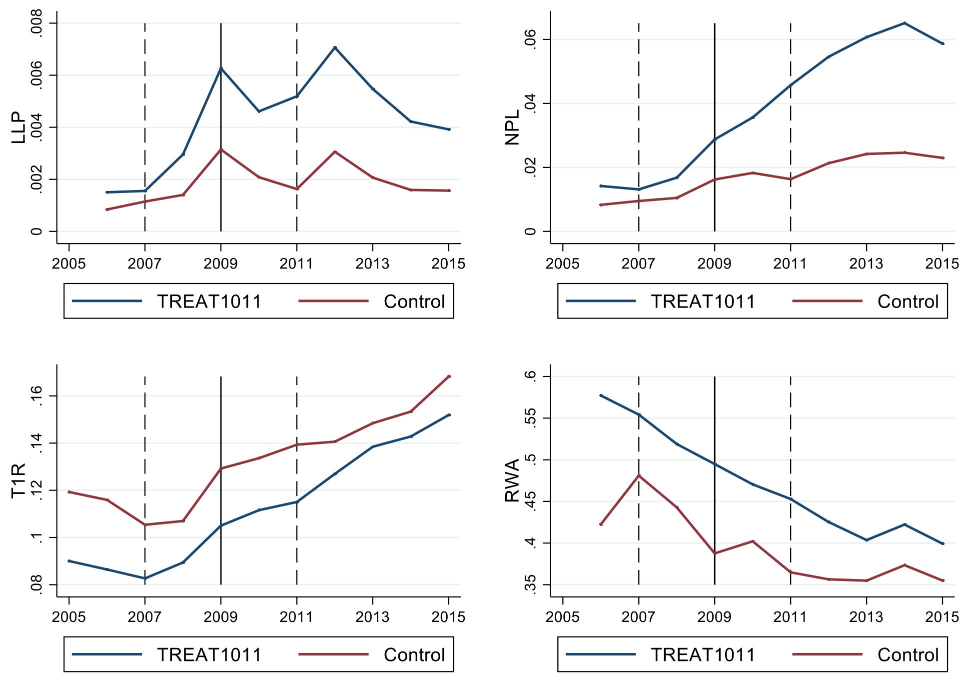

Figure 2.5 2010-11 EBA first-time participation
The graphs plot Gaussian Kernel weighted means of outcome variables for the sample of 2010-11 first-time participants (*TREAT1011*) and matched control banks. Dashed lines indicate the observed period, while the solid line marks the treatment separating pre- and post-treatment periods. I include the following variables in my analysis: Forward-looking and backward-looking asset quality measured by loan loss provisions (*LLP*) and non-performing loans (*NPL*), capital adequacy captured by regulatory Tier 1 capital ratio (*T1R*), and credit risk assessed by risk-weighted assets (*RWA*).

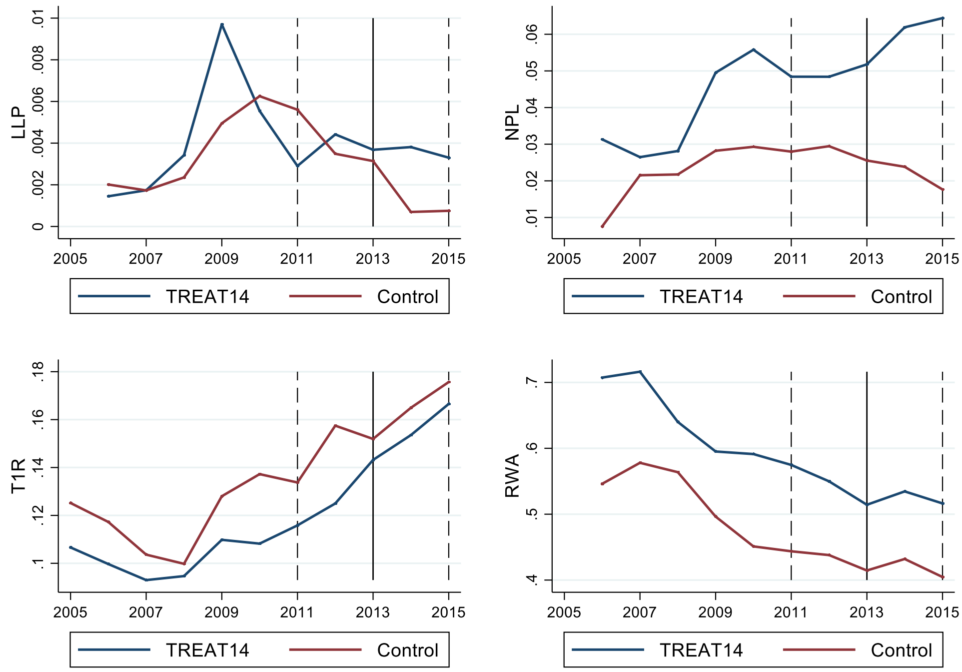

Figure 2.6 2014 EBA/ECB first-time stress test participation

The graphs plot Gaussian Kernel weighted means of outcome variables for the sample of 2014 first-time participants (*TREAT14*) and matched control banks. Dashed lines indicate the observed period, while the solid line marks the treatment separating pre- and post-treatment periods. I include the following variables in my analysis: Forward-looking and backward-looking asset quality measured by loan loss provisions (*LLP*) and non-performing loans (*NPL*), capital adequacy captured by regulatory Tier 1 capital ratio (*T1R*), and credit risk assessed by risk-weighted assets (*RWA*).

Table 2.7 Bank discretionary behaviour

Variables	(1) *TREATALL*	(2) *TREAT1011*	(3) *TREAT14*
NPL_{it-1j}	0.0441***	0.0731**	0.1291**
	(0.0103)	(0.0335)	(0.0536)
ΔNPL_{itj}	0.1469***	0.1102***	0.1283**
	(0.0302)	(0.0240)	(0.0535)
$\Delta LOAN_{itj}$	-0.0170***	0.0020	-0.0111
	(0.0037)	(0.0054)	(0.0084)
$T1R_{it-1j}$	-0.0401**	-0.0242*	-0.0367
	(0.0169)	(0.0139)	(0.0247)
$EBPT_{itj}$	-0.0615	0.0383	-0.2275
	(0.0691)	(0.0417)	(0.1577)
STHC	-0.0039		
	(0.0032)		
*TREATALL*STHC*	0.0046		
	(0.0029)		
$TREATALL{*}T1R_{it-1j}$	0.0090		
	(0.0167)		
$STHC{*}T1R_{it-1j}$	0.0420***		
	(0.0161)		
$TREATALL{*}STHC{*}T1R_{it-1j}$	-0.0310*		
	(0.0157)		
$TREATALL{*}EBPT_{itj}$	0.1522**		
	(0.0649)		
$STHC{*}EBPT_{itj}$	0.1372		
	(0.1173)		
$TREATALL{*}STHC{*}EBPT_{itj}$	-0.0217		
	(0.1206)		
BAST1011		-0.0034***	
		(0.0013)	
*TREAT1011*BAST1011*		0.0058**	
		(0.0023)	
$TREAT1011{*}T1R_{it-1j}$		0.0119	
		(0.0237)	
$BAST1011{*}T1R_{it-1j}$		0.0573***	
		(0.0142)	
$TREAT1011{*}BAST1011{*}T1R_{it-1j}$		-0.0719***	
		(0.0217)	
$TREAT1011{*}EBPT_{itj}$		0.2069**	
		(0.0937)	
$BAST1011{*}EBPT_{itj}$		-0.1461**	
		(0.0621)	
$TREAT1011{*}BAST1011{*}EBPT_{itj}$		0.2007**	
		(0.0859)	

Table 2.7 continued

BAST14			-0.0112***
			(0.0021)
*TREAT14*BAST14*			0.0081**
			(0.0036)
$TREAT14{*}T1R_{it-1j}$			-0.0303
			(0.0346)
$BAST14{*}T1R_{it-1j}$			0.0587***
			(0.0144)
$TREAT14{*}BAST14{*}T1R_{it-1j}$			-0.0263
			(0.0239)
$TREAT14{*}EBPT_{itj}$			0.3565*
			(0.1946)
$BAST14{*}EBPT_{itj}$			0.2045*
			(0.1035)
$TREAT14{*}BAST14{*}EBPT_{itj}$			-0.2984**
			(0.1131)
$SIZE_{it-1j}$	0.0000	-0.0024	0.0030
	(0.0005)	(0.0018)	(0.0033)
ΔGDP_{tj}	-0.0346***	-0.0130	-0.0703
	(0.0086)	(0.0095)	(0.0488)
$\Delta UNEM_{tj}$	-0.0029	-0.0007	0.0056
	(0.0018)	(0.0021)	(0.0044)
HPI_{tj}	0.0000	-0.0001***	0.0001
	(0.0000)	(0.0000)	(0.0001)
$IRATE_{tj}$	0.0006***	0.0003	0.0001
	(0.0002)	(0.0002)	(0.0006)
Constant	0.0030	0.0421*	-0.0342
	(0.0071)	(0.0242)	(0.0376)
Observations	1,698	649	410
Number of banks	152	119	72
Adjusted R-squared	0.3941	0.5524	0.4922
Bank fixed effects	Yes	Yes	Yes
Half-year fixed effects	Yes	Yes	Yes

This table reports the effect of stress test participation on banks' capital management and income smoothing behaviour through *LLP* in 27 European countries. Model 1 presents the total stress test effect on banks' capital management and income smoothing behaviour based on Equation 2.3_A. Model 2 illustrates the stress test effect on the discretionary behaviour of first-time participants in 2010-11 based on Equation 2.3_B. Model 3 examines the stress test effect on the discretionary behaviour of first-time participants in 2014 based on Equation 2.3_C. I include the following variables in my analysis: Forward- and (shift of) backward looking asset quality captured by loan loss provisions (LLP_{itj}) and lagged (change in) non-performing loans (NPL_{it-1j}, ΔNPL_{itj}), loan growth shown by change in outstanding loans ($\Delta LOAN_{itj}$), capital management measured by lagged regulatory Tier 1 capital ratio ($T1R_{it-1j}$), income smoothing captured by earnings before provisions and taxes ($EBPT_{itj}$); a dummy for stress test participation (*TREATALL*), first-time participation in 2010-11 (*TREAT1011*) and 2014 (*TREAT14*); a dummy for 'hot' and 'cold' stress test periods (*STHC*), a dummy for four half-year periods before and after the 2010-11 (*BAST1011*) and 2014 treatments (*BAST14*); bank size captured by lagged natural logarithm of total assets ($SIZE_{it-1j}$) and macroeconomic fundamentals to control for contemporaneous fiscal and monetary policy changes and market instabilities such as illiquidity, constrained capital and higher volatility shown by economic growth (ΔGDP_{tj}), unemployment growth ($\Delta UNEM_{tj}$), price level in the housing market (HPI_{tj}) and sovereign debt risk ($IRATE_{tj}$). Data range 2005-2015. Standard errors (parentheses) are clustered at bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 2.1.

Table 2.8 Bank discretionary behaviour considering the institutional environment

Variables	(1) *SUPERV*	(2) *CAPREG*	(3) *CORRUPT*
NPL_{it-1j}	0.0421***	0.0454***	0.0389***
	(0.0109)	(0.0107)	(0.0110)
ΔNPL_{itj}	0.1432***	0.1478***	0.1454***
	(0.0301)	(0.0308)	(0.0295)
$\Delta LOAN_{itj}$	-0.0169***	-0.0162***	-0.0164***
	(0.0035)	(0.0036)	(0.0037)
$T1R_{it-1j}$	0.3251**	0.3309**	-0.0321
	(0.1535)	(0.1317)	(0.0270)
$EBPT_{itj}$	0.5927	-1.5221**	0.1069**
	(0.6261)	(0.7121)	(0.0453)
*TREATALL*STHC*	-0.0993***	-0.0277	0.0005
	(0.0309)	(0.0226)	(0.0038)
$TREATALL*T1R_{it-1j}$	-0.3054*	-0.2885**	0.0059
	(0.1682)	(0.1399)	(0.0306)
$STHC*T1R_{it-1j}$	-0.5110***	-0.3303**	0.0278
	(0.1715)	(0.1371)	(0.0260)
$TREATALL*STHC*T1R_{it-1j}$	0.5463***	0.2511*	-0.0146
	(0.1818)	(0.1414)	(0.0312)
$TREATALL*EBPT_{itj}$	-0.0044	1.1599	-0.0267
	(0.7410)	(0.7084)	(0.0632)
$STHC*EBPT_{itj}$	-3.3378***	0.3432	-0.1731
	(1.0565)	(0.8214)	(0.1079)
$TREATALL*STHC*EBPT_{itj}$	2.8918***	0.4794	0.2823**
	(1.0918)	(0.8441)	(0.1112)
*STHC*SUPERV*	-0.0068***		
	(0.0019)		
*TREATALL*STHC*SUPERV*	0.0068***		
	(0.0020)		
$SUPERV*T1R_{it-1j}$	-0.0237**		
	(0.0101)		
$TREATALL*SUPERV*T1R_{it-1j}$	0.0205*		
	(0.0111)		
$STHC*SUPERV*T1R_{it-1j}$	0.0361***		
	(0.0111)		
$TREATALL*STHC*SUPERV*T1R_{it-1j}$	-0.0375***		
	(0.0119)		
$SUPERV*EBPT_{itj}$	-0.0455		
	(0.0417)		
$TREATALL*SUPERV*EBPT_{itj}$	0.0156		
	(0.0484)		
$STHC*SUPERV*EBPT_{itj}$	0.2248***		
	(0.0695)		
$TREATALL*STHC*SUPERV*EBPT_{itj}$	-0.1914***		
	(0.0715)		
*STHC*CAPREG*		-0.0055*	
		(0.0030)	
*TREATALL*STHC*CAPREG*		0.0041	
		(0.0031)	
$CAPREG*T1R_{it-1j}$		-0.0461**	
		(0.0181)	
$TREATALL*CAPREG*T1R_{it-1j}$		0.0371*	
		(0.0192)	
$STHC*CAPREG*T1R_{it-1j}$		0.0463**	
		(0.0185)	
$TREATALL*STHC*CAPREG*T1R_{it-1j}$		-0.0356*	
		(0.0190)	
$CAPREG*EBPT_{itj}$		0.1833**	
		(0.0926)	
$TREATALL*CAPREG*EBPT_{itj}$		-0.1301	
		(0.0918)	

Table 2.8 continued

$STHC*CAPREG*EBPT_{itj}$		-0.0256	
		(0.1154)	
$TREATALL*STHC*CAPREG*EBPT_{itj}$		-0.0589	
		(0.1173)	
$STHC$			-0.0003
			(0.0036)
$CORRUPT$			0.0001*
			(0.0000)
$TREATALL*CORRUPT$			-0.0000
			(0.0000)
$STHC*CORRUPT$			-0.0001**
			(0.0001)
$TREATALL*STHC*CORRUPT$			0.0001
			(0.0001)
$CORRUPT*T1R_{it-1j}$			-0.0000
			(0.0003)
$TREATALL*CORRUPT*T1R_{it-1j}$			-0.0002
			(0.0004)
$STHC*CORRUPT*T1R_{it-1j}$			0.0003
			(0.0003)
$TREATALL*STHC*CORRUPT*T1R_{it-1j}$			-0.0001
			(0.0004)
$CORRUPT*EBPT_{itj}$			-0.0049***
			(0.0013)
$TREATALL*CORRUPT*EBPT_{itj}$			0.0056***
			(0.0019)
$STHC*CORRUPT*EBPT_{itj}$			0.0070***
			(0.0022)
$TREATALL*STHC*CORRUPT*EBPT_{itj}$			-0.0074***
			(0.0022)
$SIZE_{it-1j}$	0.0002	0.0002	-0.0001
	(0.0005)	(0.0005)	(0.0007)
ΔGDP_{tj}	-0.0339***	-0.0354***	-0.0295***
	(0.0082)	(0.0084)	(0.0083)
$\Delta UNEM_{tj}$	-0.0024	-0.0026	-0.0027
	(0.0019)	(0.0019)	(0.0019)
HPI_{tj}	-0.0000	0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)
$IRATE_{tj}$	0.0006***	0.0006***	0.0006***
	(0.0002)	(0.0001)	(0.0002)
Constant	0.0036	0.0018	0.0042
	(0.0071)	(0.0069)	(0.0088)
Observations	1,698	1,698	1,698
Number of banks	152	152	152
Adjusted R-squared	0.4044	0.4020	0.4027
Bank fixed effects	Yes	Yes	Yes
Half-year fixed effects	Yes	Yes	Yes

This table reports the effect of stress test participation on banks' capital management and income smoothing behaviour considering the institutional environment in 27 European countries based on Equation 2.4. Model 1 assesses differences in stress test effect on banks' discretionary behaviour across countries with low versus high supervisory power regimes. Model 2 illustrates differences in stress test effect on discretionary behaviour across countries with low versus high capital regulation regimes. Model 3 evaluates differences in stress test effect on banks' discretionary behaviour across countries with low versus high corruption level. I include the following variables in my analysis: Forward- and (shift of) backward looking asset quality captured by loan loss provisions (LLP_{itj}) and lagged (change in) non-performing loans (NPL_{it-1j}, ΔNPL_{itj}), loan growth shown by change in outstanding loans ($\Delta LOAN_{itj}$), capital management measured by lagged regulatory Tier 1 capital ratio ($T1R_{it-1j}$), income smoothing captured by earnings before provisions and taxes ($EBPT_{itj}$); a dummy for stress test participation (*TREATALL*); a dummy for 'hot' and 'cold' stress test periods (*STHC*); bank size captured by lagged natural logarithm of total assets ($SIZE_{it-1j}$), countries' institutional environment assessed by local supervisory power (*SUPERV*), capital regulation stringency (*CAPREG*), and corruption level (*CORRUPT*), and macroeconomic fundamentals to control for contemporaneous fiscal and monetary policy changes and market instabilities such as illiquidity, constrained capital and higher volatility shown by economic growth (ΔGDP_{tj}), unemployment growth ($\Delta UNEM_{tj}$), price level in the housing market (HPI_{tj}) and sovereign debt risk ($IRATE_{tj}$). Data range 2005-2015. Standard errors (parentheses) are clustered at bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 2.1.

Table 2.9 Discretionary behaviour of high-, medium- and low-capitalised banks

Variables	(1) *CAPH*	(2) *CAPM*	(3) *CAPL*
NPL_{it-1j}	0.0371**	0.0496***	0.0413
	(0.0171)	(0.0080)	(0.0316)
ΔNPL_{itj}	0.1829***	0.1002***	0.0650
	(0.0588)	(0.0276)	(0.0545)
$\Delta LOAN_{itj}$	-0.0197***	-0.0125***	-0.0105*
	(0.0071)	(0.0037)	(0.0057)
$T1R_{it-1j}$	0.0235	-0.0020	-0.0615**
	(0.0305)	(0.0227)	(0.0234)
$EBPT_{itj}$	-0.0073	-0.2108*	0.1085
	(0.0689)	(0.1122)	(0.0872)
STHC	0.0087**	0.0116***	-0.0109***
	(0.0039)	(0.0036)	(0.0036)
*TREATALL*STHC*	-0.0071*	-0.0061**	0.0079
	(0.0038)	(0.0027)	(0.0051)
$TREATALL*T1R_{it-1j}$	-0.0282	-0.0023	-0.0171
	(0.0315)	(0.0274)	(0.0436)
$STHC*T1R_{it-1j}$	-0.0371	-0.0006	0.0490**
	(0.0224)	(0.0083)	(0.0208)
$TREATALL*STHC*T1R_{it-1j}$	0.0407*	0.0104	-0.0531*
	(0.0231)	(0.0145)	(0.0296)
$TREATALL*EBPT_{itj}$	-0.0158	0.3085***	-0.0289
	(0.0951)	(0.0941)	(0.0952)
$STHC*EBPT_{itj}$	-0.0332	-0.2888*	0.1725
	(0.0597)	(0.1474)	(0.1272)
$TREATALL*STHC*EBPT_{itj}$	0.1206	0.3277**	-0.0013
	(0.1079)	(0.1637)	(0.1641)
$SIZE_{it-1j}$	-0.0002	0.0011	-0.0021
	(0.0009)	(0.0022)	(0.0015)
ΔGDP_{tj}	-0.0152	-0.0275*	-0.0348**
	(0.0106)	(0.0148)	(0.0131)
$\Delta UNEM_{tj}$	-0.0031	-0.0021	-0.0018
	(0.0022)	(0.0020)	(0.0016)
HPI_{tj}	-0.0000	-0.0000**	0.0000
	(0.0000)	(0.0000)	(0.0000)
$IRATE_{tj}$	0.0005**	0.0002	0.0017*
	(0.0002)	(0.0001)	(0.0009)
Constant	0.0082	-0.0077	0.0285
	(0.0110)	(0.0243)	(0.0181)
Observations	884	486	328
Number of banks	100	75	55
Adjusted R-squared	0.3781	0.6650	0.4012
Bank fixed effects	Yes	Yes	Yes
Half-year fixed effects	Yes	Yes	Yes

This table reports the effect of stress test participation on high-, medium- and low-capitalised banks and their capital management and income smoothing behaviour in 27 European countries based on Equation 2.3$_A$. Model 1 assesses the discretionary behaviour of high-capitalised banks (*CAPH: CAP* > 10%). Model 2 estimates the discretionary behaviour of medium-capitalised banks (*CAPM:* 7% ≤ *CAP* ≤ 10%). Model 3 examines the discretionary behaviour of low-capitalised banks (*CAPL: CAP* < 7%). I include the following variables in my analysis: Forward- and (shift of) backward looking asset quality captured by loan loss provisions (LLP_{itj}) and lagged (change in) non-performing loans (NPL_{it-1j}, ΔNPL_{itj}), loan growth shown by change in outstanding loans ($\Delta LOAN_{itj}$), capital management measured by lagged regulatory Tier 1 capital ratio ($T1R_{it-1j}$), income smoothing captured by earnings before provisions and taxes ($EBPT_{itj}$); a dummy for stress test participation (*TREATALL*); a dummy for 'hot' and 'cold' stress test periods (*STHC*); bank size captured by lagged natural logarithm of total assets ($SIZE_{it-1j}$) and macroeconomic fundamentals to control for contemporaneous fiscal and monetary policy changes and market instabilities such as illiquidity, constrained capital and higher volatility shown by economic growth (ΔGDP_{tj}), unemployment growth ($\Delta UNEM_{tj}$), price level in the housing market (HPI_{tj}) and sovereign debt risk ($IRATE_{tj}$). Data range 2005-2015. Standard errors (parentheses) are clustered at bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 2.1.

Table 2.10 PSM robustness on covariate imbalance and hidden bias

Panel A: Determinants of banks' probability to participate in stress tests using an alternative robustness model

	(1) *TREATALL*		(2) *TREAT1011*		(3) *TREAT14*	
Covariates	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.
$SIZE_{itj}$	0.6743***	(0.0757)	0.7709***	(0.0903)	0.5937***	(0.0874)
GDP_{tj}	-0.2613*	(0.1582)	-0.4982***	(0.1719)	-0.0309	(0.1682)
OEA_{itj}	0.0048	(0.5539)	-1.3509**	(0.6352)	0.5424	(0.5790)
LLR_{itj}	52.6526***	(16.5193)	-3.5711	(4.8120)	1.3822	(2.0275)
$DSFR_{itj}$	0.4485	(0.6016)	0.4447	(0.7804)	1.1844	(0.7212)
$LTDR_{itj}$	-0.0107	(0.0071)	-0.0717	(0.0618)	-0.0600	(0.0895)
CAP_{itj}	-9.6389**	(4.3401)	0.5144	(4.1328)	5.9751***	(1.9900)
ROA_{itj}	42.9867***	(15.7546)	10.6378	(8.9867)	-1.5936	(4.6251)
Constant	-6.5493***	(0.9170)	-7.7272***	(1.3137)	-7.3987***	(1.0847)
Observations	483		476		400	
Pseudo R^2	0.693		0.628		0.465	
Log likelihood	-89.99		-83.67		-85.71	

Panel B: PSM/DiD treatment effect including additional confounding covariates

(1) Total stress test participation effect

	Asset quality (*LLP*)		Asset quality (*NPL*)		Capital adequacy (*T1R*)		Credit risk (*RWA*)	
	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.
TREATALL	0.0004	(0.0011)	-0.0054**	(0.0025)	-0.0106*	(0.0063)	0.0332	(0.0555)
BAST	0.0017**	(0.0007)	0.0042*	(0.0024)	0.0781***	(0.0076)	-0.1930***	(0.0632)
$\tau_{i(T_1,T_2)j}$	-0.0014	(0.0011)	0.0030	(0.0023)	-0.0119**	(0.0057)	0.0055	(0.0483)
Observations	3,223		2,749		2,440		2,650	
Adjusted R^2	0.7687		0.9044		0.4515		0.6070	

(2) 2010-11 EBA first-time stress test participation effect

	Asset quality (*LLP*)		Asset quality (*NPL*)		Capital adequacy (*T1R*)		Credit risk (*RWA*)	
	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.
TREAT1011	0.0005	(0.0005)	-0.0002	(0.0016)	-0.0115	(0.0076)	0.0155	(0.0340)
BAST1011	0.0017***	(0.0004)	0.0043***	(0.0013)	0.0424***	(0.0080)	-0.1103***	(0.0220)
$\tau_{i(T_1,T_2)j}$	-0.0013**	(0.0006)	0.0030**	(0.0014)	0.0006	(0.0067)	-0.0343*	(0.0190)
Observations	1,051		897		871		915	
Adjusted R^2	0.6855		0.8792		0.4695		0.6867	

(3) 2014 EBA/ECB first-time stress test participation effect

	Asset quality (*LLP*)		Asset quality (*NPL*)		Capital adequacy (*T1R*)		Credit risk (*RWA*)	
	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.
TREAT14	0.0004	(0.0009)	-0.0115***	(0.0041)	-0.0328***	(0.0115)	0.1026**	(0.0408)
BAST14	0.0011	(0.0011)	-0.0037	(0.0050)	0.0222**	(0.0097)	-0.0948***	(0.0218)
$\tau_{i(T_1,T_2)j}$	0.0006	(0.0011)	0.0054*	(0.0031)	0.0163*	(0.0087)	-0.0074	(0.0186)
Observations	880		751		626		720	
Adjusted R^2	0.6111		0.9033		0.4193		0.6039	

This table reports PSM robustness checks. Panel A tests covariate imbalance using an alternative covariate combination and Panel B analyses hidden bias including additional confounding covariates. I illustrate results for the samples of total stress test participation (*TREATALL*), first-time participation in 2010-11 (*TREAT1011*) and 2014 (*TREAT14*). In Panel A, I include the following covariates in my analysis: Bank size measured by natural logarithm of total assets ($SIZE_{itj}$), countries' economic strength estimated by nominal Gross Domestic Product (GDP_{tj}), non-traditional banking activities assessed by other earning assets (OEA_{itj}), credit portfolio quality predicted by loan loss reserves (LLR_{itj}), liquidity risk captured by deposit ratio and Loan-To-Deposit ratio ($DSFR_{itj}$, $LTDR_{itj}$), bank capital measured by equity divided by total assets (CAP_{itj}), and profitability predicted by return on assets (ROA_{itj}). The variables are obtained as an average value from 2005S2-2008S2 (*TREATALL*), from 2008S2-2009S2 (*TREAT1011*) and from 2012S2-2013S2 (*TREAT14*). In Panel B, I apply PSM/DiD using Gaussian Kernel weights, covariates obtained from my prior PSM analysis and control for half-year time effects. I include the following variables in my analysis: Forward- and backward-looking asset quality measured by loan loss provisions (LLP_{itj}) and non-performing loans (NPL_{itj}), capital adequacy captured by lagged regulatory Tier 1 capital ratio ($T1R_{it-1j}$), and credit risk assessed by risk-weighted assets (RWA_{itj}). I add the following covariates: Accounting standards (*GAAP*), listed banks (*PUBLIC*), bank status (*ACTIVE*), multiple stress test participation (*MULTIPLE*), capital shortage (*SHORT*), and EU membership (*EU*). $\tau_{i(T_1,T_2)j}$ yields the average double difference, or DiD, between the difference of the outcome variables before and after the treatment ($\Delta y_{i(T_1,T_2)j}$) and the difference of the treatment (*TREAT, TREAT1011*, and *TREAT14*) over the control group. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Standard errors (parentheses) are clustered at bank level. The description of the variables and the relevant data sources are provided in Table 2.1.

Table 2.11 Fixed effects robustness on common support bias with adjusted samples

Variables	(1) *TREATALL*	(2) *TREAT1011*	(3) *TREAT14*
NPL_{it-1j}	0.0450***	0.0738**	0.1282**
	(0.0101)	(0.0315)	(0.0532)
ΔNPL_{itj}	0.1454***	0.1334***	0.1389**
	(0.0298)	(0.0379)	(0.0528)
$\Delta LOAN_{itj}$	-0.0157***	-0.0019	-0.0151*
	(0.0035)	(0.0052)	(0.0089)
$T1R_{it-1j}$	-0.0391**	-0.0146	-0.0387
	(0.0165)	(0.0131)	(0.0264)
$EBPT_{itj}$	-0.0625	0.0507	-0.2534
	(0.0699)	(0.0390)	(0.1583)
STHC	-0.0049		
	(0.0030)		
*TREATALL*STHC*	0.0045		
	(0.0029)		
$TREATALL*T1R_{it-1j}$	0.0085		
	(0.0164)		
$STHC*T1R_{it-1j}$	0.0424***		
	(0.0159)		
$TREATALL*STHC*T1R_{it-1j}$	-0.0301*		
	(0.0154)		
$TREATALL*EBPT_{itj}$	0.1604**		
	(0.0637)		
$STHC*EBPT_{itj}$	0.1287		
	(0.1162)		
$TREATALL*STHC*EBPT_{itj}$	-0.0160		
	(0.1188)		
BAST1011		-0.0022	
		(0.0024)	
*TREAT1011*BAST1011*		0.0040**	
		(0.0017)	
$TREAT1011*T1R_{it-1j}$		0.0146	
		(0.0187)	
$BAST1011*T1R_{it-1j}$		0.0471***	
		(0.0137)	
$TREAT1011*BAST1011*T1R_{it-1j}$		-0.0582***	
		(0.0174)	
$TREAT1011*EBPT_{itj}$		0.1719*	
		(0.0875)	
$BAST1011*EBPT_{itj}$		-0.1557***	
		(0.0562)	
$TREAT1011*BAST1011*EBPT_{itj}$		0.2074***	
		(0.0748)	
BAST14			-0.0077***
			(0.0025)
*TREAT14*BAST14*			0.0078**
			(0.0036)
$TREAT14*T1R_{it-1j}$			-0.0359
			(0.0374)
$BAST14*T1R_{it-1j}$			0.0594***
			(0.0142)
$TREAT14*BAST14*T1R_{it-1j}$			-0.0224
			(0.0238)
$TREAT14*EBPT_{itj}$			0.3756*
			(0.2024)
$BAST14*EBPT_{itj}$			0.2066*
			(0.1044)
$TREAT14*BAST14*EBPT_{itj}$			-0.3158**
			(0.1202)

Table 2.11 continued

$SIZE_{it-1j}$	0.0002	-0.0020	0.0031
	(0.0005)	(0.0017)	(0.0034)
ΔGDP_{tj}	-0.0343***	-0.0089	-0.0829
	(0.0084)	(0.0088)	(0.0506)
$\Delta UNEM_{tj}$	-0.0023	-0.0017	0.0063
	(0.0018)	(0.0022)	(0.0049)
HPI_{tj}	0.0000	-0.0001**	0.0001
	(0.0000)	(0.0000)	(0.0001)
$IRATE_{tj}$	0.0005***	0.0004**	-0.0000
	(0.0001)	(0.0002)	(0.0006)
Constant	0.0010	0.0338	-0.0338
	(0.0070)	(0.0227)	(0.0390)
Observations	1,860	742	382
Number of banks	163	132	68
Adjusted R-squared	0.3972	0.5364	0.5099
Bank fixed effects	Yes	Yes	Yes
Half-year fixed effects	Yes	Yes	Yes

This table reports fixed effects robustness checks on common support bias using adjusted samples. Model 1 presents the total stress test effect on banks' capital management and income smoothing behaviour. Model 2 illustrates the stress test effect on the discretionary behaviour of first-time participants in 2010-11. Model 3 examines the stress test effect on the discretionary behaviour of first-time participants in 2014. I include the following variables in my analysis: Forward- and (shift of) backward looking asset quality captured by loan loss provisions (LLP_{itj}) and lagged (change in) non-performing loans (NPL_{it-1j}, ΔNPL_{itj}), loan growth shown by change in outstanding loans ($\Delta LOAN_{itj}$), capital management measured by lagged regulatory Tier 1 capital ratio ($T1R_{it-1j}$), income smoothing captured by earnings before provisions and taxes ($EBPT_{itj}$); a dummy for stress test participation (*TREATALL*), first-time participation in 2010-11 (*TREAT1011*) and 2014 (*TREAT14*); a dummy for 'hot' and 'cold' stress test periods (*STHC*), a dummy for 2010-11 (*BAST1011*) and 2014 stress test periods (*BAST14*); bank size captured by lagged natural logarithm of total assets ($SIZE_{it-1j}$) and macroeconomic fundamentals to control for contemporaneous fiscal and monetary policy changes and market instabilities such as illiquidity, constrained capital and higher volatility shown by economic growth (ΔGDP_{tj}), unemployment growth ($\Delta UNEM_{tj}$), price level in the housing market (HPI_{tj}), and sovereign debt risk ($IRATE_{tj}$). Data range 2005-2015. Standard errors (parentheses) are clustered at bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 2.1.

Chapter 3 – Transparency versus opacity: Are bank stress tests worthwhile?

3.1. Introduction

Transparency is an important instrument that maintains the smooth operation of an economy. Reducing information asymmetry between bank insiders and outsiders is a crucial element; it promotes bank performance and decreases the cost of capital through the following mechanism. First, transparency improves project identification, enabling investors to estimate a more realistic picture of the value of a bank and make better-informed investment decisions. Second, transparency encourages corporate governance and monitoring that empower different stakeholders, such as shareholders and supervisory bodies, to assess the top executive's performance (Bushman et al., 2004; Levine, 1997). Third, the markets become capable of detecting excessive risk-taking and enable managers to be disciplined in their work ethic; this mitigates moral hazards (Freixas and Laux, 2012; Nier and Baumann, 2006).

However, a recent study by Dang et al. (2017) has the opposing view, that, in regard to the funding side of a bank's balance sheet, opacity might be desirable. The authors argue that bank liquidity that arises from money creation by issuing debts may be more efficiently maintained when investors are uninformed. Nonetheless, bank transparency has been at the centre of recent controversy debates. For instance, the reviews by Acharya and Ryan (2016), Beatty and Liao (2014), and Bushman (2014) highlight the importance of this trade-off, suggesting that transparency may have both positive and negative effects on financial stability, while the advantages appear to outweigh the disadvantages.

In theory, transparency is promoted through mandatorily and voluntarily disclosed information of different sources and nature, such as financial accounting, credit ratings and supervisory disclosures. Market participants convert this information into market transactions and security prices, known as market microstructure (Madhavan, 2000). However, in practice, this transformation process is complicated and does not operate perfectly (Bloomfield, 2002; Grossman and Stiglitz, 1980). Furthermore, disclosures on their own do not seem to be sufficient in advancing transparency (Freixas and Laux, 2012).

This concern may be viewed from both a quantitative and a qualitative perspective. On the one hand, financial accounting figures do not perfectly illustrate a banks' financial situation as the quantitative disclosures might be inaccurate, incorrectly understood and intrinsically complex (Jones et al., 2012, 2013). Due to the character and composition of the bank's balance sheet (i.e., loans and trading assets), as well as the bank's size and complexity, some studies even argue that specifically banks, compared to firms of other sectors, seem to be inherently opaque to outsiders. Therefore, the traditional view on transparency identifies opacity as a threat to financial stability and an important reason why banking regulation and supervision is needed and not entirely undertaken by financial markets (e.g., Flannery et al., 2013; Iannotta, 2006; Morgan, 2002). On the other hand, and by analysing corporate narratives, research finds that information complexity and the tone of textual disclosures potentially influence firm performance (Bonsall and Miller, 2017; Loughran and McDonald, 2011b, 2011a; Li, 2008). This relationship may incentivise managers to provide more complex and abnormally positive narratives with the objective of obfuscating investors about the true value of a firm (Bushee et al., 2018; Asay et al., 2017; Ertugrul et al., 2017; Allee and Deangelis, 2015).

Consequently, according to the latest regulatory evolvements, regulators, policymakers and the public demand more and improved transparency from banks. For example, the 2008 global financial crisis showed how the absence of reliable information produced a lack of confidence about the resilience of Systemically Important Financial Institutions (SIFI) and of the entire economic system (Flannery et al., 2013). Therefore, as part of Basel III, the Basel Committee on Banking Supervision (BCBS) highlights the importance of quantitative and qualitative disclosure quality that should be clear, comprehensive, meaningful, consistent and comparable; this is to improve and supplement the effectiveness of the capital regime (BCBS, 2013, 2017). In addition, authorities attempt to improve the quality of information available to market participants through regular bank stress tests. This specific information aims to reveal bank solvency and soundness against adverse market developments to respectively rebuild and maintain the trust of market participants during both crises and normal economic times (Flannery et al., 2017; Bouvard et al., 2015; Borio et al., 2014; Schuermann, 2014).

Various event studies show that U.S. and European markets react to stress test announcements and results as they provide novel information to market participants (Carboni et al., 2017; Morgan et al., 2014; Petrella and Resti, 2013). In conceptual studies, Borio et al. (2014) and Schuermann (2014) argue that during crises, when uncertainty is high and credible information is rare, bank stress tests work well as a crisis management tool to provide markets with the additional information that they need to distinguish between sound and unsound banks. In normal times, however, stress tests should work as an early warning device, which is increasingly difficult to implement in a credible way. Bouvard et al. (2015) and Goldstein and Sapra (2013) support this view and suggest that more bank transparency during crises may lead to more financial stability, although it might cause distinct inefficiencies during relatively calm times. In particular, disclosing bank-specific information during normal times might mislead investors about the financial situation, causing incorrect conclusions, and, in a worst scenario, resulting in bank runs.

However, how do banks react to stress test participation and disclosures? The literature provides rather little insight on the impact of regulatory stress tests on bank reports. On the one hand, as stress tests provide mainly quantitative mandatory disclosures, they may encourage voluntary disclosures of such kind. Analysing European stress tests in 2010 and 2011 and the following capital exercise in 2012, Bischof and Daske (2013) find an increase in voluntarily disclosed information on sovereign risk exposures as a response to the mandatory stress test results. On the other hand, turning to the U.S. market, the literature suggests that bank managers know about the implications of 'bad' news on the markets and may attempt to mitigate potential negative consequences (Cornett et al., 2019; Acharya et al., 2018; Goldstein and Leitner, 2018; Flannery et al., 2017; Goldstein and Sapra, 2013). Therefore, stress tests may influence qualitative, textual, disclosure sentiment depending on banks' stress test participation and the individual stress test performance. For instance, banks that performed well may specifically mention stress test results to account for their soundness and resilience approved by regulatory evidence. Banks that failed stress tests might use positive language in an attempt to disperse stress test results and their reported shortcomings.

Motivated by the conflicting view on transparency and opacity and the growing regulatory influence of stress tests on the financial sector, I explore the impact of stress tests on participating banks' quantitative and textual disclosure profiles and the effect on bank transparency. Based on the obfuscation theory of textual disclosures, I believe that stress test participation and disclosures can create a stress test sentiment that may influence disclosure tone and quantitative disclosure behaviour, it might even affect bank opacity measures. In this context, I scrutinise the following research questions. Do stress test participants adjust disclosure profiles in response to stress tests? Does stress test sentiment influence the tone and language of banks' textual disclosures? Do the stress test sentiment and disclosure tone during stress test periods convert into bank opacity?

To address these research questions, I construct a unique and comprehensive dataset of stress-tested banks from 25 European countries; the dataset consists of accounting, textual analysis and market microstructure components. My data are of quarterly frequency and cover the period 2005-2017. In particular, I largely resort to hand-collected annual and interim reports for my quantitative and qualitative accounting analysis, which I combine with bank opacity measures from the market microstructure literature. Accordingly, my empirical approach is divided into three steps. First, I produce a transparency index that captures the quantity of accounting figures within bank reports and, thus, the level of transparency of these reports. Second, I apply textual analysis to measure the qualitative level of transparency. In particular, I establish a word list that comprises of specific stress test words found in stress test disclosures (i.e., stress test reports and announcements published by the European authorities). Utilising the word counts of these stress test words within bank reports, I show how these bank reports are influenced by specific stress test language. This measure of influence is defined as 'stress test sentiment'. I further measure the tone in bank reports to estimate if bank managers apply a more positive tone during stress test periods. Third, I then link these qualitative transparency attributes to evaluate how the stress test sentiment and disclosure tone affect bank opacity.

This study advances previous research by documenting that stress test participants adjust disclosure profiles during stress test periods in several ways. In particular, as I identify increased stress test terms and language within banks' textual disclosures, I conclude that narratives are evidently influenced by stress test sentiment. The number of stress test terms, in relation to the report length, has increased considerably from one exercise to another. In addition, newly involved participants utilise more stress test language within their textual disclosures than regular participants. Further, my results indicate that the variation of disclosure tone and the quantitative disclosure behaviour can influence the evolvement of the transparency process during stress test periods. This effect may differ for banks that are newly or regularly involved in stress test exercises, while I can see a slight learning curve from serial stress test participation.

Importantly, stress tests might incentivise stress test participants to change their disclosure tone towards more positive language during stress test periods, which, as traced in bank opacity measures, seems to obfuscate investors. For instance, I find that an increased stress test sentiment may lead to higher bid-ask spreads and lower analyst coverage and, therefore, more bank opacity. In turn, the results suggest that a more positive disclosure tone is related to lower bid-ask spreads and more analyst coverage, thus, less bank opacity. I conclude, therefore, that bank managers might not be able to condition the amount of stress test words precisely to the market's expectations but may attempt to compensate for stress test sentiment by amending the disclosure tone towards more positivity. Both results are consistent over distinct periods around and after individual bank report release dates. However, I am hesitant to link the results towards causal inference, as textual narratives *per se* might be at least partly responsible for the transparency effect. Nevertheless, I conclude that stress tests influence banks' disclosure strategies, which may affect bank opacity measures and influence market participants.

I combine accounting, textual and market microstructure characteristics and empirically examine how stress test participants influence disclosure profiles and whether this affects bank transparency. Therefore, my study contributes to distinct streams of the literature. First, I expand the growing literature of textual analysis (Henry and Leone, 2016; Loughran and McDonald, 2016; Li, 2010). My study is the first that measures stress test sentiment by establishing a unique word list from stress test disclosures and applying this list on hand-collected European stress-tested banks' annual and interim reports. Further, I connect the concept of stress tests with textual disclosure tone based on word lists by Loughran and McDonald (2011a). Second, Bischof and Daske (2013) study the impact of mandatory stress test disclosures on European banks' voluntarily disclosure behaviour. Based on a U.S. sample, Flannery et al. (2017) empirically explore Goldstein and Sapra's (2013) theoretical drawbacks of stress test disclosures. By analysing the impact of stress tests on banks' quantitative and textual disclosure profiles, I contribute to this literature and shed light on a rather opaque area of stress test research.

Third, I extend the literature on bank transparency and opacity (Flannery et al., 2013; Iannotta, 2006; Morgan, 2002) by exploring the implications of regulatory stress test participation and disclosures on bank opacity measures. Fourth, I expand the growing literature that applies event study designs to examine the short-term *ex post* effects of stress test disclosures on financial markets (Carboni et al., 2017; Sahin and de Haan, 2016; Morgan et al., 2014; Petrella and Resti, 2013). Further, I generally contribute to the conceptual debate on the costs and benefits of transparency through stress test disclosures that provides suggestions for regulators and policymakers on how to establish a solid disclosure strategy (Bouvard et al., 2015; Borio et al., 2014; Schuermann, 2014; Goldstein and Sapra, 2013).

The remainder of the chapter is structured as follows. Section 3.2 presents the theoretical framework and related literature; it also discusses the main arguments and the limitations of relevant studies. Section 3.3 develops the empirical hypotheses to be tested in Section 3.4. The latter section illustrates the data collection and the econometric techniques applied in my analysis. Section 3.5 reports and discusses the empirical results, whereas Section 3.6 is devoted to robustness checks. Section 3.7 concludes the chapter and presents relevant policy and business implications.

3.2. Theoretical framework and related literature

My study bases on the controversial debate on conceptional frictions between transparency and opacity and the role of stress tests within those concepts, in terms of potential consequences for financial stability. In theory, transparency is the flip-side of opacity meaning that more transparency leads to less opacity, and *vice versa*. However, the relationship between both concepts is complex. For instance, how quantitative and qualitative accounting information influences financial markets and is transferred into transactions and share prices is an ongoing area of research. The literature argues that disclosed information through stress test results may affect financial stability positively or negatively depending on the detail of disclosed information and the state of the economy (Bouvard et al., 2015; Goldstein and Sapra, 2013).

3.2.1. Bank transparency and opacity

The demand for transparency can be traced back to the principle that information efficiency ensures that financial markets and the entire economic system to operate smoothly. For example, the efficient market hypothesis assumes perfect information movement between all market participants (Allen and Santomero, 1998; Fama, 1970). Following Bushman (2014) and BCBS (1998), I define transparency as the amount of public information available to outside stakeholders. Therefore, the level of transparency depends on the precision, reliability and frequency of various components of publicly available financial accounting information such as bank reports, credit ratings and supervisory disclosures. All this credible information about a bank's solvency and soundness is a necessary condition to attract outsiders, such as depositors and creditors, and establish a trustworthy business relationship (Danisewicz et al., 2018; BCBS, 2000).

Along these lines, transparency provides outsiders with opportunities to produce private investors' information and to make better-informed investment decisions that convert information into transactions and share prices on financial markets; the so-called market microstructure (Madhavan, 2000). However, banks operate in an environment with informational frictions and uncertainty (i.e., at best the semi-strong form of Fama's (1970) efficient market hypothesis) where insiders and outsiders have asymmetric information (Goldstein and Sapra, 2013). Moreover, Bloomfield (2002) introduces the 'incomplete revelation hypothesis' (IRH); this states that market prices do not fully reflect public information due to the costs of analysing and assessing this information. This circumstance exacerbates the costs of raising external equity or regulatory capital, and gives birth to fundamental concerns such as the agency problem and adverse selection (e.g., Beatty and Liao, 2014; Bushman et al., 2004; Diamond, 1984; Diamond and Dybvig, 1983). Following Acharya and Ryan (2016), I define bank opacity as the level of uncertainty; this is based on certain market inefficiencies that make effective decision-making more difficult or even impossible for outside market players. For instance, uncertainty appears when investors face incomplete, incorrectly interpreted or too complicated public information (Jones et al., 2012, 2013).

In addition, studies argue that banks are even inherently opaque. Morgan (2002) and Iannotta (2006) examine whether bond issue ratings are differently rated by rating agencies. They conclude that banks, compared to other industries, are opaquer as they find that banks' bond ratings differ more often between agencies than bond ratings of firms in other industries. The literature identifies banks' specific asset composition from loans and trading assets, which are usually the largest items on the balance sheet, as determinants for bank opacity. On the one hand, the value of bank loans is difficult to assess from outside as banks hold confidential information about the nature of the contract and the creditworthiness of the borrower (Berlin and Loeys, 1988; Campbell and Kracaw, 1980). On the other hand, trading assets are seen to be opaque because they are inherently complex (e.g., CDOs) and therefore difficult to measure. Moreover, trading assets are very liquid and move fast on and off the trading books, sometimes within days or hours (Jones et al., 2013; Morgan, 2002).

3.2.2. Transparency related to textual disclosures

Transparency is also linked to the quality of qualitative, textual, disclosures. The literature argues that information complexity [17] and tone of textual components of corporate disclosures are related to firms' future performance. In particular, using the fog index, Li (2008) examines Bloomfield's (2002) IRH in the sense that complex textual disclosures in 10-K filings can lead to confusion, obfuscation, about the true performance of a firm.[18] He finds that firms with low earnings are more likely to publish disclosures that are more complicated. Consistent with Li (2008), recent studies conclude that firms with more complex reports tend to manage their earnings (Lo et al., 2017), while easier 10-K filings increase credit rating quality and reduce the cost of debt (Bonsall and Miller, 2017).

Moreover, Bloomfield (2008) discusses Li's (2008) results, providing an alternative explanation that low performing firms might need to disclose more complex information in response to their poor performance. Analysing conference calls, Bushee et al. (2018) disentangle disclosed information into complex but informative and deliberately obfuscating information, which respectively decreases or increases information asymmetry. They observe that low performing firms convey more of both components. Furthermore, Asay et al. (2017) suggest that the potential of the obfuscation effect of more complex disclosures to cover poor performance is limited to the extent that investors will base their investment decision on other information sources.

On the other hand, many studies analyse the tone and sentiment of corporate disclosures by resorting to dictionaries, word lists or phrases and document a relationship between tone and firms' stock performance.[19] In particular, Loughran and McDonald (2011a) create dictionaries to analyse the tone and sentiment of financial disclosures and find that specific language (e.g., 'negative', 'uncertainty', 'modal', 'litigious' words) can

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[17] Information complexity refers to the term 'readability'. Both terms are used interchangeably in the literature (see, e.g., Bushee et al., 2017; Li, 2008). Loughran and McDonald (2016) posit that the term 'readability' is problematic, as it refers only to the analysed document, which is inherently interrelated with the business' complexity that it attempts to describe. As I examine document complexity in a broader sense, I follow Loughran and McDonald (2016) and use the term 'information complexity'.

[18] There is an ongoing debate on the measurement of information complexity and tone of disclosure. Researchers have introduced various information complexity measures, dictionaries, word lists and machine learning approaches that I do not comprehensively discuss in my study (see, Henry and Leone, 2016; Loughran and McDonald, 2016 for a review).

[19] In some research areas, it might be important to distinguish between a dictionary and a word list. In my study, I do not make this distinction and, hence, use the terms interchangeably.

influence stock returns and trading volumes on the filing date and future stock return volatility. Further, Loughran and McDonald (2011b) examine negative tone and phrases connected to fraud, which indicates a warning to investors as they find lower stock prices for firms using this language. Related to the obfuscation theory, Allee and Deangelis (2015) link textual disclosures and managers' reporting incentives. They observe that managers structure the dispersion of the tone of their narratives according to their advantages in order to influence investors' perceptions of firm performance. Similarly, Ertugrul et al. (2017) document that annual reports with more ambiguous tone and complexity lead to higher future crash risk. Analysing earnings press releases, studies by Arslan-Ayaydin et al. (2016) and Huang et al. (2014) show that an abnormal positive tone can boost stock prices in the short-run, while the effect results in a negative market reaction in subsequent quarters.

3.2.3. Costs and benefits of stress test disclosures

Some conceptual studies examine the impact of stress test disclosures on financial stability and identify costs and benefits in terms of transparency. For instance, Goldstein and Sapra (2013) summarise distinct empirical studies and illustrate the consequences of reported stress test results. On the positive side, stress test disclosures provide specific information about the risk profile of banks; this enables outside stakeholders to make informed investment decisions and enforces market discipline. Further, regulators can enhance the market's trust in the system through a disclosure commitment prior to the stress test, as regulators will not deliberately hold back negative private information.

On the negative side, stress test disclosures might lead to the effect modelled by Hirshleifer (1971) and reduce risk sharing among economic agents; this is because realised losses cannot be insured. Furthermore, managers might rather choose short-term investments to pass stress tests at the cost of their long-term value. Moreover, contagion could arise, if many market players do not react on bank fundamentals but follow other market participants. In addition, regulators' information might dominate investors' privately produced information, preventing regulators from learning from market reactions. In a similar vein, Bouvard et al. (2015) support this theoretical framework; however, they posit that it is essentially connected to the state of the economy and the quantity and quality of stress test disclosures (i.e., aggregated or bank-specific information). In particular, detailed stress test disclosures during financial crises mitigate opacity, whilst those disclosures rather produce adverse market reactions. The latter incident might incentivise regulators to waive negative information, even in situations when this information should be disclosed.

Many empirical studies have illustrated that markets respond to stress test disclosures and therefore do not ignore such information. Exercising an event study design on different U.S. and European stress tests, most studies conclude that stress test disclosures provide, on certain occasions, novel and valuable information for investors; they therefore reduce the informational gap between inside and outside market participants (Carboni et al., 2017; Sahin and de Haan, 2016; Morgan et al., 2014; Petrella and Resti, 2013). Consequently, the signalling effect of stress test disclosures might incentivise bank managers to mitigate potential negative consequences.

Analysing bank holding companies that participated in U.S. stress tests from 2009 to 2015, Flannery et al. (2017) expand those studies by specifically investigating three of Goldstein and Sapra's (2013) propositions. First, they explore analysts' earnings forecasts and find no evidence for a reduction in private information production by market participants. Second, examining the growth of assets and loans three quarters after the stress test result release, they report only weak evidence that managers alter their portfolios in response to stress test participation. Third, Flannery et al. (2017) analyse interbank borrowing behaviour of participating and non-participating banks, and cannot confirm the view that stress test disclosures reduce risk-sharing activities.

Although evidence in the U.S. appears to be limited, Bischof and Daske (2013) partly support this conceptual view in Europe. Analysing the CEBS's 2010 and EBA's 2011 stress tests as well as the subsequent capital exercise in 2012, they find that stress-tested banks tend to increase their voluntary disclosure of sovereign risk exposure in response to the mandatory stress test disclosures. Consequently, banks seem to aim to mitigate any negative signalling from stress test disclosures.

3.3. Hypotheses

My hypotheses establish the theory that stress tests incentivise banks to adjust disclosure profiles, which indirectly affects bank transparency.

3.3.1. Stress tests and bank disclosure profiles

Based on the related literature, I assume that stress test disclosures operate as a transparency mechanism for soundness and solvency of stress test participants. In addition to public information through financial accounting, stress test results should increase transparency and reduce information asymmetry (Schuermann, 2014). However, the literature also suggests that bank managers are well aware of the effect of stress test disclosures on market participants as they might lead to adverse market reactions and bank runs (Bouvard et al., 2015). Consequently, stress test participation and disclosures might incentivise bank managers to influence their information strategies towards mitigation of the effects of stress tests (Flannery et al., 2017; Bischof and Daske, 2013; Goldstein and Sapra, 2013).

I hypothesise this effect on banks' disclosure profiles from both a qualitative and quantitative viewpoint. On the one hand, I capture this effect by measuring the number of stress test words used in bank filings and name it 'stress test sentiment'. The stress test sentiment refers to the prevailing attitude of managers towards stress tests as expressed by the volume and the selection of the stress test words in the bank reports. That is, the stress test sentiment captures how and to what extent the content of bank reports is related to stress tests, e.g., a larger number of stress test words in a bank report show that the report is more influenced by stress tests. Along these lines, the literature suggests that banks can manage their disclosure tone. In particular, disclosure tone and stronger language within narratives (i.e., 'negative', 'uncertainty', 'modal' and 'litigious' words) may obfuscate investors (Ertugrul et al., 2017; Arslan-Ayaydin et al., 2016; Huang et al., 2014; Loughran and McDonald, 2011a). Further, the disclosure profiles of banks relate to the actual figures and numbers within financial statements and notes, which I measure using a transparency index (Nier and Baumann, 2006). Consequently, bank managers are expected to provide an increased number of stress test terms, a more positive disclosure tone, less negative language and more quantitative figures during stress test periods, compared to the period preceding stress tests. Accordingly, I formulate the following hypothesis:

H1. *Stress test participants adjust disclosure profiles in response to stress tests.*

Moreover, an increased stress test sentiment should be compensated by a change towards more positive disclosure tone and less negative language, with the purpose of dispersing regulatory stress test information. For example, a bank produces a realistic picture of the stress test event by using increased stress test sentiment; this should lead to a slightly negative disclosure tone within their reports due to the negative nature of stress test words. However, if there is disparity within a banks' narratives (e.g., a bank increases stress test sentiment and uses a more positive (less negative) disclosure tone to hide negativity from stress tests, then, this might indicate that bank managers aim to obfuscate investors on the outcome of stress tests (Ertugrul et al., 2017; Henry and Leone, 2016; Huang et al., 2014). Hence, I provide the subsequent hypothesis:

H2. *Increased stress test sentiment during stress test periods is related to changes towards a more positive disclosure tone and less negative language.*

3.3.2. Stress tests and bank opacity

Next, based on the theoretical framework of banks' disclosure profiles displayed in Section 3.3.1, I expect that the stress test sentiment and the disclosure tone may even lead to bank opacity with the purpose of obfuscating investors. A widely used measure for information asymmetry is the bid-ask spread. In principal, the bid-ask spread shows market liquidity from both the supply (ask price) and the demand (bid price) side of a share, which may be also applied to estimate information asymmetry. A high spread indicates that there is a greater likelihood of information asymmetry (or uncertainty) among traders about the true value of a share. Uninformed investors are likely to price uncertainty into their investment to buffer potential costs from adverse selection or might even be reluctant to invest. Therefore, a high spread leads to reduced market liquidity and increases cost of capital, as banks need to discount their shares to attract investors. Accordingly, the theory states that more transparent banks should trade with a lower bid-ask spread (Flannery et al., 2013; Bushman et al., 2004; Leuz and Verrecchia, 2000; Kyle, 1985). Further, many studies show that investors and financial analysts tend to prefer firms that are more transparent, mainly because it reduces cost of information gathering and production (McNichols and O'Brien, 1997). Therefore, analyst coverage, estimated by the number of analyst recommendations, is an indicator for an individual bank's level of transparency. In other words, the higher the number of analysts that file a recommendation, the more transparent is the bank (Flannery et al., 2017; Marquardt and Wiedman, 1998).

In terms of textual disclosures, the effect on transparency may be twofold. On the one hand, if the stress test sentiment and disclosure tone of bank reports is informative, this should add to investor's and analyst's knowledge and the relevant information should transfer into market prices and analyst coverage. Importantly, this hypothesis should be true if both textual measures are meaningful and align with market expectations. In this case, stress test sentiment and disclosure tone should lead to lower bid-ask spreads and higher analyst coverage. On the other hand, if market participants perceive that banks might face more risk than is transferred by the stress test sentiment and disclosure tone, then bid-ask spreads should increase and analyst coverage should decrease, indicating a lower level of opacity (Campbell et al., 2014). As banks aim to mitigate the effect of stress test information, I hypothesise the first scenario that is stated as follows:

H3a. *Increased stress test sentiment during stress test periods is negatively related to information asymmetry and positively associated with analyst coverage.*

H3b. *More positive disclosure tone during stress test periods is negatively related to information asymmetry and positively associated with analyst coverage.*

3.4. Empirical analysis

In this section, I show the sample selection process, data construction, key variables and empirical models that I apply in my analysis. Detailed descriptions of the variables and the relevant data sources are provided in Table 3.1.

[Please refer to Table 3.1 here]

3.4.1. Sample selection

I select my sample based on the following steps. First, as I am interested in European stress-tested banks, I resort to the regulatory stress test disclosures published by CEBS/EBA and ECB to identify public and private banks that participated in European stress tests between 2009 and 2016 (EBA, 2011, 2014, 2016; ECB, 2014, 2015; CEBS, 2010). Table 3.2, Panel A, illustrates the stress test participation by country and assessment and reports 187 European stress-tested banks.[20]

[Please refer to Table 3.2 here]

[20] The relevant press release of the 2009 CEBS exercise does not provide the names of the stress-tested banks; it simply states that "22 major European cross-border banking groups" were tested (for further details, see: http://www.eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing/2009).

Second, I obtain each bank's activity status from BvD Bankscope and verify the availability of various data sources for my sample. I remove banks with general data unavailability and poor data quality due to M&As and bankruptcies. Further, as my textual analysis software, DICTION 7.0, requires reports in English and in a machine-readable quality (i.e., pdf), I remove banks that published only non-English disclosures or reports in an incompatible format. This sample construction process, shown in Table 3.2, Panel B, leads me to an initial stress test participation sample of 142 banks from 25 European countries, of which, respectively, 69 and 65 banks were tested for the first time in 2010-11 (*FTST1011*) and in 2014 (*FTST14*). Moreover, the sample comprises 61 banks that are listed on a stock exchange.[21] However, as my regression analysis of stress test periods is most accurate with quarterly frequency, the sample size reduces as about one-third of my sample does not publish quarterly reports. The combination of some variables and lags may lead to a further reduction in observations and sample size.

3.4.2. Data construction and key variables

The bank transparency and opacity dataset comprise various accounting, textual and market microstructure variables from distinct data sources. To construct my extensive dataset, I rely on stress test reports and the recent stress test and bank transparency and opacity literature (Acharya et al., 2018; Carboni et al., 2017; Flannery et al., 2017; Bischof and Daske, 2013). As discussed in the following sub-sections, I capture bank transparency from a quantitative and qualitative viewpoint by utilising, receptively, a transparency index based on accounting figures and textual measures (i.e., stress test sentiment and disclosure tone). Further, I measure bank opacity from a market perspective by resorting to information asymmetry and analyst coverage.

I thoroughly analyse my data to accommodate outliers that might screw the results. For instance, I discard observations of particularly low/high share prices, total words analysed or low number of trades. Further, I normalise and winsorise the data at the 1 and 99 percentiles, accounting and textual measures on a quarterly and market data on a daily basis. The data period of this quarterly obtained accounting and market data spans from 2005-2017, which reflects the most recent and accurate provision of this data. I follow recent standards of the accounting, textual analysis and market microstructure literature

[21] I remove delisted banks from my sample of listed banks to ensure consistent data quality.

that applies those techniques to validate observations and to mitigate estimation problems due to parsing textual documents or market inefficiencies (Flannery et al., 2013; Bushman and Williams, 2012; Loughran and McDonald, 2011a).

3.4.2.1. Bank accounting

I gather accounting-based variables from BvD Bankscope and FitchConnect[22] and use this data to compose the transparency index (*TRANX*) according to Nier and Baumann (2006) that I apply to measure quantitative disclosure behaviour of stress-tested banks. The purpose is to assess the detail of figures provided in the bank reports. I resort to the FitchConnect database and collect quarterly data of various balance sheet and income statement categories connected to bank risk-taking. The categories are divided into 19 sub-indices that are linked to credit risk, market risk, liquidity risk and capital risk. I count the disclosed figures within the sub-indices available on FitchConnect and aggregate the sub-indices to a ratio that is the transparency index (*TRANX*). The ratio ranges from 0 to 1. The higher the *TRANX* ratio, the more figures are disclosed and thus the more transparent is the bank. The definition and the categories of the sub-indices are fully described in Table 3.1 and the additional Note 1 (page 109).

At the same time, I use the accounting-based variables to establish my comprehensive accounting dataset of bank risk measures and characteristics (see, e.g., Jones et al., 2012, 2013). In particular, I utilise bank size reflected in the natural logarithm of total assets (*SIZE*); traditional- and non-traditional banking activities measured by outstanding loans (*LOAN*) and trading securities (*TRADE*); credit portfolio quality captured by loan loss reserves (*LLR*), asset quality estimated by loan loss provisions (*LLP*); capital adequacy shown by the Tier 1 regulatory capital ratio (*T1R*); liquidity risk reflected in deposits and short-term funding (*DSTF*); and profitability captured by earnings before provision and taxes (*EBPT*). Similar to Gebhardt and Novotny-Farkas (2011), I face some degree of inconsistency and incompleteness of raw European accounting data from public databases, for example, for challenging accounting variables such as capital adequacy

[22] In January 2017, BvD Bankscope was replaced by Orbis Bank Focus, which has significantly reduced the data quality. I resort to other sources such as FitchConnect, Bloomberg, Thomson Reuters Worldscope and SNL Financial. I validate the completeness of the extracted data and find that FitchConnect is the database with the richest and most accurate provision of accounting variables.

figures and loan loss provisions. Therefore, I enrich the data by hand-collecting missing figures.

3.4.2.2. Textual analysis

Next, I resort to the textual analysis methodology to test my hypotheses. I hand-collect all available annual and interim reports published on the bank's website or stored on Bloomberg's corporate filings database. I use DICTION 7.0, which is a state-of-the-art programming tool widely used in the literature, to determine the tone and the variation of a verbal message found in bank reports. As I describe below, I create my own word list based on words related to stress tests, regulation and risk management, which is a unique innovation in the context of textual analysis that is tailored to banking. In addition, I adopt the word list of Loughran and McDonald (2011a) to measure the disclosure tone (i.e., positive versus negative terms).[23] I then apply these word lists to the bank reports to retrieve the word count that estimates stress test sentiment and disclosure tone.

First, to measure the stress test sentiment (*STS*) of bank narratives, I establish a procedure that enables me to comprehensively assess the recognition of stress test, regulation and risk management language. I create a word list that is composed of six categories and based on the most frequently used words in the stress test regulatory reports, in financial accounting reports, as well as in the stress test literature. Relying on all three sources of reporting ensures the maximum degree of objectivity. In particular, I upload the relevant reports and methodology notes of the stress test assessments in 2010 (CEBS), 2011 (EBA), 2014 (EBA, ECB), 2015 (ECB) and 2016 (EBA) to DICTION to extract the full list of so-called "insistence" words.[24] Following the DICTION-manual definition, an insistence word is a noun, a verb or a noun-derived adjective that appears three times or more within a passage of 500 words. It is important to indicate here that not all the insistence words are eligible for retention. For example, some of the most frequently used words in the studied documents are 'bank/s', 'asset/s' and 'result/s', which are generic words and do not necessarily pertain to preceding stress tests. Therefore, I do not include those words in my list. Further, I resort to the stress test and accounting literature (e.g., Borio et al., 2014; Schuermann, 2014; Bischof and Daske, 2013; Bushman

[23] I follow the relevant guidelines found on McDonald's website: https://sraf.nd.edu/.

[24] The documents may be accessed on the EBA and ECB websites (see: http://www.eba. europa.eu/ risk-analysis-and-data/eu-wide-stress-testing, https://www.bankingsupervision.europa.eu/banking/tasks/comprehensive_assessment/html/index.en.html).

and Williams, 2012) and screen stress test sections of selected financial reports to identify specific language and to spot the terms that are related to stress tests. I also expand the word list by adding inflections, plurals, and alternative English or American spellings (Athanasakou et al., 2019).

After structuring the output and cleaning it from bogus words, I analyse and evaluate all the extracted words according to their relevance to stress tests, bank regulation and risk management. From this I obtain a word list that consists of a total 349 keywords that measure stress test sentiment (*STS*). The word list is displayed in the additional Note 2 of Table 3.1 (pages 110-111). Each insistence word is classified and allocated into the following six categories:

(1) 'Stress test identity' (*STS_ID*): Words that are directly linked to the stress test assessments, e.g., exercise, stress, test;
(2) 'Stress test performance' (*STS_PERF*): Words that reflect the performance of banks in stress tests, e.g., finding, pass, significant;
(3) 'Stress test procedure' (*STS_PRO*): Words that are related to the particular methodological stress test procedures, e.g., baseline, scenario, shortfall;
(4) 'Regulatory institutions' (*STS_REGIN*): Words that identify the various stress test regulatory bodies and institutions, e.g., EBA, ECB, SSM;
(5) 'Regulatory requirements' (*STS_REQ*): Words that are connected to particular regulatory requirements, e.g., Basel, floor, Tier;
(6) 'Risk management' (*STS_RM*): Words that are related to bank risk management procedures, e.g., collateral, credit, provisioning.

Second, I measure distinct forms of disclosure tone by applying widely accepted word lists of 'positive' (*POSITIVE*), 'negative' (*NEGATIVE*), 'uncertain' (*UNCERTAIN*), 'modal' (*MODAL*) words (Loughran and McDonald, 2011a), including an aggregated word list that consists of 'negative', uncertain' and 'modal' words (*AGGNUM*). As suggested by Henry and Leone (2016)[25], I combine the word count of the 'negative' and 'positive' word lists to construct disclosure tone estimates using the following formula:

$$TONE_{itj} = \frac{POSITIVE_{itj} - NEGATIVE_{itj}}{POSITIVE_{itj} + NEGATIVE_{itj}} \tag{3.1}$$

[25] An alternative formula for disclosure tone is *TONE_ALT = (POSITIVE – NEGATIVE) / TWA* as in Huang et al. (2014). I apply this measure in my robustness checks and receive similar results.

where *i* shows the bank, *t* stands for time measured in quarters, and *j* reflects the relevant country. The disclosure tone (*TONE*) yields the equally weighted word count[26] of the 'positive' word list (*POSITIVE*) subtracted from the word count of the 'negative' word list (*NEGATIVE*) and divided by the sum of the two word lists. According to Henry and Leone (2016), *TONE* yields a score of 1 for an entirely positive narrative, a score of -1 for a purely negative disclosure and 0 for a perfectly neutral narrative. Further, I calculate the variation of the disclosure tone ($\Delta TONE$), defined as $TONE_t - TONE_{t-1}$.

Third, to find the relevant bank reports, I apply Bloomberg's CFS <GO> function and search for the name of the bank and select the criteria 'annual report', 'interim report' and 'quarterly report'. I download all filings for each bank in pdf-format, which I save in a folder named by the bank. As the downloaded files have no particular name to identify the bank or the specific report, I rename all files according to my textual observation identifier that I give each bank and observation ("Nr_ID_Shortname_Period"). In case Bloomberg does not store all filings, I also visit the bank's website to download, if available, the relevant missing filings. As the Bloomberg downloading and renaming process is very resource intensive, I sometimes reverse the process, directly resorting to the bank's website, and search on Bloomberg for extensions.

I do various verification checks to ensure that I downloaded the correct reports for each bank and period. I hand-check the reports twice to ensure the bank's name and period are correctly specified.[27] When I upload the filings into DICTION, in rare cases, the file is not machine readable and automatically omitted by the software. After I run DICTION for the first time, I thoroughly check, remove and/or replace such obvious faulty filings. This test also includes duplicate filings. Further, I sort the outcome observations by the number of total words analysed (*TWA*) and by the variation of *TWA* of the filing compared to the equivalent period (ΔTWA_{t-4}). I check filings with fewer than 3,000 words (Bonsall and Miller, 2017; Li, 2008) and filings with a word count increase of greater than one. Ultimately, I delete 86 filings with fewer than 3,000 words and replace 83 reports with an inconsistent word count increase. After all these verification checks, I then proceed to

[26] Alternatively, Loughran and McDonald (2016) apply inverse document frequency weighting to reduce word misclassification. However, I follow Henry and Leone (2016) who favour equal weighting as it increases transparency and replicability.

[27] One bank, Banco Comercial Português, published from 2005 to 2011 two annual report versions (Volumes I and II), which I merge by using an online pdf-converter (https://online2pdf.com).

run DICTION to retrieve the word count of the above-mentioned word lists that estimate stress test sentiment and disclosure tone.

Although I apply DICTION as the textual analysis tool, I reject using the software-included dictionaries or other word lists such as Harvard General Inquirer or Henry (2008). Early textual analysis literature has widely employed those dictionaries, but recent research indicates that those word lists are inappropriate for analysing financial narratives (see, Loughran and McDonald, 2015, 2016 for a review). Moreover, I utilise annual and interim reports in my analysis, which creates a distinct trade-off. On the negative side, the literature argues that interim reports are, in some cases, condensed, unaudited and less regulated, leading to less informative disclosures (Loughran and McDonald, 2014). On the positive side, some studies resort to interim reports arguing that specifically less regulation enables research to measure changes of positive disclosure tone as managers might use regulatory freedom to improve the firm's picture (Huang et al., 2014). As I am interested in the variation of disclosure tone, I follow the latter stream in combination with the stress test literature, which primarily resorts to quarterly data (Flannery et al., 2017; Bischof and Daske, 2013). In particular, interim reports enable me to measure stress test periods more accurately. Further, although there are fewer requirements on interim reports, as my sample consists of the largest European SIFIs, those banks usually write their reports in close cooperation with auditors and regulators.

3.4.2.3. Market microstructure

Moreover, for the 61 listed banks in my portfolio, I collect market microstructure variables from Thomson Reuters (Datastream/IBES). In particular, I estimate bank opacity utilising information asymmetry covered by the bid-ask spread (*BIDASK*) and analyst coverage measured by the number of analyst recommendations (*RECNO*). As described in Section 3.3.2, both variables are widely acknowledged to measure bank opacity that is recognised in the level and variation of market liquidity and analyst information production (Flannery et al., 2017; Leuz and Verrecchia, 2000). Further, I gather additional market microstructure variables to control for confounding factors. I include share turnover (*TOVER*), inverse share price (*INVPRICE*), return volatility (*RETVOL*), market value (*MVALUE*), market-to-book value and analyst recommendation consensus (*RECCON*). Following Bischof and Daske (2013) and Flannery et al. (2013), I produce the market measures by obtaining transactions data on a daily basis and average those daily values to compute quarterly microstructure measures.

3.4.3. Descriptive statistics and correlation tests

I focus on variables that are relevant for regulators and investors in terms of bank risk-taking, performance and transparency (see, e.g., Flannery et al., 2013, 2017; Bischof and Daske, 2013). In particular, the accounting variables and ratios cover asset quality, capital adequacy, traditional and non-traditional banking activities as well as profitability to measure bank risk-taking. Further, I collect bank opacity measures and microstructure characteristics to estimate potential influence and obfuscation on market participants. On the other hand, my dataset consists of textual disclosure characteristics that capture the qualitative side of transparency based on stress test sentiment and disclosure tone. In addition, I incorporate macroeconomic fundamentals to control for country differences and economic inefficiencies.

[Please refer to Table 3.3 here]

Table 3.3 reports descriptive statistics of the main regression variables, whereas Panels A, B and C show respectively the accounting, textual analysis and market microstructure characteristics of my stress test participation sample. In addition, Panel D illustrates country-specific macroeconomic fundamentals. Even though stress-tested banks are relatively large, the data indicate some dispersion of bank size (*SIZE, MVALUE*). In Europe, banks may operate within unequal economies, where relatively small banks count as SIFIs. In this way, the authorities assess a range of small- and medium-sized banks. Further, I can see that stress test terms and language appear to be a central part of textual narratives (*STS*). On average, I find that 5.4% of the total words in textual disclosures is a term from my stress test disclosure dictionary, which is more than double than the word count of 2.1% of the aggregated ‘negative’, ‘uncertain’ and ‘modal’ word list (*AGGNUM*). In addition, *TONE* yields a score of -0.275 indicating an average negative disclosure tone. According to the literature, negative disclosure tone is generally a sign of stronger regulation and accounting rules as banks are less optimistic due to litigation concerns (Huang et al., 2014; Li, 2010).[28]

[Please refer to Figures 3.1, 3.2, 3.3, 3.4 and 3.5 here]

Figures 3.1 to 3.5 graphically illustrate mean development of important bank-specific accounting, textual and market microstructure characteristics for my stress test sample. Figure 3.1 shows banking activities (*LOAN, TRADE*), credit portfolio quality (*LLR*), asset quality (*LLP*), liquidity risk (*DSTF*), bank capital (*CAP*), and capital adequacy (*CET1R, T1R, TRR*). Figures 3.2 and 3.3 display the development of the stress test sentiment (*STS, STS_ID, STS_PERF, STS_PRO, STS_REGIN, STS_REQ,* and *STS_RM*) and textual disclosure tone (*TONE, ΔTONE, AGGNUM, NEGATIVE, UNCERTAIN*), while Figures 3.4 and 3.5 highlight the evolvement of information asymmetry (*BIDASK*), analyst coverage (*RECNO, RECSBUY to RECSSELL*) and market microstructure characteristics (*TOVER, INVPRICE, RETVOL, MVALUE, MTBV, RECCON*). I indicate the European stress test exercises in the second quarter of 2010, 2011, 2014 and 2016 with dashed lines.

As expected, the graphs illustrate that stress test sentiment has grown within bank disclosures, as regulatory stress tests have been undertaken after the financial crisis. Further, the bid-ask spread (*BIDASK*) indicates an increase in information asymmetry in 2008 and sharply peaks from 2008Q4 to 2009Q1 as well as from 2010Q2 to 2013Q4. The first movement reflects the burst of the U.S. housing bubble and the aftermath of the Lehman Brothers bankruptcy (which led to the 2008 global financial crisis) while the second evolvement implies the uncertainty from the European sovereign debt crisis. The time series of analyst coverage (*RECNO*) does not show such a clear pattern and appears to be slightly behind the bid-ask spreads. This indicates that analyst information production is particularly valuable when overall information asymmetry is high. In recent years, low uncertainty even seems to discourage analysts from providing information, as reflected in the decrease in analyst recommendations from 2015Q4 onwards (supporting, e.g., Bouvard et al., 2015; Goldstein and Sapra, 2013). This development in alliance with a relatively negative disclosure tone for the same period supports my expectation of the

[28] Huang et al. (2014) posit that disclosure tone could be driven by Loughran and McDonald's (2011a) 'negative' word list as it consists of seven times more words than the 'positive' word list. I consider this finding by applying alternative tone measures in my robustness checks.

increased importance of stress tests, which might influence banks' textual disclosures leading to opacity and is the basis of my following empirical analysis.

[Please refer to Table 3.4 here]

Table 3.4 provides Pearson correlation coefficients and p-values for the variables explained in the following analysis in Section 3.4.4. Panel A displays the variables of the disclosure profile and tone models (Equations 3.2 and 3.3), while Panel B shows the measures of the bank opacity models (Equations 3.4_A and 3.4_B). In general, the table reports statistically significant correlation among some related accounting variables. For instance, there is a significant correlation (respectively, -60.90% and 62.50%) between trading securities (*TRADE*) and outstanding loans (*LOAN*) as well as bank size (*SIZE*). These relationships align with the literature and illustrate the business models of stress-tested banks (Jones et al., 2012; Nier and Baumann, 2006). Nevertheless, the diagnostic techniques reject problematic correlations, except for a strong positive correlation (93.40%) between *NPL* and *LLR* that is significant at the 1% confidence level. The accounting discretion literature defines both variables as reflecting loan quality (Beatty and Liao, 2014; Gebhardt and Novotny-Farkas, 2011). Due to this conceptional relationship and to avoid potential multicollinearity, I follow Flannery et al. (2013) and include *LLR* while discarding *NPL* in my analysis.

3.4.4. Empirical models

This study examines whether stress test participants adjust disclosure profiles, which ultimately leads to improved bank transparency. I test my hypotheses from Section 3.3 utilising panel data analysis with bank and quarterly time fixed effects, as a result of the Hausman test, to control for potential time-invariant unobserved heterogeneity avoiding omitted variable bias. Related to sample selection procedures, and in alliance with the stress test literature, I reject self-selection issues for two reasons. First, as it covers about 76% of the entire stress test population, my sample is much more than a sub-sample. Second, the authorities select stress test participants in a political decision-making process that bank managers are unlikely to fully control (see, e.g., Carboni et al., 2017). Moreover, I lag all subsequent accounting and market microstructure characteristics by two quarters to address endogeneity between contemporary asset choice and stress test exercises according to recent literature standards (Acharya et al., 2018; Flannery et al., 2017). For parsimony, I reject one- to four-quarter lags, as the Akaike Information Criterion (AIC) yields no substantial improvement in model strength. I also cluster the standard errors at the bank level to mitigate bias from heteroscedasticity and autocorrelation. I believe that these methods and techniques shield my analyses from most severe estimation issues.

I begin with the analysis of banks' disclosure profiles, which contains the identification of stress test sentiment, together with the impact of stress test participation on textual disclosure tone and quantitative disclosure behaviour (*H1*). Inspired by the approach of recent stress test models by Flannery et al. (2017) and Bischof and Daske (2013) that measure the exact timing of stress test participation, I estimate the first model:

$$\begin{aligned} PROFILE_{itj} = {} & \gamma_0 + \gamma_1 ST1011 + \gamma_2 ST1415 + \gamma_3 ST16 + \gamma_4 FTST1011 + \\ & \gamma_5 ST1011 * FTST1011 + \gamma_6 ST1415 * FTST1011 + \\ & \gamma_7 ST16 * FTST1011 + \sum \gamma_8 (Bank\ characteristics)_{it-2j} + \\ & \sum \gamma_9 (Country\ characteristics)_{tj} + \alpha_i + \delta_t + \varepsilon_{itj} \end{aligned} \tag{3.2}$$

where, for bank i, quarter t and country j, the dependent variable *PROFILE* represents distinct disclosure profiles of stress-tested banks and stands for one of the subsequent measures. First, *PROFILE* is the following textual components for stress test sentiment; where *STS* is the accumulated word count of the entire stress test, regulation and risk management word list based on stress test disclosures, *STS_ID* is the word count of the 'stress test identity' word list, *STS_PERF* is the word count of the 'stress test performance' word list, *STS_PRO* is the word count of the 'stress test procedure' word list, *STS_REGIN* is the word count of the 'regulatory institutions' word list, *STS_REQ* is the word count of the 'regulatory requirements' word list, and *STS_RM* is the word count of the 'risk management' word list. These novel variables measure the recognition of stress test terms and language within banks' filings and ultimately the stress test sentiment.

Second, the dependent variable *PROFILE* stands for distinct forms of disclosure tone, based on Loughran and McDonald's (2011a) word lists and Henry and Leone's (2016) formula. Disclosure tone is captured by *TONE* that is based on the word count of 'negative' and 'positive' word lists (see, Section 3.4.2.2), *AGGNUM* that is the word count of an aggregated word list of 'negative', 'uncertainty' and 'modal' words, *NEGATIVE* that is the word count of the 'negative' word list, *UNCERTAIN* that is the word count of the 'uncertainty' word list, and *MODAL* that is the word count of the 'modal' word list. Third, the dependent variable *PROFILE* represents quantitative disclosure behaviour, which I capture using the transparency index (*TRANX*) built on the method by Nier and Baumann (2006).

The independent time-dummy variables stand for the stress test periods of 2010-11 (*ST1011*), 2014-15 (*ST1415*) and 2016 (*ST16*). The participation dummy variable *FTST1011* captures banks that participated for the first time in 2010-11. Importantly, the interaction terms of these time and participation dummies estimate the effect of stress test sentiment and disclosure tone. They compare first-time stress-tested banks of 2010-11 with 2014 first-time participants. A positive (negative) sign of the coefficients indicates that earlier first-time participants use more (less) stress test language, 'positive', 'negative', 'uncertain', 'modal' tone or quantitative disclosures than later ones.

Moreover, to disentangle the consequences of stress test participation, I include various control variables that capture potentially confounding bank-specific and macro-prudential responses to the financial and sovereign debt crisis based on extensive accounting and transparency literature (see, e.g., Beatty and Liao, 2014; Flannery et al., 2013; Jones et al., 2012, 2013). In particular, *(Bank characteristics)* control for differences of stress-tested banks using bank size assessed by the natural logarithm of total assets (*SIZE*), traditional- and non-traditional banking activities (*LOAN, TRADE*), credit portfolio quality (*LLR*), asset quality (*LLP*), capital adequacy (*T1R*), liquidity risk (*DSTF*) and profitability (*EBPT*). Further, *(Country characteristics)* considers contemporaneous fiscal and monetary policy changes by utilising countries' macroeconomic fundamentals such as economic (*ΔGDP*), and unemployment growth (*ΔUNEM*). Finally, I incorporate bank-specific fixed effects (α), quarterly fixed effects (δ) and the residual (ε).

Next, to measure the effect of stress tests on textual disclosures, I combine stress test sentiment with stress test participants' disclosure tone (*H2*). Hence, I estimate the following model:

$$\begin{aligned} DISCTONE_{itj} = \gamma_0 + \gamma_1 STHC\_I + \gamma_2 STS_{itj} + \gamma_3 STHC\_I * STS_{itj} + \\ \sum \gamma_4 (Bank\ characteristics)_{it-2j} + \\ \sum \gamma_5 (Country\ characteristics)_{tj} + \alpha_i + \delta_t + \varepsilon_{itj} \end{aligned} \quad (3.3)$$

where, for bank *i*, quarter *t* and country *j*, the dependent variable *DISCTONE* represents the estimates for the variation and distinct forms of disclosure tone (*ΔTONE, AGGNUM,* *LITIGIOUS*), employing Loughran and McDonald's (2011a) word lists and Henry and Leone's (2016) formula. The independent time-dummy variable estimates individual stress test participation of each bank in my sample (*STHC_I*). A binary variable equal to one for the period that each sample bank participated in stress tests and zero otherwise. *STS* stands for the accumulated word count of my stress test, regulation and risk management word list based on stress test disclosures as defined under Equation 3.2. The interaction term of the latter two measures (i.e., *STHC_I*STS*) captures stress test sentiment during individual stress test periods and estimates the impact on disclosure tone. When banks acknowledge stress tests in their annual and interim reports they might attempt to hide 'bad' news from stress test results by changing their disclosure tone and including more positive (fewer negative) words. Further, I control for the same confounders as defined under Equation 3.2 and include bank-specific fixed effects (α), quarterly fixed effects (δ) and the residual (ε).

Finally, I combine stress test sentiment and disclosure tone with the level of bank opacity using market microstructure variables to analyse if those textual attributes, which are influenced by stress test participation, convert into market prices and analyst coverage (*H3a, H3b*). Therefore, I estimate the following two models:

$$\begin{aligned} MARKET_{itj} = {} & \gamma_0 + \gamma_1 STHC\_I + \gamma_2 STS_{itj} + \gamma_3 STHC\_I * STS_{itj} + \\ & \textstyle\sum \gamma_4 (Market\ microstructure)_{it-2j} + \\ & \textstyle\sum \gamma_5 (Country\ characteristics)_{tj} + \alpha_i + \delta_t + \varepsilon_{itj} \end{aligned} \qquad (3.4_{\mathrm{A}})$$

$$\begin{aligned} MARKET_{itj} = {} & \gamma_0 + \gamma_1 STHC\_I + \gamma_2 TONE_{itj} + \gamma_3 STHC\_I * TONE_{itj} + \\ & \textstyle\sum \gamma_4 (Market\ microstructure)_{it-2j} + \\ & \textstyle\sum \gamma_5 (Country\ characteristics)_{tj} + \alpha_i + \delta_t + \varepsilon_{itj} \end{aligned} \qquad (3.4_{\mathrm{B}})$$

where, for bank *i*, quarter *t* and country *j*, the dependent variable *MARKET* is one of the following measures: information asymmetry captured by the bid-ask spread (*BIDASK*) and analyst coverage estimated by the number of analyst recommendations (*RECNO*). The time-dummy variable estimates the individual stress test participation of each bank in my sample (*STHC_I*), whilst *STS* and *TONE* stand respectively for stress test sentiment (i.e., *STHC_I*STS*) and disclosure tone (i.e., *STHC_I*TONE*) as defined under Equations 3.2 and 3.3. The interaction term of the time-dummy and the textual variables measure the effect of stress test sentiment and disclosure tone on market microstructure during individual stress test periods. According to *H3a* and *H3b*, when banks use a more positive (negative) tone in their disclosures, the bid-ask spread should be lower (higher) and the number of analyst recommendations should increase (decrease) (Flannery et al., 2013; Lang and Lundholm, 1996).

Further, similar to Equations 3.2 and 3.3, the setting creates various challenges due to potentially confounding factors that arise from the financial and sovereign debt crisis and may alternatively explain the movement of the dependent variables. Therefore, *(Market microstructure)* considers market instabilities such as illiquidity, constrained capital, market performance and higher volatility as well as contemporaneous fiscal and monetary policy changes (Bonner and Eijffinger, 2016). In particular, I include share turnover (*TOVER*), also known as trading volume, which is often used to capture market liquidity. The rationale here is that more liquid markets lead to lower spreads (Bamber et al., 2011; Karpoff, 1986). Next, the inverse share price controls for effects related to idiosyncratic differences in share prices. For instance, Black (1986) assumes that market movements of low-priced shares are particularly affected by 'noise', i.e., uninformed, so called speculative trading. A high share price limits the number of potential investors and may decrease market liquidity (Asparouhova et al., 2013). Another control is return volatility (*RETVOL*); I calculate this as the daily standard deviation of continuously compounded share price returns (Bischof and Daske, 2013). Higher volatility in the markets indicates uncertainty, which could affect bid-ask spreads and analyst coverage, in particular, during crises (Flannery et al., 2013, 2017).

Further, I employ the logarithm of market value of equity (*MVALUE*) and the market-to-book value (*MTBV*). Research argues that larger banks have more impact on the markets, which is why market participants follow larger banks more closely (Amiram et al., 2016; Leuz and Verrecchia, 2000). This development could result in lower spreads and higher trading, which, in turn, may attract more analyst coverage. I also control for analyst recommendation consensus (*RECCON*) that illustrates a snapshot of the current trend of analysts' sentiment. Analysts favour buy over sell recommendations; this is due to certain factors that are linked to potential investment banking relationships of their brokerage firm that provide conflicts of interest and therefore bias analyst recommendations towards more optimistic views (McNichols and O'Brien, 1997; Womack, 1996). Further, *(Country characteristics)* utilises economic growth (ΔGDP), unemployment growth ($\Delta UNEM$), and the sovereign debt risk (*IRATE*) to control for contemporaneous variations in countries' macroeconomic fundamentals such as economic cycles (Hamadi et al., 2016; Vallascas and Hagendorff, 2013; Bushman and Williams, 2012). Finally, I include bank-specific fixed effects (α), quarterly fixed effects (δ) and the residual (ε).

To ensure that Equations 3.4_A and 3.4_B precisely estimate the effect of the narratives' stress test sentiment and disclosure tone, I measure information asymmetry (*BIDASK*) and analyst coverage (*RECNO*) during the days around and after the bank report release dates. In particular, I hand-collect the release dates of the annual and interim reports and calculate the specific average of the daily bid-ask spreads (*BIDASK*) and the number of analyst recommendations (*RECNO*) for five different periods around and after the bank report release date: (1) one day before to one day after (t–1, t+1), (2) two days to 31 days after (t+2, t+31), (3) two days to 61 days after (t+2, t+61), (4) two days to 121 days after (t+2, t+121), and (5) two days to 250 days after (t+2, t+250). All other variables remain the same as in Equations 3.4_A and 3.4_B. As stated previously in this section, market variables are influenced by many other factors. Drawing attention to the particular window of interest is therefore crucial and increases the reliability of the results (Campbell et al., 2014; Huang et al., 2014; Loughran and McDonald, 2011a).

3.5. Results

This section provides and discusses empirical evidence on the effect of stress tests on bank disclosure profiles and opacity in the settings established in Sections 3.3 and 3.4.

3.5.1. Implications of stress tests on bank disclosure profiles

First, I provide the results of Equation 3.2, which estimates stress-tested banks' behaviour related to disclosure profiles; namely the stress test sentiment, disclosure tone and quantitative disclosures (*H1*). Table 3.5 illustrates the stress test sentiment of stress test participants. The table uses the textual attributes established from the word count of my stress test, regulation and risk management word lists, built on frequently used words within stress test disclosures (*STS, STS_ID, STS_PERF, STS_PRO, STS_REGIN, STS_REQ,* and *STS_RM*). As expected in *H1*, the coefficients of the time-dummies capturing stress test periods (*ST1011, ST1415,* and *ST16*) are mostly positive and significant. This implies that stress-tested banks have been using more words linked to stress tests during 'hot' stress test periods, compared to times without regulatory exercises.

[Please refer to Table 3.5 here]

In relation to stress test participants' total report length (*TWA*), the portion of the word count and recognition of stress test related terms increases from 1.99% in 2010-11, 2.91% in 2014-15 to 3.11% in 2016. Importantly, for the main dependent variable in Model 1 that stands for the accumulated stress test sentiment (*STS*), the coefficient of the interaction terms *ST1011*FTST1011,* is positive and significant at the 10% confidence level. This result indicates that first-time participants in 2010-11 utilised more stress test terms in response to stress tests in 2010-11 compared to those banks that did not participate in those early stress tests. Interestingly, the interaction terms *ST1415* FTST1011* and *ST16*FTST1011* are negative and significant at the 1% and 10% confidence levels. This result shows that for the periods of the later stress tests in 2014 and 2016, the first-time participants in 2010-11 use fewer stress test terms than those banks that participated for the first time in 2014. In other words, banks previously considered and regularly tested in stress tests seem to take less note of regulatory assessments on a later stage and make fewer adjustments to their disclosures compared to newly involved 2014 first-time participants.

Analysing significant differences between the accumulated stress test word list and the six individual categories, I find that during the first stress test period (*ST1011*), compared with their 2014 counterparts, first-time participants in 2010-11, utilise more stress test terms. However, this does not apply to all categories. In particular, regularly tested banks use more words that identify stress tests (*STS_ID*), regulatory institutions (*STS_REGIN*), and risk management (*STS_RM)* indicating the particular regulatory and supervisory impact during this time. Consistent with the accumulated results (*STS*), the identification of stress tests (*STS_ID*) then turns negative in the subsequent stress test periods. On the other hand, the word count for the regulatory institution terms (*STS_REGIN*) turns negative in later stress test periods (*ST1415, ST16*) but is statistically and economically insignificant. This result shows that during those later periods both sub-samples of first-time participants are equally affected by the regulatory enforcements and amendments. Overall, the results suggest that stress-tested banks adjust language and sentiment of textual narratives during stress test periods.

[Please refer to Table 3.6 here]

Second, in Table 3.6, I examine the tone of textual disclosures of stress-tested banks using the disclosure tone measure based on Loughran and McDonald's (2011a) financial word lists and Henry and Leone's (2016) disclosure tone definition. As expected in *H1*, in Model 1, the coefficients of the time-dummies (*ST1011, ST1415,* and *ST16*) are negative and significant at the 1% confidence level; this implies that all stress-tested banks generally apply a more negative tone during stress test periods than non-tested periods. In economic terms, on a scale of -1 (purely negative), 0 (purely natural) to 1 (purely positive), disclosure tone changes by -0.29 points in 2010-11, by -0.32 in 2014-15 and by -0.28 in 2016. Consistently, in Models 2 and 3, the relative number of 'negative', 'uncertainty' and 'modal' words used in textual narratives (*AGGNUM, NEGATIVE*) increases during those assessment periods. This result supports earlier findings arguing that more negative language is a sign of stronger regulation and accounting rules; this is because bank managers might fear litigation concerns and are less positive (Huang et al., 2014; Li, 2010).

Moreover, in Models 2, 4 and 5, the coefficients of the interaction terms *ST1415*FTST1011* and *ST16*FTST1011* are negative and significant at the 1% and 5% confidence levels. This result indicates that first-time participants in 2010-11 use relatively fewer 'negative', 'uncertainty' and 'modal' words in response to the 2014, 2015 and 2016 assessments, compared to the first-time participants in 2014. In summary, stress test participants adjust their textual narratives and utilise stronger language in their narratives (i.e., more negative, uncertainty and modal words). In particular, this result holds true for newly compared to regularly involved banks.

Third, in Table 3.7, I scrutinise quantitative disclosure behaviour by applying the transparency index based on the method of Nier and Baumann (2006). As hypothesised by *H1*, in all models, the coefficients of the time-dummies are positive and significant at the 1% and 5% confidence levels. Therefore, all stress test participants increase the number of figures within their disclosures due to the impact of stress test results. In economic terms, the transparency index (*TRANX*) increases by 6.04% in 2010-11, by 8.72% in 2014-15 to 9.33% in 2016. An alternative explanation of the result is that regulatory requirements based on Basel III have been subsequently implemented, requiring more mandatory disclosures. It is likely that the observed development is a result of both regulatory actions, while stress tests seem to exacerbate the evolvement of the transparency process during stress test periods.

[Please refer to Table 3.7 here]

Furthermore, the coefficients of the interaction terms in all models indicate an interesting change of disclosure behaviour. While the coefficients of the interaction terms *ST1011*FTST1011* and *ST1415*FTST1011* are insignificant, implying no significant difference between 2010-11 and 2014 first-time participants, the coefficients of the interaction term *ST16*FTST1011* in Models 1 and 4 are positive and significant at the 1% confidence level. This result illustrates that first-time participants in 2010-11 reported more quantitative disclosures during the 2016 stress test periods, compared to those banks that participated for the first time in 2014. I therefore see a slight learning effect implying that banks might have been educated through raised risk management requirements forwarded by the regulators. Overall, the results suggest that stress test participants adjust their disclosure profiles during stress test periods from a qualitative and quantitative view.

3.5.2. The effect of stress tests on bank opacity

I examine the impact of stress test sentiment on distinct forms of disclosure tone (*H2*) as well as the effect of stress tests on bank opacity (*H3a, H3b*). In Table 3.8, I run Equation 3.3 and scrutinise stress test sentiment based on the accumulated word count of my stress test, regulation and risk management word lists (*STS*). I estimate the impact of this word count during individual stress test periods (*STHC_I*) on the variation of disclosure tone (*ΔTONE*), aggregated 'negative', 'uncertain' and 'modal' tone (*AGGNUM*) and 'litigious' tone (*LITIGIOUS*).

[Please refer to Table 3.8 here]

In all models, I find that the coefficients of the interaction term *STHC_I*STS* are significant at the 5% and 10% confidence levels, implying that the effect of stress test sentiment, recognised in banks' disclosures, is related to the distinct forms of disclosure tone. Consistent with *H2*, whilst more stress test language indicates a positive variation of disclosure tone, the aggregated negative, uncertain and modal tone and litigious tone appear to be negative. In numerical terms, in Model 1, a 5% increase in stress test terms, during 'hot' stress test periods, is related to a positive variation of disclosure tone of 0.069 points, equal to 54.93% of the average standard deviation (SD) of *ΔTONE*. Further, considering the same 5% increase in stress test language, the portion of aggregated 'negative', 'uncertain' and 'modal' words (*AGGNUM*) and 'litigious' words

(*LITIGIOUS*), in relation to total report length, respectively decreases by -0.0010 and -0.0006 percentage points; this yields 17.00% and 32.00% of the average SD of *AGGNUM* and *LITIGIOUS*.

Therefore, I document that when stress-tested banks acknowledge stress tests in their annual and interim reports, they tend to partly reduce the number of negative and litigious words in an attempt to work against the stress test sentiment and potentially hide 'bad' news from stress tests. However, the results also suggest that the magnitude of variation towards more positive (less negative) language is limited due to regulatory and accounting rules (Huang et al., 2014; Li, 2010). Nevertheless, this change in distinct forms of disclosure tone may be an indicator that banks attempt to obfuscate investors because textual narratives report a tone that appears more positive.

In Table 3.9, I estimate Equations 3.4_A and 3.4_B and examine the individual effect of stress test participation. I analyse the impact of stress test sentiment (*STS*) and disclosure tone (*TONE*) on current and future bank opacity measures (*H3a, H3b*). In Table 3.9, Panel A, throughout all models, I find that the interaction terms *STHC_I*STS* and *STHC_I*TONE* are, respectively, positive and negative and significant at the 1% and 5% confidence levels. This result indicates that an increased stress test sentiment appears to lead to a higher current and future bid-ask spread, whilst a more positive tone may decrease the current and future bid-ask spread (*BIDASK*) of stress-tested banks during assessment periods. In economic terms, an increase of one SD of stress test sentiment during stress test periods is linked to an increase of current and future bid-ask spreads of 0.0014 and 0.0014 (9.68% and 10.16% of SD), respectively. Further, a more positive disclosure tone leads to a decrease of the current and future bid-ask spread by -0.0006 (4.22% of SD). Interestingly, it appears that, in contradiction with *H3a*, more stress test words in annual and interim reports are associated with higher information asymmetry (or uncertainty) among investors.

[Please refer to Table 3.9 here]

Furthermore, analysing analyst coverage (*RECNO*), in Table 3.9, Panel B, the coefficients of the interaction terms *STHC_I*STS* and *STHC_I*TONE* are respectively negative and positive and significant at the 1% and 10% confidence levels. Therefore, the current and future analyst coverage decreases with stress test sentiment and increases when the tone of the disclosure turns more positive. In numeric terms, an increase of one

SD of stress test sentiment is related to a decrease in analyst coverage by -0.8480 and -0.7059 (8.35% and 6.95% of SD), whilst disclosure tone is connected to a growth in analyst coverage of 0.2988 and 0.2952 (2.94% and 2.91% of SD). Thus, bank managers might not be able to condition the number of stress test words precisely to the market's expectations. However, consistent with *H3b*, this result implies that a more positive disclosure tone is related to a decrease in information asymmetry or increase in analyst coverage.

In Tables 3.10 and 3.11, I increase precision of prior analysis by estimating the effect of stress test sentiment (*STS*) and disclosure tone (*TONE*) around the dates when banks publish their reports. In particular, I measure the daily average of bid-ask spread (*BIDASK*) and the number of analyst recommendations (*RECNO*) during five periods around and after the individual bank report release dates. I calculate this average (1) one day before to one day after (t–1, t+1), (2) two days to 31 days after (t+2, t+31), (3) two days to 61 days after (t+2, t+61), (4) two days to 121 days after (t+2, t+121), and (5) two days to 250 days after (t+2, t+250). In Table 3.10, I document the impact on bid-ask spreads (*BIDASK*) by stress test sentiment (Panel A) and disclosure tone (Panel B). Further, in Table 3.11, I demonstrate the results for analyst coverage (*RECNO*) in terms of stress test sentiment (Panel A) and disclosure tone (Panel B).

[Please refer to Tables 3.10 and 3.11 here]

As expected in *H3b*, but contradicting *H3a*, I find similar results as in Table 3.9, indicating that increased stress test sentiment appears to increase information asymmetry and more positive disclosure tone increases analyst coverage. Interestingly, the effect remains relatively stable throughout various periods around and after the bank report release dates. Only in Model 5, which estimates the period 2-250 days after the bank report release date (t+2, t+250), the statistical and economic significance reduces. Consequently, stress test participants have an incentive to be cautious using stress test words and to use positive language in their annual and interim reports, especially during stress test periods. This is because market participants seem to appreciate this behaviour to an extent through more favourable market activities.

In summary, the results suggest that stress test sentiment might directly affect the variation of disclosure tone during stress test periods. Moreover, market participants appear to be effectively obfuscated, as bank opacity measures demonstrate less information asymmetry when disclosures display a positive tone during stress test periods. However, due to accounting rules and regulatory requirements (Huang et al., 2014; Li, 2010), the magnitude of altering disclosure tone is limited, as is the effect on investor and analyst obfuscation. Similar to Lang and Stice-Lawrence (2015), I am hesitant to make causal assumptions because it is difficult to rule out that the results are, at least partly, caused by the disclosure *per se*. Nevertheless, I conclude that, as expected, a more positive disclosure tone is related to less informative market measures.

3.6. Robustness analysis

The main conclusion of my study is that stress tests influence participating banks' disclosure profiles and ultimately affect their market measures. The validity of this finding depends on the correct implementation of textual and regression analyses. In this section, I run various robustness checks, which I illustrate in Tables 3.12 and 3.13. Additional robustness is displayed in the APPENDIX (Tables A.9 to A.14).

3.6.1. Textual measure robustness

To ensure that my textual measures for stress test sentiment and disclosure tone are sound and solid estimates, I follow the most recent standards of textual analysis. First, concerning textual parsing methods, I carefully construct my stress test word lists resorting to frequently used words in stress test discourses. I also select and analyse the textual disclosures including various checks, which I explain in Section 3.4.2.2. Second, I measure disclosure tone by applying Loughran and McDonald's (2011a) financial disclosure dictionaries, which are widely accepted within the textual analysis literature. However, as indicated earlier, the disclosure tone measure (*TONE*) might be influenced by the fact that the 'negative' word list consists of considerably more words than the 'positive' word list. Unlike other studies, I do not use alternative 'general' dictionaries such as Harvard General Inquirer or DICTION, as recent research suggests that those dictionaries are inaccurate for analysing financial disclosures (Loughran and McDonald, 2015, 2016). Instead, I resort to distinct variations of my disclosure tone measures. For instance, I follow Lang and Stice-Lawrence (2015) and implement a factor analysis of my stress test sentiment and disclosure tone variables. This analysis provides the opportunity to identify variances and similarities of applied word lists.

[Please refer to Tables 3.12 and 3.13 here]

Table 3.12 illustrates factor patterns before and after varimax rotation. While *STS_F1* is driven by the word count of ‘stress test identity’ (*STS_ID*), ‘stress test performance’ (*STS_PERF*) and ‘stress test procedure’ (*STS_PRO*) word lists, *STS_F2* captures the word count of ‘regulatory institutions’ (*STS_REGIN*), ‘regulatory requirements’ (*STS_REQ*) and ‘risk management’ (*STS_RM*) word lists. Further, *TONE_F1* measures ‘negative’ (*NEGATIVE*), ‘uncertainty’ (*UNCERTAIN*), ‘litigious’ (*LITIGIOUS*) and ‘superfluous’ (*SUPERFLU*) disclosure tone, whereas *TONE_F2* is mainly directed by the ‘positive’ disclosure tone (*POSITIVE*). In Table 3.13, I report results of those factor analysis variables and an alternative disclosure tone measure (*TONE_ALT*), which are consistent with my baseline analysis. Interestingly, dominant factors are driven by ‘stress test identity’, ‘performance’ and ‘procedure’ words (*STS_F1*) and ‘negative’, ‘uncertain’, ‘superfluous’ and ‘litigious’ tone (*TONE_F1*) during stress test periods. Overall, I retrieve similar results, compared to my baseline analysis, that do not alter my conclusions.

3.6.2. Additional robustness checks

Next, I ensure that the composition of the fixed effects models is robust by employing additional robustness checks (displayed in the APPENDIX, Tables A.9 to A.14). First, in Table A.9, I run an alternative model for stress test participation applying the individual stress test time-dummy (*STHC_I*). The results suggest that, during stress test periods, textual narratives include more stress test terms and tone that is more negative, while quantitative disclosure behaviour does not differ significantly. In Table A.10, I link my stress test sentiment factors with disclosure tone estimates, whereas Table A.11 illustrates the relationship between factors and bank opacity measures. Second, in Table A.12, I estimate Equation 3.3 to analyse whether stress-tested banks that participated more than four times change their disclosure tone towards less negative language. Consistent with my baseline analysis, I find significant results for variation of disclosure tone (*ΔTONE*) and aggregated ‘negative’, ‘uncertain’ and ‘modal’ tone (*AGGNUM*), while ‘litigious’ tone (*LITIGIOUS*) is not significant. The latter result supports my view and that of the literature that banks are limited owing to regulatory and accounting rules (Huang et al., 2014; Li, 2010). Third, in Table A.13, I rank stress-tested banks according to their capital adequacy performance documented by stress test disclosures and run Equations 3.4_A and 3.4_B on the lower-ranked half of the sample. The results show a slightly stronger relationship between bank opacity and stress test sentiment as well as disclosure tone; this implies that banks with weaker stress test results might influence their disclosure tone more aggressively than stronger banks.

Finally, in Table A.14, I exclude a different set of sample banks to test if inclusion of those banks, that are inherently different, might alter my conclusions. Similar to Lang and Stice-Lawrence (2015), I analyse translated disclosure narratives, which might be affected by the translation process. As almost all banks in my sample are located in countries where English is not the official language, I cannot fully rule out this issue. However, I do not believe that this limitation is a major problem as many of my sample banks are listed and internationalised, while financial reporting in English has been established over decades. Nevertheless, I exclude banks from the United Kingdom to rule out any skewness from native English language usage and retrieve similar results. Further, I remove banks from countries outside the European Monetary Union (EMU) because European regulators, in particular the ECB, are mainly focused on the stability of prices and the entire Eurozone. In addition, I delete inactive banks (i.e., bankruptcies, M&As) from my sample to ensure that my results are not influenced by any special bank survival issue (e.g., Beatty and Liao, 2011). Overall, the results from my robustness checks are similar to my baseline analysis and support my conclusions.

3.7. Concluding remarks

Stress tests have been largely studied in terms of market reactions and conceptual frameworks, while the impact of those tests on stress test participants has been widely left aside. On the other hand, bank transparency lies at the centre of a recent debate that aims to improve the market's wellbeing. Therefore, my work advances the literature by combining these two important literature streams and analyses the influence of regulatory stress tests on banks' disclosure profiles and, therefore, on bank transparency. In particular, using a unique sample and dataset from 25 European countries, I apply textual analysis to measure the effect of stress test sentiment and disclosure tone of stress-tested banks on their level of opacity. Importantly, I find that stress test participants' textual disclosures are influenced by stress test disclosure language, which I call 'stress test sentiment'. Further, my results suggest that disclosure tone and quantitative disclosure behaviour changes; they seem to affect the evolvement of the transparency process during stress test periods. Ultimately, market participants appear to be obfuscated, as bank opacity measures show less information asymmetry when banks amend disclosure tone to sound more positive, compensating regulatory stress test sentiment during times of assessment. Although I am cautious to draw causal inference, I conclude that there is a relationship between stress test language, textual disclosure tone and bank transparency.

This study is the first that links stress tests and bank transparency by introducing the innovative textual analysis approach. Hence, my novel results raise several political and business implications. I do not doubt that, besides intrinsic limitations, stress tests are useful during crises to separate sound from unsound banks (Borio et al., 2014; Schuermann, 2014). Moreover, regulatory assessments are unique opportunities for regulators and supervisors to improve the supervision of SIFIs from their in-depth insights (Carboni et al., 2017; Sahin and de Haan, 2016). However, my findings suggest that stress test participants may change their disclosure profiles to mitigate the effect of stress test disclosures on investors. Further, bank opacity measures report less information asymmetry, which appears to confirm the operation of such disclosure strategies. In combination with earlier stress test studies, my results indicate that stress tests seem to exacerbate pressure, particularly on relatively weak institutions as they expose bank-specific information in calm economic times, which can lead to financial instability (Bouvard et al., 2015). Therefore, by shedding light on banks' disclosure profiles and bank transparency, this study empirically supports previous research on stress tests that suggests, in normal economic times, to disclose mainly aggregated information, as this approach would reduce pressure on stress test participants and their signalling motives (Goldstein and Sapra, 2013).

Table 3.1 Variable definitions and data sources

Abbreviations	Variables	Description	Data sources
TRANX	Quantitative disclosure behaviour	Transparency index based on Nier and Baumann (2006); see Note 1 (page 109)	FitchConnect
SIZE	Bank size	Natural logarithm of total assets	BvD Bankscope, Bank reports, FitchConnect
LOAN	Traditional banking activities	Outstanding loans scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
LLR	Credit portfolio quality	Loan loss reserves for non-performing or impaired loans scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
LLP	(Forward-looking) asset quality	Loan loss provisions for non-performing or impaired loans scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
NPL	(Backward-looking) asset quality	Non-performing or impaired loans scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
TRADE	Non-traditional banking activities	Trading securities scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
CET1R	Capital adequacy	Core/common Tier 1 capital divided by risk-weighted assets	BvD Bankscope, Bank reports, FitchConnect
T1R	Capital adequacy	Regulatory Tier 1 capital divided by risk-weighted assets	BvD Bankscope, Bank reports, FitchConnect
TRR	Capital adequacy	Total regulatory capital divided by risk-weighted assets	BvD Bankscope, Bank reports, FitchConnect
DSTF	Liquidity risk	Deposits and short-term funding scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
CAP	Bank capital	Total equity capital divided by total assets	BvD Bankscope, Bank reports, FitchConnect
EBPT	Profitability	Earnings before provision and taxes scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
TWA	Report length	Total words analysed	Bank reports
STS	Stress test sentiment	Word count of the accumulated stress test, regulation and risk management word list scaled by TWA (sum of STS_ID, STS_PERF, STS_ PRO, STS_REGIN, STS_REQ, and STS_RM)	EBA and ECB stress test disclosures, Bank reports
STS_ID	Stress test identity	Word count of the 'stress test identity' word list scaled by TWA; see Note 2 (page 110)	EBA and ECB stress test disclosures, Bank reports
STS_PERF	Stress test performance	Word count of the 'stress test performance' word list scaled by TWA; see Note 2 (page 110)	EBA and ECB stress test disclosures, Bank reports
STS_PRO	Stress test procedure	Word count of the 'stress test procedure' word list scaled by TWA; see Note 2 (page 110)	EBA and ECB stress test disclosures, Bank reports
STS_REGIN	Regulatory institutions	Word count of the 'regulatory institutions' word list scaled by TWA; see Note 2 (page 110)	EBA and ECB stress test disclosures, Bank reports
STS_REQ	Regulatory requirements	Word count of the 'regulatory requirements' word list scaled by TWA; see Note 2 (page 110)	EBA and ECB stress test disclosures, Bank reports
STS_RM	Risk management	Word count of the 'risk management' word list scaled by TWA; see Note 2 (page 110)	EBA and ECB stress test disclosures, Bank reports
TONE	Disclosure tone	POSITIVE – NEGATIVE / (POSITIVE + NEGATIVE); 1 yields positive, 0 neutral and -1 negative tone (Henry and Leone, 2016)	Bank reports
TONE_ALT	Disclosure tone	POSITIVE – NEGATIVE / TWA according to Huang et al. (2014)	Bank reports
ΔTONE	Variation of disclosure tone	TONE – $TONE_{t-1}$ (Henry and Leone, 2016; Loughran and McDonald, 2011a)	Bank reports
NEGATIVE	'Negative' tone	Word count of 'negative' word list scaled by TWA (Loughran and McDonald, 2011a)	Bank reports
POSITIVE	'Positive' tone	Word count of 'positive' word list scaled by TWA (Loughran and McDonald, 2011a)	Bank reports
AGGNUM	Aggregated 'negative', 'uncertain' and 'modal' tone	Word count of the aggregated 'negative', 'uncertain' and 'modal' word lists scaled by TWA (Loughran and McDonald, 2011a)	Bank reports

Table 3.1 continued

UNCERTAIN	'Uncertain' tone	Word count of 'uncertainty' word list scaled by TWA (Loughran and McDonald, 2011a)	Bank reports
MODAL	'Modal' tone	Word count of 'modal' word list scaled by TWA (Loughran and McDonald, 2011a)	Bank reports
LITIGIOUS	'Litigious' tone	Word count of 'litigious' word list scaled by TWA (Loughran and McDonald, 2011a)	Bank reports
SUPERFLU	'Superfluous' tone	Word count of 'superfluous' word list scaled by TWA (Loughran and McDonald, 2011a)	Bank reports
BIDASK	Information asymmetry	Quarterly average of daily bid-ask-spreads (Ask – Bid / (Ask + Bid / 2))	Thomson Reuters (Datastream/IBES)
RECNO	Analyst coverage	Quarterly average of the daily number of analysts filing a recommendation	Thomson Reuters (Datastream/IBES)
RECSBUY	Analyst strong-buy recommendation	Quarterly average of the daily percentage of analysts' strong-buy recommendations	Thomson Reuters (Datastream/IBES)
RECMBUY	Analyst moderate-buy recommendation	Quarterly average of the daily percentage of analysts' moderate-buy recommendations	Thomson Reuters (Datastream/IBES)
RECHOLD	Analyst hold recommendation	Quarterly average of the daily percentage of analysts' hold recommendations	Thomson Reuters (Datastream/IBES)
RECMSELL	Analyst moderate-sell recommendation	Quarterly average of the daily percentage of analysts' moderate-sell recommendations	Thomson Reuters (Datastream/IBES)
RECSSELL	Analyst strong-sell recommendation	Quarterly average of the daily percentage of analysts' strong-sell recommendations	Thomson Reuters (Datastream/IBES)
RECCON	Analyst recommendation consensus	Quarterly average of the daily recommendation consensus of analysts; yields the mean of all daily recommendations: Strong-buy (1-1.49), moderate-buy (1.5-2.49), hold (2.5-3.49), moderate-sell (3.5-4.49), strong-sell (4.5-5)	Thomson Reuters (Datastream/IBES)
TOVER	Share turnover	Quarterly average of the daily number of shares outstanding divided by free float	Thomson Reuters (Datastream/IBES)
INVPRICE	Inverse share price	Quarterly average of 1 divided by daily share price	Thomson Reuters (Datastream/IBES)
RETVOL	Return volatility	Quarterly average of the daily standard deviation of continuously compounded share price returns	Thomson Reuters (Datastream/IBES)
MVALUE	Market value	Quarterly average of the daily logarithm of market value of equity	Thomson Reuters (Datastream/IBES)
MTBV	Market-to-book value	Quarterly average of the daily market value of equity divided by the book value of equity	Thomson Reuters (Datastream/IBES)
FTST1011	First-time participation in the 2010-11 stress tests	A binary variable that yields 1 for all banks that were tested for the first time in 2010-11, and 0 otherwise	EBA and ECB stress test disclosures
ST1011	Stress test period in 2010-11	A binary variable that yields 1 from 2010Q2-2012Q1, and 0 otherwise	EBA and ECB stress test disclosures
ST1415	Stress test period in 2014-15	A binary variable that yields 1 from 2014Q2-2016Q1, and 0 otherwise	EBA and ECB stress test disclosures
ST16	Stress test period in 2016	A binary variable that yields 1 from 2016Q2-2017Q1, and 0 otherwise	EBA and ECB stress test disclosures
STHC_I	Individual stress test period	A binary variable that yields 1 for the period that each bank participated in a stress test; i.e. equals 1 for the exercises in 2010 at 2010Q2-2011Q1, in 2011 at 2011Q2-2012Q1, in 2014 at 2014Q2-2015Q1, in 2015 at 2015Q2-2016Q1, and in 2016 at 2016Q2-2017Q1, and 0 otherwise	EBA and ECB stress test disclosures
ΔGDP	Economic growth	Change in Gross Domestic Product in Euros	OECD, Bloomberg
ΔUNEM	Unemployment growth	Change in unemployment rate	OECD, Bloomberg
IRATE	Sovereign debt risk	The difference between short- and long-term interest rates in government bond markets	OECD

Note 1. Detailed definition of the transparency index (*TRANX*)

The transparency index (*TRANX*) is a comprehensive measure of bank transparency inspired by Nier and Baumann (2006). I divide the categories into nineteen sub-indices and compose an aggregated transparency index by counting the disclosed figures within the sub-indices available on FitchConnect. Accordingly, *TRANX* is defined as follows:

$$TRANX = \frac{1}{19}\sum_{i=1}^{19} S_i$$

where, the nineteen sub-indices S_i relate to distinct bank risk categories (credit risk, market risk, liquidity risk, capital risk). To ensure full transparency of the data collection process, I follow the description and sorting of the items according to FitchConnect.

Transparency index components

Category	Sub-index	Item
Loans	S_1: Loans	Net loans, Gross loans, Reserves for impaired loans/NPLs
	S_2: Loans by type	Mortgages, Other consumer/retail loans, Corporate & commercial loans, Other loans and loan-related balances
	S_3: Loans by counterparty	Loans & advances to banks, Quasi government loans, Total corporate loans, Total consumer loans
	S_4: Loans by maturity	Loans & advances < 3M, Loans & advances 3-12M, Loans & advances 1-5Y, Loans & advances > 5Y
	S_5: Problem and impaired loans	NPLs - Doubtful loans, NPLs - +90 Days past due, NPLs - Restructured loans, Total impaired loans
Other earning assets	S_6: Securities by type	Reverse repo & cash collateral, Trading securities at FV through income, Derivatives (assets), Available for sales securities, Held to maturity securities, Equity investments in associates, Other securities, Total securities
	S_7: Securities by purpose	Trading securities, Investment securities
Liabilities	S_8: Deposits by type	Customer deposits (current), Customer deposits (savings), Customer deposits (term), Total customer deposits, Deposits from banks
	S_9: Deposits by maturity	Deposits - sub 3 months, Deposits - 3 months-1 year, Deposits - 1-5 years, Deposits - 5 years +
	S_{10}: Short-term funding	Repos & cash collateral, Other deposits & short-term borrowings, Total deposits, Money market & short-term funding
	S_{11}: Long-term funding	Long-term senior debts, Subordinated debts, Total long-term funding
	S_{12}: Other liabilities by type	Derivatives (liabilities), Trading liabilities
Equity	S_{13}: Equity	Total common equity, Preferred shares & hybrid capital accounted for as equity, Total equity
Off-balance sheet	S_{14}: Off-balance sheet items by type	Guarantees, acceptances & documentary credits reported off-B/S, Committed credit lines, Other off-balance sheet items, Off-balance sheet items
Income statement	S_{15}: Income by type	Net interest income, Net fees & commissions, Net gains (losses) on trading & derivatives, Net gains (losses) on assets at FV through I/S, Net gains (losses) on other securities, Total non-interest operating income
	S_{16}: Loan loss provisions	Pre-impairment operating profit, Loan impairment charge, Operating profit
Regulatory memo lines	S_{17}: Regulatory capital	Common equity Tier 1 capital, Regulatory Tier 1 capital, Total regulatory capital
	S_{18}: Risk-weighted assets	Total risk-weighted assets (RWA), Risk-weighted assets - Credit risk, Risk-weighted assets - Market risk, Risk-weighted assets - Operational market risk, Risk-weighted assets - Other
	S_{19}: Regulatory capital ratios	Common equity Tier 1 capital ratio, Regulatory Tier 1 capital ratio, Total regulatory capital ratio

Note 2. Stress test sentiment (*STS*) word list by category

Category	Keywords	Category	Keywords	Category	Keywords
STS_ID	AQR	STS_PERF	RESTRUCTURING	STS_PRO	PHASE-IN
STS_ID	ASSESSMENT	STS_PERF	ROBUST	STS_PRO	PHASING-IN
STS_ID	ASSESSMENTS	STS_PERF	ROBUSTNESS	STS_PRO	PIT
STS_ID	EU-WIDE	STS_PERF	SEVERE	STS_PRO	POINT-IN-TIME
STS_ID	EXERCISE	STS_PERF	SIGNIFICANT	STS_PRO	QA
STS_ID	EXERCISES	STS_PERF	SOLVENCY	STS_PRO	REVERSE
STS_ID	REVIEW	STS_PERF	SOLVENT	STS_PRO	SCENARIO
STS_ID	REVIEWS	STS_PERF	SOUND	STS_PRO	SCENARIOS
STS_ID	STRESS	STS_PERF	SOUNDNESS	STS_PRO	SHOCK
STS_ID	STRESS-TEST	STS_PERF	STABILITY	STS_PRO	SHOCKS
STS_ID	STRESS-TESTING	STS_PERF	STABLE	STS_PRO	SHORTFALL
STS_ID	STRESS-TESTS	STS_PERF	STRENGTH	STS_PRO	SHORTFALLS
STS_ID	STRESSED	STS_PERF	STRENGTHEN	STS_PRO	SIMULATE
STS_ID	TEST	STS_PERF	STRENGTHENED	STS_PRO	SIMULATED
STS_ID	TESTING	STS_PERF	STRENGTHENING	STS_PRO	SIMULATES
STS_ID	TESTS	STS_PERF	STRENGTHS	STS_PRO	SIMULATING
STS_ID	TREATMENT	STS_PERF	VULNERABILITIES	STS_PRO	SIMULATION
STS_ID	TREATMENTS	STS_PERF	VULNERABILITY	STS_PRO	SIMULATIONS
STS_PERF	ACCORDANCE	STS_PERF	VULNERABLE	STS_PRO	SPREAD
STS_PERF	APPROPRIATE	STS_PERF	WORSE	STS_PRO	SPREADS
STS_PERF	COMPLIANCE	STS_PERF	WORST	STS_PRO	SREP
STS_PERF	COMPLIANT	STS_PRO	ADVERSE	STS_PRO	STA
STS_PERF	CONSTRAINT	STS_PRO	APPROACH	STS_PRO	TEMPLATE
STS_PERF	CONSTRAINTS	STS_PRO	APPROACHES	STS_PRO	TEMPLATES
STS_PERF	EQUAL	STS_PRO	ASSESS	STS_PRO	THRESHOLD
STS_PERF	EXCEED	STS_PRO	ASSESSED	STS_PRO	THRESHOLDS
STS_PERF	EXCEEDING	STS_PRO	ASSESSING	STS_PRO	TOP-DOWN
STS_PERF	EXCEEDED	STS_PRO	ASSURANCE	STS_PRO	TRIGGER
STS_PERF	EXCESS	STS_PRO	BASELINE	STS_PRO	TRIGGERS
STS_PERF	EXCESSIVE	STS_PRO	BENCHMARK	STS_PRO	VALUATION
STS_PERF	EXTREME	STS_PRO	BENCHMARKS	STS_PRO	VALUATIONS
STS_PERF	FAIL	STS_PRO	BOTTOM-UP	STS_REGIN	AUDITOR
STS_PERF	FAILED	STS_PRO	CVA	STS_REGIN	AUDITORS
STS_PERF	FAILS	STS_PRO	DRIVER	STS_REGIN	AUTHORITIES
STS_PERF	FINDING	STS_PRO	DRIVERS	STS_REGIN	AUTHORITY
STS_PERF	FINDINGS	STS_PRO	EVENT	STS_REGIN	CEBS
STS_PERF	FORECAST	STS_PRO	EVENTS	STS_REGIN	COMMISSION
STS_PERF	FORECASTED	STS_PRO	FACTOR	STS_REGIN	EBA
STS_PERF	FORECASTING	STS_PRO	FACTORS	STS_REGIN	ECB
STS_PERF	FORECASTS	STS_PRO	HAIRCUT	STS_REGIN	ESRB
STS_PERF	FUTURE	STS_PRO	HAIRCUTS	STS_REGIN	EU
STS_PERF	GAIN	STS_PRO	HURDLE	STS_REGIN	GOVERNMENT
STS_PERF	GAINING	STS_PRO	HYPOTHETICAL	STS_REGIN	GOVERNMENTS
STS_PERF	GAINS	STS_PRO	IMPACT	STS_REGIN	INSTITUTION
STS_PERF	INAPPROPRIATE	STS_PRO	IMPACTS	STS_REGIN	INSTITUTIONS
STS_PERF	PASS	STS_PRO	JOIN-UP	STS_REGIN	NCA
STS_PERF	PASSED	STS_PRO	LGI	STS_REGIN	NCAS
STS_PERF	PASSING	STS_PRO	MACRO-ECONOMIC	STS_REGIN	REGULATOR
STS_PERF	PASSES	STS_PRO	MACRO-FINANCIAL	STS_REGIN	REGULATORS
STS_PERF	PROJECTED	STS_PRO	MACRO-PRUDENTIAL	STS_REGIN	SSM
STS_PERF	PROJECTING	STS_PRO	MACROECONOMIC	STS_REGIN	SUPERVISION
STS_PERF	PROJECTION	STS_PRO	MEASURE	STS_REGIN	SUPERVISOR
STS_PERF	PROJECTIONS	STS_PRO	MEASURES	STS_REGIN	SUPERVISORS
STS_PERF	QUALITY	STS_PRO	METHODOLOGICAL	STS_REGIN	SUPERVISORY
STS_PERF	RAISE	STS_PRO	METHODOLOGIES	STS_REQ	ACCORD
STS_PERF	RAISED	STS_PRO	METHODOLOGY	STS_REQ	ADEQUACY
STS_PERF	RAISING	STS_PRO	MODEL	STS_REQ	BASE
STS_PERF	REDUCTION	STS_PRO	MODELED	STS_REQ	BASEL
STS_PERF	REPUTATION	STS_PRO	MODELLING	STS_REQ	BASIS
STS_PERF	REPUTATIONAL	STS_PRO	MODELS	STS_REQ	CAPITAL
STS_PERF	RESILIENCE	STS_PRO	PARAMETER	STS_REQ	CAPITALISATION
STS_PERF	RESILIENT	STS_PRO	PARAMETERS	STS_REQ	CAPITALISED
STS_PERF	RESIST	STS_PRO	PARTICIPATE	STS_REQ	CAPITALIZATION
STS_PERF	RESISTANCE	STS_PRO	PARTICIPATED	STS_REQ	CCR
STS_PERF	RESISTING	STS_PRO	PARTICIPATING	STS_REQ	CET1
STS_PERF	RESISTED	STS_PRO	PARTICIPATION	STS_REQ	CLASS
STS_PERF	RESTRUCTION	STS_PRO	PARTICIPATIONS	STS_REQ	CLASSES
STS_PERF	RESTRUCTURE	STS_PRO	PHASE	STS_REQ	CLASSIFICATION

Category	Keywords	Category	Keywords	Category	Keywords
STS_REQ	CLASSIFICATIONS	STS_RM	ESTIMATE	STS_RM	SECURITIZATION
STS_REQ	CONFIDENCE	STS_RM	ESTIMATING	STS_RM	SECURITIZATIONS
STS_REQ	COVERAGE	STS_RM	ESTIMATES	STS_RM	SOVEREIGN
STS_REQ	CRD	STS_RM	EVOLUTION	STS_RM	SYSTEMIC
STS_REQ	CRISES	STS_RM	EXPECTED	STS_RM	UNEXPECTED
STS_REQ	CRISIS	STS_RM	EXPOSURE	STS_RM	VAR
STS_REQ	CRR	STS_RM	EXPOSURES	STS_RM	VOLATILITY
STS_REQ	CRWA	STS_RM	FORBEARANCE	STS_RM	VOLUME
STS_REQ	DISCLOSURE	STS_RM	FORBORNE	STS_RM	VOLUMES
STS_REQ	FLOOR	STS_RM	FUND		
STS_REQ	FULLY-LOADED	STS_RM	FUNDING		
STS_REQ	IMPLEMENTATION	STS_RM	FUNDS		
STS_REQ	LEVEL	STS_RM	HEDGE		
STS_REQ	LEVELS	STS_RM	HEDGED		
STS_REQ	LOADED	STS_RM	HEDGES		
STS_REQ	MINIMUM	STS_RM	HEDGING		
STS_REQ	MISCLASSIFICATION	STS_RM	IDIOSYNCRATIC		
STS_REQ	MISCLASSIFICATIONS	STS_RM	ILLIQUID		
STS_REQ	MISCLASSIFIED	STS_RM	ILLIQUIDITY		
STS_REQ	PILLAR	STS_RM	IMPAIRED		
STS_REQ	RE-CAPITALISATION	STS_RM	IMPAIRMENT		
STS_REQ	RECAPITALISATION	STS_RM	IMPAIRMENTS		
STS_REQ	RECLASSIFICATION	STS_RM	IRB		
STS_REQ	RECLASSIFICATIONS	STS_RM	LEVERAGE		
STS_REQ	RECLASSIFIED	STS_RM	LGD		
STS_REQ	REGULATE	STS_RM	LGDS		
STS_REQ	REGULATED	STS_RM	LIQUID		
STS_REQ	REGULATION	STS_RM	LIQUIDITY		
STS_REQ	REGULATORY	STS_RM	LITIGATION		
STS_REQ	REQUIRED	STS_RM	LOAN		
STS_REQ	REQUIREMENT	STS_RM	LOANS		
STS_REQ	REQUIREMENTS	STS_RM	LOSS		
STS_REQ	RISK-WEIGHTED	STS_RM	LOSSED		
STS_REQ	RWA	STS_RM	LOSSES		
STS_REQ	STANDARD	STS_RM	MITIGATING		
STS_REQ	STANDARDISED	STS_RM	MITIGATION		
STS_REQ	STANDARDS	STS_RM	MITIGATIONS		
STS_REQ	TIER	STS_RM	NON-DEFAULTED		
STS_REQ	TIER-1	STS_RM	NON-PERFORMING		
STS_REQ	TRANSPARENCY	STS_RM	NONDEFAULTED		
STS_REQ	WEIGHTED	STS_RM	NONPERFORMING		
STS_RM	ACCRUAL	STS_RM	NPE		
STS_RM	ACCRUALS	STS_RM	NPES		
STS_RM	ALLOWANCE	STS_RM	PD		
STS_RM	APPETITE	STS_RM	PDS		
STS_RM	CHARGE	STS_RM	PROBABILITIES		
STS_RM	CHARGES	STS_RM	PROBABILITY		
STS_RM	COLLATERAL	STS_RM	PROFILE		
STS_RM	COLLATERALISED	STS_RM	PROFILES		
STS_RM	COLLATERALS	STS_RM	PROVISION		
STS_RM	COUNTERPARTIES	STS_RM	PROVISIONING		
STS_RM	COUNTERPARTY	STS_RM	PROVISIONS		
STS_RM	COVER	STS_RM	PRUDENTIAL		
STS_RM	COVERED	STS_RM	QUALITATIVE		
STS_RM	COVERING	STS_RM	QUANTITATIVE		
STS_RM	COVERS	STS_RM	RATED		
STS_RM	CREDIT	STS_RM	RATING		
STS_RM	CREDITWORTHINESS	STS_RM	RATINGS		
STS_RM	DEFAULT	STS_RM	REA		
STS_RM	DEFAULTED	STS_RM	RECOVERED		
STS_RM	DEFAULTING	STS_RM	RECOVERIES		
STS_RM	DEFAULTS	STS_RM	RECOVERY		
STS_RM	DISCRETION	STS_RM	RISK		
STS_RM	DISCRETIONARY	STS_RM	RISK-BASED		
STS_RM	DTA	STS_RM	RISKS		
STS_RM	DTAS	STS_RM	RISKY		
STS_RM	DUE	STS_RM	SECURITISATION		
STS_RM	EQUITY	STS_RM	SECURITISATIONS		

Table 3.2 European stress tests and sample construction

Panel A: Geographical structure of sample banks

Country	Stress test participation CEBS/EBA[a]				Stress test participation ECB		Total stress test sample	First-time participants 2010-11 (*FTST1011*)	First-time participants 2014 (*FTST14*)
	2010	2011	2014	2016	2014	2015			
Austria	2	3	6	2	6	2	10	4	3
Belgium	2	2	5	2	6	1	7	2	4
Cyprus	2	2	3	0	4	0	5	2	3
Denmark	3	4	4	3	0	0	4	4	0
Estonia	0	0	0	0	3	0	3	0	3
Finland	1	1	1	1	3	1	4	1	2
France	4	4	11	6	13	1	15	4	9
Germany	14	12	24	9	25	0	27	14	13
Greece	6	6	4	0	4	4	6	6	0
Hungary	2	1	1	1	0	0	2	2	0
Ireland	2	3	3	2	5	0	5	3	2
Italy	5	5	15	5	15	0	15	5	10
Latvia	0	0	1	0	3	0	3	0	3
Lithuania	0	0	0	0	3	0	3	0	3
Luxembourg	2	1	2	0	6	1	8	2	5
Malta	1	1	1	0	3	1	4	1	2
Netherlands	4	4	6	4	7	0	7	4	3
Norway	0	1	1	1	0	0	1	1	0
Poland	1	1	6	1	0	0	6	1	5
Portugal	4	4	3	0	3	1	5	4	0
Slovakia	0	0	0	0	3	0	3	0	3
Slovenia	1	2	3	0	3	1	4	2	1
Spain	27	25	15	6	15	0	32	28	3
Sweden	4	4	4	4	0	0	4	4	0
United Kingdom	4	4	4	4	0	0	4	4	0
Total samples	**91**	**90**	**123**	**51**	**130**	**13**	**187**	**98**	**77**

Table 3.2 continued

Panel B: Sample construction

	Total sample	*FTST1011*	*FTST14*
Total stress test participation	187	98	77
Excluded (data unavailability due to M&As)	16	15	1
Excluded (unavailability of bank reports)	15	6	6
Excluded (unavailability of accounting data)	10	4	5
Excluded (data unavailability due to bankruptcies)	4	4	0
Total excluded stress-tested banks	45	29	12
Stress test participation sample	142	69	65
- *Thereof publicly listed*	*61*	*45*	*15*

This table presents the European stress test participation and sample construction. Panel A reports per country and assessment the number of banks that participated in CEBS/EBA and ECB stress tests over the period 2010-2016. Panel B describes the filtering criteria I apply to my samples of banks in the conduct of the empirical analysis (based on textual, accounting and market data). I exclude banks due to unavailability of bank reports and accounting data in FitchConnect. I also remove banks due to lack of data caused by either M&As, or bankruptcies.

[a]The stress tests in 2009 and 2010 were conducted by CEBS. The names of the participating banks of CEBS's stress test in 2009 were not published.

Table 3.3 Descriptive statistics

Variables	Obs.	Mean	SD	Min.	Max.	Median
Panel A: Bank accounting characteristics						
TRANX	4699	0.588	0.132	0.176	0.892	0.595
SIZE	4966	11.073	1.795	6.724	14.529	11.014
LOAN	3267	0.601	0.153	0.172	0.908	0.617
LLR	2844	0.032	0.037	0.001	0.193	0.019
LLP	3274	0.004	0.006	-0.003	0.036	0.002
NPL	2476	0.055	0.066	0.002	0.347	0.033
TRADE	2775	0.107	0.107	0.001	0.493	0.073
CET1R	2260	0.136	0.056	0.058	0.407	0.125
T1R	4278	0.129	0.058	0.056	0.413	0.117
TRR	4472	0.153	0.057	0.083	0.428	0.140
DSTF	3282	0.629	0.195	0.040	0.966	0.644
CAP	3307	0.072	0.037	0.001	0.204	0.065
EBPT	3276	0.007	0.006	-0.004	0.031	0.006
Panel B: Textual analysis characteristics						
Variables	Obs.	Mean	SD	Min.	Max.	Median
TWA	4178	56,310	59,945	3686	286,451	32,905
STS	4178	0.054	0.013	0.026	0.086	0.053
STS_ID	4178	0.001	0.001	0.000	0.004	0.001
STS_PERF	4178	0.005	0.001	0.001	0.009	0.005
STS_PRO	4178	0.004	0.002	0.001	0.010	0.004
STS_REGIN	4178	0.003	0.001	0.001	0.007	0.003
STS_REQ	4178	0.010	0.004	0.003	0.022	0.010
STS_RM	4178	0.031	0.008	0.012	0.052	0.030
TONE	4175	-0.275	0.219	-0.667	0.398	-0.316
ΔTONE	3701	-0.012	0.125	-0.457	0.361	-0.007
NEGATIVE	4178	0.012	0.004	0.004	0.024	0.012
POSITIVE	4178	0.007	0.003	0.002	0.015	0.006
AGGNUM	4178	0.021	0.006	0.007	0.038	0.021
UNCERTAIN	4178	0.009	0.004	0.002	0.020	0.009
MODAL	4178	0.004	0.002	0.000	0.009	0.004
LITIGIOUS	4178	0.004	0.002	0.000	0.011	0.004
Panel C: Market microstructure characteristics						
Variables	Obs.	Mean	SD	Min.	Max.	Median
BIDASK	2650	0.008	0.014	0.000	0.095	0.003
RECNO	2511	19.388	10.154	1.000	39.000	21.108
RECSBUY	2516	15.873	13.274	0.000	66.670	14.313
RECMBUY	2518	23.895	16.035	0.000	66.670	23.796
RECHOLD	2511	39.322	18.907	0.000	100.000	37.678
RECMSELL	2518	15.662	15.172	0.000	66.670	12.157
RECSSELL	2516	4.357	6.532	0.000	33.330	1.383
RECCON	2511	2.687	0.532	1.500	4.130	2.649
TOVER	2822	0.014	0.040	0.000	0.304	0.004
INVPRICE	2834	0.248	0.481	0.000	3.906	0.097
RETVOL	2834	0.025	0.017	0.005	0.101	0.020
MVALUE	2834	8.609	1.692	4.482	11.840	8.744
MTBV	2731	1.108	0.753	-0.100	3.890	0.922

Table 3.3 continued

Panel D: Macroeconomic fundamentals						
Country	*ΔGDP* (Mean)	*ΔGDP* (SD)	*ΔUNEM* (Mean)	*ΔUNEM* (SD)	*IRATE* (Mean)	*IRATE* (SD)
Austria	0.006	0.048	0.003	0.058	1.221	0.917
Belgium	0.006	0.049	-0.003	0.055	1.451	1.050
Cyprus	0.006	0.018	0.035	0.171	N/A	N/A
Denmark	0.006	0.050	0.011	0.071	0.746	0.794
Estonia	0.006	0.052	0.011	0.136	N/A	N/A
Finland	0.004	0.050	0.005	0.037	1.092	0.841
France	0.006	0.049	0.003	0.034	1.257	0.901
Germany	0.006	0.048	-0.017	0.040	0.825	0.793
Greece	-0.003	0.049	0.020	0.051	7.457	6.189
Hungary	0.006	0.051	-0.012	0.048	0.863	1.315
Ireland	0.015	0.075	0.009	0.076	2.660	2.529
Italy	0.003	0.049	0.014	0.048	2.407	1.511
Latvia	0.005	0.051	0.005	0.117	1.588	3.188
Lithuania	0.007	0.050	0.007	0.136	2.221	2.068
Luxembourg	0.008	0.052	0.006	0.038	1.031	0.637
Malta	0.020	0.049	-0.008	0.061	N/A	N/A
Netherlands	0.006	0.049	0.003	0.064	1.082	0.856
Norway	0.006	0.053	0.013	0.094	0.406	0.911
Poland	0.011	0.049	-0.012	0.101	1.045	0.692
Portugal	0.004	0.049	-0.002	0.043	3.789	3.123
Slovakia	0.010	0.050	-0.006	0.066	1.891	1.292
Slovenia	0.006	0.047	0.007	0.083	2.324	1.866
Spain	0.004	0.049	0.017	0.055	2.316	1.679
Sweden	0.007	0.051	0.003	0.050	1.221	0.815
United Kingdom	0.006	0.050	-0.004	0.040	1.100	1.293
Total	0.006	0.050	0.003	0.068	1.716	2.090

This table reports descriptive statistics (i.e., observation, mean, standard deviation, minimum maximum and median) of the variables I use in my analysis. Panel A presents the following accounting variables, winsorised at the 1 and 99 percentiles: Quantitative disclosure behaviour measured by the transparency index (*TRANX*), bank size captured by the natural logarithm of total assets (*SIZE*), traditional banking activities shown by outstanding loans (*LOAN*), credit portfolio quality measured by loan loss reserves (*LLR*), asset quality captured by loan loss provisions (*LLP*) and non-performing loans (*NPL*), non-traditional banking activities measured by trading securities (*TRADE*), capital adequacy shown by ratios of regulatory core/common Tier 1 capital (*CET1R*), Tier 1 capital (*T1R*) and total regulatory capital (*TRR*), liquidity risk shown by deposits and short-term funding (*DSTF*), bank capital captured by total equity capital (*CAP*), and profitability measured by earnings before provision and taxes (*EBPT*). Panel B presents the following textual analysis characteristics, winsorised at the 1 and 99 percentiles: Report length estimated by total words analysed (*TWA*), stress test sentiment measured by the word count of the accumulated stress test, regulation and risk management word list (*STS*), i.e. sum of 'stress test identity' (*STS_ID*), 'stress test performance' (*STS_PERF*), 'stress test procedure' (*STS_PRO*), 'regulatory institutions' (*STS_ REGIN*), 'regulatory requirements' (*STS_REQ*) and 'risk management' (*STS_RM*); various forms of disclosure tone captured by (variation of) disclosure tone (*TONE*, *ΔTONE*), 'negative' tone (*NEGATIVE*), 'positive' tone, (*POSITIVE*), aggregated 'negative', 'uncertain' and 'modal' tone (*AGGNUM*), 'uncertain' tone (*UNCERTAIN*), 'modal' tone (*MODAL*), and 'litigious' tone (*LITIGIOUS*). Panel C presents the following market microstructure characteristics, daily winsorised at the 1 and 99 percentiles and quarterly averaged: Information asymmetry estimated by the bid-ask-spread (*BIDASK*), analyst coverage covered by the number of analyst recommendations (*RECNO*), the percentage of analysts' strong-buy, moderate-buy, hold, moderate-sell and strong-sell recommendations (*RECSBUY, RECMBUY, RECHOLD, RECMSELL, RECSSELL*), analyst recommendation consensus (*RECCON*), share turnover (*TOVER*), inverse share price (*INVPRICE*), return volatility (*RETVOL*), market value (*MVALUE*), and market-to-book value (*MTBV*). Panel D illustrates mean and standard deviation of the following macroeconomic fundamentals: Economic growth (*ΔGDP*), unemployment growth (*ΔUNEM*) and sovereign debt risk (*IRATE*). Data range 2005-2017. The description of the variables and the relevant data sources are provided in Table 3.1.

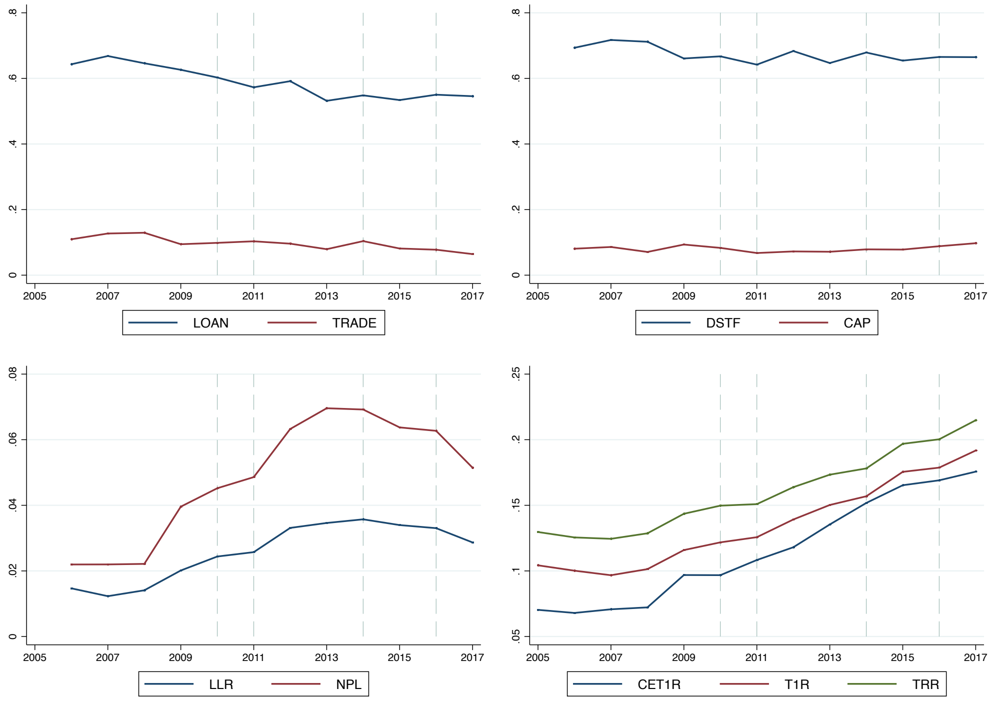

Figure 3.1 Graphical illustration of bank accounting characteristics

The charts plot mean evolvement of the following variables: Traditional and non-traditional banking activities (*LOAN, TRADE*), liquidity risk (*DSTF*) and bank capital (*CAP*), credit portfolio quality (*LLR*), asset quality (*NPL*), and capital adequacy (*CET1R, T1R, TRR*). The dashed lines indicate the European stress test exercises in 2010, 2011, 2014 and 2016. The description of the variables and the relevant data sources are provided in Table 3.1.

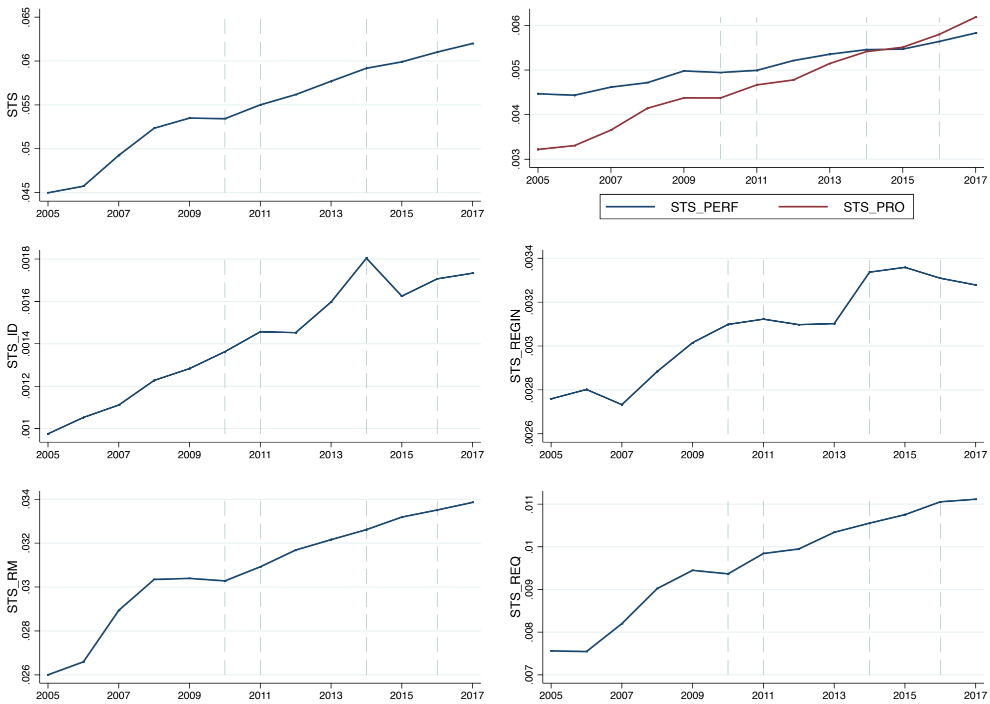

Figure 3.2 Graphical illustration of stress test sentiment.

The charts plot mean evolvement of stress test sentiment (*STS*) using the word count of the accumulated stress test, regulation and risk management, and its components of 'stress test identity' (*STS_ID*), 'stress test performance' (*STS_PERF*), 'stress test procedure' (*STS_PRO*), 'regulatory institutions' (*STS_ REGIN*), 'regulatory requirements' (*STS_REQ*), and 'risk management' (*STS_RM*). The dashed lines indicate the European stress test exercises in 2010, 2011, 2014 and 2016. The description of the variables and the relevant data sources are provided in Table 3.1.

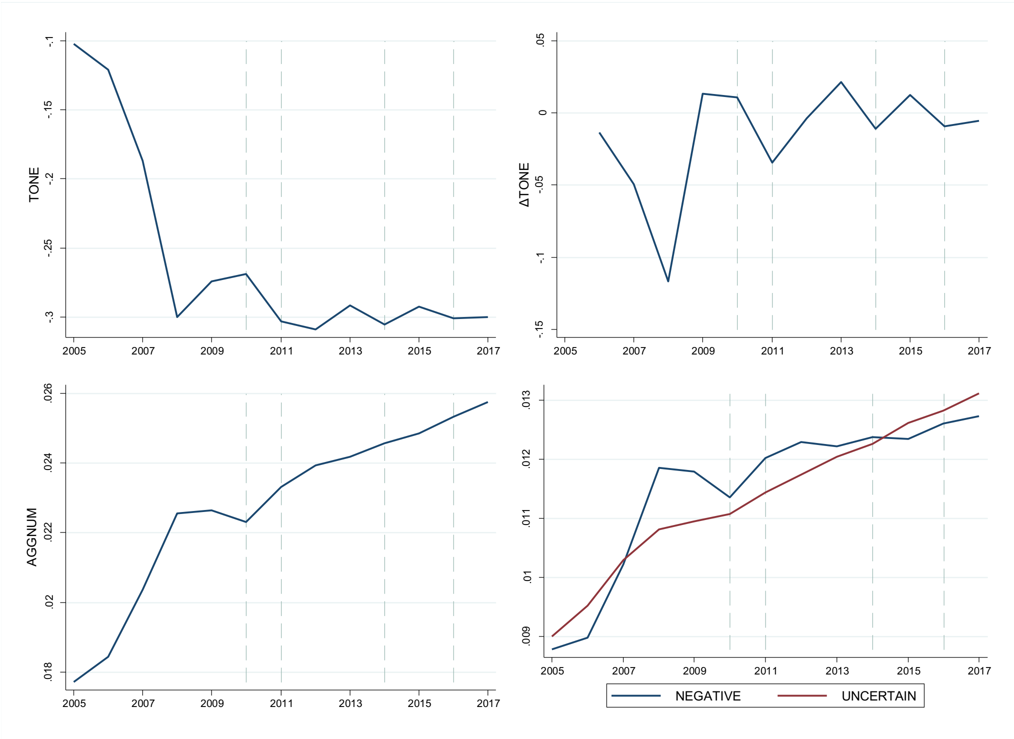

Figure 3.3 Graphical illustration of disclosure tone

The charts plot mean evolvement of the following variables: Various forms of disclosure tone captured by (variation of) disclosure tone (*TONE, ΔTONE*), aggregated 'negative', 'uncertain' and 'modal' tone (*AGGNUM*), 'negative' tone (*NEGATIVE*), and 'uncertain' tone (*UNCERTAIN*). The dashed lines indicate the European stress test exercises in 2010, 2011, 2014 and 2016. The description of the variables and the relevant data sources are provided in Table 3.1.

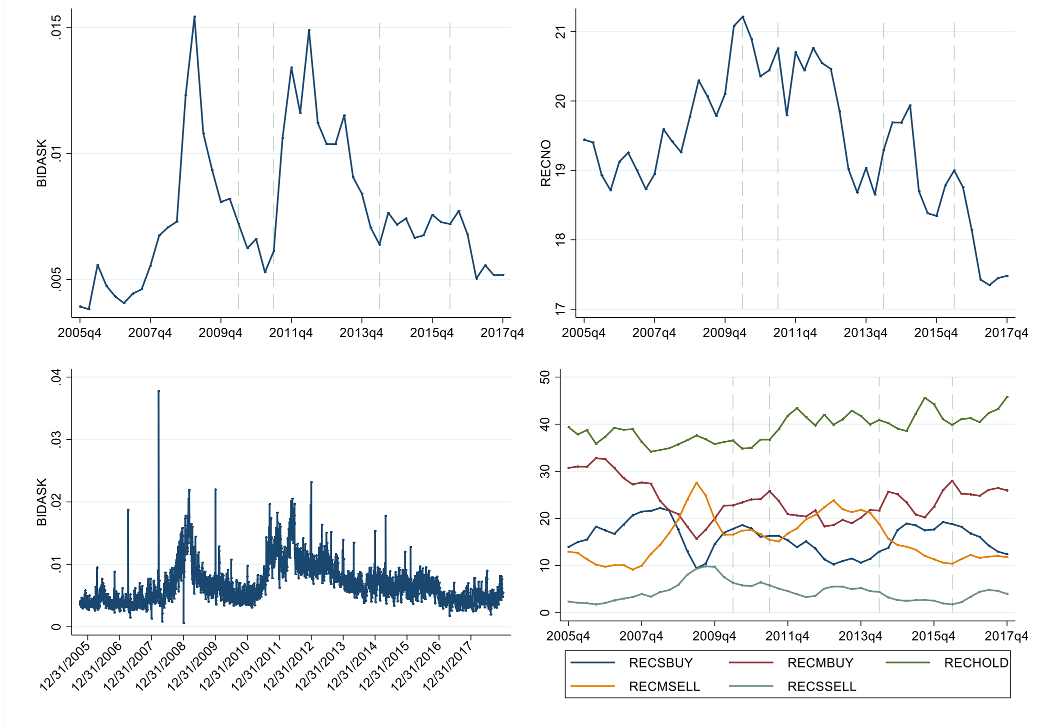

Figure 3.4 Graphical illustration of information asymmetry and analyst coverage

The charts plot quarterly and/or daily mean evolvement of bid-ask-spread (*BIDASK*), the number of analyst recommendations (*RECNO*), and the percentage of analysts' strong-buy, moderate-buy, hold, moderate-sell and strong-sell recommendations (*RECSBUY, RECMBUY, RECHOLD, RECMSELL, RECSSELL*). The dashed lines indicate the European stress test exercises in the second quarter of 2010, 2011, 2014 and 2016. The description of the variables and the relevant data sources are provided in Table 3.1.

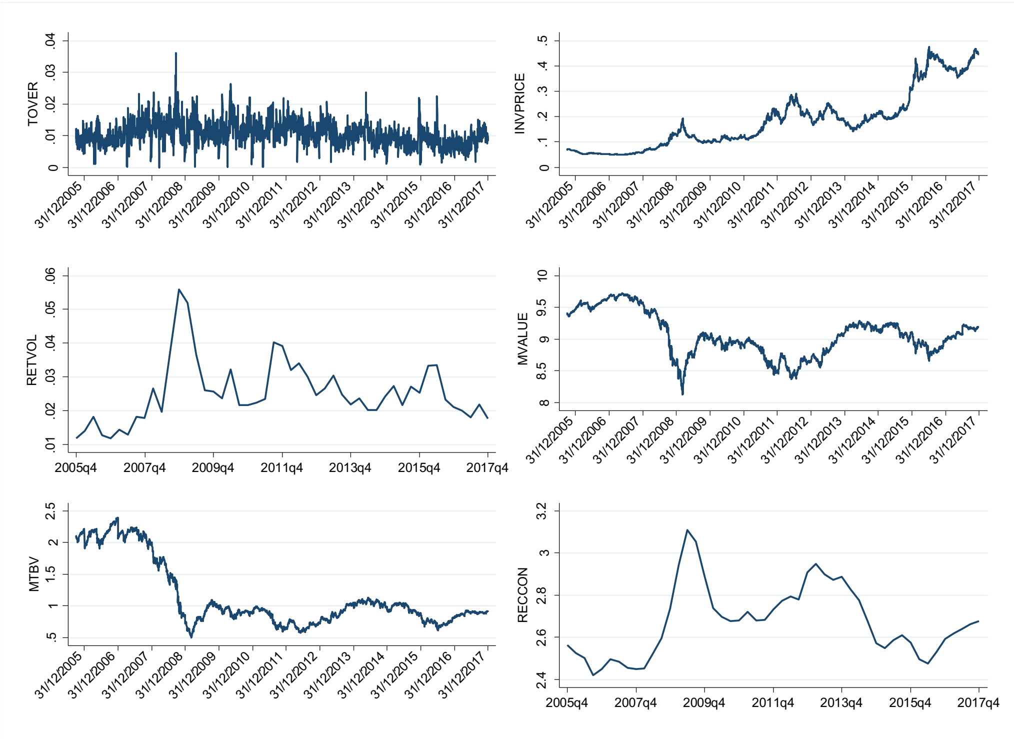

Figure 3.5 Graphical illustration of market microstructure characteristics

The charts plot quarterly or daily mean evolvement of the following variables: Share turnover (*TOVER*), inverse share price (*INVPRICE*), return volatility (*RETVOL*), market value (*MVALUE*), market-to-book value (*MTBV*) and analyst recommendation consensus (*RECCON*). The description of the variables and the relevant data sources are provided in Table 3.1.

Table 3.4 Correlation coefficients

Panel A: Disclosure profile and tone models (Equations 3.2 and 3.3)

Variables	*STS*	$SIZE_{t-2}$	$LOAN_{t-2}$	LLR_{t-2}	LLP_{t-2}	NPL_{t-2}	$TRADE_{t-2}$	$T1R_{t-2}$	$DSTF_{t-2}$	$EBPT_{t-2}$	ΔGDP	$\Delta UNEM$
STS	1.000											
$SIZE_{t-2}$	0.166***	1.000										
	(0.000)											
$LOAN_{t-2}$	-0.180***	-0.423***	1.000									
	(0.000)	(0.000)										
LLR_{t-2}	-0.019	-0.335***	0.092***	1.000								
	(0.340)	(0.000)	(0.000)									
LLP_{t-2}	-0.042**	-0.166***	0.129***	0.577***	1.000							
	(0.029)	(0.000)	(0.000)	(0.000)								
NPL_{t-2}	0.049**	-0.366***	0.122***	0.934***	0.550***	1.000						
	(0.024)	(0.000)	(0.000)	(0.000)	(0.000)							
$TRADE_{t-2}$	0.242***	0.625***	-0.609***	-0.405***	-0.270***	-0.400***	1.000					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
$T1R_{t-2}$	0.318***	-0.164***	-0.050***	0.073***	-0.134***	0.062***	-0.033	1.000				
	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)	(0.004)	(0.103)					
$DSTF_{t-2}$	-0.150***	-0.391***	0.311***	0.387***	0.253***	0.369***	-0.443***	0.041**	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.029)				
$EBPT_{t-2}$	-0.189***	-0.280***	0.245***	0.174***	0.379***	0.137***	-0.221***	0.085***	0.311***	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
ΔGDP	0.052***	-0.009	-0.024	0.025	0.046**	0.033	0.003	0.055***	0.010	-0.004	1.000	
	(0.001)	(0.550)	(0.184)	(0.188)	(0.011)	(0.108)	(0.886)	(0.000)	(0.579)	(0.806)		
$\Delta UNEM$	-0.094***	0.030**	0.120***	-0.080***	0.059***	-0.088***	-0.019	-0.155***	-0.009	0.035**	0.056***	1.000
	(0.000)	(0.039)	(0.000)	(0.000)	(0.001)	(0.000)	(0.329)	(0.000)	(0.614)	(0.050)	(0.000)	

Table 3.4 continued

Panel B: Bank opacity models (Equations 3.4_A and 3.4_B)

Variables	*STS*	*TONE*	$TOVER_{t-2}$	$INVPRICE_{t-2}$	$RETVOL_{t-2}$	$MVALUE_{t-2}$	$MTBV_{t-2}$	$RECCON_{t-2}$	ΔGDP	$\Delta UNEM$	*IRATE*
STS	1.000										
TONE	-0.339***	1.000									
	(0.000)										
$TOVER_{t-2}$	-0.005	-0.145***	1.000								
	(0.816)	(0.000)									
$INVPRICE_{t-2}$	0.061***	-0.104***	0.336***	1.000							
	(0.003)	(0.000)	(0.000)								
$RETVOL_{t-2}$	0.082***	-0.209***	0.048**	0.068***	1.000						
	(0.000)	(0.000)	(0.014)	(0.000)							
$MVALUE_{t-2}$	0.070***	0.250***	-0.131***	-0.198***	-0.219***	1.000					
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)						
$MTBV_{t-2}$	-0.293***	0.220***	-0.118***	-0.209***	-0.382***	0.180***	1.000				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
$RECCON_{t-2}$	-0.039*	-0.068***	0.085***	0.049**	0.130***	-0.187***	-0.131***	1.000			
	(0.067)	(0.002)	(0.000)	(0.016)	(0.000)	(0.000)	(0.000)				
ΔGDP	0.052***	-0.047***	-0.018	-0.003	-0.024	-0.008	-0.023	0.034	1.000		
	(0.001)	(0.003)	(0.338)	(0.891)	(0.217)	(0.665)	(0.248)	(0.100)			
$\Delta UNEM$	-0.094***	-0.031*	0.063***	-0.070***	0.230***	-0.022	-0.090***	0.050**	0.056***	1.000	
	(0.000)	(0.051)	(0.001)	(0.000)	(0.000)	(0.257)	(0.000)	(0.014)	(0.000)		
IRATE	-0.066***	-0.136***	0.060***	0.090***	0.478***	-0.259***	-0.393***	0.230***	-0.028**	0.118***	1.000
	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.017)	(0.000)	

This table reports Pearson pairwise correlation coefficients and p-values for the variables I use in my disclosure profile and tone analysis (Panel A), and for those used in the bank opacity models. I apply the following variables, winsorised at the 1 and 99 percentiles and lagged by two quarters (as indicated): Stress test sentiment measured by the word count of the accumulated stress test, regulation and risk management word list (*STS*), bank size captured by natural logarithm of total assets ($SIZE_{t-2}$), traditional banking activities shown by outstanding loans ($LOAN_{t-2}$), credit portfolio quality measured by loan loss reserves (LLR_{t-2}), asset quality captured by loan loss provisions (LLP_{t-2}) and non-performing loans (NPL_{t-2}), non-traditional banking activities measured by trading securities ($TRADE_{t-2}$), capital adequacy measured by ratio of regulatory Tier 1 capital ($T1R_{t-2}$), liquidity risk shown by deposits and short-term funding ($DSTF_{t-2}$), profitability measured by earnings before provision and taxes ($EBPT_{t-2}$), disclosure tone (*TONE*), share turnover ($TOVER_{t-2}$), inverse share price ($INVPRICE_{t-2}$), return volatility ($RETVOL_{t-2}$), market value ($MVALUE_{t-2}$), market-to-book value ($MTBV_{t-2}$), and analyst recommendation consensus ($RECCON_{t-2}$). Macroeconomic fundamentals are captured by economic growth (ΔGDP), unemployment growth ($\Delta UNEM$), and sovereign debt risk (*IRATE*). Data range 2005-2017. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 3.1.

Table 3.5 Stress test sentiment

Variables	(1) STS_{itj}	(2) STS_ID_{itj}	(3) STS_PERF_{itj}	(4) STS_PRO_{itj}	(5) STS_REGIN_{itj}	(6) STS_REQ_{itj}	(7) STS_RM_{itj}
ST1011	0.0199***	0.0002	0.0010*	0.0023***	0.0007***	0.0050***	0.0106***
	(0.0033)	(0.0002)	(0.0005)	(0.0005)	(0.0002)	(0.0012)	(0.0021)
*ST1011*FTST1011*	0.0027*	0.0003***	0.0002	0.0002	0.0004***	-0.0003	0.0019*
	(0.0016)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0004)	(0.0011)
ST1415	0.0291***	0.0005***	0.0018***	0.0036***	0.0011***	0.0066***	0.0154***
	(0.0030)	(0.0002)	(0.0005)	(0.0005)	(0.0003)	(0.0012)	(0.0018)
*ST1415*FTST1011*	-0.0022**	-0.0001	-0.0004***	-0.0003*	-0.0000	-0.0000	-0.0013**
	(0.0010)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0006)
ST16	0.0311***	0.0005***	0.0018***	0.0036***	0.0012***	0.0076***	0.0163***
	(0.0033)	(0.0002)	(0.0005)	(0.0006)	(0.0003)	(0.0012)	(0.0020)
*ST16*FTST1011*	-0.0035***	-0.0002**	-0.0003*	-0.0004**	-0.0001	-0.0007*	-0.0019**
	(0.0012)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0004)	(0.0008)
$SIZE_{it-2j}$	-0.0047**	-0.0002*	-0.0006***	-0.0003	-0.0002	-0.0010*	-0.0025*
	(0.0018)	(0.0001)	(0.0002)	(0.0003)	(0.0002)	(0.0006)	(0.0014)
$LOAN_{it-2j}$	0.0027	-0.0000	-0.0010*	0.0006	-0.0001	0.0032**	0.0003
	(0.0054)	(0.0002)	(0.0006)	(0.0008)	(0.0006)	(0.0016)	(0.0038)
LLR_{it-2j}	0.0368*	0.0025***	0.0077**	0.0041	0.0064***	-0.0125***	0.0290**
	(0.0207)	(0.0009)	(0.0031)	(0.0028)	(0.0014)	(0.0044)	(0.0142)
LLP_{it-2j}	0.0107	0.0034	0.0053	0.0025	0.0026	0.0000	-0.0029
	(0.0382)	(0.0029)	(0.0052)	(0.0070)	(0.0054)	(0.0137)	(0.0272)
$TRADE_{it-2j}$	-0.0067	-0.0007*	-0.0004	-0.0014	-0.0018***	-0.0012	-0.0006
	(0.0067)	(0.0004)	(0.0010)	(0.0009)	(0.0006)	(0.0022)	(0.0044)
$T1R_{it-2j}$	0.0081	0.0006	0.0007	0.0018	0.0014	0.0051**	-0.0003
	(0.0093)	(0.0005)	(0.0011)	(0.0018)	(0.0009)	(0.0024)	(0.0062)
$DSTF_{it-2j}$	-0.0041	-0.0000	-0.0000	-0.0004	0.0008**	-0.0006	-0.0043
	(0.0037)	(0.0002)	(0.0004)	(0.0005)	(0.0003)	(0.0008)	(0.0026)
$EBPT_{it-2j}$	-0.1394*	-0.0120**	-0.0154*	-0.0258*	-0.0119	-0.0169	-0.0664
	(0.0834)	(0.0048)	(0.0088)	(0.0145)	(0.0075)	(0.0194)	(0.0517)
ΔGDP_{tj}	0.0454***	-0.0010	0.0004	0.0021	0.0023*	0.0070*	0.0353***
	(0.0093)	(0.0015)	(0.0013)	(0.0018)	(0.0013)	(0.0036)	(0.0067)
$\Delta UNEM_{tj}$	0.0096*	-0.0004	0.0007	0.0007	0.0006	0.0002	0.0074**
	(0.0052)	(0.0003)	(0.0009)	(0.0008)	(0.0005)	(0.0015)	(0.0034)
Constant	0.0866***	0.0024**	0.0107***	0.0049	0.0040*	0.0157**	0.0509***
	(0.0218)	(0.0011)	(0.0019)	(0.0033)	(0.0021)	(0.0062)	(0.0161)

Table 3.5 continued

Observations	2,030	2,030	2,030	2,030	2,030	2,030	2,030
Number of banks	84	84	84	84	84	84	84
Adjusted R-squared	0.3350	0.3885	0.2284	0.4047	0.1733	0.2442	0.2055
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the effect of first-time stress test participation on banks' disclosure sentiment (Equation 2.2). I measure stress test sentiment using the word count of the stress test, regulation and risk management word lists (STS_{itj}, STS_ID_{itj}, STS_PERF_{itj}, STS_PRO_{itj}, STS_REGIN_{itj}, STS_REQ_{itj}, and STS_RM_{itj}). I include dummy variables in my analysis to measure first-time participation in 2010-11 (*FTST1011*) and the stress test periods in 2010-11 (*ST1011*), 2014-15 (*ST1415*), and 2016 (*ST16*). I control for bank characteristics, winsorised at the 1 and 99 percentiles and lagged by two quarters, and country-specific fundamentals, using the following variables: Bank size captured by natural logarithm of total assets ($SIZE_{it-2j}$), traditional banking activities shown by outstanding loans ($LOAN_{it-2j}$), credit portfolio quality measured by loan loss reserves (LLR_{it-2j}), asset quality captured by loan loss provisions (LLP_{it-2j}), non-traditional banking activities measured by trading securities ($TRADE_{it-2j}$), capital adequacy captured by regulatory Tier 1 capital ratio ($T1R_{it-2j}$), liquidity risk shown by deposits and short-term funding ($DSTF_{it-2j}$), profitability measured by earnings before provision and taxes ($EBPT_{it-2j}$); and macroeconomic fundamentals captured by economic growth (ΔGDP_{tj}), and unemployment growth ($\Delta UNEM_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 3.1.

Table 3.6 Disclosure tone

Variables	(1) $TONE_{itj}$	(2) $AGGNUM_{itj}$	(3) $NEGATIVE_{itj}$	(4) $UNCERTAIN_{itj}$	(5) $MODAL_{itj}$
ST1011	-0.2948***	0.0095***	0.0044***	0.0054***	0.0014**
	(0.0688)	(0.0023)	(0.0012)	(0.0013)	(0.0006)
*ST1011*FTST1011*	-0.0057	0.0013	0.0006	0.0006	0.0001
	(0.0206)	(0.0008)	(0.0004)	(0.0005)	(0.0002)
ST1415	-0.3180***	0.0137***	0.0069***	0.0071***	0.0020***
	(0.0720)	(0.0020)	(0.0012)	(0.0011)	(0.0005)
*ST1415*FTST1011*	-0.0248	-0.0016***	-0.0007*	-0.0009***	-0.0005***
	(0.0197)	(0.0005)	(0.0004)	(0.0003)	(0.0001)
ST16	-0.2776***	0.0128***	0.0059***	0.0072***	0.0023***
	(0.0735)	(0.0020)	(0.0012)	(0.0011)	(0.0005)
*ST16*FTST1011*	-0.0252	-0.0016***	-0.0005	-0.0010***	-0.0004**
	(0.0165)	(0.0006)	(0.0004)	(0.0004)	(0.0002)
$SIZE_{it-2j}$	0.0902***	-0.0020**	-0.0016***	-0.0006	0.0001
	(0.0319)	(0.0009)	(0.0006)	(0.0005)	(0.0002)
$LOAN_{it-2j}$	0.1915**	-0.0010	-0.0022	0.0016	0.0003
	(0.0843)	(0.0022)	(0.0016)	(0.0012)	(0.0007)
LLR_{it-2j}	-0.5921**	0.0317***	0.0251***	0.0057	0.0006
	(0.2819)	(0.0086)	(0.0057)	(0.0046)	(0.0021)
LLP_{it-2j}	-1.2696	0.0475**	0.0313**	0.0155	0.0074
	(0.9918)	(0.0182)	(0.0131)	(0.0139)	(0.0060)
$TRADE_{it-2j}$	-0.0638	-0.0049	-0.0013	-0.0030	-0.0016*
	(0.1662)	(0.0039)	(0.0024)	(0.0024)	(0.0009)
$T1R_{it-2j}$	0.5153**	0.0033	-0.0075***	0.0106***	0.0018
	(0.2066)	(0.0049)	(0.0028)	(0.0032)	(0.0012)
$DSTF_{it-2j}$	0.0346	-0.0047**	-0.0018	-0.0030***	-0.0004
	(0.0640)	(0.0019)	(0.0012)	(0.0011)	(0.0004)
$EBPT_{it-2j}$	2.4281*	-0.0714	-0.0770***	0.0027	-0.0083
	(1.3056)	(0.0442)	(0.0271)	(0.0300)	(0.0079)
ΔGDP_{tj}	-0.0266	0.0133***	0.0031	0.0100***	-0.0006
	(0.2281)	(0.0045)	(0.0035)	(0.0028)	(0.0020)
$\Delta UNEM_{tj}$	-0.2879**	0.0052**	0.0044***	0.0009	-0.0003
	(0.1110)	(0.0024)	(0.0017)	(0.0015)	(0.0006)
Constant	-1.2330***	0.0352***	0.0284***	0.0084	0.0005
	(0.3684)	(0.0105)	(0.0065)	(0.0064)	(0.0026)
Observations	2,029	2,030	2,030	2,030	2,030
Number of banks	84	84	84	84	84
Adjusted R-squared	0.1375	0.3589	0.2396	0.4504	0.3673
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes

This table reports the effect of first-time stress test participation on banks' disclosure tone (Equation 3.2). I measure distinct forms of disclosure tone using disclosure tone ($TONE_{itj}$), aggregated 'negative', 'uncertain' and 'modal' tone ($AGGNUM_{itj}$), 'negative' tone ($NEGATIVE_{itj}$), 'uncertain' tone ($UNCERTAIN_{itj}$), and 'modal' tone ($MODAL_{itj}$). I include dummy variables in my analysis to measure first-time participation in 2010-11 (*FTST1011*) and the stress test periods in 2010-11 (*ST1011*), 2014-15 (*ST1415*), and 2016 (*ST16*). I control for bank characteristics, winsorised at the 1 and 99 percentiles and lagged by two quarters, and country-specific fundamentals, using the following variables: Bank size captured by natural logarithm of total assets ($SIZE_{it-2j}$), traditional banking activities shown by outstanding loans ($LOAN_{it-2j}$), credit portfolio quality measured by loan loss reserves (LLR_{it-2j}), asset quality captured by and loan loss provisions (LLP_{it-2j}), non-traditional banking activities measured by trading securities ($TRADE_{it-2j}$), capital adequacy captured by regulatory Tier 1 capital ratio ($T1R_{it-2j}$), liquidity risk shown by deposits and short-term funding ($DSTF_{it-2j}$), profitability measured by earnings before provision and taxes ($EBPT_{it-2j}$); and macroeconomic fundamentals captured by economic growth (ΔGDP_{tj}), and unemployment growth ($\Delta UNEM_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 3.1.

Table 3.7 Quantitative disclosure behaviour

Variables	(1) $TRANX_{itj}$	(2) $TRANX_{itj}$	(3) $TRANX_{itj}$	(4) $TRANX_{itj}$
ST1011	0.0604**	0.0672**		
	(0.0248)	(0.0262)		
*ST1011*FTST1011*	-0.0068	-0.0136		
	(0.0095)	(0.0111)		
ST1415	0.0872***		0.0938***	
	(0.0265)		(0.0269)	
*ST1415*FTST1011*	0.0085		0.0032	
	(0.0072)		(0.0067)	
ST16	0.0933***			0.0958***
	(0.0275)			(0.0280)
*ST16*FTST1011*	0.0305***			0.0284***
	(0.0095)			(0.0088)
$SIZE_{it-2j}$	0.0371**	0.0358**	0.0353**	0.0363**
	(0.0148)	(0.0146)	(0.0146)	(0.0146)
$LOAN_{it-2j}$	-0.0447	-0.0438	-0.0421	-0.0431
	(0.0357)	(0.0361)	(0.0366)	(0.0363)
LLR_{it-2j}	0.0338	0.0353	0.0347	0.0356
	(0.1624)	(0.1591)	(0.1590)	(0.1607)
LLP_{it-2j}	-0.2972	-0.3352	-0.3245	-0.3016
	(0.4359)	(0.4334)	(0.4347)	(0.4364)
$TRADE_{it-2j}$	-0.0349	-0.0335	-0.0361	-0.0374
	(0.0625)	(0.0631)	(0.0634)	(0.0632)
$T1R_{it-2j}$	0.2243***	0.2144**	0.2126**	0.2230***
	(0.0800)	(0.0824)	(0.0828)	(0.0808)
$DSTF_{it-2j}$	-0.0261	-0.0249	-0.0248	-0.0248
	(0.0272)	(0.0274)	(0.0275)	(0.0273)
$EBPT_{it-2j}$	0.4901	0.5846	0.5626	0.4642
	(0.5495)	(0.5418)	(0.5433)	(0.5453)
ΔGDP_{tj}	-0.0716	-0.0694	-0.0654	-0.0629
	(0.0928)	(0.0941)	(0.0925)	(0.0928)
$\Delta UNEM_{tj}$	-0.0066	-0.0063	-0.0080	-0.0057
	(0.0365)	(0.0366)	(0.0368)	(0.0363)
Constant	0.0951	0.1076	0.1132	0.1024
	(0.1775)	(0.1760)	(0.1753)	(0.1751)
Observations	2,110	2,110	2,110	2,110
Number of banks	90	90	90	90
Adjusted R-squared	0.5924	0.5910	0.5906	0.5924
Bank fixed effects	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes

This table reports the effect of first-time stress test participation on banks' quantitative disclosure behaviour (Equation 3.2). I measure quantitative disclosure behaviour using a transparency index ($TRANX_{itj}$) following Nier and Baumann (2006). I include dummy variables in my analysis to measure first-time participation in 2010-11 (*FTST1011*) and the stress test periods in 2010-11 (*ST1011*), 2014-15 (*ST1415*), and 2016 (*ST16*). I control for bank characteristics, winsorised at the 1 and 99 percentiles and lagged by two quarters, and country-specific fundamentals, using the following variables: Bank size captured by natural logarithm of total assets ($SIZE_{it-2j}$), traditional banking activities shown by outstanding loans ($LOAN_{it-2j}$), credit portfolio quality measured by loan loss reserves (LLR_{it-2j}), asset quality captured by and loan loss provisions (LLP_{it-2j}), non-traditional banking activities measured by trading securities ($TRADE_{it-2j}$), capital adequacy captured by regulatory Tier 1 capital ratio ($T1R_{it-2j}$), liquidity risk shown by deposits and short-term funding ($DSTF_{it-2j}$), profitability measured by earnings before provision and taxes ($EBPT_{it-2j}$), and macroeconomic fundamentals captured by economic growth (ΔGDP_{tj}); and unemployment growth ($\Delta UNEM_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 3.1.

Table 3.8 Effect of stress test sentiment on disclosure tone

Variables	(1) $\Delta TONE_{itj}$	(2) $AGGNUM_{itj}$	(3) $LITIGIOUS_{itj}$
$STHC\_I$	-0.0971**	0.0012**	0.0008**
	(0.0475)	(0.0006)	(0.0004)
STS_{itj}	-0.6087	0.4081***	0.0369***
	(0.5246)	(0.0181)	(0.0074)
$STHC\_I*STS_{itj}$	1.3733*	-0.0204*	-0.0128**
	(0.7147)	(0.0105)	(0.0060)
$SIZE_{it-2j}$	-0.0156	-0.0001	-0.0007**
	(0.0138)	(0.0006)	(0.0003)
$LOAN_{it-2j}$	0.0731	-0.0021*	0.0009
	(0.0598)	(0.0012)	(0.0007)
LLR_{it-2j}	0.1515	0.0164***	0.0089**
	(0.1458)	(0.0042)	(0.0040)
LLP_{it-2j}	0.0100	0.0443***	0.0054
	(0.6299)	(0.0140)	(0.0090)
$TRADE_{it-2j}$	0.0637	-0.0020	-0.0009
	(0.0739)	(0.0028)	(0.0010)
$T1R_{it-2j}$	0.1749	0.0003	-0.0007
	(0.1142)	(0.0023)	(0.0017)
$DSTF_{it-2j}$	-0.0188	-0.0030***	-0.0002
	(0.0414)	(0.0011)	(0.0007)
$EBPT_{it-2j}$	1.4571*	-0.0149	-0.0228
	(0.7398)	(0.0232)	(0.0150)
ΔGDP_{tj}	0.0978	-0.0058*	-0.0033
	(0.2556)	(0.0032)	(0.0026)
$\Delta UNEM_{tj}$	-0.2786***	0.0011	0.0024***
	(0.0704)	(0.0014)	(0.0008)
Constant	0.1727	0.0001	0.0084**
	(0.1555)	(0.0067)	(0.0039)
Observations	1,959	2,030	2,030
Number of banks	84	84	84
Adjusted R-squared	0.1054	0.7533	0.4607
Bank fixed effects	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes

This table reports the individual effect of stress test participation and the stress test sentiment on banks' disclosure tone (Equation 3.3). I measure distinct forms of disclosure tone using variation of disclosure tone ($\Delta TONE_{itj}$), aggregated 'negative', 'uncertain' and 'modal' tone ($AGGNUM_{itj}$), and 'litigious' tone ($LITIGIOUS_{itj}$). I estimate the impact of stress test sentiment using the accumulated stress test, regulation and risk management word list (STS_{itj}), in combination with a time-dummy that estimates the individual stress test periods ($STHC\_I$). I control for bank characteristics, winsorised at the 1 and 99 percentiles and lagged by two quarters, and country-specific fundamentals, using the following variables: Bank size captured by natural logarithm of total assets ($SIZE_{it-2j}$), traditional banking activities shown by outstanding loans ($LOAN_{it-2j}$), credit portfolio quality measured by loan loss reserves (LLR_{it-2j}), asset quality captured by loan loss provisions (LLP_{it-2j}), non-traditional banking activities measured by trading securities ($TRADE_{it-2j}$), capital adequacy captured by regulatory Tier 1 capital ratio ($T1R_{it-2j}$), liquidity risk shown by deposits and short-term funding ($DSTF_{it-2j}$), profitability measured by earnings before provision and taxes ($EBPT_{it-2j}$); and macroeconomic fundamentals captured by economic growth (ΔGDP_{tj}), and unemployment growth ($\Delta UNEM_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 3.1.

Table 3.9 Bank opacity

Panel A: Information asymmetry				
	(1)	(2)	(3)	(4)
Variables	$BIDASK_{itj}$	$BIDASK_{it+1j}$	$BIDASK_{itj}$	$BIDASK_{it+1j}$
STHC_I	-0.0004	-0.0014	-0.0052**	-0.0065***
	(0.0012)	(0.0013)	(0.0021)	(0.0024)
STS_{itj}			-0.0540*	-0.0610*
			(0.0288)	(0.0319)
$STHC\_I*STS_{itj}$			0.1042***	0.1094***
			(0.0328)	(0.0381)
$TONE_{itj}$	-0.0008	-0.0013		
	(0.0011)	(0.0010)		
$STHC\_I*TONE_{itj}$	-0.0027**	-0.0027**		
	(0.0011)	(0.0011)		
$TOVER_{it-2j}$	-0.0098	-0.0069	-0.0073	-0.0045
	(0.0151)	(0.0155)	(0.0146)	(0.0149)
$INVPRICE_{it-2j}$	0.0031**	0.0027**	0.0032**	0.0028**
	(0.0013)	(0.0012)	(0.0013)	(0.0012)
$RETVOL_{it-2j}$	0.1398**	0.1475**	0.1394**	0.1479**
	(0.0616)	(0.0660)	(0.0610)	(0.0655)
$MVALUE_{it-2j}$	0.0028***	0.0028***	0.0027***	0.0026***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
$MTBV_{it-2j}$	0.0009	0.0013	0.0010	0.0014
	(0.0012)	(0.0013)	(0.0012)	(0.0014)
$RECCON_{it-2j}$	0.0033***	0.0030***	0.0033***	0.0030***
	(0.0011)	(0.0010)	(0.0011)	(0.0010)
ΔGDP_{tj}	0.0137	0.0051	0.0107	0.0046
	(0.0238)	(0.0195)	(0.0237)	(0.0192)
$\Delta UNEM_{tj}$	-0.0062	-0.0044	-0.0050	-0.0029
	(0.0067)	(0.0071)	(0.0065)	(0.0068)
$IRATE_{tj}$	0.0003	0.0003*	0.0003	0.0003*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	-0.0351***	-0.0355***	-0.0316***	-0.0314***
	(0.0110)	(0.0114)	(0.0101)	(0.0103)
Observations	2,015	1,968	2,016	1,969
Number of banks	55	55	55	55
Adjusted R-squared	0.2111	0.2028	0.2160	0.2077
Bank fixed effects	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes

Panel B: Analyst coverage				
	(1)	(2)	(3)	(4)
Variables	$RECNO_{itj}$	$RECNO_{it+1j}$	$RECNO_{itj}$	$RECNO_{it+1j}$
STHC_I	0.6666	0.5031	3.7504***	2.9774**
	(0.5752)	(0.5649)	(1.1907)	(1.1176)
STS_{itj}			40.0378**	36.2189*
			(17.8701)	(19.1813)
$STHC\_I*STS_{itj}$			-65.2303***	-54.2973***
			(17.9820)	(16.8632)
$TONE_{itj}$	0.6070	0.6423		
	(0.8840)	(0.8820)		
$STHC\_I*TONE_{itj}$	1.3644*	1.3481**		
	(0.6927)	(0.6193)		

Table 3.9 continued

$TOVER_{it-2j}$	6.6389	6.7238	5.0327	5.3632
	(7.1087)	(6.8686)	(7.0642)	(6.8751)
$INVPRICE_{it-2j}$	1.5438***	1.7033***	1.4552***	1.6242***
	(0.4719)	(0.4244)	(0.4578)	(0.4178)
$RETVOL_{it-2j}$	-49.2822***	-35.5995**	-48.7568**	-35.0697**
	(18.4549)	(16.9271)	(18.6897)	(17.2091)
$MVALUE_{it-2j}$	2.1434***	2.2996***	2.2705***	2.4363***
	(0.5989)	(0.5926)	(0.6031)	(0.6047)
$MTBV_{it-2j}$	-0.3799	-0.4414	-0.4196	-0.4862
	(0.7406)	(0.7353)	(0.7426)	(0.7411)
$RECCON_{it-2j}$	-0.9582**	-0.7163	-0.9525**	-0.6978
	(0.4705)	(0.4499)	(0.4682)	(0.4489)
ΔGDP_{tj}	-26.6836**	-33.4785***	-25.6021**	-32.6707***
	(11.7690)	(10.7316)	(11.0770)	(10.1336)
$\Delta UNEM_{tj}$	7.2859**	6.7710*	6.4166*	5.9394*
	(3.5260)	(3.4492)	(3.5235)	(3.4593)
$IRATE_{tj}$	-0.2890***	-0.4677***	-0.2943***	-0.4716***
	(0.0758)	(0.0716)	(0.0731)	(0.0709)
Constant	2.7316	0.5128	-0.0356	-2.2352
	(6.7370)	(6.5610)	(6.7468)	(6.7168)
Observations	2,078	2,022	2,079	2,023
Number of banks	55	55	55	55
Adjusted R-squared	0.3066	0.3597	0.3113	0.3606
Bank fixed effects	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes

This table reports the individual effect of stress test participation, stress test sentiment and disclosure tone on information asymmetry and analyst coverage (Equations 3.4_A and 3.4_B). Panel A presents information asymmetry captured by the current and future bid-ask-spread ($BIDASK_{itj}$, $BIDASK_{it+1j}$), and Panel B applies analyst coverage estimated by the current and future number of analyst recommendations ($RECNO_{itj}$, $RECNO_{it+1j}$). I estimate the impact of stress test sentiment using the word count of the accumulated stress test, regulation and risk management word list (STS_{itj}), disclosure tone using $TONE_{itj}$, in combination with a time-dummy that estimates the individual stress test periods (*STHC_I*). I control for market microstructure characteristics, daily winsorised at the 1 and 99 percentiles, quarterly averaged and lagged by two quarters, and country-specific fundamentals, using the following variables: Share turnover ($TOVER_{it-2j}$), inverse share price ($INVPRICE_{it-2j}$), return volatility ($RETVOL_{it-2j}$), market value ($MVALUE_{it-2j}$), market-to-book value ($MTBV_{it-2j}$), analyst recommendation consensus ($RECCON_{t-2}$); and macroeconomic fundamentals captured by economic growth (ΔGDP_{tj}), unemployment growth ($\Delta UNEM_{tj}$), and sovereign debt risk ($IRATE_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 3.1.

Table 3.10 Information asymmetry around bank report releases

Panel A: Stress test sentiment

Variables	(1) $BIDASK_{itj}$ (t–1, t+1)	(2) $BIDASK_{itj}$ (t+2, t+31)	(3) $BIDASK_{itj}$ (t+2, t+61)	(4) $BIDASK_{itj}$ (t+2, t+121)	(5) $BIDASK_{itj}$ (t+2, t+250)
STHC_I	-0.0048*	-0.0043*	-0.0047*	-0.0048**	-0.0043*
	(0.0027)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
STS_{itj}	-0.0163	-0.0363	-0.0408	-0.0350	-0.0346
	(0.0290)	(0.0268)	(0.0267)	(0.0277)	(0.0268)
$STHC\_I{*}STS_{itj}$	0.0883**	0.0778**	0.0747**	0.0764**	0.0652*
	(0.0399)	(0.0306)	(0.0307)	(0.0320)	(0.0334)
$TOVER_{it-2j}$	0.0210*	-0.0057	0.0041	0.0081	0.0136
	(0.0112)	(0.0190)	(0.0177)	(0.0165)	(0.0149)
$INVPRICE_{it-2j}$	0.0035**	0.0028*	0.0030**	0.0032**	0.0033**
	(0.0013)	(0.0015)	(0.0015)	(0.0015)	(0.0014)
$RETVOL_{it-2j}$	0.0542	0.0775*	0.0779*	0.0752	0.0658
	(0.0568)	(0.0435)	(0.0424)	(0.0451)	(0.0479)
$MVALUE_{it-2j}$	0.0028*	0.0019	0.0025	0.0029*	0.0032*
	(0.0016)	(0.0015)	(0.0015)	(0.0016)	(0.0018)
$MTBV_{it-2j}$	0.0003	0.0005	0.0006	0.0004	0.0002
	(0.0015)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
$RECCON_{it-2j}$	0.0026**	0.0028**	0.0032**	0.0032**	0.0034**
	(0.0012)	(0.0012)	(0.0012)	(0.0014)	(0.0015)
ΔGDP_{tj}	0.0109	-0.0057	-0.0019	-0.0027	0.0015
	(0.0279)	(0.0210)	(0.0178)	(0.0175)	(0.0164)
$\Delta UNEM_{tj}$	-0.0009	0.0046	0.0056	0.0040	0.0003
	(0.0055)	(0.0050)	(0.0048)	(0.0049)	(0.0051)
$IRATE_{tj}$	0.0007***	0.0004*	0.0003**	0.0004***	0.0004***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Constant	-0.0306*	-0.0215	-0.0276	-0.0312	-0.0349*
	(0.0164)	(0.0161)	(0.0169)	(0.0189)	(0.0208)
Observations	1,706	1,801	1,814	1,833	1,842
Number of banks	53	53	53	53	53
Adjusted R-squared	0.0929	0.1431	0.1453	0.1506	0.1496
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes

Panel B: Disclosure tone

Variables	(1) $BIDASK_{itj}$ (t–1, t+1)	(2) $BIDASK_{itj}$ (t+2, t+31)	(3) $BIDASK_{itj}$ (t+2, t+61)	(4) $BIDASK_{itj}$ (t+2, t+121)	(5) $BIDASK_{itj}$ (t+2, t+250)
STHC_I	-0.0008	-0.0007	-0.0013	-0.0014	-0.0013
	(0.0016)	(0.0014)	(0.0014)	(0.0013)	(0.0013)
$TONE_{itj}$	-0.0014	-0.0004	-0.0003	-0.0007	-0.0014
	(0.0014)	(0.0013)	(0.0012)	(0.0012)	(0.0011)
$STHC\_I{*}TONE_{itj}$	-0.0028**	-0.0024**	-0.0024**	-0.0023**	-0.0016
	(0.0012)	(0.0012)	(0.0010)	(0.0009)	(0.0011)
$TOVER_{it-2j}$	0.0206*	-0.0074	0.0021	0.0065	0.0124
	(0.0110)	(0.0192)	(0.0178)	(0.0166)	(0.0150)
$INVPRICE_{it-2j}$	0.0034**	0.0027*	0.0030**	0.0031**	0.0032**
	(0.0013)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
$RETVOL_{it-2j}$	0.0544	0.0779*	0.0785*	0.0750	0.0651
	(0.0574)	(0.0441)	(0.0430)	(0.0452)	(0.0479)

Table 3.10 continued

$MVALUE_{it-2j}$	0.0030*	0.0020	0.0027*	0.0030*	0.0034*
	(0.0016)	(0.0016)	(0.0016)	(0.0017)	(0.0019)
$MTBV_{it-2j}$	0.0003	0.0004	0.0005	0.0003	0.0002
	(0.0015)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
$RECCON_{it-2j}$	0.0026**	0.0028**	0.0031**	0.0032**	0.0034**
	(0.0012)	(0.0012)	(0.0012)	(0.0014)	(0.0015)
ΔGDP_{tj}	0.0141	-0.0032	0.0003	-0.0009	0.0031
	(0.0292)	(0.0220)	(0.0189)	(0.0187)	(0.0177)
$\Delta UNEM_{tj}$	-0.0019	0.0036	0.0046	0.0030	-0.0009
	(0.0058)	(0.0050)	(0.0048)	(0.0049)	(0.0051)
$IRATE_{tj}$	0.0007***	0.0004*	0.0003**	0.0004***	0.0004***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Constant	-0.0326*	-0.0240	-0.0304	-0.0338	-0.0379*
	(0.0168)	(0.0174)	(0.0183)	(0.0204)	(0.0224)
Observations	1,705	1,800	1,813	1,832	1,841
Number of banks	53	53	53	53	53
Adjusted R-squared	0.0927	0.1407	0.1427	0.1482	0.1489
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes

This table reports the individual effect of stress test participation, stress test sentiment and disclosure tone on the bank report release date-specific bid-ask spread (Equations 3.4_A and 3.4_B). I measure information asymmetry applying the average bid-ask spread (*$BIDASK_{itj}$*) for specific periods around and after the individual bank report release date (i.e., t–1, t+1; t+2, t+31; t+2, t+61; t+2, t+121; and t+2, t+250). Panel A illustrates the date-specific stress test sentiment (*STS_{itj}*), whilst Panel B applies the disclosure tone (*$TONE_{itj}$*). I estimate the impact of stress test sentiment using the word count of the accumulated stress test, regulation and risk management word list (*STS_{itj}*) and disclosure tone (*$TONE_{itj}$*) in combination with a time-dummy that estimates the individual stress test periods (*STHC_I*). I control for market microstructure characteristics, daily winsorised at the 1 and 99 percentiles, quarterly averaged and lagged by two quarters, and country-specific fundamentals, using the following variables: Share turnover (*$TOVER_{it-2j}$*), inverse share price (*$INVPRICE_{it-2j}$*), return volatility (*$RETVOL_{it-2j}$*), market value (*$MVALUE_{it-2j}$*), market-to-book value (*$MTBV_{it-2j}$*), analyst recommendation consensus (*$RECCON_{t-2}$*); and macroeconomic fundamentals captured by economic growth (*ΔGDP_{tj}*), unemployment growth (*$\Delta UNEM_{tj}$*), and sovereign debt risk (*$IRATE_{tj}$*). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 3.1.

Table 3.11 Analyst coverage around bank report releases

Panel A: Stress test sentiment					
	(1)	(2)	(3)	(4)	(5)
Variables	$RECNO_{itj}$	$RECNO_{itj}$	$RECNO_{itj}$	$RECNO_{itj}$	$RECNO_{itj}$
	$(t-1, t+1)$	$(t+2, t+31)$	$(t+2, t+61)$	$(t+2, t+121)$	$(t+2, t+250)$
$STHC\_I$	4.1846***	4.3250***	4.0907***	3.7598***	3.1186***
	(1.2482)	(1.2262)	(1.2204)	(1.1872)	(1.1593)
STS_{itj}	44.4389**	43.7953**	42.9277**	39.9079**	34.3887*
	(17.1699)	(18.3208)	(18.4251)	(18.4982)	(18.2649)
$STHC\_I*STS_{itj}$	-68.0147***	-68.7250***	-66.1385***	-61.2173***	-48.4032***
	(18.6808)	(17.9629)	(17.8394)	(17.3200)	(16.5282)
$TOVER_{it-2j}$	9.1030	9.4280	9.8231	9.8072	8.9114
	(7.9249)	(8.5698)	(8.5896)	(8.4727)	(8.4447)
$INVPRICE_{it-2j}$	1.8061***	1.7952***	1.8307***	1.8655***	1.9130***
	(0.4734)	(0.4650)	(0.4502)	(0.4395)	(0.4268)
$RETVOL_{it-2j}$	-30.2271*	-25.4355	-22.7631	-18.4987	-4.4050
	(17.9745)	(17.5016)	(17.0750)	(16.3626)	(14.7680)
$MVALUE_{it-2j}$	2.8898***	2.9489***	2.9954***	2.9334***	2.9241***
	(0.6709)	(0.6660)	(0.6637)	(0.6511)	(0.6345)
$MTBV_{it-2j}$	-0.1206	-0.1191	-0.1211	-0.0963	-0.1419
	(0.6338)	(0.6331)	(0.6246)	(0.6137)	(0.5999)
$RECCON_{it-2j}$	-0.5746	-0.5668	-0.5173	-0.4367	-0.3346
	(0.4528)	(0.4508)	(0.4435)	(0.4317)	(0.4220)
ΔGDP_{tj}	-28.2465**	-26.5005**	-29.0815**	-32.7790***	-30.8064***
	(11.9399)	(11.8489)	(11.7444)	(11.4124)	(10.7967)
$\Delta UNEM_{tj}$	3.7930	3.0163	2.9364	3.1503	1.8245
	(3.5234)	(3.5452)	(3.5848)	(3.6581)	(3.3802)
$IRATE_{tj}$	-0.3063***	-0.3309***	-0.3641***	-0.4357***	-0.5422***
	(0.0770)	(0.0771)	(0.0771)	(0.0764)	(0.0783)
Constant	-7.2138	-7.8588	-8.8047	-8.5360	-7.9696
	(6.1777)	(6.1505)	(6.1622)	(6.0572)	(5.8215)
Observations	1,886	1,886	1,886	1,886	1,886
Number of banks	53	53	53	53	53
Adjusted R-squared	0.3088	0.3235	0.3352	0.3571	0.3951
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes
Panel B: Disclosure tone					
	(1)	(2)	(3)	(4)	(5)
Variables	$RECNO_{itj}$	$RECNO_{itj}$	$RECNO_{itj}$	$RECNO_{itj}$	$RECNO_{itj}$
	$(t-1, t+1)$	$(t+2, t+31)$	$(t+2, t+61)$	$(t+2, t+121)$	$(t+2, t+250)$
$STHC\_I$	0.9772	1.0744*	1.0132*	0.9099	0.9420*
	(0.5995)	(0.5885)	(0.5810)	(0.5714)	(0.5286)
$TONE_{itj}$	0.0568	0.2180	0.2265	0.2911	0.5564
	(0.8553)	(0.8919)	(0.8971)	(0.8875)	(0.8391)
$STHC\_I*TONE_{itj}$	1.4497**	1.4402**	1.5328**	1.3976**	1.2955**
	(0.6823)	(0.6827)	(0.6680)	(0.6356)	(0.5645)
$TOVER_{it-2j}$	11.0231	11.2741	11.6474	11.4708	10.2816
	(7.9941)	(8.6060)	(8.5931)	(8.4678)	(8.3929)
$INVPRICE_{it-2j}$	1.8742***	1.8649***	1.8966***	1.9258***	1.9600***
	(0.5023)	(0.4916)	(0.4738)	(0.4596)	(0.4378)
$RETVOL_{it-2j}$	-31.0734*	-26.1955	-23.5596	-19.3301	-5.1482
	(17.6273)	(17.2132)	(16.7894)	(16.0490)	(14.4696)

Table 3.11 continued

$MVALUE_{it-2j}$	2.7359***	2.7875***	2.8304***	2.7689***	2.7485***
	(0.6662)	(0.6562)	(0.6500)	(0.6320)	(0.6057)
$MTBV_{it-2j}$	-0.0735	-0.0721	-0.0729	-0.0492	-0.0957
	(0.6385)	(0.6380)	(0.6284)	(0.6163)	(0.6000)
$RECCON_{it-2j}$	-0.5955	-0.5860	-0.5397	-0.4614	-0.3625
	(0.4609)	(0.4583)	(0.4511)	(0.4383)	(0.4270)
ΔGDP_{tj}	-29.2736**	-27.6352**	-30.1101**	-33.7365***	-31.3913***
	(12.7351)	(12.6887)	(12.5867)	(12.2126)	(11.3971)
$\Delta UNEM_{tj}$	4.5831	3.8522	3.7727	3.9419	2.6095
	(3.5466)	(3.5455)	(3.5829)	(3.6609)	(3.3581)
$IRATE_{tj}$	-0.3067***	-0.3311***	-0.3644***	-0.4360***	-0.5434***
	(0.0803)	(0.0799)	(0.0794)	(0.0779)	(0.0781)
Constant	-4.1074	-4.6872	-5.6215	-5.4528	-4.9251
	(6.2658)	(6.1702)	(6.1246)	(5.9414)	(5.5907)
Observations	1,885	1,885	1,885	1,885	1,885
Number of banks	53	53	53	53	53
Adjusted R-squared	0.3012	0.3161	0.3289	0.3527	0.3947
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes

This table reports the individual effect of stress test participation, stress test sentiment and disclosure tone on the bank report release date-specific analyst coverage (Equations 3.4_A and 3.4_B). I measure analyst coverage applying the average number of analyst recommendations ($RECNO_{itj}$) for specific periods around and after the individual bank report release date (i.e., t–1, t+1; t+2, t+31; t+2, t+61; t+2, t+121; and t+2, t+250). Panel A illustrates the date-specific stress test sentiment (STS_{itj}), whilst Panel B applies the disclosure tone ($TONE_{itj}$). I estimate the impact of stress test sentiment using the word count of the accumulated stress test, regulation and risk management word lists (STS_{itj}) and disclosure tone using ($TONE_{itj}$) in combination with a time-dummy that estimates the individual stress test periods (*STHC_I*). I control for market microstructure characteristics, daily winsorised at the 1 and 99 percentiles, quarterly averaged and lagged by two quarters, and country-specific fundamentals, using the following variables: Share turnover ($TOVER_{it-2j}$), inverse share price ($INVPRICE_{it-2j}$), return volatility ($RETVOL_{it-2j}$), market value ($MVALUE_{it-2j}$), market-to-book value ($MTBV_{it-2j}$), analyst recommendation consensus ($RECCON_{t-2}$); and macroeconomic fundamentals captured by economic growth (ΔGDP_{tj}), unemployment growth ($\Delta UNEM_{tj}$), and sovereign debt risk ($IRATE_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 3.1.

Table 3.12 Textual measure robustness using factor analysis

Panel A: Stress test disclosure sentiment factors				
	Factor pattern		Factor pattern: varimax rotation	
	STS_F1	*STS_F2*	*STS_F1*	*STS_F2*
STS_ID_{itj}	0.7171	-0.1667	0.7172	0.1665
STS_PERF_{itj}	0.6548	-0.4364	0.7801	-0.1031
STS_PRO_{itj}	0.7901	-0.2664	0.8266	0.1092
STS_REGIN_{itj}	0.3009	0.7991	-0.0822	0.8499
STS_REQ_{itj}	0.6875	0.3008	0.4845	0.5731
STS_RM_{itj}	0.7284	0.2314	0.5518	0.5288
Panel B: Disclosure tone factors				
	Factor pattern		Factor pattern: varimax rotation	
	TONE_F1	*TONE_F2*	*TONE_F1*	*TONE_F2*
$NEGATIVE_{itj}$	0.6883	-0.1133	0.6976	0.0024
$UNCERTAIN_{itj}$	0.8045	0.0877	0.7788	0.2199
$MODAL_{itj}$	0.7062	0.4225	0.6263	0.5338
$POSITIVE_{itj}$	0.1091	0.9128	-0.0438	0.9182
$LITIGIOUS_{itj}$	0.6605	-0.3102	0.7028	-0.1964
$SUPERFLU_{itj}$	0.7027	-0.2642	0.7368	-0.1440

This table reports the factor analysis of the textual measures. Panel A presents factors and factor pattern of the stress test disclosure sentiment estimates, using the word count of my accumulated stress test, regulation and risk management word lists based on stress test disclosures (STS_ID_{itj}, STS_PERF_{itj}, STS_PRO_{itj}, STS_REGIN_{itj}, STS_REQ_{itj}, and STS_RM_{itj}). Panel B illustrates factors and factor pattern of the disclosure tone measures using the word count of Loughran and McDonald's (2011a) word lists ($NEGATIVE_{itj}$, $UNCERTAIN_{itj}$, $MODAL_{itj}$, $POSITIVE_{itj}$, $LITIGIOUS_{itj}$, and $SUPERFLU_{itj}$). The description of the variables and the relevant data sources are provided in Table 3.1.

Table 3.13 Stress test sentiment and tone robustness using factor analysis

Variables	(1) *STS_F1*	(2) *STS_F2*	(3) *TONE_F1*	(4) *TONE_F2*	(5) *TONE_ALT*
ST1011	1.0391***	1.0481***	1.2476***	-0.0634	-0.0056***
	(0.2660)	(0.2313)	(0.3401)	(0.3657)	(0.0015)
*ST1011*FTST1011*	0.1761	0.2062**	0.1284	0.0646	-0.0004
	(0.1117)	(0.0994)	(0.1313)	(0.1069)	(0.0004)
ST1415	1.7361***	1.3852***	1.8506***	0.0647	-0.0076***
	(0.2470)	(0.2585)	(0.3057)	(0.3481)	(0.0016)
*ST1415*FTST1011*	-0.2507***	0.0231	-0.1619**	-0.2896***	0.0002
	(0.0805)	(0.0864)	(0.0791)	(0.0859)	(0.0004)
ST2016	1.7753***	1.5708***	1.9093***	0.0832	-0.0065***
	(0.2595)	(0.2511)	(0.2992)	(0.3686)	(0.0016)
*ST2016*FTST1011*	-0.2482***	-0.1293	-0.1858**	-0.1939**	0.0001
	(0.0810)	(0.1058)	(0.0796)	(0.0780)	(0.0004)
$SIZE_{it-2j}$	-0.3437***	-0.1946	-0.2578**	0.2459	0.0021***
	(0.1206)	(0.1649)	(0.1229)	(0.1481)	(0.0007)
$LOAN_{it-2j}$	-0.0327	0.4400	0.0755	0.2152	0.0027*
	(0.3133)	(0.5466)	(0.2907)	(0.4812)	(0.0016)
LLR_{it-2j}	2.9187*	1.8860*	4.5847***	-0.4292	-0.0214***
	(1.4848)	(1.1111)	(1.5427)	(1.0738)	(0.0057)
LLP_{it-2j}	2.7933	0.2553	6.3229*	-0.6108	-0.0354*
	(2.7824)	(3.4590)	(3.2228)	(4.4355)	(0.0187)
$TRADE_{it-2j}$	-0.4145	-1.0028*	-0.5683	-0.7195	0.0001
	(0.4980)	(0.5616)	(0.5452)	(0.5619)	(0.0032)
$T1R_{it-2j}$	0.7011	1.0813*	0.6289	1.7589**	0.0111***
	(0.7159)	(0.5969)	(0.8292)	(0.8704)	(0.0039)
$DSTF_{it-2j}$	-0.3420	0.2540	-0.5513*	-0.0382	0.0018
	(0.2106)	(0.2760)	(0.2943)	(0.3027)	(0.0013)
$EBPT_{it-2j}$	-13.9161**	-6.8360	-11.8389*	3.2145	0.0806***
	(6.4239)	(5.1189)	(6.3718)	(4.7260)	(0.0278)
ΔGDP_{tj}	0.5546	3.2620***	1.5224	-0.0589	-0.0025
	(0.7701)	(0.9962)	(1.1262)	(0.7972)	(0.0040)
$\Delta UNEM_{tj}$	0.2022	0.5270	1.2493***	-1.2273**	-0.0066***
	(0.3934)	(0.3568)	(0.3825)	(0.5837)	(0.0020)
Constant	2.6232*	0.9050	1.5137	-3.1452*	-0.0282***
	(1.3638)	(1.8005)	(1.4632)	(1.7696)	(0.0076)
Observations	2,030	2,030	2,030	2,030	2,030
Number of banks	84	84	84	84	84
Adjusted R-squared	0.3910	0.2147	0.4963	0.0613	0.1940
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes

This table reports the effect of first-time stress test participation on banks' disclosure sentiment and tone based on the factor analysis. I measure stress test disclosure sentiment and disclosure tone using factors created in Table 3.11, while the sentiment factors *STS_F1* and *STS_F2* are based on the word count of my accumulated word lists and tone factors *TONE_F1* and *TONE_F2* are built on the word count of Loughran and McDonald's (2011a) word lists. *TONE_ALT* is an alternative disclosure tone measure calculated as the difference of *NEGATIVE* and *POSITIVE* divided by *TWA* (Huang et al., 2014). I include dummy variables in my analysis to measure first-time participation in 2010-11 (*FTST1011*) and the stress test periods in 2010-11 (*ST1011*), 2014-15 (*ST1415*), and 2016 (*ST2016*). I control for bank characteristics, winsorised at the 1 and 99 percentiles and lagged by two quarters, and country-specific fundamentals, using the following variables: Bank size captured by natural logarithm of total assets ($SIZE_{it-2j}$), traditional banking activities shown by outstanding loans ($LOAN_{it-2j}$), credit portfolio quality measured by loan loss reserves (LLR_{it-2j}), asset quality captured by loan loss provisions (LLP_{it-2j}), non-traditional banking activities measured by trading securities ($TRADE_{it-2j}$), capital adequacy captured by regulatory Tier 1 capital ratio ($T1R_{it-2j}$), liquidity risk shown by deposits and short-term funding ($DSTF_{it-2j}$), profitability measured by earnings before provision and taxes ($EBPT_{it-2j}$); and macroeconomic fundamentals captured by economic growth (ΔGDP_{tj}), and unemployment growth ($\Delta UNEM_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 3.1.

Chapter 4 – Market discipline and financial stability: Are bank stress tests meeting expectations?

4.1. Introduction

After the 2008 financial crisis, regulators worldwide have undertaken large-scale stress tests to reveal the solvency and soundness of Systemically Important Financial Institutions (SIFI) to market participants.[29] Stress test disclosures are supposed to enhance transparency, therefore reducing information asymmetries in the market, and enabling market players to make more efficient investment decisions. It is considered that this revelation mechanism enforces market discipline, penalises excessive risk-taking and makes bank managers take more prudent decisions that can boost the level of certainty to the banking system and strengthen its stability (Cornett et al., 2019; Acharya et al., 2018; Flannery et al., 2017; Bischof and Daske, 2013).

The concept of market discipline is twofold and builds on monitoring bank activities. On the one hand, public information enables investors to assess the true value of a bank by estimating future cash flows. On the other hand, this information directs investors' pricing which creates pressure on a bank's behaviour. In principle, assuming perfect and complete information, no regulation would be necessary because markets would discipline banks when their risk-taking does not meet market expectations. However, banks are relatively opaque compared to corporate firms (Morgan, 2002). Therefore, the idea of including market discipline in banking regulation has two challenges. First, to enable investors to identify risky activities that, second, lead to influence which curbs bank risk-taking and shifting (Danisewicz et al., 2018; Nier and Baumann, 2006).

Since 2004, even before the 2008 financial crisis, market discipline became important as the third pillar within the Basel Accord. Therefore, subsequently, more detailed financial reporting and regulatory disclosures demand more transparency from SIFIs. For instance, the Basel Committee on Banking Supervision (BCBS) has consequently

[29] Since 2009, U.S. bank holding companies with $50 billion or more in total consolidated assets have been within the scope of yearly Dodd-Frank Act Stress tests (DFAST) and Comprehensive Capital Analysis and Reviews (CCAR) undertaken by the Federal Reserve. European stress tests were conducted by the European Banking Authority (EBA) (former Committee of European Banking Supervisors (CEBS)) in 2009, 2010, 2011, 2014, 2016 and 2018. In addition, the European Central Bank (ECB) assessed European SIFIs within the European Monetary Union (EMU) member states in 2014 and 2015 as part of the induction of the Single Supervisory Mechanism (SSM).

followed the strategy of introducing standardised templates as part of Pillar 3 to improve and supplement the effectiveness of the capital regime under Pillar 1 (BCBS, 2013, 2017). An important component of the authority's strategy is regular stress test disclosures; these aim to reveal a bank's solvency and soundness against adverse market developments, and to respectively rebuild and maintain the trust of market participants during crises and normal times (Goldstein and Leitner, 2018; Bouvard et al., 2015; Borio et al., 2014; Schuermann, 2014; Goldstein and Sapra, 2013).

On the European market, some event studies have shown that markets can benefit from stress test reports as those disclosures add new and valuable information, whilst other studies highlight potential negative consequences. In particular, Petrella and Resti (2013) observe positive market reactions around EBA's 2011 exercise, while Carboni et al. (2017) and Lazzari et al. (2017) show that markets reacted to ECB's 2014 comprehensive assessment. On the negative side, Goncharenko et al. (2018) provide theoretical evidence that stress tests produce negative disclosure effects which they support with empirical data from the EBA's 2011 and 2014 stress test exercises. Similarly, Sahin and de Haan (2016) document no market reactions on the ECB's 2014 stress test and argue that the outcome was aligned with market expectations. Furthermore, cross-country studies by Breckenfelder and Schwaab (2018) and Barucci et al. (2018) focus on bank risk spill-over effects and supervisory forbearance, respectively. In terms of individual bank behaviour, Bischof and Daske (2013) find that the participants of the CEBS's 2010 and EBA's 2011 stress tests as well as EBA's 2011 capital exercise issue voluntarily disclosures to curb bad signals from stress test information. Likewise, Gropp et al. (2019) show capital management practices, indicating that such assessments might unintendedly incentivise discretionary bank behaviour.

In the U.S., research examines different aspects of the assessments on a large scale, mainly agreeing that those exercises are informative. The first event studies finding market reactions around the result release of the Supervisory Capital Assessment Program (SCAP) were undertaken by Morgan et al. (2014) and Quijano (2014). In theoretical studies, researchers argue that stress test disclosures may reduce investors' risk-sharing incentives, interrupt private information production, exacerbate bank managers' short-sighted decision making and may even lead to bank runs if regulators intentionally hold back negative information (Goldstein and Leitner, 2018; Bouvard et al., 2015; Goldstein and Sapra, 2013). However, those theories have not yet been supported by empirical evidence. For example, Flannery et al. (2017) support previous findings that stress tests provide useful information on bank risk-taking. However, the information impact has decreased in recent years. Also, they do not find negative welfare effects from stress testing on analyst information production, neither have they influenced manager's investment decisions. Recently, researchers have extended their analysis towards implications of stress tests on bank lending (Acharya et al., 2018) and lobbying (Cornett et al., 2019). These studies find, respectively, that stress-tested banks reduce lending activities to large and risky borrowers and raise political spending to pass stress tests.

Motivated by the growing influence of regulatory stress tests on the financial sector, I scrutinise whether such exercises meet expectations in enhancing the market discipline that safeguards financial stability. Importantly, with regards to European stress tests, studies examine one or two stress test exercises, but no attempt has been made to jointly assess European and U.S. stress tests. However, to make sense of the debate and to draw conclusions about the cost and benefit of stress tests, I provide a comprehensive picture that might support regulators and policymakers on establishing a stress test disclosure strategy (Bouvard et al., 2015; Borio et al., 2014; Schuermann, 2014). In particular, I examine the subsequent research questions. Do stress tests provide new information to the markets that disciplines banks? Is the disciplining effect stronger when experienced for the first time? Does the disciplining effect exacerbate future abnormal return trends? Do stress tests contribute to market discipline by reducing information asymmetry, bank risk-taking and improving bank funding structure?

The stress test literature provides some theoretical and empirical evidence on stress tests; however, the effect of stress tests on market discipline has not yet been concluded (Acharya et al., 2018; Goldstein and Leitner, 2018; Flannery et al., 2017; Goldstein and Sapra, 2013). Thus, I contribute to this literature by substantiating the link between stress tests and market discipline from two perspectives. First, the stock market's sentiment reflects market discipline from stress tests as security prices quickly integrate the disclosure of new information. I measure the cumulative abnormal return (*CAR*) and buy-and-hold return (*BHAR*) over various short-term event windows. A negative market response indicates 'bad' news and market discipline, whilst a positive reaction implies 'good' news and market reward. Further, I implement a calendar-time portfolio (CTIME) approach that tests if stress-tested banks over- or under-perform the markets in the long-run after the stress test event. Second, I expand related empirical work on bank behaviour and explore the influencing power of market discipline from stress tests (Cornett et al., 2019; Gropp et al., 2019; Bischof and Daske, 2013). I conduct a fundamental analysis that captures information asymmetry, bank risk-taking and funding structure. The purpose is to scrutinise the time-series impact of stress tests on bank fundamentals and whether those exercises empower market players to influence bank behaviour. This contribution also expands the market discipline literature (Danisewicz et al., 2018; Bushman and Williams, 2012; Nier and Baumann, 2006).

The event study results that concern the disciplining effect of stress tests are mixed for both the European and U.S. market due to the intrinsic difference of the individual assessment. In Europe, I find that only the 2011 stress test stimulate significant positive market reactions, whilst the market responses of the recent stress tests in 2014, 2016 and 2018 appear to be insignificant and, therefore, correspond with the investor's expectations. Furthermore, the first-time participation event triggers significant positive market responses in short-term event windows and prove to be more informative than taking all stress test events together. As the market reactions are mainly positive, I conclude that European banks are not disciplined but rewarded, as market confidence is restored (for instance, after the 2011 stress test). Moreover, I document that stress test events may be an accelerating factor that exacerbates positive and negative share price performance. In particular, if a bank's abnormal return reports a positive or negative response in a 3-day event window around the stress test (i.e., one day before and after the event), the succeeding abnormal returns continue this positive or negative trend. Therefore, stress tests exacerbate abnormal return trends, and the disciplining effect lasts longer when the bank shares are in a downward rather than in an upward trend. This incident might harm financial stability as weaker institutions are penalised even more.

In the U.S., the results indicate that information from stress tests appears to correspond with market expectation or is seen as 'bad' news that leads to disciplining activities by the markets. In particular, I only report positive responses for the Comprehensive Capital Analysis and Review (CCAR) in 2012, whilst I see significant negative market reactions for the CCARs in 2013, 2017 and 2018 as well as for the 2016 Dodd-Frank Act Stress Test (DFAST). It appears that CCARs are more informative than the DFASTs, which could mean that investors hold back their investments until the regulatory announcement is complete. In contrast to the European stress tests, the first-time participation event does not produce significant market reactions. However, taking all stress test events together, I find negative and significant responses over a 7-day event window around the stress test observation (i.e., three days before and after the event). Therefore, U.S. banks are disciplined by the markets when regulators release stress test information. Moreover, similar to the European case, stress tests exacerbate abnormal return trends, whereas negative return trends remain more persistent than the positive equivalents. This holds true specifically for the initial stress test exercise in 2009 and total stress test participation.

In the long-run, I report that, on certain occasions, European and U.S. stress-tested banks over, but also under-perform the markets. In particular, I document that positive and negative trends observed in short-term event windows continue over a longer period following the stress test. For example, in Europe, the positive market momentum of the 2011 stress test transfers over 1-12 months after the stress test, whilst the negative tendency of the 2014 assessment was still considered for the long-term stock performance over 1-24 months after the 2014 exercise. Similarly, in the U.S., I measure this negative trend for the assessments in 2013. This result might be connected to the fact that 2013 was the first year when the regulator conducted two assessments (DFAST and CCAR).

Analysing bank fundamentals, I find several time-series variations in terms of information asymmetry, analyst behaviour, bank risk-taking and funding structure that appear during stress test periods. In particular, concerning information asymmetry and analyst behaviour, in both jurisdictions the results appear to be strong during the earlier stress test periods in Europe (in 2010-11) and in the U.S. (in 2009-13). The findings weaken in recent stress test periods, which indicate that stress test information corresponds with market expectations. For instance, I report that European first-time participation in 2010-11 not only reduces information asymmetry and raises analyst coverage, but also increases analyst estimates dispersion. In support of my event study findings, the 2011 stress test contributes to stabilising liquidity in the markets, while some uncertainty remains among analyst forecasts. Further, in the U.S., I show that information asymmetry decreases significantly. In contrast, stress tests do not appear to substantially influence U.S. analyst behaviour. I only observe a decrease in analyst coverage in 2009-13; however, I cannot confirm a conclusive impact on earnings surprises and estimate dispersion. The results supplement Flannery et al. (2017), who also report a weak relationship between analyst behaviour and stress test information.

Furthermore, European stress-tested banks show significant signs of reduced risk-taking as capital adequacy, leverage risk, insolvency risk, credit risk and credit portfolio quality improve during stress test periods. Further, in Europe, I find rewarding market discipline within the bank funding structure. For instance, depositors appear to charge lower interest rates during stress test periods. The results are particularly strong for the earlier 2010-11 than the recent 2014 first-time stress test participants and may be explained by the growing confidence in the markets and a potential learning curve to which stress tests may have contributed. In contrast, in the U.S. the results with regards to bank risk-taking and funding structure are mixed and not as conclusive as for the European case. In particular, U.S. banks seem to be less risky during stress test periods, as the insolvency risk decreases, and profitability improves. However, I cannot observe strong evidence of market discipline within the other risk-taking variables such as leverage, credit risk and credit portfolio quality as well as the funding structure analysis.

The remainder of the chapter is structured as follows. Section 4.2 presents the theoretical framework and related literature; it also discusses the main arguments and the limitations of relevant studies. Section 4.3 develops the empirical hypotheses to be tested in Section 4.4. The latter section illustrates the data collection and the econometric techniques I apply in my analysis. Section 4.5 reports and discusses the empirical results, while Section 4.6 shows robustness. Section 4.7 concludes the chapter and presents the political implications.

4.2. Theoretical framework and related literature

4.2.1. The theory of efficiently disciplined markets

The concept of market discipline may be traced back to Adam Smith's theories (Smith, 1759, 1776). Accordingly, markets should be left free from regulation because they regulate themselves through supply, demand, competition and self-interest. As argued by Flannery (2001), market discipline is a two-step process that consists of the assumptions that markets monitor a bank's condition and influence a manager's actions. However, to enable markets to monitor and impose influence, adequate information needs to be provided on the markets that display a bank's financial condition. Then, in theory, the share price includes publicly available information as market participants timely incorporate new monitoring information into their risk assessment and investment strategies.

Several researchers have worked on the theory of efficient capital markets and on building an asset pricing model. Simultaneously, Lintner (1965b, 1965a), Sharpe (1964) and Mossin (1966) independently created the Capital Asset Pricing Model (CAPM) that builds on the assumption of efficient markets. In a theoretical review, Fama (1970, p. 383) defines a market as efficient when “prices always ‘fully reflect’ available information”. He further distinguishes the extant literature of that time into tests of weak, semi-strong and strong form of market efficiency. In its weak from, market prices reflect only historical information, whereas the semi-strong form adjusts prices quickly when current information is made publicly available. The strong form includes price information that only monopolistic investors (i.e., insiders) might be able to access. In later work, Fama (1991) argues that the efficient market hypothesis is untestable because of the joint hypothesis problem. It is ambiguous to conclude that markets are inefficient because inefficacy might be at least partly explained by the asset pricing model’s inaccuracy. To improve the estimation of asset prices, researchers extended the CAPM and introduced distinct factors that control for market capitalisation, book-to-market ratio (Fama and French, 1993), return momentum (Carhart, 1997) and liquidity (Fama and French, 2015).

Nevertheless, Fama (1991) argues that the efficient market hypothesis has significantly enhanced the understanding of security returns and their movements. Therefore, bank managers need to closely examine their share price and, in some cases, respond to adverse changes to mitigate the impact. Those managerial decisions may then serve the interests of stakeholders. This potential influence is divided into a ‘direct’ and ‘indirect’ stream. While equity and debt owners impose direct impact through increased funding costs and/or reduced trading volume for riskier banks, supervisors may indirectly react to changes of a bank’s condition by stricter regulation of asset quality, liquidity and capital adequacy (Bliss and Flannery, 2002; Flannery, 2001).

This potential impact of stakeholders may concern bank risk-taking, as banks are exposed to different risk types. In particular, credit risk is based on the likelihood of a borrower defaulting and being unable to repay either principal or interest. Liquidiy risk is driven by asset transformation of short-term deposits and savings to long-term loans and the possibility of sudden extensive withdrawals by depositors. In addition, banks face other types of risk based on the variation of the financial markets (market risk and currency risk), the balance between capital and debts (leverage risk) together with operational risk (López-Espinosa et al., 2013). Therefore, a bank's degree of risk depends on the management of their business models.

Consequently, a bank's individual risk strategy is externally driven by uncertainty, volatility and sensitivity of their business models, but is also determined by the intrinsic risk appetite and the management of the risk-return dilemma that high expected returns lead to higher risk and *vice versa*. This has been analysed in various studies. First, a growing literature stream finds evidence for increased risk-taking that is related to non-interest income (Bushman et al., 2016; Demirgüç-Kunt and Huizinga, 2010). Second, global SIFIs in particular might have the incentive to increase their size by risk-taking, classified as too-big-to-fail, and be saved through governmental bail-outs in case of bankruptcy (Demirgüç-Kunt and Huizinga, 2013). Third, exogenous factors such as financial liberalisation or bank competition can influence banks' risk-taking. While the risk-increasing impact of liberalisation is well-documented, controversial debates raise the opinion that bank competition can benefit both financial stability or fragility (Boyd and De Nicolo, 2005; Allen and Gale, 2004).

4.2.2. Transparency, market discipline and financial stability

In the context of market discipline, more or qualitatively better bank transparency is generally considered to safeguard financial stability, henceforth 'good' transparency, as it aims to mitigate information asymmetry between managers and other market players such as depositors and creditors.[30] For instance, objective and solid financial accounting information, as an important transparency channel, can enable shareholders and internal controlling bodies to execute the corporate governance role to monitor decision makers. Further, 'good' transparency increases the efficiency of identifying investment opportunities to create value for managers and investors; in turn this supports and enhances financial markets to become more efficient and precise in reflecting the true value of a firm (Bushman and Smith, 2003).

In addition, this improved efficiency can specifically mitigate liquidity risk as it enhances short-term debt refinancing (Ratnovski, 2013). Moreover, studies have particularly observed that 'good' transparency strengthens market discipline, which is an

[30] Beatty and Liao (2014), Bushman (2014) and Acharya and Ryan (2016) provide excellent reviews of the bank transparency and opacity literature. For conciseness, I do not mention all references and refer to those articles for a thorough discussion.

important mechanism to monitor and penalise bank risk-taking practices (e.g., Nier and Baumann, 2006; Blum, 2002). More recently, empirical evidence indicates that market discipline varies across countries, decreases when banks become larger and becomes weaker during and after crises due to governmental intervention (Cubillas et al., 2012, 2017; Berger and Turk-Ariss, 2015).

In addition to the positive effects of transparency, the literature identifies that under specific circumstances, more transparency can negatively affect financial stability. They argue that inefficient information, henceforth ‘bad’ transparency, could irritate and misguide bank insiders and outsiders, which can lead to market failure. Consequently, it might be better to hide this information and retain a level of opacity. For example, if public information, and therefore transparency, becomes too precise, depositors might overreact particularly to negative information and, in the worst case, start bank runs. However, this inefficiency can be mitigated if a depositor insurance system is in place (Chen and Hasan, 2006; Morris and Shin, 2002).

Furthermore, Dang et al. (2017) argue that less information about the credit worthiness of banks’ loan holders is desirable to provide risk-sharing benefits to depositors and to maintain market liquidity. Morrison and White (2013) argue that a weak regulator reputation combined with a transparent regulatory procedure might lead to financial contagion in case of a bank failure of one of the regulator’s supervised banks. In this case, uninformed depositors might lose confidence in the regulator’s competence and withdraw their deposits from other banks under the same regime. In addition, more transparency might motivate managers to exercise accounting discretion to hide excessive risk-taking activities, which in turn may curb market discipline and harm financial stability (Bushman and Williams, 2012, 2015).

4.2.3. Stress tests, market discipline and financial stability

In a conceptual study, Goldstein and Sapra (2013) examine the impact of stress test disclosures on financial stability and identify positive and negative effects. For instance, stress test disclosures provide bank-specific information about the risk profile; this enhances investors’ precision in their risk assessment that ultimately leads to more share price efficiency, thus market discipline. Further, the disclosure of stress test results may enrich depositors’ trust due to supervisory discipline. In particular, when regulators are committed to reporting the methodology and results, it may enhance the market’s trust as it mitigates potential regulatory forbearance. On the other hand, stress test disclosures might reduce risk sharing among market participants (i.e., Hirshleifer (1971) effect) and exacerbate contagion. Also, investors might follow the regulator's stress test results instead of sourcing their own information, which curbs the regulator's learning curve from market prices. Moreover, bank managers might tend to make short-sighted investment decisions to avoid failing stress tests.

However, this theoretical framework is essentially connected to the state of the economy, as well as to the quantity and quality of stress test disclosures (i.e., aggregated or bank-specific information). In a theoretical paper, Bouvard et al. (2015) suggest that if the average condition of stress-tested banks is above a specified threshold, no bank-specific information (i.e., aggregated information) should be disclosed because there is a risk of a run on low-quality banks. Particularly in normal times, pooling some low-quality banks with other banks of higher quality does not negatively affect good banks but significantly decreases the rollover risk on bad banks. In times of financial distress, regulators need to show bank-specific information because uncertainty might lead to a run on the entire system. Therefore, stress test disclosures distinguish good and bad banks and limit potential bank runs to low-quality banks. However, if the regulator has private information about a potential economic downturn, this circumstance might result in a commitment problem of the regulator. The regulator might not want to disclose 'bad' news that could produce a shock and thus hold back information, in more cases than optimal. This opacity could lead to a misguidance of market players who might be more likely to run on the entire system.

4.3. Hypotheses

In the following sub-sections, I develop my hypotheses that test how effective stress tests may stimulate market discipline and thus contribute to financial stability. As discussed in Section 4.2.1, market discipline is divided into two functions, that are monitoring and influence (Schaeck et al., 2012; Bliss and Flannery, 2002; Flannery, 2001). The monitoring (i.e., disciplining) effect refers to the market players (e.g., regulators, investors, depositors, and others) ability to effectively assess bank performance and to take action on incorporating these evaluations into market prices. On the other hand, the concept of influence implies that these disciplining activities may lead to changes in bank managers behaviours.

4.3.1. The disciplining effect of new stress test information

The main purpose of stress tests is to inform investors about participating banks' risk-taking activities. In particular, stress tests provide a current snapshot of the state of each bank's capital adequacy to project the bank's financial ability to avoid severe financial distress and business disruptions in an adverse scenario (Borio et al., 2014; Schuermann, 2014). In a semi-strong efficient market, an investor's sentiment reflects the short-term disciplining effect as security prices quickly integrate the disclosure of new information (Fama, 1970). However, stress test reports are special because they disclose bank-specific regulatory information, that would be kept confidential under normal circumstances (Feldberg and Metrick, 2019; Bushman, 2014), to restore and maintain the market's trust during crises and normal economic times, respectively (Bouvard et al., 2015; Borio et al., 2014). For this reason, this improved transparency from stress test information may trigger market player's disciplining activities that may be observed by positive and negative market price reactions (Flannery et al., 2017).

Using a sample of stress-tested banks, I test the European (2010-2018) and U.S. (2009-2018) assessments and compare these particular market reactions and, therefore, the disciplining effect that the new information from stress tests may provoke in the short-term. In particular, if regulators reveal more risk-taking than markets expect, investors might reduce or even reject an investment, and *vice versa*. Therefore, a negative market response indicates 'bad' news and market discipline, whilst a positive reaction implies 'good' news and market reward. Further, taking the average market reactions of first-time and total stress test participation, I hypothesise that the information power of first-time participation is stronger because the disciplining intensity may deteriorate over time if banks participate on a regular basis (Flannery et al., 2017). In addition, I test if this short-term market response from stress tests exacerbates the abnormal return trend in either a positive or negative direction. In other words, if the initial market reaction on stress test information is negative (i.e., disciplining), abnormal returns could continue this negative trend, and *vice versa*. Accordingly, I formulate the first set of hypotheses:

H1a. *Stress tests have a disciplining effect on banks.*

H1b. *The disciplining effect of stress tests is stronger for first-time participants.*

H1c. *An initial disciplining effect of stress tests is followed by negative abnormal returns.*

4.3.2. The long-term performance of stress-tested stocks

Extending *H1c*, I investigate how the release of stress test information contributes to improve market confidence that might influence long-term stock performance of stress-tested banks. As explained earlier, stress tests provide a projection into the future performance of participating banks. A negative outlook may lead to an instant short-term market reaction (as hypothesised in Section 4.3.1) but could also affect the investor's long-term investment strategy. In particular, in normal economic times, stress test information provided by the authorities might reduce the investor's incentive to produce and trade on their own information; this might decrease the authority's ability to learn from share price movements (Bond and Goldstein, 2015; Bouvard et al., 2015; Goldstein and Sapra, 2013). Therefore, if investors follow the stress test information in the long-run, I expect that stress-tested banks' stocks over- or under-perform the market in the case of a positive or negative stress test outlook, respectively. Thus, I propose the next hypothesis:

H2. *The release of stress test information affects bank stock performance in the long-run.*

4.3.3. Market discipline towards financial stability

Can one comprehensively conclude from market reactions alone that market confidence has been restored and/or maintained as a consequence of additional stress test information that triggers market discipline? It is one perspective to analyse if markets react to stress test information, but the other side is to examine bank-individual fundamentals that should mirror the influencing effect of these imposed market disciplining activities. More specific, if the disciplining effect is transferred into a negative market response (i.e., short-term costs), this should lead to a change in bank managers behaviour to reverse the negative trend in the bank's condition (Bliss and Flannery, 2002, Flannery, 2001). Thus, I further investigate different micro-prudential market and accounting factors that are linked to information asymmetry and analyst behaviour; this is in addition to the bank risk-taking and funding structure to test the market's disciplining influence on bank-specific characteristics (Acharya et al., 2018; Flannery et al., 2017).

First, stress test disclosures improve the provision of public information that reduces information asymmetry amongst economic agents. The more transparent a bank's operation is, the more accurately outsiders can assess its value leading to better-informed investment decisions (Bushman et al., 2004). Further, lower information asymmetry magnifies the quality of information that analysts produce thus leading to a lower likelihood of disagreements among analysts (e.g., Flannery et al., 2017; Marquardt and Wiedman, 1998). Second, this transparency mechanism links to market discipline as it enables investors and depositors to identify and react to a bank's risk-taking activities by charging a higher premium for funding resources (Danisewicz et al., 2018). In particular, investors and depositors have incentives to influence bank management to *ex ante* prevent failures that might lead to a loss of their charter value (Schaeck et al., 2012; Martinez Peria and Schmukler, 2001). For instance, evidence shows that depositor preference structures and more uninsured liabilities enhance market influence and reduce bank risk-taking (Danisewicz et al., 2018; Nier and Baumann, 2006). On certain occasions, higher bank risk increases even the likelihood of bank executives to step down (Schaeck et al., 2012). Ultimately, this also refers to financial stability as stricter monitored banks are less prone to market volatility, financial distress and insolvency risk, therefore reducing the probability of a banking crisis (Bushman and Williams, 2012; Nier and Baumann, 2006; Nier, 2005). Consequently, I hypothesise that the described market discipline mechanism leads to a decline in information asymmetry and less diverse analyst behaviour as well as reduced bank risk-taking and an improved funding structure.

H3. *Information asymmetry is reduced following stress tests*

H4. *Analyst behaviour is less diverse following stress tests.*

H5. *Bank risk-taking activities are reduced following stress tests.*

H6. *Bank funding structures are improved following stress tests.*

4.4. Empirical analysis

In this section, I provide detailed description of the sample selection process, variables construction and empirical models that I employ in my analysis. The description of variables and the relevant data sources are provided in Table 4.1.

[Please refer to Table 4.1 here]

4.4.1. Sample selection

I select the sample of stress-tested banks based on the European and U.S. stress test reports published by the regulatory stress test authorities (i.e., CEBS, EBA, ECB and

Federal Reserve).[31] These reports disclose all banks that participated in the regulatory stress tests between 2009 and 2018, with detailed information about the stress test performance of each bank.[32] Similar to Flannery et al. (2017) and Bischof and Daske (2013), I illustrate both the stress test observations of each European and U.S. exercise alongside the accumulated total samples of banks and first-time participants. This enables me to examine the effect of each stress test exercise and the impact of first-time (FTSTO) and total stress test participation (TOTALSTO). Accordingly, Table 4.2, Panels A and B, shows the total samples of 188 European and 42 U.S. banks as well as 98 European first-time participants in 2010-11 (77 banks in 2014) and 19 U.S. first-time participants in 2009 (12 banks in 2014). In Europe, stress test participation varies substantially from one exercise to another and peaks in 2014, while recent observations decrease (i.e., 2016 and 2018). In the U.S., stress test participation remains steady over the period 2009-2013, increases in 2014, and varies slightly in recent years (i.e., 2015-2018).

[Please refer to Table 4.2 here]

Since I examine the samples of banks over a 10-year period, in which the market structure of the banking industry has radically changed as a result of the global financial crisis, I need to account for data limitations due to the timing of IPOs, M&As, bankruptcies and other factors. First, in Table 4.2, Panels C and D, I present how I refine my dataset to obtain the data I employed in the event study analysis. For both European and U.S. samples, I exclude a small number of bank event observations because the daily share prices are not available for the particular event and estimation windows. For instance, the listed banks Bankia, Liberbank and ABN AMRO (European) and Ally Financial, Inc. (U.S.) went public after some event dates (i.e., that of 2009-2014); this explains the unavailability of the share price data.

Second, in Table 4.2, Panel E, I prepare the European and U.S. samples for the time-series approach. For instance, 20 European banks, mainly from Spain, were merged, resolved or consolidated after the 2008 financial crisis (Bischof and Daske, 2013). This

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[31] The reports may be accessed on the EBA, ECB and Federal Reserve websites (see: https://eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing, https://www.bankingsupervision.europa.eu/banking/tasks/comprehensive_assessment/html/index.en.html, https://www.federalreserve.gov/supervisionreg/stress-tests-capital-planning.htm.

[32] The relevant press release of the CEBS does not provide the names of the stress-tested banks in 2009; it simply states that “22 major European cross border banking groups” were tested (for further details, see: http://www.eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing/2009).

circumstance results in inherent data limitations. Furthermore, I remove 25 European and 13 U.S. institutions for which the accounting data on FitchConnect is of poor quality (i.e., covers less than half of the data period from 2005-2017). In Europe, this issue concerns private institutions, whilst in the U.S. those banks are non-U.S.-owned subsidiaries that do not provide separate annual reports. Similarly, one U.S. institution (i.e., Metlife, Inc.) is excluded because it is an insurance company that exited its banking engagement in 2013 (Cornett et al., 2019; Flannery et al., 2017).[33] In sum, I reduce the initial stress test samples (Panel A) by 45 European and 13 U.S. institutions due to the explained data limitations that could not be manually corrected. This process leads to a final sample of 143 (listed: 62) European banks from 25 countries and 29 U.S. (listed: 28) banks.

4.4.2. Data construction and key variables

I use various variables to estimate market discipline from different angles based on the relevant stress test, accounting and market discipline literature and further expand my database that I describe in Chapter 3 (Section 3.4.2). I collect accounting measures from BvD Bankscope and FitchConnect (supplemented by hand-collection) and the market variables from Thomson Reuters (Datastream/IBES). To conduct the event study, I also resort to this database using the daily share prices and, in addition, factors from the Fama and French website. I accommodate outliers that potentially bias the results by removing particular low and high share prices, thin trading days, and winsorise the accounting and market data at the 1 and 99 percentiles. Accounting data are obtained and winsorised on a quarterly basis, while I collect and winsorise market data daily and average those daily values to construct quarterly frequencies. I follow the recent banking literature that employs such methods (Gropp et al., 2014; Bischof and Daske, 2013; Flannery et al., 2013; Beatty and Liao, 2011). The data period of the quarterly obtained accounting and market data spans from 2005-2017. To analyse the most recent European and U.S. stress tests in 2018, the daily share prices are extended until year-end 2018.

First, I comprehensively assess bank risk-taking (Cubillas et al., 2012, 2017; Nier and Baumann, 2006) using capital adequacy captured by the Tier 1 regulatory capital ratio (*T1R*); leverage risk measured by the natural logarithm of leverage ratio that is liabilities over equity (*LEVERAGE*); credit risk of banks reflected in the risk-weighted assets (*RWA*);

[33] The European sample consists of a wide range of commercial, savings and cooperative banks, whilst the in the U.S. regulators predominantly observe bank holding companies.

credit portfolio quality captured by loan loss reserves (*LLR*); insolvency risk estimated by the natural logarithm of Z-Score that equals return on assets plus capital over total asset ratio divided by the standard deviation of return on assets (*ZSCORE*); and profitability shown by return on assets (*ROA*). The intuition behind these bank risk-taking measures is that stress test information might enforce market discipline that should then be reflected in more capital adequacy (*T1R*), lower leverage risk (*LEVERAGE*) as well as quality and quantity of the credit portfolio (*RWA, LLR*). Further, a higher Z-Score (*ZSCORE*) and its component return on assets (*ROA*) should indicate lower insolvency risk due to the market discipline mechanism (Beck et al., 2013; Laeven and Levine, 2009).

Second, I measure bank funding structure (Danisewicz et al., 2018; Ben-David et al., 2017; Nier and Baumann, 2006) using total funding cost reflected by total interest expenses (*TIE*); uninsured funding cost captured by other interest expenses (*OIE*) and insured funding cost shown by interest paid on customer deposits (*IECD*); uninsured funding using bank deposits (*DEPBA*) and subordinated debts (*SUBD*); insured funding estimated by customer deposits (*CUSTD*) and interest margin reflected in the net interest margin ratio (*NIM*). The literature argues that lower uninsured funding and higher funding costs are signs of market discipline as such a movement of these variables indicates that depositors withdraw their funds and charge higher premiums (Danisewicz et al., 2018).

Third, I estimate information asymmetry using the bid-ask spread (*BIDASK*) and analyst behaviour captured by analyst coverage (*RECNO*), earnings surprises (*EPSSUR / PRICE*) and estimate dispersion (*ESTSD / PRICE*) both as a proportion of the bank share price. Importantly, as the level of information increases due to stress test reports, this should lead to reduced information asymmetry that might encourage more analyst coverage and precise earnings forecasts. In turn, if this mechanism is ineffective, markets should be less liquid as more diversity of recommendations and earnings forecasts is widely believed to indicate uncertainty (Flannery et al., 2013, 2017; Bischof and Daske, 2013; Leuz and Verrecchia, 2000).

4.4.3. Descriptive statistics and correlation tests

Table 4.3 provides descriptive statistics on bank risk-taking, funding structure and bank accounting characteristics as well as information asymmetry, analyst behaviour and market microstructure. Panel A presents European banks, while Panel B illustrates U.S. banks. On average, there is only a slight difference in the accounting characteristics between the U.S. and European banks. U.S. banks are marginally larger than European banks (*SIZE*) but have lower capital adequacy (*T1R*). Further, in both markets, the banks provide similar liquidity with regards to total funding (*DEPO*). However, European banks conduct more traditional banking activities (*LOAN*), whilst U.S. banks account for a higher credit risk portfolio (*RWA*). This may be explained by the higher off-balance sheet activities (*OBSI*) that are included in the calculation of risk-weighted assets and lead to a higher portion of credit portfolio risk. From a market perspective, U.S. banks account for a higher market value (*MVALUE*) and market-to-book value (*MTBV*). In terms of information asymmetry and analyst behaviour, U.S. bank shares trade at a lower bid-ask spread (*BIDASK*) and are covered by more analysts (*RECNO*). Further, the dispersion of analyst earnings surprises (*EPSSUR / PRICE, ESTSD / PRICE*) is on average lower for U.S. compared to European banks. Therefore, U.S. bank shares may be seen as more liquid (lower bid-ask spread and estimate dispersion), compared to European banks.

[Please refer to Table 4.3 here]

In Table 4.4, I provide Pearson correlation coefficients and p-values for the variables that I use in the time-series regressions (Equations $4.9_{A,B}$ and $4.10_{A,B}$). Panel A illustrates the European and Panel B shows the U.S. banks. In particular, I find statistically significant correlation within some accounting and market variables, as those are mechanically related. The correlation coefficients are consistent across both jurisdictions, but usually higher in the U.S. than in Europe. For instance, I observe a significant positive correlation (62.90% in the U.S. and 33.40% in Europe) between total deposits (*DEPO*) and outstanding loans (*LOAN*). Further, there is a significant negative correlation (-71.00% in the U.S. and -60.90% in Europe) between outstanding loans (*LOAN*) and trading securities (*TRADE*). These two relationships display the financial intermediation and business activities, respectively. Interestingly, earnings (*EBPT*) and loan loss provisions (*LLP*) are positively correlated (65.30% in the U.S. and 37.90% in Europe) at the 1% level of significance. This result is in line with the accounting discretion literature that well-documents bank loan loss provisioning to smooth income (Beatty and Liao, 2014; Bushman and Williams, 2012). Moreover, the market value *(MVALUE)* and total assets (*SIZE*) are strongly positively correlated (82.90% in the U.S. and 85.30% in Europe), due to the significant relationship between market and book value of bank size.

[Please refer to Table 4.4 here]

4.4.4. Empirical models

4.4.4.1. Short-term event study approach

I employ a short-term event study approach that is widely established in the literature (Flannery et al., 2017; Morgan et al., 2014; Petrella and Resti, 2013; Campbell et al., 1997; Mikkelson and Partch, 1986; Brown and Warner, 1985). The nature of short-term event studies is to isolate the effect of a specific event from other confounding market movements (MacKinlay, 1997). First, it is crucial to define the particular event and event dates that are in this case the regulator's release dates of the stress test results for the various European and U.S. stress tests. The importance of stress tests in the banking industry justifies the release of the outcome of such tests as an essential event that drives equity prices. As regulatory information is usually kept confidential and regulators carefully prepare the release including various *ex ante* announcements (i.e., methodology updates), investors expect this exceptional information (Feldberg and Metrick, 2019; Bushman, 2014). Second, according to the design of event studies, the days around this event date are of main interest that form the event window and are usually the day of the event and one day or multiple days before and after. As the event window sheds the spotlight on these particular days on and around the event, the possible influences of other confounding market movements are significantly mitigated (Flannery et al., 2017; Petrella and Resti, 2013; MacKinlay, 1997). Third, the abnormal return, that is explained later in this section, is the crucial measure to assess the impact of an event. The abnormal return of a bank and event over the event window is defined as the difference of the realised return and the expected return given the absence of the event.

In this way, I test $H1a$, $H1b$ and $H1c$ that concern the short-term information value of stress testing and the potential disciplining effect arising from this new information. 'Short-term' refers to the length of event windows that are defined below Equations 4.2 and 4.7. I employ this methodology for each European and U.S. stress test, in addition, I accumulate the observations of individual first-time and total participation as explained later in this section. I calculate the abnormal return (AR) that separates the impact of the event from generic market activities, for each stress test event as follows:

$$AR_{it} = (R_{it}) - E(R_{it}) \tag{4.1}$$

where, for bank *i* at event date *t*, R_{it} is the individual realised stress test event return and $E(R_{it})$ is the corresponding expected (or also called 'normal')[34] return.

I calculate the cumulative abnormal return (*CAR*) over a period *T* around the stress test events, which is:

$$CAR_T = \sum_{t=0}^{T} AR_{it} \tag{4.2}$$

where, the period *T* is defined as the subsequent short-term event windows, that are (a) one day prior and after (t–1, t+1), (b) one day prior and two days after (t–1, t+2), (c) three days prior and after (t–3, t+3), and (d) one day prior and five days after (t–1, t+5) the release of the stress test results. I follow the stress test literature that employs various event windows (Carboni et al., 2017; Flannery et al., 2017; Morgan et al., 2014; Petrella and Resti, 2013). The one or three days prior to the event captures potential information leaks, whilst the short-term event windows reduce the risk from being confounded by other market factors and events.

Then, I measure the cross-sectional average of the cumulative abnormal returns (*CAAR*) over the four event periods *T* defined in Equation 4.2 as follows:

$$CAAR_T = \frac{1}{N}\sum_{i=1}^{N} CAR_T \tag{4.3}$$

To calculate the expected returns for the *CAAR*, I resort to three distinct models; these are the standard models for conducting an event study (Campbell et al., 1997; MacKinlay, 1997) and enable me to examine the implications of different market factors. First, I apply the standard capital asset pricing model (CAPM). Second, I employ the Fama and French (1993) three-factors model that comprises of two additional factors, 'small minus big market capitalisation' (*SMB*) and 'high minus low book-to-market ratio' (*HML*). Third, I use the model by Carhart (1997) that extends the Fama and French three-factors model by the 'high minus low momentum' (*MOM*) factor. As the third model is the most developed one that not only captures bank size features (*SMB, HML*) but also stock performance (*MOM*) to explain expected returns, I consider the Carhart (1997) four-factors model (C4F) the baseline model, whilst I show the other two models as robustness tests. Thus, the most robust event study results should be consistent over the three models.

[34] MacKinlay (1997) defines the normal return as the "expected return without conditioning the event taking place". I use 'expected' and 'normal' return as synonyms.

Model 1: Capital asset pricing model (CAPM)

$$(R_{it} - R_{ft}) = a_i + \beta_i(R_{mt} - R_{ft}) + \varepsilon_{it} \tag{4.4}$$

where, for bank *i* at event date *t*, $(R_{it} - R_{ft})$ is the daily expected return for each security, R_{it} is the daily realised return, R_{ft} is the risk-free rate, α_i is the constant, β_i is the CAPM beta coefficient (*BETA*), R_{mt} is the daily return of a benchmark portfolio and ε_{it} is the error term.

Model 2: Fama and French (1993) three-factors model (FF3F)

The CAPM can be extended to increase explanatory power as follows:

$$(R_{it} - R_{ft}) = a_i + \beta_{im}(R_{mt} - R_{ft}) + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + \varepsilon_{it} \tag{4.5}$$

where, all other variables equally defined as in Equation 4.4, SMB_t stands for the excess return of 'small versus big market capitalisation shares' and HML_t is the excess return of 'high versus low book-to-market ratio shares'.

Model 3: Carhart (1997) four-factors model (C4F)

Another common extension of Model 2 is as follows:

$$(R_{it} - R_{ft}) = a_i + \beta_{im}(R_{mt} - R_{ft}) + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + \beta_{iMOM}MOM_t + \varepsilon_{it} \tag{4.6}$$

where, all other variables equally defined as in Equation 4.4, MOM_t is the excess return of 'high versus low momentum shares'.

In all models, I apply the 'FTSE Europe Banks Index' (European sample) and the 'S&P 500 Banks Index' (U.S. sample) to calculate the daily returns of the benchmark portfolio. Further, I gather the risk-free rate (U.S. one-month T-bill rate) and three as well as four European and U.S. factors from the Fama and French website.[35] I employ a 200-day estimation window that is from t–11 to t–210 to calculate the normal returns. This approach is consistent with the literature (see, e.g., Petrella and Resti, 2013). For robustness (see, Section 4.6.1), I run the analysis with a 120-day estimation window that produces similar results (Flannery et al., 2017; MacKinlay, 1997).

[35] Please visit: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Further, I test the significance of *CAAR* using the non-parametric generalised sign test proposed by Cowan (1992). As discussed by the event study literature, researchers have a choice between several parametric (Boehmer et al., 1991; Patell, 1976) and non-parametric (Cowan, 1992; Corrado, 1989) tests. However, daily returns are right-skewed (Brown and Warner, 1985), suggesting non-parametric tests to be more robust because, compared to parametric tests, they do not require as strict assumptions about the probability distribution of daily returns. The Cowan (1992) generalised sign test estimates the difference between the positive *CAAR* within the event and the estimation windows. As it only considers the sign of the *CAAR*, it is unaffected by potential asymmetric distribution of daily returns. Moreover, Cowan (1992) argues that the generalised sign test is more powerful than other non-parametric tests such as the Corrado (1989) rank test. This is because it can be applied to event windows longer than one day (i.e., up to eleven days), and it is less sensitive to return outliers and thin trading volumes.

As an alternative measure to *CAAR*, I calculate the abnormal buy-and-hold return (*BHAR*), which is defined as follows (Barber and Lyon, 1997; Ritter, 1991):

$$BHAR_T = \prod_{t=0}^{T}(1 + R_{it}) - \prod_{t=0}^{T}(1 + E(R_{it})) \tag{4.7}$$

where, for bank *i*, at event date *t*, R_{it} is the realised and $E(R_{it})$ the expected buy-and-hold returns over the period *T*, which is the event window that is (a) one day prior and after (t–1, t+1), (b) one day prior and two days after (t–1, t+2), (c) one day prior and four days after (t–1, t+4), and (d) one day prior and seven days after (t–1, t+7) the release of the stress test results. I extend the event period up to seven days to measure the persistence of the abnormal buy-and-hold return (MacKinlay, 1997).

Accordingly, the mean *BHAR* over the period *T* defined in Equation 4.7 is as follows:

$$\overline{BHAR_T} = \frac{1}{N}\sum_{i=1}^{N} BHAR_T \tag{4.8}$$

To calculate *BHAR*, I resort to a simple market return model (MRM), where the banks' returns are subtracted by the contemporaneous returns of the market index (MacKinlay, 1997). As for the prior measure *CAAR*, I employ the 'FTSE Europe Banks Index' (European sample) and the 'S&P 500 Banks Index' (U.S. sample) to calculate the daily returns of the benchmark portfolio. As *BHAR* is positively skewed (Barber and Lyon, 1997), I test the significance of *BHAR* using the skewness-adjusted t-test proposed by Lyon et al. (1999).

In the context of *H1b*, I employ the event study approach on the 59 European and 25 U.S. first-time stress test observations (FTSTO) as well as 206 European and 195 (339)[36] U.S. total stress test observations (TOTALSTO). This provides me with an overall picture of the impact of stress tests (Flannery et al., 2017). In terms of *H1c*, and based on the baseline model (C4F) results, I split my sample into banks that experience a positive (i.e., 'good' news) or negative (i.e., 'bad' news) market response within the 3-day event window, one day before and after the stress test (i.e., $CAR_{t-1,\ t+1}$). I then examine the development of *CAR* for the same event windows as in Equations 4.2 and 4.7 and, in addition, plot average *CARs* over a 21-day window (i.e., $CAR_{t-10,\ t+10}$) to analyse the persistence of positive and negative responses from stress tests (MacKinlay, 1997).

4.4.4.2. Calendar time portfolio approach

To analyse the long-term effect of stress tests on participating banks' stock performance in the context of *H2*, I employ the calendar-time portfolio (CTIME) methodology, also known as 'Jensen's alpha' (Jensen, 1968). I calculate the abnormal returns based on the baseline approach of the Carhart (1997) four-factors model (C4F)[37] developed in Section 4.4.4.1 and consider a period of 1 to 12, 24 and 36 months after the individual stress test exercise, first-time participation and total stress test participation. Further, I estimate the CTIME-coefficients applying equal and value weights. The value weights are based on the bank's market value (*MVALUE*) that is calculated as a quarterly average of daily market values of the year-end quarter (Q4) prior to the stress test event. I employ this quarter because regulators select stress test participants based on the last year-end figures before the stress test. The purpose of this approach is to estimate if stress-tested banks generate significant 'alphas' that show that those banks perform better (positive) or worse (negative) than the market in the long-run. If stress test information does significantly influence market confidence on stress-tested banks, I would expect that a positive (negative) outlook from stress tests would be reflected in stress-tested banks' abnormal returns that over- or under-perform the markets.

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[36] Since 2013, the Federal Reserve has conducted DFAST and CCAR each year. The number in parentheses includes both DFAST and CCAR observations.

[37] I also employ the Fama and French (1993) three-factors model (FF3F) in a robustness test with a similar outcome. Results are available in Section 4.6.1.

4.4.4.3. Time-series effects

Finally, I construct two time-series approaches to analyse the long-term disciplining effect of stress tests on information asymmetry (*H3*) and analyst behaviour (*H4*), as well as bank risk-taking (*H5*) and funding structure (*H6*). In the context of *H3* and *H4*, I estimate if stress test information leads to a market influence in the change of information asymmetry and/or analyst behaviour (*INFO*); for *H5* and *H6*, I test if the market discipline effect (*MARKET*) can be measured in certain accounting variables on bank risk-taking and funding structure. I construct the equations separately for the European (4.9_A, 4.10_A) and U.S. (4.9_B, 4.10_B) markets because the period and participation effects vary significantly for those two jurisdictions. In all Equations $4.9_{A,B}$ and $4.10_{A,B}$, I employ recent literature standards and lag the accounting and market microstructure controls by two quarters based on the Akaike information criterion (AIC).[38] This mitigates endogeneity concerns between current asset choice and stress test effects. Moreover, I resort to bank-specific and quarterly fixed effects to account respectively for time-invariant unobserved heterogeneity and time-variant common shocks that might not be covered by the various bank- and country-specific control variables. In addition, I cluster the standard errors at the bank level to mitigate bias from heteroscedasticity and autocorrelation (Acharya et al., 2018; Flannery et al., 2017).

First, I estimate the following fixed effects models on *H3* and *H4* that are constructed for the European (Equation 4.9_A) and U.S. (Equation 4.9_B) markets:

$$\begin{aligned} INFO_{itj} = {} & \gamma_0 + \gamma_1 ST1011EU + \gamma_2 ST1415EU + \gamma_3 ST16EU + \gamma_4 FTST1011EU + \\ & \gamma_5 ST1011EU * FTST1011EU + \gamma_6 ST1415EU * FTST1011EU + \\ & \gamma_7 ST16EU * FTST1011EU + \sum \gamma_8 (Market\ microstructure)_{it-2j} + \\ & \sum \gamma_9 (Country\ characteristics)_{tj} + \alpha_i + \delta_t + \varepsilon_{itj} \end{aligned} \qquad (4.9_A)$$

$$\begin{aligned} INFO_{itj} = {} & \gamma_0 + \gamma_1 ST0913US + \gamma_2 ST1417US + \gamma_3 FTST09US + \gamma_4 ST0913US * \\ & FTST09US + \gamma_5 ST1417US * FTST09US + \\ & \sum \gamma_6 (Market\ microstructure)_{it-2j} + \\ & \sum \gamma_7 (Country\ characteristics)_{tj} + \alpha_i + \delta_t + \varepsilon_{itj} \end{aligned} \qquad (4.9_B)$$

where, for bank *i*, quarter *t* and country *j*, the dependent variable *INFO* is one of the following market measures based on the stress test literature (Flannery et al., 2013, 2017;

[38] I find no substantial improvement in model strength when I consider one- to four-quarter lags.

Bischof and Daske, 2013): Information asymmetry captured by the bid-ask spread (*BIDASK*), analyst behaviour estimated by analyst coverage (*RECNO*), earnings surprises and estimate dispersion (*EPSSUR / PRICE*, *ESTSD / PRICE*).

The time-dummies in Equation 4.9_A show the different European stress test periods of 2010-11 (*ST1011EU*), 2014-15 (*ST1415EU*) and 2016 (*ST16EU*), while the participation dummy *FTST1011EU* captures European banks that participated for the first time in 2010-11. In the U.S. case, the time-dummies in Equation 4.9_B measure the U.S. stress test periods from 2009-13 and 2014-17, while the participation dummy *FTST09US* captures U.S. banks that participated for the first time in 2009 (Flannery et al., 2017). In both markets, the interaction terms of the time- and participation dummies estimate the effect of stress tests on information asymmetry and analyst behaviour. They compare first-time stress-tested banks of 2010-11 (in Europe) and 2009 (in the U.S.) with banks that participate for the first time at a later point in time. A positive (negative) sign of the coefficients indicates that earlier first-time participants experience more (less) information asymmetry and analyst behaviour than later ones.

The setting might be influenced by confounding factors that arise from the 2008 financial and sovereign debt crises. Therefore, *(Market microstructure)* controls for instabilities that concern market illiquidity, performance, constrained capital and higher volatility (Bonner and Eijffinger, 2016). First, I consider share turnover (*TOVER*), or trading volume, which is an alternative measure to capture market liquidity. More liquidity on the markets lead to lower spreads (Bamber et al., 2011; Karpoff, 1986). Second, the inverse share price (*INVPRICE*) controls for effects related to idiosyncratic differences in share prices. For instance, Black (1986) assumes that market movements of shares that are lower priced are affected by 'noise', i.e., uninformed or speculative trading; this is because more expensive shares limit potential investors which decreases market liquidity (Asparouhova et al., 2013).

Moreover, I control for return volatility (*RETVOL*) that I estimate as the daily standard deviation of continuously compounded share price returns (Bischof and Daske, 2013). More volatile markets, in particular during crises, infer uncertainty, which affects bid-ask spreads and analyst information production (Flannery et al., 2013, 2017). In addition, I include the logarithm of market value of equity (*MVALUE*) and the market-to-book value (*MTBV*). Studies show that market participants follow larger firms closely due to their stronger influence on the markets (Amiram et al., 2016; Leuz and Verrecchia, 2000). This could result in lower spreads and higher trading volume that could also attract analyst coverage.

I also control for analyst recommendation consensus (*RECCON*) that constitutes the current analyst sentiment. Analyst recommendations are positively biased due to conflict of interest between investment banking and brokerage activities leading to analysts publishing buy over sell recommendations (McNichols and O'Brien, 1997; Womack, 1996). In addition, *(Country characteristics)* yields recent fiscal and monetary policy changes (Bonner and Eijffinger, 2016). I utilise economic growth (*ΔGDP*), unemployment growth (*ΔUNEM*), and sovereign debt risk (*IRATE*) to control for current variations in countries' macroeconomic fundamentals such as economic cycles (Hamadi et al., 2016; Vallascas and Hagendorff, 2013; Bushman and Williams, 2012). Finally, I specify bank-specific fixed effects (α), quarterly fixed effects (δ) and the residual (ε).

To test *H5* and *H6*, I amend Equations 4.9_A and 4.9_B and resort to bank accounting instead of market measures. I estimate the subsequent models for the European (Equation 4.10_A) and the U.S. market (Equation 4.10_B):

$$\begin{aligned} MARKET_{itj} = {} & \gamma_0 + \gamma_1 ST1011EU + \gamma_2 ST1415EU + \gamma_3 ST16EU + \gamma_4 FTST1011EU + \\ & \gamma_5 ST1011EU * FTST1011EU + \gamma_6 ST1415EU * FTST1011EU + \\ & \gamma_7 ST16EU * FTST1011EU + \sum \gamma_8 (Bank\ accounting)_{it-2j} + \\ & \sum \gamma_9 (Country\ characteristics)_{tj} + \alpha_i + \delta_t + \varepsilon_{itj} \end{aligned} \tag{4.10_A}$$

$$\begin{aligned} MARKET_{itj} = {} & \gamma_0 + \gamma_1 ST0913US + \gamma_2 ST1417US + \gamma_3 FTST09US + \\ & \gamma_4 ST0913US * FTST09US + \gamma_5 ST1417US * FTST09US + \\ & \sum \gamma_6 (Bank\ accounting)_{it-2j} + \sum \gamma_7 (Country\ characteristics)_{tj} + \\ & \alpha_i + \delta_t + \varepsilon_{itj} \end{aligned} \tag{4.10_B}$$

where, for bank *i*, quarter *t* and country *j*, the dependent variable *MARKET* yields one of the following individual bank risk measures to estimate the strength of market discipline (Danisewicz et al., 2018; Berger and Turk-Ariss, 2015; Nier and Baumann, 2006): The level of capital adequacy (*T1R*), leverage risk (*LEVERAGE*) and credit risk (*RWA*) are regulatory indicators for a banks' risk-taking behaviour as more capital increases survival likelihood during crises and normal times (Berger and Bouwman, 2013; Thakor, 2012; Allen et al., 2011). Therefore, banks with more capital are expected to be more robust against adverse financial shocks. Another regulatory predictor for bank risk-taking is loan quality. Based on stress test results and the related literature, I identify credit portfolio quality (*LLR*) as an important idiosyncratic risk measure (Nier and Baumann, 2006; Martinez Peria and Schmukler, 2001). In total, the insolvency risk (*ZSCORE*) is a widely-applied measure to assess bank insolvency risk, whilst return-on-assets (*ROA*) is a component of *ZSCORE* and may be used to estimate profitability (e.g., Beck et al., 2013; Houston et al., 2010; Laeven and Levine, 2009).

Furthermore, increased cost of funding (*TIE, OIE, IECD, NIM*) and reduced level of uninsured (*DEPBA, SUBD*) and insured (*CUSTD*) funding are indicators for market discipline (Danisewicz et al., 2018; Berger and Turk-Ariss, 2015). In addition, to disentangle stress test participation, *(Bank accounting)* controls for confounding bank-specific and macro-economic factors arising from the recent financial and sovereign debt crisis (Beatty and Liao, 2014; Flannery et al., 2013; Jones et al., 2012). In particular, I include bank size assessed by the natural logarithm of total assets (*SIZE*), traditional- and non-traditional banking activities (*LOAN, TRADE*), asset quality (*LLP*), liquidity risk (*DEPO*) and profitability (*EBPT*). Further, *(Country characteristics)* considers current fiscal and monetary policy changes by utilising countries' macroeconomic fundamentals such as economic growth (ΔGDP), and unemployment growth ($\Delta UNEM$). Finally, I incorporate bank-specific fixed effects (α), quarterly fixed effects (δ) and the residual (ε).

4.5. Results

4.5.1. Event study results

First, I conduct a short-term event study to test if stress tests provide new information that disciplines banks (*H1a*, *H1b* and *H1c*). I display the event study results for the European and U.S. markets in the following sub-sections.

4.5.1.1. Short-term disciplining effects in Europe

In Table 4.5, Panels A, B and C, I illustrate the average *CARs* of the three distinct models (CAPM, FF3F and C4F), whilst Panel D shows the average *BHARs* of the market return model (MRM). I estimate the average *CARs* and *BHARs* separately for each European stress test event (i.e., for the assessments in 2010, 2011, 2014, 2015, 2016 and 2018), for the observations of the first-time (FTSTO) and total (TOTALSTO) stress test participation.

[Please refer to Table 4.5 here]

In the context of *H1a*, I observe the separate impact of each stress test exercise on share price returns of participating banks. It may be seen that, on average, stress tests do, on certain occasions, affect share price returns in the short-term. For example, for the EBA stress test in 2011, the event window t–1, t+5 accounts for a model-consistent positive *CAAR* that is statistically significant at the confidence levels of 1% and 10%. In economic terms, when applying the C4F baseline model (Panel C), the realised return of the stress-tested bank's share is 3.18% higher than the expected return measured within the estimation window. In support of the results, I find statistically significant average *BHARs* at event windows t–1, t+4. I also document significant *BHARs* for the initial stress test exercise in 2010 at different event windows (i.e., that of t–1, t+1; t–1, t+2; t–1, t+4; and t–1, t+7); however, these results are not supported by significant average *CARs* across the other models. Similarly, the ECB's comprehensive assessment in 2014 states average *CARs* that are positive and statistically significant at the 5% confidence level (i.e., that of t–1, t+1). The 2015 ECB's Greek assessment is a special case and includes four large Greek banks as a follow up to the 2014 exercise. The results for this stress test show positive, but insignificant, short-term *BHARs* (t–1, t+1 event window) that turn into a significant negative impact in the longer run (t–1, t+5 event window). On the other hand, the recent EBA stress tests in 2016 and 2018 do not trigger any statistically significant market responses.

After analysing the stress tests on a separate basis, I scrutinise the impact of first-time (FTSTO) and total (TOTALSTO) stress test participation. First-time participation may be more informative or surprising than subsequent participation, in particular, if banks are stress-tested on a regular basis (*H1b*). In Table 4.5, the *CARs* and *BHARs* for first-time participation (FTSTO) are positive and statistically significant at the 3-day event window (t–1, t+1). In economic terms, employing the C4F baseline model (Panel C), the realised return of the stress-tested bank's share is 1.34% higher than the expected return measured within the estimation window. In contrast, for total stress test participation (TOTALSTO), I do not find significant average *CARs*. It is only in Panel D, that the 3-day *BAHR* (at t–1, t+1 event window) is positive and statistically significant (0.65%), whilst the 4-day *BHAR* (t–1, t+2) for FTSTO is also positive and significant (2.08%). This result indicates that, in support of *H1b*, the effect of stress tests is stronger and lasts marginally longer when experienced for the first time, compared to taking all stress test events together (TOTALSTO).

The results of the recent European stress tests from 2014 to 2018 imply that, on average, the provided information mainly conforms with market expectation (Sahin and de Haan, 2016). On the other hand, the latter results indicate that the earlier stress test in 2011 and the first-time stress test event provide additional information that is new to the markets (Petrella and Resti, 2013). As it is a positive market response, stress-tested banks are rewarded and not disciplined. This could be also explained by the growing confidence in the banking system after the 2008 financial crisis (Schuermann, 2014). However, the average market reaction on stress-tested banks' abnormal returns is not immediate and takes a few days to develop. The slight delay could be also partly explained by the stress test result release dates, which were on a Friday afternoon, when European markets were already closed (Petrella and Resti, 2013).

Interestingly, in the context of *H1c*, the truth may be deeper than within the average *CAR* and *BHAR* analysis. In Tables 4.5A and 4.5B, I evaluate the individual *CARs* of the baseline model C4F at the standard 3-day event window (t–1, t+1) for each stress-tested bank. I find that the observations are usually split into an almost equal number of banks with positive (Table 4.5A) and negative (Table 4.5B) abnormal returns. This holds true in particular for the recent stress test exercises in 2016 and 2018. Therefore, this discrepancy of stress test experience among participating banks might contribute to the fact that the average results reported in Table 4.5 are only occasionally significant. This tendency may also be seen in Figures 4.1 and 4.2, where I illustrate the evolvement of the average *CARs* for banks that experience a positive and a negative *CAR* at the 3-day event window.

[Please refer to Tables 4.5A and 4.5B here]
[Please refer to Figures 4.1 and 4.2 here]

Accordingly, Tables 4.5A and 4.5B show that, for all exercises (and in support of *H1c*), the stress test event is an accelerating factor that contributes to the general trend of the share price. In 2010-11, the stress test exercises exacerbate both the positive and negative market trend. In particular, in Figure 4.1, the stress test effect of both assessments remains stable over the 10-day period after the event date (t_0) and is on average positive. However, supported by the average *CARs* in Table 4.5A, in 2011 the positive response is numerically stronger, compared to 2010, and increases from the shorter (t–1, t+1) to the longer (t–1, t+5) event windows. The converse holds true for the 2010 stress test, where the negative trend is more persistent in the longer (t–1, t+5) event window (see

Table 4.5B). This result is consistent with previous studies who confirm the market success of the 2011 over the 2010 stress test (Borio et al., 2014; Schuermann, 2014). In 2014, the stress test event exacerbates almost equally the positive and negative trend, whilst both the negative and positive effects decline over the 10-day period after the event. In 2016 and 2018, there is a positive and a negative short-term market reaction (t–1, t+1 event window). Although in 2016 both responses are not significant among all models over the longer event windows (t–3, t+3; t–1, t+5), in 2018 the negative trend remains strong for those windows. Interestingly, in 2016 and 2018, the stress test event appears to be a turning point for share performance. Banks that report positive average *CARs* before the stress test event turn negative after the event and *vice versa*.

Analysing the positive and negative market responses of first-time participation (FTSTO) and total stress test participation (TOTALSTO), it may be seen that the negative market responses are more persistent than the positive responses. On the positive side (Table 4.5A), the response for the 3-day stress test event window (t–1, t+1) does not differ much, whether it is for the first time or total stress test participation. However, the first-time positive response remains stronger in the longer event windows in comparison to the positive market response of the total participation. On the negative side, the two market responses show a similar pattern. However, for both cases, the negative market response remains equally strong or gets even more powerful, while the positive response slightly deteriorates in longer event windows. Therefore, the market's reward seems to be forgotten quickly, but the market's punishment appears to damage the reputation sustainably.

In summary, I may conclude that stress test participation in Europe is acknowledged by the markets on certain occasions. In particular, the earlier stress test in 2011 and the first-time participation event provide more surprising (positive) results that are rewarded by the markets, whilst the recent exercises are mainly insignificant and therefore anticipated. Moreover, stress tests may exacerbate positive and negative share performance. Hence, regulators should be mindful of the consequences for weaker institutions, as investors may punish those banks even more.

4.5.1.2. Short-term disciplining effects in the U.S.

In Table 4.6, Panels A, B and C, I illustrate the average *CARs* of the three distinct models (CAPM, FF3F and C4F), whilst Panel D shows the average *BHARs* of the market return model (MRM). I estimate the average CARs and BHARs separately for each U.S. stress test event (i.e., for the assessments in 2009, 2011, 2012, 2013, 2014, 2015, 2016, 2017 and 2018), for the observations of the first-time (FTSTO) and total (TOTALSTO) stress test participation. Since 2013, the Federal Reserve discloses DFAST and CCAR within a very short period (usually 4-5 trading days) and the first event (DFAST) might influence the market response of the subsequent event (CCAR). Therefore, I not only provide results including all stress test observations but also show separate results excluding potentially related CCAR results.

Analysing the individual assessments to test *H1a*, I find that only one third of the stress tests indicate statistically significant abnormal returns and if significant, the overall market reaction is mainly affirmed by a negative abnormal return (four out of five cases). On average, therefore, the release of stress test information in the U.S. appears to either align with market expectation or 'bad' news that leads to disciplining actions by the markets. In particular, I document positive *CAARs* for the CCAR 2012 that are statistically significant at the 10% confidence level. In economic terms, applying the C4F baseline model (Table 4.6, Panel C) and a 7-day event window (t–1, t+5), the realised return of the stress-tested bank's share yields 2.12% higher, compared to the return that I would expect based on the estimation window.

[Please refer to Table 4.6 here]

On the other hand, the assessments in 2013 (CCAR), 2016 (DFAST), 2017 (CCAR) and 2018 (CCAR) show negative and statistically significant abnormal returns. Therefore, the capital exercise seems to provide more interesting and surprising results than the DFAST. Investors might also wait for the final results to pursue their investment decision. In all cases, the abnormal return and market reaction is purely negative across short-term (t–1, t+1; t–1, t+2) and longer event windows (t–3, t+3; t–1, t+5). In economic terms, considering the C4F baseline model (Table 4.6, Panel C) and a 3-day (t–1, t+1) event window, the realised return of the stress-tested bank's share is -1.41% (CCAR 2013), -1.13% (CCAR 2017) and -0.83% (CCAR 2018) lower compared to the expected return within the estimation window. For the longer 7-day event window (t–3, t+3) the abnormal returns yield -2.12% (CCAR 2013), -0.95% (CCAR 2017) and -1.08% (CCAR 2018). In support of Flannery et al. (2017), the market response is numerically stronger for the earlier exercises in 2012 and 2013, compared to the later assessments in 2017 and 2018.

In terms of *H1b* and the first-time (FTSTO) and total (TOTALSTO) stress test participation, the results indicate that on average, first-time participation is not consistently significant, while the abnormal return for total participation is negative and significant for the 7-day event window (t–3, t+3). In economic terms, considering the C4F baseline model (Table 4.6, Panel C) and a 7-day event window, the realised return of the stress-tested bank's share is -0.69% (-0.71% excluding double CCARs) below the expected return based on the estimation window. The results are mainly the same whether I include or exclude the CCAR exercises (due to the double stress test approach).

Next, I split the stress test observations into banks that experience a positive or negative ($CAR_{t-1,\ t+1}$) employing the C4F baseline model to test *H1c*. In contrast to the European case, the number of banks that report a positive and a negative market response ($CAR_{t-1,\ t+1}$) may vary significantly from one exercise to another. In particular, the SCAP 2009 exercise reports an almost even proportional split and indicates strong positive development for eight participating banks, whilst nine banks experience a strong negative development. In economic terms, applying the C4F baseline model and a 3-day event window, the realised return of the stress-tested bank's share yields 13.66% above (Table 4.6A, Panel C) or -9.63% below (Table 4.6B, Panel C) the return that I would expect based on the estimation window, respectively. This is consistent with previous literature (Flannery et al., 2017; Morgan et al., 2014) who also found significant market reactions for this exercise, as well.

[Please refer to Tables 4.6A and 4.6B here]

[Please refer to Figures 4.3, 4.4, 4.5, 4.6 and 4.7 here]

On the other hand, the majority of banks (11 out of 17 banks) of the CCAR 2012 experience a positive market response which supports my previous results in Table 4.6. Similarly, I find that both DFAST and CCAR assessments in 2015 report more banks (17 and 15 out of 26 banks) with positive abnormal returns ($CAR_{t-1,\ t+1}$), whilst both the DFAST and CCAR exercises in 2013 (11 and 15 out of 17 banks) and 2017 (22 and 20 out of 28 banks) document more banks with negative abnormal returns ($CAR_{t-1,\ t+1}$). Interestingly, for the stress tests in 2014, 2016 and 2018, the number of banks may even vary from DFAST to CCAR. For example, more banks report a negative abnormal return at DFAST 2014 (13 out of 23 banks), but at CCAR 2014 (just 5 days later), the number turns to a majority of banks with a positive abnormal return (17 out of 23 banks). This is the same for the 2016 DFAST (17 out of 26 banks) and CCAR (16 out of 26 banks) that report a negative and then a positive abnormal return, respectively. The converse holds true for the 2018 exercise where the DFAST reports more banks with a positive abnormal return (13 out of 24 banks) that turns negative at the CCAR (20 out of 24 banks).

Consequently, I document that the stress tests in 2012 and 2015 exacerbate the positive trend of stress-tested banks, while the 2013 and 2017 show a negative trend. Further, the market response may even change from DFAST to CCAR, as indicated by the results of the assessments in 2014 and 2016 that turn positive and the stress test in 2018 that turns negative.

When I analyse the positive and negative observations for first-time (FTSTO) and the total (TOTALSTO) participation, the abnormal returns are statistically significant across all event windows and almost evenly split between positive and negative market responses ($CAR_{t-1,\, t+1}$). In particular, the positive market reaction is numerically stronger than the negative market reaction for the short-term 3-day and 4-day event windows (i.e., t–1, t+1; t–1, t+2), whilst the negative market reaction is more forceful in the long-term 7-day and 6-day event windows (i.e., t–3, t+3; t–1, t+5). Overall, I may conclude that the positive and negative returns are equally strong in numeric terms but may vary significantly from one exercise to another, whilst the negative abnormal returns usually remain stable over the longer event windows compared to the positive responses that deteriorate over time. This holds true, in particular, for the initial SCAP in 2009 as well as for the first-time (FTSTO) and total stress test participation (TOTALSTO).

4.5.1.3. Long-term disciplining effects of stress test exercises

Next, I analyse the long-term effect of stress test information on bank returns. In particular, I am interested whether stress-tested banks over- or under-perform the markets following a stress test event (*H2*). In Table 4.7, I show the calendar-time portfolio (CTIME) results for the European (Panel A) and the U.S. (Panel B) samples. I illustrate the results for both jurisdictions and all stress test events 1 to 12, 24 and 36 months after the stress test event using the baseline Carhart (1997) four-factors model (C4F). Further, I estimate the CTIME-coefficients employing equal and value weights. The value weights are based on bank market value (*MVALUE*). The variable of interest is ‘alpha’ (also known as ‘Jensen’s alpha’) which denotes the intercept of the four-factor model. A significant ‘alpha’ means that the stress-tested banks’ portfolio produces abnormal returns that either over (positive coefficient) or under-perform (negative coefficient) the market.

In addition, the four factors capture asset sensitivity to market risk (*BETA*), the difference between small and big firms' shares (*SMB*), the difference between high and low market-to-book ratio shares (*HML*) and the momentum of the shares (*MOM*).

[Please refer to Table 4.7 here]

In Table 4.7, Panel A, the results of the equally- or *MVALUE*-weighted portfolio show that, on average, European stress-tested banks do, on certain occasions, over- or under-perform the market portfolio after a stress test event (which is indicated by a significant 'alpha'). First, scrutinising the individual EBA stress test in 2011 (2), I can see stress test participants over-perform the market in the period 1-12 months following the stress test event. The 'alpha' coefficient is positive and statistically significant at the 10% confidence level. In economic terms, the portfolio of stress-tested banks outperforms the market by 0.34% in the long-run. Second, the EBA/ECB assessments in 2014 (3) of which the results were jointly announced produce negative and statistically significant 'alphas' at the 1% and 5% confidence levels; however, this is only for the *MVALUE*-weighted portfolio. Therefore, when I weight larger banks more than smaller ones, stress-tested banks under-perform the market by -0.22% and -0.18% in the periods 1-12 and 1-24 months following the stress test event, respectively. Both results are in support of the overall market sentiment that I could measure in the short-term event study, which show a positive and negative trend in 2011 and 2014, respectively. On the other hand, when I analyse the individual CEBS 2010 (1) and EBA 2016 (4) stress test, as well as the first-time participation (5) and the total stress test participation (6), stress-tested banks' stocks do not perform significantly different from the market.

Similar to the European market, I find that U.S. stress-tested banks occasionally over- and under-perform the market in the long-run. In Table 4.7, Panel B, the results of the equally- or *MVALUE*-weighted portfolio show that, on average, U.S. stress-tested banks produce statistically significant 'alphas' for the individual U.S. stress tests in 2011, 2012, 2013, 2015 and 2016. In particular, in 2011 and 2012, the 'alphas' of the equally-weighted portfolios are positive and statistically significant at the 5% and 10% confidence levels, respectively. This result indicates that stress-tested banks' stocks over perform the market by 0.12% and 0.20% in the period 1-12 months following the 2011 and 2012 assessments, respectively. Interestingly, as the short-term results (in Table 4.6) are not strongly significant for those two exercises, the markets' confidence might have been restored in the long-run due to the regulatory changes made at that time (i.e., Dodd-Frank Act).

Similarly, for the CCARs in 2015 and 2016, I report positive and statistically significant ‘alphas’, which are, however, numerically lower (i.e., 0.08% and 0.11%, respectively) than for the earlier stress tests in 2011 and 2012. In contrast, the CCAR 2013 yields negative and statistically significant ‘alphas’ at the 1% and 5% confidence levels. The result of stocks’ under-performance remains persistent, in particular, for the *MVALUE*-weighted portfolio, which is significant for the periods 1-12 (-0.23%) and 1-24 (-0.18%) months after the exercise. This result might be partly explained by the intensity of the stress test, as it was the first time that two exercises were released in such a short period of time (i.e., DFAST and CCAR). On the other hand, when I analyse the individual SCAP 2009 (1), CCAR 2014 (5) and CCAR 2017 (8) as well as the first-time participation (9) and the total stress test participation (10), stress-tested banks’ stocks do not perform significantly differently from the market.

In another vein, the results for the European and U.S. stress-tested banks show that the beta coefficient (*BETA*) that represents the asset’s sensitivity to market risk is in most cases statistically significant at the 1% confidence level. Further, *BETA* is usually below 1, indicating that stress-tested banks stocks have lower volatility than the market. Only for the 2011 and 2014 European stress test exercises, does the *MVALUE*-weighted portfolio yield a *BETA* exceeding 1. This implies that when I give a stronger weight on larger banks than smaller ones, the stress-tested banks’ stocks have a higher volatility and, therefore, sensitivity to market risk. This might contribute towards the under-performance of the European stress-tested banks in 2014. Similarly, the U.S. banks that over- or under-perform in the periods after the CCAR 2012, 2013, 2015 and 2016 have a *BETA* exceeding 1, which is consistent with the performance and perhaps a contributing factor. In addition, I find that in the U.S. the momentum factor is negative and statistically significant, in particular analysing first-time (FTSTO) and total (TOTALSTO) stress test participation. This further strengthens the overall result that stress tests appear to be seen as ‘bad’ news leading to the trend that stock performance might be influenced negatively.

4.5.2. Fundamental analysis

In this section, I analyse whether stress tests may incentivise investors and debtholders to influence bank behaviour. I first explore the conversion of stress test information into reduced information asymmetry and increased analyst coverage. Second, I scrutinise if the influencing effect leads to decreased bank risk-taking behaviour and improved funding structures.

4.5.2.1. Information asymmetry and analyst behaviour

In the context of *H3* and *H4*, I analyse the impact of stress test disclosures on information asymmetry and analyst information production. In Table 4.8, I illustrate the results of the time-series analysis for the European (Panel A) and the U.S. (Panel B) samples. I measure information asymmetry using the bid-ask spread (*BIDASK*) as well as analyst behaviour applying analyst coverage (*RECNO*), earnings surprises (*EPSSUR / PRICE*) and estimate dispersion (*ESTSD / PRICE*).

[Please refer to Table 4.8 here]

In Europe, I report mixed results on information asymmetry (Model 1) when analysing the various stress test periods in 2010-11 (*ST1011EU*), 2014-15 (*ST1415EU*) and 2016 (*ST16EU*). First, the time-dummy *ST1011EU* is positive and significant at the 10% confidence level, implying an increased level of information asymmetry in the stress test period in 2010-11. Then, information asymmetry in 2014-15 decreases as the time-dummy *ST1415EU* turns negative and significant at the 5% confidence level. Further, in 2016, the level of information asymmetry remains negative (*ST16EU*), but the coefficient is statistically insignificant. Comparing the first-time participants in 2010-11 with later first-time participants, I find that the interaction term *ST1011EU*FTST1011EU* is negative and significant at the 10% confidence level, whilst the interaction term *ST1415EU*FTST1011EU* is positive and significant at the 5% confidence level. This result indicates that first-time participants in 2010-11 experience less information asymmetry when they were stress-tested for the first time. However, the effect of the stress test on the level of information asymmetry deteriorates at the later exercises.

In terms of analyst behaviour, I document in Model 2 that the time-dummy *ST1011EU* and interaction term *ST1011EU*FTST1011EU* are positive and statistically significant at the 5% confidence level. This result implies that analysts produce more analyst recommendations (*RECNO*) during stress test periods in 2010-11. Interestingly, this result turns negative for the later stress test in 2016. Further, examining the analyst earnings surprises and estimate dispersion in Models 3 and 4, only the stress tests in 2010-11 affect analyst earnings forecasts. Therefore, in support of prior analysis stress test results influence analyst behaviour in the earlier stress tests in terms of analyst coverage and earnings forecasts, however, this deteriorates for the recent stress tests.

In the U.S., the time-dummy variables *ST0913US* and *ST1417US* in Model 1 are negative and significant at the 5% and 10% confidence levels, respectively. Therefore, information asymmetry is reduced during the initial (2009-2013) and recent (2014-2017) exercise periods. Considering analyst coverage (Model 2), only the time-dummy variable *ST0913US* is negative and significant at the 10% confidence level, while the time-dummy *ST1417US* is negative but insignificant. This result indicates that the analyst coverage significantly decreases during the initial but not the recent stress test periods. Moreover, the results are supported by the analyst earnings surprises in Model 3. In particular, I find that in this model the time-dummies (*ST0913US* and *ST1417US*) are positive and significant at the 5% and 10% confidence levels, whilst the interaction term *ST0913US*FTST09US* is negative and significant. In economic terms, earnings surprises rise 10.57% and 4.41% during the initial and recent stress test periods, respectively. The results indicate, therefore, that the actual earnings are higher than analyst expectations. Further, the actual earnings of the first-time participants in 2009 are lower than expected by analysts (-2.23%). On the other hand, in Model 4, the variables of interest are not statistically significant, implying that analyst estimates are not significantly dispersed.

Overall, I find mixed results on information asymmetry and analyst behaviour in both European and U.S. markets. In Europe, it appears that the 2010-11 first-time stress test participants, compared to the 2014 counterparts, may experience reduced information asymmetry and increased analyst coverage, whilst the dispersion of analyst earnings forecasts may be higher indicating some uncertainty among analysts. In the U.S., I conclude that stress tests may have some effect on information asymmetry, analyst coverage and earnings surprises. However, in compliance with Flannery et al. (2017), the results are inconclusive and do not fully support Goldstein and Sapra's (2013) hypothesis that analysts follow stress test results more than their own produced information.

4.5.2.2. Bank risk-taking and funding structure

To test *H5* and *H6*, I examine the influencing effect of investors and depositors on bank risk-taking activities and funding structure. I show the results for bank risk-taking in Table 4.9 and funding structure in Table 4.10. Both tables are split into the European (Panel A) and the U.S. (Panel B) samples. I measure bank risk-taking by employing capital adequacy (*T1R*), leverage risk (*LEVERAGE*) and credit risk (*RWA*). In addition, I estimate credit portfolio quality (*LLR*), insolvency risk (*ZSCORE*) and profitability (*ROA*). In terms of bank funding structure, I shed light on total (*TIE*) uninsured (*OIE*) and insured (*IECD*) funding cost as well as uninsured (*DEPBA, SUBD*), insured funding (*CUSTD*) and interest margin (*NIM*).

[Please refer to Tables 4.9 and 4.10 here]

Table 4.9 (Panel A), that displays bank-risk taking (*H5*), illustrates that almost all time-dummies (except that of Model 5) that measure the 2010-11 (*ST1011EU*), 2014-15 (*ST1415EU*) and 2016 (*ST16EU*) stress test periods are statistically significant. In particular, the results show that for European stress-tested banks capital adequacy (*T1R*) and credit portfolio quality (*LLR*) has increased, whilst the credit risk (*RWA*) and leverage risk (*LEVERAGE*) has decreased during stress test periods. Also, both the insolvency risk (*ZSCORE*) and profitability (*ROA*) have fallen. Therefore, the variables mainly indicate that bank-risk taking significantly decreased during stress test periods. Further, in Model 5 (that yields insolvency risk) the interaction term *ST1011EU*FTST1011EU* is positive and statistically significant at the 1% confidence level, while the one in Model 6 (that is on profitability) is negative and significant at the 1% confidence level. This result suggests that first-time participants in 2010-11 are sounder compared to banks that are tested at a later stage. However, at the same time, these banks generate fewer earnings. Moreover, in Model 1 the interaction term *ST1415EU*FTST1011EU* is negative and significant at the 10% confidence level, indicating that newly involved first-time participants in 2014 have more adequate capital than regular participants from 2010-11.

In contrast, in the U.S. (Panel B), the results for bank risk-taking are mixed. On the one hand, I find that in Models 1, 5 and 6 the time-dummies that indicate the initial 2009-13 (*ST0913US*) and 2014-17 (*ST1417US*) stress test periods are positive and statistically significant at the 1% and 10% confidence levels. Therefore, stress-tested banks account higher capital adequacy (*T1R*), profitability (*ROA*) and lower insolvency risk (*ZSCORE*) during stress test periods. On the other hand, in Models 3 and 4, credit portfolio quality (*LLR*) and credit risk (*RWA*) are only occasionally significant comparing stress test participants and periods, whilst in Model 2 leverage risk (*LEVERAGE*) is entirely insignificant. The results suggest that banks react during stress test periods by raising the capital base (*T1R*) consistent with regulatory requirements; this affects their insolvency risk (*ZSCORE*) and overall soundness. However, in terms of leverage risk

(*LEVERAGE*), credit risk (*RWA*) and credit portfolio quality (*LLR*), stress test participants do not change during stress test periods. This result is consistent with the increase in profitability (*ROA*). Overall, I conclude that in both jurisdictions (Europe and U.S.), bank risk-taking is reduced as, in particular, higher capital base (*T1R*) and lower insolvency risk (*ZSCORE*) indicate a more robust banking system. The results are more profound in Europe (than in the U.S.), as decreased risk-taking is also reflected in leverage risk (*LEVERAGE*), credit risk (*RWA*) and credit portfolio quality (*LLR*).

Table 4.10 (Panel A), that displays the funding structure (*H6*), shows that almost all time-dummies (except those of Models 3 and 5) that measure the 2010-11 (*ST1011EU*), 2014-15 (*ST1415EU*) and 2016 (*ST16EU*) stress test periods are statistically significant. Importantly, stress-tested banks have lower total (*TIE*), insured (*IECD*) and uninsured (*OIE*) funding costs during stress test periods, indicating that those banks experience lower market discipline from depositors. However, the interest margin (*NIM*) in Model 6 is negative; this shows that stress-tested banks also appear to earn less interest income, which is consistent with prior results on profitability (*ROA*). Further, the insured funding (*CUSTD*) is not statistically significant, whilst uninsured funding (*DEPBA*) is negative and significant at the 1% confidence level. This result indicates that stress-tested banks experience market discipline from decreased bank deposits but not from customer deposits. Further, in Model 3, the interaction term *ST1011EU*FTST1011EU* is negative and statistically significant, while both later interaction terms *ST1415EU*FTST1011EU* and *ST16EU*FTST1011EU* are positive and significant. Hence, the first-time participants in 2010-11 experienced stronger market discipline from decreased uninsured funding (*DEPBA*). In recent years, confidence has been restored and the earlier first-time participants experience lower market discipline from uninsured funding than recent ones.

In the U.S. (Panel B), I report mixed results on funding structure for banks during stress test periods. In Model 1, the time-dummies that measure the 2009-13 (*ST0913US*) and the 2014-17 (*ST1417US*) stress test periods are positive and statistically significant, indicating higher total funding costs (*TIE*) during stress test periods. Further, for both periods, stress-tested banks experience higher customer deposits (*CUSTD*) and a higher interest margin (*NIM*). This result indicates that stress-tested banks are exposed to higher total interest expenses (*TIE*), which are, however, due to increased customer deposits (*CUSTD*). In turn, banks are capable of generating interest margins (*NIM*), which are consistent with prior results on profitability (*ROA*). On the other hand, in Models 2, 3 and 4, the variables of interests are insignificant, indicating that the uninsured funding (*SUBD*), together with the costs for uninsured (*OIE*) and insured funding (*IECD*) are unaffected by stress tests. Overall, I conclude that U.S. stress-tested banks' funding structure is generally unaltered by market discipline.

The result may be also partly explained by the significantly lower interest rates imposed by the ECB and Federal Reserve and by deposit insurance schemes that have been implemented during and after the 2008 financial crisis. Nevertheless, the results show that, on certain occasions, stress-tested banks experience stronger market discipline which is reflected in their accounting fundamentals.

4.6. Robustness analysis

In this section, I run several robustness checks to ensure that the results of my econometric analysis are valid and free from confounding factors. Main tests are shown in Table 4.11 and additional robustness checks are provided in the APPENDIX (Tables A.15 to A.19).

4.6.1. Event study robustness

Based on the recent stress test literature, the main concern for event study analyses is the choice of the relevant event and estimation windows, the underlying asset pricing model and the statistical significance tests. As explained in Section 4.4.4.1, I construct numerous models to estimate the abnormal returns. In particular, I calculate average *CAR* and *BHAR* estimates for different event windows using the capital asset pricing model (CAPM), the Fama and French (1993) three-factors model (FF3F) and the Carhart (1997) four-factors model (C4F). The combination of these three models already confirms statistical robustness of my findings across the models. However, the baseline results depend on the defined 200-day estimation window. The literature employs different lengths of estimation windows that are usually between 120-250 days (Flannery et al., 2017; Morgan et al., 2014; Petrella and Resti, 2013). As I use a long-term 200-day estimation window in the baseline analysis that, on some occasions, overlaps with the previous year's stress tests (e.g., 2010-11), I apply a shorter 120-day estimation window to verify the results.

[Please refer to Table 4.11 here]

In Table 4.11 (Panel A: Europe; Panel B: U.S.), I display the results of the baseline C4F-model for the 120-day estimation window. I find that the results do not differ when I use a shorter event window. Further, as abnormal returns are usually right-skewed, I test the statistical significance of the abnormal returns using an alternative significance test. In Table 4.11 (Panel C: Europe; Panel D: U.S.), I show the statistical significance of the abnormal returns based on Patell (1976). As the Patell (1976) standardised residual test is of parametric nature, the results are marginally different in contrast to the baseline analysis; however, these do not alter my conclusions. Overall, I constitute that the robustness checks provide similar results that are in support of the baseline analysis.

4.6.2. Additional robustness checks

In addition, to the robustness checks in Section 4.6.1, I run various additional tests to further support the resilience of the baseline results (shown in the APPENDIX, Tables A.15 to A.19). First, in Table A.15 (Panel A: Europe; Panel B: U.S.) I run the calendar-time portfolio (CTIME) analysis using the Fama and French (1993) three-factors model (FF3F) as an alternative approach. Due to the nature of the FF3F model, which does not consider the momentum factor, the results vary slightly compared to the baseline analysis, which, however, support my main conclusions. Second, in Table A.16, I test the baseline time-series approach on funding structure using an additional control variable for sovereign debt risk; this is measured by the difference in short- and long-term government bonds' interest rates (*IRATE*). Part of the results on the cost and structure of bank funding could be explained by the low interest rates and the European sovereign debt crisis. The findings do not differ when I include sovereign debt risk.

Finally, I follow studies that exclude certain banks that might drive the results. From the European sample, I remove inactive banks (i.e., bankruptcies, M&As) because the results might be influenced by bank survival actions (Beatty and Liao, 2011). Further, following other U.S. research (Cornett et al., 2019; Flannery et al., 2017), I adjust the U.S. sample by deleting banks that are owned by foreign parent banks (i.e., non-U.S. subsidiaries) and are not purely representative of the U.S. market. In Table A.17 (Panel A: Europe; Panel B: U.S.), I provide the results on information asymmetry. Table A.18 (Panel A: Europe; Panel B: U.S.) shows banks' risk-taking and Table A.19 (Panel A: Europe; Panel B: U.S.) illustrates bank funding structure. In summary, the findings are similar compared to the baseline analysis and in support of my main conclusions.

4.7. Concluding remarks

The literature has analysed certain aspects of bank stress tests and their potential costs and benefits. For instance, U.S. studies by Flannery et al. (2017) provide implications of stress tests on transparency and analyst information production. Acharya et al. (2018) display that stress-tested banks reduce credit supply with the intention of enhancing capital adequacy, while Cornett et al. (2019) find increased lobbying activities of stress test participants. In Europe, Bischof and Daske (2013) show that banks disclose additional sovereign risk information and Gropp et al. (2019) conclude that banks manage capital ratios. However, the studies do not comprehensively scrutinise how stress tests contribute to market discipline to safeguard financial stability. Therefore, my study provides an empirical analysis on all European and U.S. stress tests that further sheds light on the disciplining effect of stress tests concerning market sentiment and bank fundamentals.

In particular, I document that in Europe and the U.S. market responses depend on the particular stress test exercise and do not follow a certain pattern. On certain occasions, in Europe, I constitute positive market responses (e.g., the 2011 exercise), while in the U.S., I report mainly negative responses (e.g., the assessments in 2013, 2016, 2017 and 2018). However, whilst the majority of stress tests largely conform to market expectations, my analysis shows that there is an on-going trend of abnormal returns triggered by the initial stress test market response. In particular, bank shares that experience a positive or negative market response around the event day (3-day window), are largely exacerbated towards this upward or downward trend, respectively. Furthermore, I show that the positive or negative momentum may convert into long-term ‘alphas’ implying that bank stocks over- or under-perform in relation to the market portfolio. Consequently, market discipline is enforced on weaker banks, while stronger banks are rewarded (Bouvard et al., 2015). Analysing bank fundamentals, I find consistent evidence of market discipline as information asymmetry declines and European banks reduce risk-taking activities; in addition, they report improved funding structures during stress test periods. In contrast, U.S. banks only display partial signs of market discipline within their accounting figures.

I conclude from this study that regulators and supervisors need to consider the market sentiment to identify the specific purpose of the stress test. A stress test may be useful at restoring or maintaining market confidence (Borio et al., 2014). However, a regular stress test setting may not be needed for this purpose, as markets only occasionally respond to stress test information. This indicates that markets are already well-informed about bank risk profiles and might not need a particular regulatory signal. Further, more transparency from stress tests does not automatically promote market discipline where it is most needed. In recent years, regular European (in 2014) and U.S. (in 2016, 2017 and 2018) stress tests have led to negative abnormal returns that penalise bank behaviour. However, the results also show that stress tests exacerbate abnormal returns in either positive or negative direction. In this way, stress test information may lead to market discipline on weaker institutions. This might be an unintended consequence as weak banks might struggle more contributing to financial instability. Overall regulators need to be mindful of the information provided by stress tests. As suggested by the literature, more intense regulation and supervision without detailed disclosures could be a more suitable approach (Goldstein and Sapra, 2013).

Table 4.1 Variable definitions and data sources

Abbreviation	Variable	Description	Data source
T1R	Capital adequacy	Regulatory Tier 1 capital divided by risk-weighted assets	BvD Bankscope, Bank reports, FitchConnect
LEVERAGE	Leverage risk	Natural logarithm of leverage ratio: total liabilities divided by total equity	BvD Bankscope, Bank reports, FitchConnect
RWA	Credit risk	Risk-weighted assets scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
LLR	Credit portfolio quality	Loan loss reserves for non-performing or impaired loans scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
ZSCORE	Insolvency risk	Natural logarithm of Z-Score that equals return on assets plus capital asset ratio divided by standard deviation of asset returns	BvD Bankscope, Bank reports, FitchConnect
ROA	Profitability	Return on assets: earnings before taxes divided by total assets	BvD Bankscope, Bank reports, FitchConnect
TIE	Total funding cost	Total interest expenses scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
OIE	Uninsured funding cost	Interest expense on all non-customer deposit liabilities (uninsured) scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
DEPBA	Uninsured funding	Deposits from banks (uninsured) scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
SUBD	Uninsured funding	Subordinated debts (uninsured) scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
IECD	Insured funding cost	Interest paid on customer deposits (insured) scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
CUSTD	Insured funding	Customer deposits (insured) scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
NIM	Interest margin	Net interest margin (net interest divided by total average earning assets)	BvD Bankscope, Bank reports, FitchConnect
SIZE	Bank size	Natural logarithm of total assets	BvD Bankscope, Bank reports, FitchConnect
LOAN	Traditional banking activities	Outstanding loans scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
LLP	(Forward-looking) asset quality	Loan loss provisions for non-performing or impaired loans scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
TRADE	Non-traditional banking activities	Trading securities scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
DEPO	Liquidity risk	Total deposits (market share of deposits) scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
EBPT	Profitability	Earnings before provision and taxes scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
OBSI	Off-balance sheet activities	Off-balance sheet items scaled by lagged total assets	BvD Bankscope, Bank reports, FitchConnect
BIDASK	Information asymmetry	Quarterly average of daily bid-ask-spreads (Ask – Bid / (Ask + Bid / 2))	Thomson Reuters (Datastream/IBES)
RECNO	Analyst coverage	Quarterly average of the daily number of analysts filing a recommendation	Thomson Reuters (Datastream/IBES)
EPSSUR / PRICE	Earnings surprise	Quarterly average of the daily difference between the actual and estimated earnings per share scaled by the average share price of the previous quarter	Thomson Reuters (Datastream/IBES)
ESTSD / PRICE	Estimate dispersion	Quarterly average of daily standard deviation of all earnings per share estimates scaled by the average share price of the previous quarter	Thomson Reuters (Datastream/IBES)
TOVER	Share turnover	Quarterly average of the daily number of shares outstanding scaled by free float	Thomson Reuters (Datastream/IBES)
INVPRICE	Inverse share price	Quarterly average of 1 divided by daily share price	Thomson Reuters (Datastream/IBES)
RETVOL	Return volatility	Quarterly average of the daily standard deviation of continuously compounded share price returns	Thomson Reuters (Datastream/IBES)
MVALUE	Market value	Quarterly average of the daily natural logarithm of market value of equity	Thomson Reuters (Datastream/IBES)

Table 4.1 continued

MTBV	Market-to-book value	Quarterly average of the daily market value of equity divided by the book value of equity	Thomson Reuters (Datastream/IBES)
RECCON	Analyst recommendation consensus	Quarterly average of the daily recommendation consensus of analysts; yields the mean of all daily recommendations: Strong-buy (1-1.49), moderate-buy (1.5-2.49), hold (2.5-3.49), moderate-sell (3.5-4.49), strong-sell (4.5-5)	Thomson Reuters (Datastream/IBES)
FTST1011EU	European first-time participation in the 2010-11 stress tests	A binary variable that yields 1 for all banks that were tested for the first time in 2010-11, and 0 otherwise	EBA and ECB stress test disclosures
ST1011EU	European stress test period in 2010-11	A binary variable that yields 1 for the European 2010-11 stress test period (2010Q2-2012Q1), and 0 otherwise	EBA and ECB stress test disclosures
ST1415EU	European stress test period in 2014-15	A binary variable that yields 1 for the European 2014-15 stress test period (2014Q2-2016Q1), and 0 otherwise	EBA and ECB stress test disclosures
ST2016EU	European stress test period in 2016	A binary variable that yields 1 for the European 2016 stress test period (2016Q2-2017Q1), and 0 otherwise	EBA and ECB stress test disclosures
FTST09US	U.S. first-time participation in the 2009 stress test	A binary variable that yields 1 for all banks that were tested for the first time in 2009, and 0 otherwise	Federal Reserve stress test disclosures
ST0913US	U.S. stress test period in 2009-13	A binary variable that yields 1 for the initial U.S. 2009-13 stress test period (2009Q3-2013Q4), and 0 otherwise	Federal Reserve stress test disclosures
ST1417US	U.S. stress test period in 2014-17	A binary variable that yields 1 for the recent U.S. 2014-17 stress test period (2014Q2-2017Q4), and 0 otherwise	Federal Reserve stress test disclosures
ΔGDP	Economic growth	Change in Gross Domestic Product in Euros	OECD, Bloomberg
ΔUNEM	Unemployment growth	Change in unemployment rate	OECD, Bloomberg
IRATE	Sovereign debt risk	The difference between the short- and long-term interest rates in the government bond markets	OECD
BETA	Asset sensitivity to market risk	Beta coefficient of the capital asset pricing model, which yields the sensitivity of the asset in relation to the return of the market portfolio	Thomson Reuters (Datastream/IBES)
SMB	Capitalisation factor	Small minus big market capitalisation factor of the FF3F and C4F	Fama and French database
HML	Book-to-market factor	High minus low book-to-market ratio factor of the FF3F and C4F	Fama and French database
MOM	Momentum factor	High minus low momentum shares factor of the FF3F and C4F	Fama and French database

Table 4.2 Sample construction

Panel A: European stress test participation

Country	CEBS/EBA[a] 2010	CEBS/EBA[a] 2011	CEBS/EBA[a] 2014	CEBS/EBA[a] 2016	CEBS/EBA[a] 2018	ECB 2014	ECB 2015	Stress test sample (*TOTALEU*)	First-time participants 2010-11 (*FTST1011EU*)	First-time participants 2014 (*FTST14EU*)
Austria	2	3	6	2	2	6	2	10	4	3
Belgium	2	2	5	2	2	6	1	7	2	4
Cyprus	2	2	3	0	0	4	0	5	2	3
Denmark	3	4	4	3	3	0	0	4	4	0
Estonia	0	0	0	0	0	3	0	3	0	3
Finland	1	1	1	1	1	3	1	4	1	2
France	4	4	11	6	6	13	1	15	4	9
Germany	14	12	24	9	8	25	0	27	14	13
Greece	6	6	4	0	0	4	4	6	6	0
Hungary	2	1	1	1	1	0	0	2	2	0
Ireland	2	3	3	2	2	5	0	5	3	2
Italy	5	5	15	5	4	15	0	15	5	10
Latvia	0	0	1	0	0	3	0	3	0	3
Lithuania	0	0	0	0	0	3	0	3	0	3
Luxembourg	2	1	2	0	0	6	1	8	2	5
Malta	1	1	1	0	0	3	1	4	1	2
Netherlands	4	4	6	4	4	7	0	7	4	3
Norway	0	1	1	1	1	0	0	1	1	0
Poland	1	1	6	1	2	0	0	7	1	5
Portugal	4	4	3	0	0	3	1	5	4	0
Slovakia	0	0	0	0	0	3	0	3	0	3
Slovenia	1	2	3	0	0	3	1	4	2	1
Spain	27	25	15	6	4	15	0	32	28	3
Sweden	4	4	4	4	4	0	0	4	4	0
United Kingdom	4	4	4	4	4	0	0	4	4	0
Total samples	**91**	**90**	**123**	**51**	**48**	**130**	**13**	**188**	**98**	**77**
- of which listed	*42*	*44*	*58*	*32*	*32*	*58*	*4*	*62*	*45*	*15*

Panel B: U.S. stress test participation

Country	Federal Reserve 2009	Federal Reserve 2011	Federal Reserve 2012	Federal Reserve 2013	Federal Reserve 2014	Federal Reserve 2015	Federal Reserve 2016	Federal Reserve 2017	Federal Reserve 2018	Stress test sample (*TOTALUS*)	First-time participants 2009 (*FTST09US*)	First-time participants 2014 (*FTST14US*)
U.S.-Owned	19	19	19	18	24	24	24	25	22	26	19	6
Non-U.S.-Owned	-	-	-	-	6	7	9	9	13	16	-	6
Total sample	**19**	**19**	**19**	**18**	**30**	**31**	**33**	**34**	**35**	**42**	**19**	**12**
- of which listed	*19*	*19*	*19*	*18*	*27*	*28*	*30*	*31*	*27*	*32*	*19*	*9*

Table 4.2 continued

Panel C: European event study preparations

Stress test observations	CEBS 2010	EBA 2011	EBA/ECB 2014	ECB 2015	EBA 2016	EBA 2018	First-time observations (FTSTO)	Total observations (TOTALSTO)
Listed banks / event observations	42	44	58	4	32	32	62	212
Excluded due to data limitations	2	3	1	-	-	-	3	6
Short-term event study sample	**40**	**41**	**57**	**4**	**32**	**32**	**59**	**206**
Calendar-time portfolio sample	**40**	**41**	**57**	**-**	**32**[b]	**-**	**57**[b]	**138**[b]

Panel D: U.S. event study preparations

Stress test observations	SCAP 2009	CCAR 2011	CCAR 2012	DFAST/ CCAR 2013	DFAST/ CCAR 2014	DFAST/ CCAR 2015	DFAST/ CCAR 2016	DFAST/ CCAR 2017	DFAST/ CCAR 2018	First-time observations (FTSTO)	Total observations (TOTALSTO)
Listed banks / event observations	19	19	19	18	27	28	30	31	27	32 (45)	218 (379)
Excluded due to data limitations	2	2	2	1	4	2	4	3	3	7 (12)	23 (40)
Short-term event study sample	**17**	**17**	**17**	**17**	**23**	**26**	**26**	**28**	**24**	**25 (33)**	**195 (339)**
Calendar-time portfolio sample	**17**	**17**	**17**	**17**	**23**	**26**	**26**[b]	**28**[b]	**-**	**23 (29)**[b,c]	**117 (183)**[b,c]

Panel E: European and U.S. time-series preparations

	Europe			U.S.		
	TOTALEU	*FTST1011EU*	*FTST14EU*	*TOTALUS*	*FTST09US*	*FTST14US*
Total stress-tested banks	188	98	77	42	19	12
Excluded banks due to M&As / bankruptcy / consolidation	20	19	1	-	-	-
Excluded banks due to accounting data limitations	25	10	11	13	1	4
Number of sample banks	**143**	**69**	**65**	**29**	**18**	**8**
- *of which listed*	*62*	*45*	*15*	*28*	*17*	*8*

This table presents the stress test participation in Europe and the U.S. and the construction of the final samples. Panel A reports the number of stress-tested banks by European country and stress test exercise. Participation in either the CEBS/EBA, or the ECB stress tests over the period 2010-2018 is considered. Panel B shows the number of stress test participants in the U.S. by ownership and year of assessment. Participation in the Federal Reserve's SCAP, DFAST and CCAR over the period 2009-2018 is considered. The subsequent panels describe the preparation process for the European (Panel C) and the U.S. (Panel D) event studies and the time series analysis (Panel E). I exclude stress test observations and banks due to lack of data caused by IPOs, M&As, bankruptcies and other factors.

[a]The stress tests in 2010 were conducted by CEBS, whilst the subsequent assessments were undertaken by EBA.

[b]The observations of the recent European and U.S. stress tests (i.e., that between 2016-2018) are not considered in the CTIME approach and thus not included in the portfolios of first-time (FTSTO) and total stress test observations (TOTALSTO). The long-term period of 1-36 months following those exercises cannot be fully captured (as of December 2018).

[c]Since 2013, the Federal Reserve undertakes DFAST and CCAR each year. The numbers in parentheses include both DFAST and CCAR observations.

Table 4.3 Descriptive statistics

Panel A: European banks	Obs.	Mean	SD	Min.	Max.	Median
Bank risk-taking						
T1R	4278	0.129	0.058	0.056	0.413	0.117
LEVERAGE	4626	2.743	0.652	1.107	5.161	2.698
RWA	2850	0.497	0.178	0.162	0.899	0.491
LLR	2844	0.032	0.037	0.001	0.193	0.019
ZSCORE	4241	3.292	0.976	0.542	6.203	3.273
ROA	3296	0.003	0.008	-0.028	0.027	0.003
Bank funding structure						
TIE	2721	0.012	0.011	0.001	0.061	0.009
OIE	2687	0.008	0.009	0.000	0.052	0.006
DEPBA	3007	0.115	0.102	0.000	0.489	0.090
IECD	1620	0.006	0.006	0.000	0.031	0.004
CUSTD	3032	0.471	0.197	0.000	0.901	0.462
NIM	4523	0.012	0.009	0.001	0.043	0.010
Bank accounting characteristics						
SIZE	4966	11.073	1.795	6.724	14.529	11.014
LOAN	3267	0.601	0.153	0.172	0.908	0.617
LLP	3274	0.004	0.006	-0.003	0.036	0.002
TRADE	2775	0.107	0.107	0.001	0.493	0.073
DEPO	3068	0.579	0.205	0.004	0.940	0.571
EBPT	3276	0.007	0.006	-0.004	0.031	0.006
OBSI	2396	0.172	0.162	0.010	1.130	0.136
Information asymmetry and analyst behaviour						
BIDASK	2650	0.008	0.014	0.000	0.095	0.003
RECNO	2511	19.388	10.154	1.000	39.000	21.108
EPSSUR / PRICE	2513	0.042	0.237	-0.171	1.768	-0.004
ESTSD / PRICE	2455	0.048	0.139	0.001	1.024	0.012
Market microstructure						
TOVER	2822	0.014	0.040	0.000	0.304	0.004
INVPRICE	2834	0.248	0.481	0.000	3.906	0.097
RETVOL	2834	0.025	0.017	0.005	0.101	0.020
MVALUE	2834	8.609	1.692	4.482	11.840	8.744
MTBV	2731	1.108	0.753	-0.100	3.890	0.922
RECCON	2511	2.687	0.532	1.500	4.130	2.649

Panel A: U.S. banks	Obs.	Mean	SD	Min.	Max.	Median
Bank risk-taking						
T1R	1504	0.119	0.038	-0.055	0.245	0.119
LEVERAGE	1594	2.155	0.407	1.412	4.370	2.097
RWA	1299	0.712	0.218	0.000	1.122	0.768
LLR	1463	0.011	0.011	0.000	0.087	0.009
ZSCORE	1492	3.163	0.758	1.265	5.516	3.126
ROA	1517	0.005	0.007	-0.018	0.041	0.003
Bank funding structure						
TIE	1517	0.005	0.007	0.000	0.039	0.003
OIE	1517	0.004	0.006	0.000	0.037	0.002
SUBD	1150	0.016	0.011	0.000	0.055	0.015
IECD	1223	0.002	0.003	0.000	0.017	0.001
CUSTD	1451	0.607	0.209	0.033	0.939	0.670
NIM	1555	0.014	0.013	0.000	0.068	0.008
Bank accounting characteristics						
SIZE	1595	11.928	1.151	10.100	14.513	11.660
LOAN	1517	0.512	0.230	0.000	0.861	0.597
LLP	1443	0.003	0.006	-0.001	0.034	0.001
TRADE	1421	0.068	0.104	0.000	0.418	0.016
DEPO	1446	0.604	0.219	0.016	0.939	0.672
EBPT	1517	0.008	0.010	-0.007	0.065	0.005
OBSI	1174	0.467	0.495	0.000	3.077	0.378
Information asymmetry and analyst behaviour						
BIDASK	1347	0.001	0.001	0.000	0.007	0.001
RECNO	1414	22.473	7.906	1.000	35.000	22.946
EPSSUR / PRICE	1384	-0.002	0.041	-0.111	0.247	-0.004
ESTSD / PRICE	1370	0.006	0.010	0.000	0.074	0.003

Table 4.3 continued

Market microstructure						
TOVER	1401	0.011	0.009	0.000	0.061	0.008
INVPRICE	1402	0.040	0.041	0.004	0.216	0.026
RETVOL	1402	0.020	0.017	0.006	0.102	0.015
MVALUE	1402	10.260	1.095	7.959	12.522	10.231
MTBV	1353	1.375	0.857	0.330	6.020	1.141
RECCON	1414	2.451	0.462	1.000	3.470	2.447

This table reports descriptive statistics (i.e., observation, mean, standard deviation, minimum maximum and median) of the variables I use in my analysis. Panel A illustrates the European sample and Panel B shows the U.S. sample. I include the following accounting variables to measure market discipline, quarterly winsorised at the 1 and 99 percentiles, in my analysis: Bank risk-taking using capital adequacy (*T1R*), leverage risk (*LEVERAGE*), credit risk (*RWA*), credit portfolio quality (*LLR*), insolvency risk (*ZSCORE*), profitability (*ROA*). I estimate bank funding structure using total (*TIE*) uninsured (*OIE*) and insured (*IECD*) funding cost, uninsured (*DEPBA, SUBD*), insured funding (*CUSTD*), and interest margin (*NIM*). I measure bank accounting characteristics using bank size captured by natural logarithm of total assets (*SIZE*), traditional banking activity shown by outstanding loans (*LOAN*), asset quality measured by loan loss provisions (*LLP*), non-traditional banking activity measured by trading securities *(TRADE)*, liquidity shown by total deposits *(DEPO)*, profitability measured by earnings before provision and taxes (*EBPT*), and off-balance sheet activities (*OBSI*). I include the following market variables, daily winsorised at the 1 and 99 percentiles and quarterly averaged, in my analysis: Information asymmetry using the bid-ask spread (*BIDASK*) and analyst behaviour employing analyst coverage (*RECNO*), earnings surprises (*EPSSUR / PRICE*) and estimate dispersion (*ESTSD / PRICE*). I measure market microstructure characteristics using share turnover (*TOVER*), inverse share price (*INVPRICE*), return volatility (*RETVOL*), market value (*MVALUE*), market-to-book value (*MTBV*), and analyst recommendation consensus (*RECCON*). The description of the variables and the relevant data sources are provided in Table 4.1.

Table 4.4 Correlation coefficients

Panel A: European banks

Variables	*SIZE*	*LOAN*	*LLP*	*TRADE*	*DEPO*	*EBPT*	*TOVER*	*INVPRICE*	*RETVOL*	*MVALUE*	*MTBV*	*RECCON*	*ΔGDP*	*ΔUNEM*	*IRATE*
SIZE	1.000														
LOAN	-0.423***	1.000													
	(0.000)														
LLP	-0.166***	0.129***	1.000												
	(0.000)	(0.000)													
TRADE	0.625***	-0.609***	-0.270***	1.000											
	(0.000)	(0.000)	(0.000)												
DEPO	-0.424***	0.334***	0.200***	-0.419***	1.000										
	(0.000)	(0.000)	(0.000)	(0.000)											
EBPT	-0.280***	0.245***	0.379***	-0.221***	0.277***	1.000									
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)										
TOVER	-0.106***	0.179***	0.087***	-0.203***	0.045**	-0.042*	1.000								
	(0.000)	(0.000)	(0.000)	(0.000)	(0.046)	(0.053)									
INVPRICE	-0.118***	0.096***	0.106***	-0.249***	0.122***	-0.106***	0.336***	1.000							
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)								
RETVOL	0.035*	0.037*	0.364***	-0.143***	0.072***	-0.065***	0.048**	0.068***	1.000						
	(0.085)	(0.094)	(0.000)	(0.000)	(0.002)	(0.003)	(0.014)	(0.000)							
MVALUE	0.853***	-0.395***	-0.304***	0.550***	-0.335***	-0.057***	-0.131***	-0.198***	-0.219***	1.000					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.000)	(0.000)	(0.000)						
MTBV	-0.225***	0.198***	-0.244***	-0.043*	0.120***	0.372***	-0.118***	-0.209***	-0.382***	0.180***	1.000				
	(0.000)	(0.000)	(0.000)	(0.069)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
RECCON	-0.077***	0.152***	0.098***	-0.109***	-0.050**	-0.105***	0.085***	0.049**	0.130***	-0.187***	-0.131***	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.030)	(0.000)	(0.000)	(0.016)	(0.000)	(0.000)	(0.000)				
ΔGDP	-0.009	-0.024	0.046**	0.003	0.000	-0.004	-0.018	-0.003	-0.024	-0.008	-0.023	0.034	1.000		
	(0.550)	(0.184)	(0.011)	(0.886)	(0.996)	(0.806)	(0.338)	(0.891)	(0.217)	(0.665)	(0.248)	(0.100)			
ΔUNEM	0.030**	0.120***	0.059***	-0.019	-0.038**	0.035*	0.063***	-0.070***	0.230***	-0.022	-0.090***	0.050**	0.056***	1.000	
	(0.039)	(0.000)	(0.001)	(0.329)	(0.039)	(0.050)	(0.001)	(0.000)	(0.000)	(0.257)	(0.000)	(0.014)	(0.000)		
IRATE	-0.030**	0.107***	0.418***	-0.249***	0.104***	0.020	0.060***	0.090***	0.478***	-0.259***	-0.393***	0.230***	-0.028**	0.118***	1.000
	(0.045)	(0.000)	(0.000)	(0.000)	(0.000)	(0.285)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.017)	(0.000)	

Table 4.4 continued

Panel B: U.S. banks

	SIZE	*LOAN*	*LLP*	*TRADE*	*DEPO*	*EBPT*	*TOVER*	*INVPRICE*	*RETVOL*	*MVALUE*	*MTBV*	*RECCON*	*ΔGDP*	*ΔUNEM*	*IRATE*
SIZE	1.000														
LOAN	-0.507***	1.000													
	(0.000)														
LLP	-0.101***	0.206***	1.000												
	(0.000)	(0.000)													
TRADE	0.674***	-0.710***	-0.091***	1.000											
	(0.000)	(0.000)	(0.001)												
DEPO	-0.448***	0.629***	-0.063**	-0.745***	1.000										
	(0.000)	(0.000)	(0.024)	(0.000)											
EBPT	-0.096***	0.207***	0.653***	-0.174***	0.043	1.000									
	(0.000)	(0.000)	(0.000)	(0.000)	(0.109)										
TOVER	-0.094***	0.081***	0.259***	0.085***	-0.025	-0.044	1.000								
	(0.001)	(0.006)	(0.000)	(0.005)	(0.400)	(0.136)									
INVPRICE	-0.249***	0.282***	0.139***	-0.209***	0.252***	-0.064**	0.292***	1.000							
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.029)	(0.000)								
RETVOL	-0.057**	0.062**	0.323***	0.043	-0.015	0.020	0.729***	0.297***	1.000						
	(0.045)	(0.034)	(0.000)	(0.157)	(0.612)	(0.504)	(0.000)	(0.000)							
MVALUE	0.829***	-0.429***	-0.183***	0.497***	-0.462***	-0.029	-0.436***	-0.248***	-0.260***	1.000					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.329)	(0.000)	(0.000)	(0.000)						
MTBV	-0.137***	-0.058*	0.145***	-0.101***	-0.188***	0.371***	-0.312***	-0.322***	-0.248***	0.153***	1.000				
	(0.000)	(0.051)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
RECCON	-0.253***	0.117***	0.084***	-0.146***	0.113***	-0.067**	0.254***	-0.093***	0.193***	-0.408***	-0.016	1.000			
	(0.000)	(0.000)	(0.006)	(0.000)	(0.000)	(0.023)	(0.000)	(0.001)	(0.000)	(0.000)	(0.568)				
ΔGDP	-0.034	0.027	0.069**	-0.005	0.034	0.092***	0.013	0.056**	0.007	-0.034	-0.034	-0.036	1.000		
	(0.193)	(0.308)	(0.011)	(0.847)	(0.203)	(0.001)	(0.633)	(0.042)	(0.808)	(0.217)	(0.225)	(0.183)			
ΔUNEM	-0.059**	0.050*	0.160***	0.078***	-0.080***	-0.013	0.299***	-0.014	0.562***	-0.063**	0.076***	0.192***	-0.124***	1.000	
	(0.022)	(0.057)	(0.000)	(0.004)	(0.003)	(0.617)	(0.000)	(0.603)	(0.000)	(0.020)	(0.007)	(0.000)	(0.000)		
IRATE	-0.017	0.004	0.269***	-0.083***	0.036	0.059**	0.385***	0.251***	0.353***	-0.142***	-0.371***	-0.011	0.156***	-0.148***	1.000
	(0.516)	(0.879)	(0.000)	(0.002)	(0.180)	(0.026)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.687)	(0.000)	(0.000)	

This table reports Pearson pairwise correlation coefficients and p-values for the variables I use in my regression models. Panel A illustrates the European sample and Panel B shows the U.S. sample. I include the following accounting variables, quarterly winsorised at the 1 and 99 percentiles and lagged by two quarters, in my analysis: Bank size captured by natural logarithm of total assets (*SIZE*), traditional banking activity shown by outstanding loans (*LOAN*), asset quality measured by loan loss provisions (*LLP*), non-traditional banking activity measured by trading securities *(TRADE)*, liquidity shown by total deposits *(DEPO)*, and profitability measured by earnings before provision and taxes (*EBPT*). I include the following market variables, daily winsorised at the 1 and 99 percentiles, quarterly averaged and lagged by two quarters, in my analysis: Share turnover (*TOVER*), inverse share price (*INVPRICE*), return volatility (*RETVOL*), market value (*MVALUE*), market-to-book value (*MTBV*), and analyst recommendation consensus (*RECCON*). Macroeconomic fundamentals are captured by economic growth (*ΔGDP*), unemployment growth (*ΔUNEM*), and sovereign debt risk (*IRATE*). Data range 2005-2017. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 4.1.

Table 4.5 European short-term event study results

Panel A: Capital asset pricing model (CAPM)						
			Average *CARs* (*CAAR*)			
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	CEBS 2010 (23 July)	40	0.0084	0.0116	-0.0031	0.0130
(2)	EBA 2011 (15 July)	41	0.0003	0.0087	0.0072	0.0347***
(3)	EBA/ECB 2014 (27 Oct.)	57	0.0036**	-0.0024	-0.0084	-0.0158
(4)	ECB 2015 (2 Nov.)	4	0.1386	-0.0087	-0.2061	-0.2422
(5)	EBA 2016 (29 July)	32	0.0069	-0.0006	-0.0102	-0.0092
(6)	EBA 2018 (2 Nov.)	32	0.0018	0.0019	0.0031	0.0080
(7)	FTSTO	59	0.0133**	0.0161	-0.0037	0.0058*
(8)	TOTALSTO	206	0.0067*	0.0034	-0.0066	0.0002*
Panel B: Fama and French (1993) three-factors model (FF3F)						
			Average *CARs* (*CAAR*)			
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	CEBS 2010 (23 July)	40	0.0078	0.0047	-0.0063	0.0005
(2)	EBA 2011 (15 July)	41	0.0048	0.0146	0.0180	0.0321*
(3)	EBA/ECB 2014 (27 Oct.)	57	0.0061**	0.0028	0.0040	-0.0080
(4)	ECB 2015 (2 Nov.)	4	0.1331	-0.0053	-0.1127	-0.2324
(5)	EBA 2016 (29 July)	32	0.0083	0.0014	-0.0102	-0.0085
(6)	EBA 2018 (2 Nov.)	32	0.0007	0.0006	0.0022	0.0067
(7)	FTSTO	59	0.0148**	0.0145	0.0010	0.0014
(8)	TOTALSTO	206	0.0081	0.0048	0.0000	-0.0005
Panel C: Carhart (1997) four-factors model (C4F)						
			Average *CARs* (*CAAR*)			
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	CEBS 2010 (23 July)	40	0.0062	0.0002	-0.0106	-0.0042
(2)	EBA 2011 (15 July)	41	0.0054	0.0149	0.0181	0.0318*
(3)	EBA/ECB 2014 (27 Oct.)	57	0.0025	-0.0023	-0.0074	-0.0129
(4)	ECB 2015 (2 Nov.)	4	0.1158	-0.0356	-0.1480	-0.2520
(5)	EBA 2016 (29 July)	32	0.0081	0.0016	-0.0094	-0.0091
(6)	EBA 2018 (2 Nov.)	32	0.0007	0.0006	0.0022	0.0067
(7)	FTSTO	59	0.0134**	0.0110	-0.0031	-0.0023
(8)	TOTALSTO	206	0.0066	0.0020	-0.0045	-0.0033
Panel D: Market return model (MRM)						
			Average *BHARs*			
		Obs.	t–1, t+1	t–1, t+2	t–1, t+4	t–1, t+7
(1)	CEBS 2010 (23 July)	40	0.0107*	0.0169*	0.0189**	0.0256***
(2)	EBA 2011 (15 July)	41	-0.0081	0.0017	0.0149**	0.0101
(3)	EBA/ECB 2014 (27 Oct.)	57	-0.0051	-0.0060	-0.0016	-0.0029
(4)	ECB 2015 (2 Nov.)	4	0.1328	-0.0292	-0.2515**	-0.3792*
(5)	EBA 2016 (29 July)	32	0.0013	-0.0013	-0.0039	-0.0025
(6)	EBA 2018 (2 Nov.)	32	0.0017	0.0019	0.0044	0.0032
(7)	FTSTO	59	0.0153***	0.0208**	0.0137	0.0176*
(8)	TOTALSTO	206	0.0065**	0.0034	-0.0016	-0.0027

This table reports short-term market reactions around the European stress test events. Models 1 to 6 show the results for the individual European stress tests in 2010, 2011, 2014, 2015, 2016 and 2018, whilst Models 7 and 8 illustrate first-time and total stress test observations (FTSTO, TOTALSTO). For the indicated event windows, Panel A illustrates the average *CARs* of the capital asset pricing model (CAPM), Panel B estimates the average *CARs* of the Fama and French (1993) three-factors model (FF3F), Panel C examines the average *CARs* of the Carhart (1997) four-factors model (C4F), and Panel D shows the average *BHARs* of the market return model (MRM). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 4.1.

Table 4.5A European positive *CAR* (t–1, t+1) analysis

Panel A: Capital asset pricing model (CAPM)						
			Average *CARs* (*CAAR*)			
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	CEBS 2010 (23 July)	23	0.0256***	0.0352***	0.0168***	0.0334**
(2)	EBA 2011 (15 July)	17	0.0385***	0.0397***	0.0081	0.0619***
(3)	EBA/ECB 2014 (27 Oct.)	32	0.0239***	0.0164	0.0069	0.0098
(4)	EBA 2016 (29 July)	17	0.0293***	0.0125	0.0061	-0.0056
(5)	EBA 2018 (2 Nov.)	17	0.0189***	0.0172***	0.0218	0.0273
(6)	FTSTO	38	0.0314***	0.0392***	0.0182***	0.0292***
(7)	TOTALSTO	109	0.0319***	0.0241***	0.0063***	0.0169***
Panel B: Fama and French (1993) three-factors model (FF3F)						
			Average *CARs* (*CAAR*)			
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	CEBS 2010 (23 July)	23	0.0261***	0.0272**	0.0142**	0.0180*
(2)	EBA 2011 (15 July)	17	0.0494***	0.0537***	0.0335	0.0633***
(3)	EBA/ECB 2014 (27 Oct.)	32	0.0266***	0.0223**	0.0204	0.0189**
(4)	EBA 2016 (29 July)	17	0.0296***	0.0119**	0.0045	-0.0055*
(5)	EBA 2018 (2 Nov.)	17	0.0180***	0.0162**	0.0223	0.0272**
(6)	FTSTO	38	0.0344***	0.0389***	0.0261**	0.0253***
(7)	TOTALSTO	109	0.0344***	0.0263***	0.0161***	0.0169***
Panel C: Carhart (1997) four-factors model (C4F)						
			Average *CARs* (*CAAR*)			
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	CEBS 2010 (23 July)	23	0.0290***	0.0352*	0.0219*	0.0265**
(2)	EBA 2011 (15 July)	17	0.0526***	0.0552***	0.0341	0.0615***
(3)	EBA/ECB 2014 (27 Oct.)	32	0.0240***	0.0186*	0.0120	0.0153*
(4)	EBA 2016 (29 July)	17	0.0295***	0.0120***	0.0047	-0.0057*
(5)	EBA 2018 (2 Nov.)	17	0.0182***	0.0164	0.0225	0.0274
(6)	FTSTO	38	0.0356***	0.0429***	0.0287**	0.0296**
(7)	TOTALSTO	109	0.0344***	0.0265***	0.0147**	0.0170***
Panel D: Market return model (MRM)						
			Average *BHARs*			
		Obs.	t–1, t+1	t–1, t+2	t–1, t+4	t–1, t+7
(1)	CEBS 2010 (23 July)	23	0.0159**	0.0300**	0.0253**	0.0316**
(2)	EBA 2011 (15 July)	17	0.0209	0.0176	0.0071	0.0170
(3)	EBA/ECB 2014 (27 Oct.)	32	0.0134***	0.0002	0.0077	0.0067
(4)	EBA 2016 (29 July)	17	0.0252***	0.0154*	0.0132	0.0101
(5)	EBA 2018 (2 Nov.)	17	0.0189***	0.0171***	0.0277***	0.0179**
(6)	FTSTO	38	0.0343***	0.0455***	0.0361***	0.0421***
(7)	TOTALSTO	109	0.0323***	0.0248***	0.0150*	0.0139

This table reports short-term market reactions around the European stress test events for the banks that experience a positive *CAR* (t–1, t+1). Models 1 to 5 show the results for the individual European stress tests in 2010, 2011, 2014, 2015, 2016 and 2018, whilst Models 6 and 7 illustrate first-time and total stress test observations (FTSTO, TOTALSTO). For the indicated event windows, Panel A illustrates the average *CARs* of the capital asset pricing model (CAPM), Panel B estimates the average *CARs* of the Fama and French (1993) three-factors model (FF3F), Panel C examines the average CARs of the Carhart (1997) four-factors model (C4F), and Panel D shows the average *BHARs* of the market return model (MRM). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 4.1.

Table 4.5B European negative *CAR* (t–1, t+1) analysis

			Average *CARs* (*CAAR*)			
Panel A: Capital asset pricing model (CAPM)		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	CEBS 2010 (23 July)	17	-0.0149**	-0.0204	-0.0301**	-0.0148
(2)	EBA 2011 (15 July)	24	-0.0268***	-0.0132	0.0066	0.0155
(3)	EBA/ECB 2014 (27 Oct.)	25	-0.0225***	-0.0264***	-0.0279	-0.0484
(4)	EBA 2016 (29 July)	15	-0.0185***	-0.0154	-0.0286	-0.0134
(5)	EBA 2018 (2 Nov.)	15	-0.0176***	-0.0154**	-0.0181**	-0.0138***
(6)	FTSTO	21	-0.0196**	-0.0259*	-0.0434***	-0.0365
(7)	TOTALSTO	97	-0.0216***	-0.0199***	-0.0211**	-0.0186**
Panel B: Fama and French (1993) three-factors model (FF3F)			Average *CARs* (*CAAR*)			
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	CEBS 2010 (23 July)	17	-0.0169**	-0.0257**	-0.0341**	-0.0231
(2)	EBA 2011 (15 July)	24	-0.0269***	-0.0131***	0.0070	0.0101
(3)	EBA/ECB 2014 (27 Oct.)	25	-0.0202***	-0.0222**	-0.0170	-0.0425
(4)	EBA 2016 (29 July)	15	-0.0158***	-0.0104***	-0.0269*	-0.0119
(5)	EBA 2018 (2 Nov.)	15	-0.0189***	-0.0171**	-0.0206***	-0.0165***
(6)	FTSTO	21	-0.0207***	-0.0295***	-0.0445***	-0.0418
(7)	TOTALSTO	97	-0.0214***	-0.0193***	-0.0181***	-0.0201***
Panel C: Carhart (1997) four-factors model (C4F)			Average *CARs* (*CAAR*)			
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	CEBS 2010 (23 July)	17	-0.0246***	-0.0471***	-0.0546***	-0.0458**
(2)	EBA 2011 (15 July)	24	-0.0280***	-0.0137**	0.0068	0.0107
(3)	EBA/ECB 2014 (27 Oct.)	25	-0.0249***	-0.0290***	-0.0323**	-0.0490**
(4)	EBA 2016 (29 July)	15	-0.0163***	-0.0102***	-0.0253*	-0.0129
(5)	EBA 2018 (2 Nov.)	15	-0.0192***	-0.0174***	-0.0209***	-0.0166***
(6)	FTSTO	21	-0.0268***	-0.0467***	-0.0606***	-0.0600***
(7)	TOTALSTO	97	-0.0246***	-0.0255***	-0.0261***	-0.0261***
Panel D: Market return model (MRM)			Average *BHARs*			
		Obs.	t–1, t+1	t–1, t+2	t–1, t+4	t–1, t+7
(1)	CEBS 2010 (23 July)	17	0.0039	0.0007	-0.0011	-0.0001
(2)	EBA 2011 (15 July)	24	-0.0244***	-0.0072	0.0192***	0.0062
(3)	EBA/ECB 2014 (27 Oct.)	25	-0.0176***	-0.0101	-0.0079	-0.0094
(4)	EBA 2016 (29 July)	15	-0.0182***	-0.0149	-0.0179	-0.0128
(5)	EBA 2018 (2 Nov.)	15	-0.0178***	-0.0154***	-0.0220***	-0.0134*
(6)	FTSTO	21	-0.0190***	-0.0240***	-0.0269***	-0.0269**
(7)	TOTALSTO	97	-0.0224***	-0.0206***	-0.0203***	-0.0213***

This table reports short-term market reactions around the European stress test events for the banks that experience a negative *CAR* (t–1, t+1). Models 1 to 5 show the results for the individual European stress tests in 2010, 2011, 2014, 2015, 2016 and 2018, whilst Models 6 and 7 illustrate first-time and total stress test observations (FTSTO, TOTALSTO). For the indicated event windows, Panel A illustrates the average *CARs* of the capital asset pricing model (CAPM), Panel B estimates the average *CARs* of the Fama and French (1993) three-factors model (FF3F), Panel C examines the average *CARs* of the Carhart (1997) four-factors model (C4F), and Panel D shows the average *BHARs* of the market return model (MRM). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 4.1.

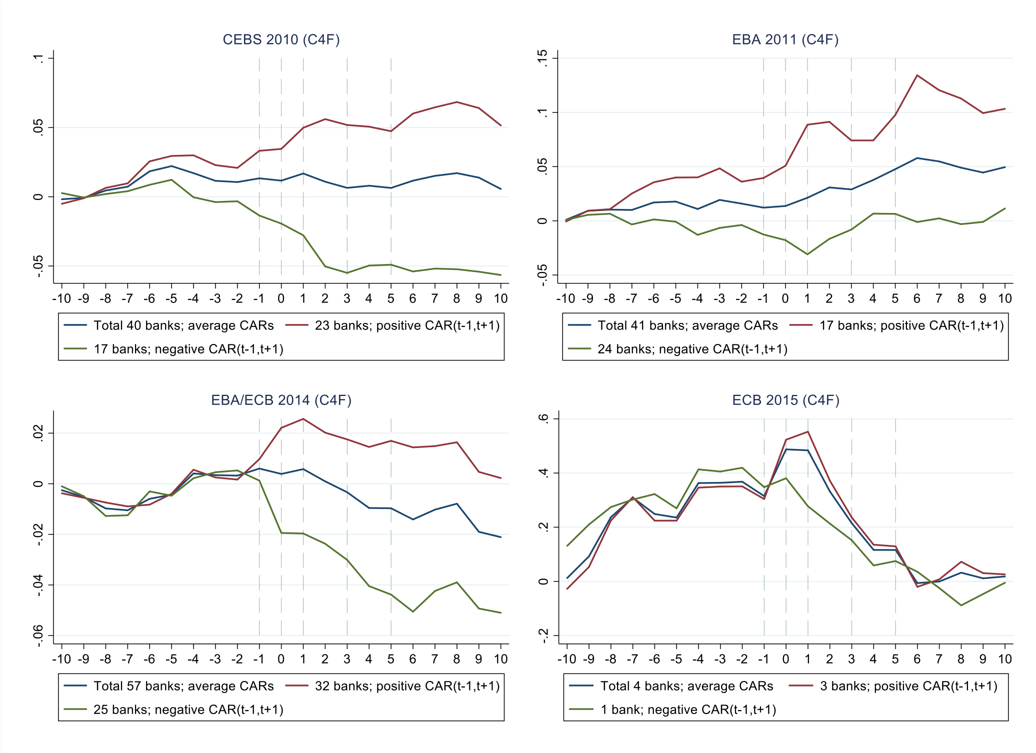

Figure 4.1 European stress test events (2010, 2011, 2014 and 2015)

The graphs plot the average *CARs* (*CAAR*) of the stress-tested banks within a 21-day event window (t–10, t+10). Based on the baseline Carhart (1997) four-factors model (C4F), the observations are split into banks that experience a positive ('good' news) and a negative ('bad' news) $CAR_{t-1,\,t+1}$. The stress tests in 2010, 2011, 2014 and 2015 are considered.

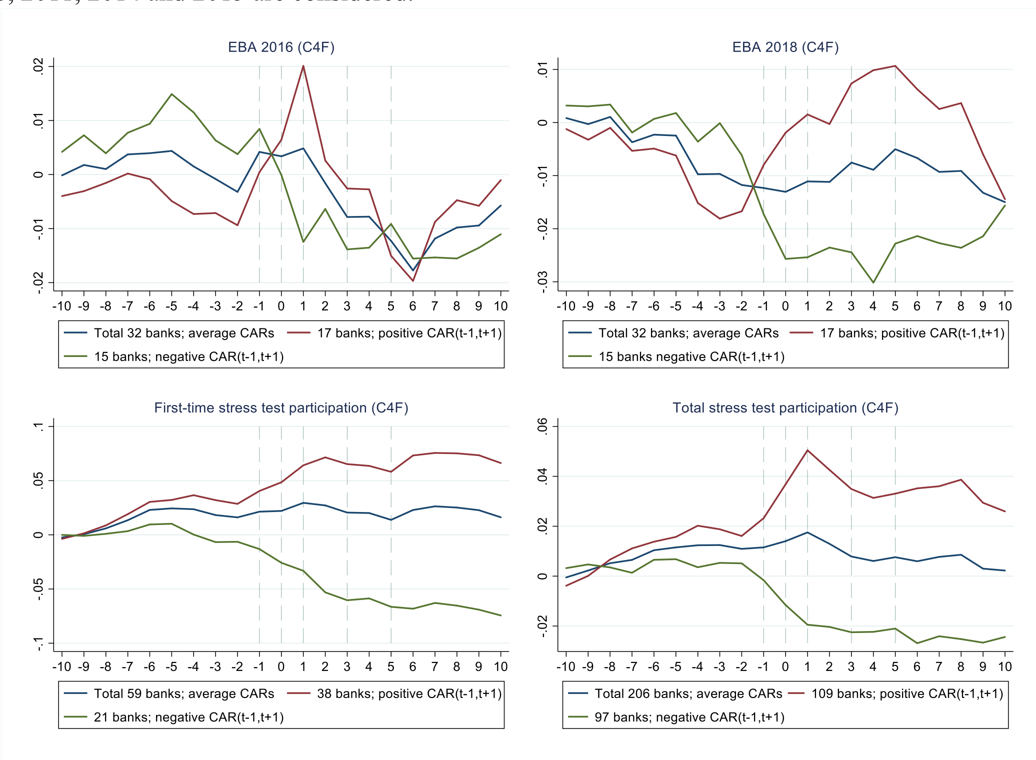

Figure 4.2 European stress test events (2016, 2018, FTSTO and TOTALSTO)

The graphs plot the average *CARs* (*CAAR*) of the stress-tested banks within a 21-day event window (t–10, t+10). Based on the baseline Carhart (1997) four-factors model (C4F), the observations are is split into banks that experience a positive ('good' news) and a negative ('bad' news) $CAR_{t-1,\,t+1}$. The stress tests in 2016, 2018, the first-time (FTSTO), and total (TOTALSTO) stress test participation are considered.

Table 4.6 U.S. short-term event study results

Panel A: Capital asset pricing model (CAPM)

			Average *CARs* (*CAAR*)			
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	SCAP 2009 (7 May)	17	0.0409	0.0266	-0.0014	0.0092
(2)	CCAR 2011 (18 March)	17	0.0051	0.0090	0.0096	0.0014
(3)	CCAR 2012 (13 March)	17	-0.0046	0.0004	-0.0069	0.0107*
(4)	DFAST 2013 (7 March)	17	0.0044	0.0008	0.0092	0.0037
(5)	CCAR 2013 (14 March)	17	-0.0078**	-0.0088**	-0.0130**	-0.0105
(6)	DFAST 2014 (20 March)	23	-0.0011	-0.0030	-0.0092	-0.0035
(7)	CCAR 2014 (26 March)	23	-0.0006	0.0033	0.0007	0.0063
(8)	DFAST 2015 (5 March)	26	0.0062	0.0072	0.0005	0.0103
(9)	CCAR 2015 (11 March)	26	0.0032	0.0012	0.0086	0.0014
(10)	DFAST 2016 (23 June)	26	-0.0034	-0.0175***	-0.0216***	-0.0120
(11)	CCAR 2016 (29 June)	26	0.0054	0.0056	-0.0168*	-0.0021
(12)	DFAST 2017 (22 June)	28	-0.0038*	-0.0014	-0.0065**	-0.0140***
(13)	CCAR 2017 (28 June)	28	-0.0126***	-0.0107**	-0.0100**	-0.0120**
(14)	DFAST 2018 (21 June)	24	0.0017	0.0005	-0.0054**	-0.0092**
(15)	CCAR 2018 (28 June)	24	-0.0092***	-0.0088***	-0.0103***	-0.0069***
(16)	FTSTO (Excl. 5, 7, 9, 11, 13, 15)	25	0.0280	0.0175	-0.0074	0.0042
(17)	FTSTO	33	0.0201	0.0144	-0.0050	0.0068
(18)	TOTALSTO (Excl. 5, 7, 9, 11, 13, 15)	195	0.0039	0.0013	-0.0046***	-0.0016
(19)	TOTALSTO	339	0.0008	-0.0004	-0.0054***	-0.0026**

Panel B: Fama and French (1993) three-factors model (FF3F)

			Average *CARs* (*CAAR*)			
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	SCAP 2009 (7 May)	17	0.0188	0.0150	-0.0167	-0.0100
(2)	CCAR 2011 (18 March)	17	0.0028	0.0068	0.0051	0.0028
(3)	CCAR 2012 (13 March)	17	0.0031	0.0076	-0.0011	0.0205*
(4)	DFAST 2013 (7 March)	17	-0.0014	-0.0047	0.0038	-0.0072
(5)	CCAR 2013 (14 March)	17	-0.0141***	-0.0153**	-0.0199**	-0.0192
(6)	DFAST 2014 (20 March)	23	-0.0001	-0.0001	-0.0052	0.0026
(7)	CCAR 2014 (26 March)	23	0.0024*	0.0069*	0.0041	0.0068
(8)	DFAST 2015 (5 March)	26	0.0057	0.0068*	-0.0005	0.0092*
(9)	CCAR 2015 (11 March)	26	0.0025	0.0002	0.0085	0.0014
(10)	DFAST 2016 (23 June)	26	-0.0049	-0.0178***	-0.0207***	-0.0114
(11)	CCAR 2016 (29 June)	26	0.0065	0.0059	-0.0172	-0.0009
(12)	DFAST 2017 (22 June)	28	-0.0075***	-0.0050	-0.0090**	-0.0163**
(13)	CCAR 2017 (28 June)	28	-0.0113**	-0.0096**	-0.0104**	-0.0096**
(14)	DFAST 2018 (21 June)	24	0.0020	0.0014	-0.0060*	-0.0079**
(15)	CCAR 2018 (28 June)	24	-0.0083***	-0.0083***	-0.0108**	-0.0079**
(16)	FTSTO (Excl. 5, 7, 9, 11, 13, 15)	25	0.0132	0.0106	-0.0166**	-0.0068
(17)	FTSTO	33	0.0097	0.0100	-0.0111	-0.0015
(18)	TOTALSTO (Excl. 5, 7, 9, 11, 13, 15)	195	0.0013	0.0001	-0.0062***	-0.0028
(19)	TOTALSTO	339	-0.0006**	-0.0011	-0.0066***	-0.0034*

Panel C: Carhart (1997) four-factors model (C4F)

			Average *CARs* (*CAAR*)			
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	SCAP 2009 (7 May)	17	0.0133	0.0103	-0.0278	-0.0016
(2)	CCAR 2011 (18 March)	17	0.0012	0.0054	0.0036	0.0003
(3)	CCAR 2012 (13 March)	17	0.0054	0.0089	-0.0019	0.0212*
(4)	DFAST 2013 (7 March)	17	-0.0025	-0.0065	0.0043	-0.0089
(5)	CCAR 2013 (14 March)	17	-0.0141***	-0.0156**	-0.0212**	-0.0186
(6)	DFAST 2014 (20 March)	23	0.0011	0.0022	-0.0033	0.0060
(7)	CCAR 2014 (26 March)	23	0.0035**	0.0080**	0.0068*	0.0053
(8)	DFAST 2015 (5 March)	26	0.0057	0.0067*	-0.0008	0.0086*
(9)	CCAR 2015 (11 March)	26	0.0022	-0.0002	0.0079	0.0009
(10)	DFAST 2016 (23 June)	26	-0.0044	-0.0169***	-0.0198***	-0.0105
(11)	CCAR 2016 (29 June)	26	0.0064	0.0055	-0.0163*	-0.0009
(12)	DFAST 2017 (22 June)	28	-0.0076***	-0.0046	-0.0089**	-0.0158**
(13)	CCAR 2017 (28 June)	28	-0.0113**	-0.0094**	-0.0095**	-0.0100**
(14)	DFAST 2018 (21 June)	24	0.0020	0.0014	-0.0060	-0.0079**
(15)	CCAR 2018 (28 June)	24	-0.0083***	-0.0083***	-0.0108**	-0.0079**
(16)	FTSTO (Excl. 5, 7, 9, 11, 13, 15)	25	0.0098	0.0080	-0.0238**	-0.0003
(17)	FTSTO	33	0.0073	0.0083	-0.0159	0.0032
(18)	TOTALSTO (Excl. 5, 7, 9, 11, 13, 15)	195	0.0010	0.0000	-0.0071**	-0.0018
(19)	TOTALSTO	339	-0.0008*	-0.0012	-0.0069***	-0.0030*

Table 4.6 continued

Panel D: Market return model (MRM)						
			Average *BHARs*			
		Obs.	t–1, t+1	t–1, t+2	t–1, t+4	t–1, t+7
(1)	SCAP 2009 (7 May)	17	0.0540	0.0345	0.0163	0.0130
(2)	CCAR 2011 (18 March)	17	0.0039	0.0083**	0.0071	0.0063
(3)	CCAR 2012 (13 March)	17	-0.0024	0.0039	0.0092*	0.0177***
(4)	DFAST 2013 (7 March)	17	0.0053	0.0021	0.0041	-0.0059
(5)	CCAR 2013 (14 March)	17	-0.0068	-0.0082*	-0.0045	-0.0099*
(6)	DFAST 2014 (20 March)	23	-0.0007	-0.0025	-0.0039	0.0002
(7)	CCAR 2014 (26 March)	23	0.0003	0.0006	0.0001	-0.0006
(8)	DFAST 2015 (5 March)	26	0.0065**	0.0073**	0.0055*	0.0088***
(9)	CCAR 2015 (11 March)	26	0.0026	0.0009	0.0020	0.0051
(10)	DFAST 2016 (23 June)	26	-0.0027	-0.0147***	-0.021***	-0.0122***
(11)	CCAR 2016 (29 June)	26	0.0036	0.0040	-0.0019	0.0020
(12)	DFAST 2017 (22 June)	28	-0.0030	-0.0009	-0.0068*	-0.0122***
(13)	CCAR 2017 (28 June)	28	-0.0146***	-0.0125***	-0.0113***	-0.0184***
(14)	DFAST 2018 (21 June)	24	0.0022	0.0013	-0.0027	-0.0101*
(15)	CCAR 2018 (28 June)	24	-0.0091**	-0.0091	-0.0059*	-0.0093*
(16)	FTSTO (Excl. 5, 7, 9, 11, 13, 15)	25	0.0372	0.0230	0.0087	0.0108
(17)	FTSTO	33	0.0266	0.0182	0.0089	0.0109
(18)	TOTALSTO (Excl. 5, 7, 9, 11, 13, 15)	195	0.0056	0.0030	-0.0006	-0.0007
(19)	TOTALSTO	339	0.0014	0.0002	-0.0016	-0.0021

This table reports short-term market reactions around the U.S. stress test events. Models 1 to 15 show the results for the individual U.S. stress tests in 2009, 2011, 2012, 2013, 2014, 2015, 2016, 2017 and 2018, whilst Models 16 and 19 illustrate first-time and total stress test observations (FTSTO, TOTALSTO). For the indicated event windows, Panel A illustrates the average *CARs* of the capital asset pricing model (CAPM), Panel B estimates the average *CARs* of the Fama and French (1993) three-factors model (FF3F), Panel C examines the average *CARs* of the Carhart (1997) four-factors model (C4F), and Panel D shows the average *BHARs* of the market return model (MRM). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 4.1.

Table 4.6A U.S. positive *CAR* (t–1, t+1) analysis

Panel A: Capital asset pricing model (CAPM)						
			Average *CARs* (*CAAR*)			
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	SCAP 2009 (7 May)	8	0.1573***	0.1382***	0.1210	0.1077**
(2)	CCAR 2011 (18 March)	9	0.0163***	0.0207**	0.0139	0.0065
(3)	CCAR 2012 (13 March)	11	0.0047	0.0096	0.0008	0.0184**
(4)	DFAST 2013 (7 March)	6	0.0218**	0.0183**	0.0258	0.0223**
(5)	CCAR 2013 (14 March)	2	0.0183	0.0225	0.0264	0.0294
(6)	DFAST 2014 (20 March)	10	0.0129***	0.0159**	0.0121*	0.0138*
(7)	CCAR 2014 (26 March)	17	0.0053	0.0100***	0.0050	0.0121
(8)	DFAST 2015 (5 March)	17	0.0160***	0.0161***	0.0081**	0.0166**
(9)	CCAR 2015 (11 March)	15	0.0109***	0.0088***	0.0132*	0.0065*
(10)	DFAST 2016 (23 June)	9	0.0078***	0.0007	-0.0060	-0.0062
(11)	CCAR 2016 (29 June)	16	0.0178***	0.0165***	-0.0074	0.0078**
(12)	DFAST 2017 (22 June)	6	0.0129**	0.0145**	0.0110	0.0071
(13)	CCAR 2017 (28 June)	8	0.0064**	0.0073**	0.0092***	0.0042**
(14)	DFAST 2018 (21 June)	13	0.0083***	0.0033	-0.0015	-0.0058
(15)	CCAR 2018 (28 June)	4	0.0171**	0.0179	0.0170	0.0218
(16)	FTSTO (Excl. 5, 7, 9, 11, 13, 15)	12	0.1105***	0.0978***	0.0783	0.0763***
(17)	FTSTO	17	0.0792***	0.073***	0.0541	0.0607***
(18)	TOTALSTO (Excl. 5, 7, 9, 11, 13, 15)	89	0.0252***	0.0233***	0.0170***	0.0178***
(19)	TOTALSTO	151	0.0194***	0.0187***	0.0124***	0.0145***

Panel B: Fama and French (1993) three-factors model (FF3F)						
			Average *CARs* (*CAAR*)			
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	SCAP 2009 (7 May)	8	0.1405***	0.1287	0.1048	0.0912
(2)	CCAR 2011 (18 March)	9	0.0139***	0.0184***	0.0089	0.0084
(3)	CCAR 2012 (13 March)	11	0.0136**	0.0186	0.0088	0.0305***
(4)	DFAST 2013 (7 March)	6	0.0145***	0.0111*	0.0189*	0.0084*
(5)	CCAR 2013 (14 March)	2	0.0108	0.0161	0.0195	0.0227
(6)	DFAST 2014 (20 March)	10	0.0169***	0.0227***	0.0208**	0.0244*
(7)	CCAR 2014 (26 March)	17	0.0088***	0.0146***	0.0107**	0.0131**

Table 4.6A continued

(8)	DFAST 2015 (5 March)	17	0.0156***	0.0160***	0.0075**	0.0145**
(9)	CCAR 2015 (11 March)	15	0.0109***	0.0087***	0.0139**	0.0074
(10)	DFAST 2016 (23 June)	9	0.0069***	0.0000	-0.0056	-0.0057
(11)	CCAR 2016 (29 June)	16	0.019***	0.0168**	-0.0084	0.0088**
(12)	DFAST 2017 (22 June)	6	0.0107**	0.0127**	0.0115	0.0077
(13)	CCAR 2017 (28 June)	8	0.0069***	0.0077***	0.0081	0.0058
(14)	DFAST 2018 (21 June)	13	0.0093***	0.0055	-0.0010	-0.0030
(15)	CCAR 2018 (28 June)	4	0.0186*	0.0194	0.0180	0.0227
(16)	FTSTO (Excl. 5, 7, 9, 11, 13, 15)	12	0.0996***	0.0924**	0.0685	0.0668*
(17)	FTSTO	17	0.0729***	0.0709***	0.0495	0.0543***
(18)	TOTALSTO (Excl. 5, 7, 9, 11, 13, 15)	89	0.0243***	0.0237***	0.0165***	0.0184***
(19)	TOTALSTO	151	0.0194***	0.0194***	0.0126***	0.0152***

Panel C: Carhart (1997) four-factors model (C4F)

			Average *CARs* (*CAAR*)			
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	SCAP 2009 (7 May)	8	0.1366***	0.1254	0.0969	0.0972
(2)	CCAR 2011 (18 March)	9	0.0121***	0.0168**	0.0069	0.0053
(3)	CCAR 2012 (13 March)	11	0.0157***	0.0197**	0.0081	0.0311***
(4)	DFAST 2013 (7 March)	6	0.0130***	0.0088	0.0195*	0.0062*
(5)	CCAR 2013 (14 March)	2	0.0108	0.0157	0.0179	0.0234
(6)	DFAST 2014 (20 March)	10	0.0182***	0.0251***	0.0228**	0.0280*
(7)	CCAR 2014 (26 March)	17	0.0099***	0.0158***	0.0135***	0.0115*
(8)	DFAST 2015 (5 March)	17	0.0156***	0.0159***	0.0073**	0.014**
(9)	CCAR 2015 (11 March)	15	0.0107***	0.0084***	0.0135*	0.0071**
(10)	DFAST 2016 (23 June)	9	0.0073***	0.0008	-0.0049	-0.0049
(11)	CCAR 2016 (29 June)	16	0.0190***	0.0162**	-0.0072	0.0087*
(12)	DFAST 2017 (22 June)	6	0.0108**	0.0120**	0.0113	0.0066
(13)	CCAR 2017 (28 June)	8	0.0069***	0.0079**	0.0088	0.0055
(14)	DFAST 2018 (21 June)	13	0.0092***	0.0055	-0.0012	-0.0030
(15)	CCAR 2018 (28 June)	4	0.0186*	0.0194	0.0180	0.0228
(16)	FTSTO (Excl. 5, 7, 9, 11, 13, 15)	12	0.0972***	0.0907**	0.0635	0.0713**
(17)	FTSTO	17	0.0716***	0.0701***	0.0469	0.0570***
(18)	TOTALSTO (Excl. 5, 7, 9, 11, 13, 15)	89	0.0241***	0.0236***	0.0158***	0.0188***
(19)	TOTALSTO	151	0.0194***	0.0194***	0.0126***	0.0152***

Panel D: Market return model (MRM)

			Average *BHARs*			
		Obs.	t–1, t+1	t–1, t+2	t–1, t+4	t–1, t+7
(1)	SCAP 2009 (7 May)	8	0.1097	0.0841	0.0544	0.0451
(2)	CCAR 2011 (18 March)	9	0.0148***	0.0199***	0.0164*	0.0127
(3)	CCAR 2012 (13 March)	11	0.0060	0.0121*	0.0163**	0.0276**
(4)	DFAST 2013 (7 March)	6	0.0238***	0.0215***	0.0248***	0.0105
(5)	CCAR 2013 (14 March)	2	0.0214***	0.0227***	0.0275	0.0193**
(6)	DFAST 2014 (20 March)	10	0.0126***	0.0158***	0.0172***	0.0158*
(7)	CCAR 2014 (26 March)	17	0.005***	0.0097***	0.0124***	0.0129***
(8)	DFAST 2015 (5 March)	17	0.0162***	0.0162***	0.0137***	0.0141***
(9)	CCAR 2015 (11 March)	15	0.0110***	0.0089***	0.0085**	0.0125**
(10)	DFAST 2016 (23 June)	9	0.0092***	0.0033	-0.0070	-0.0021
(11)	CCAR 2016 (29 June)	16	0.0125***	0.0119***	0.0083***	0.0129***
(12)	DFAST 2017 (22 June)	6	0.0080	0.0087	0.0071	0.0074
(13)	CCAR 2017 (28 June)	8	0.0031	0.0034	0.0026	0.0009
(14)	DFAST 2018 (21 June)	13	0.0088***	0.0041	-0.0002	-0.0075
(15)	CCAR 2018 (28 June)	4	0.0171**	0.0176	0.0213*	0.0189
(16)	FTSTO (Excl. 5, 7, 9, 11, 13, 15)	12	0.1369***	0.1106**	0.0778**	0.0831*
(17)	FTSTO	17	0.0978***	0.0819***	0.0612**	0.0663**
(18)	TOTALSTO (Excl. 5, 7, 9, 11, 13, 15)	89	0.0292***	0.0260***	0.0200***	0.0189***
(19)	TOTALSTO	151	0.0215***	0.0199***	0.0160***	0.0159***

This table reports short-term market reactions around the U.S. stress test events for the banks that experience a positive CAR (t–1, t+1). Models 1 to 15 show the results for the individual U.S. stress tests in 2009, 2011, 2012, 2013, 2014, 2015, 2016, 2017 and 2018, whilst Models 16 and 19 illustrate first-time and total stress test observations (FTSTO, TOTALSTO). For the indicated event windows, Panel A illustrates the average *CARs* of the capital asset pricing model (CAPM), Panel B estimates the average *CARs* of the Fama and French (1993) three-factors model (FF3F), Panel C examines the average *CARs* of the Carhart (1997) four-factors model (C4F), and Panel D shows the average *BHARs* of the market return model (MRM). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 4.1.

Table 4.6B U.S. negative *CAR* (t–1, t+1) analysis

Panel A: Capital asset pricing model (CAPM)

			Average *CARs* (*CAAR*)			
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	SCAP 2009 (7 May)	9	-0.0625*	-0.0726*	-0.1101**	-0.0784**
(2)	CCAR 2011 (18 March)	8	-0.0075	-0.0042	0.0048	-0.0043
(3)	CCAR 2012 (13 March)	6	-0.0216*	-0.0165*	-0.0209*	-0.0035
(4)	DFAST 2013 (7 March)	11	-0.0050*	-0.0088*	0.0002	-0.0065
(5)	CCAR 2013 (14 March)	15	-0.0113***	-0.0130***	-0.0183***	-0.0158
(6)	DFAST 2014 (20 March)	13	-0.0120***	-0.0154**	-0.0234***	-0.0109
(7)	CCAR 2014 (26 March)	6	-0.0170**	-0.0158**	-0.0116	-0.0099*
(8)	DFAST 2015 (5 March)	9	-0.0123***	-0.0097***	-0.0138***	-0.0016
(9)	CCAR 2015 (11 March)	11	-0.0074**	-0.0093*	0.0022	-0.0056*
(10)	DFAST 2016 (23 June)	17	-0.0094**	-0.0271***	-0.0299***	-0.0151
(11)	CCAR 2016 (29 June)	10	-0.0145***	-0.0119**	-0.0318**	-0.0181**
(12)	DFAST 2017 (22 June)	22	-0.0084***	-0.0058*	-0.0113***	-0.0198***
(13)	CCAR 2017 (28 June)	20	-0.0202***	-0.0178***	-0.0177***	-0.0184***
(14)	DFAST 2018 (21 June)	11	-0.0060***	-0.0028	-0.0100**	-0.0131**
(15)	CCAR 2018 (28 June)	20	-0.0145***	-0.0141***	-0.0158***	-0.0127***
(16)	FTSTO (Excl. 5, 7, 9, 11, 13, 15)	13	-0.0481**	-0.0567**	-0.0864***	-0.0623***
(17)	FTSTO	16	-0.0427***	-0.0479**	-0.0677**	-0.0504***
(18)	TOTALSTO (Excl. 5, 7, 9, 11, 13, 15)	106	-0.0140***	-0.0171***	-0.0226***	-0.0179***
(19)	TOTALSTO	188	-0.0142***	-0.0158***	-0.0197***	-0.0163***

Panel B: Fama and French (1993) three-factors model (FF3F)

			Average *CARs* (*CAAR*)			
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	SCAP 2009 (7 May)	9	-0.0893***	-0.0861**	-0.1247***	-0.0999**
(2)	CCAR 2011 (18 March)	8	-0.0098***	-0.0064***	0.0009	-0.0035
(3)	CCAR 2012 (13 March)	6	-0.0162**	-0.0123**	-0.0193	0.0022
(4)	DFAST 2013 (7 March)	11	-0.0100***	-0.0134	-0.0044	-0.0157
(5)	CCAR 2013 (14 March)	15	-0.0174***	-0.0195***	-0.0252***	-0.0248
(6)	DFAST 2014 (20 March)	13	-0.0131***	-0.0176***	-0.0252***	-0.0142
(7)	CCAR 2014 (26 March)	6	-0.0155**	-0.0150	-0.0146	-0.0111
(8)	DFAST 2015 (5 March)	9	-0.0130***	-0.0106**	-0.0158**	-0.0008
(9)	CCAR 2015 (11 March)	11	-0.0090***	-0.0113**	0.0011	-0.0069**
(10)	DFAST 2016 (23 June)	17	-0.0111***	-0.0273***	-0.0286***	-0.0145
(11)	CCAR 2016 (29 June)	10	-0.0136***	-0.0115***	-0.0313**	-0.0163**
(12)	DFAST 2017 (22 June)	22	-0.0125***	-0.0098**	-0.0146***	-0.0228***
(13)	CCAR 2017 (28 June)	20	-0.0186***	-0.0165***	-0.0178***	-0.0158***
(14)	DFAST 2018 (21 June)	11	-0.0066***	-0.0034	-0.0119**	-0.0137**
(15)	CCAR 2018 (28 June)	20	-0.0137***	-0.0139***	-0.0165***	-0.014***
(16)	FTSTO (Excl. 5, 7, 9, 11, 13, 15)	13	-0.0665***	-0.0650**	-0.0952***	-0.0747**
(17)	FTSTO	16	-0.0574***	-0.0547*	-0.0754***	-0.0607**
(18)	TOTALSTO (Excl. 5, 7, 9, 11, 13, 15)	106	-0.0181***	-0.0197***	-0.0254***	-0.0205***
(19)	TOTALSTO	188	-0.0167***	-0.0176***	-0.022***	-0.0184***

Panel C: Carhart (1997) four-factors model (C4F)

			Average *CARs* (*CAAR*)			
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	SCAP 2009 (7 May)	9	-0.0963***	-0.0920**	-0.1387***	-0.0893**
(2)	CCAR 2011 (18 March)	8	-0.0109***	-0.0073	-0.0002	-0.0054
(3)	CCAR 2012 (13 March)	6	-0.0133**	-0.0107**	-0.0202	0.003
(4)	DFAST 2013 (7 March)	11	-0.0109***	-0.0149	-0.0040	-0.0172
(5)	CCAR 2013 (14 March)	15	-0.0174***	-0.0198***	-0.0264***	-0.0242
(6)	DFAST 2014 (20 March)	13	-0.0120***	-0.0154**	-0.0234***	-0.0109
(7)	CCAR 2014 (26 March)	6	-0.0147**	-0.0141	-0.0125	-0.0123
(8)	DFAST 2015 (5 March)	9	-0.0129***	-0.0108**	-0.0162**	-0.0017
(9)	CCAR 2015 (11 March)	11	-0.0094***	-0.0119***	0.0003	-0.0075**
(10)	DFAST 2016 (23 June)	17	-0.0106***	-0.0263***	-0.0277***	-0.0135*
(11)	CCAR 2016 (29 June)	10	-0.0136***	-0.0117*	-0.0309*	-0.0164*
(12)	DFAST 2017 (22 June)	22	-0.0126***	-0.0092**	-0.0144***	-0.0219***
(13)	CCAR 2017 (28 June)	20	-0.0186***	-0.0163***	-0.0168***	-0.0162***
(14)	DFAST 2018 (21 June)	11	-0.0064***	-0.0035	-0.0116	-0.0136**
(15)	CCAR 2018 (28 June)	20	-0.0137***	-0.0139***	-0.0166***	-0.0141***
(16)	FTSTO (Excl. 5, 7, 9, 11, 13, 15)	13	-0.0709***	-0.0683**	-0.1044***	-0.0663**
(17)	FTSTO	16	-0.0610***	-0.0573*	-0.0826***	-0.0539**
(18)	TOTALSTO (Excl. 5, 7, 9, 11, 13, 15)	106	-0.0184***	-0.0198***	-0.0262***	-0.0192***
(19)	TOTALSTO	188	-0.0170***	-0.0177***	-0.0225***	-0.0177***

Table 4.6B continued

Panel D: Market return model (MRM)

		Obs.	Average *BHARs* t–1, t+1	t–1, t+2	t–1, t+4	t–1, t+7
(1)	SCAP 2009 (7 May)	9	-0.0609**	-0.0586**	-0.0334	-0.0405*
(2)	CCAR 2011 (18 March)	8	-0.0084***	-0.0048***	-0.0034	-0.0008
(3)	CCAR 2012 (13 March)	6	-0.0114**	-0.0055	0.0023	0.0060
(4)	DFAST 2013 (7 March)	11	-0.0048*	-0.0085**	-0.0072	-0.0148**
(5)	CCAR 2013 (14 March)	15	-0.0150***	-0.0183***	-0.0186**	-0.0254***
(6)	DFAST 2014 (20 March)	13	-0.0109***	-0.0166***	-0.0201***	-0.0118**
(7)	CCAR 2014 (26 March)	6	-0.0177***	-0.0164***	-0.0149**	-0.0137*
(8)	DFAST 2015 (5 March)	9	-0.0118***	-0.0095***	-0.0100*	-0.0012
(9)	CCAR 2015 (11 March)	11	-0.0104***	-0.0079***	-0.0069	-0.0059
(10)	DFAST 2016 (23 June)	17	-0.0090***	-0.0242***	-0.0285***	-0.0175**
(11)	CCAR 2016 (29 June)	10	-0.0255***	-0.0208***	-0.0168***	-0.0217***
(12)	DFAST 2017 (22 June)	22	-0.0056**	-0.0049*	-0.0079**	-0.0167***
(13)	CCAR 2017 (28 June)	20	-0.0255***	-0.0238***	-0.0228	-0.0284***
(14)	DFAST 2018 (21 June)	11	-0.0055***	-0.0019	-0.0055	-0.0132
(15)	CCAR 2018 (28 June)	20	-0.0144***	-0.0144***	-0.0113***	-0.0149***
(16)	FTSTO (Excl. 5, 7, 9, 11, 13, 15)	13	-0.0548***	-0.0577***	-0.0550***	-0.0560***
(17)	FTSTO	16	-0.0490***	-0.0495***	-0.0467***	-0.0481***
(18)	TOTALSTO (Excl. 5, 7, 9, 11, 13, 15)	106	-0.0143***	-0.0163***	-0.0180***	-0.0172***
(19)	TOTALSTO	188	-0.0147***	-0.0156***	-0.0157***	-0.0166***

This table reports short-term market reactions around the U.S. stress test events for the banks that experience a negative *CAR* (t–1, t+1). Models 1 to 15 show the results for the individual U.S. stress tests in 2009, 2011, 2012, 2013, 2014, 2015, 2016, 2017 and 2018, whilst Models 16 and 19 first-time and total stress test observations (FTSTO, TOTALSTO). For the indicated event windows, Panel A illustrates the average *CARs* of the capital asset pricing model (CAPM), Panel B estimates the average *CARs* of the Fama and French (1993) three-factors model (FF3F), Panel C examines the average *CARs* of the Carhart (1997) four-factors model (C4F), and Panel D shows the average *BHARs* of the market return model (MRM). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 4.1.

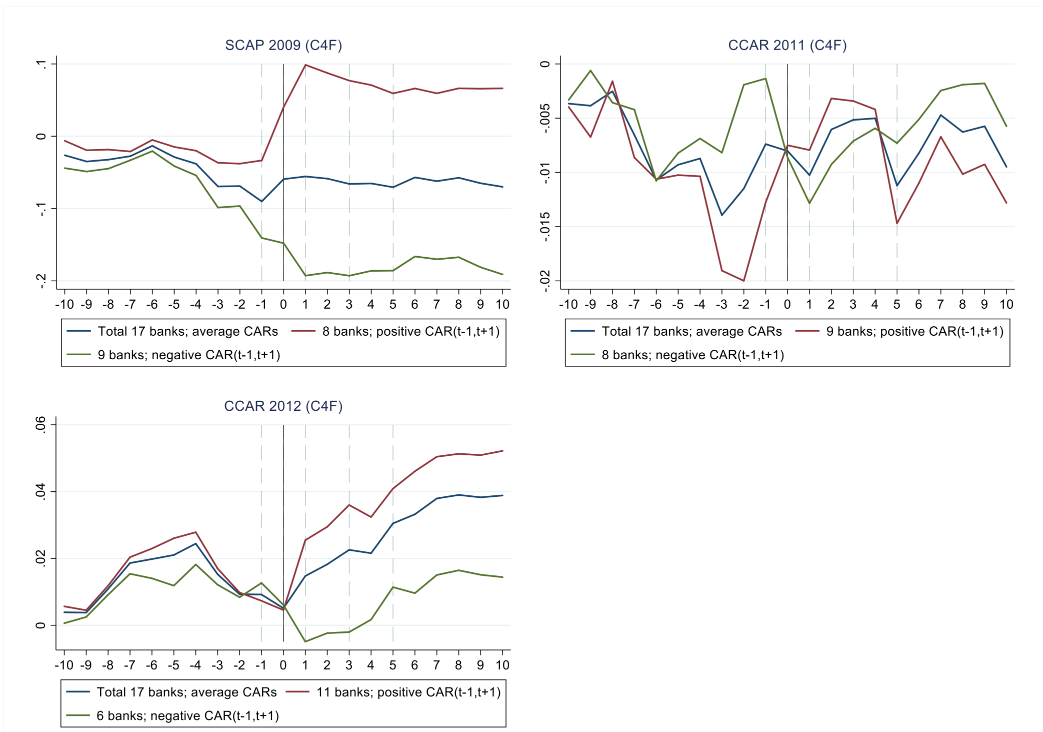

Figure 4.3 U.S. stress test events (2009-2012)

The graphs plot the average *CARs* (*CAAR*) of the stress-tested banks within a 21-day event window (t–10, t+10). Based on the baseline Carhart (1997) four-factors model (C4F), the observations are split into banks that experience a positive ('good' news) and a negative ('bad' news) $CAR_{t-1,\, t+1}$. The SCAP 2009 as well as the CCARs in 2011 and 2012 are considered.

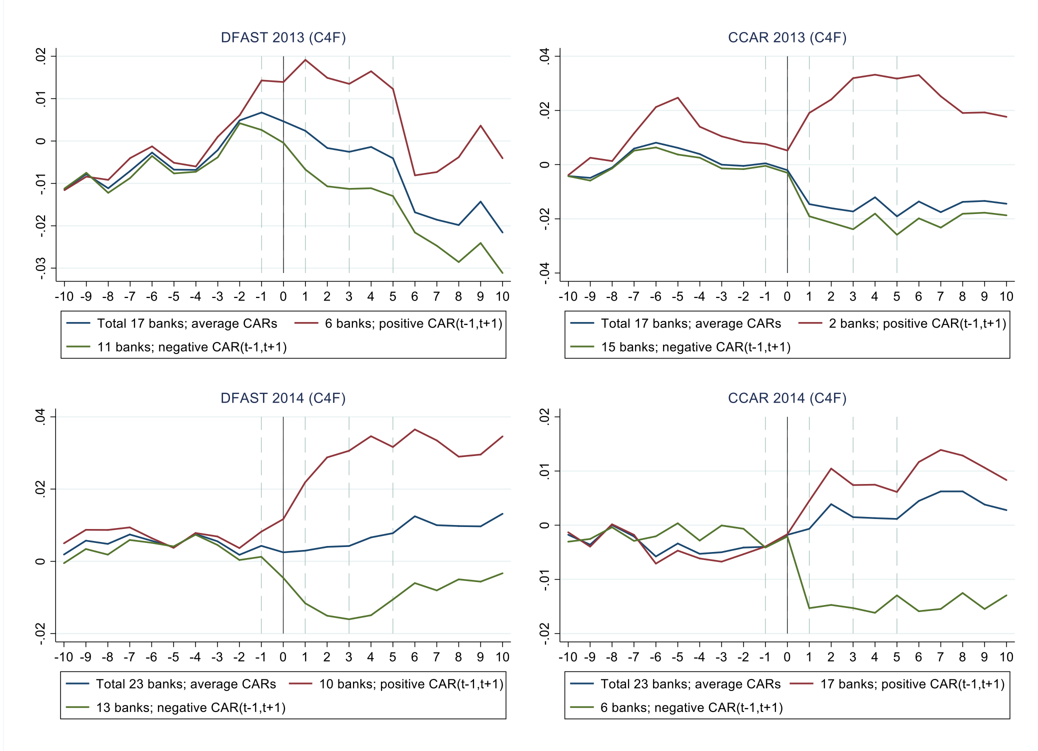

Figure 4.4 U.S. stress test events (2013-2014)

The graphs plot the average *CARs* (*CAAR*) of the stress-tested banks within a 21-day event window (t–10, t+10). Based on the baseline Carhart (1997) four-factors model (C4F), the observations are split into banks that experience a positive ('good' news) and a negative ('bad' news) $CAR_{t-1,\ t+1}$. The DFASTs and CCARs in 2013 and 2014 are considered.

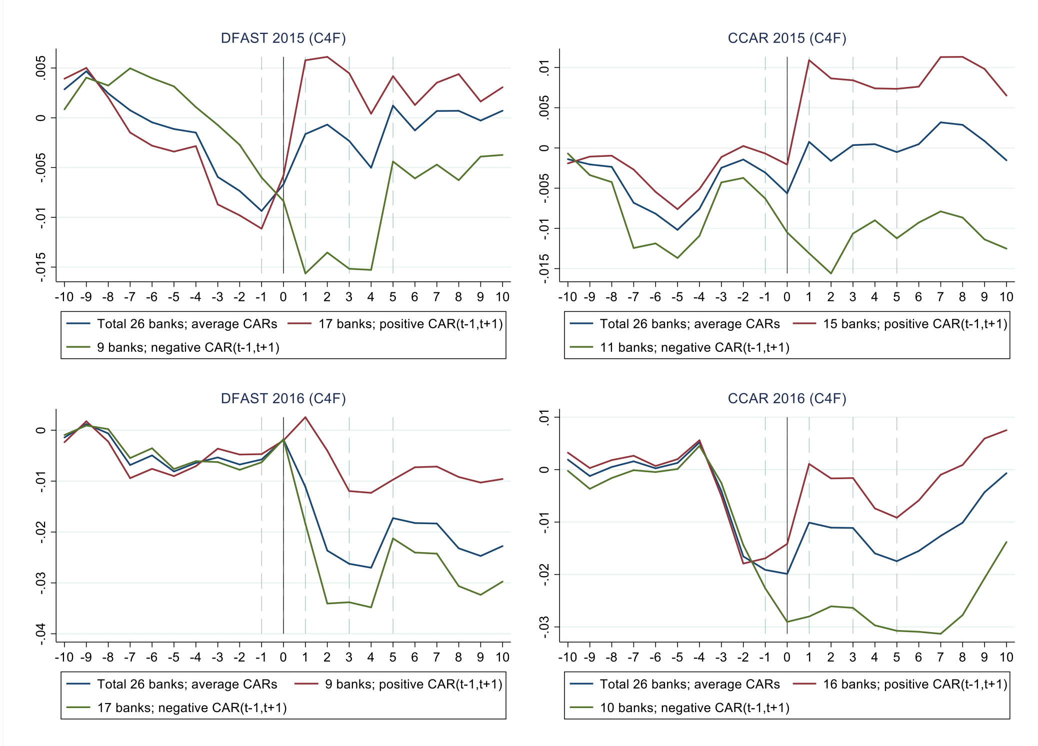

Figure 4.5 U.S. stress test events (2015-2016)

The graphs plot the average *CARs* (*CAAR*) of the stress-tested banks within a 21-day event window (t–10, t+10). Based on the baseline Carhart (1997) four-factors model (C4F), the observations are split into banks that experience a positive ('good' news) and a negative ('bad' news) $CAR_{t-1,\ t+1}$. The DFASTs and CCARs in 2015 and 2016 are considered.

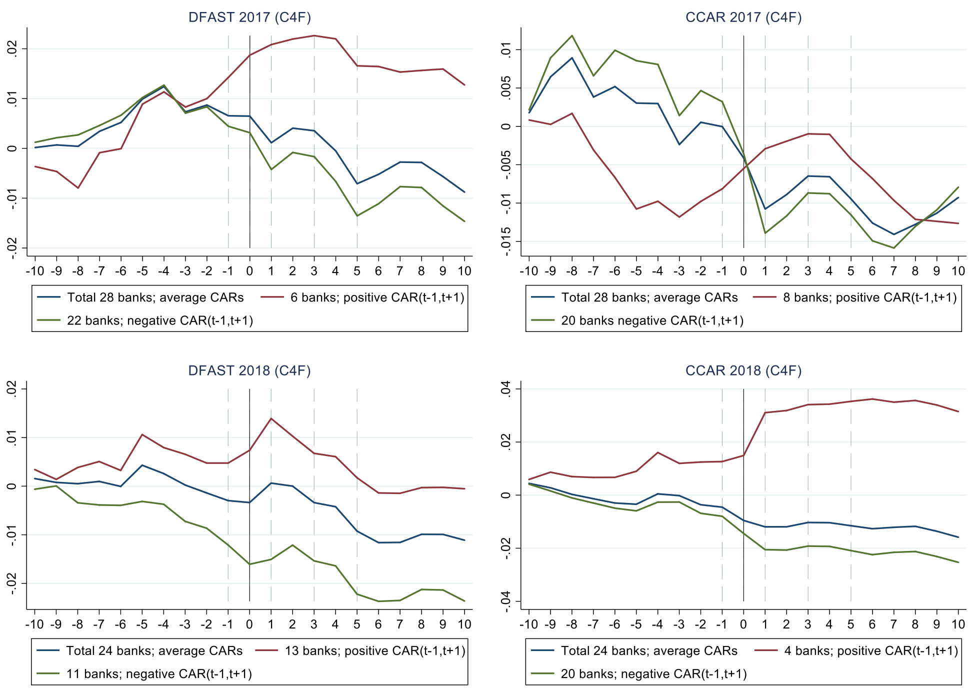

Figure 4.6 U.S. stress test events (2017-2018)

The graphs plot the average *CARs* (*CAAR*) of the stress-tested banks within a 21-day event window (t–10, t+10). Based on the baseline Carhart (1997) four-factors model (C4F), observations are split into banks that experience a positive ('good' news) and a negative ('bad' news) $CAR_{t-1,\ t+1}$. The DFASTs and CCARs in 2017 and 2018 are considered.

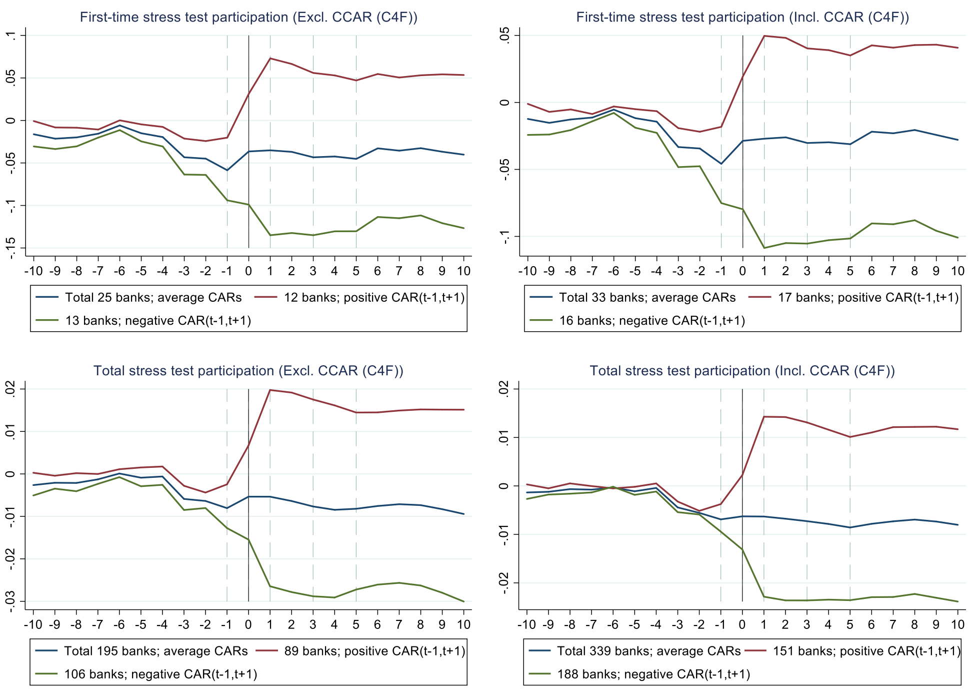

Figure 4.7 U.S. stress test events (FTSTO, TOTALSTO)

The graphs plot the average *CARs* (*CAAR*) of the stress-tested banks within a 21-day event window (t–10, t+10). Based on the baseline Carhart (1997) four-factors model (C4F), the observations are split into banks that experience a positive ('good' news) and a negative ('bad' news) $CAR_{t-1,\ t+1}$. The first-time (FTSTO) and total stress test observations (TOTALSTO) including and excluding CCARs in 2013, 2014, 2015, 2016, 2017, and 2018 are considered.

Table 4.7 Calendar-time portfolio (CTIME) analysis

Panel A: European banks

		Equally-weighted (C4F)			*MVALUE*-weighted (C4F)		
		1-12 mths.	1-24 mths.	1-36 mths.	1-12 mths.	1-24 mths.	1-36 mths.
(1)	CEBS 2010						
	Alpha	-0.0005	-0.0003	-0.0004	0.0005	0.0000	0.0000
	BETA	0.5557	0.8740***	0.7944***	0.7942***	0.9631***	0.9587***
	SMB	-0.5896	-0.0687	-0.1090	-0.6785**	-0.2736	-0.2272*
	HML	1.0640	1.2243**	1.4280***	0.5388	0.1443	0.2093
	MOM	-0.5272	0.3043	0.2219	-0.1608	-0.2100	-0.1976*
	Observations	12	24	36	12	24	36
	R-squared	0.971	0.9749	0.9745	0.9965	0.9959	0.9944
(2)	EBA 2011						
	Alpha	0.0034*	0.0019	0.0005	-0.0002	0.0005	0.0005
	BETA	0.7594***	0.9845***	0.9118***	1.0867***	1.1293***	1.1049***
	SMB	0.1318	0.4050	0.4374	-0.5808	0.1510	0.1284
	HML	3.0088***	0.9207	1.4213***	-0.1846	0.0386	0.2346
	MOM	1.5203***	0.2879	0.2694	-0.3994	-0.2178	-0.0773*
	Observations	12	24	36	12	24	36
	R-squared	0.9673	0.9551	0.936	0.9904	0.992	0.991
(3)	EBA/ECB 2014						
	Alpha	-0.0033	-0.0009	-0.0002	-0.0022***	-0.0018**	-0.0005
	BETA	0.9823**	0.8396***	0.8992***	1.2939***	1.1369***	1.0254***
	SMB	0.0987	-0.1486	0.0705	0.2074	-0.0765	-0.1633
	HML	0.1642	0.6123*	0.6401**	-0.7469***	-0.6366***	-0.3562
	MOM	-0.0634	0.1734	0.1559	-0.3636***	-0.3491**	-0.2785*
	Observations	12	24	36	12	24	36
	R-squared	0.9151	0.8942	0.9256	0.9923	0.9686	0.9576
(4)	EBA 2016						
	Alpha	-0.0005	-0.0006		-0.0001	0.0000	
	BETA	0.8797**	1.0636***		0.8667***	0.9492***	
	SMB	-0.5944	-0.1540		-0.1950	-0.0240	
	HML	0.2150	-0.2424		0.0927	-0.1037	
	MOM	-0.0334	-0.0752		-0.2879	-0.3367	
	Observations	12	24		12	24	
	R-squared	0.9541	0.9603		0.9845	0.9857	
(5)	FTSTO						
	Alpha	-0.0002	-0.0007	-0.0001	0.0001	-0.0002	0.0002
	BETA	0.6871	0.9013**	0.8032**	0.7738*	0.9286***	0.8759***
	SMB	-0.3718	0.1536	0.1670	-0.5846	-0.1256	-0.1804
	HML	1.4399	1.0278	1.3089	1.1463*	0.7220*	0.8494
	MOM	0.3547	0.3070	0.2842	0.2869	0.1854	0.1845
	Observations	36	72	108	36	72	108
	R-squared	0.0655	0.2388	0.2341	0.8374	0.8702	0.8043
(6)	TOTALSTO						
	Alpha	-0.0005	0.0001	0.0000	-0.0008	-0.0006*	-0.0001
	BETA	0.9770***	0.9730***	0.9296***	1.1480***	1.1390***	1.1011***
	SMB	0.1369	0.2605	0.2571	-0.0842	0.0440	0.0241
	HML	0.8678***	0.7090**	0.9622***	-0.2978	-0.3563***	-0.1217
	MOM	0.1620	0.1622	0.1259	-0.3772***	-0.3383***	-0.2178***
	Observations	36	72	108	36	72	108
	R-squared	0.9437	0.9511	0.9417	0.9867	0.9883	0.9849

Panel B: U.S. banks

		Equally-weighted (C4F)			*MVALUE*-weighted (C4F)		
		1-12 mths.	1-24 mths.	1-36 mths.	1-12 mths	1-24 mths	1-36 mths
(1)	SCAP 2009						
	Alpha	-0.0010	0.0021	0.0014	0.0023	0.0015	0.0005
	BETA	0.8093***	0.5773***	0.7144***	0.3770**	0.6347***	0.8049***
	SMB	-0.3065	0.1559	0.1843	0.2814	-0.1103	-0.0780
	HML	0.3863	1.5043*	0.8132*	2.3637**	1.0287**	0.1582
	MOM	-0.5236**	-0.3857**	-0.4077**	-0.0079	-0.1565*	-0.2088***
	Observations	12	24	36	12	24	36
	R-squared	0.9899	0.9772	0.9727	0.9919	0.986	0.9763
(2)	CCAR 2011						
	Alpha	0.0012**	0.0008	0.0006	0.0003	0.0005	0.0002
	BETA	0.4624***	0.5033**	0.5720***	0.5796**	0.6277***	0.6244***
	SMB	-0.2668	0.2306	0.1128	0.1555	0.1435	0.1118
	HML	0.4133	0.5108	0.3166	0.1193	0.3743	0.2966
	MOM	0.0849	0.0239	0.0237	-0.2258	-0.0010	-0.0564
	Observations	12	24	36	12	24	36
	R-squared	0.8786	0.7279	0.7818	0.8262	0.7538	0.7886

Table 4.7 continued

(3)	CCAR 2012						
	Alpha	0.0020*	0.0007	0.0004	0.0019	0.0008	0.0000
	BETA	1.0296***	1.0822***	1.0034***	0.9340***	1.0157***	0.9727***
	SMB	-0.4778	-0.1157	0.0198	-0.0973	0.0920	-0.0434
	HML	-0.8240	-0.3952	-0.1938	-0.2912	-0.3008	-0.1918
	MOM	-0.7007**	-0.4239***	-0.3996***	-0.5907*	-0.5234***	-0.5590***
	Observations	12	24	36	12	24	36
	R-squared	0.9627	0.9661	0.9561	0.9408	0.9635	0.9507
(4)	DFAST/CCAR 2013						
	Alpha	-0.0025***	-0.0017	-0.0004	-0.0023***	-0.0018**	-0.0007
	BETA	1.2039***	1.0949***	1.0747***	1.0551***	1.0419***	1.0488***
	SMB	0.1651	0.1065	0.1086	-0.3807	-0.2284	-0.1054
	HML	-0.8632	-0.0429	0.2107	-0.2984	0.6308	0.3731
	MOM	0.9232	0.7743***	0.4816***	0.3979	0.8101***	0.4512***
	Observations	12	24	36	12	24	36
	R-squared	0.8813	0.8827	0.8915	0.9048	0.8694	0.8817
(5)	DFAST/CCAR 2014						
	Alpha	0.0005	-0.0002	0.0004	0.0001	0.0002	0.0003
	BETA	0.9115***	0.8017***	0.8919***	0.8558***	0.8697***	0.9474***
	SMB	-0.3017*	-0.2007	0.0761	-0.1694	-0.1990**	-0.0841
	HML	0.5110***	0.0351	0.1329	0.2006	-0.0116	-0.0155
	MOM	0.5404***	0.3385**	0.2027	0.3653	0.2603***	0.1320*
	Observations	12	24	36	12	24	36
	R-squared	0.9929	0.9567	0.9381	0.9885	0.9879	0.986
(6)	DFAST/CCAR 2015						
	Alpha	0.0008*	0.0002	0.0004	0.0007	0.0004	0.0004
	BETA	1.1271***	0.9994***	0.9732***	1.0741***	0.9997***	0.9863***
	SMB	0.1560	0.1988	0.1473	-0.0314	0.0190	0.0177
	HML	-0.2171	0.0917	0.0846	-0.0474	0.0458	-0.0278
	MOM	-0.0950	0.0305	0.0495	-0.0109	-0.0115	-0.0073
	Observations	12	24	36	12	24	36
	R-squared	0.9912	0.9432	0.929	0.9923	0.9623	0.9599
(7)	DFAST/CCAR 2016						
	Alpha	0.0014	0.0010*		0.0011*	0.0005	
	BETA	1.0460***	1.0491***		0.8964***	0.9334***	
	SMB	0.5330*	0.6763***		0.1956*	0.3308**	
	HML	0.3030	0.1975*		0.2294*	0.0750	
	MOM	0.1413	0.2032		-0.0703	0.0086	
	Observations	12	24		12	24	
	R-squared	0.9705	0.9573		0.9933	0.9741	
(8)	DFAST/CCAR 2017						
	Alpha	0.0007			0.0001		
	BETA	0.8606***			0.9343***		
	SMB	0.2383			-0.0219		
	HML	-0.3967*			-0.2560**		
	MOM	-0.3538***			-0.1995***		
	Observations	12			12		
	R-squared	0.9365			0.9826		
(9)	FTSTO						
	Alpha	-0.0016	-0.0005	0.0004	-0.0006	-0.0003	0.0003
	BETA	0.9993***	0.8269***	0.8420***	0.7762***	0.8043***	0.8554***
	SMB	-0.2352	0.2060	0.2018	0.0727	-0.0447	-0.0668
	HML	-0.4564	0.2064	0.1843	0.4071	0.1532	-0.0674
	MOM	-0.4770**	-0.3942***	-0.3478***	-0.0715	-0.1548	-0.1726**
	Observations	36	72	108	36	72	108
	R-squared	0.9349	0.8921	0.8424	0.9151	0.8903	0.8361
(10)	TOTALSTO						
	Alpha	0.0002	0.0003	0.0003	-0.0002	0.0000	0.0001
	BETA	1.0283***	0.9390***	0.9353***	0.8893***	0.8910***	0.9036***
	SMB	-0.0140	0.2378*	0.2198**	-0.0070	0.0806	0.0529
	HML	-0.3964*	-0.2043	-0.1188	-0.0362	-0.1208	-0.1161
	MOM	-0.2934**	-0.2574***	-0.1963***	-0.0613	-0.1044	-0.1032*
	Observations	72	144	216	72	144	216
	R-squared	0.9703	0.9399	0.9393	0.9673	0.9517	0.9476

This table reports the results of the calendar-time portfolio (CTIME) approach. Panel A illustrates the European sample. Models 1 to 4 show the results for the stress tests in 2010, 2011, 2014 and 2016, whilst Models 5 and 6 display first-time and total stress test observations (FTSTO, TOTALSTO). Panel B illustrates the U.S. sample. Models 1 to 8 show the results for the stress tests in 2009, 2011, 2012, 2013, 2014, 2015, 2016 and 2017, whilst Models 9 and 10 assess first-time and total stress test observations (FTSTO, TOTALSTO). I estimate the coefficients, equally-weighted and *MVALUE*-weighted (year-end quarter 4 prior to each stress test event) for 1 to 12, 24 and 36 months after the stress test using the baseline Carhart (1997) four-factors model (C4F). Bank performance is measured by Jensen's alpha (*Alpha*), and the four factors are asset sensitivity (*BETA*), capitalisation (*SMB*), book-to-market (*HML*) and momentum (*MOM*)*, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 4.1.

Table 4.8 Information asymmetry and analyst behaviour

Panel A: European banks				
Variables	(1) $BIDASK_{itj}$	(2) $RECNO_{itj}$	(3) $EPSSUR$ / $PRICE_{itj}$	(4) $ESTSD$ / $PRICE_{itj}$
ST1011EU	0.0059*	2.9847**	-0.0948**	-0.0408*
	(0.0030)	(1.4092)	(0.0390)	(0.0232)
*ST1011EU*FTST1011EU*	-0.0038*	2.2601**	0.0070	0.0307**
	(0.0021)	(0.9071)	(0.0179)	(0.0130)
ST1415EU	-0.0038**	2.7382	0.0490	0.0307
	(0.0016)	(1.8490)	(0.0362)	(0.0201)
*ST1415EU*FTST1011EU*	0.0026**	-1.9743	-0.0296	0.0067
	(0.0011)	(1.4639)	(0.0222)	(0.0158)
ST16EU	-0.0021	2.6641	0.0399	-0.0125
	(0.0016)	(2.1266)	(0.0532)	(0.0246)
*ST16EU*FTST1011EU*	0.0019	-3.1897*	-0.0866	0.0060
	(0.0016)	(1.6067)	(0.0534)	(0.0239)
$TOVER_{it-2j}$	-0.0153	3.1699	-0.4539	-0.1537
	(0.0169)	(6.5492)	(0.4876)	(0.3218)
$INVPRICE_{it-2j}$	0.0031**	0.8785*	-0.0421	-0.0389**
	(0.0013)	(0.5154)	(0.0420)	(0.0180)
$RETVOL_{it-2j}$	0.2045**	-48.9321**	1.8337*	1.6021***
	(0.0863)	(19.9484)	(0.9406)	(0.5396)
$MVALUE_{it-2j}$	0.0030***	2.0336***	-0.1781***	-0.1038***
	(0.0009)	(0.5916)	(0.0490)	(0.0189)
$MTBV_{it-2j}$	0.0013	-0.6076	0.0194	0.0120
	(0.0011)	(0.8274)	(0.0174)	(0.0103)
$RECCON_{it-2j}$	0.0035***	-1.1167**	-0.0085	-0.0184**
	(0.0012)	(0.5234)	(0.0232)	(0.0082)
ΔGDP_{tj}	0.0109	-23.4682*	-0.6040***	-0.1625
	(0.0128)	(12.2361)	(0.2116)	(0.1057)
$\Delta UNEM_{tj}$	-0.0121	7.2052*	-0.1246	-0.1522*
	(0.0090)	(3.9419)	(0.1018)	(0.0853)
$IRATE_{tj}$	0.0003	-0.3152***	0.0143**	0.0130***
	(0.0002)	(0.0742)	(0.0058)	(0.0031)
Constant	-0.0388***	4.6796	1.5629***	0.9495***
	(0.0117)	(7.0424)	(0.4823)	(0.1756)
Observations	2,212	2,271	2,272	2,234
Number of banks	55	55	55	53
Adjusted R-squared	0.2491	0.3008	0.2952	0.4280
Bank fixed effects	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes

Panel B: U.S. banks				
Variables	(1) $BIDASK_{itj}$	(2) $RECNO_{itj}$	(3) $EPSSUR$ / $PRICE_{itj}$	(4) $ESTSD$ / $PRICE_{itj}$
ST0913US	0.0002	-6.4443*	0.1057***	0.0018
	(0.0002)	(3.2171)	(0.0201)	(0.0045)
*ST0913US*FTST09US*	-0.0003**	0.9900	-0.0223**	-0.0010
	(0.0001)	(1.1519)	(0.0089)	(0.0017)
ST1417US	-0.0001	-1.5527	0.0441**	-0.0003
	(0.0002)	(1.8933)	(0.0175)	(0.0043)
*ST1417US*FTST09US*	-0.0003*	0.7666	-0.0004	0.0016
	(0.0001)	(1.4336)	(0.0090)	(0.0020)
$TOVER_{it-2j}$	-0.0006	50.0157	0.1142	0.0540
	(0.0082)	(32.4836)	(0.6673)	(0.1341)
$INVPRICE_{it-2j}$	0.0028	-19.5172*	0.1623	0.0144
	(0.0028)	(10.7102)	(0.1431)	(0.0495)
$RETVOL_{it-2j}$	0.0077	-24.9992	1.2614**	0.3664***
	(0.0046)	(18.6754)	(0.5735)	(0.1267)
$MVALUE_{it-2j}$	-0.0004	0.0552	-0.0071	-0.0030
	(0.0002)	(0.9506)	(0.0161)	(0.0054)
$MTBV_{it-2j}$	0.0001	0.6915	-0.0071	0.0001
	(0.0001)	(0.6251)	(0.0077)	(0.0022)

Table 4.8 continued

$RECCON_{it-2j}$	0.0001	-2.1535***	0.0037	0.0024**
	(0.0001)	(0.6062)	(0.0059)	(0.0011)
ΔGDP_{tj}	-0.0015***	-3.5250	0.0735***	0.0022
	(0.0003)	(2.2308)	(0.0259)	(0.0048)
$\Delta UNEM_{tj}$	-0.0010**	-13.7281*	0.2304***	0.0130
	(0.0004)	(6.8467)	(0.0762)	(0.0143)
$IRATE_{tj}$	0.0000	4.5368***	-0.0364***	-0.0009
	(0.0001)	(1.0063)	(0.0071)	(0.0012)
Constant	0.0039*	25.1055**	0.0560	0.0223
	(0.0022)	(10.0820)	(0.1624)	(0.0511)
Observations	1,178	1,176	1,171	1,155
Number of banks	28	28	27	27
Adjusted R-squared	0.8131	0.7916	0.2399	0.5891
Bank fixed effects	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes

This table reports the effect of stress tests on information asymmetry. Panel A illustrates the European sample and Panel B shows the U.S. sample. I use the following dependent variables, daily winsorised at the 1 and 99 percentiles and quarterly averaged, in my analysis: Information asymmetry captured by the bid-ask spread ($BIDASK_{itj}$) and analyst behaviour using analyst coverage ($RECNO_{itj}$), earnings surprises ($EPSSUR / PRICE_{itj}$) and estimate dispersion ($ESTSD / PRICE_{itj}$). In Panel A, I include dummy variable to measure European first-time participation in 2010-11 (*FTST1011EU*) and the stress test periods in 2010-11 (*ST1011EU*), 2014-15 (*ST1415EU*), and 2016 (*ST16EU*). In Panel B, I include dummy variables to estimate U.S. first-time participation in 2009 (*FTST09US*) and the stress test periods in 2009-13 (*ST0913US*) and 2014-17 (*ST1417US*). In both panels, I control for market microstructure characteristics, lagged by two quarters, and country-specific fundamentals using the following variables: Share turnover ($TOVER_{it-2j}$), inverse share price ($INVPRICE_{it-2j}$), return volatility ($RETVOL_{it-2j}$), market value ($MVALUE_{it-2j}$), market-to-book value ($MTBV_{it-2j}$), analyst recommendation consensus ($RECCON_{t-2}$); and macroeconomic fundamentals captured by the economic growth (ΔGDP_{tj}), the unemployment growth ($\Delta UNEM_{tj}$), and sovereign debt risk ($IRATE_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 4.1.

Table 4.9 Bank risk-taking

Panel A: European banks						
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	$T1R_{itj}$	$LEVERAGE_{itj}$	RWA_{itj}	LLR_{itj}	$ZSCORE_{itj}$	ROA_{itj}
ST1011EU	0.0329***	-0.2055**	-0.0518*	0.0225**	0.4068	-0.0044***
	(0.0120)	(0.0819)	(0.0303)	(0.0088)	(0.2912)	(0.0015)
*ST1011EU*FTST1011EU*	0.0012	0.0431	0.0001	-0.0030	0.2742*	-0.0020***
	(0.0067)	(0.0370)	(0.0164)	(0.0041)	(0.1512)	(0.0007)
ST1415EU	0.0836***	-0.4451***	-0.1311***	0.0271***	0.8808***	-0.0052***
	(0.0124)	(0.0714)	(0.0330)	(0.0098)	(0.2323)	(0.0018)
*ST1415EU*FTST1011EU*	-0.0167*	-0.0426	0.0227	0.0043	-0.0679	-0.0010
	(0.0087)	(0.0393)	(0.0174)	(0.0042)	(0.1367)	(0.0009)
ST16EU	0.0815***	-0.3904***	-0.1409***	0.0335***	0.7668***	-0.0067***
	(0.0128)	(0.0670)	(0.0336)	(0.0125)	(0.2648)	(0.0017)
*ST16EU*FTST1011EU*	-0.0090	-0.0812*	0.0394*	0.0012	-0.1081	-0.0002
	(0.0079)	(0.0456)	(0.0209)	(0.0080)	(0.1397)	(0.0010)
$SIZE_{it-2j}$	-0.0133	0.4598***	-0.1126***	-0.0129	-0.2998*	-0.0024**
	(0.0118)	(0.0878)	(0.0265)	(0.0082)	(0.1799)	(0.0009)
$LOAN_{it-2j}$	-0.0534**	-0.0831	0.2799***	-0.0346*	-0.5115	0.0059
	(0.0266)	(0.2021)	(0.0694)	(0.0190)	(0.4945)	(0.0046)
LLP_{it-2j}	-0.8493***	7.9604***	0.9187	2.0874***	-50.5358***	-0.3130***
	(0.2447)	(1.9307)	(0.5722)	(0.2507)	(6.2923)	(0.0561)
$TRADE_{it-2j}$	0.0400	-0.8548***	-0.0543	-0.0313	0.6741	0.0087*
	(0.0324)	(0.3126)	(0.0650)	(0.0208)	(0.5478)	(0.0050)
$DEPO_{it-2j}$	-0.0339***	0.1230	-0.0516*	-0.0146	0.4791*	0.0011
	(0.0101)	(0.1000)	(0.0290)	(0.0151)	(0.2767)	(0.0022)
$EBPT_{it-2j}$	1.2173***	-10.4602***	-1.0924	-0.3189	26.8717***	0.1283*
	(0.2906)	(2.7519)	(0.9147)	(0.3116)	(7.9974)	(0.0729)
ΔGDP_{tj}	0.0719	-0.2892	-0.2438	0.0442	1.6333**	0.0304**
	(0.0442)	(0.5831)	(0.1585)	(0.0531)	(0.7469)	(0.0139)
$\Delta UNEM_{tj}$	0.0087	0.3628***	-0.1511***	-0.0472***	-0.3501	-0.0021
	(0.0172)	(0.1223)	(0.0478)	(0.0105)	(0.3195)	(0.0024)
Constant	0.2816*	-2.1791**	1.7356***	0.1846**	6.1171***	0.0309***
	(0.1418)	(0.9833)	(0.3107)	(0.0896)	(2.0888)	(0.0102)
Observations	2,346	2,461	2,228	2,232	2,519	2,497
Number of banks	89	91	87	87	91	87
Adjusted R-squared	0.5176	0.3424	0.4681	0.3527	0.1611	0.1727
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: U.S. banks						
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	$T1R_{itj}$	$LEVERAGE_{itj}$	RWA_{itj}	LLR_{itj}	$ZSCORE_{itj}$	ROA_{itj}
ST0913US	0.0209*	-0.0615	0.0428	0.0045*	1.0947***	0.0466***
	(0.0109)	(0.1086)	(0.0308)	(0.0022)	(0.3757)	(0.0044)
*ST0913US*FTST09US*	0.0014	-0.0222	0.0020	0.0002	0.3335	-0.0001
	(0.0035)	(0.0570)	(0.0172)	(0.0012)	(0.1997)	(0.0009)
ST1417US	0.0275*	0.0071	-0.0209	0.0031	1.0959***	0.0506***
	(0.0144)	(0.1317)	(0.0471)	(0.0023)	(0.3927)	(0.0042)
*ST1417US*FTST09US*	-0.0079	-0.0418	0.1021**	-0.0005	0.0520	-0.0007
	(0.0073)	(0.0699)	(0.0475)	(0.0007)	(0.1868)	(0.0009)
$SIZE_{it-2j}$	-0.0085	0.0123	-0.0826***	0.0001	0.3092	-0.0037***
	(0.0071)	(0.0740)	(0.0215)	(0.0010)	(0.2038)	(0.0007)
$LOAN_{it-2j}$	-0.0451*	0.3073	0.2789**	-0.0022	0.0075	-0.0023
	(0.0231)	(0.2347)	(0.1064)	(0.0052)	(0.8789)	(0.0036)
LLP_{it-2j}	0.2754	2.6425	-1.5346	0.5046***	-11.6537	-0.1522**
	(0.2833)	(2.5256)	(1.0395)	(0.0611)	(12.0168)	(0.0603)
$TRADE_{it-2j}$	-0.0041	1.2690	-0.3897	-0.0134	-1.1196	-0.0041
	(0.0503)	(0.8178)	(0.2840)	(0.0089)	(1.8932)	(0.0080)
$DEPO_{it-2j}$	0.0051	0.0648	-0.2143***	0.0044	0.6967	0.0097***
	(0.0233)	(0.2351)	(0.0542)	(0.0036)	(0.5689)	(0.0035)
$EBPT_{it-2j}$	-0.0797	0.1156	0.5572	-0.0708*	6.1589	-0.0945***
	(0.0992)	(0.9378)	(0.4519)	(0.0387)	(4.5171)	(0.0265)
ΔGDP_{tj}	-0.1213**	1.5014**	0.5605***	0.0206**	2.7718**	0.2689***
	(0.0491)	(0.5625)	(0.1374)	(0.0081)	(1.1662)	(0.0206)

Table 4.9 continued

$\Delta UNEM_{tj}$	-0.4239**	5.3577**	2.2763***	0.0825**	10.9336**	0.8174***
	(0.1789)	(2.0990)	(0.5240)	(0.0339)	(4.6195)	(0.0600)
Constant	0.2062**	1.9650**	1.7977***	0.0059	-1.6162	0.0461***
	(0.0745)	(0.8137)	(0.2435)	(0.0112)	(2.1155)	(0.0081)
Observations	975	993	894	973	993	992
Number of banks	28	28	28	27	28	28
Adjusted R-squared	0.5474	0.3274	0.2606	0.7472	0.1517	0.5932
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the effect of stress tests on bank risk-taking. Panel A illustrates the European sample and Panel B shows the U.S. sample. I use the following dependent variables, winsorised at the 1 and 99 percentiles, in my analysis: Bank risk-taking using capital adequacy ($T1R_{itj}$), leverage risk ($LEVERAGE_{itj}$), credit risk (RWA_{itj}), credit portfolio quality (LLR_{itj}), insolvency risk ($ZSCORE_{itj}$) and profitability (ROA_{itj}). In Panel A, I include dummy variable to measure European first-time participation in 2010-11 (*FTST1011EU*) and the stress test periods in 2010-11 (*ST1011EU*), 2014-15 (*ST1415EU*), and 2016 (*ST16EU*). In Panel B, I include dummy variables to estimate U.S. first-time participation in 2009 (*FTST09US*) and the stress test periods in 2009-13 (*ST0913US*) and 2014-17 (*ST1417US*). In both panels, I control for bank characteristics, lagged by two quarters, and country-specific fundamentals using the following variables: Bank size captured by natural logarithm of total assets ($SIZE_{it-2j}$), traditional banking activities shown by outstanding loans ($LOAN_{it-2j}$), asset quality measured by loan loss provisions (LLP_{it-2j}), non-traditional banking activities measured by trading securities ($TRADE_{it-2j}$), liquidity shown by total deposits ($DEPO_{it-2j}$), profitability measured by earnings before provision and taxes ($EBPT_{it-2j}$); and macroeconomic fundamentals captured by economic growth (ΔGDP_{tj}), and unemployment growth ($\Delta UNEM_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 4.1.

Table 4.10 Bank funding structure

Panel A: European banks						
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	TIE_{itj}	OIE_{itj}	$DEPBA_{itj}$	$IECD_{itj}$	$CUSTD_{itj}$	NIM_{itj}
ST1011EU	-0.0157***	-0.0119***	-0.0063	-0.0069***	-0.0001	-0.0088***
	(0.0020)	(0.0029)	(0.0252)	(0.0012)	(0.0435)	(0.0011)
*ST1011EU*FTST1011EU*	0.0011	0.0006	-0.0350**	0.0005	0.0187	0.0004
	(0.0008)	(0.0009)	(0.0158)	(0.0005)	(0.0146)	(0.0005)
ST1415EU	-0.0180***	-0.0131***	-0.1065***	-0.0090***	0.0514	-0.0101***
	(0.0019)	(0.0028)	(0.0250)	(0.0014)	(0.0446)	(0.0012)
*ST1415EU*FTST1011EU*	0.0002	0.0000	0.0235*	0.0001	-0.0066	0.0011*
	(0.0006)	(0.0005)	(0.0123)	(0.0005)	(0.0106)	(0.0006)
ST16EU	-0.0181***	-0.0130***	-0.1140***	-0.0092***	0.0820*	-0.0097***
	(0.0019)	(0.0028)	(0.0272)	(0.0014)	(0.0453)	(0.0012)
*ST16EU*FTST1011EU*	-0.0004	-0.0005	0.0432***	0.0002	-0.0184	0.0012
	(0.0008)	(0.0007)	(0.0155)	(0.0007)	(0.0181)	(0.0007)
$SIZE_{it-2j}$	-0.0003	0.0008	0.0405***	-0.0015*	-0.0976***	-0.0017*
	(0.0017)	(0.0017)	(0.0130)	(0.0008)	(0.0258)	(0.0009)
$LOAN_{it-2j}$	0.0096**	0.0072*	-0.1074**	0.0011	-0.0211	0.0052**
	(0.0042)	(0.0041)	(0.0459)	(0.0025)	(0.0734)	(0.0025)
LLP_{it-2j}	0.0122	0.0497	3.0388***	-0.0076	-2.4236***	-0.0622**
	(0.0344)	(0.0348)	(0.6080)	(0.0362)	(0.6618)	(0.0312)
$TRADE_{it-2j}$	-0.0202***	-0.0155***	-0.1816***	-0.0112***	-0.0812	0.0030
	(0.0046)	(0.0041)	(0.0593)	(0.0036)	(0.0811)	(0.0031)
$DEPO_{it-2j}$	0.0010	-0.0014	0.1712***	0.0036**	0.2923***	0.0014
	(0.0017)	(0.0018)	(0.0502)	(0.0016)	(0.0431)	(0.0016)
$EBPT_{it-2j}$	0.0300	0.0556	-1.5403**	-0.0838**	0.1116	-0.0577
	(0.0668)	(0.0634)	(0.6503)	(0.0372)	(0.8231)	(0.0533)
ΔGDP_{tj}	0.0021	-0.0042	-0.0227	-0.0048	0.2519	-0.0113*
	(0.0069)	(0.0089)	(0.1073)	(0.0116)	(0.1983)	(0.0066)
$\Delta UNEM_{tj}$	-0.0008	-0.0037	-0.0030	0.0066***	-0.0648**	-0.0006
	(0.0027)	(0.0032)	(0.0327)	(0.0025)	(0.0317)	(0.0024)
Constant	0.0194	0.0036	-0.3092**	0.0255***	1.4398***	0.0290***
	(0.0188)	(0.0180)	(0.1470)	(0.0087)	(0.3012)	(0.0103)
Observations	2,155	2,132	2,388	1,345	2,415	2,422
Number of banks	87	87	87	81	87	91
Adjusted R-squared	0.7061	0.4766	0.2355	0.6301	0.3363	0.7381
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: U.S. banks						
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	TIE_{itj}	OIE_{itj}	$SUBD_{itj}$	$IECD_{itj}$	$CUSTD_{itj}$	NIM_{itj}
ST0913US	0.0074***	-0.0010	-0.0050	-0.0033	0.3169***	0.1041***
	(0.0024)	(0.0017)	(0.0069)	(0.0026)	(0.0484)	(0.0087)
*ST0913US*FTST09US*	-0.0004	0.0003	0.0009	0.0008**	-0.0067	-0.0007
	(0.0005)	(0.0005)	(0.0018)	(0.0003)	(0.0093)	(0.0009)
ST1417US	0.0077***	-0.0014	-0.0080	-0.0029	0.3513***	0.1080***
	(0.0024)	(0.0019)	(0.0072)	(0.0029)	(0.0606)	(0.0095)
*ST1417US*FTST09US*	-0.0004	0.0002	-0.0005	0.0008	0.0141	0.0001
	(0.0006)	(0.0005)	(0.0028)	(0.0005)	(0.0156)	(0.0008)
$SIZE_{it-2j}$	0.0024***	0.0026**	0.0004	0.0003	-0.1066***	-0.0021*
	(0.0007)	(0.0010)	(0.0045)	(0.0005)	(0.0141)	(0.0010)
$LOAN_{it-2j}$	-0.0009	-0.0021	0.0273	-0.0000	0.0004	0.0052
	(0.0019)	(0.0026)	(0.0162)	(0.0017)	(0.0656)	(0.0063)
LLP_{it-2j}	0.0222	0.0136	-0.0048	0.0109	0.7689	-0.2058***
	(0.0265)	(0.0298)	(0.1636)	(0.0166)	(0.5550)	(0.0551)
$TRADE_{it-2j}$	0.0008	0.0014	-0.0038	-0.0047	-0.0712	-0.0021
	(0.0051)	(0.0069)	(0.0159)	(0.0037)	(0.1311)	(0.0095)
$DEPO_{it-2j}$	-0.0029	-0.0048*	-0.0241**	0.0029**	0.3380***	0.0026
	(0.0018)	(0.0025)	(0.0094)	(0.0014)	(0.0880)	(0.0038)
$EBPT_{it-2j}$	-0.0468***	-0.0282**	0.0135	-0.0150	0.1108	-0.1211***
	(0.0152)	(0.0131)	(0.0618)	(0.0109)	(0.3260)	(0.0358)
ΔGDP_{tj}	0.0930***	0.0481***	0.0098	0.0462***	1.2342***	0.5750***
	(0.0133)	(0.0069)	(0.0284)	(0.0088)	(0.2019)	(0.0524)

Table 4.10 continued

$\Delta UNEM_{tj}$	0.2798***	0.1397***	0.0377	0.1454***	4.6164***	1.7648***
	(0.0407)	(0.0223)	(0.0967)	(0.0299)	(0.7784)	(0.1610)
Constant	-0.0146*	-0.0161	0.0170	0.0060	1.6397***	0.0322***
	(0.0073)	(0.0096)	(0.0545)	(0.0048)	(0.1407)	(0.0113)
Observations	992	992	718	869	975	993
Number of banks	28	28	28	27	28	28
Adjusted R-squared	0.8689	0.7125	0.3317	0.8728	0.5801	0.8532
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the effect of stress tests on bank funding structure. Panel A illustrates the European sample and Panel B shows the U.S. sample. I estimate bank funding structure using total (TIE_{itj}) uninsured (OIE_{itj}) and insured ($IECD_{itj}$) funding cost as well as uninsured ($DEPBA_{itj}$, $SUBD_{itj}$), insured funding ($CUSTD_{itj}$), and interest margin (NIM_{itj}). In Panel A, I include dummy variable to measure European first-time participation in 2010-11 (*FTST1011EU*) and the stress test periods in 2010-11 (*ST1011EU*), 2014-15 (*ST1415EU*), and 2016 (*ST16EU*). In Panel B, I include dummy variables to estimate U.S. first-time participation in 2009 (*FTST09US*) and the stress test periods in 2009-13 (*ST0913US*) and 2014-17 (*ST1417US*). In both panels, I control for bank characteristics, lagged by two quarters, and country-specific fundamentals using the following variables: Bank size captured by natural logarithm of total assets ($SIZE_{it-2j}$), traditional banking activities shown by outstanding loans ($LOAN_{it-2j}$), asset quality measured by loan loss provisions (LLP_{it-2j}), non-traditional banking activities measured by trading securities $(TRADE_{it-2j})$, liquidity shown by total deposits $(DEPO_{it-2j})$, profitability measured by earnings before provision and taxes ($EBPT_{it-2j}$); and macroeconomic fundamentals captured by economic growth (ΔGDP_{tj}), and unemployment growth ($\Delta UNEM_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 4.1.

Table 4.11 Event study robustness checks

		Obs.	Average CARs (CAAR) t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
Panel A: C4F baseline model using 120-day estimation window on European banks						
(1)	CEBS 2010 (23 July)	40	0.0061	0.0003	-0.0111	-0.0031
(2)	EBA 2011 (15 July)	41	0.0060	0.0152	0.0177	0.0300*
(3)	EBA/ECB 2014 (27 Oct.)	57	0.0024	-0.0028	-0.0122	-0.0143
(4)	ECB 2015 (2 Nov.)	4	0.1255	-0.0189	-0.1478	-0.2580
(5)	EBA 2016 (29 July)	32	0.0078	0.0014	-0.0096	-0.0098
(6)	EBA 2018 (2 Nov.)	32	-0.0023	-0.0026	-0.0021	0.0035
(7)	FTSTO	59	0.0125*	0.0103	-0.006	-0.0017
(8)	TOTALSTO	206	0.0063	0.0018	-0.0067	-0.0046
Panel B: C4F baseline model using 120-day estimation window on U.S. banks						
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	SCAP 2009 (7 May)	17	0.0027	0.0038	-0.0330	-0.0059
(2)	CCAR 2011 (18 March)	17	0.0049	0.0090*	0.0077	0.0058
(3)	CCAR 2012 (13 March)	17	0.0178**	0.0208**	0.0076	0.0306*
(4)	DFAST 2013 (7 March)	17	-0.0015	-0.0058	0.0041	-0.0077
(5)	CCAR 2013 (14 March)	17	-0.0136***	-0.0152**	-0.0216**	-0.0189
(6)	DFAST 2014 (20 March)	23	-0.0017	-0.0019	-0.0081	0.0011
(7)	CCAR 2014 (26 March)	23	0.0026**	0.0065	0.0033	0.0054
(8)	DFAST 2015 (5 March)	26	0.0059	0.0071*	0.0001	0.0096**
(9)	CCAR 2015 (11 March)	26	0.0026	0.0006	0.0089**	0.0017
(10)	DFAST 2016 (23 June)	26	-0.0053	-0.0185**	-0.0211***	-0.0111
(11)	CCAR 2016 (29 June)	26	0.0070	0.0056	-0.0173	-0.0013
(12)	DFAST 2017 (22 June)	28	-0.0058	-0.0027	-0.0067**	-0.0137**
(13)	CCAR 2017 (28 June)	28	-0.0112**	-0.0090*	-0.0081	-0.0092**
(14)	DFAST 2018 (21 June)	24	0.0023	0.0020	-0.0061**	-0.0065
(15)	CCAR 2018 (28 June)	24	-0.0072***	-0.0072***	-0.0095**	-0.0070**
(16)	FTSTO (Excl. 5, 7, 9, 11, 13, 15)	25	0.0017	0.0021	-0.0288*	-0.0053
(17)	FTSTO	33	0.0007	0.0033	-0.0210	-0.0008
(18)	TOTALSTO (Excl. 5, 7, 9, 11, 13, 15)	195	0.0014	0.0005	-0.0066**	-0.0009
(19)	TOTALSTO	339	-0.0004	-0.0008	-0.0067***	-0.0023*
Panel C: C4F baseline model using Patell (1976) standardised residual test on European banks						
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	CEBS 2010 (23 July)	40	0.0062	0.0002	-0.0106**	-0.0042
(2)	EBA 2011 (15 July)	41	0.0054**	0.0149	0.0181**	0.0318***
(3)	EBA/ECB 2014 (27 Oct.)	57	0.0025	-0.0023	-0.0074	-0.0129
(4)	ECB 2015 (2 Nov.)	4	0.1158	-0.0356	-0.1480	-0.2520**
(5)	EBA 2016 (29 July)	32	0.0081	0.0016	-0.0094	-0.0091
(6)	EBA 2018 (2 Nov.)	32	0.0007	0.0006	0.0022	0.0067
(7)	FTSTO	59	0.0134	0.011	-0.0031	-0.0023
(8)	TOTALSTO	206	0.0066	0.002	-0.0045	-0.0033
Panel D: C4F baseline model using the Patell (1976) standardised residual test on U.S. banks						
		Obs.	t–1, t+1	t–1, t+2	t–3, t+3	t–1, t+5
(1)	SCAP 2009 (7 May)	17	0.0133	0.0103	-0.0278	-0.0016
(2)	CCAR 2011 (18 March)	17	0.0012	0.0054	0.0036	0.0003
(3)	CCAR 2012 (13 March)	17	0.0054	0.0089	-0.0019	0.0212*
(4)	DFAST 2013 (7 March)	17	-0.0025	-0.0065	0.0043	-0.0089
(5)	CCAR 2013 (14 March)	17	-0.0141***	-0.0156***	-0.0212***	-0.0186***
(6)	DFAST 2014 (20 March)	23	0.0011	0.0022	-0.0033	0.0060*
(7)	CCAR 2014 (26 March)	23	0.0035	0.0080***	0.0068**	0.0053
(8)	DFAST 2015 (5 March)	26	0.0057**	0.0067***	-0.0008	0.0086**
(9)	CCAR 2015 (11 March)	26	0.0022	-0.0002	0.0079**	0.0009
(10)	DFAST 2016 (23 June)	26	-0.0044	-0.0169***	-0.0198***	-0.0105**
(11)	CCAR 2016 (29 June)	26	0.0064	0.0055	-0.0163***	-0.0009
(12)	DFAST 2017 (22 June)	28	-0.0076***	-0.0046*	-0.0089**	-0.0158***
(13)	CCAR 2017 (28 June)	28	-0.0113***	-0.0094***	-0.0095***	-0.0100***
(14)	DFAST 2018 (21 June)	24	0.0020	0.0014	-0.0060	-0.0079**
(15)	CCAR 2018 (28 June)	24	-0.0083***	-0.0083***	-0.0108***	-0.0079**
(16)	FTSTO (Excl. 5, 7, 9, 11, 13, 15)	25	0.0098	0.0080	-0.0238**	-0.0003
(17)	FTSTO	33	0.0073	0.0083	-0.0159	0.0032
(18)	TOTALSTO (Excl. 5, 7, 9, 11, 13, 15)	195	0.0010	0.0000	-0.0071***	-0.0018*
(19)	TOTALSTO	339	-0.0008**	-0.0012**	-0.0069***	-0.0030***

This table reports robustness checks on the event studies. Panels A (European) and B (U.S.) indicate the C4F baseline model using a 120-day estimation window. Panels C (European) and D (U.S.) show the C4F baseline model using the Patell (1976) standardised residual test. For Europe (Panels A and C), Models 1 to 5 display the results for the European stress tests in 2010, 2011, 2014, 2015, 2016 and 2018, and Models 6 and 7 illustrate first-time and total observations (FTSTO, TOTALSTO). For the U.S. (Panels B and D), Models 1 to 15 show the results for the U.S. stress tests in 2009, 2011, 2012, 2013, 2014, 2015, 2016, 2017 and 2018, and Models 16 and 19 illustrate first-time and total stress test observations (FTSTO, TOTALSTO). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 4.1.

Chapter 5 – Conclusions

The main objective of this thesis is to evaluate the costs and benefits of regulatory stress tests and if those exercises effectively contribute towards sustainable financial stability. Given the growing importance of bank stress tests within the financial industry and the extant literature (Gropp et al., 2019; Flannery et al., 2017; Bischof and Daske, 2013), this thesis scrutinises the impact of stress tests concerning bank behaviour. The analysis is threefold. I examine the implications of bank stress tests on accounting discretion (Chapter 2), transparency and opacity (Chapter 3) and market discipline (Chapter 4).

In particular, in my first empirical study (Chapter 2), I scrutinise the stress-tested bank's accounting discretion practices, and if stress tests incentivise banks to exercise discretion over loan loss provisions. I find that stress tests produce a treatment effect that significantly affects banks' capital adequacy, asset quality and credit risk. Further, stress-tested banks delay discretionary loan loss provisions to strengthen their capital base. In support of prior research, my evidence suggests that the 2010-11 stress tests motivate banks to manage capital and earnings, while the 2014 assessment is more effective at preventing discretionary activities.

In my second empirical work (Chapter 3), I focus on bank transparency from a quantitative and qualitative perspective. The purpose is to analyse bank disclosure profiles, and the strength of stress test language and disclosure tone on bank transparency. My results suggest that stress test participants adjust their textual disclosures using particular stress test language, i.e. 'stress test sentiment' that incentivises banks to change their disclosure tone in a positive direction. Ultimately, I report that a more positive disclosure tone is related to a reduction in information asymmetry that indicate investor's obfuscation.

Finally, in my third empirical study (Chapter 4), I explore market discipline within the market sentiment and bank-specific fundamentals that should display investor's influence on bank behaviour. I conclude that the disciplining effect of stress tests is mixed in the U.S. and European markets and depends on the individual assessment. On certain occasions, stress test information exacerbates negative trends, which may harm financial stability as weaker institutions are penalised. Further, stress tests have contributed to reduce information asymmetry; however, this does not affect analyst behaviour. Also, mainly in Europe, I find significant evidence for improved risk-taking and funding structure, while this is not conclusive for U.S. banks.

The results from this thesis have important business and policy implications. Stress tests are seen as a useful regulatory tool; however, they need to be well-implemented to be effective in stimulating market discipline and financial stability (Borio et al., 2014; Schuermann, 2014). Importantly, despite potential difficulties that arise from their implementation, the authorities must commit to a specific disclosure policy (i.e., bank-specific or aggregated) to inform market participants (Goldstein and Sapra, 2013). Further, regulatory assessments provide unique insights to the authorities that have improved the regulation and supervision of SIFIs (Carboni et al., 2017; Sahin and de Haan, 2016).

However, my findings suggest that stress-tested banks tend to apply more discretion over loan loss provisions than untested banks. In particular, stress-tested banks manage their capital and earnings to boost accounting figures during stress test periods. Further, stress test sentiment affects a bank's textual narratives, and stress-tested banks appear to amend their reports towards a more positive (or less negative) disclosure tone. The results from both studies imply that bank managers aim to mitigate the specific impact from stress test exercises. Importantly, the latter results show that a more positive disclosure tone that compensates for stress test sentiment is transferred into reduced information asymmetry, which could be an indication for investors' obfuscation.

As suggested by the literature, the regulatory transparency from bank-specific (widely employed in stress tests), compared to aggregated, stress test disclosures could be a contributing factor for the above described bank behaviour. I contribute empirical support to the propositions of the stress test theory (Goldstein and Leitner, 2018; Bouvard et al., 2015; Goldstein and Sapra, 2013); this posits that, in normal economic times, the authorities should disclose aggregated rather than bank-specific results. The benefits for regulators and the public could be threefold. First, banks would perhaps be more open-minded towards stress tests, effectively cooperate with regulators, and might share more information because they do not need to fear that this information might be disclosed (Prescott, 2008). Second, analyst's information production would not be influenced by regulatory transparency and, therefore, regulators could learn from market movements. Third, banks would not undertake short-sighted investment decisions that assist in passing stress tests but potentially harm long-term cash flow prospects (Goldstein and Sapra, 2013). A disadvantage, however, could be that markets suspect potential regulatory forbearance (Wheeler, 2019; Bhat et al., 2011) and question political independence (García Osma et al., 2019), which could reduce the market's trust in regulatory activities.

Moreover, analysing market reactions on bank-specific disclosures, I find that markets seem to be well informed and mainly correspond to stress test information. Only on certain occasions, i.e., those that depend on the particular market sentiment, do stress tests stimulate market discipline or reward (e.g., EBA's 2011 stress test). A closer look at market responses reveals that stress test disclosures exacerbate negative and positive abnormal return trends. Further, stress test information may even transfer into significant 'alphas', indicating influence on long-term bank stock performance. This specifically penalises banks that perform poorly and could harm financial stability. Thus, market participants might not always need bank-specific disclosures to make conclusions about the solvency of stress-tested banks, while the additional information may trigger previously discussed unintended consequences.

Therefore, I conclude that transparency from stress tests is a channel that promotes market discipline in both a positive and a negative direction. The one-size-fits-all approach might further contribute to this fact and, in turn, the authorities should disclose stress test information in a carefully executed disclosure policy. As the results vary depending on the particular stress test exercise, I am hesitant to fully support one 'magic' disclosure practice. Rather, regulators should closely examine the market sentiment at the specific point in time and act according to the individual situation. As such, stress tests certainly increase regulatory awareness within the financial industry that can contribute to financial stability. Specifically, stress tests are an important cornerstone that enhances the Basel Accord in Pillar 2 (supervisory review) and has led to a considerable learning curve for the authorities. The message that regulators convey to the markets must be strongly integrated into the regulatory culture.

I am hesitant to draw overly strong conclusions from the studies of this thesis. It should be noted that the above conclusions arise from the analysis of bank-specific disclosures only; this is because I am unable to examine what would have happened if aggregated or no results had been disclosed. Furthermore, measuring the impact of bank stress tests is challenging because of some confounding factors. For instance, the consistently low interest rates in the U.S. and Europe, the on-going sovereign debt risk, as well as regulatory amendments such as Basel III, amongst other factors, might be partly responsible for certain results. It is therefore difficult to conclude that stress test exercises are the sole contributing factor. I tackle these empirical challenges, employing robust and widely recognised methodologies, such as propensity score matching, to analyse accounting quality and discretion (Chapter 2). I also apply a textual analysis approach to measure disclosure profiles (Chapter 3), and event study techniques to estimate market discipline (Chapter 4). Moreover, in all studies, I control for various bank-specific and institutional factors such as sovereign debt risk, economic and unemployment growth. In summary, I believe that my studies provide robust results that are based on recent cutting-edge econometric methods and techniques.

Lastly, there are various avenues for future research on bank stress tests that could be explored. As stress tests are a crucial component of legislation and regulatory policies, the authorities will continue to conduct stress tests on SIFIs. In addition to the large-scale exercises in the U.S. and Europe, local supervisors have also implemented such tests. For instance, in the United Kingdom, the Bank of England has stress-tested locally important banks, insurances and building societies since 2014.[39] In a joint exercise, the German Federal Financial Supervisory Authority (BaFin) and the Deutsche Bundesbank have assessed German small- and medium-sized banks concerning the impact of the low interest rates.[40]

Due to the importance of stress tests to financial stability and the entire economy, it is of public interest to examine the success of such exercises. This may help regulators and supervisors to further amend and improve their policies. In another vein, to analyse the full effect and utility of stress tests during crises, only another financial crisis might shed further light on the resilience of the regulatory mechanisms in place (Acharya et al., 2018). In general, researchers should focus on different aspects (i.e., bank accounting, textual and market microstructure interactions) regarding bank transparency to better understand its impact on bank environments. Banks are seen to be opaque compared to other corporate firms (Morgan, 2002); however, do we need banks to be more or fully transparent? Dang et al. (2017) provides an interesting novel theoretical view on bank opacity, which might be worth analysing in an empirical study.

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[39] Please visit the Bank of England website: https://www.bankofengland.co.uk/stress-testing.

[40] Please visit the Bundesbank website: https://www.bundesbank.de/en/press/press-releases/results-of-the-2017-low-interest-rate-survey-667444.

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APPENDIX

Theoretical framework of the PSM approach

According to Rosenbaum and Rubin (1983), the treatment effect of a binary treatment on the treated τ_i, in a setting of a quasi-natural experiment, may be defined as:

$$\tau_i = Y_i(1) - Y_i(0) \qquad \text{(A.1)}$$

where, Y_i is the outcome of the bank i (with i = 1,…,N and N is the total population) if the bank is treated (1) or not treated (0). Therefore, assuming that the treatment of bank i affects only the outcome of i, accepted as stable unit treatment value assumption (SUTVA) (Rubin, 1980), the purest result would be achieved if one could observe what would have happened to treatment banks had they not been treated. In the context of my study, the treatment effect on stress-tested banks may be defined as followed:

$$\tau_{i(T_1,T_2)j} = E\left(\Delta y_{i(T_1,T_2)j}(1) \middle| TREAT = 1\right) - E\left(\Delta y_{i(T_1,T_2)j}(0) \middle| TREAT = 1\right) \qquad \text{(A.2)}$$

where, $E\left(\Delta y_{i(T_1,T_2)j}(1) \middle| TREAT = 1\right)$ stands for the change in the outcome of stress-tested banks and $E\left(\Delta y_{i(T_1,T_2)j}(0) \middle| TREAT = 1\right)$ is the counterfactual (or hypothetical) change in the outcome if these banks had they not been stress-tested. The binary variable that yields stress test participation is *TREAT*. It takes the value of 1 for any of the three stress test samples (i.e., *TREATALL, TREAT1011,* and *TREAT14*) as discussed in Section 2.4.1. $\Delta y_{i(T_1,T_2)j}$ denotes the change in the outcome variables (y) of each bank i at country j over the treatment period T_2 compared to the pre-treatment period T_1.

However, observational studies face the problem of causal inference meaning that one can either examine banks with stress test treatment or without (Holland, 1986). As the counterfactual outcome is unobservable, to measure average treatment effects, I need to implement a proxy, which is the outcome of similar untested banks defined as $E\left(\Delta y_{i(T_1,T_2)j}(0) \middle| TREAT = 0\right)$. The literature distinguishes between the average treatment effect (ATE) and average treatment effect on the treated (ATT). While ATE includes banks randomly and also those that would never receive the treatment, ATT focuses on banks for whom the treatment was designed (Heckman et al. 1997). As the latter is the effect of my interest, the stated formulas only refer to the ATT, which I state as (average) treatment effect of stress tests. Consequently, the equation yields:

$$\tau_{i(T_1,T_2)j} = E\left(\Delta y_{i(T_1,T_2)j}(1)\middle|TREAT = 1\right) - E\left(\Delta y_{i(T_1,T_2)j}(0)\middle|TREAT = 0\right) \quad \text{(A.3)}$$

To find appropriate untreated (control) banks, I implement the conditioning covariate vector X_{iT_0j} of bank i observed in the period T_0 prior to stress testing leading to the following equation:

$$\tau_{i(T_1,T_2)j} = E\left(\Delta y_{i(T_1,T_2)j}(1)\middle|TREAT = 1, X_{iT_0j}\right) - E\left(\Delta y_{i(T_1,T_2)j}(0)\middle|TREAT = 0, X_{iT_0j}\right) \quad \text{(A.4)}$$

As I use various covariates in the matching model, direct matching on a multi-dimensional covariate vector may be impractical. Therefore, I use propensity scores as suggested by Rosenbaum and Rubin (1983). Hence, the equation can be written as:

$$\tau_{i(T_1,T_2)j} = E\left(\Delta y_{i(T_1,T_2)j}(1)\middle|TREAT = 1, P(X_{iT_0j})\right) - E\left(\Delta y_{i(T_1,T_2)j}(0)\middle|TREAT = 0, P(X_{iT_0j})\right) \quad \text{(A.5)}$$

where P is the propensity score conditional on the covariate vector X_{iT_0j}. Hence, $(\tau_{i(T_1,T_2)j})$ yields the average difference, or DiD, in the outcome variables (y) of the treatment over the control group. In other words, the average treatment effect of stress tests is predicted as the difference between the mean change in the outcome of treated and untreated banks that had similar likelihood of being assessed by regulators but were not included.

The main benefit of PSM is the design of the above described quasi-natural experiment that enables to rule out observed confounding heterogeneity between the two banking groups. In particular, the implementation of a matched control group mitigates misspecification between the dependent and independent variables that may occur in multiple regressions (Rubin, 1979). In this way, the remaining difference after matching represents the ultimate treatment effect of the stress tests.

However, one need to consider that in observational studies the treatment assignment process might not be an exogenous shock and therefore might not be fully random causing selection bias. Consequently, to obtain a consistent treatment effect of stress tests, the unconfoundedness and common support assumptions must endure (Heckman et al. 1998). When these conditions, also known as internal validity, hold, the mean outcome of the matched control banks stands for the previously mentioned missing hypothetical change in the outcome of the treated banks (Smith and Todd 2005).

On the one hand, the concept of unconfoundedness, also referred to as conditional independence or selection on observables assumption (Heckman and Robb 1985; Lechner

1999), suggests that after matching the individuals based on the covariate vector X_{iT_0j}, the average outcomes are independent of the treatment. Hence, any systematic differences in the outcome between stress-tested and untested (control) banks are defined as an expression of the stress test treatment (Imbens 2004; Smith and Todd 2005). The unconfoundedness assumption may be written as:

$$\left(\Delta y_{i(T_1,T_2)j}(1), \Delta y_{i(T_1,T_2)j}(0)) \perp TREAT \middle| P\left(X_{iT_0j}\right)\right) \tag{A.6}$$

However, this is a powerful assumption as systematic bias might occur even after matching. First, as stress test participation is not fully random and depends on the regulator's choice based on particular bank characteristics it is likely that this causes biased estimates and compromises causal inference. Therefore, a quasi-experimental setting allows to restore this randomisation condition if one controls for the observed rule (i.e., certain bank characteristics) behind the selection process (e.g., Dehejia and Wahba, 2002; Heckman et al., 1997). This means that only variables that influence the participation decision and the outcome at the same time should be included. Further, the matching literature states that variables selection and balance of the covariate vector is essential. Omitted variable bias might occur if significant variables are left out (Heckman et al., 1997), but too many variables might produce weaker results owing to the higher likelihood of including insignificant variables, which in turn might increase the estimates' variance (Bryson et al., 2002). In particular, for smaller samples such as the employed European sample, a higher variance might lead to exclusion of sample elements and intensify scarcity. Moreover, Smith and Todd (2005) argue that the most inclusive set of covariates might ultimately not be the best one to satisfy the matching condition.

Second, some portion of unobserved heterogeneity may remain even after matching, because, for instance, the impact of stress tests on treated and untreated banks is possible to vary due to regional differences. For this reason, the literature suggests relaxing the unconfoundedness condition by either applying instrumental variables (IVs) or a DiD approach. In my study, the latter DiD concept is more applicable due to the long data period 2005-2015. Furthermore, the literature prefers DiD as the most robust approach (Heckman et al. 1998; Smith and Todd 2005). More specific, I estimate the treatment effect of stress tests by measuring the DiD of the change in the outcome before and after stress testing. The time series difference controls for unobserved heterogeneity between the two groups and the cross-sectional difference addresses omitted trends. Importantly, this approach assumes similar trends in the outcome variables during the pre-treatment period for both treatment and control groups (parallel trend assumption). As discussed in Section 2.5.1, the PSM approach removes meaningful differences between both groups so that the parallel trend assumption has been satisfied.

On the other hand, the matching approach requires an overhang in the distribution of covariates between tested and untested banks (Heckman et al. 1998; Imbens 2004). The so-called common support (or overlap) assumption may be defined as:

$$0 < Pr\left(TREAT = 1 \middle| P\left(X_{iT_0j}\right)\right) < 1 \tag{A.7}$$

This condition assumes a positive probability of being treated (*TREAT* = 1) or not treated (*TREAT* = 0) within a unit interval. Therefore, this assumption ensures sufficient overlap of characteristics between treated and untreated banks to find adequate matches.

In addition, in case of multiple treatments or comparison groups, the (external) validity of the results of a quasi-experiment is strengthened when the possible maximum number of data points are identified and assessed (Gippel et al., 2015). Since the intensity of treatment and the timing of the first assessment for some banks vary, I have constructed three distinct samples to conduct PSM (i.e., *TREATALL*, *TREAT1011*, and *TREAT14*) as discussed in Section 2.4.1.

Table A.1 PSM robustness checks on covariate imbalance and matching equality

Panel A: Determinants of banks' probability to participate in stress tests of alternative robustness model			
	(1)	(2)	(3)
Covariates	*TREATALL*	*TREAT1011*	*TREAT14*
$SIZE_{itj}$	0.6912***	0.8066***	0.6074***
	(0.0754)	(0.0953)	(0.0882)
GDP_{tj}	-0.2505	-0.4807***	-0.0417
	(0.1551)	(0.1638)	(0.1669)
$LOAN_{itj}$	0.2381	1.3786**	-0.1788
	(0.5710)	(0.6581)	(0.5405)
LLR_{itj}	52.3723***	-2.5009	1.1851
	(16.6939)	(4.8451)	(2.0000)
$DSFR_{itj}$	0.6191	1.0240	1.3628**
	(0.5683)	(0.7011)	(0.5695)
CAP_{itj}	-9.2976**	1.1475	6.0233***
	(4.3436)	(4.0276)	(2.0635)
ROA_{itj}	43.0225***	10.9350	-1.9824
	(15.9550)	(9.2963)	(4.5279)
Constant	-7.0180***	-9.9177***	-7.4318***
	(1.0490)	(1.4825)	(1.1361)
Observations	483	476	400
Pseudo R^2	0.693	0.628	0.458
Log likelihood	-90.19	-83.58	-86.80

Panel B: Determinants of banks' probability to participate in stress tests using common support samples			
	(1)	(2)	(3)
Covariates	*TREATALL*	*TREAT1011*	*TREAT14*
$SIZE_{itj}$	0.6461***	0.7595***	0.5601***
	(0.0841)	(0.1125)	(0.1335)
GDP_{tj}	-0.2392	-0.4589***	-0.0848
	(0.1543)	(0.1625)	(0.1612)
OEA_{itj}	0.0404	-1.1686*	0.7278
	(0.5384)	(0.6733)	(0.5844)
LLR_{itj}	49.6264***	-3.3725	0.9953
	(16.8155)	(4.8944)	(2.0697)
$DSFR_{itj}$	0.6344	1.0021	1.6917***
	(0.5613)	(0.6814)	(0.6093)
CAP_{itj}	-9.1602**	0.8047	4.3314
	(4.6633)	(4.6329)	(3.0334)
ROA_{itj}	40.8198**	10.3742	0.5106
	(16.1080)	(9.3365)	(4.7977)
Constant	-6.4122***	-8.1456***	-7.1909***
	(1.0018)	(1.5954)	(1.6239)
Observations	265	194	142
Pseudo R^2	0.511	0.370	0.197
Log likelihood	-89.46	-83.90	-76.08

Panel C: Matching results of t-Test for equality of means of covariates with alternative matching algorithms including all treatment banks

	Matched sample: Radius matching			Matched sample: Nearest-neighbour		
Covariates	*TREATALL*	Control banks	Difference in means	*TREATALL*	Control banks	Difference in means
$SIZE_{itj}$	10.7470	10.7230	0.0240	10.7470	10.7300	0.0170
GDP_{tj}	0.9464	0.9488	-0.0024	0.9464	1.0209	-0.0745
OEA_{itj}	0.3505	0.3671	-0.0166	0.3505	0.3720	-0.0215
LLR_{itj}	0.0133	0.0113	0.0021	0.0133	0.0121	0.0012
$DSFR_{itj}$	0.5974	0.6133	-0.0159	0.5974	0.6150	-0.0177
CAP_{itj}	0.0636	0.0640	-0.0005	0.0636	0.0633	0.0002
ROA_{itj}	0.0069	0.0084	-0.0014	0.0069	0.0077	-0.0008
Observations	132	122	254	132	122	254
Pseudo-R^2		0.011			0.010	

Table A.1 continued

Panel D: Matching results of t-Test for equality of means of covariates applying alternative matching algorithms including first-time participants in 2010-11

Covariates	Matched sample: Radius matching			Matched sample: Nearest-neighbour		
	TREAT1011	Control banks	Difference in means	*TREAT1011*	Control banks	Difference in means
$SIZE_{itj}$	11.7870	11.6510	0.1360	11.5740	11.7000	-0.1260
GDP_{tj}	0.8882	0.9091	-0.0209	0.8504	0.9384	-0.0880
OEA_{itj}	0.3561	0.3745	-0.0185	0.3509	0.4088	-0.0578
LLR_{itj}	0.0149	0.0116	0.0032	0.0150	0.0119	0.0031
$DSFR_{itj}$	0.5864	0.6065	-0.0201	0.5864	0.5803	0.0061
CAP_{itj}	0.0549	0.0511	0.0039	0.0550	0.0550	0.0000
ROA_{itj}	0.0031	0.0028	0.0004	0.0031	0.0023	0.0008
Observations	71	108	179	62	62	124
Pseudo-R^2		0.020			0.054	

Panel E: Matching results of t-Test for equality of means of covariates applying alternative matching algorithms including first-time participants in 2014

Covariates	Matched sample: Radius matching			Matched sample: Nearest-neighbour		
	TREAT14	Control banks	Difference in means	*TREAT14*	Control banks	Difference in means
$SIZE_{itj}$	10.0510	9.9726	0.0784	10.0510	10.1040	-0.0530
GDP_{tj}	0.9849	1.0356	-0.0507	0.9849	1.0609	-0.0760
OEA_{itj}	0.3453	0.3356	0.0097	0.3453	0.3633	-0.0180
LLR_{itj}	0.0273	0.0453	-0.0180	0.0273	0.0382	-0.0109
$DSFR_{itj}$	0.6444	0.6213	0.0231	0.6444	0.6012	0.0432
CAP_{itj}	0.0819	0.0855	-0.0037	0.0819	0.0821	-0.0003
ROA_{itj}	0.0015	0.0013	0.0002	0.0015	0.0011	0.0004
Observations	55	87	142	55	55	110
Pseudo-R^2		0.015			0.013	

This table reports additional PSM robustness checks. Panels A and B test covariate imbalance by using an alternative covariate combination for the samples of total stress test participation (*TREATALL*), first-time participation in 2010-11 (*TREAT1011*) and 2014 (*TREAT14*), and repeated estimation on the final matched samples. Panel C, D and E illustrate the mean comparison of bank-specific covariates of treatment and untreated banks after matching with Radius and Nearest-neighbour matching applying caliper and replacement options. The difference in means is calculated as the difference between treatment and untreated banks' means. The two rows below the covariates show the number of observations before and after matching and the pseudo-R^2. I include the following covariates in my analysis: Bank size measured by natural logarithm of total assets ($SIZE_{itj}$), economic growth estimated by Gross Domestic Product (GDP_{tj}), (non-) traditional banking activities assessed by other earning assets and outstanding loans (OEA_{itj}, $LOAN_{itj}$), credit portfolio quality predicted by loan loss reserves (LLR_{itj}), liquidity risk captured by deposit ratio ($DSFR_{itj}$), bank capital measured by equity divided by total assets (CAP_{itj}), and profitability predicted by return on assets (ROA_{itj}). The covariates are obtained as an average value from 2005S2-2008S2 (*TREATALL*), from 2008S2-2009S2 (*TREAT1011*) and from 2012S2-2013S2 (*TREAT14*). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Standard errors of the coefficients in Panels A and B are clustered at bank level. The description of the variables and the relevant data sources are provided in Table 2.1.

Table A.2 PSM/DiD robustness checks on common support bias using adjusted samples

Panel A: Total stress test participation effect				
	Coefficients	Standard errors	Coefficients	Standard errors
	Asset quality (LLP)		*Asset quality (NPL)*	
TREATALL	0.0004	(0.0009)	-0.0037*	(0.0022)
$\Delta y_{i(T_1,T_2)j}$	0.0018**	(0.0008)	0.0046**	(0.0023)
$\tau_{i(T_1,T_2)j}$	-0.0014	(0.0011)	0.0028	(0.0022)
Observations	3,418		2,935	
Adjusted R-squared	0.7596		0.9002	
	Capital adequacy (T1R)		*Credit risk (RWA)*	
TREATALL	-0.0118***	(0.0041)	0.0348	(0.0422)
$\Delta y_{i(T_1,T_2)j}$	0.0786***	(0.0074)	-0.1947***	(0.0584)
$\tau_{i(T_1,T_2)j}$	-0.0115**	(0.0055)	0.0089	(0.0489)
Observations	2,634		2,845	
Adjusted R-squared	0.4502		0.5998	
Panel B: 2010-11 EBA first-time stress test participation effect				
	Coefficients	Standard errors	Coefficients	Standard errors
	Asset quality (LLP)		*Asset quality (NPL)*	
TREAT1011	0.0006	(0.0005)	-0.0021*	(0.0013)
$\Delta y_{i(T_1,T_2)j}$	0.0017***	(0.0004)	0.0034***	(0.0011)
$\tau_{i(T_1,T_2)j}$	-0.0010*	(0.0006)	0.0033**	(0.0013)
Observations	1,167		1,011	
Adjusted R-squared	0.6652		0.8622	
	Capital adequacy (T1R)		*Credit risk (RWA)*	
TREAT1011	-0.0155***	(0.0052)	0.0248	(0.0280)
$\Delta y_{i(T_1,T_2)j}$	0.0441***	(0.0074)	-0.1113***	(0.0214)
$\tau_{i(T_1,T_2)j}$	0.0023	(0.0068)	-0.0312*	(0.0186)
Observations	984		1,024	
Adjusted R-squared	0.4082		0.6674	
Panel C: 2014 EBA/ECB first-time stress test participation effect				
	Coefficients	Standard errors	Coefficients	Standard errors
	Asset quality (LLP)		*Asset quality (NPL)*	
TREAT14	0.0003	(0.0008)	-0.0059	(0.0039)
$\Delta y_{i(T_1,T_2)j}$	0.0011	(0.0011)	-0.0041	(0.0052)
$\tau_{i(T_1,T_2)j}$	0.0004	(0.0011)	0.0058*	(0.0032)
Observations	848		720	
Adjusted R-squared	0.5717		0.8869	
	Capital adequacy (T1R)		*Credit risk (RWA)*	
TREAT14	-0.0273**	(0.0129)	0.0719**	(0.0357)
$\Delta y_{i(T_1,T_2)j}$	0.0234**	(0.0093)	-0.1010***	(0.0228)
$\tau_{i(T_1,T_2)j}$	0.0200**	(0.0091)	-0.0202	(0.0214)
Observations	626		689	
Adjusted R-squared	0.3532		0.5251	

This table reports additional robustness checks of hidden bias adjusting samples according to common support option Panel A illustrates the total stress test participation effect (*TREATALL*). Panel B estimates the effect of the 2010-11 treatments (*TREAT1011*). Panel C analyses the effect of the 2014 EBA/ECB treatments (*TREAT14*). I apply a DiD design using Gaussian Kernel probability weights and covariates obtained from the prior PSM analysis and control for half-year time effects. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Standard errors (parentheses) are clustered at bank level. I include the following variables in my analysis: Forward- and backward-looking asset quality measured by loan loss provisions (LLP_{itj}) and non-performing loans (NPL_{itj}), capital adequacy captured by lagged regulatory Tier 1 capital ratio ($T1R_{it-1j}$), and credit risk assessed by risk-weighted assets (RWA_{itj}). $\tau_{i(T_1,T_2)j}$ yields the average double difference, or DiD, between the difference of the outcome variables before and after the treatment ($\Delta y_{i(T_1,T_2)j}$) and the difference of the treatment (*TREAT, TREAT1011*, and *TREAT14*) over the control group. The description of the variables and the relevant data sources are provided in Table 2.1.

Table A.3 Fixed effects robustness checks on the entire treatment sample (*TREATALL*) excluding banks from non-EU countries, banks with multiple stress test participation, banks using local GAAP and inactive banks

Variables	(1) *EU*	(2) *MULTIPLE*	(3) *GAAP*	(4) *ACTIVE*
NPL_{it-1j}	0.0388***	0.0456***	0.0401***	0.0447***
	(0.0116)	(0.0108)	(0.0115)	(0.0104)
ΔNPL_{itj}	0.1439***	0.1509***	0.1432***	0.1451***
	(0.0295)	(0.0307)	(0.0296)	(0.0313)
$\Delta LOAN_{itj}$	-0.0168***	-0.0190***	-0.0159***	-0.0167***
	(0.0038)	(0.0040)	(0.0036)	(0.0037)
$T1R_{it-1j}$	-0.0626***	-0.0398**	-0.0570***	-0.0408**
	(0.0110)	(0.0176)	(0.0117)	(0.0168)
$EBPT_{it-1j}$	-0.1807**	-0.0687	-0.1816**	-0.0570
	(0.0887)	(0.0720)	(0.0780)	(0.0713)
STHC	-0.0081***	-0.0041	-0.0068***	-0.0038
	(0.0022)	(0.0033)	(0.0022)	(0.0031)
*TREATALL*ST*	0.0088***	0.0042	0.0075***	0.0047
	(0.0022)	(0.0031)	(0.0022)	(0.0029)
$TREATALL{*}T1R_{it-1j}$	0.0336***	0.0063	0.0269**	0.0065
	(0.0121)	(0.0188)	(0.0126)	(0.0168)
$STHC{*}T1R_{it-1j}$	0.0641***	0.0417**	0.0564***	0.0418***
	(0.0110)	(0.0169)	(0.0110)	(0.0159)
$TREATALL{*}STHC{*}T1R_{it-1j}$	-0.0546***	-0.0291*	-0.0463***	-0.0296*
	(0.0125)	(0.0166)	(0.0127)	(0.0157)
$TREATALL{*}EBPT_{it-1j}$	0.2463***	0.1607**	0.2423***	0.1535**
	(0.0842)	(0.0672)	(0.0729)	(0.0660)
$STHC{*}EBPT_{it-1j}$	0.2791***	0.1436	0.2575***	0.1388
	(0.0768)	(0.1215)	(0.0815)	(0.1155)
$TREATALL{*}STHC{*}EBPT_{it-1j}$	-0.1612*	-0.0203	-0.1287	-0.0293
	(0.0840)	(0.1242)	(0.0877)	(0.1192)
$SIZE_{it-1j}$	0.0002	-0.0001	0.0001	0.0000
	(0.0005)	(0.0006)	(0.0005)	(0.0006)
ΔGDP_{tj}	-0.0282***	-0.0334***	-0.0303***	-0.0355***
	(0.0082)	(0.0088)	(0.0081)	(0.0087)
$\Delta UNEM_{tj}$	-0.0014	-0.0044***	-0.0017	-0.0024
	(0.0020)	(0.0016)	(0.0018)	(0.0018)
HPI_{tj}	-0.0000	0.0000	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$IRATE_{tj}$	0.0006***	0.0006***	0.0006***	0.0006***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	0.0048	0.0056	0.0061	0.0031
	(0.0072)	(0.0078)	(0.0070)	(0.0077)
Observations	1,477	1,542	1,617	1,613
Number of banks	131	141	142	142
Adjusted R-squared	0.4125	0.4026	0.4084	0.4032
Bank fixed effects	Yes	Yes	Yes	Yes
Half-year fixed effects	Yes	Yes	Yes	Yes

This table reports additional fixed effects robustness checks on the entire treatment sample (*TREATALL*) excluding banks from non-EU countries, banks with multiple stress test participation, banks using local GAAP and inactive banks. Model 1 assesses the stress test effect on discretionary behaviour excluding banks from non-EU countries (*EU*). Model 2 shows the stress test effect on discretionary behaviour without banks with multiple stress test participation (*MULTIPLE*). Model 3 examines the stress test effect on discretionary behaviour discarding banks using local GAAP (*GAAP*). Model 4 estimates the stress test effect on discretionary behaviour without inactive banks (*ACTIVE*). Standard errors (parentheses) are clustered at bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. I include the following variables in my analysis: Forward- and (shift of) backward looking asset quality captured by loan loss provisions (LLP_{itj}) and lagged (change in) non-performing loans (NPL_{it-1j}, ΔNPL_{itj}), loan growth shown by change in outstanding loans ($\Delta LOAN_{itj}$); capital management measured by lagged regulatory Tier 1 capital ratio ($T1R_{it-1j}$); income smoothing captured by earnings before provisions and taxes ($EBPT_{it-1j}$); a dummy for stress test participation (*TREATALL*); a dummy for the 'hot and 'cold' stress test periods (*STHC*); bank size captured by lagged natural logarithm of total assets ($SIZE_{it-1j}$), and macroeconomic fundamentals to control for contemporaneous fiscal and monetary policy changes and market instabilities such as illiquidity, constrained capital and higher volatility shown by economic growth (ΔGDP_{tj}), unemployment growth ($\Delta UNEM_{tj}$), price level in the housing market (HPI_{tj}), and sovereign debt risk ($IRATE_{tj}$). Data range 2005-2015. The description of the variables and the relevant data sources are provided in Table 2.1.

Table A.4 Fixed effects robustness checks on the first-time participants in 2010-11 (*TREAT1011*) excluding banks from non-EU countries, banks with multiple stress test participation, banks using local GAAP and inactive banks

Variables	(1) *EU*	(2) *MULTIPLE*	(3) *GAAP*	(4) *ACTIVE*
NPL_{it-1j}	0.0704**	0.0690**	0.0705**	0.0764**
	(0.0319)	(0.0343)	(0.0321)	(0.0328)
ΔNPL_{itj}	0.1026***	0.1017***	0.1049***	0.1219***
	(0.0237)	(0.0237)	(0.0239)	(0.0250)
$\Delta LOAN_{itj}$	0.0028	0.0019	0.0027	0.0016
	(0.0059)	(0.0063)	(0.0058)	(0.0055)
$T1R_{it-1j}$	-0.0229	-0.0448***	-0.0225	-0.0244*
	(0.0147)	(0.0125)	(0.0147)	(0.0142)
$EBPT_{it-1j}$	0.0148	0.0949**	0.0217	0.0453
	(0.0880)	(0.0401)	(0.0857)	(0.0420)
BAST1011	-0.0018	-0.0009	-0.0016	-0.0034***
	(0.0014)	(0.0031)	(0.0014)	(0.0013)
*TREAT1011*BAST1011*	0.0044*	0.0046**	0.0043*	0.0060**
	(0.0024)	(0.0019)	(0.0024)	(0.0023)
*TREAT1011**$T1R_{it-1j}$	0.0097	0.0260	0.0105	-0.0072
	(0.0239)	(0.0225)	(0.0240)	(0.0203)
*BAST1011**$T1R_{it-1j}$	0.0445***	0.0668***	0.0427***	0.0569***
	(0.0145)	(0.0120)	(0.0141)	(0.0140)
*TREAT1011*BAST1011**$T1R_{it-1j}$	-0.0580***	-0.0752***	-0.0578**	-0.0678***
	(0.0219)	(0.0203)	(0.0221)	(0.0221)
*TREAT1011**$EBPT_{it-1j}$	0.2222**	0.1351	0.2129**	0.2089**
	(0.0881)	(0.1042)	(0.0866)	(0.0887)
*BAST1011**$EBPT_{it-1j}$	-0.1278***	-0.2463***	-0.1303***	-0.1457**
	(0.0397)	(0.0835)	(0.0405)	(0.0617)
*TREAT1011*BAST1011**$EBPT_{it-1j}$	0.1866**	0.3144***	0.1895**	0.1912**
	(0.0817)	(0.1066)	(0.0817)	(0.0834)
$SIZE_{it-1j}$	-0.0026	-0.0022	-0.0026	-0.0024
	(0.0018)	(0.0023)	(0.0018)	(0.0018)
ΔGDP_{tj}	-0.0133	-0.0125	-0.0139	-0.0134
	(0.0107)	(0.0117)	(0.0102)	(0.0105)
$\Delta UNEM_{tj}$	0.0014	-0.0006	0.0010	-0.0004
	(0.0019)	(0.0023)	(0.0019)	(0.0022)
HPI_{tj}	-0.0001**	-0.0001***	-0.0001**	-0.0001***
	(0.0001)	(0.0000)	(0.0001)	(0.0000)
$IRATE_{tj}$	0.0002	0.0002	0.0002	0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	0.0455*	0.0450	0.0432*	0.0435*
	(0.0233)	(0.0294)	(0.0227)	(0.0246)
Observations	579	557	628	611
Number of banks	106	105	114	110
Adjusted R-squared	0.5650	0.5681	0.5615	0.5967
Bank fixed effects	Yes	Yes	Yes	Yes
Half-year fixed effects	Yes	Yes	Yes	Yes

This table reports additional fixed effects robustness checks on the first-time participants in 2010-11 (*TREAT1011*) excluding banks from non-EU countries, banks with multiple stress test participation, banks using local GAAP and inactive banks. Model 1 assesses the stress test effect on discretionary behaviour excluding banks from non-EU countries (*EU*). Model 2 shows the stress test effect on discretionary behaviour without banks with multiple stress test participation (*MULTIPLE*). Model 3 examines the stress test effect on discretionary behaviour discarding banks using local GAAP (*GAAP*). Model 4 estimates the stress test effect on discretionary behaviour without inactive banks (*ACTIVE*). Standard errors (parentheses) are clustered at bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. I include the following variables in my analysis: Forward- and (shift of) backward looking asset quality captured by loan loss provisions (LLP_{itj}) and lagged (change in) non-performing loans (NPL_{it-1j}, ΔNPL_{itj}), loan growth shown by change in outstanding loans ($\Delta LOAN_{itj}$); capital management measured by lagged regulatory Tier 1 capital ratio ($T1R_{it-1j}$); income smoothing captured by earnings before provisions and taxes ($EBPT_{it-1j}$); a dummy for first-time participation in 2010-11 (*TREAT1011*); a dummy for 2010-11 (*BAST1011*); bank size captured by lagged natural logarithm of total assets ($SIZE_{it-1j}$), and macroeconomic fundamentals to control for contemporaneous fiscal and monetary policy changes and market instabilities such as illiquidity, constrained capital and higher volatility shown by economic growth (ΔGDP_{tj}), unemployment growth ($\Delta UNEM_{tj}$), price level in the housing market (HPI_{tj}), and sovereign debt risk ($IRATE_{tj}$). Data range 2005-2015. The description of the variables and the relevant data sources are provided in Table 2.1.

Table A.5 Fixed effects robustness checks on the first-time participants in 2014 (*TREAT14*) excluding banks from non-EU countries, banks with multiple stress test participation, banks using local GAAP and inactive banks

Variables	(1) *EU*	(2) *MULTIPLE*	(3) *GAAP*	(4) *ACTIVE*
NPL_{it-1j}	0.1336**	0.1385**	0.1303**	0.1291**
	(0.0551)	(0.0535)	(0.0535)	(0.0536)
ΔNPL_{itj}	0.1370**	0.1600***	0.1272**	0.1283**
	(0.0524)	(0.0498)	(0.0545)	(0.0535)
$\Delta LOAN_{itj}$	-0.0157	-0.0155*	-0.0111	-0.0111
	(0.0108)	(0.0089)	(0.0084)	(0.0084)
$T1R_{it-1j}$	-0.0683***	-0.0333	-0.0363	-0.0367
	(0.0184)	(0.0246)	(0.0258)	(0.0247)
$EBPT_{it-1j}$	-0.1156	-0.2689	-0.2300	-0.2275
	(0.1399)	(0.1776)	(0.1581)	(0.1577)
BAST14	-0.0076***	-0.0113***	-0.0113***	-0.0112***
	(0.0021)	(0.0022)	(0.0020)	(0.0021)
*TREAT14*BAST14*	0.0091***	0.0071*	0.0080**	0.0081**
	(0.0031)	(0.0036)	(0.0038)	(0.0036)
$TREAT14{*}T1R_{it-1j}$	0.0069	-0.0364	-0.0321	-0.0303
	(0.0263)	(0.0340)	(0.0352)	(0.0346)
$BAST14{*}T1R_{it-1j}$	0.0714***	0.0603***	0.0588***	0.0587***
	(0.0139)	(0.0151)	(0.0148)	(0.0144)
$TREAT14{*}BAST14{*}T1R_{it-1j}$	-0.0397*	-0.0235	-0.0262	-0.0263
	(0.0202)	(0.0236)	(0.0242)	(0.0239)
$TREAT14{*}EBPT_{it-1j}$	0.2374	0.4055*	0.3449*	0.3565*
	(0.1908)	(0.2098)	(0.1977)	(0.1946)
$BAST14{*}EBPT_{it-1j}$	0.1697*	0.2114*	0.2089*	0.2045*
	(0.0943)	(0.1066)	(0.1056)	(0.1035)
$TREAT14{*}BAST14{*}EBPT_{it-1j}$	-0.2887**	-0.2983**	-0.2952**	-0.2984**
	(0.1090)	(0.1183)	(0.1176)	(0.1131)
$SIZE_{it-1j}$	0.0051	0.0026	0.0033	0.0030
	(0.0042)	(0.0034)	(0.0036)	(0.0033)
ΔGDP_{tj}	-0.0912	-0.0932*	-0.0771	-0.0703
	(0.0687)	(0.0489)	(0.0518)	(0.0488)
$\Delta UNEM_{tj}$	0.0125*	0.0052	0.0044	0.0056
	(0.0067)	(0.0049)	(0.0047)	(0.0044)
HPI_{tj}	0.0001	-0.0000	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$IRATE_{tj}$	-0.0001	0.0005	0.0001	0.0001
	(0.0006)	(0.0005)	(0.0006)	(0.0006)
Constant	-0.0566	-0.0208	-0.0370	-0.0342
	(0.0492)	(0.0365)	(0.0402)	(0.0376)
Observations	345	390	367	410
Number of banks	61	69	60	72
Adjusted R-squared	0.5149	0.5303	0.4942	0.4922
Bank fixed effects	Yes	Yes	Yes	Yes
Half-year fixed effects	Yes	Yes	Yes	Yes

This table reports additional fixed effects robustness checks on the first-time participants in 2014 (*TREAT14*) excluding banks from non-EU countries, banks with multiple stress test participation, banks using local GAAP and inactive banks. Model 1 assesses the stress test effect on discretionary behaviour excluding banks from non-EU countries (*EU*). Model 2 shows the stress test effect on discretionary behaviour without banks with multiple stress test participation (*MULTIPLE*). Model 3 examines the stress test effect on discretionary behaviour discarding banks using local GAAP (*GAAP*). Model 4 estimates the stress test effect on discretionary behaviour without inactive banks (*ACTIVE*). Standard errors (parentheses) are clustered at bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. I include the following variables in my analysis: Forward- and (shift of) backward looking asset quality captured by loan loss provisions (LLP_{itj}) and lagged (change in) non-performing loans (NPL_{it-1j}, ΔNPL_{itj}), loan growth shown by change in outstanding loans ($\Delta LOAN_{itj}$); capital management measured by lagged regulatory Tier 1 capital ratio ($T1R_{it-1j}$); income smoothing captured by earnings before provisions and taxes ($EBPT_{it-1j}$); a dummy for first-time participation in 2014 (*TREAT14*); a dummy for the 2014 stress test periods (*BAST14*); bank size captured by lagged natural logarithm of total assets ($SIZE_{it-1j}$), and macroeconomic fundamentals to control for contemporaneous fiscal and monetary policy changes and market instabilities such as illiquidity, constrained capital and higher volatility shown by economic growth (ΔGDP_{tj}), unemployment growth ($\Delta UNEM_{tj}$), price level in the housing market (HPI_{tj}), and sovereign debt risk ($IRATE_{tj}$). Data range 2005-2015. The description of the variables and the relevant data sources are provided in Table 2.1.

Table A.6 Additional robustness including interaction between the treatment groups and unemployment rate (based on Table 2.7)

Variables	(1) *TREATALL*	(2) *TREAT1011*	(3) *TREAT14*
$TREATALL*\Delta UNEM_{tj}$	0.0029		
	(0.0023)		
$TREAT1011*\Delta UNEM_{tj}$		0.0012	
		(0.0026)	
$TREAT14*\Delta UNEM_{tj}$			0.0077
			(0.0090)
NPL_{it-1j}	0.0450***	0.0733**	0.1302**
	(0.0106)	(0.0336)	(0.0543)
ΔNPL_{itj}	0.1463***	0.1091***	0.1307**
	(0.0302)	(0.0240)	(0.0532)
$\Delta LOAN_{itj}$	-0.0168***	0.0022	-0.0111
	(0.0037)	(0.0053)	(0.0084)
$T1R_{it-1j}$	-0.0401**	-0.0239*	-0.0362
	(0.0168)	(0.0138)	(0.0244)
$EBPT_{itj}$	-0.0627	0.0363	-0.2287
	(0.0636)	(0.0431)	(0.1594)
STHC	-0.0037		
	(0.0032)		
*TREATALL*STHC*	0.0045		
	(0.0030)		
$TREATALL*T1R_{it-1j}$	0.0095		
	(0.0166)		
$STHC*T1R_{it-1j}$	0.0411**		
	(0.0164)		
$TREATALL*STHC*T1R_{it-1j}$	-0.0297*		
	(0.0161)		
$TREATALL*EBPT_{itj}$	0.1511**		
	(0.0624)		
$STHC*EBPT_{itj}$	0.1412		
	(0.1158)		
$TREATALL*STHC*EBPT_{itj}$	-0.0263		
	(0.1196)		
BAST1011		-0.0014	
		(0.0026)	
*TREAT1011*BAST1011*		0.0058**	
		(0.0023)	
$TREAT1011*T1R_{it-1j}$		0.0108	
		(0.0236)	
$BAST1011*T1R_{it-1j}$		0.0566***	
		(0.0145)	
$TREAT1011*BAST1011*T1R_{it-1j}$		-0.0709***	
		(0.0223)	
$TREAT1011*EBPT_{itj}$		0.2074**	
		(0.0941)	
$BAST1011*EBPT_{itj}$		-0.1457**	
		(0.0625)	
$TREAT1011*BAST1011*EBPT_{itj}$		0.1990**	
		(0.0865)	

Table A.6 continued

BAST14			-0.0077***
			(0.0024)
*TREAT14*BAST14*			0.0082**
			(0.0035)
$TREAT14*T1R_{it-1j}$			-0.0303
			(0.0343)
$BAST14*T1R_{it-1j}$			0.0586***
			(0.0145)
$TREAT14*BAST14*T1R_{it-1j}$			-0.0253
			(0.0244)
$TREAT14*EBPT_{itj}$			0.3588*
			(0.1961)
$BAST14*EBPT_{itj}$			0.2079*
			(0.1052)
$TREAT14*BAST14*EBPT_{itj}$			-0.2981**
			(0.1140)
$SIZE_{it-1j}$	-0.0001	-0.0024	0.0031
	(0.0005)	(0.0018)	(0.0033)
ΔGDP_{tj}	-0.0341***	-0.0130	-0.0702
	(0.0085)	(0.0096)	(0.0485)
$\Delta UNEM_{tj}$	-0.0045***	-0.0016	0.0031
	(0.0016)	(0.0025)	(0.0045)
HPI_{tj}	0.0000	-0.0001**	0.0001
	(0.0000)	(0.0000)	(0.0001)
$IRATE_{tj}$	0.0006***	0.0003	0.0001
	(0.0002)	(0.0002)	(0.0006)
Constant	0.0046	0.0421*	-0.0346
	(0.0067)	(0.0242)	(0.0378)
Observations	1,698	649	410
Number of banks	152	119	72
Adjusted R-squared	0.3945	0.5519	0.4920
Bank fixed effects	Yes	Yes	Yes
Half-year fixed effects	Yes	Yes	Yes

This table reports additional robustness including interactions between the treatment groups and unemployment rate (based on Table 2.7). Model 1 presents the total stress test effect on banks' capital management and income smoothing behaviour. Model 2 illustrates the stress test effect on the discretionary behaviour of first-time participants in 2010-11. Model 3 examines the stress test effect on the discretionary behaviour of first-time participants in 2014. I include the following variables in my analysis: Forward- and (shift of) backward looking asset quality captured by loan loss provisions (LLP_{itj}) and lagged (change in) non-performing loans (NPL_{it-1j}, ΔNPL_{itj}), loan growth shown by change in outstanding loans ($\Delta LOAN_{itj}$), capital management measured by lagged regulatory Tier 1 capital ratio ($T1R_{it-1j}$), income smoothing captured by earnings before provisions and taxes ($EBPT_{itj}$); a dummy for stress test participation (*TREATALL*), first-time participation in 2010-11 (*TREAT1011*) and 2014 (*TREAT14*); a dummy for 'hot' and 'cold' stress test periods (*STHC*), a dummy for four half-year periods before and after the 2010-11 (*BAST1011*) and 2014 treatments (*BAST14*); bank size captured by lagged natural logarithm of total assets ($SIZE_{it-1j}$) and macroeconomic fundamentals to control for contemporaneous fiscal and monetary policy changes and market instabilities such as illiquidity, constrained capital and higher volatility shown by economic growth (ΔGDP_{tj}), unemployment growth ($\Delta UNEM_{tj}$), price level in the housing market (HPI_{tj}) and sovereign debt risk ($IRATE_{tj}$). Data range 2005-2015. Standard errors (parentheses) are clustered at bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 2.1.

Table A.7 Marginal effects of capital management and income smoothing interaction terms

Panel A: Marginal effects on bank discretionary behaviour (Table 2.7)						
	Overall: Capital management (*T1R*)			**Overall: Income smoothing (*EBPT*)**		
	TREATALL	Control	Diff (T–C)	*TREATALL*	Control	Diff (T–C)
STHC (1)	-0.0200	0.0020	-0.0220	0.2062	0.0757	0.1305
STHC (0)	-0.0311	-0.0401	0.0090	0.0907	-0.0615	0.1522
Diff (1–0)	0.0111	0.0420		0.1155	0.1372	
DiD			**-0.0310***			**-0.0217**
	2010-11: Capital management (*T1R*)			**2010-11: Income smoothing (*EBPT*)**		
	TREAT1011	Control	Diff (T–C)	*TREAT1011*	Control	Diff (T–C)
BAST1011 (1)	-0.0269	0.0331	-0.0600	0.2998	-0.1077	0.4076
BAST1011 (0)	-0.0123	-0.0242	0.0119	0.2452	0.0383	0.2069
Diff (1–0)	-0.0147	0.0573		0.0546	-0.1461	
DiD			**-0.0719*****			**0.2007****
	2014: Capital management (*T1R*)			**2014: Income smoothing (*EBPT*)**		
	TREAT14	Control	Diff (T–C)	*TREAT14*	Control	Diff (T–C)
BAST14 (1)	-0.0347	0.0220	-0.0567	0.0351	-0.0230	0.0581
BAST14 (0)	-0.0671	-0.0367	-0.0303	0.1290	-0.2275	0.3565
Diff (1–0)	0.0324	0.0587		-0.0938	0.2045	
DiD			**-0.0263**			**-0.2984****
Panel B: Marginal effects on discretionary behaviour of high-, medium- and low-capitalised banks (Table 2.9)						
	High capital: Capital management (*T1R*)			**High capital: Income smoothing (*EBPT*)**		
	CAPH	Control	Diff (T–C)	*CAPH*	Control	Diff (T–C)
STHC (1)	-0.0011	-0.0136	0.0125	0.0642	-0.0406	0.1048
STHC (0)	-0.0047	0.0235	-0.0282	-0.0231	-0.0073	-0.0158
Diff (1–0)	0.0036	-0.0371		0.0874	-0.0332	
DiD			**0.0407***			**0.1206**
	Med. capital: Capital management (*T1R*)			**Med. capital: Income smoothing (*EBPT*)**		
	CAPM	Control	Diff (T–C)	*CAPM*	Control	Diff (T–C)
STHC (1)	0.0055	-0.0026	0.0081	0.1366	-0.4995	0.6362
STHC (0)	-0.0043	-0.0020	-0.0023	0.0977	-0.2108	0.3085
Diff (1–0)	0.0098	-0.0006		0.0389	-0.2888	
DiD			**0.0104**			**0.3277****
	Low capital: Capital management (*T1R*)			**Low capital: Income smoothing (*EBPT*)**		
	CAPL	Control	Diff (T–C)	*CAPL*	Control	Diff (T–C)
STHC (1)	-0.0826	-0.0125	-0.0702	0.2508	0.2810	-0.0302
STHC (0)	-0.0785	-0.0615	-0.0171	0.0796	0.1085	-0.0289
Diff (1–0)	-0.0041	0.0490		0.1712	0.1725	
DiD			**-0.0531***			**-0.0013**
Panel C: Marginal effects on fixed effects robustness on common support bias with adjusted samples (Table 2.11)						
	Overall: Capital management (*T1R*)			**Overall: Income smoothing (*EBPT*)**		
	TREATALL	Control	Diff (T–C)	*TREATALL*	Control	Diff (T–C)
STHC (1)	-0.0184	0.0032	-0.0216	0.2105	0.0661	0.1444
STHC (0)	-0.0307	-0.0391	0.0085	0.0978	-0.0625	0.1604
Diff (1–0)	0.0123	0.0424		0.1127	0.1287	
DiD			**-0.0301***			**-0.0160**
	2010-11: Capital management (*T1R*)			**2010-11: Income smoothing (*EBPT*)**		
	TREAT1011	Control	Diff (T–C)	*TREAT1011*	Control	Diff (T–C)
BAST1011 (1)	-0.0112	0.0325	-0.0437	0.2743	-0.1050	0.3793
BAST1011 (0)	0.0000	-0.0146	0.0146	0.2226	0.0507	0.1719
Diff (1–0)	-0.0111	0.0471		0.0517	-0.1557	
DiD			**-0.0582*****			**0.2074*****
	2014: Capital management (*T1R*)			**2014: Income smoothing (*EBPT*)**		
	TREAT14	Control	Diff (T–C)	*TREAT14*	Control	Diff (T–C)
BAST14 (1)	-0.0376	0.0207	-0.0583	0.0130	-0.0467	0.0597
BAST14 (0)	-0.0746	-0.0387	-0.0359	0.1222	-0.2534	0.3756
Diff (1–0)	0.0370	0.0594		-0.1092	0.2066	
DiD			**-0.0224**			**-0.3158****

This table reports the marginal effects of the interaction terms in Tables 2.7, 2.9 and 2.11. Panel A illustrates the marginal effects on bank discretionary behaviour (Table 2.7). Panel B estimates marginal effects on discretionary behaviour of high-, medium- and low-capitalised banks (Table 2.9). Panel C analyses marginal effects on fixed effects robustness on common support bias with adjusted samples (Table 2.11). I include the following variables in my analysis: Capital management measured by lagged regulatory Tier 1 capital ratio ($T1R_{it-1j}$), income smoothing captured by earnings before provisions and taxes ($EBPT_{itj}$); a dummy for stress test participation (*TREATALL*), first-time participation in 2010-11 (*TREAT1011*) and 2014 (*TREAT14*); a dummy for 'hot' and 'cold' stress test periods (*STHC*), a dummy for four half-year periods before and after the 2010-11 (*BAST1011*) and 2014 treatments (*BAST14*). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 2.1.

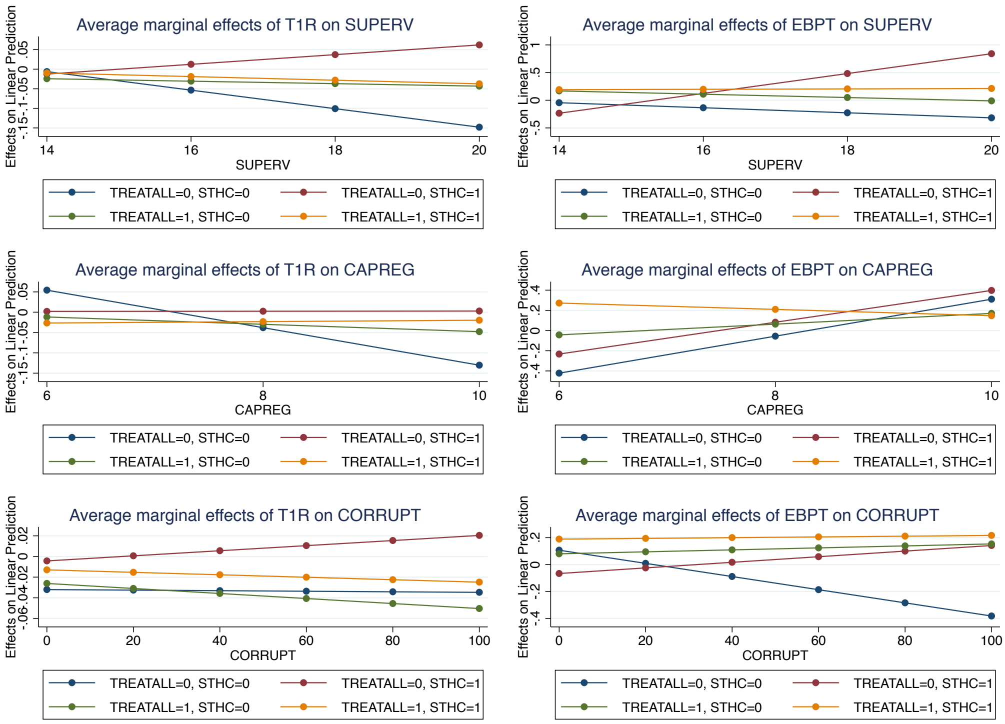

Figure A.1 Marginal effects of capital and income smoothing interaction terms in Table 2.8.
The graphs plot average marginal effects of capital management (*T1R*) and income smoothing (*EBPT*) on a range of the three institutional variables bank supervisory strength (*SUPERV*), regulatory capital stringency (*CAPREG*) and corruption level (*CORRUPT*). The marginal effects are provided for each binary case of the treatment versus control groups (*TREATALL* = 1/0) and 'hot' versus 'cold' stress test periods (*STHC* = 1/0).

Description of marginal effects

In Table A.7, Panel A, concerning capital management (left hand side), the results show that current *LLP* decreases with *T1R*, suggesting that treatment banks, in contrast to untreated banks, delay more loan losses to manage their capital adequacy (as in Table 2.7). In particular, the overall and 2010-11 treatment effect (DiD) is statistically significant at the 1% and 10% level, indicating that treatment banks, compared to their untreated peers, manage capital to reduce pressure on earnings figures, to recover from regulatory re-capitalisation. This result is supported by the marginal effects that indicate that treatment banks remain delaying *LLPs* during the overall treatment period (*STHC* =1) and the 2010-11 treatment period (*BAST1011* = 1). On the other hand, in Table A.7, Panel A, referring to income smoothing (right hand side), after the 2010-11 stress tests, first-time participants appear to influence their earnings by applying discretionary *LLP*, while the effect on 2014 first-time participants is negative (as in Table 2.7). The marginal effects confirm this result as the treatment banks increase their income smoothing during the 2010-11 treatment period (*BAST1011* = 1), whilst their income smoothing is decreased during the 2014 treatment period (*BAST14* = 1).

Similar results are provided in Table A.7, Panel B, which shows the marginal effects of the modification on low-, medium and high-capitalised banks (Table 2.9). In support of *H5*, low-capitalised treatment banks apply more discretionary practices, by further delaying *LLPs* during stress test periods (*STHC* =1).

Moreover, Table A.7, Panel C, illustrates the marginal effects of the robustness check that includes adjusted samples to control for the common support bias (Table 2.11). The results are similar to the findings in Panel A and further support the main conclusion that stress-tested banks exercise discretion over *LLPs* to manage capital and earnings.

Figure A.1 plots the marginal effects of the interaction terms in Table 2.8, the first modification of the baseline model that includes institutional variables (i.e., *SUPERV*, *CAPREG*, and *CORRUPT*) as suggested by Gebhardt and Novotny-Farkas (2011). The marginal effects of *T1R* and *EBPT* on *SUPERV*, *CAPREG* and *CORRUPT* show that the capital and earnings management of treatment banks remain relatively unchanged when the local supervisor's strength, capital requirements and corruption level vary. In contrast, the control banks seem to exercise more discretion over *LLP* to manage capital and earnings depending on the supervisor's strength during stress test periods (*STHC* = 1). I observe similar marginal effects of *T1R* on *CAPREG* and *EBPT* on *CORRUPT* as control banks appear to manage capital and earnings, respectively, during non-stress test periods (*STHC* = 0). In support of the baseline results in Table 2.8, a stricter institutional environment relates to both capital and earnings management. However, while stress-tested banks are more closely regulated by European institutions (e.g., EBA, ECB), the control banks' accounting discretions are more related to local institutional environments.

Table A.8 Additional robustness on multicollinearity (Table 2.7 excluding time fixed effects)

	(1)	(2)	(3)
Variables	*TREATALL*	*TREAT1011*	*TREAT14*
NPL_{it-1j}	0.0464***	0.0865**	0.1334**
	(0.0092)	(0.0374)	(0.0595)
ΔNPL_{itj}	0.1577***	0.1356***	0.0959
	(0.0334)	(0.0264)	(0.0625)
$\Delta LOAN_{itj}$	-0.0219***	-0.0035	-0.0177*
	(0.0040)	(0.0050)	(0.0095)
$T1R_{it-1j}$	-0.0388***	-0.0150	-0.0266
	(0.0121)	(0.0148)	(0.0300)
$EBPT_{itj}$	0.0647***	0.1669**	0.0295
	(0.0233)	(0.0730)	(0.1813)
STHC	-0.0080***		
	(0.0023)		
*TREATALL*STHC*	0.0054**		
	(0.0024)		
$TREATALL*T1R_{it-1j}$	0.0108		
	(0.0139)		
$STHC*T1R_{it-1j}$	0.0465***		
	(0.0127)		
$TREATALL*STHC*T1R_{it-1j}$	-0.0366**		
	(0.0144)		
$TREATALL*EBPT_{itj}$	0.1389***		
	(0.0508)		
$STHC*EBPT_{itj}$	0.1493*		
	(0.0758)		
$TREATALL*STHC*EBPT_{itj}$	-0.0342		
	(0.0900)		
BAST1011		-0.0065***	
		(0.0019)	
*TREAT1011*BAST1011*		0.0070**	
		(0.0028)	
$TREAT1011*T1R_{it-1j}$		0.0279	
		(0.0285)	
$BAST1011*T1R_{it-1j}$		0.0547***	
		(0.0158)	
$TREAT1011*BAST1011*T1R_{it-1j}$		-0.0841***	
		(0.0268)	
$TREAT1011*EBPT_{itj}$		0.2238**	
		(0.1062)	
$BAST1011*EBPT_{itj}$		-0.0881	
		(0.0589)	
$TREAT1011*BAST1011*EBPT_{itj}$		0.1515	
		(0.0962)	

Table A.8 continued

BAST14			-0.0115***
			(0.0032)
*TREAT14*BAST14*			0.0087*
			(0.0046)
$TREAT14*T1R_{it-1j}$			-0.0396
			(0.0470)
$BAST14*T1R_{it-1j}$			0.0638***
			(0.0215)
$TREAT14*BAST14*T1R_{it-1j}$			-0.0280
			(0.0320)
$TREAT14*EBPT_{itj}$			0.3025
			(0.2150)
$BAST14*EBPT_{itj}$			0.1713
			(0.1041)
$TREAT14*BAST14*EBPT_{itj}$			-0.2892**
			(0.1223)
$SIZE_{it-1j}$	0.0007*	-0.0007	0.0026
	(0.0004)	(0.0018)	(0.0038)
ΔGDP_{tj}	0.0013	0.0021*	-0.0072*
	(0.0010)	(0.0011)	(0.0041)
$\Delta UNEM_{tj}$	0.0009	-0.0007	0.0043
	(0.0013)	(0.0017)	(0.0051)
HPI_{tj}	0.0000*	-0.0001**	0.0001
	(0.0000)	(0.0000)	(0.0001)
$IRATE_{tj}$	0.0006***	0.0004***	0.0003
	(0.0001)	(0.0001)	(0.0006)
Constant	-0.0058	0.0187	-0.0342
	(0.0050)	(0.0232)	(0.0432)
Observations	1,698	649	410
Number of banks	152	119	72
Adjusted R-squared	0.3247	0.4990	0.4058
Bank fixed effects	Yes	Yes	Yes
Half-year fixed effects	No	No	No

This table reports additional robustness on multicollinearity (Table 2.7 excluding time fixed effects). Model 1 presents the total stress test effect on banks' capital management and income smoothing behaviour. Model 2 illustrates the stress test effect on the discretionary behaviour of first-time participants in 2010-11. Model 3 examines the stress test effect on the discretionary behaviour of first-time participants in 2014. I include the following variables in my analysis: Forward- and (shift of) backward looking asset quality captured by loan loss provisions (LLP_{itj}) and lagged (change in) non-performing loans (NPL_{it-1j}, ΔNPL_{itj}), loan growth shown by change in outstanding loans ($\Delta LOAN_{itj}$), capital management measured by lagged regulatory Tier 1 capital ratio ($T1R_{it-1j}$), income smoothing captured by earnings before provisions and taxes ($EBPT_{itj}$); a dummy for stress test participation (*TREATALL*), first-time participation in 2010-11 (*TREAT1011*) and 2014 (*TREAT14*); a dummy for 'hot' and 'cold' stress test periods (*STHC*), a dummy for four half-year periods before and after the 2010-11 (*BAST1011*) and 2014 treatments (*BAST14*); bank size captured by lagged natural logarithm of total assets ($SIZE_{it-1j}$) and macroeconomic fundamentals to control for contemporaneous fiscal and monetary policy changes and market instabilities such as illiquidity, constrained capital and higher volatility shown by economic growth (ΔGDP_{tj}), unemployment growth ($\Delta UNEM_{tj}$), price level in the housing market (HPI_{tj}) and sovereign debt risk ($IRATE_{tj}$). Data range 2005-2015. Standard errors (parentheses) are clustered at bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 2.1.

Table A.9 Alternative model for stress test participation

Panel A: Stress test disclosure sentiment

Variables	(1) STS_{itj}	(2) STS_ID_{itj}	(3) STS_PERF_{itj}	(4) STS_PRO_{itj}	(5) STS_REGIN_{itj}	(6) STS_REQ_{itj}	(7) STS_RM_{itj}
$STHC\_I$	0.0014**	0.0002***	0.0001*	0.0003***	0.0002**	-0.0002	0.0007
	(0.0007)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0004)
$SIZE_{it-2j}$	-0.0045**	-0.0002*	-0.0006***	-0.0003	-0.0002	-0.0009*	-0.0024*
	(0.0019)	(0.0001)	(0.0002)	(0.0003)	(0.0002)	(0.0005)	(0.0014)
$LOAN_{it-2j}$	0.0024	-0.0000	-0.0011*	0.0006	-0.0001	0.0032**	0.0001
	(0.0054)	(0.0003)	(0.0006)	(0.0008)	(0.0006)	(0.0016)	(0.0038)
LLR_{it-2j}	0.0368*	0.0027***	0.0076**	0.0043	0.0066***	-0.0126***	0.0288*
	(0.0212)	(0.0009)	(0.0031)	(0.0029)	(0.0015)	(0.0043)	(0.0145)
LLP_{it-2j}	0.0079	0.0025	0.0052	0.0013	0.0017	0.0013	-0.0037
	(0.0393)	(0.0028)	(0.0053)	(0.0071)	(0.0051)	(0.0140)	(0.0277)
$TRADE_{it-2j}$	-0.0061	-0.0006	-0.0003	-0.0014	-0.0017***	-0.0013	-0.0002
	(0.0067)	(0.0004)	(0.0010)	(0.0009)	(0.0006)	(0.0022)	(0.0044)
$T1R_{it-2j}$	0.0099	0.0007	0.0008	0.0020	0.0015*	0.0051**	0.0008
	(0.0090)	(0.0005)	(0.0011)	(0.0017)	(0.0008)	(0.0024)	(0.0062)
$DSTF_{it-2j}$	-0.0044	-0.0000	-0.0001	-0.0005	0.0008**	-0.0006	-0.0044*
	(0.0036)	(0.0002)	(0.0004)	(0.0005)	(0.0003)	(0.0008)	(0.0025)
$EBPT_{it-2j}$	-0.1430*	-0.0121**	-0.0152*	-0.0264*	-0.0119	-0.0189	-0.0673
	(0.0852)	(0.0049)	(0.0089)	(0.0146)	(0.0073)	(0.0197)	(0.0530)
ΔGDP_{tj}	0.0435***	-0.0010	0.0001	0.0022	0.0023*	0.0069*	0.0335***
	(0.0079)	(0.0016)	(0.0014)	(0.0016)	(0.0013)	(0.0036)	(0.0059)
$\Delta UNEM_{tj}$	0.0092*	-0.0004	0.0006	0.0007	0.0007	0.0002	0.0071**
	(0.0051)	(0.0003)	(0.0009)	(0.0008)	(0.0005)	(0.0015)	(0.0034)
Constant	0.0852***	0.0025**	0.0106***	0.0050	0.0040*	0.0154**	0.0497***
	(0.0220)	(0.0011)	(0.0020)	(0.0034)	(0.0021)	(0.0062)	(0.0161)
Observations	2,030	2,030	2,030	2,030	2,030	2,030	2,030
Number of banks	84	84	84	84	84	84	84
Adjusted R-squared	0.3297	0.3885	0.2230	0.4056	0.1731	0.2435	0.1991
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.9 continued

Panel B: Textual disclosure tone and quantitative disclosure behaviour

Variables	(1) $TONE_{itj}$	(2) $AGGNUM_{itj}$	(3) $NEGATIVE_{itj}$	(4) $UNCERTAIN_{itj}$	(5) $MODAL_{itj}$	(6) $TRANX_{itj}$
STHC_I	-0.0256**	0.0006*	0.0004**	0.0002	0.0001	0.0054
	(0.0122)	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0056)
$SIZE_{it-2j}$	0.0946***	-0.0019**	-0.0015***	-0.0005	0.0001	0.0345**
	(0.0315)	(0.0009)	(0.0006)	(0.0005)	(0.0002)	(0.0143)
$LOAN_{it-2j}$	0.1895**	-0.0012	-0.0023	0.0015	0.0002	-0.0415
	(0.0833)	(0.0022)	(0.0015)	(0.0013)	(0.0007)	(0.0367)
LLR_{it-2j}	-0.6308**	0.0313***	0.0251***	0.0054	0.0004	0.0404
	(0.2824)	(0.0089)	(0.0058)	(0.0047)	(0.0022)	(0.1593)
LLP_{it-2j}	-1.1054	0.0471**	0.0301**	0.0159	0.0077	-0.3488
	(0.9840)	(0.0184)	(0.0132)	(0.0139)	(0.0060)	(0.4403)
$TRADE_{it-2j}$	-0.0580	-0.0046	-0.0012	-0.0028	-0.0016*	-0.0373
	(0.1648)	(0.0039)	(0.0024)	(0.0024)	(0.0009)	(0.0637)
$T1R_{it-2j}$	0.5195**	0.0042	-0.0072**	0.0111***	0.0020*	0.2146**
	(0.2082)	(0.0048)	(0.0028)	(0.0032)	(0.0012)	(0.0833)
$DSTF_{it-2j}$	0.0308	-0.0049**	-0.0019	-0.0031***	-0.0004	-0.0242
	(0.0634)	(0.0019)	(0.0011)	(0.0011)	(0.0004)	(0.0275)
$EBPT_{it-2j}$	2.4250*	-0.0717	-0.0768***	0.0022	-0.0084	0.5466
	(1.2943)	(0.0454)	(0.0274)	(0.0304)	(0.0080)	(0.5461)
ΔGDP_{tj}	-0.0908	0.0117***	0.0028	0.0090***	-0.0010	-0.0558
	(0.2216)	(0.0041)	(0.0033)	(0.0027)	(0.0018)	(0.0913)
$\Delta UNEM_{tj}$	-0.3003***	0.0049**	0.0043**	0.0007	-0.0004	-0.0066
	(0.1112)	(0.0024)	(0.0016)	(0.0015)	(0.0006)	(0.0368)
Constant	-1.2793***	0.0343***	0.0283***	0.0078	0.0003	0.1217
	(0.3631)	(0.0107)	(0.0066)	(0.0065)	(0.0025)	(0.1727)
Observations	2,029	2,030	2,030	2,030	2,030	2,110
Number of banks	84	84	84	84	84	90
Adjusted R-squared	0.1391	0.3519	0.2376	0.4455	0.3623	0.5908
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table reports an alternative model of the individual effect of stress test participation on banks' disclosure profiles. Panel A presents stress test disclosure sentiment. Panel B illustrates disclosure tone and quantitative disclosure behaviour. I measure stress test disclosure sentiment using the word count of my accumulated stress test, regulation and risk management word lists based on stress test disclosures (STS_ALL_{itj}, STS_ID_{itj}, STS_PERF_{itj}, STS_PRO_{itj}, STS_REGIN_{itj}, STS_REQ_{itj}, and STS_RM_{itj}). I estimate disclosure tone using the word count of Loughran and McDonald's (2011a) word lists and Henry and Leone's (2016) formulas ($TONE_{itj}$, $AGGNUM_{itj}$, $NEGATIVE_{itj}$, $UNCERTAIN_{itj}$ and $MODAL_{itj}$), and quantitative disclosure behaviour using a transparency index ($TRANX_{itj}$) following Nier and Baumann (2006). I illustrate the individual stress test periods with a time-dummy (*STHC_I*). I control for bank characteristics, winsorised at the 1 and 99 percentiles and lagged by two quarters, and country-specific fundamentals using the following variables: Bank size captured by natural logarithm of total assets ($SIZE_{it-2j}$), traditional banking activities shown by outstanding loans ($LOAN_{it-2j}$), credit portfolio quality measured by loan loss reserves (LLR_{it-2j}), asset quality captured by loan loss provisions (LLP_{it-2j}), non-traditional banking activities measured by trading securities ($TRADE_{it-2j}$), capital adequacy captured by regulatory Tier 1 capital ratio ($T1R_{it-2j}$), liquidity risk shown by deposits and short-term funding ($DSTF_{it-2j}$), profitability measured by earnings before provision and taxes ($EBPT_{it-2j}$); and macroeconomic fundamentals captured by economic growth (ΔGDP_{tj}), and unemployment growth ($\Delta UNEM_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 3.1.

Table A.10 Effect of stress test disclosure sentiment on (future) disclosure tone using alternative textual estimates and factor analysis

Variables	(1) $\Delta TONE_{itj}$	(2) $AGGNUM_{itj}$	(3) $LITIGIOUS_{itj}$
STHC_I	-0.0248*	-0.0002	0.0001
	(0.0146)	(0.0002)	(0.0001)
STS_F1	0.0070	0.0045***	0.0005***
	(0.0061)	(0.0003)	(0.0001)
*STHC_I*STS_F1*	0.0088	-0.0007***	-0.0002**
	(0.0065)	(0.0001)	(0.0001)
STS_F2	-0.0102	0.0018***	0.0004***
	(0.0070)	(0.0002)	(0.0001)
*STHC_I*STS_F2*	0.0131	-0.0000	-0.0001
	(0.0094)	(0.0002)	(0.0001)
$SIZE_{it-2j}$	-0.0129	-0.0001	-0.0006*
	(0.0142)	(0.0006)	(0.0003)
$LOAN_{it-2j}$	0.0747	-0.0017	0.0008
	(0.0608)	(0.0014)	(0.0007)
LLR_{it-2j}	0.1255	0.0152***	0.0083**
	(0.1461)	(0.0046)	(0.0039)
LLP_{it-2j}	-0.0198	0.0371**	0.0047
	(0.6328)	(0.0159)	(0.0088)
$TRADE_{it-2j}$	0.0621	-0.0012	-0.0006
	(0.0723)	(0.0027)	(0.0010)
$T1R_{it-2j}$	0.1742	-0.0015	-0.0012
	(0.1159)	(0.0030)	(0.0017)
$DSTF_{it-2j}$	-0.0094	-0.0035***	-0.0002
	(0.0421)	(0.0012)	(0.0007)
$EBPT_{it-2j}$	1.6022**	0.0009	-0.0192
	(0.7557)	(0.0232)	(0.0142)
ΔGDP_{tj}	0.1114	0.0030	-0.0035
	(0.2523)	(0.0029)	(0.0027)
$\Delta UNEM_{tj}$	-0.2768***	0.0033**	0.0025***
	(0.0690)	(0.0016)	(0.0008)
Constant	0.1051	0.0218***	0.0100***
	(0.1639)	(0.0070)	(0.0037)
Observations	1,959	2,030	2,030
Number of banks	84	84	84
Adjusted R-squared	0.1064	0.7026	0.4767
Bank fixed effects	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes

This table reports banks' individual effect of stress test participation and stress test disclosure sentiment on banks' disclosure tone using alternative estimates. I measure distinct forms of disclosure tone using variation of disclosure tone ($\Delta TONE_{itj}$), aggregated 'negative', 'uncertain' and 'modal' tone ($AGGNUM_{itj}$), and 'litigious' tone ($LITIGIOUS_{itj}$). I estimate the impact of stress test disclosure sentiment using factor analysis measures from Table 3.12 (*STS_F1* and *STS_F2*), which are built on the accumulated word count of my accumulated stress test, regulation and risk management word lists in combination with a time-dummy that estimates the individual stress test periods (*STHC_I*). I control for bank characteristics, winsorised at the 1 and 99 percentiles and lagged by two quarters, and country-specific fundamentals using the following variables: Bank size captured by natural logarithm of total assets ($SIZE_{it-2j}$), traditional banking activities shown by outstanding loans ($LOAN_{it-2j}$), credit portfolio quality measured by loan loss reserves (LLR_{it-2j}), asset quality captured by loan loss provisions (LLP_{it-2j}), non-traditional banking activities measured by trading securities ($TRADE_{it-2j}$), capital adequacy captured by regulatory Tier 1 capital ratio ($T1R_{it-2j}$), liquidity risk shown by deposits and short-term funding ($DSTF_{it-2j}$), profitability measured by earnings before provision and taxes ($EBPT_{it-2j}$); and macroeconomic fundamentals captured by economic growth (ΔGDP_{tj}), and unemployment growth ($\Delta UNEM_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 3.1.

Table A.11 Effect of stress tests on bank opacity using alternative textual estimates

Panel A: Bid-ask spreads and alternative textual measures

Variables	(1) $BIDASK_{itj}$	(2) $BIDASK_{it+1j}$	(3) $BIDASK_{itj}$	(4) $BIDASK_{it+1j}$	(5) $BIDASK_{itj}$	(6) $BIDASK_{it+1j}$
STHC_I	0.0002	-0.0009	0.0003	-0.0007	-0.0008	-0.0018
	(0.0012)	(0.0014)	(0.0012)	(0.0014)	(0.0012)	(0.0013)
STS_F1	-0.0008*	-0.0007				
	(0.0004)	(0.0005)				
*STHC_I*STS_F1*	0.0016***	0.0018***				
	(0.0005)	(0.0006)				
STS_F2	-0.0004	-0.0004				
	(0.0004)	(0.0004)				
*STHC_I*STS_F2*	0.0007**	0.0008**				
	(0.0003)	(0.0003)				
TONE_F1			-0.0008**	-0.0008*		
			(0.0004)	(0.0005)		
*STHC_I*TONE_F1*			0.0016***	0.0018***		
			(0.0004)	(0.0005)		
TONE_F2			-0.0005**	-0.0006**		
			(0.0002)	(0.0003)		
*STHC_I*TONE_F2*			-0.0001	-0.0001		
			(0.0002)	(0.0002)		
TONE_ALT					-0.0177	-0.0375
					(0.0542)	(0.0548)
*STHC_I*TONE_ALT*					-0.2056***	-0.2023***
					(0.0598)	(0.0648)
$TOVER_{it-2j}$	-0.0067	-0.0043	-0.0079	-0.0053	-0.0103	-0.0077
	(0.0148)	(0.0149)	(0.0151)	(0.0153)	(0.0152)	(0.0156)
$INVPRICE_{it-2j}$	0.0032**	0.0029**	0.0033**	0.0029**	0.0031**	0.0027**
	(0.0013)	(0.0012)	(0.0013)	(0.0012)	(0.0013)	(0.0012)
$RETVOL_{it-2j}$	0.1374**	0.1458**	0.1395**	0.1483**	0.1395**	0.1473**
	(0.0601)	(0.0644)	(0.0606)	(0.0651)	(0.0612)	(0.0657)
$MVALUE_{it-2j}$	0.0026***	0.0026***	0.0027***	0.0027***	0.0029***	0.0028***
	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
$MTBV_{it-2j}$	0.0010	0.0014	0.0010	0.0014	0.0009	0.0013
	(0.0012)	(0.0014)	(0.0012)	(0.0014)	(0.0012)	(0.0013)
$RECCON_{it-2j}$	0.0033***	0.0030***	0.0034***	0.0031***	0.0033***	0.0030***
	(0.0011)	(0.0010)	(0.0011)	(0.0010)	(0.0011)	(0.0010)
ΔGDP_{tj}	0.0089	0.0012	0.0113	0.0048	0.0117	0.0031
	(0.0234)	(0.0186)	(0.0236)	(0.0197)	(0.0237)	(0.0190)
$\Delta UNEM_{tj}$	-0.0051	-0.0031	-0.0062	-0.0044	-0.0061	-0.0044
	(0.0064)	(0.0068)	(0.0067)	(0.0070)	(0.0067)	(0.0070)
$IRATE_{tj}$	0.0003	0.0003*	0.0002	0.0003*	0.0003	0.0003*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	-0.0344***	-0.0349***	-0.0353***	-0.0359***	-0.0354***	-0.0358***
	(0.0106)	(0.0108)	(0.0108)	(0.0111)	(0.0110)	(0.0114)
Observations	2,016	1,969	2,016	1,969	2,016	1,969
Number of banks	55	55	55	55	55	55
Adjusted R-squared	0.2197	0.2135	0.2221	0.2166	0.2137	0.2049
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Analyst coverage and alternative textual measures

Variables	(1) $RECNO_{itj}$	(2) $RECNO_{it+1j}$	(3) $RECNO_{itj}$	(4) $RECNO_{it+1j}$	(5) $RECNO_{itj}$	(6) $RECNO_{it+1j}$
STHC_I	0.3158	0.1271	0.2485	0.0772	0.8984	0.6830
	(0.5041)	(0.5159)	(0.5300)	(0.5402)	(0.5440)	(0.5520)
STS_F1	0.2393	0.1785				
	(0.2258)	(0.2368)				
*STHC_I*STS_F1*	-0.7293***	-0.6361***				
	(0.2043)	(0.1931)				

Table A.11 continued

STS_F2	0.2133	0.2339				
	(0.3003)	(0.2968)				
*STHC_I*STS_F2*	-0.5619**	-0.4996**				
	(0.2284)	(0.2386)				
TONE_F1			-0.0337	-0.0420		
			(0.2466)	(0.2619)		
*STHC_I*TONE_F1*			-0.7236***	-0.6257***		
			(0.1821)	(0.1725)		
TONE_F2			0.0164	0.0097		
			(0.2093)	(0.2005)		
*STHC_I*TONE_F2*			-0.0786	-0.0393		
			(0.1678)	(0.1505)		
TONE_ALT					25.9700	30.4701
					(43.1915)	(44.4616)
*STHC_I*TONE_ALT*					113.8923***	105.2607***
					(29.4869)	(30.4278)
$TOVER_{it-2j}$	5.5376	5.8286	6.7030	6.8644	7.0279	7.1240
	(7.2204)	(6.9781)	(7.3584)	(7.0971)	(7.1675)	(6.9453)
$INVPRICE_{it-2j}$	1.4640***	1.6290***	1.5260***	1.6905***	1.5458***	1.7125***
	(0.4635)	(0.4216)	(0.4813)	(0.4367)	(0.4750)	(0.4297)
$RETVOL_{it-2j}$	-48.1656**	-34.4110**	-48.2124**	-34.5209**	-48.0802**	-34.2634**
	(18.2825)	(16.8508)	(18.1725)	(16.7242)	(18.5079)	(17.0400)
$MVALUE_{it-2j}$	2.2524***	2.4185***	2.2058***	2.3730***	2.1501***	2.3118***
	(0.6090)	(0.6100)	(0.6066)	(0.6068)	(0.6140)	(0.6117)
$MTBV_{it-2j}$	-0.4216	-0.4859	-0.4278	-0.4891	-0.4105	-0.4742
	(0.7458)	(0.7455)	(0.7446)	(0.7399)	(0.7399)	(0.7348)
$RECCON_{it-2j}$	-0.9562**	-0.7032	-0.9624**	-0.7087	-0.9367*	-0.6869
	(0.4705)	(0.4503)	(0.4732)	(0.4547)	(0.4701)	(0.4523)
ΔGDP_{tj}	-24.7660**	-31.8731***	-24.4347**	-31.5249***	-25.3737**	-32.1669***
	(11.0348)	(10.0880)	(11.3422)	(10.3980)	(11.8316)	(10.7440)
$\Delta UNEM_{tj}$	6.6536*	6.1546*	7.1230**	6.6244*	7.4092**	6.9087**
	(3.5638)	(3.5289)	(3.4831)	(3.3997)	(3.5317)	(3.4449)
$IRATE_{tj}$	-0.2966***	-0.4755***	-0.2965***	-0.4741***	-0.2950***	-0.4740***
	(0.0734)	(0.0711)	(0.0740)	(0.0709)	(0.0754)	(0.0717)
Constant	2.1354	-0.2461	2.1917	-0.1900	2.6721	0.3888
	(6.6876)	(6.5313)	(6.6220)	(6.4917)	(6.8353)	(6.6941)
Observations	2,079	2,023	2,079	2,023	2,079	2,023
Number of banks	55	55	55	55	55	55
Adjusted R-squared	0.3102	0.3602	0.3078	0.3582	0.3065	0.3585
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the individual effect of stress test participation and disclosure tone on information asymmetry and private information production using alternative textual estimates. I measure bank opacity using bid-ask-spread (Panel A: $BIDASK_{itj}$) and analyst coverage employing the number of analyst recommendations (Panel B: $RECNO_{itj}$). I estimate the impact of stress test disclosure sentiment and disclosure tone using factor analysis measures from Table 3.12 (*STS_F1, STS_F2, TONE_F1*, and *TONE_F2*) and *TONE_ALT*, which are built on the word count of my accumulated stress test, regulation and risk management word lists based on stress test disclosures, the word lists by Loughran and McDonald (2011a), and the formula as in Henry and Leone (2016). I combine latter measures with a time-dummy that estimates the individual stress test periods (*STHC_I*). I control for market microstructure characteristics, daily winsorised at the 1 and 99 percentiles, quarterly averaged and lagged by two quarters, using the following variables: Share turnover ($TOVER_{it-2j}$), inverse share price ($INVPRICE_{it-2j}$), return volatility ($RETVOL_{it-2j}$), market value ($MVALUE_{it-2j}$), market-to-book value ($MTBV_{it-2j}$), analyst recommendation consensus ($RECCON_{t-2}$), and macroeconomic fundamentals captured by economic growth (ΔGDP_{tj}); unemployment growth ($\Delta UNEM_{tj}$), and sovereign debt risk ($IRATE_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 3.1.

Table A.12 Effect of stress test disclosure sentiment on disclosure tone of stress-tested banks that participated more than four times

Variables	(1) $\Delta TONE_{itj}$	(2) $AGGNUM_{itj}$	(3) $LITIGIOUS_{itj}$
STHC_I	-0.1725***	0.0016*	0.0007
	(0.0573)	(0.0008)	(0.0006)
STS_{itj}	-1.0884	0.4241***	0.0379**
	(0.9138)	(0.0307)	(0.0149)
$STHC\_I*STS_{itj}$	1.8503*	-0.0244**	-0.0113
	(0.9438)	(0.0115)	(0.0104)
$SIZE_{it-2j}$	-0.0466	0.0005	-0.0009
	(0.0373)	(0.0009)	(0.0005)
$LOAN_{it-2j}$	0.0811	-0.0029	0.0018
	(0.1284)	(0.0024)	(0.0016)
LLR_{it-2j}	0.0336	0.0203***	0.0082
	(0.1904)	(0.0056)	(0.0064)
LLP_{it-2j}	1.3288	0.0299	0.0142
	(0.8679)	(0.0211)	(0.0118)
$TRADE_{it-2j}$	0.0140	0.0014	-0.0006
	(0.1751)	(0.0043)	(0.0021)
$T1R_{it-2j}$	0.0561	0.0040	0.0035
	(0.2830)	(0.0082)	(0.0055)
$DSTF_{it-2j}$	0.0390	-0.0018	0.0006
	(0.0677)	(0.0019)	(0.0014)
$EBPT_{it-2j}$	-0.3769	-0.0371	-0.0851***
	(1.2790)	(0.0273)	(0.0293)
ΔGDP_{tj}	0.3885	-0.0006	-0.0015
	(0.9766)	(0.0128)	(0.0053)
$\Delta UNEM_{tj}$	-0.4961**	0.0052	0.0045**
	(0.2220)	(0.0045)	(0.0019)
Constant	0.5982	-0.0089	0.0115
	(0.4815)	(0.0109)	(0.0069)
Observations	766	784	784
Number of banks	25	25	25
Adjusted R-squared	0.1510	0.7508	0.4087
Bank fixed effects	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes

This table analyses the individual effect of stress test participation and stress test disclosure sentiment on disclosure tone of banks that participated three or more times in stress tests. I measure distinct forms of disclosure tone using variation of disclosure tone ($\Delta TONE_{itj}$), aggregated 'negative', 'uncertain' and 'modal' tone ($AGGNUM_{itj}$), and 'litigious' tone ($LITIGIOUS_{itj}$). I estimate the impact of stress test disclosure sentiment using the accumulated word count of my accumulated stress test, regulation and risk management word lists (STS_{itj}), in combination with a time-dummy that estimates the individual stress test periods (*STHC_I*). I control for bank characteristics, winsorised at the 1 and 99 percentiles and lagged by two quarters, and country-specific fundamentals using the following variables: Bank size captured by natural logarithm of total assets ($SIZE_{it-2j}$), traditional banking activities shown by outstanding loans ($LOAN_{it-2j}$), credit portfolio quality measured by loan loss reserves (LLR_{it-2j}), asset quality captured by loan loss provisions (LLP_{it-2j}), non-traditional banking activities measured by trading securities ($TRADE_{it-2j}$), capital adequacy captured by regulatory Tier 1 capital ratio ($T1R_{it-2j}$), liquidity risk shown by deposits and short-term funding ($DSTF_{it-2j}$), profitability measured by earnings before provision and taxes ($EBPT_{it-2j}$); and macroeconomic fundamentals captured by economic growth (ΔGDP_{tj}), and unemployment growth ($\Delta UNEM_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 3.1.

Table A.13 Effect of stress tests on bank opacity of low-ranked stress-tested banks

Panel A: Information asymmetry				
	(1)	(2)	(3)	(4)
Variables	$BIDASK_{itj}$	$BIDASK_{it+1j}$	$BIDASK_{itj}$	$BIDASK_{it+1j}$
STHC_I	-0.0018	-0.0033**	-0.0080***	-0.0099***
	(0.0012)	(0.0014)	(0.0025)	(0.0030)
STS_{itj}			-0.0822**	-0.0852**
			(0.0362)	(0.0386)
$STHC\_I{*}STS_{itj}$			0.1360***	0.1443**
			(0.0486)	(0.0578)
$TONE_{itj}$	-0.0010	-0.0012		
	(0.0011)	(0.0011)		
$STHC\_I{*}TONE_{itj}$	-0.0038***	-0.0041***		
	(0.0013)	(0.0015)		
$TOVER_{it-2j}$	-0.0110	-0.0098	-0.0072	-0.0060
	(0.0156)	(0.0168)	(0.0149)	(0.0161)
$INVPRICE_{it-2j}$	0.0024*	0.0020	0.0026*	0.0022
	(0.0014)	(0.0013)	(0.0014)	(0.0013)
$RETVOL_{it-2j}$	0.1207	0.1299	0.1211	0.1317
	(0.0778)	(0.0837)	(0.0768)	(0.0827)
$MVALUE_{it-2j}$	0.0020*	0.0017**	0.0018*	0.0016*
	(0.0010)	(0.0008)	(0.0010)	(0.0008)
$MTBV_{it-2j}$	0.0007	0.0009	0.0007	0.0008
	(0.0022)	(0.0025)	(0.0023)	(0.0026)
$RECCON_{it-2j}$	0.0032**	0.0024**	0.0032**	0.0024**
	(0.0013)	(0.0010)	(0.0013)	(0.0010)
ΔGDP_{tj}	0.0123	0.0008	0.0064	-0.0026
	(0.0367)	(0.0286)	(0.0373)	(0.0283)
$\Delta UNEM_{tj}$	-0.0191*	-0.0217*	-0.0166	-0.0188*
	(0.0106)	(0.0119)	(0.0098)	(0.0110)
$IRATE_{tj}$	0.0001	0.0002	0.0001	0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Constant	-0.0280**	-0.0251***	-0.0237**	-0.0207**
	(0.0105)	(0.0084)	(0.0102)	(0.0083)
Observations	1,233	1,204	1,234	1,205
Number of banks	34	34	34	34
Adjusted R-squared	0.2466	0.2413	0.2529	0.2473
Bank fixed effects	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes

Panel B: Analyst coverage				
	(1)	(2)	(3)	(4)
Variables	$RECNO_{itj}$	$RECNO_{it+1j}$	$RECNO_{itj}$	$RECNO_{it+1j}$
STHC_I	0.6525	0.2663	3.6247**	2.9495*
	(0.7252)	(0.7100)	(1.6369)	(1.6369)
STS_{itj}			48.0104*	45.8916*
			(25.0956)	(26.6326)
$STHC\_I{*}STS_{itj}$			-66.9573***	-61.2051**
			(23.0071)	(23.4357)
$TONE_{itj}$	0.9785	1.0346		
	(1.0081)	(0.9889)		
$STHC\_I{*}TONE_{itj}$	1.8087**	1.6847**		
	(0.7524)	(0.7080)		
$TOVER_{it-2j}$	4.5925	5.0995	2.6280	3.3515
	(7.2298)	(7.3685)	(7.3707)	(7.5414)

Table A.13 continued

$INVPRICE_{it-2j}$	1.3989**	1.6152***	1.2913**	1.5088***
	(0.5123)	(0.4691)	(0.4941)	(0.4558)
$RETVOL_{it-2j}$	-47.5052**	-29.9698	-46.8280**	-29.3832
	(20.6807)	(19.4037)	(21.1459)	(19.8066)
$MVALUE_{it-2j}$	2.2022***	2.5111***	2.3713***	2.6909***
	(0.6162)	(0.6691)	(0.6585)	(0.7239)
$MTBV_{it-2j}$	-1.6927	-1.8601	-1.6771	-1.8544
	(1.2054)	(1.2573)	(1.2447)	(1.3044)
$RECCON_{it-2j}$	-1.6929***	-1.3909***	-1.6501***	-1.3413***
	(0.4265)	(0.3930)	(0.4363)	(0.4053)
ΔGDP_{tj}	-23.7610	-34.7506**	-22.9173	-33.8215**
	(15.5215)	(14.7592)	(15.0268)	(14.2556)
$\Delta UNEM_{tj}$	12.1584***	9.8698**	10.5235**	8.1860*
	(4.2529)	(3.8902)	(4.3419)	(4.0308)
$IRATE_{tj}$	-0.3357***	-0.5360***	-0.3439***	-0.5419***
	(0.1222)	(0.1154)	(0.1194)	(0.1150)
Constant	8.7183	4.6982	4.9982	0.9461
	(7.1598)	(7.2078)	(7.7489)	(8.0778)
Observations	1,268	1,233	1,269	1,234
Number of banks	34	34	34	34
Adjusted R-squared	0.3422	0.3961	0.3407	0.3921
Bank fixed effects	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes

This table reports the individual effect of stress test participation and disclosure tone on information asymmetry and private information production of low-ranked stress-tested banks. I rank stress-tested banks according to their capital adequacy performance based on stress test disclosures and run the regression on the banks in the lower half of my ranking. Panel A presents information asymmetry captured by the current and future bid-ask-spread ($BIDASK_{itj}$, $BIDASK_{it+1j}$), and Panel B applies analyst coverage estimated by the current and future number of analyst recommendations ($RECNO_{itj}$, $RECNO_{it+1j}$). I estimate the impact of stress test sentiment using the accumulated word count of my stress test, regulation and risk management word lists based on stress test disclosures (STS_{itj}), disclosure tone using $TONE_{itj}$, in combination with a time-dummy that estimates the individual stress test periods (*STHC_I*). I control for market microstructure characteristics, daily winsorised at the 1 and 99 percentiles, quarterly averaged and lagged by two quarters, using the following variables: Share turnover ($TOVER_{it-2j}$), inverse share price ($INVPRICE_{it-2j}$), return volatility ($RETVOL_{it-2j}$), market value ($MVALUE_{it-2j}$), market-to-book value ($MTBV_{it-2j}$), analyst recommendation consensus ($RECCON_{t-2}$); and macroeconomic fundamentals captured by economic growth (ΔGDP_{tj}), unemployment growth ($\Delta UNEM_{tj}$), and sovereign debt risk ($IRATE_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 3.1.

Table A.14 Robustness checks using sample adjustments

Panel A: Stress test disclosure sentiment, disclosure tone and quantitative disclosure behaviour

Variables	(1) STS_{itj}	(2) $TONE_{itj}$	(3) $TRANX_{itj}$	(4) STS_{itj}	(5) $TONE_{itj}$	(6) $TRANX_{itj}$	(7) STS_{itj}	(8) $TONE_{itj}$	(9) $TRANX_{itj}$
ST1011	0.0193***	-0.2976***	0.0619**	0.0199***	-0.3281***	0.0419**	0.0191***	-0.2893***	0.0667**
	(0.0033)	(0.0692)	(0.0246)	(0.0037)	(0.0742)	(0.0180)	(0.0035)	(0.0781)	(0.0277)
*ST1011*FTST1011*	0.0027*	-0.0067	-0.0052	0.0034**	-0.0045	0.0027	0.0027*	-0.0070	-0.0073
	(0.0016)	(0.0209)	(0.0095)	(0.0016)	(0.0238)	(0.0116)	(0.0016)	(0.0212)	(0.0096)
ST1415	0.0292***	-0.3166***	0.0882***	0.0318***	-0.3230***	0.0696***	0.0286***	-0.3171***	0.0978***
	(0.0030)	(0.0727)	(0.0269)	(0.0034)	(0.0849)	(0.0242)	(0.0032)	(0.0820)	(0.0291)
*ST1415*FTST1011*	-0.0021**	-0.0257	0.0096	-0.0037***	-0.0423*	-0.0022	-0.0022**	-0.0252	0.0095
	(0.0010)	(0.0204)	(0.0074)	(0.0012)	(0.0247)	(0.0080)	(0.0010)	(0.0201)	(0.0073)
ST2016	0.0312***	-0.2763***	0.0959***	0.0335***	-0.2979***	0.0723***	0.0303***	-0.2713***	0.1031***
	(0.0033)	(0.0743)	(0.0278)	(0.0036)	(0.0849)	(0.0261)	(0.0034)	(0.0833)	(0.0308)
*ST2016*FTST1011*	-0.0031**	-0.0225	0.0307***	-0.0047***	-0.0410**	0.0286**	-0.0036***	-0.0259	0.0282***
	(0.0012)	(0.0170)	(0.0096)	(0.0014)	(0.0193)	(0.0112)	(0.0012)	(0.0165)	(0.0095)
$SIZE_{it-2j}$	-0.0050**	0.0859**	0.0357**	-0.0079***	0.1000**	0.0305	-0.0044**	0.0856**	0.0246
	(0.0019)	(0.0333)	(0.0153)	(0.0023)	(0.0434)	(0.0188)	(0.0021)	(0.0358)	(0.0156)
$LOAN_{it-2j}$	0.0032	0.1940**	-0.0416	-0.0005	0.1956	-0.0469	0.0004	0.1633*	-0.0360
	(0.0053)	(0.0849)	(0.0360)	(0.0070)	(0.1177)	(0.0521)	(0.0059)	(0.0892)	(0.0357)
LLR_{it-2j}	0.0356*	-0.6113**	0.0324	0.0386*	-0.6408**	0.1480	0.0364*	-0.5756*	0.0054
	(0.0206)	(0.2848)	(0.1629)	(0.0222)	(0.3004)	(0.1536)	(0.0209)	(0.2892)	(0.1619)
LLP_{it-2j}	0.0064	-1.3646	-0.2224	0.0135	-1.5904	-0.6670	0.0159	-1.3626	-0.3509
	(0.0382)	(0.9909)	(0.4373)	(0.0421)	(1.0852)	(0.4950)	(0.0380)	(0.9989)	(0.4442)
$TRADE_{it-2j}$	-0.0071	-0.0868	-0.0144	0.0021	-0.0276	0.0196	-0.0078	-0.0410	-0.0476
	(0.0070)	(0.1749)	(0.0649)	(0.0119)	(0.3195)	(0.0943)	(0.0068)	(0.1707)	(0.0624)
$T1R_{it-2j}$	0.0073	0.5206**	0.2171***	0.0045	0.5046**	0.0847	0.0061	0.4960**	0.2078**
	(0.0094)	(0.2101)	(0.0801)	(0.0132)	(0.2307)	(0.0792)	(0.0094)	(0.2094)	(0.0819)
$DSTF_{it-2j}$	-0.0046	0.0314	-0.0274	-0.0028	-0.0033	-0.0277	-0.0034	0.0382	-0.0330
	(0.0037)	(0.0646)	(0.0275)	(0.0052)	(0.0970)	(0.0392)	(0.0038)	(0.0654)	(0.0276)
$EBPT_{it-2j}$	-0.1577*	2.1224	0.5939	-0.2766**	2.1109	0.4778	-0.1340	2.7077**	0.3772
	(0.0862)	(1.3077)	(0.5559)	(0.1061)	(1.5378)	(0.7695)	(0.0844)	(1.3548)	(0.5415)
ΔGDP_{tj}	0.0428***	-0.0594	-0.0676	0.0453***	0.0502	-0.1633	0.0440***	-0.0688	-0.0835
	(0.0093)	(0.2278)	(0.0932)	(0.0120)	(0.2516)	(0.1115)	(0.0091)	(0.2259)	(0.0961)
$\Delta UNEM_{tj}$	0.0119**	-0.2777**	-0.0118	0.0112*	-0.2983**	-0.0045	0.0092*	-0.3066***	-0.0036
	(0.0051)	(0.1131)	(0.0363)	(0.0056)	(0.1367)	(0.0443)	(0.0055)	(0.1147)	(0.0374)
Constant	0.0896***	-1.1702***	0.1093	0.1244***	-1.2774**	0.1904	0.0859***	-1.1771***	0.2388
	(0.0220)	(0.3796)	(0.1799)	(0.0278)	(0.5125)	(0.2252)	(0.0253)	(0.4058)	(0.1847)
Observations	1,957	1,956	2,037	1,422	1,421	1,501	1,970	1,969	2,037
Number of banks	80	80	86	63	63	69	80	80	85
Adjusted R-squared	0.3480	0.1355	0.5948	0.3791	0.1450	0.5546	0.3254	0.1285	0.5973
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.14 continued

Panel B: Effect of stress test disclosure sentiment on disclosure tone

Variables	(1) $\Delta TONE_{itj}$	(2) $AGGNUM_{itj}$	(3) $LITIGIOUS_{itj}$	(4) $\Delta TONE_{itj}$	(5) $AGGNUM_{itj}$	(6) $LITIGIOUS_{itj}$	(7) $\Delta TONE_{itj}$	(8) $AGGNUM_{itj}$	(9) $LITIGIOUS_{itj}$
STHC_I	-0.0990**	0.0009	0.0008**	-0.1140*	0.0009	0.0009**	-0.1031**	0.0012**	0.0008**
	(0.0486)	(0.0006)	(0.0004)	(0.0630)	(0.0007)	(0.0005)	(0.0479)	(0.0006)	(0.0004)
STS_{itj}	-0.6628	0.4194***	0.0410***	-0.2938	0.4277***	0.0494***	-0.9159*	0.4083***	0.0358***
	(0.5469)	(0.0177)	(0.0073)	(0.7229)	(0.0176)	(0.0081)	(0.4611)	(0.0189)	(0.0077)
$STHC\_I*STS_{itj}$	1.4058*	-0.0174*	-0.0136**	1.4709	-0.0171	-0.0159**	1.4926**	-0.0217**	-0.0121**
	(0.7332)	(0.0104)	(0.0062)	(0.9753)	(0.0131)	(0.0076)	(0.7135)	(0.0107)	(0.0060)
$SIZE_{it-2j}$	-0.0196	0.0003	-0.0004*	-0.0218	0.0007	-0.0004	-0.0127	-0.0002	-0.0007*
	(0.0138)	(0.0005)	(0.0003)	(0.0213)	(0.0007)	(0.0003)	(0.0153)	(0.0007)	(0.0004)
$LOAN_{it-2j}$	0.0817	-0.0023**	0.0007	0.0861	-0.0024	0.0012	0.0497	-0.0016	0.0008
	(0.0599)	(0.0012)	(0.0007)	(0.0848)	(0.0017)	(0.0009)	(0.0616)	(0.0013)	(0.0008)
LLR_{it-2j}	0.1507	0.0168***	0.0093**	0.1389	0.0176***	0.0096**	0.1794	0.0162***	0.0088**
	(0.1466)	(0.0043)	(0.0040)	(0.1513)	(0.0049)	(0.0045)	(0.1485)	(0.0042)	(0.0041)
LLP_{it-2j}	-0.0284	0.0466***	0.0093	0.1055	0.0364**	0.0011	0.1296	0.0425***	0.0057
	(0.6364)	(0.0141)	(0.0086)	(0.7371)	(0.0149)	(0.0093)	(0.6200)	(0.0140)	(0.0092)
$TRADE_{it-2j}$	0.0865	-0.0010	-0.0004	0.1203	0.0032	-0.0002	0.0651	-0.0023	-0.0009
	(0.0764)	(0.0030)	(0.0010)	(0.1330)	(0.0037)	(0.0017)	(0.0776)	(0.0028)	(0.0011)
$T1R_{it-2j}$	0.1698	-0.0000	-0.0006	0.2369*	-0.0020	-0.0011	0.1804	0.0008	-0.0009
	(0.1159)	(0.0024)	(0.0017)	(0.1318)	(0.0034)	(0.0026)	(0.1171)	(0.0023)	(0.0018)
$DSTF_{it-2j}$	-0.0204	-0.0029***	-0.0001	-0.0127	-0.0028*	-0.0003	-0.0150	-0.0030***	-0.0002
	(0.0416)	(0.0011)	(0.0006)	(0.0536)	(0.0014)	(0.0009)	(0.0426)	(0.0011)	(0.0007)
$EBPT_{it-2j}$	1.3953*	-0.0014	-0.0129	1.7469*	0.0003	-0.0226	1.3475*	-0.0169	-0.0245
	(0.7560)	(0.0209)	(0.0129)	(1.0174)	(0.0220)	(0.0173)	(0.7313)	(0.0242)	(0.0159)
ΔGDP_{tj}	0.0956	-0.0048	-0.0029	0.1380	-0.0045	-0.0020	0.0303	-0.0058*	-0.0035
	(0.2541)	(0.0032)	(0.0026)	(0.2654)	(0.0042)	(0.0029)	(0.2452)	(0.0033)	(0.0027)
$\Delta UNEM_{tj}$	-0.2828***	0.0004	0.0023***	-0.2801***	-0.0001	0.0028***	-0.2975***	0.0014	0.0024***
	(0.0707)	(0.0014)	(0.0008)	(0.0799)	(0.0017)	(0.0010)	(0.0726)	(0.0014)	(0.0008)
Constant	0.2119	-0.0047	0.0054*	0.1994	-0.0107	0.0053	0.1694	0.0008	0.0091**
	(0.1565)	(0.0060)	(0.0030)	(0.2417)	(0.0077)	(0.0038)	(0.1789)	(0.0078)	(0.0044)
Observations	1,886	1,957	1,957	1,361	1,422	1,422	1,903	1,970	1,970
Number of banks	80	80	80	63	63	63	80	80	80
Adjusted R-squared	0.1054	0.7724	0.4779	0.1225	0.7659	0.4665	0.0969	0.7512	0.4523
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Effect of stress test disclosure sentiment on information asymmetry

Variables	(1) $BIDASK_{itj}$	(2) $BIDASK_{itj}$	(3) $BIDASK_{itj}$	(4) $BIDASK_{itj}$	(5) $BIDASK_{itj}$	(6) $BIDASK_{itj}$
STHC_I	-0.0005	-0.0054**	-0.0012	-0.0079***	-0.0004	-0.0049**
	(0.0012)	(0.0022)	(0.0011)	(0.0025)	(0.0012)	(0.0021)

Table A.14 continued

STS_{itj}		-0.0506*		-0.0862**		-0.0428
		(0.0296)		(0.0372)		(0.0270)
$STHC\_I{*}STS_{itj}$		0.1067***		0.1481***		0.0957***
		(0.0347)		(0.0493)		(0.0325)
$TONE_{itj}$	-0.0007		-0.0017		-0.0005	
	(0.0012)		(0.0012)		(0.0010)	
$STHC\_I{*}TONE_{itj}$	-0.0029***		-0.0037***		-0.0025**	
	(0.0011)		(0.0012)		(0.0010)	
$TOVER_{it-2j}$	-0.0096	-0.0076	-0.0129	-0.0102	-0.0110	-0.0090
	(0.0147)	(0.0143)	(0.0136)	(0.0133)	(0.0150)	(0.0145)
$INVPRICE_{it-2j}$	0.0028**	0.0030**	0.0020**	0.0022**	0.0027**	0.0028**
	(0.0013)	(0.0014)	(0.0009)	(0.0010)	(0.0013)	(0.0013)
$RETVOL_{it-2j}$	0.1460**	0.1459**	0.1462**	0.1467**	0.1201*	0.1200*
	(0.0643)	(0.0638)	(0.0677)	(0.0668)	(0.0631)	(0.0626)
$MVALUE_{it-2j}$	0.0026***	0.0025***	0.0031***	0.0030***	0.0022***	0.0021***
	(0.0010)	(0.0009)	(0.0010)	(0.0010)	(0.0008)	(0.0007)
$MTBV_{it-2j}$	0.0012	0.0013	0.0007	0.0007	0.0006	0.0007
	(0.0013)	(0.0013)	(0.0014)	(0.0014)	(0.0012)	(0.0012)
$RECCON_{it-2j}$	0.0034***	0.0034***	0.0036**	0.0035**	0.0027**	0.0027***
	(0.0011)	(0.0011)	(0.0014)	(0.0013)	(0.0010)	(0.0010)
ΔGDP_{tj}	0.0129	0.0101	0.0106	0.0039	0.0136	0.0105
	(0.0249)	(0.0248)	(0.0348)	(0.0353)	(0.0244)	(0.0242)
$\Delta UNEM_{tj}$	-0.0067	-0.0054	-0.0159*	-0.0133	-0.0065	-0.0055
	(0.0070)	(0.0067)	(0.0088)	(0.0082)	(0.0068)	(0.0065)
$IRATE_{tj}$	0.0002	0.0002	0.0001	0.0001	0.0003	0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	-0.0334***	-0.0302***	-0.0396***	-0.0344***	-0.0271***	-0.0246***
	(0.0113)	(0.0103)	(0.0125)	(0.0115)	(0.0092)	(0.0088)
Observations	1,865	1,866	1,372	1,373	2,007	2,008
Number of banks	51	51	38	38	54	54
Adjusted R-squared	0.2143	0.2186	0.2479	0.2534	0.1956	0.2001
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel D: Effect of stress test disclosure sentiment on analyst coverage

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	$RECNO_{itj}$	$RECNO_{itj}$	$RECNO_{itj}$	$RECNO_{itj}$	$RECNO_{itj}$	$RECNO_{itj}$
$STHC\_I$	0.7596	4.0663***	0.7501	4.2643**	0.6690	3.7981***
	(0.5701)	(1.1798)	(0.6872)	(1.6240)	(0.5765)	(1.1947)
STS_{itj}		36.9178*		40.4635		40.3494**
		(19.5443)		(27.7460)		(17.9522)
$STHC\_I{*}STS_{itj}$		-70.0783***		-75.8792***		-66.0121***
		(17.5267)		(23.3100)		(18.0800)

Table A.14 continued

$TONE_{itj}$	0.7146		0.9406		0.6103	
	(0.9143)		(1.0185)		(0.8876)	
$STHC\_I*TONE_{itj}$	1.3971*		1.5533**		1.3590*	
	(0.7027)		(0.7612)		(0.6985)	
$TOVER_{it-2j}$	6.6221	5.3728	5.1703	4.0999	6.7085	5.0904
	(7.0948)	(7.1142)	(6.8856)	(7.0299)	(7.0561)	(7.0159)
$INVPRICE_{it-2j}$	1.5239***	1.4364***	1.5992***	1.5026***	1.5146***	1.4234***
	(0.5147)	(0.5015)	(0.5500)	(0.5385)	(0.4757)	(0.4619)
$RETVOL_{it-2j}$	-47.7307**	-47.3525**	-44.4683**	-44.0584**	-52.5776***	-52.2005***
	(19.5887)	(19.8771)	(19.3981)	(19.6333)	(18.8633)	(19.0815)
$MVALUE_{it-2j}$	2.1963***	2.3184***	1.8245***	1.9473***	2.0726***	2.1958***
	(0.6421)	(0.6504)	(0.6145)	(0.6394)	(0.6061)	(0.6088)
$MTBV_{it-2j}$	-0.4982	-0.5267	-0.9259	-0.9166	-0.3948	-0.4352
	(0.7755)	(0.7802)	(0.8520)	(0.8662)	(0.7528)	(0.7545)
$RECCON_{it-2j}$	-0.7881	-0.7698	-1.3099**	-1.2260**	-1.0162**	-1.0125**
	(0.4706)	(0.4675)	(0.4957)	(0.5115)	(0.4829)	(0.4802)
ΔGDP_{tj}	-32.3039***	-31.1604***	-28.3422*	-26.3696*	-26.6412**	-25.5520**
	(11.5954)	(10.9726)	(14.4009)	(14.0006)	(11.8016)	(11.1062)
$\Delta UNEM_{tj}$	9.1195**	8.1474**	11.8719***	10.5098**	7.3023**	6.4096*
	(3.4589)	(3.4884)	(4.1777)	(4.2759)	(3.5250)	(3.5242)
$IRATE_{tj}$	-0.3049***	-0.3138***	-0.3242***	-0.3314***	-0.2865***	-0.2919***
	(0.0758)	(0.0732)	(0.0861)	(0.0838)	(0.0758)	(0.0731)
Constant	1.8550	-0.7968	9.3598	6.3612	3.6228	0.8854
	(6.9507)	(7.0039)	(6.9582)	(7.4089)	(6.9356)	(6.9178)
Observations	1,924	1,925	1,423	1,424	2,071	2,072
Number of banks	51	51	38	38	54	54
Adjusted R-squared	0.3034	0.3077	0.3264	0.3260	0.3075	0.3124
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table reports robustness checks using adjusted samples. Panel A presents stress test disclosure sentiment, disclosure tone and quantitative disclosure behaviour. Panel B illustrates the effect of stress test disclosure sentiment on (future change in) disclosure tone. Panel C shows the effect of stress tests on bank opacity. In Panels A/B and C/D, respectively, I exclude banks from the United Kingdom (Models 1 to 3 and 1 to 2), of non-EMU countries (Models 4 to 6 and 3 to 4) and inactive banks (Models 7 to 9 and 5 to 6). I measure stress test disclosure sentiment using the word count of my accumulated stress test, regulation and risk management word list (STS_{itj}). I estimate distinct forms of disclosure tone using variation of disclosure tone ($\Delta TONE_{itj}$), aggregated 'negative', 'uncertain' and 'modal' tone ($AGGNUM_{itj}$), and 'litigious' tone ($LITIGIOUS_{itj}$). I capture quantitative disclosure behaviour using a transparency index ($TRANX_{itj}$) following Nier and Baumann (2006). I measure bank opacity using bid-ask-spread ($BIDASK_{itj}$) and analyst coverage ($RECNO_{itj}$). The following dummy variables measure first-time participation in 2010-11 (*FTST1011*) and the stress test periods in 2010-11 (*ST1011*), 2014-15 (*ST1415*), and 2016 (*ST2016*), and the individual stress test periods (*STHC_I*). I control for bank characteristics, winsorised at the 1 and 99 percentiles and lagged by two quarters, and country-specific fundamentals using the following variables: Bank size captured by natural logarithm of total assets ($SIZE_{it-2j}$), traditional banking activities shown by outstanding loans ($LOAN_{it-2j}$), credit portfolio quality measured by loan loss reserves (LLR_{it-2j}), asset quality captured by and loan loss provisions (LLP_{it-2j}), non-traditional banking activities measured by trading securities ($TRADE_{it-2j}$), capital adequacy captured by regulatory Tier 1 capital ratio ($T1R_{it-2j}$), liquidity risk shown by deposits and short-term funding ($DSTF_{it-2j}$), and profitability measured by earnings before provision and taxes ($EBPT_{it-2j}$). I control for market microstructure characteristics, daily winsorised at the 1 and 99 percentiles, quarterly averaged and lagged by two quarters, using the following variables: Share turnover ($TOVER_{it-2j}$), inverse share price ($INVPRICE_{it-2j}$), return volatility ($RETVOL_{it-2j}$), market value ($MVALUE_{it-2j}$), market-to-book value ($MTBV_{it-2j}$), analyst recommendation consensus ($RECCON_{t-2}$), and macroeconomic fundamentals captured by economic growth (ΔGDP_{tj}), unemployment growth ($\Delta UNEM_{tj}$), and sovereign debt risk ($IRATE_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 3.1.

Table A.15 Robustness checks on CTIME-analysis using the Fama and French (1993) three-factors model (FF3F)

Panel A: European banks

		Equally-weighted (FF3F)			*MVALUE*-weighted (FF3F)		
		1-12 mths.	1-24 mths.	1-36 mths.	1-12 mths.	1-24 mths.	1-36 mths.
(1)	CEBS 2010						
	Alpha	-0.0002	-0.0003	-0.0003***	0.0006	0.0000	-0.0001
	BETA	0.5512	0.8782***	0.7863	0.7928***	0.9603***	0.9660***
	SMB	-0.6879	-0.0497	-0.1374	-0.7084**	-0.2867	-0.2019
	HML	1.6210*	0.8961*	1.2168***	0.7086*	0.3709***	0.3974***
	Observations	12	24	36	12	24	36
	R-squared	0.9698	0.9739	0.9739	0.9964	0.9954	0.9939
(2)	EBA 2011						
	Alpha	0.0012	0.0017	0.0004	0.0004	0.0007	0.0006
	BETA	0.9633***	1.0444***	0.9529***	1.0331***	1.0840***	1.0931***
	SMB	0.2225	0.4536*	0.5017	-0.6046	0.1143	0.1100
	HML	0.9919	0.4818	1.0736**	0.3453	0.3707***	0.3345***
	Observations	12	24	36	12	24	36
	R-squared	0.9417	0.9531	0.9339	0.9886	0.991	0.9909
(3)	EBA/ECB 2014						
	Alpha	-0.0033	-0.0010	-0.0002	-0.0017*	-0.0017**	-0.0006
	BETA	0.9787**	0.8593***	0.9168***	1.2732***	1.0972***	0.9938***
	SMB	0.0999	-0.1334	0.1186	0.2142	-0.1071	-0.2493
	HML	0.1926	0.5113	0.5512**	-0.5837***	-0.4332**	-0.1973
	Observations	12	24	36	12	24	36
	R-squared	0.9148	0.8918	0.9245	0.9833	0.9593	0.9545
(4)	EBA 2016						
	Alpha	-0.0006	-0.0007		-0.0004	-0.0003	
	BETA	0.8954**	1.0939***		1.0028***	1.0848***	
	SMB	-0.5623	-0.0979		0.0811	0.2270	
	HML	0.2171	-0.2276		0.1115	-0.0378	
	Observations	12.0000	24.0000		12.0000	24.0000	
	R-squared	0.9541	0.9602		0.9822	0.9832	
(5)	FTSTO						
	Alpha	-0.0006	-0.0007	-0.0001	-0.0002	-0.0003	0.0002
	BETA	0.6549	0.9057**	0.8109***	0.7478	0.9313***	0.8809***
	SMB	-0.3948	0.1631	0.1793	-0.6032	-0.1198	-0.1724
	HML	1.1839	0.7298	1.0355	0.9392	0.5420	0.6720**
	Observations	36	72	108	36	72	108
	R-squared	0.0486	0.2314	0.2291	0.8260	0.8647	0.7989
(6)	TOTALSTO						
	Alpha	-0.0008	0.0000	0.0000	-0.0001	-0.0004	0.0000
	BETA	0.9777***	0.9975***	0.9448***	1.1465***	1.0878***	1.0747***
	SMB	0.1400	0.2945*	0.2878*	-0.0916	-0.0270	-0.0291
	HML	0.7306*	0.5206***	0.8287***	0.0216	0.0368	0.1094
	Observations	36	72	108	36	72	108
	R-squared	0.9426	0.9502	0.9411	0.9836	0.9853	0.9839

Panel B: U.S. banks

		Equally-weighted (FF3F)			*MVALUE*-weighted (FF3F)		
		1-12 mths.	1-24 mths.	1-36 mths.	1-12 mths	1-24 mths	1-36 mths
(1)	SCAP 2009						
	Alpha	0.0022	0.0045*	0.0019	0.0023	0.0025*	0.0007
	BETA	0.5672	0.5080***	0.7656***	0.3734**	0.6066***	0.8312***
	SMB	0.3357	0.3411	0.3002	0.2911	-0.0352	-0.0186
	HML	2.1352	2.3157***	1.1139*	2.3901***	1.3578***	0.3122
	Observations	12	24	36	12	24	36
	R-squared	0.9804	0.9664	0.9573	0.9919	0.9838	0.9714
(2)	CCAR 2011						
	Alpha	0.0012*	0.0008	0.0006	0.0004	0.0005	0.0003
	BETA	0.4883***	0.5064***	0.5755***	0.5109***	0.6276***	0.6160***
	SMB	-0.2015	0.2493	0.1347	-0.0180	0.1427	0.0596
	HML	0.3420	0.4821	0.2866	0.3089	0.3755	0.3680
	Observations	12	24	36	12	24	36
	R-squared	0.876	0.7277	0.7816	0.8093	0.7538	0.7876

Table A.15 continued

(3)	CCAR 2012						
	Alpha	0.0016	0.0001	-0.0001	0.0015	0.0001	-0.0008
	BETA	1.0069***	1.1277***	1.0744***	0.9149***	1.0719***	1.0720***
	SMB	-0.0462	0.0820	0.0560	0.2665	0.3361	0.0072
	HML	0.3162	-0.0866	0.0489	0.6700	0.0803	0.1476
	Observations	12	24	36	12	24	36
	R-squared	0.9254	0.9501	0.9391	0.914	0.9394	0.9181
(4)	CCAR 2013						
	Alpha	-0.0021	-0.0007	0.0001	-0.0021**	-0.0007	-0.0004
	BETA	1.1891***	1.1608***	1.1573***	1.0487***	1.1109***	1.1261***
	SMB	-0.1824	0.1490	0.1032	-0.5305**	-0.1839	-0.1105
	HML	-1.5303**	-0.7859	-0.2672	-0.5860	-0.1466	-0.0747
	Observations	12	24	36	12	24	36
	R-squared	0.8061	0.835	0.8598	0.8898	0.8147	0.8508
(5)	CCAR 2014						
	Alpha	0.0007	0.0000	0.0005	0.0002	0.0003	0.0004
	BETA	1.1205***	0.9297***	0.9719***	0.9971***	0.9682***	0.9995***
	SMB	-0.1005	0.0187	0.1347	-0.0334	-0.0303	-0.0459
	HML	0.0630	-0.1434	0.0050	-0.1023	-0.1488**	-0.0988*
	Observations	12	24	36	12	24	36
	R-squared	0.9811	0.9475	0.9335	0.9825	0.9825	0.9839
(6)	CCAR 2015						
	Alpha	0.0007*	0.0002	0.0004	0.0007*	0.0004	0.0004
	BETA	1.1093***	1.0051***	0.9781***	1.0721***	0.9976***	0.9856***
	SMB	0.1372*	0.2141	0.1603	-0.0335	0.0132	0.0157
	HML	-0.0977	0.0560	0.0200	-0.0337	0.0593	-0.0183
	Observations	12	24	36	12	24	36
	R-squared	0.9908	0.9431	0.9287	0.9923	0.9623	0.9599
(7)	CCAR 2016						
	Alpha	0.0016	0.0011*		0.0010*	0.0005	
	BETA	1.0104***	0.9878***		0.9141***	0.9308***	
	SMB	0.3950*	0.5158***		0.2642**	0.3240***	
	HML	0.3215	0.2562**		0.2202	0.0775	
	Observations	12	24		12	24	
	R-squared	0.9687	0.9531		0.9927	0.9741	
(8)	CCAR 2017						
	Alpha	0.0005			-0.0001		
	BETA	0.7393***			0.8659***		
	SMB	0.5261**			0.1404		
	HML	-0.0494			-0.0601		
	Observations	12			12		
	R-squared	0.9092			0.9749		
(9)	FTSTO						
	Alpha	-0.0001	0.0008	0.0009	-0.0004	0.0003	0.0006
	BETA	0.9126***	0.7966***	0.8655***	0.7632***	0.7924***	0.8670***
	SMB	0.1627	0.3697	0.2644	0.1323	0.0197	-0.0358
	HML	0.5081	0.8170***	0.5447**	0.5517	0.3930*	0.1115
	Observations	36	72	108	36	72	108
	R-squared	0.9319	0.8829	0.8362	0.9154	0.8901	0.8348
(10)	TOTALSTO						
	Alpha	0.0002	0.0003	0.0004	-0.0002	0.0000	0.0001
	BETA	1.0074***	0.9303***	0.9422***	0.8850***	0.8875***	0.9073***
	SMB	0.0228*	0.2480**	0.1935	0.0007	0.0847	0.0391
	HML	0.0412	0.1270	0.0922	0.0553	0.0135	-0.0051
	Observations	72	144	216	72	144	216
	R-squared	0.9637	0.9318	0.9333	0.9668	0.95	0.9456

This table reports the robustness checks on the calendar-time portfolio approach (CTIME). Panel A illustrates the European sample. Models 1 to 4 show the results for the individual European stress tests in 2010, 2011, 2014 and 2016, whilst Models 5 and 6 display first-time and total stress test observations (FTSTO, TOTALSTO). Panel B illustrates the U.S. sample. Models 1 to 8 display the results for the individual U.S. stress tests in 2009, 2011, 2012, 2013, 2014, 2015, 2016 and 2017, whilst Models 9 and 10 show first-time and total stress test observations (FTSTO, TOTALSTO). I estimate the coefficients, equally-weighted and *MVALUE*-weighted (year-end quarter 4 prior to each stress test event) for 1 to 12, 24 and 36 months after the stress test using the Fama and French (1993) three-factors model (FF3F). Bank performance is measured by Jensen's alpha (*Alpha*), and the three factors are asset sensitivity (*BETA*), capitalisation (*SMB*) and book-to-market (*HML*). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 4.1.

Table A.16 Robustness check on bank funding structure including sovereign debt risk

Panel A: European banks						
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	TIE_{itj}	OIE_{itj}	$DEPBA_{itj}$	$IECD_{itj}$	$CUSTD_{itj}$	NIM_{itj}
ST1011EU	-0.0153***	-0.0124***	-0.0107	-0.0061***	0.0020	-0.0077***
	(0.0020)	(0.0027)	(0.0248)	(0.0013)	(0.0441)	(0.0011)
*ST1011EU*FTST1011EU*	0.0012	0.0008	-0.0327**	0.0005	0.0172	0.0004
	(0.0008)	(0.0009)	(0.0160)	(0.0005)	(0.0155)	(0.0005)
ST1415EU	-0.0177***	-0.0128***	-0.1012***	-0.0086***	0.0396	-0.0095***
	(0.0020)	(0.0027)	(0.0261)	(0.0015)	(0.0438)	(0.0011)
*ST1415EU*FTST1011EU*	0.0002	0.0000	0.0228*	0.0001	0.0009	0.0013**
	(0.0006)	(0.0005)	(0.0133)	(0.0005)	(0.0105)	(0.0006)
ST16EU	-0.0181***	-0.0131***	-0.1181***	-0.0089***	0.0847*	-0.0095***
	(0.0020)	(0.0027)	(0.0280)	(0.0015)	(0.0470)	(0.0012)
*ST16EU*FTST1011EU*	-0.0003	-0.0004	0.0425**	0.0003	-0.0189	0.0015*
	(0.0008)	(0.0007)	(0.0170)	(0.0007)	(0.0199)	(0.0008)
$SIZE_{it-2j}$	-0.0006	0.0004	0.0403***	-0.0016**	-0.1006***	-0.0012
	(0.0018)	(0.0016)	(0.0129)	(0.0008)	(0.0271)	(0.0008)
$LOAN_{it-2j}$	0.0103**	0.0083*	-0.1114**	0.0016	-0.0154	0.0039*
	(0.0044)	(0.0043)	(0.0477)	(0.0025)	(0.0731)	(0.0024)
LLP_{it-2j}	0.0210	0.0485	2.9362***	0.0183	-1.7707***	-0.0779**
	(0.0380)	(0.0390)	(0.6315)	(0.0390)	(0.6582)	(0.0301)
$TRADE_{it-2j}$	-0.0204***	-0.0139***	-0.1747***	-0.0117***	-0.0862	0.0018
	(0.0049)	(0.0041)	(0.0613)	(0.0037)	(0.0792)	(0.0031)
$DEPO_{it-2j}$	0.0003	-0.0018	0.1909***	0.0027*	0.2723***	0.0020
	(0.0020)	(0.0021)	(0.0558)	(0.0015)	(0.0384)	(0.0016)
$EBPT_{it-2j}$	0.0359	0.0807	-1.3384*	-0.0951**	0.1958	-0.0783
	(0.0693)	(0.0645)	(0.6801)	(0.0385)	(0.8149)	(0.0560)
ΔGDP_{tj}	0.0084	0.0068	0.2997	0.0006	0.0180	0.0026
	(0.0142)	(0.0150)	(0.2064)	(0.0107)	(0.2473)	(0.0100)
$\Delta UNEM_{tj}$	-0.0028	-0.0081**	0.0012	0.0073**	-0.0835**	0.0050**
	(0.0038)	(0.0038)	(0.0505)	(0.0032)	(0.0406)	(0.0025)
$IRATE_{tj}$	-0.0000	0.0003***	0.0031	-0.0002	-0.0033***	-0.0002***
	(0.0001)	(0.0001)	(0.0023)	(0.0001)	(0.0012)	(0.0001)
Constant	0.0234	0.0068	-0.3186**	0.0273***	1.4877***	0.0237**
	(0.0191)	(0.0176)	(0.1492)	(0.0085)	(0.3186)	(0.0094)
Observations	2,067	2,047	2,280	1,297	2,311	2,312
Number of banks	83	83	83	78	83	86
Adjusted R-squared	0.7049	0.4890	0.2428	0.6340	0.3384	0.7438
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: U.S. banks						
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	TIE_{itj}	OIE_{itj}	$SUBD_{itj}$	$IECD_{itj}$	$CUSTD_{itj}$	NIM_{itj}
ST0913US	0.0450***	0.0179***	-0.0019	0.0149**	0.8166***	0.3381***
	(0.0071)	(0.0034)	(0.0169)	(0.0062)	(0.1379)	(0.0300)
*ST0913US*FTST09US*	-0.0004	0.0003	0.0009	0.0008**	-0.0067	-0.0007
	(0.0005)	(0.0005)	(0.0018)	(0.0003)	(0.0093)	(0.0009)
ST1417US	0.0207***	0.0051**	-0.0070	0.0029	0.5246***	0.1891***
	(0.0039)	(0.0022)	(0.0103)	(0.0040)	(0.0909)	(0.0169)
*ST1417US*FTST09US*	-0.0004	0.0002	-0.0005	0.0008	0.0141	0.0001
	(0.0006)	(0.0005)	(0.0028)	(0.0005)	(0.0156)	(0.0008)
$SIZE_{it-2j}$	0.0024***	0.0026**	0.0004	0.0003	-0.1066***	-0.0021*
	(0.0007)	(0.0010)	(0.0045)	(0.0005)	(0.0141)	(0.0010)
$LOAN_{it-2j}$	-0.0009	-0.0021	0.0273	-0.0000	0.0004	0.0052
	(0.0019)	(0.0026)	(0.0162)	(0.0017)	(0.0656)	(0.0063)
LLP_{it-2j}	0.0222	0.0136	-0.0048	0.0109	0.7689	-0.2058***
	(0.0265)	(0.0298)	(0.1636)	(0.0166)	(0.5550)	(0.0551)
$TRADE_{it-2j}$	0.0008	0.0014	-0.0038	-0.0047	-0.0712	-0.0021
	(0.0051)	(0.0069)	(0.0159)	(0.0037)	(0.1311)	(0.0095)

Table A.16 continued

$DEPO_{it-2j}$	-0.0029	-0.0048*	-0.0241**	0.0029**	0.3380***	0.0026
	(0.0018)	(0.0025)	(0.0094)	(0.0014)	(0.0880)	(0.0038)
$EBPT_{it-2j}$	-0.0468***	-0.0282**	0.0135	-0.0150	0.1108	-0.1211***
	(0.0152)	(0.0131)	(0.0618)	(0.0109)	(0.3260)	(0.0358)
ΔGDP_{tj}	0.0480***	0.0255***	0.0062	0.0234***	0.6371***	0.2954***
	(0.0069)	(0.0037)	(0.0148)	(0.0043)	(0.0952)	(0.0268)
$\Delta UNEM_{tj}$	0.0832***	0.0407***	0.0219	0.0454***	2.0042***	0.5418***
	(0.0135)	(0.0085)	(0.0370)	(0.0105)	(0.3155)	(0.0504)
$IRATE_{tj}$	-0.0151***	-0.0076***	-0.0012	-0.0077***	-0.2007***	-0.0940***
	(0.0021)	(0.0011)	(0.0047)	(0.0015)	(0.0368)	(0.0086)
Constant	-0.0221***	-0.0199*	0.0164	0.0030	1.5405***	-0.0143
	(0.0077)	(0.0097)	(0.0551)	(0.0046)	(0.1398)	(0.0131)
Observations	992	992	718	869	975	993
Number of banks	28	28	28	27	28	28
Adjusted R-squared	0.8689	0.7125	0.3317	0.8728	0.5801	0.8532
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table robustness checks on bank funding structure including sovereign debt risk. Panel A illustrates the European sample and Panel B shows the U.S. sample. I estimate bank funding structure using total (TIE_{itj}) uninsured (OIE_{itj}) and insured ($IECD_{itj}$) funding cost as well as uninsured ($DEPBA_{itj}$, $SUBD_{itj}$), insured funding ($CUSTD_{itj}$) and interest margin (NIM_{itj}). In Panel A, I include dummy variable to measure European first-time participation in 2010-11 (*FTST1011EU*) and the stress test periods in 2010-11 (*ST1011EU*), 2014-15 (*ST1415EU*), and 2016 (*ST16EU*). In Panel B, I include dummy variables to estimate U.S. first-time participation in 2009 (*FTST09US*) and the stress test periods in 2009-13 (*ST0913US*) and 2014-17 (*ST1417US*). In both panels, I control for bank characteristics, lagged by two quarters, and country-specific fundamentals using the following variables: Bank size captured by natural logarithm of total assets ($SIZE_{it-2j}$), traditional banking activities shown by outstanding loans ($LOAN_{it-2j}$), asset quality measured by loan loss provisions (LLP_{it-2j}), non-traditional banking activities measured by trading securities ($TRADE_{it-2j}$), liquidity shown by total deposits ($DEPO_{it-2j}$), profitability measured by earnings before provision and taxes ($EBPT_{it-2j}$); and macroeconomic fundamentals captured by economic growth (ΔGDP_{tj}), and unemployment growth ($\Delta UNEM_{tj}$), and sovereign debt risk ($IRATE_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 4.1.

Table A.17 Robustness checks on information asymmetry and analyst behaviour using sample adjustments

Panel A: European sample without inactive banks				
	(1)	(2)	(3)	(4)
Variables	$BIDASK_{itj}$	$RECNO_{itj}$	$EPSSUR / PRICE_{itj}$	$ESTSD / PRICE_{itj}$
ST1011EU	0.0060*	3.0198**	-0.0816**	-0.0414*
	(0.0031)	(1.4417)	(0.0373)	(0.0233)
*ST1011EU*FTST1011EU*	-0.0038*	2.2591**	0.0075	0.0307**
	(0.0021)	(0.9058)	(0.0185)	(0.0129)
ST1415EU	-0.0039**	2.7529	0.0596	0.0298
	(0.0018)	(1.8820)	(0.0357)	(0.0203)
*ST1415EU*FTST1011EU*	0.0032***	-1.9336	-0.0206	0.0073
	(0.0010)	(1.4690)	(0.0212)	(0.0159)
ST16EU	-0.0028*	2.6360	0.0415	-0.0135
	(0.0016)	(2.1708)	(0.0541)	(0.0251)
*ST16EU*FTST1011EU*	0.0022	-3.1748*	-0.0856	0.0061
	(0.0016)	(1.6119)	(0.0529)	(0.0240)
$TOVER_{it-2j}$	-0.0154	3.3005	-0.3799	-0.1568
	(0.0178)	(6.5231)	(0.4594)	(0.3227)
$INVPRICE_{it-2j}$	0.0027**	0.8477	-0.0469	-0.0392**
	(0.0012)	(0.5233)	(0.0411)	(0.0180)
$RETVOL_{it-2j}$	0.1750*	-53.1435**	1.0360	1.6057***
	(0.0927)	(20.6367)	(0.6196)	(0.5616)
$MVALUE_{it-2j}$	0.0022***	1.9501***	-0.1942***	-0.1045***
	(0.0006)	(0.6004)	(0.0457)	(0.0190)
$MTBV_{it-2j}$	0.0009	-0.6334	0.0187	0.0115
	(0.0012)	(0.8672)	(0.0175)	(0.0103)
$RECCON_{it-2j}$	0.0027**	-1.1825**	-0.0208	-0.0188**
	(0.0011)	(0.5419)	(0.0215)	(0.0083)
ΔGDP_{tj}	0.0124	-23.3765*	-0.5989***	-0.1626
	(0.0127)	(12.1582)	(0.2082)	(0.1059)
$\Delta UNEM_{tj}$	-0.0131	7.2586*	-0.1443	-0.1550*
	(0.0090)	(3.9504)	(0.1013)	(0.0855)
$IRATE_{tj}$	0.0003	-0.3131***	0.0149**	0.0129***
	(0.0002)	(0.0753)	(0.0058)	(0.0031)
Constant	-0.0282***	5.7632	1.7484***	0.9554***
	(0.0086)	(7.3117)	(0.4473)	(0.1785)
Observations	2,196	2,257	2,256	2,224
Number of banks	54	54	54	52
Adjusted R-squared	0.2331	0.3012	0.3138	0.4284
Bank fixed effects	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes

Panel B: U.S. sample without non-U.S. subsidiaries				
	(1)	(2)	(3)	(4)
Variables	$BIDASK_{itj}$	$RECNO_{itj}$	$EPSSUR / PRICE_{itj}$	$ESTSD / PRICE_{itj}$
ST0913US	0.0002	-6.5945*	0.1024***	0.0011
	(0.0002)	(3.3830)	(0.0205)	(0.0046)
*ST0913US*FTST09US*	-0.0003*	0.2420	-0.0220**	-0.0006
	(0.0002)	(1.0534)	(0.0091)	(0.0018)
ST1417US	-0.0001	-1.4134	0.0425**	-0.0004
	(0.0002)	(1.9340)	(0.0179)	(0.0044)
*ST1417US*FTST09US*	-0.0003*	-0.0157	0.0007	0.0015
	(0.0002)	(1.4820)	(0.0098)	(0.0021)
$TOVER_{it-2j}$	0.0019	38.1083	-0.0256	0.0632
	(0.0090)	(35.4803)	(0.7358)	(0.1365)
$INVPRICE_{it-2j}$	0.0025	-9.9568	0.1405	0.0054
	(0.0033)	(7.9852)	(0.1719)	(0.0527)
$RETVOL_{it-2j}$	0.0086*	-22.3631	1.2066*	0.3985***
	(0.0048)	(19.8636)	(0.6498)	(0.1253)

Table A.17 continued

$MVALUE_{it-2j}$	-0.0004	0.0940	-0.0085	-0.0031
	(0.0002)	(0.9454)	(0.0166)	(0.0054)
$MTBV_{it-2j}$	0.0001	0.4486	-0.0063	0.0002
	(0.0001)	(0.6159)	(0.0079)	(0.0021)
$RECCON_{it-2j}$	0.0001	-2.1858**	0.0013	0.0029**
	(0.0001)	(0.7889)	(0.0076)	(0.0011)
ΔGDP_{tj}	-0.0014***	-4.0967*	0.0694**	0.0033
	(0.0003)	(2.3839)	(0.0283)	(0.0048)
$\Delta UNEM_{tj}$	-0.0007	-15.2514**	0.2169**	0.0166
	(0.0005)	(7.3323)	(0.0854)	(0.0148)
$IRATE_{tj}$	0.0000	4.6804***	-0.0345***	-0.0005
	(0.0001)	(1.1032)	(0.0072)	(0.0012)
Constant	0.0038*	26.0057**	0.0766	0.0211
	(0.0020)	(10.5791)	(0.1706)	(0.0515)
Observations	1,119	1,119	1,116	1,119
Number of banks	25	25	25	25
Adjusted R-squared	0.8157	0.8110	0.2432	0.6105
Bank fixed effects	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes

This table reports robustness checks the effect of stress tests on information asymmetry using sample adjustments. Panel A illustrates the European sample (without inactive banks) and Panel B shows the U.S. sample (without non-U.S. subsidiaries). I use the following dependent variables, daily winsorised at the 1 and 99 percentiles and quarterly averaged, in my analysis: Information asymmetry captured by the bid-ask spread ($BIDASK_{itj}$) and analyst behaviour using analyst coverage ($RECNO_{itj}$), earnings surprises ($EPSSUR / PRICE_{itj}$) and estimate dispersion ($ESTSD / PRICE_{itj}$). In Panel A, I include dummy variable to measure European first-time participation in 2010-11 (*FTST1011EU*) and the stress test periods in 2010-11 (*ST1011EU*), 2014-15 (*ST1415EU*), and 2016 (*ST16EU*). In Panel B, I include dummy variables to estimate U.S. first-time participation in 2009 (*FTST09US*) and the stress test periods in 2009-13 (*ST0913US*) and 2014-17 (*ST1417US*). In both panels, I control for market microstructure characteristics, lagged by two quarters, and country-specific fundamentals using the following variables: Share turnover ($TOVER_{it-2j}$), inverse share price ($INVPRICE_{it-2j}$), return volatility ($RETVOL_{it-2j}$), market value ($MVALUE_{it-2j}$), market-to-book value ($MTBV_{it-2j}$), analyst recommendation consensus ($RECCON_{t-2}$); and macroeconomic fundamentals captured by the economic growth (ΔGDP_{tj}), unemployment growth ($\Delta UNEM_{tj}$), and sovereign debt risk ($IRATE_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 4.1.

Table A.18 Robustness checks on bank risk-taking using sample adjustments

Panel A: European sample without inactive banks

Variables	(1) $T1R_{itj}$	(2) $LEVERAGE_{itj}$	(3) RWA_{itj}	(4) LLR_{itj}	(5) $ZSCORE_{itj}$	(6) ROA_{itj}
ST1011EU	0.0350***	-0.2080**	-0.0358	0.0267***	0.4854*	-0.0049***
	(0.0127)	(0.0877)	(0.0291)	(0.0099)	(0.2895)	(0.0016)
*ST1011EU*FTST1011EU*	0.0014	0.0364	0.0005	-0.0032	0.2406	-0.0019**
	(0.0067)	(0.0367)	(0.0163)	(0.0042)	(0.1561)	(0.0007)
ST1415EU	0.0856***	-0.4186***	-0.1141***	0.0311***	0.9054***	-0.0056***
	(0.0131)	(0.0754)	(0.0320)	(0.0109)	(0.2367)	(0.0018)
*ST1415EU*FTST1011EU*	-0.0159*	-0.0404	0.0224	0.0048	-0.0702	-0.0009
	(0.0086)	(0.0407)	(0.0174)	(0.0041)	(0.1378)	(0.0009)
ST16EU	0.0837***	-0.3717***	-0.1257***	0.0373***	0.7768***	-0.0071***
	(0.0136)	(0.0728)	(0.0326)	(0.0135)	(0.2785)	(0.0018)
*ST16EU*FTST1011EU*	-0.0088	-0.0882*	0.0399*	0.0014	-0.1138	-0.0001
	(0.0080)	(0.0459)	(0.0208)	(0.0080)	(0.1400)	(0.0010)
$SIZE_{it-2j}$	-0.0182	0.3685***	-0.1204***	-0.0167	-0.4056*	-0.0024**
	(0.0123)	(0.0843)	(0.0298)	(0.0103)	(0.2050)	(0.0011)
$LOAN_{it-2j}$	-0.0580**	-0.0304	0.3008***	-0.0318	-0.9408*	0.0064
	(0.0284)	(0.2065)	(0.0763)	(0.0201)	(0.4805)	(0.0050)
LLP_{it-2j}	-0.9127***	7.7302***	0.9731*	2.0799***	-50.1736***	-0.3148***
	(0.2488)	(1.9400)	(0.5727)	(0.2419)	(6.3173)	(0.0575)
$TRADE_{it-2j}$	0.0459	-0.8828***	-0.0560	-0.0313	0.7919	0.0091*
	(0.0331)	(0.3186)	(0.0658)	(0.0217)	(0.5587)	(0.0052)
$DEPO_{it-2j}$	-0.0345***	0.1196	-0.0534*	-0.0151	0.3894	0.0009
	(0.0103)	(0.1097)	(0.0292)	(0.0156)	(0.2836)	(0.0022)
$EBPT_{it-2j}$	1.1538***	-8.4877***	-1.3262	-0.3677	28.1053***	0.1575**
	(0.2941)	(2.3853)	(0.9226)	(0.3307)	(8.7121)	(0.0739)
ΔGDP_{tj}	0.0705	-0.2971	-0.2530	0.0429	1.6789**	0.0300**
	(0.0440)	(0.5981)	(0.1584)	(0.0516)	(0.7509)	(0.0135)
$\Delta UNEM_{tj}$	0.0097	0.3916***	-0.1592***	-0.0480***	-0.3432	-0.0025
	(0.0178)	(0.1285)	(0.0495)	(0.0108)	(0.3188)	(0.0025)
Constant	0.3396**	-1.2006	1.8050***	0.2240*	7.6198***	0.0317**
	(0.1466)	(0.9386)	(0.3484)	(0.1147)	(2.3142)	(0.0129)
Observations	2,265	2,364	2,150	2,154	2,421	2,408
Number of banks	84	86	82	82	86	82
Adjusted R-squared	0.5253	0.2938	0.4742	0.3598	0.1560	0.1802
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: U.S. sample without non-U.S. subsidiaries

Variables	(1) $T1R_{itj}$	(2) $LEVERAGE_{itj}$	(3) RWA_{itj}	(4) LLR_{itj}	(5) $ZSCORE_{itj}$	(6) ROA_{itj}
ST0913US	0.0160	0.0186	0.0991**	0.0039	0.9994**	0.0495***
	(0.0120)	(0.1486)	(0.0407)	(0.0031)	(0.4718)	(0.0050)
*ST0913US*FTST09US*	0.0022	-0.0771	-0.0126	-0.0000	0.4334	-0.0008
	(0.0048)	(0.0623)	(0.0202)	(0.0017)	(0.2805)	(0.0009)
ST1417US	0.0129	0.0333	0.1057**	0.0021	1.1291**	0.0536***
	(0.0152)	(0.1891)	(0.0421)	(0.0030)	(0.4608)	(0.0050)
*ST1417US*FTST09US*	0.0011	-0.0775	0.0123	-0.0003	0.1134	-0.0013
	(0.0073)	(0.0820)	(0.0268)	(0.0007)	(0.2190)	(0.0012)
$SIZE_{it-2j}$	0.0000	0.0847	-0.0970***	0.0006	0.0038	-0.0042***
	(0.0080)	(0.1110)	(0.0281)	(0.0016)	(0.1841)	(0.0011)
$LOAN_{it-2j}$	-0.0358	0.1198	0.4554***	-0.0039	-0.0350	-0.0034
	(0.0246)	(0.1931)	(0.0805)	(0.0072)	(0.9957)	(0.0048)
LLP_{it-2j}	0.1888	2.6210	-1.5245	0.5126***	-9.4642	-0.1589**
	(0.2651)	(2.6498)	(1.0106)	(0.0650)	(11.9784)	(0.0633)
$TRADE_{it-2j}$	-0.0397	0.7894	-0.1576	-0.0174	-0.9395	-0.0052
	(0.0484)	(0.7352)	(0.2026)	(0.0109)	(1.9613)	(0.0085)
$DEPO_{it-2j}$	0.0062	0.1971	-0.2582***	0.0052	1.2287*	0.0120***
	(0.0203)	(0.3013)	(0.0612)	(0.0050)	(0.5970)	(0.0039)

Table A.18 continued

$EBPT_{it-2j}$	-0.0882	-0.1581	0.1343	-0.0804*	5.4578	-0.0880***
	(0.1026)	(0.8662)	(0.3567)	(0.0438)	(4.8422)	(0.0266)
ΔGDP_{tj}	-0.1142**	1.5966**	0.5811***	0.0199*	2.8606*	0.2818***
	(0.0541)	(0.6991)	(0.1986)	(0.0101)	(1.4865)	(0.0228)
$\Delta UNEM_{tj}$	-0.4061**	5.5705**	2.3353***	0.0782*	11.1989*	0.8590***
	(0.1955)	(2.5677)	(0.7487)	(0.0419)	(5.7441)	(0.0658)
Constant	0.1060	1.1380	1.8712***	0.0011	1.6738	0.0531***
	(0.0866)	(1.2395)	(0.3292)	(0.0186)	(2.0902)	(0.0136)
Observations	830	848	749	828	848	847
Number of banks	24	24	24	23	24	24
Adjusted R-squared	0.5528	0.3535	0.4179	0.7337	0.1319	0.5996
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table reports robustness checks on the effect of stress tests on bank risk-taking using sample adjustments. Panel A illustrates the European sample (without inactive banks) and Panel B shows the U.S. sample (without non-U.S. subsidiaries). I use the following dependent variables, winsorised at the 1 and 99 percentiles, in my analysis: Bank risk-taking using capital adequacy ($T1R_{itj}$), leverage risk ($LEVERAGE_{itj}$), credit risk (RWA_{itj}), credit portfolio quality (LLR_{itj}), insolvency risk ($ZSCORE_{itj}$), and profitability (ROA_{itj}). In Panel A, I include dummy variable to measure European first-time participation in 2010-11 (*FTST1011EU*) and the stress test periods in 2010-11 (*ST1011EU*), 2014-15 (*ST1415EU*), and 2016 (*ST16EU*). In Panel B, I include dummy variables to estimate U.S. first-time participation in 2009 (*FTST09US*) and the stress test periods in 2009-13 (*ST0913US*) and 2014-17 (*ST1417US*). In both panels, I control for bank characteristics, lagged by two quarters, and country-specific fundamentals using the following variables: Bank size captured by natural logarithm of total assets ($SIZE_{it-2j}$), traditional banking activities shown by outstanding loans ($LOAN_{it-2j}$), asset quality measured by loan loss provisions (LLP_{it-2j}), non-traditional banking activities measured by trading securities ($TRADE_{it-2j}$), liquidity shown by total deposits ($DEPO_{it-2j}$), profitability measured by earnings before provision and taxes ($EBPT_{it-2j}$); and macroeconomic fundamentals captured by economic growth (ΔGDP_{tj}), and unemployment growth ($\Delta UNEM_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 4.1.

Table A.19 Robustness checks on bank funding structure using sample adjustments

Panel A: European sample without inactive banks

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	TIE_{itj}	OIE_{itj}	$DEPBA_{itj}$	$IECD_{itj}$	$CUSTD_{itj}$	NIM_{itj}
ST1011EU	-0.0155***	-0.0124***	-0.0024	-0.0065***	-0.0015	-0.0086***
	(0.0023)	(0.0032)	(0.0268)	(0.0013)	(0.0439)	(0.0011)
*ST1011EU*FTST1011EU*	0.0013	0.0007	-0.0329**	0.0005	0.0161	0.0004
	(0.0008)	(0.0009)	(0.0161)	(0.0005)	(0.0150)	(0.0005)
ST1415EU	-0.0176***	-0.0135***	-0.1000***	-0.0085***	0.0476	-0.0101***
	(0.0022)	(0.0031)	(0.0268)	(0.0015)	(0.0444)	(0.0012)
*ST1415EU*FTST1011EU*	0.0002	-0.0000	0.0247**	0.0001	-0.0064	0.0011*
	(0.0006)	(0.0005)	(0.0122)	(0.0005)	(0.0104)	(0.0006)
ST16EU	-0.0179***	-0.0135***	-0.1106***	-0.0087***	0.0783*	-0.0096***
	(0.0022)	(0.0032)	(0.0288)	(0.0015)	(0.0454)	(0.0013)
*ST16EU*FTST1011EU*	-0.0004	-0.0006	0.0445***	0.0001	-0.0198	0.0013*
	(0.0008)	(0.0007)	(0.0156)	(0.0007)	(0.0180)	(0.0007)
$SIZE_{it-2j}$	-0.0002	0.0013	0.0320**	-0.0014	-0.1230***	-0.0021**
	(0.0022)	(0.0021)	(0.0155)	(0.0009)	(0.0193)	(0.0011)
$LOAN_{it-2j}$	0.0111**	0.0074	-0.0849*	0.0024	-0.0685	0.0043*
	(0.0046)	(0.0045)	(0.0460)	(0.0025)	(0.0633)	(0.0025)
LLP_{it-2j}	0.0110	0.0537	2.9514***	-0.0109	-2.4118***	-0.0637**
	(0.0352)	(0.0349)	(0.6179)	(0.0363)	(0.6625)	(0.0310)
$TRADE_{it-2j}$	-0.0208***	-0.0160***	-0.1879***	-0.0112***	-0.0528	0.0041
	(0.0047)	(0.0041)	(0.0603)	(0.0037)	(0.0806)	(0.0032)
$DEPO_{it-2j}$	0.0009	-0.0014	0.1686***	0.0038**	0.2839***	0.0014
	(0.0017)	(0.0018)	(0.0516)	(0.0016)	(0.0437)	(0.0017)
$EBPT_{it-2j}$	0.0211	0.0558	-1.2783**	-0.0963**	0.3184	-0.0570
	(0.0700)	(0.0664)	(0.6264)	(0.0402)	(0.8994)	(0.0583)
ΔGDP_{tj}	0.0031	-0.0027	0.0040	-0.0043	0.2249	-0.0123*
	(0.0071)	(0.0088)	(0.1061)	(0.0118)	(0.2018)	(0.0062)
$\Delta UNEM_{tj}$	-0.0009	-0.0036	0.0004	0.0070***	-0.0642*	-0.0013
	(0.0028)	(0.0032)	(0.0334)	(0.0026)	(0.0332)	(0.0023)
Constant	0.0167	-0.0020	-0.2293	0.0238**	1.7679***	0.0344***
	(0.0239)	(0.0226)	(0.1796)	(0.0102)	(0.2243)	(0.0123)
Observations	2,072	2,049	2,300	1,289	2,327	2,324
Number of banks	82	82	82	77	82	86
Adjusted R-squared	0.7042	0.4830	0.2170	0.6245	0.3497	0.7442
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: U.S. sample without non-U.S. subsidiaries

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	TIE_{itj}	OIE_{itj}	$SUBD_{itj}$	$IECD_{itj}$	$CUSTD_{itj}$	NIM_{itj}
ST0913US	0.0060**	-0.0014	0.0002	-0.0035	0.3261***	0.1045***
	(0.0029)	(0.0023)	(0.0066)	(0.0030)	(0.0429)	(0.0102)
*ST0913US*FTST09US*	0.0002	-0.0000	0.0008	0.0009**	-0.0014	-0.0002
	(0.0004)	(0.0004)	(0.0015)	(0.0004)	(0.0080)	(0.0008)
ST1417US	0.0056*	-0.0022	-0.0044	-0.0033	0.3733***	0.1099***
	(0.0029)	(0.0025)	(0.0074)	(0.0033)	(0.0547)	(0.0112)
*ST1417US*FTST09US*	0.0006	0.0001	-0.0001	0.0012**	0.0061	-0.0005
	(0.0004)	(0.0005)	(0.0031)	(0.0005)	(0.0137)	(0.0009)
$SIZE_{it-2j}$	0.0028***	0.0029*	0.0040	0.0006	-0.0992***	-0.0029**
	(0.0009)	(0.0015)	(0.0042)	(0.0008)	(0.0204)	(0.0012)
$LOAN_{it-2j}$	-0.0036	-0.0034	0.0260	-0.0003	0.0788	0.0090
	(0.0022)	(0.0033)	(0.0202)	(0.0020)	(0.0532)	(0.0075)
LLP_{it-2j}	0.0224	0.0188	-0.0191	0.0053	0.6182	-0.2068***
	(0.0270)	(0.0312)	(0.1955)	(0.0166)	(0.6064)	(0.0532)
$TRADE_{it-2j}$	-0.0034	0.0010	-0.0060	-0.0074*	0.0056	0.0033
	(0.0052)	(0.0081)	(0.0163)	(0.0037)	(0.1109)	(0.0089)
$DEPO_{it-2j}$	-0.0024	-0.0060*	-0.0309***	0.0046**	0.3342***	0.0016
	(0.0025)	(0.0033)	(0.0105)	(0.0019)	(0.0879)	(0.0043)

Table A.19 continued

$EBPT_{it-2j}$	-0.0442**	-0.0277*	0.0071	-0.0163	-0.1079	-0.1368***
	(0.0182)	(0.0157)	(0.0792)	(0.0116)	(0.3230)	(0.0391)
ΔGDP_{tj}	0.0945***	0.0494***	0.0047	0.0476***	1.2729***	0.5837***
	(0.0156)	(0.0083)	(0.0342)	(0.0101)	(0.2116)	(0.0620)
$\Delta UNEM_{tj}$	0.2826***	0.1417***	0.0100	0.1495***	4.7305***	1.7869***
	(0.0482)	(0.0274)	(0.1182)	(0.0344)	(0.8417)	(0.1914)
Constant	-0.0176*	-0.0177	-0.0258	0.0016	1.5137***	0.0413***
	(0.0091)	(0.0150)	(0.0519)	(0.0080)	(0.2012)	(0.0143)
Observations	847	847	586	748	830	848
Number of banks	24	24	24	23	24	24
Adjusted R-squared	0.8651	0.6972	0.3457	0.8666	0.6282	0.8405
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table reports robustness checks on the effect of stress tests on bank funding structure using sample adjustments. Panel A illustrates the European sample (without inactive banks) and Panel B shows the U.S. sample (without non-U.S. subsidiaries). I estimate bank funding structure using total (TIE_{itj}) uninsured (OIE_{itj}) and insured ($IECD_{itj}$) funding cost as well as uninsured ($DEPBA_{itj}$, $SUBD_{itj}$), insured funding ($CUSTD_{itj}$), and interest margin (NIM_{itj}). In Panel A, I include dummy variable to measure European first-time participation in 2010-11 (*FTST1011EU*) and the stress test periods in 2010-11 (*ST1011EU*), 2014-15 (*ST1415EU*), and 2016 (*ST16EU*). In Panel B, I include dummy variables to estimate U.S. first-time participation in 2009 (*FTST09US*) and the stress test periods in 2009-13 (*ST0913US*) and 2014-17 (*ST1417US*). In both panels, I control for bank characteristics, lagged by two quarters, and country-specific fundamentals using the following variables: Bank size captured by natural logarithm of total assets ($SIZE_{it-2j}$), traditional banking activities shown by outstanding loans ($LOAN_{it-2j}$), asset quality measured by loan loss provisions (LLP_{it-2j}), non-traditional banking activities measured by trading securities ($TRADE_{it-2j}$), liquidity shown by total deposits ($DEPO_{it-2j}$), profitability measured by earnings before provision and taxes ($EBPT_{it-2j}$); and macroeconomic fundamentals captured by economic growth (ΔGDP_{tj}), and unemployment growth ($\Delta UNEM_{tj}$). Standard errors (in parentheses) are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The description of the variables and the relevant data sources are provided in Table 4.1.