Euro-Denominated High-Yield Corporate Bonds

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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.

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Summary

High-yield bonds are a unique and increasingly important asset class. They are different from investment-grade bonds because they exhibit higher default risk and are less sensitive to changes in interest rates. There is, however, a paucity of literature on the high-yield bond market, regardless of its market size and economic importance. This thesis concentrates on Euro-denominated high-yield corporate bonds from the perspective of the secondary and primary markets.

In the first empirical chapter, we critically compare three major databases: Bloomberg, Refinitiv Eikon, and Refinitiv Datastream, which provide data for Euro-denominated high-yield corporate bonds. We find that Bloomberg provides more comprehensive data than Refinitiv Eikon and includes a higher number of bonds with available clean prices than Refinitiv Datastream. In addition, we observe that accrued interest, prices, and price returns differ from an individual bond viewpoint. Therefore, we use Bloomberg as our primary data source for sample size and data consistency purposes.

In the second empirical chapter, we investigate the term, default, illiquidity, and downside factors in pricing Euro-denominated high-yield corporate bonds between 2000 and 2021. We find that the term, default, illiquidity, and downside factors are positively related to excess returns. Results of our Markov-switching model suggest that the illiquidity factor plays a vital role in explaining excess returns and fluctuates in different market scenarios, particularly for high-yield bonds with the lowest credit ratings (e.g., CCC and below). The effect of illiquidity on BB-rated

bonds is different from the effect on the high-yield bonds with the lowest credit ratings.

In the third empirical chapter, we investigate the extent of underpricing in the primary market for Euro-denominated high-yield corporate bonds. Determinants of underpricing are examined with an ordinary least squares (OLS) regression with year, industry, and country fixed effects. Our evidence suggests that high-yield bonds are underpriced. The underpricing is more likely caused by information asymmetry problems and the frequency of trading following issuance in the secondary market.

Overall, our findings provide valuable information that may be used for performance analysis and asset allocation in the high-yield bond market.

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List of Abbreviations

ES	Expected Shortfall
FZR	Fraction of Zero Returns
IBOs	Initial Bond Offerings
ISIN	International Securities Identification Number
OLS	Ordinary Least Squares
PC	Principal Component
SBOs	Seasoned Bond Offerings
S&P	Standard & Poor's
TRACE	Trade Reporting and Compliance Engine
VaR	Value at Risk

Chapter One

Introduction

1.1 Euro-Denominated High-Yield Corporate Bond Market

High-yield bonds are rated below BBB, Baa, and BBB by major rating agencies: Standard & Poor's (S&P), Moody's, and Fitch, respectively. The Euro-denominated high-yield corporate bond market is less developed and liquid than the US market. After the introduction of the TRACE (Trade Reporting and Compliance Engine) database in the US corporate bond market, brokers are required to disclose all transactions according to Securities and Exchange Commission regulations, substantially enhancing transparency and liquidity in the secondary market. In addition, the Euro-denominated bond market has a smaller market size than the US one, making it more illiquid. For instance, the number of deals and issuance volumes were 7,123 and \$3,299,846.79 million for the US high-yield corporate bond market, while 1,389 and €589,663.62 million for the Euro-denominated high-yield corporate bond market between 2009 and 2019.[1]

Euro-denominated high-yield corporate bonds are out of line with investment-grade bonds. The market for high-yield bonds is much smaller than the market for investment-grade bonds, indicating that the former is more illiquid than the latter. For instance, from 2009 to 2019, the number of deals for Euro-denominated high-yield bond offerings was 1,389 compared to 13,928 for investment-grade ones; the issuance volumes of the high-yield bond offerings were €589,663.62 million compared to €6,675,116.72 million for investment-grade bonds.[2]

1 The number of deals and the issuance volumes for high-yield corporate bonds between the Euro and US markets are reported by Bloomberg. These bonds have fixed coupon rates and have no self-underwritten issues.

2 The Euro-denominated investment-grade corporate bonds also have fixed coupon rates and have

1.2 Issuers of High-Yield Bonds

Issuers of high-yield corporate bonds can be classified into the following groups: rising stars, fallen angels, leveraged buyouts, and capital-intensive companies.

Rising stars are companies that are still in their early stages and have not achieved their full potential. They do not meet the criteria for an investment-grade rating due to their small size and lack of financial strength. Furthermore, credit rating agencies are reluctant to give them high ratings because they have no previous experience rating them. Under certain circumstances, bonds may provide investors with their first opportunity to invest in growing companies prior to their initial public offering of stock. Gradually, rising stars may develop into larger firms with superior credit ratings (Bagaria, 2016).

Fallen angels are previous issuers of investment-grade bonds that have run into financial difficulties, causing their credit ratings to fall from investment-grade to high-yield ratings. Some fallen angels may recover their investment-grade ratings if their situation improves (Bagaria, 2016). In Chapter 3, our sample comprises 1,275 Euro-denominated high-yield corporate bonds issued between 1st January 2000 and 31st December 2021. 420 sample bonds (32.94%) were originally issued as investment-grade (i.e., BBB or better) but downgraded to a high-yield rating before maturity. For example, Tesco PLC issued original investment-grade bonds that were downgraded to high-yield bonds between 2015 and 2021, which may have been caused by their accounting scandal.

Leveraged buyouts are usually financed via high-yield bonds, a typical transaction used by private equity firms interested in acquiring ownership for as little money as possible. A leveraged buyout is based on the principle of maximising high-yield debt borrowing to cover an acquisition. As a result, a private equity company can reduce its equity investment while still reaping all of the benefits of growth (Bagaria, 2016).

When capital-intensive companies' profits or bank borrowings are insufficient to

no self-underwritten issues. The data source is Bloomberg.

cover all their capital requirements, they turn to the high-yield bond market. For instance, cable television providers need substantial funds to develop or improve their networks (Bagaria, 2016).

Euro-denominated high-yield corporate bond issuers are from various industries, including communications, consumer discretionary, technology, consumer staples, utilities, industrials, materials, energy, health care, government-related, and financial industries. For example, Leonardo SpA, an Italian conglomerate with expertise in aerospace, defence, and security, issued a nominal amount of €700 million with a rating of BB+ (S&P), Ba1 (Moody's), and BB+ (Fitch) in 2013 for their general corporate purposes.[3]

Major issuers of high-yield bonds have different characteristics from their investment-grade counterparts. Cyclical and capital-intensive industries are more substantially represented by high-yield bonds, while financial and government-related sectors are primary issuers in the investment-grade bond market. For instance, consumer discretionary and communication sectors account for approximately 40% of the Euro-denominated high-yield corporate bond market share; financial and government-related issuers represent about 67% of the Euro-denominated investment-grade corporate bond market share by issuance volumes between 2009 and 2019.[4]

1.3 Investors of High-Yield Bonds

Primary investors in the high-yield bond market are financial institutions. Insurance companies represent about 29% of the investor universe. Pension funds, mutual funds, and collateralized debt obligations account for approximately 28%, 13%, and 16% of the market share, respectively. Exchange-traded funds, hedge funds, and other specialised investors share the remainder (S&P, 2019).

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3 Data is available from Leonardo SpAs bond prospectus, collected from Refinitiv Eikon. The bond's International Securities Identification Number (ISIN) is XS0999654873.

4 The source of the data is Bloomberg.

According to the data reported by Bloomberg, 1,571 Euro-denominated high-yield corporate bonds were actively traded until 20th June 2022. These bonds were issued between January 2000 and December 2021, with a total amount held by investors of €268 billion. Asset management institutions have become the largest holders, representing 90% of the market share. The top 5 investors of these high-yield bonds are Allianz SE, BlackRock, Credit Agricole Group, Schroders plc, and Nordea Bank Apb, accounting for approximately 5.77%, 5.55%, 3.44%, 2.69%, and 2.58% of the €268 billion, respectively.

1.4 Research Motivation

In Chapter 2, we focus on comparing Bloomberg, Refinitiv Eikon, and Refinitiv Datastream, which have been widely used in previous studies (e.g., Cici et al., 2011; Schestag et al., 2016; Rischen and Theissen, 2021; Pieterse-Bloem et al., 2016; Galariotis et al., 2016). Our data collection procedure consists of two steps. We firstly collect bonds that meet our sample selection criteria and then collect time-series data (e.g., clean price) based on the bond collected from the first step. As there is no consensus on which database is superior, we aim to compare these databases and determine the ideal one for our research purposes. The results of this chapter may provide some guidance on the database selection for Euro-denominated high-yield corporate bond studies.

Chapter 3 analyses the term, default, illiquidity, and downside factors in pricing Euro-denominated high-yield corporate bonds between 2000 and 2021. Previous studies have investigated the association between illiquidity and bond returns or yields, focusing on the US corporate bond market (Chen et al., 2007; Bao et al., 2011; Lin et al., 2011; Dick-Nielsen, 2009; Friewald et al., 2012; Acharya et al., 2013; Bongaerts et al., 2017). Only some of the above studies include a sub-sample of high-yield bonds. Evidence from the European markets primarily focuses on investment-grade bonds (Houweling et al., 2005; Aussenegg et al., 2015; Galliani et al., 2014; Aussenegg et al., 2017). High-yield bonds are traded less frequently than their investment-grade counterparts. The Euro-denominated high-yield corporate bond market is smaller than the US one, making it even more illiquid. According to Bai et al. (2019), downside risk is positively associated with returns in the US corporate bond market. However, whether this factor affects returns in the Euro-denominated high-yield corporate bond is unclear. The findings of this chapter may shed light on the performance evaluation, asset selection and allocation, and assist investors in comprehending the underlying risks of Euro-denominated high-yield corporate bonds.

We make several contributions to the literature. We extend the Fama and French (1993) 2-factor model by adding illiquidity and downside factors. In addition, we examine the time-varying effects of common factors on Euro-denominated high-yield corporate bond returns across ratings, maturities, and industries. Aussenegg et al. (2017) find that the effect of illiquidity on investment-grade corporate bond returns varies substantially across ratings, maturities, and industries. Bai et al. (2019) examine the impact of downside risk on bond returns in a cross-sectional model. Not all high-yield bonds possess the same degree of sensitivity and exposure to illiquidity and downside factors. Different ratings, maturities, and industries of high-yield bonds may produce substantially different results across state changes. Furthermore, we construct a novel illiquidity measure at the bond level using principal component analysis of three illiquidity proxies, particularly for Euro-denominated high-yield corporate bonds.

Chapter 4 investigates the extent and determinants of underpricing in the primary market for Euro-denominated high-yield corporate bonds between 2009 and 2019. Our findings may be useful in evaluating corporate finance decisions, including calculating the cost of borrowing.

The analysis in this chapter is related to several studies that concentrate on underpricing in the US corporate bond market (Datta et al., 1997; Cai et al., 2007, 2021; Liu and Magnan, 2014; Nagler and Ottonello, 2018; Helwege and Wang, 2021), and the Euro-denominated corporate bond market (Rischen and Theissen, 2021). It is also related to decisions of underwriters on the allocation of the first-day profits to investors (Nikolova et al., 2020), the connection between underpricing and transparency in the secondary market (Brugler et al., 2022), and the relationship between underpricing and expected secondary market liquidity in the US corporate bond market (Goldstein et al., 2019). However, few studies examine the European corporate bond primary market, and these studies do not examine high-yield bonds separately (see, e.g., Rischen and Theissen, 2021; Wasserfallen and Wydler, 1988; Zaremba, 2014; Mietzner et al., 2018).

1.5 Key Research Questions

In Chapter 2, regarding the first phase data, we have two options for downloading Euro-denominated high-yield corporate bonds from Bloomberg or Refinitiv Eikon. Therefore, we evaluate the number of bonds available from each database based on the same criteria.

In terms of the second phase data, we compare Bloomberg with Refinitiv Datastream. As high-yield bonds are traded in the over-the-counter market, prices are usually provided by dealers. Each database has a unique set of dealers offering quotes and a proprietary mechanism for generating quoted prices. If the data varies with databases, which database is preferable?

In Chapter 3, illiquidity is priced in the Euro-denominated investment-grade bond market (Aussenegg et al., 2017). High-yield bonds are traded less frequently than their investment-grade counterparts. The level of liquidity decreases with the deterioration in ratings (Lin et al., 2011). Bonds with a rating of CCC and below have the lowest credit ratings, and these bonds tend to be more illiquid than BB-rated bonds.

Hypothesis 1a: Illiquidity is an important factor in pricing the Euro-denominated high-yield corporate bond market.

Hypothesis 1b: The effect of illiquidity on returns is more pronounced for bonds with a rating of CCC and below.

High-yield bond excess returns are inclined to be affected by economic conditions (Fama and French, 1989). Beber et al. (2009) and Longstaff (2004) find that investors tend to choose liquid assets during periods of economic and financial crisis. Furthermore, Acharya et al. (2013) suggest that prices of high-yield bonds drop considerably in periods of financial stress because of the flight to liquidity phenomenon. CCC and below-rated bonds are less liquid than BB-rated bonds. As investors prefer to invest in liquid assets, the prices of bonds with a rating of CCC or below tend to be affected more during economic downturns.

Hypothesis 2a: Illiquidity exhibits time-varying behaviour.

Hypothesis 2b: The price effect of time-varying illiquidity differs between bonds with a BB rating and those with a rating of CCC and below.

Bai et al. (2019) suggest a positive association between downside risk and returns for high-yield bonds. High-yield bond returns fluctuate with changes in economic conditions (Fama and French, 1989), and they are more volatile in times of adverse economic conditions than in normal periods.

Hypothesis 3a: Downside risk exhibits time-varying.

Hypothesis 3b: The price effect of time-varying downside risk differs between bonds with a BB rating and those with a rating of CCC and below.

In Chapter 4, analogous to equity investors, bond investors are rewarded for revealing private and valuable information to underwriters during the bookbuilding process. Issuers of high-yield bonds are normally private or small companies with more severe information asymmetry problems and are, therefore, more difficult to value. Institutional investors require a greater reward for generating useful information. If an issuer has recently issued a bond, the historical information gathered throughout the bookbuilding process and the previous valuation of that bond may provide guidance for determining the value of the bond issued by the same issuer.

Hypothesis 1: The degree of underpricing is lower for recently repeated issuers.

In the bond markets, rating agencies regularly collect information and assess issuers in order to provide credit ratings. The bond ratings may reduce information asymmetry and affect decisions on signal quality via underpricing. According to the signalling theory, bond issuers with high quality prefer to use greater underpricing to indicate that their bonds will perform better than others. The superior performance may be reflected by ratings upgraded following issuance. Accordingly, greater underpricing of high-yield bonds is expected to be positively related to a rating upgraded subsequent issuance. On the other hand, issuers of high-yield bonds often have a significant debt load, and it is doubtful whether they can afford the additional expenses resulting from higher underpricing.

Hypothesis 2a: The degree of underpricing is positively related to a first rating upgraded subsequent to issuance in the Euro-denominated high-yield corporate bond market.

Hypothesis 2b: The degree of underpricing is not related to a first rating upgraded subsequent to issuance in the Euro-denominated high-yield corporate bond market.

According to the traditional certification hypothesis, the level of information asymmetry can be lessened between issuers and investors, capitalising on the reputation of underwriters to guarantee the issuer's quality, and therefore the issuer's informational costs may be reduced (Beatty and Ritter, 1986; Booth and Smith, 1986; Titman and Trueman, 1986; Allen, 1990; Carter and Manaster, 1990; Chemmanur and Fulghieri, 1994). Issuers of high-yield bonds tend to be less well-known companies or those in financial trouble. The certification role of reputable underwriters with top rankings may add additional value to issuance, and it is thus more critical to high-yield bonds than their investment-grade counterparts. If a high-yield bond is backed by top-rated underwriters, which may certify the bond's future performance, we expect the degree of underpricing will be reduced.

Hypothesis 3: The degree of underpricing is negatively related to reputable underwriters.

Two views are used to explain the underpricing from the perspective of expected secondary market liquidity in the equity market. Ellul and Pagano (2006) document that underpricing compensates for the risk that the stock may become illiquid following the initial public offering. However, Booth and Chua (1996) suggest that greater underpricing can motivate oversubscription, disperse ownership, and enhance secondary-market liquidity. High-yield bonds are traded infrequently in the secondary market, and their investors tend to have a long-term investment strategy. Thus, illiquidity plays an important role in the high-yield bond market. Previous studies do not separately examine the effect of expected secondary market liquidity on underpricing between investment-grade and high-yield bonds. Two predictions may be made in light of the role of expected secondary market liquidity in explaining underpricing in the high-yield bond market.

Hypothesis 4a: The degree of underpricing is positively associated with the expected secondary market liquidity.

Hypothesis 4b: The degree of underpricing is negatively associated with the expected secondary market liquidity.

1.6 Key Research Results

Chapter 2 compares Bloomberg, Refinitiv Eikon, and Refinitiv Datastream and determines the ideal one for our research purposes. We find that Bloomberg provides more comprehensive data than Refinitiv Eikon, and it includes a greater number of bonds with available clean prices than Refinitiv Datastream. In addition, we observe that accrued interest, prices, and price returns differ from an individual bond viewpoint. Consequently, we pick Bloomberg as our primary data source for sample size and data consistency purposes.

In Chapter 3, we add illiquidity and downside factors to the Fama and French (1993) 2-factor model, and find that term (TERM), default (DEF), illiquidity, and downside factors are positively related to excess returns by using pooled regression models with year and industry fixed effects. The coefficients of TERM, DEF, illiquidity, and downside factors tend to increase with decreasing ratings, particularly for bonds with a rating of CCC and below. In addition, the illiquidity factor is higher for bonds with a maturity of five to seven years, while the downside risk factor is more prominent for bonds with more than ten years of maturity. We also find that TERM, DEF, and illiquidity factors have a more substantial impact on excess returns for high-yield bonds issued by non-financial than financial industries.

Results of our Markov-switching model suggest that the illiquidity factor plays a vital role in explaining returns and fluctuates in different market scenarios, particularly for bonds with a rating of CCC and below. The time-varying illiquidity effect on BB-rated bonds differs from the effect on bonds with a rating of CCC and below. We find that the effect of the downside risk on returns for short-maturity high-yield bonds (e.g., maturity 1-3 years) becomes more significant in the high-volatility state than in the low-volatility state.

In Chapter 4, we investigate the extent of underpricing in the primary market for Euro-denominated high-yield corporate bonds. Determinants of underpricing are examined with an OLS regression with year, industry, and country fixed effects. We find that the average underpricing of initial and seasoned bond offerings is 74 bps and 49 bps, respectively. Our evidence suggests that underpricing is likely relevant to information asymmetry problems. For instance, issuers who have recently issued a bond are inversely related to the degree of underpricing, consistent with the bookbuilding-based explanation. In addition, we find that underpricing is likely to be negatively associated with the frequency of trading following issuance in the secondary market, supporting the explanation of underpricing from Booth and Chua (1996)'s view.

The remainder of this thesis is organised as follows. Chapter 2 compares major databases, including Bloomberg, Refinitiv Eikon, and Refinitiv Datastream. Chapter 3 investigates unconditional, and time-varying term, default, illiquidity and downside factors that impact excess returns by ratings, maturities, and industries for Euro-denominated high-yield corporate bonds in the secondary market. Chapter 4 investigates the extent and determinants of underpricing for Euro-denominated high-yield corporate bonds in the primary market. We conclude the thesis in Chapter 5.

Chapter Two

Comparing Databases

2.1 Introduction

TRACE is widely used in US studies to collect transaction data (Lin et al., 2011; Acharya et al., 2013; Nikolova et al., 2020). Markit is a reliable database that has been adopted in previous European corporate bond studies (Aussenegg et al., 2015, 2017). Bloomberg, Refinitiv Eikon, and Refinitiv Datastream are popular databases used in related studies (e.g., Cici et al., 2011; Schestag et al., 2016; Rischen and Theissen, 2021; Pieterse-Bloem et al., 2016; Galariotis et al., 2016; Zaremba, 2014). However, TRACE only provides transaction prices in the US market, and Markit only includes investment-grade bonds. Therefore, the purpose of this chapter is to compare Bloomberg, Refinitiv Eikon, and Refinitiv Datastream to identify the optimal one for collecting data on Euro-denominated high-yield corporate bonds.

We find that Bloomberg provides more comprehensive data than Refinitiv Eikon, and it includes a higher number of bonds with available clean prices than Refinitiv Datastream. In addition, we observe that accrued interest, prices, and price returns differ from an individual bond viewpoint. Therefore, we use Bloomberg as our primary data source for sample size and data consistency purposes.

The remainder of this chapter proceeds as follows. Section 2.2 compares the number of bonds collected from Bloomberg and Refinitiv Eikon based on the same selection criteria. Section 2.3 compares Bloomberg and Refinitiv Datastream. Section 2.4 summarises the chapter.

2.2 Bloomberg versus Refinitiv Eikon

We have two options for downloading Euro-denominated high-yield corporate bonds from Bloomberg or Refinitiv Eikon. To determine which database is superior, we evaluate the quantity of high-yield bonds accessible from each database based on the same selection criteria.

We download 2,124 and 390 Euro-denominated high-yield corporate bonds issued between 1^{st} January 2000 and 31^{st} December 2021 from Bloomberg and Refinitiv Eikon, respectively. These bonds have a fixed coupon type, have a bullet type of maturity (e.g., no early redemption), and have ratings of BB+/Ba1 or lower by S&P, Moody's, or Fitch. Furthermore, callable, puttable, convertible bonds, and bonds without data on the amount outstanding, are removed from the sample. The selection criteria are the same as in Panel A of Table 3.1.

As shown in Table 2.1, Bloomberg reports more than five times as many bonds as Refinitiv Eikon, with a total of 2,142 compared to 390 bonds from 2000 to 2021. Bloomberg covers both actively traded bonds and those that have reached maturity dates. However, Refinitiv Eikon only incorporates bonds that are being traded. Furthermore, 20 and 8 actively traded high-yield bonds were issued in 2021, as reported by Bloomberg and Refinitiv Eikon. This result indicates that Bloomberg has fewer missing high-yield bonds than Refinitiv Eikon. Bloomberg is used to obtain the first step data because it provides more comprehensive data than Refinitiv Eikon, minimising the potential for sample survivorship bias.

Table 2.1: Number of bonds reported by Bloomberg and Refinitiv Eikon.

Issue year	Number of bonds		
	Bloomberg	Eikon	Duplication
2000	68	0	0
2001	51	2	0
2002	57	0	0
2003	69	6	6
2004	114	1	1
2005	74	3	3
2006	63	6	5
2007	110	18	16
2008	119	14	13
2009	177	13	10
2010	148	25	25
2011	223	21	17
2012	177	36	34
2013	183	48	44
2014	184	63	55
2015	98	35	26
2016	61	25	22
2017	34	13	11
2018	28	11	9
2019	59	26	25
2020	25	16	11
2021	20	8	3
Total	2,142	390	336

The table presents the yearly number of Euro-denominated high-yield corporate bonds issued between January 2000 and December 2021, as reported by Bloomberg and Refinitiv Eikon. The issue year shows the year when the bond was issued. The duplication column shows the number of bonds available from both databases.

2.3 Bloomberg versus Refinitiv Datastream

Bloomberg and Refinitiv Datastream are common databases to collect accrued interest and quoted prices. For example, Cici et al. (2011) and Schestag et al. (2016) use bid and ask prices retrieved from Bloomberg, Galariotis et al. (2016) use clean prices downloaded from Refinitiv Datastream, and Pieterse-Bloem et al. (2016) use clean prices obtained from Bloomberg.

Chapter 3 uses bid, ask, and clean prices to create illiquidity measures, including bid-ask spread, Fraction of trading days with zero returns (FZR), and the Roll measure. The dependent variable is the monthly bond return, which is determined by accrued interest and clean prices. In Chapter 4, bid, ask, and clean prices are crucial data in estimating the expected secondary market liquidity. The dependent variable is underpricing, which is calculated using accrued interest and clean prices. Thus, we examine whether these data vary across databases.

2.3.1 Comparing Accrued Interest and Prices

Observing the data is an intuitive approach to comparing them across databases. We randomly select five corporate bonds and compare their accrued interest, ask, bid, and clean prices on the same day between Bloomberg and Refinitiv Datastream.

Accrued interest, ask, bid, and clean prices for the same five bonds on the same day, obtained from Bloomberg and Refinitiv Datastream, are shown in Table 2.2. The T-test examines whether the difference between these two databases is statistically significant. In Panel A of Table 2.2, the accrued interest from Bloomberg and Refinitiv Datastream is denoted by INT_ACC and AC, respectively. We observe that the accrued interest differs on the same day for the same bond. Particularly, the accrued interest reported by Bloomberg is lower than that reported by Refinitiv Datastream. The corresponding p-value indicates that the difference in accrued interest is statistically significant between these two databases.

Panels B and C exhibit the ask and bid prices gathered from Bloomberg and Refinitiv Datastream. PX_ASK and PX_BID are the codes used to obtain the ask and bid prices, which are submitted by multiple contributors and assessed using a proprietary algorithm developed by Bloomberg. The ask and bid prices from Refinitiv Datastream are denoted by CMPA and CMPB, representing the average from all the available contributors' ask and bid quotes. In addition, the highest and lowest ask or bid values are eliminated if there are over four contributors. The composite ask or bid prices are determined by averaging the remaining ask or bid prices (Datastream, 2017). These two databases may have distinct contributors and methods for computing the ask or bid prices. As expected, prices for the same bond on the same day vary with databases. Typically, the ask (bid) price reported by Bloomberg tends to be higher (lower) than the one reported by Refinitiv Datastream. The corresponding p-values in Panels B and C are less than 0.01, indicating that the differences in ask or bid prices for the same coverage are statistically significant between these two databases. Therefore, the consistency of the bid-ask spread is enhanced when ask and bid prices originate from the same database.

Panel D of Table 2.2 displays the clean prices collected from Bloomberg and Refinitiv Datastream. The clean price codes are PX_LAST from Bloomberg and CP from Refinitiv Datastream. The corresponding p-value is higher than 0.01, implying that the differences in the clean prices given by these two databases are not statistically significant.

Table 2.2: Comparing accrued interest and prices between Bloomberg and Refinitiv Datastream.

Panel A: Accrued interest.				
		Bloomberg	Datastream	Test statistics
Date	ISIN	INT_ACC	AC	P-value
31/12/2014	AT0000383864	2.894	2.928	
31/12/2014	AT0000385745	4.459	4.484	
31/12/2014	AT0000386115	1.806	1.827	0.000***
31/12/2014	BE0000291972	4.189	4.219	
31/12/2014	BE0000300096	1.416	1.447	
Panel B: Ask price.				
		Bloomberg	Datastream	Test statistics
Date	ISIN	PX_ASK	CMPA	P-value
31/12/2014	AT0000383864	164.205	163.753	
31/12/2014	AT0000385745	114.495	114.236	
31/12/2014	AT0000386115	120.895	120.601	0.009***
31/12/2014	BE0000291972	152.690	152.600	
31/12/2014	BE0000300096	115.545	115.146	
Panel C: Bid price.				
		Bloomberg	Datastream	Test statistics
Date	ISIN	PX_BID	CMPB	P-value
31/12/2014	AT0000383864	163.045	163.490	
31/12/2014	AT0000385745	113.855	114.174	
31/12/2014	AT0000386115	120.215	120.541	0.007***
31/12/2014	BE0000291972	152.285	152.370	
31/12/2014	BE0000300096	114.680	115.086	
Panel D: Clean price.				
		Bloomberg	Datastream	Test statistics
Date	ISIN	PX_LAST	CP	P-value
31/12/2014	AT0000383864	163.625	163.490	
31/12/2014	AT0000385745	114.175	114.174	
31/12/2014	AT0000386115	120.555	120.541	0.103
31/12/2014	BE0000291972	152.488	152.370	
31/12/2014	BE0000300096	115.113	115.086	

The table compares the accrued interest, ask, bid, and clean prices of five common bonds collected between Bloomberg and Refinitiv Datastream. ISIN is the code that uniquely identifies a specific bond. INT_ACC and AC are the codes used to obtain the accrued interest from Bloomberg and Refinitiv Datastream. The ask, bid, and clean prices from Bloomberg are denoted by PX_ASK, PX_BID, and PX_LAST, and these prices from Refintiv Datastream are denoted by CMPA, CMPB, and CP, respectively. The last column shows the corresponding p-value of the two-sample t-test, testing whether the mean of the data between these two databases is equal or not. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

2.3.2 Sample Size

The monthly return and underpricing are computed from clean prices to serve as dependent variables in Chapters 3 and 4. The quantity of bonds with accessible clean prices is proportional to the sample size. We collect daily clean prices from Bloomberg (code PX_LAST) and Refinitiv Datastream (code CP) based on 2,124 high-yield bonds issued between January 2000 and December 2021.

Table 2.3 presents the yearly number of bonds with available clean prices as reported by Bloomberg and Refinitiv Datastream from 2000 to 2021. For instance, 68 high-yield bonds were issued in 2000 and collected from Bloomberg as the first stage data, with 38 and 11 of these bonds having clean prices available from Bloomberg and Refinitiv Datastream (see Table 2.3), respectively. From 2000 until 2021, Bloomberg and Refinitiv Datastream provide access to a total of 1,819 and 1,167 bonds with clean prices, a difference of 651 bonds. Therefore, the former has a sample size advantage over the latter.

Table 2.3: Number of bonds with available clean prices reported by Bloomberg and Refinitiv Datastream.

Issue year	Number of bonds	
	Bloomberg	Datastream
2000	38	11
2001	23	16
2002	18	15
2003	30	19
2004	61	22
2005	35	17
2006	42	34
2007	79	38
2008	114	34
2009	174	99
2010	144	141
2011	217	154
2012	172	138
2013	183	90
2014	184	84
2015	97	61
2016	60	56
2017	34	33
2018	27	25
2019	54	49
2020	21	20
2021	12	11
Total	1,819	1,167

The table presents the yearly number of bonds with available clean prices between 2000 and 2021. The clean price codes are PX_LAST and CP from Bloomberg and Refinitiv Datastream, respectively. The issue year shows the year when the bond was issued.

2.3.3 Comparing Price Returns

Bloomberg covers a greater number of bonds with available clean prices than Refinitiv Datastream. Are the differences in monthly price returns statistically significant if we use clean prices from these two databases independently? Do the trends of returns follow a similar pattern over time?

We compute the monthly price return of high-yield bonds issued between 2017 and 2021 using clean prices reported by Bloomberg and Refinitiv Datastream. The monthly price return of bond i at time t is defined as:

$$Price\ return_{i,t} = \frac{(P_{i,t} - P_{i,t-1})}{P_{i,t-1}} \tag{2.1}$$

where, $P_{i,t}$ is the quoted month-end clean price of bond i at time t.

Table 2.4 compares the monthly price returns calculated using clean prices obtained from Bloomberg and Refinitiv Datastream, respectively. The mean, median, and standard deviation of the returns are distributed by the bond's issue year. The T-test and Wilcoxon rank-sum (Man-Whitney) test the equality of mean and median returns across two samples.

Panel A of Table 2.4 shows that the return estimated using Bloomberg's prices is lower on average than that calculated using Refinitiv Datastream's but higher at the median value. In addition, the standard deviation of the return calculated by the former database is marginally greater than that predicted by the latter. Neither of the test statistics exhibits statistically significant p-values.

The mean, median, and standard deviation of the return for the bonds issued in 2018, 2019, 2020, and 2021 are shown in Panels B, C, D, and E, respectively. In Panel B, Bloomberg's mean return exceeds Refinitiv Datastream's. However, Panel C shows the opposite result.

Panel F of Table 2.4 shows that 148 and 138 bonds have available clean prices from respective databases between 2017 and 2021. The mean and median returns calculated using clean prices reported by Bloomberg are comparable, while the mean return is much higher than the median one using clean prices reported by Refinitiv Datastream.

In general, our results imply that returns vary, but the differences in returns are not statistically significant between these two databases.

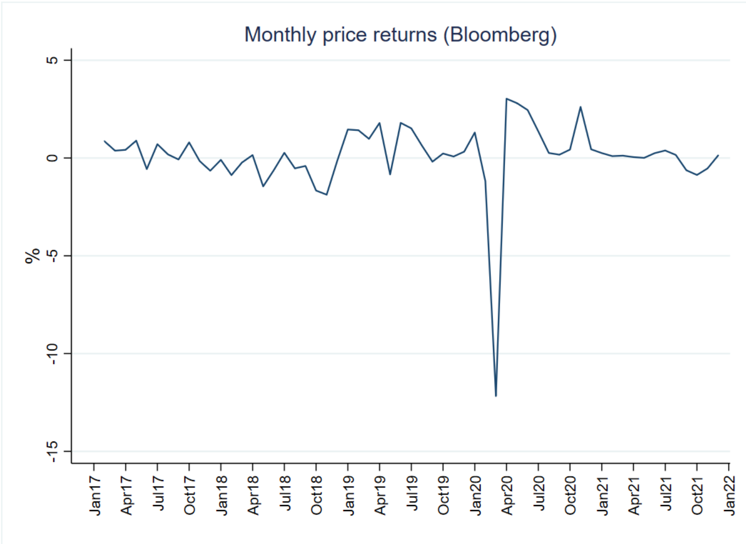
Table 2.4: Monthly price returns.

Panel A: Bonds issued in 2017.			
	Monthly price returns		Test statistics
	Bloomberg	Datastream	P-value
Mean	0.072	0.084	0.905
Median	0.081	0.067	0.891
SD	2.996	2.991	
N	34	33	
Obs.	1,845	1,781	
Panel B: Bonds issued in 2018.			
	Monthly price returns		Test statistics
	Bloomberg	Datastream	P-value
Mean	0.099	0.091	0.947
Median	0.090	0.042	0.851
SD	2.910	2.857	
N	27	25	
Obs.	1,147	1,067	
Panel C: Bonds issued in 2019.			
	Monthly price returns		Test statistics
	Bloomberg	Datastream	P-value
Mean	0.113	0.125	0.933
Median	0.130	0.079	0.346
SD	3.929	4.005	
N	54	49	
Obs.	1,550	1,356	
Panel D: Bonds issued in 2020.			
	Monthly price returns		Test statistics
	Bloomberg	Datastream	P-value
Mean	0.114	0.097	0.934
Median	0.083	0.076	0.743
SD	2.640	2.786	
N	21	20	
Obs.	352	339	
Panel E: Bonds issued in 2021.			
	Monthly price returns		Test statistics
	Bloomberg	Datastream	P-value
Mean	-0.202	-0.310	0.467
Median	-0.103	-0.130	0.802
SD	0.828	0.954	
N	12	11	
Obs.	72	74	
Panel F: Bonds issued between 2017 and 2021.			
	Monthly price returns		Test statistics
	Bloomberg	Datastream	P-value
Mean	0.090	0.091	0.972
Median	0.092	0.061	0.449
SD	3.257	3.260	
N	148	138	
Obs.	4,966	4,617	

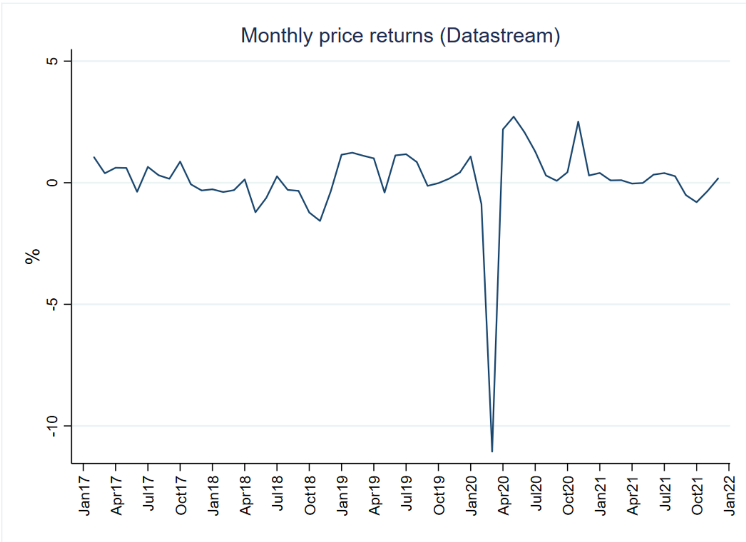
The table presents the mean, median, and standard deviation of monthly price returns (in percentage terms) distributed by the issue year, which is the year the bond was issued. The calculation of the monthly price return is defined as Equation 2.1. SD is the abbreviation of standard deviation, N stands for the number of bonds, and Obs. is the number of monthly price returns for each category. Reported test statistics show the corresponding p-value for the two-sample t-test and the Wilcoxon rank-sum (Mann-Whitney) test, testing whether the mean and median returns of the two samples are equal or not. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 2.1 shows the time series of average monthly price returns between January 2017 and December 2021. The returns plummeted to an all-time low in March 2020, simultaneously captured by Bloomberg and Refinitiv Datastream. Overall, these two databases exhibit a similar pattern of returns over time.

Figure 2.1: Time series of price returns.



(a)



(b)

The figure displays the monthly time series of average price returns between February 2017 and December 2021, calculated using clean prices from Bloomberg and Refinitiv Datastream.

2.4 Summary

This chapter primarily compares Bloomberg, Refinitiv Eikon, and Refinitiv Datastream, to determine which database is more favourable for collecting data on Euro-denominated high-yield corporate bonds. We find that Bloomberg provides more comprehensive data than Refinitiv Eikon. In particular, it offers more than five times as many high-yield bonds as Refinitiv Eikon based on identical selection criteria. Bloomberg is selected to gather the preliminary data, thereby minimising the possibility of sample survivorship bias.

As high-yield bonds are traded in the over-the-counter market, prices are usually provided by dealers. Each database has a unique set of dealers offering quotes and a proprietary mechanism for generating quoted prices. Selecting five bonds at random and comparing their accrued interest, ask, bid, and clean prices on the same day, we observe that Bloomberg and Refinitiv Datastream's data differ from an individual bond viewpoint.

Given the importance of clean prices to the sample size, we collect 1,819 and 1,167 bonds with available daily clean prices from Bloomberg and Refinitiv Datastream, respectively, based on 2,142 high-yield bonds from the first data collection stage. Results show that Bloomberg has a sample size advantage over Refinitiv Datastream. To further compare these two databases, we use high-yield bonds issued between 2017 and 2021 and calculate their monthly price returns separately using month-end clean prices reported by Bloomberg and Refinitiv Datastream. We discover that the returns vary, but the differences in returns are statistically insignificant between these two databases. Moreover, the trends of the returns, as represented by these two databases, follow a similar pattern throughout time.

For reasons of sample size and data consistency, we use Bloomberg as our primary data source.

Chapter Three

Common Factors in the Pricing of Euro-Denominated High-Yield Corporate Bonds

3.1 Introduction

High-yield bonds have played a pivotal role in European corporate debt financing, with the market value of outstanding bonds growing from €108 billion in 2009 to €508 billion in 2019 (Credit Suisse, 2020). Asset-management institutions, including insurance companies, pension funds, and mutual funds, are increasingly investing in high-yield bonds as a means of generating profits and supplementing their dividend-paying portfolios (Bagaria, 2016). There is, however, a paucity of academic research on Euro-denominated high-yield corporate bonds, regardless of their market size and economic value. The objective of this chapter is to fill the vacuum by examining the common factors that drive excess returns and how they vary according to market scenarios by ratings, maturities, and industries.

High-yield bonds are a unique and attractive asset class, distinct from investment-grade bonds and equity. They are traded through the over-the-counter market, less frequently than investment-grade bonds. Previous studies have investigated the association between illiquidity and bond returns or yields, focusing on the US corporate bond market (Chen et al., 2007; Bao et al., 2011; Lin et al., 2011; Dick-Nielsen, 2009; Friewald et al., 2012; Acharya et al., 2013; Bongaerts et al., 2017). Only some of the above studies include a subsample of high-yield bonds. Evidence from the European markets primarily focuses on investment-grade bonds (Houweling et al., 2005; Aussenegg et al., 2015; Galliani et al., 2014; Aussenegg et al., 2017).

Bondholders typically receive the fixed coupon payment and the principal back when the bond matures, so they have limited upside payoffs. In contrast, equity payoffs are linear and fluctuate with investors' expectations of the equity performance (Merton, 1974; Collin-Dufresn et al., 2001). According to Bai et al. (2019), downside risk is essential in explaining US corporate bond returns. Furthermore, downside risk differs from default risk, which is measured by credit ratings. The ratings of high-yield bonds often change during maturity. For instance, some bonds were issued as high-yield grades and were subsequently upgraded to investment-grade status. Similarly, some original investment-grade bonds end up as high-yield bonds and become so-called fallen angels.

Fama and French (1993) identify term (TERM) and default (DEF) as common factors to explain corporate bond returns, but these two factors may not be sufficient to capture the returns for high-yield bonds. For example, due to the limited liquidity in the high-yield bond market, the illiquidity factor may play a more important role in the high-yield bond market than in the investment-grade bond market. Due to the high probability of default in the high-yield bond market, investors may be particularly concerned about downside risk.

Therefore, we augment the Fama and French (1993) 2-factor model with illiquidity and downside risk. We also examine the time-varying effect of the TERM, DEF, illiquidity, and downside risk factors in different market scenarios.

This chapter has two main contributions. First, we contribute to the literature by augmenting the Fama and French (1993) 2-factor model with illiquidity and downside risk factors. Second, we examine the time-varying effect of common factors on Euro-denominated high-yield corporate bond returns across ratings, maturities, and industries. Previous related studies examine the effect of the downside risk factor on future bond returns in a cross-sectional model (Bai et al., 2019). In addition, the effect of the illiquidity factor on returns fluctuates significantly among bond indices for various ratings, maturities, and industries in the Euro-denominated investment-grade corporate bond market (Aussenegg et al., 2017). Not all high-yield bonds have the same sensitivity and exposure to illiquidity and downside risk factors. Different ratings, maturities, and industries of high-yield bonds may produce substantially different results across state changes. We also construct a novel illiquidity measure at the bond level using principal component analysis, particularly for high-yield corporate bonds.

The remainder of this chapter is organised as follows. Section 3.2 reviews relevant literature. Section 3.3 describes the data sources, the sample construction, and the sample descriptive statistics. Section 3.4 describes the methodology, starting from the pooled regression to a Markov-switching model. Section 3.5 discusses the empirical results. Robustness checks are presented in Section 3.6. We conclude in Section 3.7.

3.2 Literature Review and Hypotheses

Previous studies have documented the importance of illiquidity for the pricing of US corporate bonds. For example, illiquidity risk is priced in the cross-sectional regression of corporate bonds (Lin et al., 2011; Acharya et al., 2013). Bonds with a higher degree of illiquidity are accompanied by higher yield spreads (Chen et al., 2007; Bao et al., 2011; Dick-Nielsen et al., 2012; Friewald et al., 2012). Similar evidence was provided for Euro-denominated investment-grade corporate bonds (e.g., Houweling et al., 2005; Aussenegg et al., 2015). For instance, Houweling et al. (2005) use nine bond liquidity measures derived from bond characteristics and trading activities to determine the presence of the liquidity premium between 1st January 1999 and 31st May 2001. They find around 13 to 23 basis points in the liquidity premia. Furthermore, Aussenegg et al. (2015) conclude that illiquidity risk is an essential determinant of Euro-denominated investment-grade corporate bond returns.

Typically, high-yield bonds are traded less frequently than their investment-grade counterparts. We, therefore, anticipate that illiquidity will be priced and an important factor of returns for high-yield corporate bonds. Furthermore, illiquidity risk tends to increase as the rating deteriorates (e.g., Lin et al., 2011; Acharya et al., 2013). Therefore, we anticipate that bonds with a rating of CCC and below are more illiquid than BB-rated bonds.

Hypothesis 1a: Illiquidity is an important factor in pricing the Euro-denominated high-yield corporate bond market.

Hypothesis 1b: The effect of illiquidity on returns is more pronounced for bonds with a rating of CCC and below.

High-yield bond excess returns tend to be affected by economic conditions. For instance, returns tend to be higher during recessions and lower during economic booms (Fama and French, 1989). Furthermore, Beber et al. (2009) and Longstaff (2004) find that investors prefer liquid assets during periods of economic and financial crisis. Dick-Nielsen et al. (2012) and Friewald et al. (2012) find a time-varying effect of illiquidity on yield spreads for high-yield bonds. Acharya et al. (2013) adopt the Markov-switching model to examine a significant difference in illiquidity between high-yield and investment-grade bonds under two regimes. Bond prices are not significantly influenced by illiquidity risk in normal periods. Prices of high-yield bonds tend to fall dramatically in periods of crisis because of the flight to liquidity phenomenon. Aussenegg et al. (2017) demonstrate that illiquidity risk has a time-varying influence on Euro-denominated investment-grade corporate bond returns, using a Markov threshold model. As investment-grade bonds have better credit quality and liquidity, they tend to be more popular than high-yield bonds during crisis periods. High-yield bonds and investment-grade bonds may react differently to adverse economic conditions.

Primary investors in the high-yield bond markets are institutional investors who must follow strict regulatory requirements. In times of financial market stress, institutional investors become increasingly restricted in their capital investments. They are more likely to sell bonds with a rating of CCC and below due to their lower credit quality and liquidity. In addition, institutional investors are essential liquidity providers in the high-yield bond market, and they are all simultaneously cash-strapped, implying a higher liquidity premium is required. Given the limited liquidity in the high-yield bond market, the liquidity shock may be reflected in the price. It is expected that prices of high-yield bonds will be significantly different between normal periods and adverse economic conditions. Due to the flight to liquidity phenomenon, the adverse economic condition exacerbates the illiquidity of high-yield bonds with the lowest credit ratings. Investors prefer to invest in liquid assets, and prices of bonds with a rating of CCC and below tend to be affected more during economic downturns. Therefore,

Hypothesis 2a: Illiquidity exhibits time-varying behaviour.

Hypothesis 2b: The price effect of time-varying illiquidity differs between bonds with a BB rating and those with a rating of CCC and below.

Bai et al. (2019) conclude that downside risk is an essential determinant of future bond returns. The downside risk factor is proxied by estimating the 5% Value at Risk (VaR) from the left tail of the bonds' empirical return distribution. In particular, the 5% VaR is the second-lowest month return observation using a rolling window of 36 months. They find a positive association between the downside risk factor and expected returns more prominent for high-yield bonds. High-yield bondholders may be more sensitive to downside risk than investment-grade bondholders. First, high-yield bonds tend to have a higher probability of default than investment-grade bonds. Second, primary investors in the high-yield bond market are insurance companies, pension funds, mutual funds, and collateralized debt obligations (S&P, 2019). As many asset-management institutions have strict investment rules, the potential loss of investing in high-yield bonds may be essential to consider. Third, the downside risk factor may be a better proxy than credit ratings. Abad et al. (2020) highlight disagreements on the ratings among credit rating agencies due to problems of information opacity of issuers. This problem is particularly relevant to high-yield bonds issued by smaller and less-known issuers.

High-yield bond excess returns fluctuate with changes in economic conditions (Fama and French, 1989). The downside risk factor is associated with excess returns (Bai et al., 2019). Moreover, excess returns become more volatile in times of adverse economic conditions. Thus, it is expected that downside risk will become more significant than in times of normal periods. Therefore,

Hypothesis 3a: Downside risk exhibits time-varying.

Hypothesis 3b: The price effect of time-varying downside risk differs between bonds with a BB rating and those with a rating of CCC and below.

3.3 Data and Sample Description

3.3.1 Sample Construction

The primary data source is Bloomberg. This chapter examines active and matured Euro-denominated high-yield corporate bonds issued between 1st January 2000 and 31st December 2021. These bonds have a fixed coupon rate, a bullet type of maturity, and are rated as high-yield grades by at least one of the following agencies: S&P, Moody's, and Fitch. We include bonds with a maturity of over one year, and those with an annual or semi-annual frequency of coupon payment.[1] To reduce the confusing effects of embedded options, we also eliminate callable, puttable, convertible, and sinking fund bonds (Lin et al., 2011; Aussenegg et al., 2015). In addition, we exclude bonds without data on the amount outstanding. Therefore, we collect 2,142 bonds from Bloomberg.

We use several price and rating filters similar to previous studies (Dick-Nielsen, 2009; Lin et al., 2011; Dick-Nielsen et al., 2012; Acharya et al., 2013; Aussenegg et al., 2015). Price filters are used to remove bond outliers or potential errors from the sample to improve the quality and reliability of the sample bonds. We exclude bonds with missing or odd prices. For instance, bonds are excluded if their daily clean, bid, or ask prices are below 30 or over 200, and those with a higher daily bid than the ask price. Furthermore, we exclude bonds whose ratings are not identified and those that are rated as investment-grade status due to inconsistent ratings among S&P, Moody's, and Fitch. We start with the S&P rating. If this rating is not available, Moody's or Fitch ratings are applied. If there are still some missing bond ratings, the issuer's ratings are used (Dick-Nielsen et al., 2012). The above price and rating filters resulted in a sample of 1,275 Euro-denominated high-yield corporate bonds (see Table 3.1).

1 A bond with a maturity of less than one year is subject to low liquidity and potentially high pricing error (Lin et al., 2011; Aussenegg et al., 2015).

Table 3.1: Sample selection criteria and filters.

Panel A: Selection criteria.		N
	Active and matured corporate bonds	
And	Euro Currency	
And	Fixed coupon type	
And	Bullet maturity type	
And	Issue date between 1st January 2000 and 31st December 2021	
And	S&P Rating (BB+, BB, BB-, B+, B, B-, CCC+, CCC, CCC-, CC, C, D)	
Or	S&P Issuer Rating (BB+, BB, BB-, B+, B, B-, CCC+, CCC, CCC-, CC, C, D)	
Or	Fitch Rating (BB+, BB, BB-, B+, B, B-, CCC+, CCC, CCC-, CC, C, DDD, DD, RD)	
Or	Fitch Issuer Rating (BB+, BB, BB-, B+, B, B-, CCC+, CCC, CCC-, CC, C, DDD, DD, RD)	
Or	Moody's Rating (Ba1, Ba2, Ba3, B1, B2, B3, Caa1, Caa2, Caa3, Ca, C)	
Or	Moody's Issuer Rating (Ba1, Ba2, Ba3, B1, B2, B3, Caa1, Caa2, Caa3, Ca, C)	
And	Bond's tenor is greater than one year	
And	Bonds with an annual or semi-annual frequency of coupon payment	
And	Bonds with embedded options are excluded	
Less	Bonds without data on the amount outstanding	2,142
Panel B: Price and rating filters.		N
Less	Bonds with missing daily clean prices	323
Less	Daily clean price with a value below 30 or over 200	51
Less	Daily bid price with a value below 30 or over 200	3
Less	Daily ask price with a value below 30 or over 200	0
Less	Bonds have a higher daily bid than ask price	7
Less	Bonds with missing daily bid prices	1
Less	Bonds with missing daily ask prices	20
Less	Bonds without ratings assigned	9
Less	Bonds with investment-grade ratings due to mismatch ratings	453
Total		1,275

This table describes the sample selection criteria and filters. Panel A presents 2,142 high-yield bonds downloaded from Bloomberg based on the above sample selection criteria. Panel B presents bond price and rating filters used to remove potential pricing errors and outliers. Therefore, there are 1,275 Euro-denominated high-yield corporate bonds left in the sample. N stands for the number of bonds.

Table 3.2 exhibits the descriptive statistics of the market value-weighted results on yield to maturity, term to maturity, and modified duration for sample bonds across ratings, maturities, and industries. The weight is determined by the bond's month-end market value, which is the amount outstanding multiplied by the month-end quoted price of the bond. The sample comprises 1,275 Euro-denominated high-yield corporate bonds issued between 1st January 2000 and 31st December 2021. 855 sample bonds (67.06%) were initially rated as high-yield (i.e., BB, B, and CCC categories). 420 sample bonds (32.94%) were initially issued as investment-grade (i.e., BBB or better) but downgraded to a high-yield rating before maturity. As our sample includes the dot-com bubble, the financial crisis, and the COVID-19 panic periods, a high number of fallen angels is expected with the incredible number of downgrades. In addition, 69% of high-yield corporate bonds are issued by financial firms dominated by banks. Government-related, materials, and consumer discretionary industries are the top three non-financial high-yield bond issuers, representing 6.2%, 5.3%, and 5.3%, respectively. For instance, government-related companies include winding up agencies, government agencies, and government development banks. Overall, issuers of Euro-denominated high-yield corporate bonds are primarily occupied by cyclical industries.

The average yield to maturity of the sample bonds is 3.21%. Bonds with lower ratings tend to have a higher yield, suggesting that investors may require a higher yield as compensation for bearing additional credit risk. Bonds with longer years of maturity are more likely to have a higher yield, indicating that investors may require a higher yield as compensation for additional holding period risk. On average, the bonds issued by financial firms present a higher yield (3.61%) than those issued by non-financial companies (2.97%), consistent with the results presented in Aussenegg et al. (2017).

The average term to maturity of the sample bonds is 8.08 years, compared to the 5.49 years of Euro investment-grade bonds presented in Aussenegg et al. (2017). The bonds issued by financial firms tend to have a shorter term to maturity (7.10 years) than those issued by their non-financial counterparts (8.68 years). Amongst the non-financial companies, communications and consumer staples exhibit the highest term to maturity, 11.88 and 10.11 years, respectively.

The average modified duration of the sample bonds is 3.23 years, which is less than the result (4.42 years) of the investment-grade bonds presented in Aussenegg et al. (2017). This result shows that high-yield bonds have a lower duration exposure than investment-grade bonds. Among the high-yield bonds, those with BB ratings have a higher modified duration than those with ratings CCC and below, implying that bonds with lower ratings are less sensitive to changes in interest rates. In addition, the modified duration rises with an increase in the years of maturity, suggesting that prices of short-term high-yield bonds have less sensitivity to changes in interest rates. Furthermore, the modified duration varies with industries. For instance, the average modified duration of financial bonds is 2.80 years, compared to 3.49 years for non-financial bonds.

Table 3.2: Summary statistics.

Bond index	N	Yield to maturity		Term to maturity		Modified duration	
		Mean	Median	Mean	Median	Mean	Median
Sample bonds	1,275	3.21	2.42	8.08	7.00	3.23	2.84
Rating BB	1,228	2.65	2.17	8.28	7.00	3.34	3.00
Rating B	333	5.38	3.87	6.81	5.00	2.61	2.39
Rating CCC and below	146	9.61	5.82	8.42	7.00	3.03	2.29
Maturity 1-3 years	311	3.24	2.66	2.14	2.00	0.79	0.71
Maturity 3-5 years	264	3.01	1.89	3.43	3.00	1.50	1.41
Maturity 5-7 years	291	3.17	2.29	5.17	5.00	2.22	2.18
Maturity 7-10 years	168	3.14	2.03	7.27	7.00	3.20	3.23
Maturity 10+ years	241	3.32	2.93	12.31	10.00	4.55	4.21
Financials	878	3.61	2.69	7.10	5.20	2.80	2.49
Banks	794	3.16	2.43	7.45	7.00	2.92	2.58
Consumer Finance	51	9.56	6.43	5.38	5.00	1.50	1.11
Others	33	2.93	2.69	6.56	5.00	2.87	2.63
Non-financials	397	2.97	2.28	8.68	7.00	3.49	3.15
Communications	38	2.23	1.96	11.88	8.00	4.59	3.76
Consumer Discretionary	67	3.64	3.04	7.30	7.00	3.14	2.88
Consumer Staples	21	2.15	1.69	10.11	8.00	3.59	2.57
Energy	27	3.64	2.46	8.07	7.00	3.12	2.90
Government-related	79	3.50	2.61	11.43	10.00	3.97	3.96
Health Care	19	1.98	1.83	7.23	7.00	4.09	4.09
Industrials	27	2.89	2.43	9.08	7.10	3.56	3.56
Materials	68	3.14	2.04	7.18	7.00	3.01	2.99
Technology	8	4.15	3.34	6.81	5.10	2.44	2.17
Utilities	43	2.58	2.00	8.19	7.00	3.12	2.85

This table presents the yield to maturity, term to maturity, and modified duration distributed by ratings, maturities and industries between March 2000 and December 2021. We use the data on yield to maturity in percentage terms and modified duration in years reported by Bloomberg. Term to maturity in years is calculated as the actual number of calendar days from the bond's issue date to the maturity date divided by 365.25 days. We use the market value-weighted approach for each group. The market value of a bond is equal to the value of the amount outstanding multiplied by the quoted month-end price of the bond. The rating of bonds often changes during maturity. For instance, some BB-rated bonds are downgraded to B, or some CCC-rated bonds are upgraded to B. Therefore, the number of bonds in each rating group does not equal the total number of sample bonds. N stands for the number of bonds.

3.3.2 Bond Excess Returns

Following related literature by Lin et al. (2011), Acharya et al. (2013), and Bai et al. (2019), we compute the monthly high-yield bond return at time t as:

$$r_{i,t} = \frac{(P_{i,t} + AI_{i,t}) + C_{i,t} - (P_{i,t-1} + AI_{i,t-1})}{P_{i,t-1} + AI_{i,t-1}} \tag{3.1}$$

where, $P_{i,t}$ is the quoted month-end price of bond i at time t, $AI_{i,t}$ is the accrued interest of bond i at time t, and $C_{i,t}$ is the (annual or semi-annual) coupon payment (if any) of bond i at time t.

Monthly high-yield bond excess return is calculated as:

$$\mathrm{er}_{i,t} = ln(1 + r_{i,t}) - r_{f,t-1} \tag{3.2}$$

where, $er_{i,t}$ is the monthly high-yield bond excess return of bond i at time t, which is calculated as the continuously compounded monthly bond return in excess of the one-month Euribor rate at time $t-1$. The one-month Euribor rate is commonly used as a risk-free rate in the European corporate bond market (Aussenegg et al., 2015, 2017).

Table 3.3 presents the market-value weighted monthly excess returns on high-yield bonds grouped into portfolios according to their respective ratings, maturities, and industries. The weight is determined by the bond's month-end market value, which is the amount outstanding multiplied by the month-end quoted price of the bond. The monthly excess returns are in percentage terms, denoted %.

Typically, bonds with lower ratings have a larger mean and standard deviation of excess returns. The monthly mean excess return on BB-rated bonds is 0.52%, with a standard deviation of 2.19%, and for bonds with ratings of CCC and below, the mean and standard deviation are 1.34% and 6.59%. The mean and standard deviation of excess returns increase as the rating deteriorates, consistent with the results presented by Acharya et al. (2013) and Aussenegg et al. (2017).

Bonds with longer years of maturity are associated with greater monthly excess returns and standard deviation. Comparing the monthly excess returns between the financial and non-financial sectors, the former tends to be smaller than the latter. These results are in line with those reported by Aussenegg et al. (2017).

The sample bonds have a negative skewness of excess returns, describing the peak value of the distribution leftward and indicating that most excess returns are on the left side of the tail. The sizeable excess kurtosis implies that bondholders are inclined to acquire extreme excess returns, either positive or negative. The distribution of excess returns suggests that high-yield bonds have heavy tails and outliers. This is to be expected, considering that we cover crisis periods and include high-yield corporate bonds with various ratings, maturities, and industries.

Table 3.3: Summary statistics on monthly excess returns.

Bond index	N	Monthly excess returns				
		Mean	Median	SD	Excess kurtosis	Skewness
Sample bonds	1,275	0.57	0.37	2.65	79.74***	0.55***
Rating BB	1,228	0.52	0.33	2.19	78.09***	-0.58***
Rating B	333	0.70	0.43	3.20	30.15***	-0.54***
Rating CCC and below	146	1.34	0.69	6.59	25.92***	1.35***
Maturity 1-3 years	311	0.53	0.28	1.15	12.77***	1.38***
Maturity 3-5 years	264	0.45	0.26	1.95	222.81***	5.45***
Maturity 5-7 years	291	0.54	0.36	2.56	124.17***	1.51***
Maturity 7-10 years	168	0.58	0.37	2.61	67.99***	0.57***
Maturity 10+ years	241	0.63	0.45	2.89	51.23***	-0.34***
Financials	878	0.52	0.39	2.88	102.61***	1.31***
Banks	794	0.49	0.35	2.60	76.92***	-0.44***
Consumer Finance	51	0.68	0.30	6.12	41.71***	2.45***
Others	33	0.56	0.40	2.01	68.55***	-2.21***
Non-financials	397	0.61	0.36	2.49	51.45***	-0.15***
Communications	38	0.56	0.33	2.14	8.53***	-0.22***
Consumer Discretionary	67	0.62	0.39	2.96	69.13***	0.95***
Consumer Staples	21	0.37	0.20	1.99	13.63***	0.29***
Energy	27	0.71	0.45	2.76	38.63***	-1.25***
Government-related	79	1.01	0.37	3.07	96.26***	-2.16***
Health Care	19	0.70	0.44	1.54	7.03***	0.32***
Industrials	27	0.57	0.37	2.46	13.23***	-0.88***
Materials	68	0.66	0.36	2.40	59.13***	-1.17***
Technology	8	0.77	0.32	3.19	17.99***	0.67***
Utilities	43	0.50	0.32	2.20	11.72***	-0.54***

This table presents market value-weighted monthly excess returns (in percentage terms) distributed by ratings, maturities, and industries between March 2000 and December 2021. The data source is Bloomberg. The weight is determined by the bond's month-end market value, which is the amount outstanding multiplied by the month-end quoted price of the bond. Monthly excess returns are the continuously compounded returns of an individual bond over the one-month Euribor rate in the previous month. The ratings of bonds often change during maturity. For instance, some BB-rated bonds are downgraded to B, or some CCC-rated bonds are upgraded to B. Therefore, the number of bonds in each rating group does not equal the total number of sample bonds. Excess kurtosis is the difference between the value of kurtosis and 3. Skewness and kurtosis normality tests are used. *** represents a 1% significance level, ** represents a 5% significance level, and * represents a 10% significance level

3.4 Methodology

3.4.1 Time-Varying Illiquidity Measures

Previous studies have documented the importance of illiquidity effects in the pricing of corporate bonds (Houweling et al., 2005; Chen et al., 2007; Dick-Nielsen, 2009; Lin et al., 2011; Bao et al., 2011; De Jong and Driessen, 2012; Dick-Nielsen et al., 2012; Friewald et al., 2012; Acharya et al., 2013; Aussenegg et al., 2015, 2017; Bongaerts et al., 2017). To investigate the effect of time-varying market illiquidity on high-yield bond excess returns, we adopt several proxies that have been widely used in the literature. In particular, we compute the Kim and Lee (2014)'s format of Roll (1984) measure, used by Aussenegg et al. (2017); the fraction of zero returns (FZR) measure, used by Dick-Nielsen et al. (2012), Friewald et al. (2012), and Aussenegg et al. (2017); and the bid-ask spread measure widely used among academics and market participants (Cai et al., 2007; European Commission, 2017*b*; Rischen and Theissen, 2021).

Roll measure, developed by Roll (1984), interpreted as the strength of the correlation of price movements, is a good proxy for liquidity. Crucial to the efficiency of the measure is the trading frequency of the bond. High-yield bonds are typically infrequently traded. They usually have many zero returns each month, thus making it hard to provide a non-zero covariance. Following Pastor and Stambaugh (2019), we exclude those zero-volume days that produce zero returns before implementing the Roll measure. The higher the value of the Roll measure, the more severe the liquidity drains we observe in the bond market. The Roll measure is defined for bond i in month t as:

$$Roll_{i,t} = 2 \cdot \sqrt{\left|cov\left(r_{i,\tau}, r_{i,\tau-1}\right)\right|} \tag{3.3}$$

where $cov\left(r_{i,\tau}, r_{i,\tau-1}\right)$ is the covariance of the two consecutive daily returns of bond i in month t.

FZR is an activity-based illiquidity measure that effectively captures the percentage of trading days having a zero return. This illiquidity proxy is used by Houweling et al. (2005), Dick-Nielsen et al. (2012), Friewald et al. (2012), and Aussenegg et al. (2017). Bond prices that remain unchanged over time for a given period are more likely to be less liquid. According to Aussenegg et al. (2017), we calculate FZR for each bond i in month t as follows:

$$FZR_{i,t} = \frac{NZR_{i,t}}{NTD_{i,t}} \tag{3.4}$$

where, $FZR_{i,t}$ is the proportion of days in a month t when the bond i has a zero return, $NZR_{i,t}$ is the number of zero return days in month t for bond i, and $NTD_{i,t}$ denotes the number of trading days in month t for bond i.

Bid-ask spread is a price-based illiquidity proxy capturing the level of market participation or supply and demand in the market. Wider spreads are directly associated with low levels of participation in the market, suggesting that those bonds are less popular and thus more illiquid. We follow European Commission (2017*b*) and calculate the bid-ask spread as follows:

$$Bid - ask\ spread_{i,t} = \frac{\sum_t \frac{ask_{i,\tau}\ -\ bid_{i,\tau}}{mid_{i,\tau}}}{number\ of\ daily\ observations\ in\ month\ t} \times\ 100 \tag{3.5}$$

where $ask_{i,\tau}$ and $bid_{i,\tau}$ are daily ask and bid prices for bond i, respectively. $mid_{i,\tau}$ is the average of the $ask_{i,\tau}$ and $bid_{i,\tau}$. $Bid - ask\ spread_{i,t}$ is the average monthly spread for bond i in month t in percentage terms.

3.4.2 Composite Illiquidity Measure

There are no perfect measures for illiquidity in previous studies. As a single illiquidity measure may not be sufficient to capture all the dimensions of illiquidity in the market, we follow Dick-Nielsen et al. (2012) and construct a composite illiquidity measure, denoted by LAMBDA. We estimate the LAMBDA based on the first principal component (PC) extracted from the three distinct illiquidity measures: the Roll, FZR, and bid-ask spread. The approach initially standardises all different illiquidity measures to a common scale, and then we aggregate the products of each measure with its associated PC loading.

In the first step, the Roll, FZR, and bid-ask spread illiquidity measures are normalised to a standard scale using Dick-Nielsen et al. (2012):

$$\widetilde{L}_{i,t}^{j} = \left(L_{i,t}^{j} - \mu^{j} \right) / \sigma^{j} \tag{3.6}$$

where, $L_{i,t}^{j}$ is an index for the illiquidity measure j (Roll, FZR, and bid-ask spread) for bond i in month t, and μ^{j} and σ^{j} are the mean and standard deviation of L^{j}, respectively.

In the second step, we use principal component analysis to extract the main factors from these illiquidity measures.[2] The LAMBDA is the sum of the normalised illiquidity proxies multiplied by their respective first PC loadings. The higher the LAMBDA, the more illiquid the bonds become.

3.4.3 Pooled Regression Model

Fama and French (1993) investigate common characteristics of corporate bonds and conclude that term and default factors explain the majority of the variation in corporate bond returns. To assess the importance of illiquidity in the high-yield bond market, we add the composite illiquidity measure to the Fama and French (1993) 2-factor model. Corporate bonds with higher risks are more likely to have higher returns. If the illiquidity factor plays a pivotal role in explaining the returns in the high-yield bond market, β_3 should be significantly positive. The sample includes the periods of the dot-com crash (from January 2000 to December 2002)

2 The first PC explains 44% of the variation in illiquidity proxies, suggesting that the first PC is enough to capture most of the relevant information regarding illiquidity in the high-yield corporate bond market. The results of the principal component analysis are presented in Table A1 in Appendix A.

and the financial crisis (from June 2007 to December 2009), which may have had a simultaneous impact on all sample bonds. So, we incorporate year fixed effects to control for these volatile periods. The sample includes high-yield bonds issued by financial and non-financial industries, so we also incorporate industry fixed effects to control for variations among different industries that may affect our results.

In particular, we adopt the following factor model for individual bonds with year and industry fixed effects:

$$er_{i,t} = \alpha_0 + \beta_1 \, TERM_{i,t} + \beta_2 \, DEF_{i,t} + \beta_3 \, LAMBDA_{i,t} + \varepsilon_{i,t} \tag{3.7}$$

where $er_{i,t}$ is the monthly excess return of bond i in month t, described in Equation 3.2. TERM denotes the term premium as the difference between the monthly return of the 10-year German government bond index and the one-month Euribor rate in the previous month. DEF denotes the default premium, measured as the difference between the monthly return of the Bloomberg Pan-European High-Yield Index and the monthly return of the 10-year German government bond.[3] LAMBDA is the sum of the normalised illiquidity proxies (Roll, FZR, and bid-ask spread) multiplied by their respective first principal component eigenvectors.

A recent study by Bai et al. (2019) finds evidence that the strongest predictor of future bond returns is downside risk. Looking at the characteristics of the high-yield bond market, we observe that the empirical distribution is skewed and exhibits fat tails (see Table 3.3). Thus, we attempt to assess the effect of downside risk on high-yield bond excess returns. We enhance the information set by adding to the illiquidity augmented 3-factor model a fourth factor associated with the downside risk factor.

Following Bai et al. (2019), we begin by calculating monthly bond raw returns

3 Clean prices of the 10-year German government bond index (code: BMBD10Y) are collected from Refinitiv Datastream, and prices for the Bloomberg Pan-European High-Yield Index (legacy ticker: LP02TREU), and the one-month Euribor rate are collected from Bloomberg.

(see Equation 3.1) and then convert the panel data to monthly time-series data using equal weights for each bond.[4] The downside risk factor is the 5% VaR of the bond's empirical return distribution. That is the second-lowest monthly bond return observation in the previous 36 months on a rolling window basis.[5] The first available return starts in March 2000, so the first downside risk factor starts in March 2003. Given the distributional characteristics of the high-yield bonds, we expect downside risk to play an essential role in explaining excess returns. The higher the VaR, the higher the downside risk, and the higher the excess returns. In order to assess the importance of the downside risk factor (denoted as DOWNSIDE), the following pooled regression model for individual bonds with year and industry fixed effects is given:

$$\begin{aligned} er_{i,t} \; &= \alpha_0 \; + \; \beta_1 \; TERM_{i,t} + \beta_2 \; DEF_{i,t} \; + \beta_3 \; LAMBDA_{i,t} \\ &+ \; \beta_4 \; DOWNSIDE_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{3.8}$$

3.4.4 Markov-Switching Model

Given the observed leptokurtic distribution of high-yield bond excess returns and time-varying factors, it is necessary to consider nonlinearity and regime changes. For example, the empirical distribution of high-yield bond excess returns is skewed and exhibits fat tails in Table 3.3. Furthermore, the excess returns changed dramatically during the crisis periods of the dot-com crash and the 2008 financial crisis, as presented in Figure 3.2, suggesting that excess returns are state-dependent. The Markov-switching model is reasonably adopted to capture the liner effect of common factors on excess returns in each regime, and the nonlinear behaviour associated with

4 In our sample, 33% of sample bonds were initially issued as investment-grade but downgraded to a high-yield rating before maturity (fallen angels); 67% of sample bonds were initially rated as high-yield status. Fallen angels' bond market values tend to be higher than those issued by original high-yield bonds. The downside risk factor derived from the market-value weighted return is more likely to underestimate the downside risk of small issuers.

5 We multiply the original VaR measure by -1 to interpret the results more accurately, as suggested by Bai et al. (2019).

the probabilistic characteristics of regime transitions. The model relies on the data to determine whether there is a group of occasions when betas deviate significantly from other times and quantify the likelihood of each conceivable regime.

The Markov-switching model has been widely used in previous studies. Hamilton (1989) examines the apparent propensity of gross domestic growth to perform considerably differently between the economic downturn and boom. The transition between the two states is determined by the output of an unobserved Markov chain, which can track long-term economic trends. The behaviour of financial markets frequently fluctuates unexpectedly, affecting the pattern of asset prices persistently for many periods (Ang and Timmermann, 2012). Acharya et al. (2013) estimate the Markov-switching model for US corporate bond returns and find different behaviour of prices in two regimes. Aussenegg et al. (2016) also adopt this model and study the drivers of asset swap spreads on European corporate bond indices, suggesting that asset swap spreads are regime dependent.

We estimate a Markov-switching model with two states to investigate the time-varying coefficients of common factors (i.e., TERM, DEF, LAMBDA, and DOWNSIDE) that impact high-yield bond excess returns. The model allows the intercepts, coefficients, and variances of excess returns to vary over time and take distinct values based on the state of the economy.

The Markov-switching model requires data to be time-series type, so we convert our panel data to time-series data. We estimate the time series of the monthly average excess return for each group k (i.e., Sample bonds, Rating BB, Maturity 1-3 years, and so on). We initially examine the effect of the time-varying illiquidity factor on excess returns. Then we add the downside factor to the 3-factor model to investigate the fluctuation of DOWNSIDE across two states. Excess returns in regime S, with S_t=S for $S \in \{1, 2\}$. The following specifies the two-state Markov-switching models for each portfolio:

$$R_{k,t} \; = \alpha^{S}_{k,0} \; + \beta^{S}_{k,1} \; TERM_t + \beta^{S}_{k,2} \; DEF_t + \beta^{S}_{k,3} \; LAMBDA_t + \varepsilon^{S}_{k,t} \tag{3.9}$$

$$\begin{aligned} R_{k,t} \; &= \alpha^{S}_{k,0} \; + \beta^{S}_{k,1} \; TERM_t + \beta^{S}_{k,2} \; DEF_t + \beta^{S}_{k,3} \; LAMBDA_t \\ &+ \beta^{S}_{k,4} \; DOWNSIDE_t + \varepsilon^{S}_{k,t} \end{aligned} \tag{3.10}$$

where $R_{k,t}$ represents the monthly excess return for bond portfolio k in month t. TERM denotes the term premium as the difference between the monthly return of the 10-year German government bond index and the one-month Euribor rate in the previous month. DEF denotes the default premium, measured as the difference between the monthly return of the Bloomberg Pan-European High-Yield Index and the monthly return of the 10-year German government bond. LAMBDA is the sum of the normalised illiquidity proxies (Roll, FZR, and bid-ask spread) multiplied by their respective first principal component eigenvectors. DOWNSIDE is the 5% VaR of the composite bond's monthly empirical return distribution over the past 36 months on a rolling basis. Following Bai et al. (2019), we multiply the 5% VaR by -1 for the convenience of the interpretation. The coefficients of TERM, DEF, LAMBDA, and DOWNSIDE factors are regime dependent. $\varepsilon^{S}_{k,t}$ is a regime-dependent error with variance $\sigma^2_{k,S}$.

S_t is unobserved, it is impossible to predict with certainty which regime the process is in, but the likelihood that the process is in each state can be estimated. As a result, the transition probabilities are more critical in a Markov process. The following equations specify the one-step transition probability for two states:

$$P(S_{t=1}| \; S_{t+1=1}) = p_{11} \quad and \tag{3.11}$$

$$P(S_{t=2}| \; S_{t+1=2}) = p_{22} \tag{3.12}$$

where p_{11} and p_{22} determine the one-step switching probabilities for a two-state process. $P(S_{t=1}| \; S_{t+1=1})$ denotes the probability of remaining in state 1 in the next period. Similarly, $P(S_{t=2}|\ S_{t+1=2})$ denotes the probability of remaining in state 2 in the next period. The value of p_{11} or p_{22} indicates whether the transition process is persistent or not. For instance, if the value of p_{11} is close to 1, it implies that the process is more likely to be persistent; that is to say, it has a potentially high probability of staying in state 1 for a long time.

3.5 Empirical Results

3.5.1 Results of Illiquidity Measures

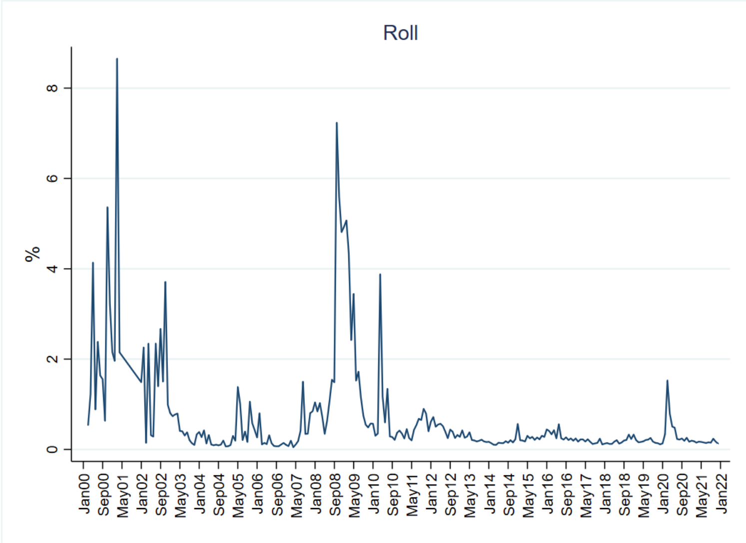
Figure 3.1 depicts the fluctuation of the illiquidity measures between 2000 and 2021. The Roll and bid-ask spread variables are proxies for the price-based illiquidity measures. The Roll measure is built on estimates of the autocovariance of consecutive daily returns in a given month. A higher Roll indicates a higher degree of illiquidity. The graph of the Roll measure captures a major peak during the periods of the dot-com crash and financial crisis, and a mild peak during the COVID-19 panic periods.[6] Figure 3.1 (b) exhibits the FZR variable, which is an activity-based indicator. A higher FZR means a higher number of trading days with zero returns in a given month, indicating greater illiquidity. The trend of FZR is generally consistent with Roll, being significantly higher during these crisis periods.

In Figure 3.1 (c), the bid-ask spread plot shows a prominent spike during the European sovereign debt crisis. Lower spreads in times of financial crisis do not indicate that high-yield bonds are liquid; a market could have tight spreads but lack liquidity if an agent is not able to trade bonds immediately. The peak of the bid-ask spread in 2011 demonstrates that the European sovereign debt crisis reinforces market concerns and intensifies the risk of illiquidity and default for high-yield bonds. As central banks took decisive steps to overcome the crisis, the spread narrowed significantly in 2012 and 2013. Then, the spread continues to rise; a mild increasing trend has been visible since early 2014. The trend of bid-ask spreads is overall in line with the one presented in the European Commission (2017*b*), which also uses the bid and ask prices reported by Bloomberg.

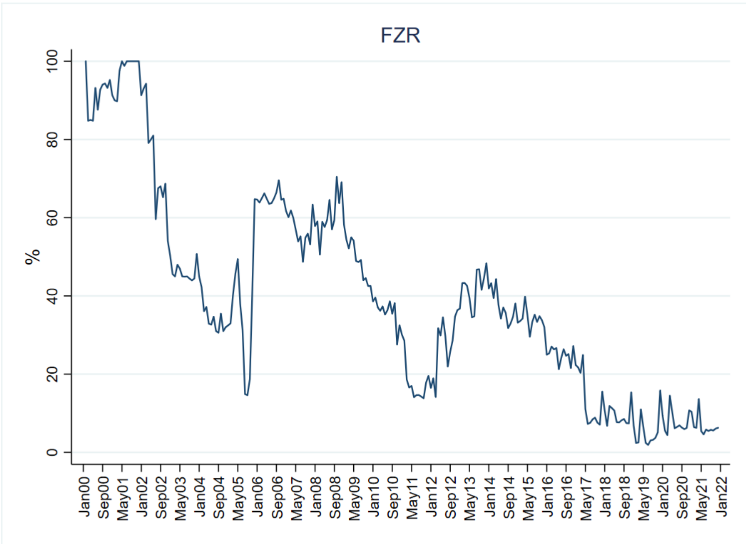
An illiquidity measure is insufficient to capture all the dimensions of the market illiquidity. We thus adopt the principal component analysis and calculate a composite illiquidity measure, denoted as LAMBDA, presented in Figure 3.2 (d).

6 The table of descriptive statistics for the Roll measure, FZR variable, and bid-ask spread across ratings, maturities, and industries is presented in Table A2 in Appendix A.

Figure 3.1: Time series of illiquidity measures.

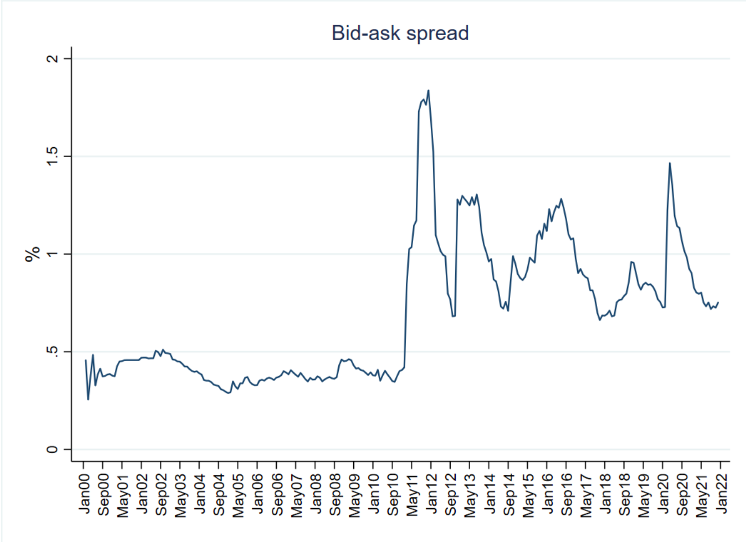


(a)



(b)

Figure 3.1 continued: Time series of illiquidity measures



(c)

The figure shows the trend of the Roll, FZR, and bid-ask spread illiquidity variables, measured in percentage terms. The data are quoted prices for Euro-denominated high-yield corporate bonds reported by Bloomberg, spanning 2000 to 2021. Every illiquidity variable is calculated monthly for each bond. The monthly mean value of illiquidity variables across all bonds is plotted.

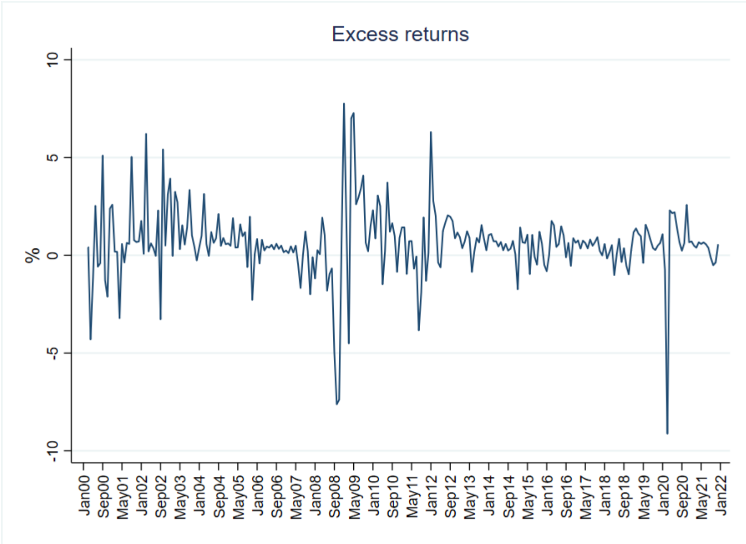
3.5.2 Results of Common Factors

Figure 3.2 plots the monthly time series of average excess returns and common factors, including TERM, DEF, LAMBDA, and DOWNSIDE, for the sample period from 2000 to 2021. The monthly excess returns became highly volatile during the crisis periods, including the dot-com crash (between 2000 and 2002), the 2008 financial crisis, the European sovereign debt crisis (between 2011 and 2012), and the COVID-19 pandemic at the beginning of March 2020. The DEF factor shows a similar trend to the excess return graph. Crisis periods deteriorate the financial condition of high-yield bond issuers, giving rise to an enhanced probability of default. Thus, the spikes in the DEF factor are more pronounced during these crisis periods than in normal periods.

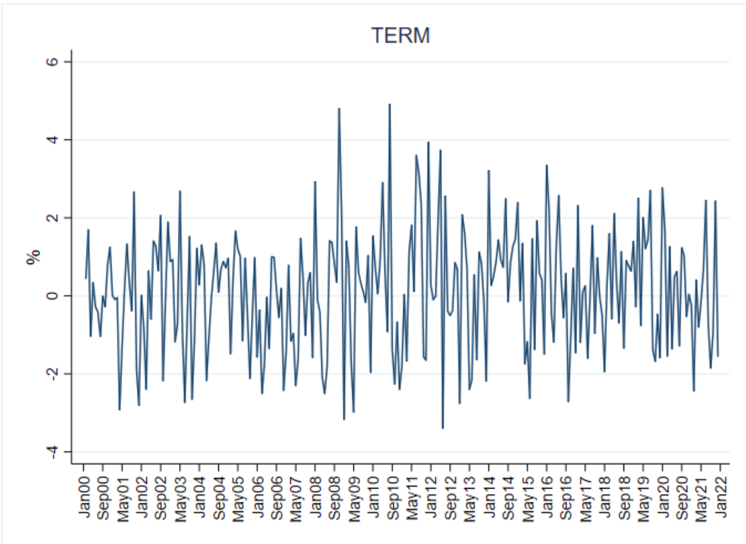
In addition, LAMBDA fluctuates over time, being significantly variable during these crisis periods. This trend indicates that this composite illiquidity measure can capture the dry-up of liquidity in the high-yield bond market during stressed market conditions.[7] DOWNSIDE reaches a peak and remains at an elevated level between December 2008 and December 2011. This result indicates that the level of downside risk may be conditional on economic conditions.

7 The table of descriptive statistics for LAMBDA distributed by ratings, maturities, and industries is presented in Table A3 in Appendix A.

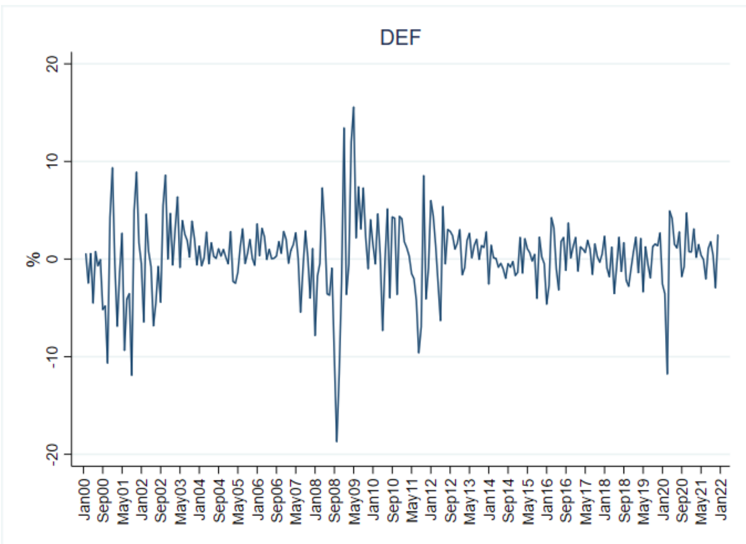
Figure 3.2: Excess returns, TERM, DEF, LAMBDA, and DOWNSIDE factors.



(a)

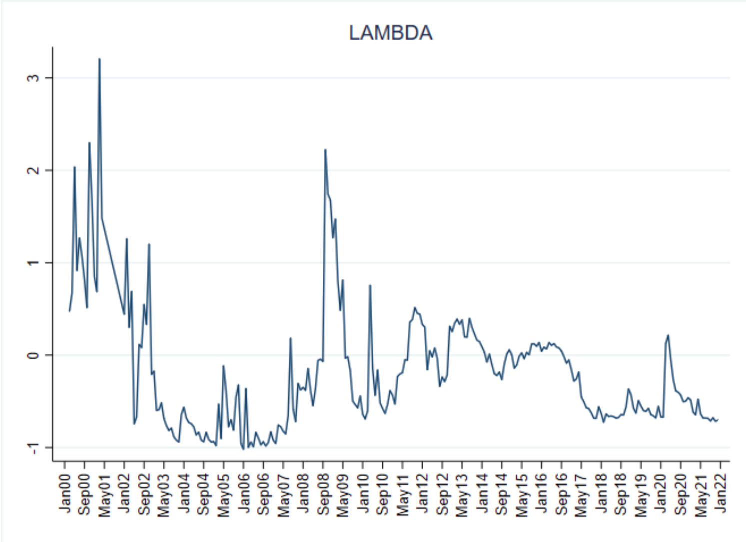


(b)

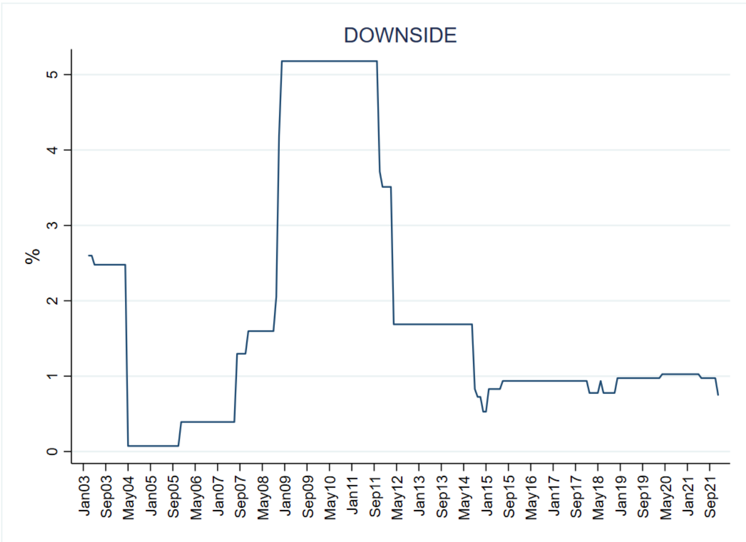


(c)

Figure 3.2 continued: Excess returns, TERM, DEF, LAMBDA, and DOWNSIDE factors.



(d)



(e)

This figure depicts the trend of common factors and excess returns during the sample period from 2000 to 2021. Monthly excess returns are the continuously compounded returns of an individual bond over the one-month Euribor rate in the previous month. TERM denotes the term premium as the difference between the monthly return of the 10-year German government bond index and the one-month Euribor rate in the previous month. DEF denotes the default premium, measured as the difference between the monthly return of the Bloomberg Pan-European High-Yield Index and the monthly return of the 10-year German government bond. LAMBDA is the sum of the normalised illiquidity proxies (Roll, FZR, and bid-ask spread) multiplied by their respective first principal component eigenvectors. DOWNSIDE is the 5% VaR of the composite bond's monthly empirical return distribution over the past 36 months on a rolling basis. Following Bai et al. (2019), we multiply the 5% VaR by -1 for the convenience of the interpretation. The excess return and LAMBDA variables are calculated monthly for each bond. The monthly mean value of excess returns and LAMBDA across all bonds are plotted.

Table 3.4 provides the pairwise correlation among TERM, DEF, LAMBDA, and DOWNSIDE. TERM and DEF are two common factors explaining the returns in the corporate bond market, as identified by Fama and French (1993). The correlation between these two factors is -0.638, which is statistically significant at a 1% level. Acharya et al. (2013) also find a negative correlation between the TERM and DEF factors (correlation = -0.529 at a 1% statistical significance level). There is less correlation between LAMBDA and DOWNSIDE (correlation = 0.094). Furthermore, LAMBDA and DOWNSIDE are also less correlated with TERM and DEF. As a result, we can make a clean interpretation of the illiquidity and downside risk implications that we aim to investigate.

Table 3.4: Pairwise correlation.

	TERM	DEF	LAMBDA	DOWNSIDE
TERM	1.000			
DEF	-0.638***	1.000		
	(0.000)			
LAMBDA	0.014***	-0.002	1.000	
	(0.004)	(0.701)		
DOWNSIDE	0.041***	0.108***	0.094***	1.000
	(0.000)	(0.000)	(0.000)	

The table presents the pairwise correlation of TERM, DEF, LAMBDA, and DOWNSIDE. TERM denotes the term premium as the difference between the monthly return of the 10-year German government bond index and the one-month Euribor rate in the previous month. DEF denotes the default premium, measured as the difference between the monthly return of the Bloomberg Pan-European High-Yield Index and the monthly return of the 10-year German government bond. LAMBDA is the sum of the normalised illiquidity proxies (Roll, FZR, and bid-ask spread) multiplied by their respective first principal component eigenvectors. DOWNSIDE is the 5% VaR of the total sample bond's monthly empirical return distribution over the past 36 months on a rolling basis. Following Bai et al. (2019), we multiply the 5% VaR by -1 for the convenience of the interpretation. The value in the bracket is the p-value. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

3.5.3 Results of Pooled Regression Models

Table 3.5 shows the results of pooled regression for the illiquidity augmented Fama and French 2-factor model with year and industry fixed effects across ratings, maturities, and industries from 2000 to 2021. The overall results suggest that excess returns are significantly related to TERM, DEF, and LAMBDA. Model 1 reports the estimated coefficients for the entire sample of bonds. The TERM, DEF, and LAMBDA coefficients are positively significant at 0.540, 0.610, and 0.194, respectively. The adjusted R^2 has increased to 11.9%, compared to 9.4% of the Fama and French 2-factor model, presented in Table A4 Model 1 in Appendix A. These results imply that all three factors positively affect the excess returns of Euro-denominated high-yield corporate bonds. Thus, adding the illiquidity factor to the Fama and French 2-factor model can enhance the explanatory power of the regression model.

With regard to TERM, comparing bonds with different ratings sheds light on the effect of interest rate risk on high-yield bonds. In particular, our results suggest that the TERM coefficient increases from 0.584 (at a 1% statistical significance level) for BB-rated bonds to 0.654 (at a 1% statistical significance level) for lowest-quality bonds with ratings of CCC and below. Furthermore, the BB-rated bond's coefficient is higher than the B-rated bond, suggesting that the BB-rated bond generally has a higher duration than the B-rated bond. By comparing the coefficients of the TERM by maturities, our results show that short-maturity bonds are less sensitive to interest rate fluctuations than long-maturity bonds, suggesting that the longer the maturity, the more sensitive bonds are to changes in the yield curve. For instance, the coefficient of TERM increases substantially from 0.088 (Maturity 1-3 years) to 0.615 (Maturity 10+ years).

The default risk factor, measured by DEF, increases as the bond's credit quality deteriorates. DEF has risen to 0.821 and is highly significant for bonds with a rating of CCC and below, from 0.586 and highly significant for BB-rated bonds. Using the coefficients of DEF across maturities, our results indicate that default risk is an increasing function of maturity, reaching the peak value for bonds with a maturity of over ten years. More specifically, the DEF coefficient is highly significant at 0.135

for short-maturity bonds (Maturity 1-3 years). It has increased substantially in value, up to 0.704 for bonds with a maturity of over ten years (at a 1% statistical significance level).

Of paramount importance to the analysis is the illiquidity factor, denoted as LAMBDA. The higher the coefficients of LAMBDA, the more sensitive the excess bond returns are to the illiquidity. The LAMBDA coefficients are generally positive and statistically significant across ratings, maturities, and industries, suggesting that illiquidity is an essential determinant of high-yield corporate bond returns. This result indicates that investors require a higher return as compensation for the illiquidity and supports hypothesis 1a.

Comparing the coefficients of LAMBDA by ratings, the coefficients tend to increase as ratings move from the BB to the CCC and below rating. In particular, the LAMBDA coefficient on bonds with a rating of CCC and below is 0.375, with a 1% statistical significance level, which is the largest among rating groups. Furthermore, multiplying its coefficient by the standard deviation of excess returns, indicating a standard deviation increase in LAMBDA, the excess returns are expected to increase by 2.47% (0.375 x 6.59% = 2.47%). The increase in the LAMBDA coefficient from BB-rated bonds to bonds rated CCC and below aligns with the flight to quality phenomenon and supports hypothesis 1b, that the effect of illiquidity on returns is more pronounced for bonds with a rating of CCC and below. The value of lowest-rated bonds deteriorates because investors are inclined to desert such bonds and relocate their money to safer assets. Under these circumstances, these bonds are difficult to liquidate, and their prices may plummet if the market becomes insufficiently liquid. As investors require a greater premium for the risk associated with owning these risky bonds, the lowest-rated high-yield corporate bonds (e.g., bonds with a rating of CCC and below) have a higher coefficient of the illiquidity factor.

In terms of the coefficient of LAMBDA by maturities, the pattern suggests that the illiquidity component tends to increase with maturity, in line with Dick-Nielsen et al. (2012). The LAMBDA coefficient is highest for the bond with a maturity of five to seven years among the maturity groups, almost eight times as high as the short-maturity bonds (Maturity 1-3 years). It increases from 0.041 (at a 10% statistical significance level) to 0.326 (at a 1% statistical significance level) before deteriorating for bonds with maturities longer than seven years. This result suggests that the effect of illiquidity on excess returns is different across maturities. In addition, the coefficient of LAMBDA is 0.139 and 0.317 for financial and non-financial bonds, respectively. Both these coefficients are statistically significant at a 1% level.

Table 3.5: Results of illiquidity augmented Fama and French 2-factor model.

Panel A: By ratings.

	Model 1 Sample bonds	Model 2 Rating BB	Model 3 Rating B	Model 4 Rating CCC and below
TERM	0.540***	0.584***	0.197**	0.654***
	(0.000)	(0.000)	(0.011)	(0.000)
DEF	0.610***	0.586***	0.617***	0.821***
	(0.000)	(0.000)	(0.000)	(0.000)
LAMBDA	0.194***	0.268***	-0.142	0.375***
	(0.000)	(0.000)	(0.142)	(0.004)
Constant	0.060	-3.998*	0.468	-12.212***
	(0.948)	(0.082)	(0.803)	(0.000)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	39,591	32,677	4,868	2,046
N	1,215	1,146	281	104
Adjusted R^2	0.119	0.196	0.062	0.114

Panel B: By maturities.

	Model 5 1-3 years	Model 6 3-5 years	Model 7 5-7 years	Model 8 7-10 years	Model 9 10+ years
TERM	0.088***	0.306***	0.546***	0.664***	0.615***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DEF	0.135***	0.360***	0.600***	0.691***	0.704***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LAMBDA	0.041*	0.134***	0.326***	-0.028	0.224***
	(0.069)	(0.000)	(0.000)	(0.674)	(0.000)
Constant	-0.081	0.542**	-3.970	1.022	0.709
	(0.701)	(0.048)	(0.158)	(0.250)	(0.645)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	4,651	5,487	9,257	6,915	13,281
N	298	247	276	164	230
Adjusted R^2	0.0517	0.126	0.168	0.191	0.100

Table 3.5 continued: Results of illiquidity augmented Fama and French 2-factor model.

Panel C: By industries.

	Model 10 Financials	Model 11 Non-financials
TERM	0.501***	0.586***
	(0.000)	(0.000)
DEF	0.570***	0.651***
	(0.000)	(0.000)
LAMBDA	0.139***	0.317***
	(0.000)	(0.000)
Constant	0.015	-0.097
	(0.949)	(0.923)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	23,126	16,465
N	839	376
Adjusted R^2	0.115	0.130

This table exhibits the results of the regression model (see Equation 3.7) with year and industry fixed effects across ratings, maturities, and industries spanning March 2000 to December 2021. The dependent variable is the monthly excess returns are the continuously compounded returns of an individual bond over the one-month Euribor rate in the previous month. TERM denotes the term premium as the difference between the monthly return of the 10-year German government bond index and the one-month Euribor rate in the previous month. DEF denotes the default premium, measured as the difference between the monthly return of the Bloomberg Pan-European High-Yield Index and the monthly return of the 10-year German government bond. LAMBDA is the sum of the normalised illiquidity proxies (Roll, FZR, and bid-ask spread) multiplied by their respective first principal component eigenvectors. The average excess returns for each rating, maturity, and industry group are equally weighted. The value in the bracket is the p-value. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

According to the results presented in Table 3.3, the empirical distribution of excess returns is skewed and exhibits fat tails. These results indicate that high-yield corporate bonds tend to have extreme returns. Hence, we add the downside risk factor to the illiquidity augmented Fama and French 2-factor model.

Table 3.6 presents the results of pooled regressions for the 4-factor model with year and industry fixed effects between March 2003 and December 2021. The results reveal the importance of TERM, DEF, LAMBDA, and DOWNSIDE for the pricing of high-yield corporate bonds. The estimated TERM, DEF, and LAMBDA coefficients exhibit similar qualitative and quantitative characteristics to the 3-factor model in Table 3.5. The DEF coefficient increases as the credit quality deteriorates and the bond's maturity increases. The illiquidity factor has a greater impact on excess returns for high-yield bonds with the lowest credit ratings. For instance, the excess return changes approximately by 2.39% (0.362 x 6.59% = 2.39%), and 0.59% (0.268 x 2.19% = 0.59%) for a standard deviation change in LAMBDA for bonds with a rating of CCC and below and BB-rated bonds, respectively. Additionally, bonds with a maturity between five and seven years tend to have the highest coefficient of LAMBDA among the maturity groups. This result may confirm that the illiquidity factor has a greater impact on Maturity 5-7 than on other maturity groups in the high-yield corporate bond market.

The DOWNSIDE coefficient is positive and statistically significant for the sample bonds, showing a positive relationship between the downside risk and excess bond returns, similar to the result reported by Bai et al. (2019). From Models 2 to 4, the DOWNSIDE coefficient increases from 0.116 (with a 5% statistical significance level) to 2.203 (with a 5% statistical significance level). The significant increase in the DOWNSIDE coefficient indicates that the downside risk is much higher for high-yield bonds with the lowest credit ratings. Investors are willing to take higher downside risks in exchange for possibly large profits.

The DOWNSIDE coefficients are statistically significant at a 1% level for bonds with a maturity of five to seven years and those over ten years. Particularly for long-maturity bonds, the DOWNSIDE coefficient is 0.498 (with a 1% statistical significance level), which is nearly twice as high as the coefficient of the bonds with a maturity of five to seven years. High-yield bonds are risky assets. Investors care about whether they will receive their coupon payments and principal back when bonds are matured. Long-maturity high-yield bonds may enhance the risk of negative returns and the uncertainty of receiving the principal and associated coupon payments. Therefore, the DOWNSIDE coefficient of long-maturity bonds is much higher than other maturity bonds after controlling for the year and industry fixed effects.

In Models 10 and 11 in Table 3.6, the DOWNSIDE coefficient is 0.109 without statistical significance and 0.507 with a 1% statistical significance level for financial and non-financial bonds, respectively. This result implies that the downside risk is more prominent for non-financial high-yield corporate bonds.

In summary, we find that TERM, DEF, LAMBDA, and DOWNSIDE are important common factors in pricing high-yield corporate bonds based on pooled regression models with year and industry fixed effects. In particular, the illiquidity and downside risk factors that impact excess returns are more prominent for Rating CCC and below, Maturity 5-7 years, Maturity 10+ years, and Non-financials.

Table 3.6: Results of downside and illiquidity augmented Fama and French 2-factor model.

Panel A: By ratings.

	Model 1 Sample bonds	Model 2 Rating BB	Model 3 Rating B	Model 4 Rating CCC and below
TERM	0.535***	0.584***	0.170**	0.642***
	(0.000)	(0.000)	(0.030)	(0.000)
DEF	0.605***	0.585***	0.595***	0.808***
	(0.000)	(0.000)	(0.000)	(0.000)
LAMBDA	0.194***	0.269***	-0.145	0.362***
	(0.000)	(0.000)	(0.135)	(0.006)
DOWNSIDE	0.290***	0.116**	1.588***	2.203**
	(0.000)	(0.015)	(0.000)	(0.024)
Constant	-0.609	-0.526	-4.253***	-22.546***
	(0.222)	(0.311)	(0.004)	(0.000)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	39,537	32,650	4,841	2,046
N	1,212	1,145	278	104
Adjusted R^2	0.119	0.197	0.063	0.116

Panel B: By maturities.

	Model 5 1-3 years	Model 6 3-5 years	Model 7 5-7 years	Model 8 7-10 years	Model 9 10+ years
TERM	0.088***	0.306***	0.545***	0.653***	0.608***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DEF	0.135***	0.359***	0.595***	0.683***	0.697***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LAMBDA	0.041*	0.133***	0.340***	-0.028	0.223***
	(0.073)	(0.000)	(0.000)	(0.682)	(0.000)
DOWNSIDE	0.013	0.040	0.270***	0.206	0.498***
	(0.832)	(0.666)	(0.006)	(0.155)	(0.001)
Constant	-0.082	0.540**	-0.508	-0.209	0.545
	(0.697)	(0.048)	(0.302)	(0.837)	(0.724)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	4,651	5,487	9,219	6,899	13,281
N	298	247	276	161	230
Adjusted R^2	0.052	0.126	0.171	0.187	0.100

Table 3.6 continued: Results of downside and illiquidity augmented Fama and French 2-factor model.

Panel C: By industries.

	Model 10 Financials	Model 11 Non-financials
TERM	0.499***	0.577***
	(0.000)	(0.000)
DEF	0.569***	0.643***
	(0.000)	(0.000)
LAMBDA	0.137***	0.328***
	(0.000)	(0.000)
DOWNSIDE	0.109	0.507***
	(0.155)	(0.000)
Constant	0.005	-1.164**
	(0.983)	(0.044)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	23,126	16,411
N	839	373
Adjusted R^2	0.115	0.130

This table exhibits the results of the regression model (see Equation 3.8) with industry and year fixed effects across ratings, maturities, and industries spanning March 2003 to December 2021. The dependent variable is the monthly excess returns are the continuously compounded returns of an individual bond over the one-month Euribor rate in the previous month. TERM denotes the term premium as the difference between the monthly return of the 10-year German government bond index and the one-month Euribor rate in the previous month. DEF denotes the default premium, measured as the difference between the monthly return of the Bloomberg Pan-European High-Yield Index and the monthly return of the 10-year German government bond. LAMBDA is the sum of the normalised illiquidity proxies (Roll, FZR, and bid-ask spread) multiplied by their respective first principal component eigenvectors. DOWNSIDE is the 5% VaR of the composite bond's monthly empirical return distribution over the past 36 months on a rolling basis. Following Bai et al. (2019), we multiply the 5% VaR by -1 for the convenience of the interpretation. The average excess returns for each rating, maturity, and industry group are based on equal weights. The value in the bracket is the p-value. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

3.5.4 Results of Markov-Switching Models

Table 3.7 reports the results for the 2-state Markov-switching regressions by ratings, maturities, and industries. According to the trend of excess returns exhibited in Figure 3.2 (a), we notice that returns are more volatile during crisis periods than in normal periods. Hence, the Markov-switching model with two regimes seems reasonable.[8] Sigma is a proxy for the estimated standard deviation of excess returns. Sigma with high values refers to the high-volatility state, while sigma with low values refers to the low-volatility state. We find time-varying effects of TERM, DEF, and LAMBDA on excess returns.

With regard to the total sample, the coefficients on TERM are positive and do not fluctuate much, decreasing from 0.538 (highly significant) during the high-volatility state down to 0.382 (highly significant) during the low-volatility state. As expected, default risk increases during stressed periods, as indicated by the increase in the DEF coefficient from 0.469 (highly significant) for the low-volatility state to 0.496 (highly significant) for the high-volatility state. This result implies higher credit risk premia in the Euro-denominated high-yield corporate bond market in times of financial distress.

The coefficient of LAMBDA is 0.618 (highly significant) during low-volatility periods, and -1.919 (highly significant) during high-volatility periods. The LAMBDA has the opposite effect on excess returns between the two states, being positive in the low-volatility state while negative in the high-volatility state. This result supports hypothesis 2a, that illiquidity exhibits time-varying behaviour. Due to the poor liquidity in the high-yield bond market, the market turmoil heightens the illiquidity risk. In addition, as investors tend to chase liquidity in times of market turmoil, the illiquid high-yield bonds become even more illiquid. In this case, the prices of these bonds decline significantly relative to those in the less volatile market. This flight to liquidity phenomenon is in line with previous empirical studies. For example, Chen et al. (2007) find that high-yield bonds provide a greater yield than investment-grade

8 We also produce a Markov-switching model with three regimes compared to the model with two regimes. The former model's AIC and SBIC are higher than the latter one. The model with a lower AIC or SBIC indicates a better description of the data. Thus, the two-regime model is more favourable than the three-regime one.

bonds after controlling for default risk and other bond characteristics, indicating that bond prices drop due to increased illiquidity. Beber et al. (2009) find that illiquidity plays a more significant role in a highly volatile market, after controlling for credit risk, in the Euro-area government bond market. Additionally, Acharya et al. (2013) find that coefficients of two innovative illiquidity measures are significantly negative for high-yield bonds while positive for investment-grade bonds in times of economic stress, suggesting that investors switch from a less liquid asset to a more liquid one.

In terms of the rating groups, the betas of TERM, DEF, and LAMBDA behave differently according to different levels of volatility. Results suggest that high-yield bonds with different ratings show different sensitivity to changes in interest rates, conditional on the volatility of the financial market. The betas of DEF are statistically significant across rating groups, being higher during the high-volatility state than during the low-volatility state. The risk of bonds tends to increase with the deterioration of credit ratings. The highly volatile market may enhance the risk of these bonds, so the beta of DEF for the rating CCC and below group (0.730 and highly significant) is much higher than for other rating groups.

For BB-rated bonds, the beta of LAMBDA is 0.185 with a 5% statistical significance level during the low-volatility state and -0.299 without statistical significance levels during the high-volatility state. The LAMBDA beta for bonds rated as CCC and below shows a distinctive picture from other rating groups. The beta is -0.153 with a 1% statistically significant level in the low-volatility state, and -1.230 with a 5% statistical significance level in the high-volatility state. This result supports hypothesis 2b that the price effect of time-varying illiquidity differs between bonds with a BB rating and those with a rating of CCC and below. The more negative LAMBDA beta of lower-rated high-yield bonds confirms the flight to liquidity phenomenon. Illiquidity increases as a function of deteriorating ratings: bonds rated as CCC and below are less liquid than those rated as B and above. In times of economic stress, investors are more likely to switch from lower-rated bonds (e.g., bonds rated as CCC and below) to higher-rated bonds (e.g., BB-rated or investment-grade bonds), exacerbating the illiquidity in the lower-rated bond market. Investors have to sell at a considerable discount. Therefore, the prices of high-yield bonds with the lowest credit ratings drop significantly.

With respect to maturity groups, the coefficients of TERM, DEF, and LAMBDA are different among short-, medium-, and long-maturity bonds across the two states. During the low-volatility state, the TERM beta rises with increased maturity years. For example, the TERM beta rises from 0.223 (statistically significant at a 1% level) for bonds with a maturity of between three and five years, to 0.779 (statistically significant at a 1% level) for those with more than ten years of maturity. While in the high-volatility state, short-maturity (Maturity 1-3 years) and long-maturity bonds (Maturity 10+ years) are more sensitive to sudden changes in the term structure of interest rates.

A similar pattern is displayed for DEF. The coefficient of DEF rises as maturity years increase, being 0.038 for bonds with a maturity of fewer than three years, and 0.637 for bonds with a maturity of over ten years during the low-volatility state. Furthermore, DEF betas are more significant in a high-volatile market than in a low-volatile market. For example, the DEF beta (Maturity 1-3 years) rises from 0.038 with a 1% statistical significance level in the low-volatility state, to 0.302 with a 5% statistical significance level in the high-volatility state. Default risk increases significantly when economic conditions deteriorate, especially for long-maturity bonds.

High-yield bonds with a maturity of more than five years have a sign change from positive to negative in the coefficient of LAMBDA during the high-volatility state. According to Chen et al. (2007), short-maturity bonds are more liquid than long-maturity bonds. Investors prefer to invest in liquid assets when the market is highly volatile. In this case, prices of less liquid high-yield bonds drop significantly, and the sign of the LAMBDA factor becomes negative.

The coefficients of TERM, DEF, and LAMBDA respond differently to bonds issued by financial and non-financial industries across the two states, particularly for LAMBDA. The LAMBDA betas are higher in magnitude for bonds issued by financial industries than their non-financial counterparts. In the low-volatility state, the LAMBDA beta is 1.058 (with a 1% statistical significance level) for financial bonds, and 0.273 (with a 1% statistical significance level) for non-financial bonds. When the market is highly volatile, the LAMBDA beta is -2.918 (and highly significant) for bonds issued by financial industries, compared to -0.161 (without statistical significance levels) for bonds issued by non-financial counterparts. A similar result was found in the European investment-grade corporate bond market by Aussenegg et al. (2017), with a higher illiquidity coefficient (in an absolute value) for financial bonds than non-financial bonds in a stress regime. These results may arise from heightened uncertainty over bank bailouts in the aftermath of the 2008 financial crisis. The prices of financial bonds are affected more by the LAMBDA factor than of non-financial bonds.

Comparing variables across two states, we find that the coefficients of LAMBDA are higher (in absolute terms) than other risk factors for the total sample. The coefficients of LAMBDA for Rating CCC and below, and Financials are more significant in the high-volatility state. Our results suggest that illiquidity becomes a dominant driver in pricing high-yield corporate bonds during market turmoil, particularly for high-yield bonds with the lowest credit ratings and bonds issued by financial issuers.

The estimated high likelihood of remaining in different states is indicative of a persistent market. The last column of Table 3.7 shows that bonds with a rating of B and above have higher persistence of staying in the low-volatility state, and those with a rating of CCC and below exhibit higher persistence of remaining in the high-volatility state.

Table 3.7: Results of Markov-switching regressions for the 3-factor model.

	Obs.	TERM	DEF	LAMBDA	Constant	Sigma	P_{ii}
Total sample	254						
High-volatility state		0.538***	0.496***	-1.919***	-0.578**	1.128	0.001
		(0.000)	(0.000)	(0.000)	(0.018)		
Low-volatility state		0.382***	0.469***	0.618***	0.695***	0.878	0.794
		(0.000)	(0.000)	(0.000)	(0.000)		
Rating BB	247						
High-volatility state		0.336	0.562***	-0.299	0.239	2.830	0.898
		(0.110)	(0.000)	(0.441)	(0.457)		
Low-volatility state		0.519***	0.490***	0.185**	0.270***	0.274	0.948
		(0.000)	(0.000)	(0.015)	(0.000)		
Rating B	234						
High-volatility state		0.161	0.440***	0.267	1.139*	3.985	0.787
		(0.640)	(0.000)	(0.710)	(0.050)		
Low-volatility state		0.345***	0.406***	0.093	0.353***	0.662	0.920
		(0.000)	(0.000)	(0.461)	(0.000)		
Rating CCC and below	230						
High-volatility state		0.710***	0.730***	-1.230**	0.689**	2.761	0.748
		(0.001)	(0.000)	(0.014)	(0.017)		
Low-volatility state		0.024	0.016*	-0.153***	0.684***	0.234	0.681
		(0.314)	(0.070)	(0.002)	(0.000)		
Maturity 1-3 years	125						
High-volatility state		0.603**	0.302**	0.565	0.521	1.355	0.781
		(0.024)	(0.041)	(0.567)	(0.253)		
Low-volatility state		0.020	0.038***	0.088	0.319***	0.280	0.948
		(0.414)	(0.003)	(0.184)	(0.000)		
Maturity 3-5 years	190						
High-volatility state		-0.072	0.482***	1.839**	1.039*	3.859	0.756
		(0.857)	(0.000)	(0.032)	(0.092)		
Low-volatility state		0.223***	0.226***	0.067	0.267***	0.359	0.928
		(0.000)	(0.000)	(0.414)	(0.000)		
Maturity 5-7 years	247						
High-volatility state		-0.387	0.376***	-0.096	0.728	3.230	0.872
		(0.217)	(0.000)	(0.861)	(0.158)		
Low-volatility state		0.336***	0.327***	0.165*	0.364***	0.452	0.965
		(0.000)	(0.000)	(0.063)	(0.000)		
Maturity 7-10 years	254						
High-volatility state		0.360*	0.422***	-0.258	1.054***	2.673	0.861
		(0.086)	(0.000)	(0.432)	(0.000)		
Low-volatility state		0.595***	0.578***	0.107	0.280***	0.408	0.919
		(0.000)	(0.000)	(0.223)	(0.000)		
Maturity 10+ years	213						
High-volatility state		0.609**	0.779***	-0.239	0.269	2.618	0.804
		(0.020)	(0.000)	(0.700)	(0.514)		
Low-volatility state		0.779***	0.637***	0.043	0.280***	0.506	0.941
		(0.000)	(0.000)	(0.720)	(0.000)		

Table 3.7 continued: Results of Markov-switching regressions for the 3-factor model.

	Obs.	TERM	DEF	LAMBDA	Constant	Sigma	P_{ii}
Financials	201						
High-volatility state		0.551***	0.532***	-2.918***	-1.539***	1.129	0.262
		(0.003)	(0.000)	(0.000)	(0.000)		
Low-volatility state		0.309***	0.412***	1.058***	0.773***	1.008	0.882
		(0.000)	(0.000)	(0.000)	(0.000)		
Non-financials	254						
High-volatility state		0.359**	0.470***	-0.161	0.719***	1.948	0.858
		(0.010)	(0.000)	(0.490)	(0.000)		
Low-volatility state		0.684***	0.645***	0.273***	0.318***	0.273	0.890
		(0.000)	(0.000)	(0.000)	(0.000)		

The table presents the results of a two-state Markov-switching model with TERM, DEF, and LAMBDA (see Equation 3.9), allowing the intercepts and coefficients of factors to change between the two states. The dependent variable is the monthly time series of average excess returns, which are based on equal weights for each portfolio (i.e., rating, maturity, and industry). TERM denotes the term premium as the difference between the monthly return of the 10-year German government bond index and the one-month Euribor rate in the previous month. DEF denotes the default premium, measured as the difference between the monthly return of the Bloomberg Pan-European High-Yield Index and the monthly return of the 10-year German government bond. LAMBDA is the sum of the normalised illiquidity proxies (Roll, FZR, and bid-ask spread) multiplied by their respective first principal component eigenvectors. Obs. reports the number of monthly returns for each group. P_{ii} denotes the probability of staying in the same state in the next period. The estimated standard deviation of excess return is reported as sigma. Sigma with a high value refers to high-volatility periods, while sigma with a low value refers to low-volatility periods. The value in the bracket is the p-value. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3.8 reports the results of Wald tests for differences in the coefficients of TERM, DEF, and LAMBDA between the high-volatility and low-volatility states. In most cases, the null hypothesis of equal factor loadings across states is rejected.

Notably, the coefficients of LAMBDA are significantly different between the high-volatility and low-volatility states for Total sample, Rating CCC and below, Maturity 3-5 years, Financials and non-Financials. These results support the existence of time-varying illiquidity on excess returns and suggest that investors prefer liquid assets in times of financial stress.

Table 3.8: Wald tests of equality of coefficients across states for the 3-factor model.

	TERM		DEF		LAMBDA	
	Chi-sq	P-value	Chi-sq	P-value	Chi-sq	P-value
Total sample	1.100	0.294	0.250	0.619	46.570	0.000
Rating BB	0.730	0.393	1.120	0.289	1.490	0.223
Rating B	0.270	0.601	0.090	0.760	0.060	0.811
Rating CCC and below	9.310	0.002	39.040	0.000	4.520	0.034
Maturity 1-3 years	4.690	0.030	3.170	0.075	0.230	0.630
Maturity 3-5 years	0.530	0.465	4.440	0.035	4.210	0.040
Maturity 5-7 years	5.270	0.022	0.330	0.568	0.220	0.637
Maturity 7-10 years	1.220	0.270	5.500	0.019	1.160	0.282
Maturity 10+ years	0.400	0.527	2.460	0.117	0.190	0.664
Financials	1.500	0.221	3.660	0.056	57.080	0.000
Non-financials	5.270	0.022	12.630	0.000	3.140	0.076

The table presents Wald tests on the equality of coefficients between the high-volatility and low-volatility states, as distributed by ratings, maturities, and industries. The null hypothesis is that the coefficients of TERM, DEF, and LAMBDA are not significantly different across the two states.

Table 3.9 presents the results for the Markov-switching model of the 4-factor model. Overall, results indicate that returns are significantly related to TERM, DEF, and LAMBDA across two states, suggesting that these factors are essential contributors to excess returns in the high-yield corporate bond market. As expected, the coefficients of these risk factors are higher (in absolute terms) in the high-volatility state than in the low-volatility state. The time-varying coefficients of DOWNSIDE on excess returns are different across portfolio groups. In the low-volatility state, the DOWNSIDE coefficients are statistically significant for the groups of the total sample, Maturity 1-3 years, Maturity 5-7 years, and Non-financials. In the high-volatility state, the DOWNSIDE coefficients are statistically significant for bonds with a maturity of fewer than three years, and those issued by the financial industry. In general, the estimated coefficients of all four factors have a sizeable difference across the two states. Factor coefficients for TERM, DEF, and LAMBDA are qualitatively similar to those of the 3-factor model, presented in Table 3.7

In terms of the total sample, TERM marginally decreases from 0.459 in the low volatility period down to 0.369 during the high volatility period, while the DEF coefficient increases from 0.450 (at a 1% statistical significance level) in the low volatility state, up to 0.561 (at a 1% statistical significance level) during stressed periods, suggesting higher credit pressures in the Euro-denominated high-yield corporate bond market in times of financial strains. The LAMBDA coefficient switches the sign from positive in the low-volatility state to negative in the high-volatility state, which is similar to the result presented in Table 3.7. The coefficient of DOWNSIDE risk increases from 0.043 during the low-volatility state, to 0.087 during the high-volatility state, indicating the adverse economic condition enhances the probability of loss, as reflected by DOWNSIDE.

With regard to the rating groups, the TERM beta is much higher for bonds with a rating of CCC and below than for other rating groups in times of market stress, indicating that the uncertainty of the market leads to lower-rated bonds being more sensitive to changes in interest rates. As expected, lower-rated high-yield bonds (e.g., Rating CCC and below) tend to have a higher DEF beta than those with better credit quality (e.g., Rating BB) in high-volatility periods. The default risk also increases with enhanced market volatility. The LAMBDA beta has a higher value in magnitude for bonds with a rating of CCC and below than those with a rating of BB, suggesting a flight to liquidity phenomenon in the high-volatility state, consistent with hypothesis 2b.

With respect to DOWNSIDE across rating groups, the DOWNSIDE coefficient is higher in magnitude during the high-volatility state than during the low-volatility state. For instance, the coefficient of DOWNSIDE increases from 0.042 in the low-volatility state to 0.137 in the high-volatility state for BB-rated bonds. This result implies that the effect of downside risk on excess returns is stronger in times of a more volatile market. Additionally, in the high-volatility state, the DOWNSIDE beta is 0.137 for BB-rated, while -0.162 for CCC-rated (or lower) bonds, indicating a substantial drop in prices for high-yield bonds with the lowest credit ratings. As investors prefer to hold liquid assets in a volatile market, the liquidity dries up for high-yield bonds with the lowest credit ratings (e.g. Rating CCC and below). Investors have to sell these bonds at a considerable discount, giving rise to a high possibility of loss, resulting in a negative relationship between the coefficient of DOWNSIDE and excess returns for high-yield bonds with the lowest credit ratings.

The coefficients of TERM by maturity groups across the two states are consistent with the 3-factor results presented in Table 3.7. The TERM beta is an increasing function of maturity during the low-volatility state, from 0.009 (Maturity 1-3 years) to 0.783 (Maturity 10+ years), indicating that high-yield bonds with longer maturity years are more sensitive to changes in interest rates when the market is in normal conditions. When the market becomes highly volatile, bonds with a maturity of fewer than three years (0.421 with a 10% statistical significance level) and those with a maturity of over ten years (0.559 with a 5% statistical significance level) are more affected by the fluctuation of interest rates than other maturity groups. This result suggests that TERM has a greater impact on excess returns for high-yield bonds with short and long maturities than those with medium ones.

In line with the results shown in Table 3.7, in the high-volatility state, the coefficient of DEF is more pronounced than in the low-volatility state. The DEF coefficient tends to be an increasing function of maturity in the respective states. The LAMBDA beta is also conditional on the market's volatility, being higher in magnitude during the high-volatility state than during the low-volatility state for high-yield bonds with a maturity of fewer than five years or more than seven years.

DOWNSIDE betas are statistically significant for bonds with fewer than three years of maturity across the two states. The beta increases from 0.033 (with a 10% statistical significance level) in the low-volatility state, to 0.337 (with a 5% statistical significance level) in the high-volatility state, suggesting that investors require a high premium to hold these bonds in a highly volatile market. The positive association between the downside risk factor and excess returns is also consistent with the result presented by Bai et al. (2019).

Regarding the industry group, the coefficient of DOWNSIDE is 0.177 (with a 1% statistical significance level) and 0.116 in times of market stress for financial and non-financial bonds, respectively. While in the low-volatility state, the DOWNSIDE beta is 0.483 and -0.042 (with a 10% statistical significance level) for the respective financial and non-financial bonds. This result indicates that the time-varying effect of downside risk on excess returns is different for high-yield bonds issued by financial and non-financial industries. In addition, comparing coefficients of TERM, DEF, LAMBDA, and DOWNSIDE, we find that the default and illiquidity factors are crucial drivers of explaining excess returns in the high-yield corporate bond market, particularly during the high-volatility state.

The estimated high likelihood of remaining in different states is indicative of a persistent market. The last column of Table 3.9 shows that the persistence is likely higher in the low-volatility state than in the high-volatility state. Bonds with a rating of CCC and below and those issued by financial institutions are an exception. These results are generally consistent with the result presented in Table 3.7.

Table 3.9: Results of Markov-switching regressions for the 4-factor model.

	Obs.	TERM	DEF	LAMBDA	DOWNSIDE	Constant	Sigma	P_{ii}
Total sample	226							
High-volatility state		0.369**	0.561***	-0.504	0.087	0.057	1.462	0.646
		(0.020)	(0.000)	(0.271)	(0.519)	(0.897)		
Low-volatility state		0.459***	0.450***	0.109*	0.043*	0.287***	0.298	0.881
		(0.000)	(0.000)	(0.096)	(0.052)	(0.000)		
Rating BB	226							
High-volatility state		0.675***	0.698***	-0.680*	0.137	-0.468	1.942	0.893
		(0.000)	(0.000)	(0.088)	(0.397)	(0.402)		
Low-volatility state		0.517***	0.480***	0.177***	0.042	0.231***	0.257	0.951
		(0.000)	(0.000)	(0.006)	(0.254)	(0.000)		
Rating B	215							
High-volatility state		0.195	0.438***	0.617	-0.064	0.970	3.441	0.810
		(0.556)	(0.000)	(0.501)	(0.832)	(0.268)		
Low-volatility state		0.376***	0.435***	-0.144	0.061	0.119	0.652	0.941
		(0.000)	(0.000)	(0.371)	(0.115)	(0.315)		
Rating CCC and below	216							
High-volatility state		0.805***	0.807***	-1.314***	-0.162	0.772*	2.557	0.774
		(0.000)	(0.000)	(0.009)	(0.341)	(0.062)		
Low-volatility state		0.010	0.007	-0.269***	-0.026	0.613***	0.196	0.643
		(0.677)	(0.505)	(0.000)	(0.246)	(0.000)		
Maturity 1-3 years	125							
High-volatility state		0.421*	0.250*	0.289	0.337**	-0.153	1.220	0.780
		(0.098)	(0.062)	(0.756)	(0.049)	(0.761)		
Low-volatility state		0.009	0.026*	0.074	0.033*	0.266***	0.273	0.946
		(0.720)	(0.067)	(0.264)	(0.066)	(0.000)		
Maturity 3-5 years	190							
High-volatility state		-0.074	0.481***	1.837*	-0.003	1.043	3.860	0.758
		(0.855)	(0.000)	(0.083)	(0.993)	(0.357)		
Low-volatility state		0.213***	0.218***	0.053	0.030	0.226***	0.358	0.929
		(0.000)	(0.000)	(0.526)	(0.318)	(0.000)		
Maturity 5-7 years	226							
High-volatility state		-0.004	0.471***	0.085	0.018	0.227	3.083	0.718
		(0.992)	(0.000)	(0.939)	(0.967)	(0.852)		
Low-volatility state		0.324***	0.319***	0.125	0.050**	0.277***	0.435	0.956
		(0.000)	(0.000)	(0.134)	(0.027)	(0.000)		
Maturity 7-10 years	226							
High-volatility state		0.457*	0.531***	-0.544	-0.074	1.004	2.609	0.772
		(0.067)	(0.000)	(0.338)	(0.728)	(0.131)		
Low-volatility state		0.589***	0.575***	0.092	0.022	0.247***	0.404	0.907
		(0.000)	(0.000)	(0.351)	(0.465)	(0.001)		
Maturity 10+ years	213							
High-volatility state		0.559**	0.745***	-0.621	0.278	-0.353	2.589	0.806
		(0.034)	(0.000)	(0.406)	(0.324)	(0.628)		
Low-volatility state		0.783***	0.640***	0.071	-0.028	0.333***	0.503	0.941
		(0.000)	(0.000)	(0.571)	(0.335)	(0.000)		

Table 3.9 continued: Results of Markov-switching regressions for the 4-factor model.

	Obs.	TERM	DEF	LAMBDA	DOWNSIDE	Constant	Sigma	P_{ii}
Financials	201							
High-volatility state		0.271***	0.366***	0.820***	0.177***	0.458***	0.961	0.932
		(0.000)	(0.000)	(0.000)	(0.008)	(0.001)		
Low-volatility state		0.550**	0.397***	-4.042***	0.483	-3.679**	0.779	0.462
		(0.021)	(0.000)	(0.000)	(0.134)	(0.019)		
Non-financials	226							
High-volatility state		0.588***	0.589***	-0.777**	0.116	0.054	1.603	0.694
		(0.000)	(0.000)	(0.032)	(0.353)	(0.877)		
Low-volatility state		0.620***	0.594***	0.372***	-0.042*	0.427***	0.248	0.817
		(0.000)	(0.000)	(0.000)	(0.070)	(0.000)		

The table presents the results of a two-state Markov-switching model with TERM, DEF, LAMBDA, and DOWNSIDE (see Equation 3.10), allowing the intercepts and coefficients of factors to change between the two states. The dependent variable is the monthly time-series of average excess returns, which are based on equal weights for each portfolio (i.e., rating, maturity, and industry). TERM denotes the term premium as the difference between the monthly return of the 10-year German government bond index and the one-month Euribor rate in the previous month. DEF denotes the default premium, measured as the difference between the monthly return of the Bloomberg Pan-European High-Yield Index and the monthly return of the 10-year German government bond. LAMBDA is the sum of the normalised illiquidity proxies (Roll, FZR, and bid-ask spread) multiplied by their respective first principal component eigenvectors. DOWNSIDE is 5% VaR of the composite bond's monthly empirical return distribution over the past 36 months on a rolling basis. Following Bai et al. (2019), we multiply the 5% VaR by -1 for the convenience of the interpretation. Obs. reports the number of monthly returns. P_{ii} denotes the probability of staying in the same state in the next period. The estimated standard deviation of excess return is reported as sigma. Sigma with high values refers to high-volatility periods, while sigma with low values refers to low-volatility periods. The value in the bracket is the p-value. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3.10 reports the results of Wald tests for differences in the coefficients of TERM, DEF, LAMBDA, and DOWNSIDE between the high-volatility and low-volatility states. The switching coefficients of TERM, DEF, and LAMBDA are generally similar to the results presented in Table 3.8. The result shows significant differences in the DOWNSIDE coefficients for high-yield bonds with a maturity of fewer than three years across the two states.

Table 3.10: Wald tests of equality of coefficients across regimes for the 4-factor model.

	TERM		DEF		LAMBDA		DOWNSIDE	
	Chi-sq	P-value	Chi-sq	P-value	Chi-sq	P-value	Chi-sq	P-value
Total sample	0.310	0.575	3.670	0.055	1.700	0.192	0.100	0.752
Rating BB	0.840	0.360	13.510	0.000	4.410	0.036	0.310	0.579
Rating B	0.290	0.591	0.000	0.980	0.670	0.414	0.170	0.684
Rating CCC and below	11.480	0.001	37.540	0.000	4.200	0.041	0.610	0.434
Maturity 1-3 years	2.570	0.109	2.740	0.098	0.050	0.818	3.120	0.077
Maturity 3-5 years	0.490	0.482	4.210	0.040	2.820	0.093	0.010	0.931
Maturity 5-7 years	0.700	0.403	1.750	0.186	0.000	0.972	0.000	0.944
Maturity 7-10 years	0.270	0.602	0.260	0.614	1.210	0.272	0.200	0.657
Maturity 10+ years	0.270	0.602	0.260	0.614	1.210	0.272	0.200	0.657
Financials	1.060	0.304	0.150	0.696	49.020	0.000	0.780	0.377
Non-financials	0.060	0.811	0.010	0.926	9.620	0.002	1.440	0.230

The table presents Wald tests on the equality of coefficients between the high-volatility and low-volatility states, as distributed by ratings, maturities, and industries. The null hypothesis is that the coefficients of TERM, DEF, LAMBDA, and DOWNSIDE are not significantly different across the two states.

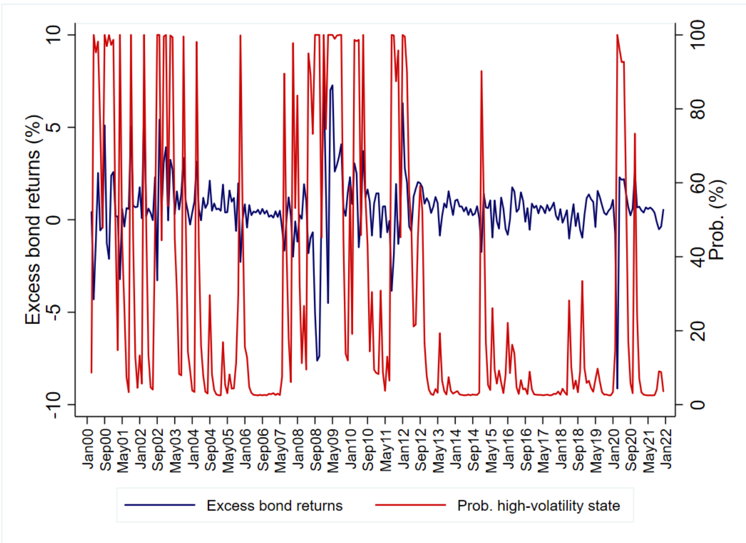
Given the reported differences in the estimated coefficients of factors across the two states, they reveal evidence of state-switching in the data. The Markov-switching model estimates the probabilities of transition to different states. However, it neither economically identifies the number of states nor provides a date for state changes. We plot the estimated state probabilities and excess returns for the total sample presented in Figure 3.3. The figure illustrates a positive correlation between the probability of being in a high-volatility state and the volatility of excess returns. The peaks indicate a rise in the volatility of excess return, which is related to a strong possibility of being in a high-volatility state. We select some specific events and examine whether these events are related to the filtered probabilities between March 2000 and December 2021.

In the early 2000s, a downturn in economic activity could harm the Euro-denominated high-yield corporate bond market. For example, France and Germany experienced a recession at the end of 2001, but by May 2002, their respective recessions were deemed over. As a result of the dot-com bubble crash, many European countries' economies suffered. The negative effect was reflected in the high volatility of excess returns in the high-yield corporate bond market between 2000 and 2003.

The global financial crisis started in 2007 with a problem in the subprime mortgage market in the US. It culminated on 15$^{\text{th}}$ September 2008 with the bankruptcy of the investment bank Lehman Brothers. The European debt crisis subsequently followed. In 2010, the sovereign debt markets of the PIIGS (Portugal, Ireland, Italy, Greece, and Spain) faced enormous financial strain, which expanded to the Eurozone national banks and the European Central Bank. In April 2010, Greece's debt was downgraded to high-yield status. Following the publication of the Federal Open Market Committee (FOMC) minutes in July 2014, the FOMC cautioned that the high-yield bond market was overvalued. High-yield bonds fell dramatically in value, and bond funds faced abrupt outflows (Bisschop Steins et al., 2016). In addition, the German government's debt suffered a humbling drop in April 2015, with tremors extending to bond markets in the periphery of the Eurozone (Davies, 2015). A significant decline in prices in the Euro-denominated high-yield corporate bond market between September 2014 and May 2015 is captured in Figure 3.3.

In March 2020, as the COVID-19 crisis escalated, treasury securities were under pressure in the market. For example, a 64-basis-point jump in the 10-year yield accompanied the stock market's continuing decline (Jørgensen, 2021). This uncertainty in the financial market could also have affected the high-yield corporate bond market, which potentially led to a highly volatile market between March and August of 2020. Overall, the estimated outcome exhibited in Figure 3.3 offers strong support for the conclusion that our high-volatility state is connected to actual events from the recent economic downturn.

Figure 3.3: Estimated probability of being in the high-volatility state.



The figure shows the estimated state probabilities and excess returns for the total sample. The estimated state probability is based on the filtered probability, shown in the red line. A value of 100% implies being in the high-volatility state, and a value of 0% indicates being in the low-volatility state. The monthly time series of average excess returns for the total sample is presented in the blue line.

3.6 Robustness Checks

3.6.1 Alternative Proxy for Downside Risk

We follow Bai et al. (2019) and use a 10% expected shortfall (ES) as an alternative proxy for the downside risk factor. The 10% ES is calculated as the average of the four observations with the lowest monthly return during the last 36 months on a rolling basis. To accurately interpret the results, we multiply the original 10% ES by -1. The higher the ES, the higher the excess returns. We firstly investigate the effect of the 10% ES on excess returns using pooled regressions with year and industry fixed effects across ratings, maturities, and industries. Then, we examine the time-varying effect of the 10% ES on excess returns using a two-state Markov-switching model. Results remain similar with an alternative proxy for the downside risk factor, presented in Table A5, Table A6, and Table A7 in Appendix A.[9]

9 As the correlation between TERM and DEF is high (-0.638 with a 1% statistical significance level, presented in Table 3.4) and high-yield corporate bonds have a high probability of default, we drop the TERM variable from the regression models to reduce the potential collinearity issues. Results of pooled regression models and Markov-switching models remain robust. Results are available upon request.

3.7 Summary

This chapter investigates the common factors in pricing Euro-denominated high-yield corporate bonds, distributed by ratings, maturities, and industries. Given the infrequency of trading and high volatility of returns in the high-yield bond market, we add the illiquidity and downside risk factors to the Fama and French 2-factor model. The illiquidity factor is derived from the Roll, FZR, and bid-ask spread variables based on the principal component analysis, and the downside risk factor is motivated by Bai et al. (2019).

We start from the pooled regression models to examine the effects of the term, default, illiquidity, and downside factors on excess returns after controlling for year and industry fixed effects based on the bond level. We find that these factors are essential in explaining excess returns. The coefficients of the term, default, illiquidity and downside factors tend to increase with decreasing ratings, particularly for bonds with a rating of CCC and below. The effect of illiquidity and downside risk on excess returns is different across maturities. The illiquidity is greater for bonds with a maturity of five to seven years, while the downside risk is more prominent for bonds with more than ten years of maturity. We find that the term, default, and illiquidity have a more substantial impact on excess returns for high-yield bonds issued by non-financial than financial industries.

We further investigate the time-varying effects of the term, default, illiquidity, and downside factors on excess returns by adopting a two-state Markov-switching model across ratings, maturities, and industries. We find that Illiquidity is the dominant driver in pricing high-yield bonds, far more than in the low-volatility state. Particularly, prices of bonds with a rating of CCC and below drop in response to liquidity shocks. This flight to liquidity phenomenon is more prominent in times of market distress than in normal periods. Additionally, the downside risk factor may explain the excess returns for short-maturity high-yield corporate bonds (e.g., Maturity 1-3 years). This factor becomes more pronounced in the high-volatility state than in the low-volatility state.

Our findings provide valuable information that may be used for performance analysis and asset allocation in the high-yield bond market. Investing in high-yield bonds and determining the essential factors for explaining excess returns are of fundamental significance to academics and professionals. For academics, understanding the causes of borrowing costs necessitates investigating the role of common factors in high-yield bond pricing. For finance professionals, understanding the sensitivities of bond prices to common factors facilitates their investment decisions.

Chapter Four

Underpricing in the Euro-Denominated High-Yield Corporate Bond Market

4.1 Introduction

Banking regulations have become more stringent after the financial crisis, making traditional bank loans more difficult to obtain. The Euro-denominated high-yield corporate bond market provides an important opportunity for companies to raise their capital. This explains the popularity of high-yield bonds in recent years. In this chapter, we examine pricing in the high-yield bond primary market. Specifically, we provide evidence on the degree and determinants of underpricing.

The high-yield bond is a distinct asset class with characteristics distinguishing it from an investment-grade bond. Previous studies have reported differences in the underpricing of high-yield and investment-grade bonds. Datta et al. (1997) find evidence that initial offerings of high-yield bonds are underpriced, while initial offerings of investment-grade bonds are overpriced. Cai et al. (2007) examine the initial and seasoned bond offerings in the US corporate bond market. They report the existence of underpricing for high-yield bonds but not for investment-grade bonds. Nagler and Ottonello (2018) find that high-yield bonds have a greater underpricing (by 27 bps) than investment-grade bonds in the US corporate bond market. Overall, the evidence suggests a higher degree of underpricing for high-yield bonds compared to their investment-grade counterparts.

Most issuers of high-yield bonds are less well-known than investment-grade bonds.

They tend to be private companies, small public companies, and fallen angels that have previously issued investment-grade bonds but are currently undergoing hard times. Information asymmetry problems are more prominent in the high-yield bond market than in the investment-grade bond market. For example, the bookbuilding theory sees underpricing as remuneration for informed investors providing information to the underwriters (Benveniste and Spindt, 1989; Benveniste et al., 2002). The degree of underpricing rises when there is a large degree of information asymmetry throughout the bookbuilding process (Cai et al., 2007; Nikolova et al., 2020; Rischen and Theissen, 2021). In contrast, underpricing is a costly signal to discern between excellent and poor firms caused by information asymmetry problems between firms and issuers (Allen and Paulhaber, 1989; Grinblatt and Hwang, 1989; Welch, 1989). For instance, issuers of high-quality bonds tend to use greater underpricing as a positive signal to set themselves apart from others (Liu and Magnan, 2014). Due to the high information asymmetry problems associated with high-yield bonds, it is worth investigating whether the underpricing can be explained by either the bookbuilding theory or the signalling theory.

Compared to investment-grade bonds, high-yield bonds have a lower credit quality and a higher probability of default. The prestige of reputable underwriters, therefore, may play a more critical role in providing underwriting services in this market. Questions arise about whether the reputation of underwriters can certify the issuers and reduce the level of information asymmetry between issuers and investors, weakening the degree of underpricing. Prior studies highlight the role of underwriter reputation from two perspectives in the corporate bond market. Datta et al. (1997) and Fang (2005) suggest that the involvement of reputable underwriters can effectively reduce the degree of bond underpricing and offering yield. However, Andres et al. (2014) point out that a high-yield bond backed by an underwriter, having a position in the top ranking of the league table, is more likely to have a higher downgrade and default risk.

It is worth mentioning that the above studies examine the period before the recent financial crisis in 2008. Since then, banking regulations have become more stringent. The effect of reputable underwriters, therefore, may differ before and after the financial crisis. In a recent study by Rischen and Theissen (2021), the underwriter reputation does not affect the degree of underpricing during the 2002-2017 sample period in the Euro-denominated corporate bond market. As high-yield bonds are generally underwritten by multiple lead underwriters in Europe, we adopt a syndicate market share as a measure of underwriter reputation by following Carbó-Valverde et al. (2017) and further explore the role of top-rated underwriters in explaining the extent of underpricing.

High-yield bonds are traded less frequently than investment-grade bonds. Investors in the high-yield bond market are primarily insurance companies, pension funds, and mutual funds. These institutional investors have strict regulations imposed, low trading activities, and long-term holding periods (S&P, 2019). Cai et al. (2007) and Rischen and Theissen (2021) report that the degree of underpricing is irrelevant to the expected secondary market liquidity. However, Goldstein et al. (2019) suggest a connection between a corporate bond's secondary market liquidity and its yield spread at issuance. The evidence for the relationship between the bond's secondary market liquidity and the underpricing in the primary market is, therefore, inconclusive.

The analysis in this chapter is related to several studies that concentrate on underpricing in the US corporate bond market (Datta et al., 1997; Cai et al., 2007, 2021; Liu and Magnan, 2014; Nagler and Ottonello, 2018; Helwege and Wang, 2021), and the Euro-denominated corporate bond market (Rischen and Theissen, 2021). It is also related to the decisions of underwriters regarding the allocation of the first-day profits to investors (Nikolova et al., 2020), the connection between underpricing and transparency in the secondary market (Brugler et al., 2022), and the relationship between underpricing and expected secondary market liquidity in the US corporate bond market (Goldstein et al., 2019). However, few studies examine the European corporate bond primary market, and these studies do not examine high-yield bonds separately (e.g., Rischen and Theissen, 2021; Wasserfallen and Wydler, 1988; Zaremba, 2014; Mietzner et al., 2018).

Our analysis focuses on a sample of 224 original high-yield bonds issued by 102 issuers between 2009 and 2019. We initially use univariate analysis to assess the magnitude of underpricing, and then use ordinary least squares (OLS) regression with year, industry, and country fixed effects to investigate the determinants of underpricing. These effects capture the endogeneity originating from year events, unobservable industry issuing activities, and nationalities of issuers.

We find that Euro-denominated high-yield corporate bonds are underpriced. The degree of underpricing is higher for initial bond offerings (IBOs) than for seasoned bond offerings (SBOs). We find new evidence about the link between the degree of underpricing and expected secondary market liquidity. Greater underpricing attracts more investors to be involved in trading bonds in the secondary market, enhancing the frequency of trading. This finding gives support to Booth and Chua (1996)'s view. In addition, our results are in line with the bookbuilding theory (Benveniste and Spindt, 1989; Cai et al., 2007; Nikolova et al., 2020). With respect to bond and issuer's characteristics, we report a higher degree of underpricing in small and privately held firms.

We find no evidence that underwriter reputation impacts the degree of underpricing, consistent with Rischen and Theissen (2021). Two potential reasons cause the different effects of reputable underwriters between the US and Euro-denominated high-yield corporate bond market. First, the effect of reputable underwriters on underpricing may differ before and after the financial crisis. Many US studies' sample periods are before 2009 (e.g., Datta et al., 1997; Fang, 2005; Andres et al., 2014. We suspect that stricter regulation after the financial crisis may weaken the effect of underwriter reputation on underpricing in the Euro-denominated high-yield bond market. Second, Euro-denominated high-yield bonds are normally underwritten by multiple lead underwriters. For example, on average, one bond was backed by five lead underwriters in the sample. In this case, the certification role or the power of top-rated underwriters may be mitigated.

Our results are inconsistent with signalling-based underpricing. Unlike initial public offerings in the equity market, many firms have multiple bonds outstanding.

The history of bond ratings may provide insights into the new bond issuance. In addition, we only have 26 IBOs. Due to the small sample size, whether the signalling theory can explain the underpricing in the high-yield bond market for IBOs is unclear. Further research could be conducted to analyse the role of signalling theory, particularly for IBOs, in the high-yield bond market with a larger sample size.

The remainder of this chapter is organised as follows. Section 4.2 describes the issuance process; Section 4.3 reviews the relevant literature and develops our hypotheses; Section 4.4 describes the data; Section 4.5 outlines the methodology; Section 4.6 discusses the empirical results; Section 4.7 provides robustness checks, and Section 4.8 concludes this chapter.

4.2 Bond Issuance Process

There are four stages involved when issuing bonds in the primary market: (i) pre-launch, (ii) launch and roadshow, (iii) issuance, and (iv) post-issuance (Practical Law Finance, 2018).

The company initially approaches investment banks and elucidates its need to issue bonds to raise capital. The bank assesses the company's financial situation to determine whether the company can issue bonds and meet the fundamental requirements of the corporate bond market. The bank may suggest the company have a rating assigned from rating agencies and assist the company in arranging preparatory meetings with them (Practical Law Finance, 2018).

During the launch and roadshow stage, the lead underwriter sends proposed bond issuance terms to potential managers who decide whether to cooperate with the lead manager to form a syndicate. The roadshow's objective is to make presentations to prospective investors and answer their queries. The information acquired from investors can help underwriters position the company in the corporate bond market and determine the bond's issue price range and maturity (Practical Law Finance, 2018).

After one to three weeks of the launch stage, bonds will be issued when sufficient investors have established an interest in purchasing them. Lead underwriters allocate investment-grade bonds to investors according to explicit and transparent regulations and try to reach an agreement with the issuer. However, the allocation process of high-yield bonds largely depends on one or more lead underwriters and may not always be transparent. As the allocation process of high-yield bonds is more opaque than investment-grade bonds, lead underwriters play an essential role in the allocation process (European Commission, 2017*c*).

During the post-issuance stage, bondholders regularly receive the interest stipulated in the bond prospectus from the issuer until the bond matures (Practical Law Finance, 2018).

4.3 Literature Review and Hypotheses

A range of theories is commonly used to explain underpricing in the equity market. In the winner's curse theory, underpricing is compensation for uninformed investors (Rock, 1986). The winner's curse theory arises from differences in acquiring information between informed and uninformed investors. Commonly, institutional investors and retail investors are regarded as informed investors and uninformed investors, respectively. Institutional investors tend to be allocated fair value or underpriced IPOs, and they leave unprofitable or overpriced ones to retail investors. The winner's curse theory tries to address this problem by allocating underpriced IPOs to retail investors (Rock, 1986). Cai et al. (2007) find no supportive evidence of underpricing based on the winner's curse theory in the corporate bond market. Primary investors in the high-yield bond market are institutional investors, accounting for approximately 86% of the market share (S&P, 2019). Therefore, the winner's curse theory may be irrelevant to explaining the underpricing in the high-yield bond market.

Different from equity and investment-grade bond issuers, issuers of high-yield bonds are usually private or small firms with more information asymmetry problems. Therefore, the bookbuilding or signalling theory should be more relevant to explaining the underpricing in the high-yield bond market. The bookbuilding theory sees underpricing as remuneration for informed investors providing information to underwriters during the bookbuilding process (Benveniste and Spindt, 1989; Benveniste et al., 2002). According to the signalling theory, underpricing is a costly signal to discern between good and bad firms and is caused by information asymmetry problems between firms and issuers (Allen and Paulhaber, 1989; Welch, 1989).

High-yield bonds are riskier and have higher levels of information asymmetry than investment-grade bonds. The role of underwriters is to establish a bridge between issuers and investors. The underwriter reputation may be associated with the issuer's quality, affecting the issue price of high-yield bonds (e.g., Fang, 2005; Carbó-Valverde et al., 2017).

High-yield bonds are more illiquid than equities and investment-grade bonds. Corporate bonds are traded over the counter, which has limited liquidity. Furthermore, investors of high-yield bonds tend to have a long-term investment strategy, resulting in lower trading frequency in the high-yield bond market. Hence, underpricing may be caused by expected secondary market liquidity (e.g., Booth and Chua, 1996; Goldstein et al., 2019).

Therefore, this chapter focuses on bookbuilding theory, signalling theory, underwriter reputation, and secondary market liquidity that could explain the degree of underpricing in the high-yield corporate bond market.

4.3.1 Bookbuilding Theory

The bookbuilding process is divided into three stages: first, underwriters identify investors who are more likely to have an interest in purchasing the issuance; second, they invite investors to assess the value of the issuance and submit a preliminary indication of interest; and third, they determine the issue price and allocations. As it is costly for underwriters to collect information, underpricing is regarded as a reward for revealing private information during the bookbuilding process (Benveniste and Spindt, 1989; Benveniste et al., 2002; Sherman and Titman, 2002); the allocation amount also provides incentives for investors to disclose truthful information.

Analogous to equity investors, bond investors are rewarded for revealing private information to underwriters during the bookbuilding process. Cai et al. (2007) find that an issuer that has issued bonds within two years of issuance tends to reduce the degree of underpricing in the US corporate bond market. Rischen and Theissen (2021) provide evidence in line with the bookbuilding theory in the Euro-denominated corporate bond market. When issuers have greater information asymmetry problems, the degree of underpricing increases with compensation for investors' generating valuable information (Nikolova et al., 2020).

High-yield bond issuers, as opposed to equity and investment-grade bond issuers, are typically private or small companies with more severe information asymmetry problems and are more difficult to value. In this case, information-based theories are relevant to explaining underpricing; institutional investors require a greater reward for generating useful information. If an issuer has recently issued a bond, the historical information gathered throughout the bookbuilding process, and the previous valuation of the bond may provide guidance for determining the value of the new bond issued by the same issuer. The history of credit ratings for outstanding bonds may also be valuable for investors in assessing the risk of the issuer (Brugler et al., 2022). Accordingly, the information asymmetry problems can be attenuated for a recent issuer, and less compensation for generating relevant information would be required throughout the bookbuilding process.

Hypothesis 1: The degree of underpricing is lower for recently repeated issuers.

4.3.2 Signalling Theory

The signalling theory of underpricing assumes that firms are well-informed issuers and know their prospects very well. Investors, on the other hand, are unable to identify the quality of firms. When good firms are confident in their future performance, they use the underpricing as a positive signal to set themselves apart from other competitors in the equity market (Allen and Paulhaber, 1989; Grinblatt and Hwang, 1989; Welch, 1989).

In the bond market, rating agencies regularly collect information and assess issuers in order to provide credit ratings. The bond ratings may reduce information asymmetry and affect decisions to signal quality via underpricing. According to the signalling theory, bond issuers with good quality tend to use greater underpricing to signal that their bonds will have better performance than others. The quality of bonds can be reflected by the rating changes after issuance. Bonds with a higher probability of rating upgrades tend to perform better and therefore have greater underpricing.

Prior studies have shown mixed findings regarding the role of the signalling theory in explaining underpricing in the corporate bond market. Cai et al. (2007) adopt the subsequent rating downgrades within 12 months of the initial bond offering as a proxy for signalling theory. They document that the variable of future downgrades is negatively related to the degree of underpricing. The result is statistically significant only when high-yield bond ratings are controlled in the IBO sample. Rischen and Theissen (2021) use a similar measure to Cai et al. (2007), and report a positive relationship between the bond's future downgrades and the underpricing at a 5% statistical significance level in the Euro-denominated corporate bond market for a combination of initial and seasoned bond offerings. This result is inconsistent with the signalling theory that good-quality firms are more likely to have ratings upgraded after issuance. Liu and Magnan (2014) employ conditional conservative reporting to measure information risk, and state that bond issuers with less information risk are positively related to underpricing to set themselves apart from other issuers, consistent with the signalling theory.

Issuers of high-yield bonds have a higher level of information asymmetry than investment-grade bonds and equities. Moreover, primary investors in the high-yield bond market are insurance companies, pension funds, and mutual funds with strict and prudent investment rules (S&P, 2019). Rating downgrades have a significant negative impact on these investors (Kisgen, 2006; Andres et al., 2014). For instance, insurance companies have capital requirement rules imposed on the credit rating score system. Rating downgrades bring about additional costs, either immediate or potential future costs, by selling downgraded bonds at a lower price to meet the capital requirement. High-yield bond issuers may use greater underpricing as a positive signal to distinguish themselves from others and attract more investors. On the other hand, the signalling theory of underpricing may not apply to the high-yield bond market. As these issuers tend to have a high level of debt burden, it is doubtful whether they can afford the extra costs associated with greater underpricing.

Two predictions may be made in light of the above discussion regarding whether the signalling theory can explain the underpricing in the high-yield bond market. If this theory is relevant to high-yield bonds, we expect the degree of underpricing will be greater for bonds with subsequent upgrades.

Hypothesis 2a: The degree of underpricing is positively related to a first rating upgraded subsequent to issuance in the Euro-denominated high-yield corporate bond market.

Hypothesis 2b: The degree of underpricing is not related to a first rating upgraded subsequent to issuance in the Euro-denominated high-yield corporate bond market.

4.3.3 Underwriter Reputation

Previous finance literature has established a connection between the services provided by financial intermediaries in the capital market and their reputation. According to the traditional certification hypothesis, information asymmetry can be lessened between issuers and investors, capitalising on the reputation of underwriters to guarantee the issuer's quality, and therefore the issuer's informational costs may be reduced (Beatty and Ritter, 1986; Booth and Smith, 1986; Titman and Trueman, 1986; Allen, 1990; Carter and Manaster, 1990; Chemmanur and Fulghieri, 1994). Underwriters have no inducements to falsify at the expense of losing their distinguished capital when they use their reputation to verify the issuer's intrinsic value. Any poor future performance may impair their reputation and adversely impact their amount of business received, so they are compelled to preserve their reputation (Beatty and Ritter, 1986; Carter and Manaster, 1990). In this case, reputable underwriters execute stringent standards to assess issuers toward minimising the probability of poor performance in the future. They are inclined to effectively weaken the information asymmetry problems between the issuer and investors (Chemmanur and Fulghieri, 1994). However, recent studies have indicated a change from the certification purpose to a market-power hypothesis. Reputable underwriters with higher market shares can attract large institutional investors and entice them to push up the issue price rather than validate the actual worth of the equity (Chemmanur and Krishnan, 2012).

There are mixed empirical results regarding the role of underwriter reputation in pricing the primary corporate bond market. Fang (2005) demonstrates that US high-yield bonds underwritten by reputable underwriters have lower yields, because these underwriters have strict underwriting procedures and only choose ones with upper-level quality.[1] In contrast, Andres et al. (2014) argue that US high-yield bonds backed by top-rated underwriters are more likely to be downgraded or in default. Investors are aware of the inverse relationship between the reputation of underwriters and the quality of bonds, thus incorporating this information into the yield spread at issuance, indicating that bonds underwritten by reputable underwriters have a higher yield spread at issuance.

In addition, the effect of underwriter reputation on the pricing may vary between the US and Euro-denominated corporate bond markets.[2] For instance, Rischen and Theissen (2021) find no association between underwriter reputation and the degree of underpricing in the Euro-denominated corporate bond market.[3] Their results are inconsistent with either the traditional certification or the market-power hypotheses.

Compared to investment-grade bonds, the certification role of reputable underwriters with top rankings is more critical for high-yield bonds due to their high probability of default and inferior credit quality. Highly reputable underwriters have established trust with institutional investors and built long-term relationships with them, while less reputable underwriters primarily focus on retail investors (Neupane and Thapa, 2013). As most investors in the high-yield bond market are institutional investors, prestigious underwriters can add additional value to an issuance. According to Fernando et al. (2005), there is a positive mutual selection process in which high-quality issuers link with reputable underwriters. If a high-yield bond is underwritten by top-rated underwriters, which may certify the bond's future performance, we expect the degree of underpricing will be reduced.

Hypothesis 3: The degree of underpricing is negatively related to reputable underwriters.

1 Datta et al. (1997) support the traditional certification hypothesis, and they find that bonds backed by less reputable underwriters are significantly and positively related to underpricing.

2 Compared to the US market, it is common to have one bond placed by multiple lead underwriters in the Euro-denominated market (Carbó-Valverde et al., 2017).

3 They do not separately investigate investment-grade bonds and high-yield bonds.

4.3.4 Expected Secondary Market Liquidity

Two views are used to explain the underpricing from the perspective of expected secondary market liquidity in the equity market. Ellul and Pagano (2006) document that underpricing compensates for the risk that the stock may become illiquid following the initial public offering (IPO). The less expected secondary market liquidity there is, the greater the IPO underpricing will be. However, Booth and Chua (1996) find indirect evidence that IPO underpricing is a positive function of expected secondary market liquidity. Greater underpricing can motivate oversubscription, disperse ownership, and enhance secondary-market liquidity.

The effect of expected secondary market liquidity on underpricing of corporate bonds is inconclusive. Cai et al. (2007) adopt the trading frequency after issuance as a measure of liquidity, which positively affects the degree of underpricing. This result indicates that more liquid bonds are associated with greater underpricing. Rischen and Theissen (2021) document that there is no relationship between underpricing and secondary market liquidity subsequent to issuance, which is measured by the bid-ask spread. Goldstein et al. (2019) adopt trading frequency, riskless trading volume, and round-trip spreads as measures of expected secondary market liquidity, and find a connection between the liquidity and the yield spread at issuance.

Corporate bonds are mainly traded over the counter. Primary high-yield bondholders are institutional investors who tend to have a long-term investment strategy, resulting in lower liquidity than the investment-grade bond market. In Chapter 3, we find that illiquidity risk is an essential factor in pricing the high-yield bond market. Previous studies do not separately examine the effect of expected secondary market liquidity on underpricing between investment-grade and high-yield bonds (e.g., Cai et al., 2007; Rischen and Theissen, 2021). A separate examination of high-yield bonds is warranted due to the essential differences between the investment-grade and high-yield bond markets. Therefore, we test whether underpricing can be elucidated from the expected secondary market liquidity, which is measured by the fraction of zero returns and bid-ask spreads during the first 90 trading days after issuance.

Hypothesis 4a: The degree of underpricing is positively associated with the expected secondary market liquidity.

Hypothesis 4b: The degree of underpricing is negatively associated with the expected secondary market liquidity.

4.4 Data

4.4.1 Sample Construction

Data on 398 original high-yield corporate bonds denominated in Euro currency between 1st January 2000 and 31st December 2019, including active and matured bonds, are collected from Bloomberg. This database includes data on bond and issuer characteristics. Our sample criteria are consistent with previous bond studies. For example, we include bonds with a fixed coupon and bullet type of maturity and exclude bonds with embedded options due to their complexities, potentially affecting their pricing (Lin et al., 2011; Acharya et al., 2013; Carbó-Valverde et al., 2017). We also exclude convertible bonds and bonds with an original maturity of less than one year, which causes them to be less comparable (Cai et al., 2007; Andres et al., 2014; Zhang and Zhou, 2018).

With respect to a bond's multiple original ratings, we first use the S&P rating if available, then Moody's, and the Fitch rating lastly.[4] In addition, we download historical S&P, Mood's and Fitch bond ratings from Bloomberg.[5]

Daily mid-prices from Bloomberg are collected using Bloomberg's Evaluated Pricing Service (BVAL). Bloomberg Generic Price (BGN) and BVAL are typically used as pricing sources for downloading historical bond prices. Considering the sample size and data consistency, BVAL provides more mid-prices than the BGN pricing source. Hence, we include bonds with available mid-prices from BVAL. We drop 48 bonds that do not have an available mid-price. Many bonds do not have available prices from pricing dates, and the number of days between the pricing date and the first available price date spreads, widely ranging from 0 to 2,086 days. We keep bonds with a first available mid-price within 30 days of the pricing date.[6] 71 bonds are

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4 If a bond has no available rating from S&P, Moody's, or Fitch rating agencies within one month of its issue date, it is excluded from the sample.

5 The mnemonic codes for downloading historical S&P, Moody's, and Fitch bond ratings from Bloomberg are RTG_SP, RTG_MOODY, and RTG_FITCH, respectively. According to the description from Bloomberg, these codes can provide either a long-term or a short-term bond rating subject to what is allocated by these rating agencies. A long-term rating is first assigned if available. If the long-term rating is not available, a short-term rating is assigned.

6 Cai et al. (2007) use the first available price within 7 days and 14 days of issuance, respectively,

out of the event window size and are removed from the sample. We also remove 1 bond with an extremely and unusually large first available mid-price from the sample.[7]

We then exclude 52 self-lead bonds, which conduct underwriting services by themselves. When issuers are the same as underwriters, there are no information asymmetry problems between issuers and underwriters. Therefore, these bonds are irrelevant to examining the bookbuilding theory, and the underwriter reputation hypothesis. We exclude 2 bonds issued by government development banks, as bonds backed by local governments are examined differently from typical corporate bonds. The detailed sample criteria and selection are presented in Table 4.1. We end up with a sample of 224 original high-yield bonds issued by 102 issuers between 2009 and 2019.[8]

An initial bond offering (IBO) of sample bonds is identified manually based on historical records of bonds offered by a sample issuer through Refinitiv Eikon. We compare the twelve-character ISIN and the issue date of the initial bond to sample bonds offered by the same issuer. If a sample bond's ISIN and issue date are the same as the first bond issued by the same issuer, the sample bond is an IBO; otherwise, it is a seasoned bond offering (SBO). Therefore, sample bonds include 26 IBOs and 198 SBOs.

and find similar results. Rischen and Theissen (2021) adopt 40 days as their event window size. There is no specific number of days after issuance that is regarded as the first secondary market price in the corporate bond market. Consequently, it is reasonable to use the first available price within 30 days of the pricing date as its initial price in the secondary market.

7 Based on 278 (398 - 48 - 71 - 1 = 278) sample high-yield bonds, we primarily use issue prices collected from Bloomberg. If an issue price is unavailable, we use the issue price downloaded from Refinitiv Eikon. Therefore, issue prices for 254 and 24 high-yield bonds are downloaded from Bloomberg and Refinitiv Eikon, respectively.

8 After adopting the sample selection (See Table 4.1, Panel B), the sample period has been reduced from 20 years (pricing years range from 2000 to 2019) to 11 years (pricing years range from 2009 to 2019).

Table 4.1: Sample selection criteria and filters.

Panel A: Selection criteria.		N
	Active and matured corporate bonds	
And	Euro currency	
And	Fixed coupon type	
And	Bullet type of maturity	
And	Not convertible bonds	
And	The term between the issue date and the maturity date is more than one year	
And	Pricing date is between 1st January 2000 and 31st December 2019	
And	S&P Rating at issuance is below BBB-	
Or	Moody's rating at issuance is below Baa3	
Or	Fitch Rating at issuance is below BBB-	398
Panel B: Bond filters.		**N**
	Number of original high-yield bonds stems from Bloomberg	398
Less	Bonds have unavailable dirty mid prices	48
Less	Bonds have the first available dirty mid prices more than 30 days from the pricing date.	71
Less	Bonds have unusual large first available dirty mid prices	1
Less	Bonds' issuers are the same as their underwriters (self-lead bonds)	52
Less	Bonds' issuer is a government development bank	2
Remaining bonds		224

This table describes the sample criteria and filters. Panel A presents the sample selection criteria we use to collect original high-yield corporate bonds from Bloomberg. Panel B presents the bond filters we apply to form our final sample. Therefore, there are 224 original high-yield bonds left in the sample. N stands for the number of bonds.

4.4.2 Sample Descriptive Statistics

Table 4.2 presents the sample descriptive statistics based on firm and bond characteristics by mean, median, and standard deviation values. Experience is defined as the number of years between the issue date of the sample bond and the first bond issued by the same issuer. The average years of experience are 19 years, the median value is 17 years, and the standard deviation value is 17 years, demonstrating that the experience in issuing bonds varies significantly across issuers. These results indicate that the extent of information asymmetry differs considerably in the high-yield corporate bond market. We use total assets (denoted as TA) as a proxy for the size of the firm. The large standard deviation of TA implies that the variations of the firm size fluctuate substantially. The N_bondswithin2Y variable refers to the number of bonds issued in the past two years. The average N_bondswithin2Y variable is 28, and the median value is 3, suggesting that some firms issue bonds more frequently than others. FZR_90d and Bid-ask spread_90d are proxies for expected secondary market liquidity after the bond issuance. FZR_90d represents the number of zero returns following 90 working days after issuance. On average, 21.51 days (23.90% x 90 days) have zero returns during 90 days after the first available market price, indicating a low frequency of trading in the secondary market. Bid-ask spread_90d refers to the average bid-ask spreads during the 90 working days, and the average value is 57.3 bps.

Table 4.2: Descriptive statistics.

Variables	N	Mean	Median	Standard deviation
Experience (years)	224	18.948	16.969	16.941
LNExperience	224	2.482	2.889	1.218
TA (€ million)	199	107395.600	26321.000	210569.300
LNTA	199	10.279	10.178	1.649
N_bondswithin2Y	224	28.348	3.000	63.571
FZR_90d (%)	224	0.239	0.222	0.169
Bid-ask spread_90d (%)	215	0.573	0.484	0.407
N_lead underwriters	217	4.972	4.000	3.790

The table presents the descriptive statistics of variables based on the issuer and bond characteristics. Experience (years) is the number of years since the same issuer issued its first bond. LNExperience = Ln (1 + Experience). TA (€ million) is the issuer's total assets in the year before the bond issuance. LNTA is the natural logarithm of the issuer's total assets in the year before the bond issuance. N_bondswithin2Y is the number of bonds that have been issued in the past two years by the same issuer. FZR_90d (%) is the proportion of observations with zero returns during the first 90 working days following the first market price for each bond. Bid-ask spread_90d (%) is the average daily bid-ask spread during the 90 working days following the first market price for each bond. N_lead underwriters is the number of lead underwriters providing underwriting services for each bond. N is the number of high-yield bonds in the sample.

Table 4.3 shows the pairwise correlation matrix of explanatory variables. In general, these variables are less correlated. The correlation between IBO and LNExperience is -0.740, because the first-time bond issuer has no previous experience in issuing bonds. These two variables are not included together in the regression to avoid the potential multicollinearity issue.

Table 4.3: Pairwise correlation.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) N_bondswithin2Y	1					
(2) First rating upgraded	-0.182**	1				
(3) First rating downgraded	0.182**	-1	1			
(4) Corp_top 7_annual	-0.007	0.027	-0.027	1		
(5) FZR_90d	0.317***	-0.018	0.018	0.301***	1	
(6) Bid-ask spread_90d	0.052	-0.246***	0.246***	0.079	0.085	1
(7) IBO	-0.162**	-0.003	0.003	0.026	-0.026	0.096
(8) English	-0.061	-0.043	0.043	-0.126*	-0.145**	-0.165**
(9) LNExperience	0.322***	-0.058	0.058	-0.155**	0.084	-0.036
(10) Private placement	-0.065	-0.091	0.091	0.132*	0.084	0.107
(11) Private	-0.177***	-0.048	0.048	0.025	0.02	0.073
(12) LNTA	0.497***	-0.136*	0.136*	-0.121*	0.210***	-0.103

Table 4.3 continued: Pairwise correlation.

Variables	(7)	(8)	(9)	(10)	(11)	(12)
(7) IBO	1					
(8) English	-0.051	1				
(9) LNExperience	-0.740***	0.075	1			
(10) Private placment	0.086	-0.219***	-0.133**	1		
(11) Private	0.263***	-0.059	-0.379***	0.04	1	
(12) LNTA	-0.242***	0.078	0.389***	-0.003	0.045	1

The table presents the pairwise correlation of explanatory variables. N_bondswithin2Y is the number of bonds that have been issued in the past two years by the same issuer. First rating upgraded is a categorical variable that equals one if the bond has a first rating upgraded after issuance, and zero otherwise. First rating downgraded is a categorical variable that equals one if the bond has a first rating downgraded after issuance, and zero otherwise. Corp_top 7_annual is a categorical variable that equals one if the bond is placed by reputable underwriters, whose syndicate market share is higher than the top seventh of the underwriter's market share in the league table of the bond's pricing year, and zero otherwise. The rankings of annual league tables are based on Euro-denominated fixed corporate bonds (see Table 4.4). FZR_90d is the proportion of observations with zero returns during the 90 trading days following the first market price for each bond. Bid-ask spread_90d is the average daily bid-ask spread during the 90 trading days following the first market price for each bond. IBO stands for initial bond offering, which is the first bond issued by the issuer. English is a categorical variable that equals one if the bond adopts English governing law, and zero otherwise. LNExperience = Ln (1 + Experience). Private placement is a categorical variable that equals one if the bond is issued through private placement, and zero otherwise. Private is a categorical variable that equals one if the issuer has no publicly traded equity, and zero otherwise. LNTA is the natural logarithm of the issuer's total assets in the year before the bond issuance. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.5 Methodology

This section describes the measure of underpricing, the motivation of the baseline model, and proxies for bookbuilding theory, signalling theory, underwriter reputation, and expected secondary market liquidity.

4.5.1 Calculation of Underpricing

In the equity market, underpricing is typically initial returns, calculated as the percentage change from the issue price to the closing price on the first day. As high-yield bonds are traded over the counter, not all bonds have the first secondary market price on the same day as the pricing date, and the first secondary market price may occur a few days after the bond's pricing date. We adopt the Nikolova et al. (2020) method of calculating underpricing. For bonds with the first available secondary market price on the pricing date, underpricing is the percentage difference between the issue price and the secondary end-of-day dirty mid price on the pricing date. For bonds that do not have the first available secondary market price on the pricing date, underpricing is the market-adjusted return between the return of an individual bond and a comparable bond index. A positive initial raw return or market-adjusted return implies that a bond is underpriced.

We initially calculate the raw return of bond i over n days after the pricing date t as:

$$Ret^{\mathrm{B}}_{i,t+n} = \frac{P_{i,t+n} + AI_{i,t+n} - IP_{i,t}}{IP_{i,t}} \tag{4.1}$$

where, $P_{i,t+n}$ is the first available secondary mid price for bond i at time $t+n$, t is the pricing date of the bond, n is the number of days following the pricing date (i.e., $0 \leqslant n \leqslant 30$); $AI_{i,t+n}$ is the accrued interest between t and $t+n$; $IP_{i,t}$ is the issue price in the primary market.

Adapted to market fluctuations and bond accrued interest during the first 30 working days after the pricing date, we calculate the market-adjusted return, which is the difference between the raw return of an individual bond and the return of the

Bloomberg Barclays Pan-European bond index with a comparable rating to the bond i over n days. The high-yield bond indices of Bloomberg Barclays measure the market of high-yield grade, fixed-rate corporate bonds denominated in Euro, which are consistent with our sample criteria.

Due to the limited Euro-denominated high-yield bond indices, we cannot match each bond in our sample with an accurate rating and maturity. So, we use the index with a matched letter rating as a benchmark to calculate the underpricing. Ding et al. (2020) also have similar issues with matching indices in their Chinese bond sample and use a rating-matched index as a benchmark to calculate the underpricing.

We use the Bloomberg Barclays Pan-Euro HY BB rating index to match sample bonds with BB ratings. 192 bonds with original ratings of BB are in the sample. Their average (median) years between issue and maturity date is 6.03 (6.00), similar to the matched index of 4.99 years. We use B rating index to match 26 sample bonds with original ratings of B. Their average (median) maturity years is 5.40 (5.00), close to the matched index of 4.68 years. CCC rating index is used to match 6 sample bonds that have ratings of CCC or below. Their average (median) maturity years is 3.67 (3.50), analogous to the matched index of 4.66 years.[9] As the maturity years of the sample bonds are similar to those of the matched bond index, and it is reasonable to use these matched indices as a benchmark to calculate the underpricing.

The underpricing of bond i is defined as:

$$UP_i = \begin{cases} Ret^{\mathrm{B}}_{i,t+n} & \text{if } n = 0 \\ Ret^{\mathrm{B}}_{i,t+n} - Ret^{\mathrm{Index}}_{i,t+n} & \text{if } 0 \leqslant n \leqslant 30 \end{cases} \tag{4.2}$$

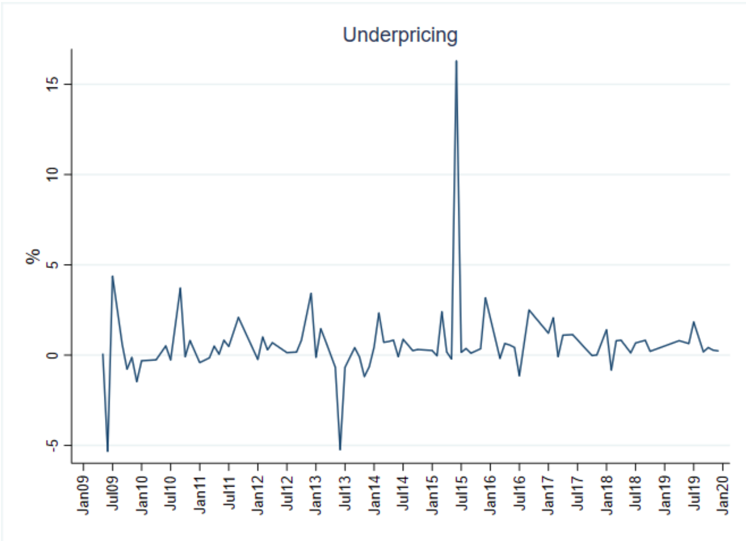
$$Ret^{\mathrm{Index}}_{i,t+n} = \frac{P^{\mathrm{Index}}_{i,t+n} - P^{\mathrm{Index}}_{i,t}}{P^{\mathrm{Index}}_{i,t}} \tag{4.3}$$

9 The Bloomberg Barclays Pan-Euro HY BB rating index (code: I05446EU), B rating index (code: I05445EU), and CCC rating index (code: I05447EU) include 386, 202, and 74 high-yield bonds, respectively. These indices are market value-weighted and are rebalanced monthly.

where $Ret^{\text{Index}}_{i,t+n}$ is the cumulative return of a comparable rating-matched high-yield bond index over n days beginning on the bond's pricing date t for bond i. $P^{\text{Index}}_{i,t}$ is the price of a comparable rating-matched bond index on the pricing date t of bond i, and $P^{\text{Index}}_{i,t+n}$ is the price of a comparable rating-matched bond index on the day $t+n$ of bond i.

Figure 4.1 presents the monthly time series of average underpricing from May 2009 to December 2019. Overall, high-yield bonds are underpriced. The peak was potentially caused by the European sovereign debt crisis, intensifying the degree of underpricing in the high-yield bond market. We incorporate year-fixed effects in the baseline model (see Equation 4.4), to account for year-specific occurrences that may affect all bonds concurrently.

Figure 4.1: Time series of underpricing.



The figure shows the monthly time series of average underpricing between May 2009 and December 2019.

4.5.2 Baseline Model

To investigate the determinants of underpricing, we use the following baseline model:

$$\begin{aligned} UP_{i,t} = \alpha_0 \ &+ \beta_1\ English_i + \beta_2\ LNExperience_i\ + \beta_3\ Private\ placement_i \\ &+ \beta_4\ Private_i + \beta_5\ LNTA_{i,t-1} + \theta\ Y_t + \eta\ X_{industry} + \mu\ Z_{country} + \varepsilon_{i,t} \end{aligned} \tag{4.4}$$

where i is a bond, t is a bond's issuing year, *industry* is a bond issuer's industry, and *country* is a bond issuer's nationality. UP is defined in Equation 4.2. We use year (Y_t), industry ($X_{industry}$), and country ($Z_{country}$) fixed effects to capture the endogeneity originating from year events, unobservable industry issuing activities, and nationalities of the issuers.

English is a categorical variable, which equals one if the bond adopts English governing law, and zero otherwise. Previous studies document that stronger creditor protection laws are associated with a lower cost of debt in the bank loan market (Qian and Strahan, 2007; Bae and Goyal, 2009) and in the private credit market (Djankov et al., 2007). English law countries have the strongest creditor protection among all legal families (La Porta et al., 1998). As high-yield bonds have a higher probability of default than investment-grade bonds, the choice of governing law may affect the degree of underpricing.

LNExperience is the natural logarithm of the number of years between the issue date of the sample bond and the first bond issued by the same issuer. According to Diamond (1989) and Cai et al. (2007), we use the number of years a firm has been issuing in the bond market to measure the level of information asymmetry. The information asymmetry problems can be diminished with increasing years of experience in the bond market (Chemmanur and Paeglis, 2005). Therefore, we expect the issuer's experience in the bond market will affect the degree of underpricing.

Private placement is a categorical variable, which equals one if the bond is issued through private placement, and zero otherwise. Bonds are sold to a small group of accredited investors following a private placement. Hence, we expect that the private placement variable is positively related to underpricing.

Private is a categorical variable, which equals one if the issuer has no publicly traded equity, and zero otherwise. Public companies have undergone an equity IPO by issuing shares that can be publicly traded on a stock market. A private company has no traded shares available to the public. According to Helwege and Kleiman (1998), if the issuer is a public company, its equity offering, the stock price listed on the stock exchange, and public financial data provide plenty of information for underwriters and investors to assess the demand for the security and potential future performance. In other words, private companies are less transparent than public companies. Investors require more underpricing as compensation for a higher degree of information asymmetry from a private company (Cai et al., 2007). Therefore, we anticipate a positive relationship between the private variable and underpricing.

LNTA is the natural logarithm of the issuer's total assets at the end of the previous year prior to the pricing year to measure the firm's size. Smaller firms are less popular than larger ones and may experience more intense market competition pressure and a higher probability of default (Cai et al., 2007). Therefore, we expect that the LNTA will negatively affect the degree of underpricing.

4.5.3 Proxy for Bookbuilding Theory

Underpricing is the compensation for information collection costs to institutional investors during the bookbuilding process. According to Cai et al. (2007) and Rischen and Theissen (2021), IBO is used as a proxy for bookbuilding theory and defined as a categorical variable, which equals one if the bond is the first bond issued by the issuer, and zero otherwise. As we only have 26 IBOs in the sample, we also adopt Bondswithin2Y_dummy as an alternative measure of bookbuilding theory by following Cai et al. (2007). Bondswithin2Y_dummy is a categorical variable that equals one if the firm issued a bond within the last two years, and zero otherwise. If a high-yield bond issuer has issued a bond in the previous two years; the information collection costs will be reduced throughout the bookbuilding process. Therefore, we expect that the degree of underpricing will reduce.

4.5.4 Proxy for Signalling Theory

We use similar measures of signalling theory to Cai et al. (2007) and Rischen and Theissen (2021). One variable is First rating upgraded, and the other is First rating downgraded. First rating upgraded is a categorical variable that equals one if the bond has a first rating upgraded subsequent to issuance. First rating downgraded is another categorical variable that equals one if the bond has a first rating downgraded after issuance. If the signalling theory is relevant to explaining underpricing in the high-yield bond market, we expect that bonds with a first rating upgraded (downgraded) will underprice more (less).

4.5.5 Proxy for Underwriter Reputation

Corp_top 7_annual is a categorical variable that equals one if the bond is placed by reputable underwriters, whose syndicate market share is on average higher than the top seventh of the underwriter's market share in the league table of the bond's pricing year, and zero otherwise. The market share is commonly regarded as a precise measure of the underwriter's reputation for providing underwriting services. Underwriters that cover a larger market share are more reputable, because the more reputable underwriters are, the more likely they attract and gain underwriting contracts (Carbó-Valverde et al., 2017).

We prefer an ordinal measure and take the position of the league table as a proxy for the reputation of a lead underwriter (Fang, 2005; Ross, 2010; Andres et al., 2014; Carbó-Valverde et al., 2017; Anand et al., 2019). Banks are repeated players and can generate higher issuance volumes and represent a larger market share, so they are typically regarded as heavyweights in the capital market (Fang, 2005). We collect annual underwriters' league tables between 2009 and 2019 from Bloomberg. The rankings of underwriters are based on the annual issuance volume for Euro-denominated investment-grade and high-yield corporate bonds with fixed coupon rates.[10] The issuance volumes of self-underwritten transactions are excluded from the league table.[11] According to Carbó-Valverde et al. (2017), although some subsidiaries conduct underwriting services, their reputation largely depends on their parent banks. When we match the lead underwriters of sample bonds to Bloomberg annual league tables, we use the subsidiary's parent instead of the subsidiary not listed on the league table.

An outline of the annual top ten largest underwriters by market share from 2009 to 2019 is presented in Table 4.4.[12] These top 10 underwriters cover over 50% of the market share, indicating that the top-rated underwriters dominate the corporate bond market. The concentration of top-ranked underwriters is different between the US and Euro-denominated corporate bond markets. The US top 3 underwriters have a similar level of market share to the European top 7. For instance, Andres et al. (2014) mainly use the top 3 underwriters as measures of reputable underwriters, accounting for 39.3% of the market share in the US corporate bond market between 2000 and 2008. Carbó-Valverde et al. (2017) adopt the top 7 underwriters as a proxy for reputable underwriters, presenting 43.17% of the market share in the European corporate market between 2003 and 2013. Broadly, our top 7 underwriters account for 41.65% of the market share per year, similar to the percentage of top reputable underwriters' market share used in Andres et al. (2014) and Carbó-Valverde et al. (2017).[13] We thus regard a reputable underwriter as having a position in the top 7 of the annual league table. As underwriters' rankings differ year after year, we use the underwriter's rankings from the annual league table to match with lead underwriters of sample bonds in the pricing year, to determine whether bonds are placed by reputable underwriters or not.[14]

10 As a robustness check, we collect the annual underwriters' rankings for Euro-denominated fixed high-yield corporate bonds between 2009 and 2019 from Bloomberg.

11 In their league tables, Andres et al. (2014) and Carbó-Valverde et al. (2017) exclude self-underwritten transactions.

12 Deutsche Bank, BNP Paribas, and HSBC were consistently among the top 7 underwriters from 2009 to 2019, while Commerzbank only appeared once in 2018 as one of the top 7 underwriters.

13 41.65% is the average market share of the top 7 underwriters in the annual league tables between 2009 and 2019, presented in Table 4.4.

14 Carbó-Valverde et al. (2017) calculate the syndicate market share for each bond using annual

Sole underwriters are straightforwardly allocated to the more reputable or less reputable group based on their respective market share presented in the annual league table. We have 29 bonds placed by a sole underwriter and 188 bonds placed by multiple lead underwriters in the sample.[15] On average, 5 lead underwriters participate in underwriting services for one bond (see Table 4.2). In the previous US studies, a deal is considered as being placed by reputable underwriters if at least one underwriter's position is in the top designated ranking of the league table (Fang, 2005; Fernando et al., 2005; Andres et al., 2014). Given a syndicated deal's composite reputation, we follow a similar approach to Carbó-Valverde et al. (2017) in terms of calculating the syndicate market share. A deal is deemed to be placed by a reputable underwriter if the average syndicate market share is higher than the top seventh of the underwriter's market share in the league table of the bond's pricing year.

The syndicate market share is computed as:

$$Average\ issuance\ volume_{i,j} = \frac{\sum_{k=1}^{N} Issuance\ volume\ UW_{k,j}}{N_i} \tag{4.5}$$

$$Syndicate\ Market\ Share_{i,j} = \frac{Average\ issuance\ volume_{i,j}}{Total\ issuance\ volume\ in\ year j}\ x\ 100 \tag{4.6}$$

where, N_i is the number of lead underwriters involved in a deal for bond i, and $\sum_{k=1}^{N} Issuance\ volume\ UW_{k,j}$ is the sum of issuance volume generated by these involved lead underwriters in year j. The total issuance volume in year j is the sum of issuance volumes for all underwriters listed in the league table in year j.

league tables.

15 7 sample bonds have no data on lead underwriters from Bloomberg.

Table 4.4: Annual top 10 underwriters in the Euro-denominated fixed corporate bond market from 2009 to 2019.

2009			
Underwriter	Rank	Issuance volume (€ in million)	Market share
Deutsche Bank	1	72,702.50	9.06%
BNP Paribas	2	66,247.67	8.25%
Societe Generale	3	52,971.32	6.60%
HSBC	4	50,732.04	6.32%
JP Morgan	5	46,473.55	5.79%
Credit Agricole CIB	6	43,367.95	5.40%
Barclays	7	42,345.58	5.28%
RBS	8	41,644.96	5.19%
UniCredit	9	39,007.18	4.86%
DZ Bank	10	25,751.69	3.21%
Total market share of top 7 underwriters		46.70%	
Total number of underwriters		141	
Total issuance volume (€ in million)		802,596.00	
2010			
Underwriter	Rank	Issuance volume (€ in million)	Market share
BNP Paribas	1	49,626.76	9.03%
Deutsche Bank	2	43,373.85	7.89%
HSBC	3	35,395.98	6.44%
UniCredit	4	32,362.71	5.89%
Barclays	5	31,808.89	5.78%
Societe Generale	6	28,002.24	5.09%
JP Morgan	7	23,018.77	4.19%
Natixis	8	21,089.32	3.84%
Credit Suisse	9	20,566.28	3.74%
Credit Agricole CIB	10	19,701.33	3.58%
Total market share of top 7 underwriters		44.30%	
Total number of underwriters		141	
Total issuance volume (€ in million)		549,870.85	
2011			
Underwriter	Rank	Issuance volume (€ in million)	Market share
Deutsche Bank	1	45,773.04	8.31%
BNP Paribas	2	45,089.45	8.19%
HSBC	3	37,619.84	6.83%
Barclays	4	35,863.11	6.51%
UniCredit	5	29,374.12	5.33%
Societe Generale	6	26,206.45	4.76%
Credit Agricole CIB	7	24,439.05	4.44%
UBS	8	23,066.90	4.19%
Natixis	9	22,817.58	4.14%
Citi	10	21,883.92	3.97%
Total market share of top 7 underwriters		44.38%	
Total number of underwriters		142.00	
Total issuance volume (€ in million)		550,593.53	

Table 4.4 continued: Annual top 10 underwriters in the Euro-denominated fixed corporate bond market from 2009 to 2019.

		2012	
Underwriter	Rank	Issuance volume (€ in million)	Market share
Deutsche Bank	1	64,817.83	9.84%
BNP Paribas	2	43,731.73	6.64%
UniCredit	3	38,800.99	5.89%
HSBC	4	36,611.43	5.56%
Barclays	5	34,599.71	5.25%
JP Morgan	6	34,302.39	5.21%
Credit Agricole CIB	7	33,836.94	5.14%
Societe Generale	8	29,303.13	4.45%
Citi	9	26,098.27	3.96%
Natixis	10	25,719.70	3.90%
Total market share of top 7 underwriters		43.52%	
Total number of underwriters		140	
Total issuance volume (€ in million)		658,795.91	
		2013	
Underwriter	Rank	Issuance volume (€ in million)	Market share
Deutsche Bank	1	48,882.27	7.99%
BNP Paribas	2	42,551.07	6.96%
HSBC	3	40,345.99	6.60%
JP Morgan	4	36,646.07	5.99%
Barclays	5	36,479.78	5.96%
Societe Generale	6	31,880.39	5.21%
UniCredit	7	31,405.80	5.13%
Credit Agricole CIB	8	29,052.94	4.75%
RBS	9	23,508.21	3.84%
Goldman Sachs	10	23,100.55	3.78%
Total market share of top 7 underwriters		43.85%	
Total number of underwriters		174	
Total issuance volume (€ in million)		611,651.89	
		2014	
Underwriter	Rank	Issuance volume (€ in million)	Market share
BNP Paribas	1	43,201.24	7.15%
Deutsche Bank	2	42,498.13	7.03%
HSBC	3	37,577.86	6.22%
Barclays	4	35,785.39	5.92%
Societe Generale	5	29,586.59	4.90%
JP Morgan	6	29,569.33	4.89%
Credit Agricole CIB	7	28,976.26	4.80%
UniCredit	8	26,777.85	4.43%
Goldman Sachs	9	24,030.13	3.98%
RBS	10	23,814.08	3.94%
Total market share of top 7 underwriters		40.91%	
Total number of underwriters		172	
Total issuance volume (€ in million)		604,282.00	

Table 4.4 continued: Annual top 10 underwriters in the Euro-denominated fixed corporate bond market from 2009 to 2019.

2015			
Underwriter	Rank	Issuance volume (€ in million)	Market share
Deutsche Bank	1	43,041.69	6.93%
HSBC	2	39,616.67	6.38%
BNP Paribas	3	39,055.43	6.29%
Barclays	4	38,305.74	6.16%
JP Morgan	5	32,161.57	5.18%
UniCredit	6	30,631.59	4.93%
Credit Agricole CIB	7	30,337.18	4.88%
Societe Generale	8	27,675.71	4.45%
Goldman Sachs	9	25,265.31	4.07%
Commerzbank	10	24,135.99	3.88%
Total market share of top 7 underwriters		40.74%	
Total number of underwriters		183	
Total issuance volume (€ in million)		621,361.73	
2016			
Underwriter	Rank	Issuance volume (€ in million)	Market share
BNP Paribas	1	43,934.11	6.51%
Deutsche Bank	2	42,761.38	6.33%
HSBC	3	38,965.88	5.77%
Barclays	4	38,799.05	5.75%
Credit Agricole CIB	5	35,067.26	5.19%
Societe Generale	6	32,296.87	4.78%
JP Morgan	7	31,121.47	4.61%
Citi	8	31,061.91	4.60%
UniCredit	9	30,081.50	4.46%
Goldman Sachs	10	28,739.62	4.26%
Total market share of top 7 underwriters		38.95%	
Total number of underwriters		186	
Total issuance volume (€ in million)		675,127.09	
2017			
Underwriter	Rank	Issuance volume (€ in million)	Market share
BNP Paribas	1	50,241.47	7.04%
Barclays	2	43,602.35	6.11%
Deutsche Bank	3	43,513.16	6.09%
HSBC	4	39,149.39	5.48%
UniCredit	5	38,433.68	5.38%
Societe Generale	6	36,869.26	5.16%
JP Morgan	7	36,797.78	5.15%
Credit Agricole CIB	8	31,869.77	4.46%
Goldman Sachs	9	31,514.10	4.41%
Citi	10	30,160.94	4.22%
Total market share of top 7 underwriters		40.42%	
Total number of underwriters		200	
Total issuance volume (€ in million)		714,101.83	

Table 4.4 continued: Annual top 10 underwriters in the Euro-denominated fixed corporate bond market from 2009 to 2019.

2018			
Underwriter	Rank	Issuance volume (€ in million)	Market share
BNP Paribas	1	43,025.67	6.35%
Deutsche Bank	2	39,061.34	5.77%
HSBC	3	36,861.01	5.44%
Commerzbank	4	34,245.06	5.06%
UniCredit	5	33,935.98	5.01%
Societe Generale	6	33,044.25	4.88%
JP Morgan	7	32,724.12	4.83%
Credit Agricole CIB	8	32,564.18	4.81%
Barclays	9	30,560.44	4.51%
Goldman Sachs	10	27,022.97	3.99%
Total market share of top 7 underwriters		37.34%	
Total number of underwriters		213	
Total issuance volume (€ in million)		677,199.32	
2019			
Underwriter	Rank	Issuance volume (€ in million)	Market share
BNP Paribas	1	53,441.61	6.31%
Barclays	2	46,042.84	5.44%
JP Morgan	3	44,881.28	5.30%
Deutsche Bank	4	44,789.78	5.29%
HSBC	5	42,981.44	5.08%
Credit Agricole CIB	6	41,605.13	4.91%
UniCredit	7	39,976.01	4.72%
BofA Securities	8	37,653.32	4.45%
Societe Generale	9	35,122.48	4.15%
Citi	10	34,927.52	4.13%
Total market share of top 7 underwriters		37.05%	
Total number of underwriters		207	
Total issuance volume (€ in million)		846,725.20	

This table exhibits summary statistics for the annual ten largest underwriters in the Euro-denominated fixed corporate bond market between 2009 and 2019, collected from Bloomberg league tables. The Euro-denominated fixed corporate bond market includes both investment-grade and high-yield bonds. The league table excludes self-led transactions, which means that the issuer is different from the underwriter, or the issuer's ultimate parent owns less than 50% of the underwriters. The ranking of underwriters is based on the issuance volume annually. The individual market share is the respective underwriter's issuance volume divided by the yearly total issuance volume. The total number of underwriters is the total number of underwriters listed in the Bloomberg league table in that year. The total issuance volume is the sum of all the issuance volumes in that year.

4.5.6 Proxy for Expected Secondary Market Liquidity

Several liquidity measures have been used in previous studies. There is no consensus on the foremost liquidity measures in the corporate bond market. We adopt two liquidity measures that are extensively used in the literature. These measures are FZR and bid-ask spreads during the first 90 trading days after issuance.[16]

FZR is an activity-based illiquidity measure. A greater FZR signifies a greater frequency of trading days with zero returns, suggesting that the bond is less liquid. We follow a similar method of calculating FZR to Aussenegg et al. (2017). The calculation of FZR for each bond i during the first 90 trading days following issuance is as follows:

$$FZR_{i,90d} = \frac{NZR_{i,90d}}{90} \tag{4.7}$$

where $FZR_{i,90d}$ is the proportion of the number of observations with zero returns during the 90 trading days for bond i following the first market price. $NZR_{i,90d}$ is the number of days with zero returns during 90 trading days for bond i. We start to count the number of zero returns from the first available date of the market price; in this case, every bond has 90 trading days equally.

Clean prices are used to calculate daily returns.[17] $r_{i,\tau}$ is the daily return on a trading day τ for bond i, and $p_{i,\tau}$ is the clean price of bond i on a trading day τ, then:

16 Several studies have used different sizes of the event window for the calculation of the expected secondary market liquidity. For instance, Goldstein et al. (2019)'s liquidity measures capture one or two months subsequent to issuance, and Rischen and Theissen (2021) use bid-ask spreads within 40 days of trading following issuance. According to European Commission (2017*a*), the active trading period for corporate bonds is between one and three weeks, after which the liquidity reduces. High-yield bonds are traded less frequently and are more likely to be held by investors with a long-term investment horizon. We initially use 90 days of trading subsequent to issuance, and then use 30 days as robustness checks.

17 We download daily clean prices from Bloomberg based on the BVAL pricing source. The mnemonic of the clean price is PX_LAST.

$$r_{i,\tau} = \frac{p_{i,\tau} - p_{i,\tau-1}}{p_{i,\tau-1}} \tag{4.8}$$

The bid-ask spread is a price-based illiquidity proxy capturing market participation or the level of supply and demand in the market.[18] Wider spreads are directly associated with low levels of participation in the market, suggesting that these bonds are less popular, thus, less liquid.

The calculation of the bid-ask spread is inspired by European Commission (2017*b*), the average bid-ask spread for bond i during the 90 trading days after the first market price is calculated as:

$$Bid - ask\ spread_{i,90d} = \frac{\sum_{90d} \frac{ask_{i,\tau} - bid_{i,\tau}}{mid_{i,\tau}}}{Number\ of\ obs._{i,90d}}\ x\ 100 \tag{4.9}$$

where, $ask_{i,\tau}$ is the daily ask price for bond i on day τ, $bid_{i,\tau}$ is the daily bid price for bond i on day τ, $mid_{i,\tau}$ is the average of the $ask_{i,\tau}$ and $bid_{i,\tau}$, and $Number\ of\ obs._{i,90d}$ is the number of available daily observations during 90 trading days.

18 Rischen and Theissen (2021) use bid-ask spreads during the 40 trading days following the first market price as a proxy for liquidity in the secondary market, and investigate the effect of liquidity on underpricing. Their results do not support the liquidity-based explanation of underpricing due to the insignificant coefficient of bid-ask spreads.

4.6 Empirical Results

4.6.1 Univariate Analysis Results

Table 4.5 presents the mean and median underpricing distributed by the characteristics of bonds and issuers. The T-test and Wilcoxon rank-sum (Mann-Whitney) test the equality of means and medians across two samples.

Panel A of Table 4.5 reports the results of underpricing in percentage terms between IBOs and SBOs. The IBOs and SBOs present an average underpricing of 74 and 49 bps, respectively. The greater underpricing of IBOs than of SBOs aligns with the results presented by Cai et al. (2007) and Rischen and Theissen (2021). Cai et al. (2007) find that the average underpricing for US high-yield bonds is 47 bps for IBOs and 15 bps for SBOs during the sample period between 1995 and 1999. Our Euro-denominated high-yield bonds tend to have greater underpricing than the US ones, reflecting that the high-yield corporate bond market is less developed in the Euro-denominated than the US market. In addition, Rischen and Theissen (2021) find that the respective average underpricing for IBOs and SBOs is 66 bps and 25 bps in the Euro-denominated corporate bond market, including both investment-grade and high-yield bonds. As expected, high-yield bonds have a higher underpricing than investment-grade bonds due to higher default risk, greater information asymmetry problems, and lower secondary market liquidity.

Panel B compares the degree of underpricing between two groups of issuers. One group of issuers has not issued any bonds in the last two years, and the other has issued at least one bond within two years of issuance. As expected, the former is underpriced more than the latter. The difference in average underpricing between these two groups is statistically significant at a 10% level. Results indicate that information production and transmission costs during the bookbuilding process affect the magnitude of underpricing, which is in line with hypothesis 1.

Panel C of Table 4.5 compares the underpricing between bonds with a first rating downgrade, and those with a first rating upgrade. The average underpricing is greater for bonds with a first rating upgrade, but the test statistic is insignificant. Panel D compares the underpricing of bonds underwritten by the top 7 and non-top 7 lead underwriters. The degree of underpricing is higher for bonds backed by non-top 7 lead underwriters. The test statistics between these two samples are not statistically significant. At this stage, the results of Panels C and D do not support the signalling theory and underwriter reputation hypothesis, which will be investigated further after controlling for the bond and issuer characteristics.

Panel E shows the univariate analysis of the underpricing across the industry. We have 154 high-yield bonds issued by non-financial companies with the underpricing of 64.8 bps, and 70 high-yield bonds issued by financial institutions with the underpricing of 44.8 bps. The greater underpricing for bonds issued by non-financial industries than their financial counterparts is consistent with the result shown in Rischen and Theissen (2021).

Panels F and G of Table 4.5 present the results of underpricing distributed by ratings. BB+ and BB are at the edge of the high-yield grade by a notch and alphabetic levels, respectively. In addition, we have 86% (192 out of the 224) sample bonds rated as the BB alphabetic rating group.[19] We separately investigate the degree of underpricing for BB+ and BB groups. Panel F shows that bonds with a BB rating are less underpriced than those below BB. The mean and median underpricing between these two groups are not statistically significant. However, Panel G shows a different story. Normally, a bond with a better credit rating tends to be less risky, and it is expected to have a lower degree of underpricing. BB+ is the closest to an investment-grade bond rating. Bonds with a rating of BB+ have the best credit quality among all high-yield bonds, but have a greater underpricing than those below BB+. The equality of means between these two groups is statistically significant at a 10% level. Our results suggest that the degree of underpricing is not exclusively dependent on their ratings, supporting Fridson and Gao (1996) and Datta et al. (1997)'s view that high-yield bonds are not sold merely on their ratings.

19 In the sample, 98 bonds are rated as BB+, 73 bonds are rated as BB, 21 bonds are rated as BB-. 26 are rated as B, and 6 bonds are rated as CCC or below.

Panel H compares the underpricing for bonds issued between a private and a public issuer. A private company has no responsibility to disclose annual reports regarding its performance and outlook, and tends to have less information available than a public company in the public market. The average underpricing is expected to be larger for high-yield bonds issued by private companies than public ones. The difference in mean value between these two groups is statistically significant at a 5% level. This result is in line with the conception that underpricing resolves information asymmetry problems, consistent with Cai et al. (2007).

Table 4.5: Univariate analysis.

Panel A: By IBO /SBO.			
	IBO	SBO	Test statistics
Underpricing (mean)	0.742	0.488	-0.648
Underpricing (median)	0.470	0.216	-0.595
N. bonds	26	198	
Panel B: By number of bonds within two years of the issuance.			
	Zero bond	More than one bond	Test statistics
Underpricing (mean)	0.815	0.406	1.455*
Underpricing (median)	0.384	0.188	1.416
N	61	163	
Panel C: First rating action.			
	Downgrade	Upgrade	Test statistics
Underpricing (mean)	0.246	0.450	0.839
Underpricing (median)	0.221	0.150	0.160
N	78	106	
Panel D: By underwriter reputation.			
	Top 7 underwriter	Non-top 7 underwriter	Test statistics
Underpricing (mean)	0.398	0.648	0.901
Underpricing (median)	0.099	0.353	1.055
N	60	157	
Panel E: Industry.			
	Financials	Non-financials	Test statistics
Underpricing (mean)	0.448	0.549	0.373
Underpricing (median)	0.237	0.216	0.687
N	70	154	
Panel F: Rating.			
	BB	Below to BB	Test statistics
Underpricing (mean)	0.510	0.563	0.145
Underpricing (median)	0.222	0.244	0.094
N	192	32	
Panel G: Rating.			
	BB+	Below to BB+	Test statistics
Underpricing (mean)	0.741	0.250	-1.576*
Underpricing (median)	0.344	0.230	-1.198
N	98	126	
Panel H: By Private / Public issuer.			
	Private	Public	Test statistics
Underpricing (mean)	0.773	0.239	-2.143**
Underpricing (median)	0.224	0.235	-0.473
N	117	107	

Table 4.5 continued: Univariate analysis.

Panel A presents the mean and median underpricing for IBOs and SBOs in percentage terms. IBOs are the first bond issued by the issuer, and SBOs are seasoned bond offerings. Panel B presents the mean and median underpricing by two types of issuers. The zero bond group includes issuers that have not issued any bonds, and the more than one bond group includes those that have issued more than one bond in the past two years. Panel C presents the mean and median underpricing across the first rating actions, either a downgrade or upgrade. Panel D presents the mean and median underpricing based on the reputation of underwriters. Panel E presents the mean and median underpricing by industry. Financial includes high-yield bonds issued by financial industries. Non-financial includes bonds issued by non-financial industries, including communications (11 bonds), consumer discretionary (41 bonds), consumer staples (8 bonds), energy (5 bonds), health care (22 bonds), industrials (12 bonds), materials (46 bonds), technology (2 bonds), and utilities (7 bonds). Panel F presents the underpricing for bonds with BB ratings and those with ratings below BB according to an alphabetical level. Panel G presents the underpricing for bonds with BB+ and those with ratings below BB+ based on a notch level. Panel H presents the mean and median underpricing for bonds issued by private and public firms. Private issuers have not issued any shares traded on public exchanges, while public issuers do. N is the number of bonds. Reported test statistics show t-statistics and z-statistics for the two-sample t-test and the Wilcoxon rank-sum (Mann-Whitney) test, testing whether the mean and median underpricing of two samples are equal or not. *, **,*** is significant at <10%, <5%, <1% levels.

4.6.2 Multivariate Analysis Results

Our univariate analysis in Table 4.5 shows that underpricing is caused by information asymmetry problems. We further investigate the determinants of underpricing by adopting OLS regression models. Table 4.6 presents the results for high-yield bond offerings, and Table 4.7 exhibits the results for only SBOs.

Model 1 in Table 4.6 shows that the key determinants of underpricing for high-yield bond offerings are the private company and the firm's size. Given the high information asymmetry problems of private companies, bonds issued by these companies are underpriced more than public companies. The issuer's total asset measures the firm's size, which is negatively related to the degree of underpricing. Our result suggests that the larger the size of the firm, the smaller the degree of underpricing. One of the biggest concerns for high-yield bond investors may be whether they can receive both the coupon payments and the principal back when the bond matures. Larger firms tend to have fewer information asymmetry problems, are less likely to default, and hence have a lower degree of underpricing than smaller ones.

Models 2 and 3 in Table 4.6 test whether the bookbuilding theory can explain the degree of underpricing. Results in Model 2 provide evidence for the bookbuilding theory. The negative coefficient of the Bondswithin2Y_dummy variable with a 10% statistical significance implies that the degree of underpricing can be reduced for high-yield bonds issued by issuers that have issued at least one bond in the past two years. This result is consistent with Cai et al. (2007) and hypothesis 1, that the degree of underpricing is lower for high-yield corporate bonds issued by recently repeated issuers. As the correlation between IBO and LNExperience is -0.740 (see Table 4.3), we remove the LNExperience variable from Model 3 to reduce the potential multicollinearity issues. The sign of the IBO coefficient is negative without any statistical significance level. We only have 26 IBOs in the sample, which may affect the results.

According to the signalling theory of underpricing, good issuers of high-yield bonds use underpricing as a positive signal to differentiate themselves from others, and then the ratings of these bonds are more likely to be upgraded following issuance. We use Models 4 and 5 in Table 4.6 to investigate whether the degree of underpricing is delineated by the signalling theory. The coefficients of the first rating upgraded and the first rating downgraded variables are statistically insignificant. Rischen and Theissen (2021) find a similar result, that the coefficient of the bond upgraded variable is insignificant. These results do not support the signalling theory of underpricing. Therefore, our results imply that the degree of underpricing is not related to a high-yield bond offering with a first rating upgraded following issuance (hypothesis 2b).

Model 6 tests whether high-yield bonds backed by top-rated underwriters can certify issuers and alleviate the degree of underpricing. The coefficient is negative without statistical significance, so we cannot state that reputable underwriters can reduce the degree of underpricing. Our results are not in line with our hypothesis 3 that the degree of underpricing is negatively related to reputable underwriters.

We measure the expected liquidity with the FZR and bid-ask spreads during the initial 90 days following the first secondary market price, presented in Models 7 and 8 in Table 4.6. A higher FZR_90d variable shows that the bond has a higher proportion of unchanged prices, indicating that the bond is more illiquid than others. The coefficient of the FZR is negative with a 1% statistical significance level, which indicates a larger underpricing when the bond has a more frequent trading activity. The secondary market liquidity is unknown when the bond is issued in the primary market. A greater underpricing may attract more investors to be involved in the trading, which would enhance the frequency of trading in the secondary market. The bid-ask spread variable is not statistically significant, consistent with the result presented by Rischen and Theissen (2021). Therefore, there is a link between the degree of underpricing and the frequency of trading in the secondary market. Our results agree with Booth and Chua (1996)'s opinion and support hypothesis 4b that the degree of underpricing is negatively associated with the expected secondary market liquidity.

Table 4.6: Multivariate analysis of high-yield bond offerings.

	Model 1 Underpricing	Model 2 Underpricing	Model 3 Underpricing	Model 4 Underpricing
Bondswithin2Y_dummy		-0.559*		
		(0.051)		
IBO			-0.206	
			(0.658)	
First rating upgraded				0.155
				(0.595)
English	-0.434	-0.403	-0.349	-0.216
	(0.429)	(0.461)	(0.492)	(0.734)
LNExperience	0.263	0.373*		0.168
	(0.189)	(0.051)		(0.567)
Private placement	0.105	0.156	0.048	0.094
	(0.717)	(0.592)	(0.858)	(0.799)
Private	0.711*	0.656	0.596	0.854
	(0.097)	(0.117)	(0.145)	(0.220)
LNTA	-0.230*	-0.214*	-0.160	-0.228
	(0.084)	(0.098)	(0.173)	(0.344)
Constant	3.237**	3.178**	2.870*	2.278
	(0.024)	(0.020)	(0.052)	(0.207)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
N	199	199	199	162
Adjusted R-squared	0.061	0.074	0.045	0.021

Table 4.6 continued: Multivariate analysis of high-yield bond offerings.

	Model 5 Underpricing	Model 6 Underpricing	Model 7 Underpricing	Model 8 Underpricing
First rating downgraded	-0.155			
	(0.595)			
Corp_top7_annual		-0.388		
		(0.367)		
FZR_90d			-3.409***	
			(0.007)	
Bid-ask spread_90d				-0.017
				(0.984)
English	-0.216	-0.471	-0.478	-0.443
	(0.734)	(0.388)	(0.368)	(0.384)
LNExperience	0.168	0.311	0.255	0.296
	(0.567)	(0.112)	(0.182)	(0.149)
Private placement	0.094	0.190	0.169	0.134
	(0.799)	(0.491)	(0.557)	(0.601)
Private	0.854	0.740*	0.779*	0.650*
	(0.220)	(0.094)	(0.064)	(0.085)
LNTA	-0.228	-0.255**	-0.218*	-0.241*
	(0.344)	(0.048)	(0.094)	(0.058)
Constant	2.433	2.700**	3.765***	3.577*
	(0.186)	(0.042)	(0.008)	(0.052)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
N	162	192	199	192
Adjusted R-squared	0.021	0.019	0.117	0.008

The table exhibits the multivariate analysis of underpricing for high-yield bond offerings between 2009 and 2019. The dependent variable is underpricing, described in Section 4.5.1. Model 1 is the baseline model, which investigates the determinants of underpricing (see Equation 4.4). Model 2 presents the results of the baseline model augmented with the Bondswithin2Y_dummy variable, testing the bookbuilding theory. Model 3 tests the effect of the IBO variable on underpricing. Models 4 and 5 present the results of the baseline model augmented with the first rating upgraded and first rating downgraded variables, respectively. These two models are used to test the signalling theory-based underpricing. Model 6 presents the results of the baseline model augmented with Corp_top 7_annual, investigating the role of underwriter reputation in explaining underpricing. Models 7 and 8 present the results of the baseline model augmented with FZR_90d and Bid-ask spread_90d, respectively. These two models investigate the relationship between underpricing and the expected secondary market liquidity. Definitions of all variables are presented in Table A8 in Appendix A. Year FE refers to the bond's pricing year fixed effects. Industry FE refers to the industry fixed effects. Country FE refers to the bond's nationality fixed effects. P-values are in parentheses. *, **,*** is significant at <10%, <5%, <1% levels.

We exclude IBOs from the sample and re-run the OLS regression models to test whether bookbuilding theory, signalling theory, underwriter reputation, and expected secondary market liquidity can explain underpricing for SBOs in the high-yield corporate bond market.

Model 1 in Table 4.7 shows the results of determinants of underpricing for SBOs in the high-yield bond market. The LNTA coefficient is negative with a 10% statistical significance level, showing that a firm's size is negatively correlated with the degree of underpricing. As expected, larger firms tend to have fewer information problems and, therefore, a lower degree of underpricing than smaller firms.

Compared to the results presented in Model 2 (Table 4.6), the coefficient of the bondswihin2y_dummy variable loses its statistical significance in Table 4.7. According to Table 4.5, only 18% (35 out of 198) of SBOs have not issued any bonds, and 82% of SBOs have issued at least one bond within two years of issuance. The results suggest that the role of information collection costs in determining the degree of underpricing is more critical to IBOs than to SBOs.

Models 3 and 4 in Table 4.7 investigate whether the signalling theory can be used to explain the underpricing in SBOs. The coefficients of the First rating upgraded and First rating downgraded variables are insignificant, the same as the results presented in Table 4.6. The results are inconsistent with the signalling theory-based underpricing. Given the small sample size, the results may be explained with caution.

The Corp_top 7_annual coefficient is negative without any statistical significance level, presented in Model 5, indicating that high-yield bonds backed by reputable underwriters may not reduce the degree of underpricing for SBOs.

Regarding the role of expected secondary market liquidity in explaining the underpricing for SBOs, results are presented in Models 6 and 7 in Table 4.7. The coefficient of FZR_90d is negative and statistically at a 5% significance level, suggesting that high-yield bonds with greater underpricing tend to be correlated with more frequent trading activity in the secondary market. The bid-ask spread_90d coefficient remains insignificant for SBOs.

Table 4.7: Multivariate analysis of high-yield bond seasoned offerings.

	Model 1 Underpricing	Model 2 Underpricing	Model 3 Underpricing	Model 4 Underpricing
Bondswithin2Y_dummy		-0.548		
		(0.148)		
First rating upgraded			0.107	
			(0.782)	
First rating downgraded				-0.107
				(0.782)
English	-0.210	-0.187	-0.033	-0.033
	(0.691)	(0.723)	(0.951)	(0.951)
LNExperience	0.332	0.354	0.251	0.251
	(0.213)	(0.154)	(0.531)	(0.531)
Private placement	0.020	0.060	-0.029	-0.029
	(0.948)	(0.847)	(0.931)	(0.931)
Private	0.778	0.695	0.911	0.911
	(0.116)	(0.170)	(0.230)	(0.230)
LNTA	-0.288*	-0.257	-0.294	-0.294
	(0.070)	(0.115)	(0.224)	(0.224)
Constant	4.596**	4.728**	3.344	3.451
	(0.027)	(0.016)	(0.232)	(0.209)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
N	176	176	143	143
Adjusted R-squared	0.079	0.088	0.024	0.024

Table 4.7 continued: Multivariate analysis of high-yield bond seasoned offerings.

	Model 5 Underpricing	Model 6 Underpricing	Model 7 Underpricing
Corp_top 7_annual	-0.016		
	(0.976)		
FZR_90d		-3.293**	
		(0.014)	
Bid-ask spread_90d			-0.214
			(0.814)
English	-0.136	-0.292	-0.212
	(0.784)	(0.570)	(0.687)
LNExperience	0.451*	0.347	0.429*
	(0.083)	(0.180)	(0.085)
Private placement	0.054	0.088	0.099
	(0.843)	(0.777)	(0.719)
Private	0.854*	0.883*	0.723*
	(0.098)	(0.068)	(0.080)
LNTA	-0.298**	-0.268*	-0.324**
	(0.045)	(0.086)	(0.028)
Constant	2.485	4.946**	4.809**
	(0.204)	(0.018)	(0.043)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
N	169	176	169
Adjusted R-squared	0.040	0.131	0.023

The table exhibits the multivariate analysis of underpricing for high-yield bond seasoned offerings between 2009 and 2019. The dependent variable is underpricing, described in Section 4.5.1. Model 1 is the baseline model, which investigates the determinants of underpricing for SBOs (see Equation 4.4). Model 2 presents the results of the baseline model augmented with the Bondswithin2Y_dummy variable, testing the bookbuilding theory for SBOs. Models 3 and 4 present the results of the baseline model augmented with the first rating upgraded and first rating downgraded variables, respectively. These two models are used to test the signalling theory-based underpricing for SBOs. Model 5 presents the results of the baseline model augmented with Corp_top 7_annual, investigating the role of underwriter reputation in explaining underpricing for SBOs. Models 6 and 7 present the results of the baseline model augmented with FZR_90d and Bid-ask spread_90d, respectively. These two models investigate the relationship between underpricing and the expected secondary market liquidity for SBOs. Definitions of all variables are presented in Table A8 in Appendix A. Year FE refers to the bond's pricing year fixed effects. Industry FE refers to the industry fixed effects. Country FE refers to the bond's nationality fixed effects. P-values are in parentheses. *, **,*** is significant at <10%, <5%, <1% levels.

4.7 Robustness Checks

In this section, we present additional results to further lend credence to our results. First, we use an alternative league table for rankings of lead underwriters. Second, we use the expected market liquidity measures with a different size of the event window after issuance.

4.7.1 Alternative League Table for Measuring Underwriter Reputation

Andres et al. (2014) use rankings of underwriters based on the issuance volume of high-yield corporate bonds as an alternative league table, examining the role of underwriter reputation in the US high-yield corporate bond market. Similar to Andres et al. (2014)'s league table, we adopt the annual underwriters' rankings based on the issuance volumes of Euro-denominated fixed high-yield corporate bonds as alternative league tables. We collect these annual league tables for bonds issued between 2009 and 2019 from Bloomberg and present them in Table A9 in Appendix A.

HY_top 7_annual is an alternative measure of reputable underwriters. It is a categorical variable, which equals one if the average syndicate market share is higher than the top seventh of the underwriter's market share in the annual league table, and zero otherwise.

The results presented in Table 4.8 and Table 4.9 are consistent with our findings that the degree of underpricing may not be associated with high-yield bonds backed by reputable underwriters.

4.7.2 Alternative Event Window Size for Expected Secondary Market Liquidity

No precise days following issuance may be used to assess the expected secondary market liquidity. For instance, Goldstein et al. (2019)'s liquidity measures capture one or two months subsequent to issuance, and Rischen and Theissen (2021) use bid-ask spreads within 40 days of trading following issuance. According to European Commission (2017*a*), the active trading period for corporate bonds is between one and three weeks, after which the liquidity reduces. High-yield bonds are traded less frequently and are more likely to be held by investors with a long-term investment horizon. Therefore, we use the initial 30 days following the first secondary market price as robustness checks.

The coefficient of FZR_30d is negatively related to the underpricing in the high-yield bond offerings and SBOs, presented in Table 4.8 and Table 4.9, respectively. Results remain robust after adjusting the size of the event window for the FZR and bid-ask spread measures.

Table 4.8: Multivariate analysis of high-yield bond offerings.

	Model 1 Underpricing	Model 2 Underpricing	Model 3 Underpricing
HY_top 7_annual	0.499		
	(0.262)		
FZR_30d		-2.545**	
		(0.021)	
Bid-ask spread_30d			0.301
			(0.688)
English	-0.464	-0.516	-0.429
	(0.388)	(0.346)	(0.406)
LNExperience	0.285	0.291	0.303
	(0.125)	(0.145)	(0.134)
Private placement	0.195	0.167	0.115
	(0.495)	(0.562)	(0.666)
Private	0.678*	0.742*	0.626*
	(0.097)	(0.078)	(0.099)
LNTA	-0.242*	-0.210	-0.242*
	(0.073)	(0.101)	(0.052)
Constant	1.908	3.983***	4.418**
	(0.215)	(0.007)	(0.013)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
N	192	199	186
Adjusted R-squared	0.028	0.116	0.013

The table exhibits the multivariate analysis of underpricing for high-yield bond offerings between 2009 and 2019. The dependent variable is underpricing, described in Section 4.5.1. Model 1 presents the results of the baseline model augmented with HY_top 7_annual, investigating the role of underwriter reputation in explaining underpricing. Models 2 and 3 present the results of the baseline model augmented with FZR_30d and Bid-ask spread_30d, respectively. These two models investigate the relationship between underpricing and the expected secondary market liquidity. Definitions of all variables are presented in Table A8 in Appendix A. Year FE refers to the bond's pricing year fixed effects. Industry FE refers to the industry fixed effects. Country FE refers to the bond's nationality fixed effects. P-values are in parentheses. *, **,*** is significant at <10%, <5%, <1% levels.

Table 4.9: Multivariate analysis of high-yield bond seasoned offerings.

	Model 1 Underpricing	Model 2 Underpricing	Model 3 Underpricing
HY_top 7_annual	0.743		
	(0.117)		
FZR_30d		-2.419**	
		(0.043)	
Bid-ask spread_30d			0.102
			(0.894)
English	-0.154	-0.318	-0.212
	(0.754)	(0.550)	(0.686)
LNExperience	0.510*	0.380	0.412*
	(0.057)	(0.167)	(0.094)
Private placement	0.089	0.053	0.074
	(0.743)	(0.864)	(0.794)
Private	0.795*	0.825*	0.675
	(0.090)	(0.087)	(0.111)
LNTA	-0.327**	-0.256*	-0.312**
	(0.029)	(0.094)	(0.034)
Constant	1.587	5.240**	5.954**
	(0.412)	(0.017)	(0.012)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
N	169	176	165
Adjusted R-squared	0.083	0.125	0.027

The table exhibits the multivariate analysis of underpricing for high-yield bond seasoned offerings between 2009 and 2019. The dependent variable is underpricing, described in Section 4.5.1. Model 1 presents the results of the baseline model augmented with HY_top 7_annual, investigating the role of underwriter reputation in explaining underpricing for SBOs. Models 2 and 3 present the results of the baseline model augmented with FZR_30d and Bid-ask spread_30d, respectively. These two models investigate the relationship between underpricing and the expected secondary market liquidity for SBOs. Definitions of all variables are presented in Table A8 in Appendix A. Year FE refers to the bond's pricing year fixed effects. Industry FE refers to the industry fixed effects. Country FE refers to the bond's nationality fixed effects. P-values are in parentheses. *, **,*** is significant at <10%, <5%, <1% levels.

4.8 Summary

We investigate the magnitude and determinants of underpricing in the Euro-denominated high-yield corporate bond market. We find that the average underpricing of IBOs and SBOs is 74 bps and 49 bps, respectively. Our evidence suggests that underpricing is more likely relevant to information asymmetry problems and the frequency of trading following issuance in the secondary market.

Issuers with a higher level of information asymmetry are more likely to be associated with greater underpricing. For example, we find that high-yield bonds issued by private or small firms expectedly have substantially high underpricing. We also further investigate theories of underpricing, which are used to solve information asymmetry problems. We find that any issuers who have recently issued a bond are inversely related to the degree of underpricing, consistent with the bookbuilding-based explanation. On the other hand, the coefficients of the first rating upgraded or downgraded variables are not statistically significant, indicating that underpricing potentially is not caused by the signalling theory.

In addition, we investigate whether the reputation of lead underwriters can reduce the level of information asymmetry between issuers and investors, but do not find any evidence supporting either the traditional certification or the market power hypothesis.

Given the low liquidity in the high-yield bond market, underpricing can be regarded as compensation for expected low secondary market liquidity (Ellul and Pagano, 2006), or motivation for investors to trade more (Booth and Chua, 1996). We find that underpricing is more likely to be negatively associated with the frequency of trading. This result suggests that greater underpricing attracts more investors involved in trading in the secondary market and spreading the ownership. Therefore, our findings support the explanation of underpricing from Booth and Chua (1996)'s point.

Overall, our results suggest that Euro-denominated high-yield corporate bonds are underpriced. The degree of underpricing is relevant to information asymmetry problems, coming from the bookbuilding theory. There is also a link between the level of underpricing and expected secondary market liquidity.

Chapter Five

Conclusion

This doctoral thesis focuses on the Euro-denominated high-yield corporate bond market from three perspectives: comparing databases (Chapter 2), unconditional and time-varying effect of common factors on excess returns across ratings, maturities, and industries in the secondary market (Chapter 3), and magnitude and determinants of underpricing in the primary market (Chapter 4).

Chapter 2 primarily compares Bloomberg, Refinitiv Eikon, and Refinitiv Datastream to determine which database is more favourable for collecting data on Euro-denominated high-yield corporate bonds. We find that Bloomberg's data coverage is more extensive than that of Refinitiv Eikon's. Specifically, it provides over five times as many high-yield bonds as Refinitiv Eikon using the same selection criteria. Bloomberg is chosen to collect the first phase data, minimising the likelihood of sample survivorship bias.

We randomly select five bonds, compare their accrued interest, ask, bid, and clean prices on the same day, and discover that the data provided by Bloomberg and Refinitiv Datastream differ from an individual bond perspective. We use clean prices to estimate the excess returns and underpricing, which are dependent variables for Chapters 3 and 4. Given the importance of clean prices to the sample size, we gather clean prices from these databases and find Bloomberg provides 652 more bonds with available clean prices than Refinitiv Datastream. Consequently, the former has a sample size advantage over the latter.

In addition, we use high-yield bonds issued between 2017 and 2021 and calculate their monthly price returns separately using clean prices reported by Bloomberg and Refinitiv Datastream. Our results show that the returns vary, but the differences in returns are statistically insignificant between these two databases. Furthermore, the monthly time series of average returns, as reflected by these two databases, exhibit a comparable pattern over time.

Therefore, we use Bloomberg as our primary data source for sample size and data consistency purposes.

Chapter 3 investigates the common factors in pricing Euro-denominated high-yield corporate bonds in the secondary market between 2000 and 2021. As high-yield bonds are traded infrequently, we initially add a novel illiquidity factor to Fama and French (1993) 2-factor model. Bondholders typically receive fixed coupon payments and the principal back when the bond matures, so they gain limited upside payoffs but unlimited downside potential. Given the higher probability of default for high-yield bonds than for investment-grade bonds, we add the downside risk to the illiquidity augmented Fama and French 2-factor model. The illiquidity factor is estimated using principal component analysis from three distinct illiquidity measures, the Roll, FRZ, and bid-ask spread. The downside factor is constructed by following Bai et al. (2019). We run pooled regression models with year and industry fixed effects across ratings, maturities, and industries for the 3-factor and 4-factor models, respectively. We then investigate the time-varying effects of these factors on excess returns by ratings, maturities, and industries, employing a Markov-switching model with two states.

We find the illiquidity factor plays a vital role in explaining excess returns and fluctuates in different market scenarios, particularly for bonds with a rating of CCC and below and those issued by financial industries. In the high-volatility state, the prices of CCC and below-rated bonds drop significantly relative to BB-rated bonds, indicating a flight to liquidity phenomenon. Investors prefer to invest in liquid assets during a high market volatility period, exacerbating the illiquidity of lower-rated high-yield bonds. While in the low-volatility state, we find the opposite effect of the illiquidity factor on excess returns between CCC and below-rated and BB-rated bonds. The former bonds experience a price decrease, whereas the latter have a price increase. In addition, the prices of financial bonds drop more than non-financial bonds in the high-volatility state.

In terms of the downside risk factor, we find a positive association between the downside risk factor and excess returns based on pooled regression models with year and industry fixed effects. In addition, the time-varying effect of the downside risk factor on excess returns is significantly different between the two states for bonds with a maturity of one to three years. Specifically, we find that the positive association between the downside risk factor and excess returns is higher in the high-volatility than in the low-volatility states.

Term, default, illiquidity, and downside are common factors in pricing Euro-denominated high-yield corporate bonds after controlling for year and industry fixed effects. We find that the default and illiquidity factors are more important in explaining excess returns than the other factors, especially in the high-volatility state.

Chapter 4 investigates the magnitude and determinants of underpricing for Euro-denominated high-yield corporate bonds in the primary market between 2009 and 2019. Most issuers of high-yield bonds are private, small public companies, or fallen angels that have previously issued investment-grade bonds but are currently undergoing hard times. These issuers may have a high level of information asymmetry, some extent of financial difficulties, and may need reputable underwriters to assist them and add additional value to issuance. In addition, high-yield bonds have low frequency of trading in the secondary market. Therefore, we investigate whether the degree of underpricing can be explained by bookbuilding theory, signalling theory, underwriter reputation, and expected secondary market liquidity.

We examine the magnitude of underpricing using univariate analysis and find that the average underpricing of IBOs and SBOs is 74 bps and 49 bps, respectively. Then, we investigate the determinants of underpricing by using OLS regression models with year, industry, and country fixed effects for high-yield bond offerings and only SBOs, respectively. Our evidence suggests that underpricing is likely relevant to information asymmetry problems arising from the bookbuilding theory. There is also a link between underpricing and trading frequency following issuance in the secondary market.

Overall, our findings provide valuable information that may be used for performance analysis and asset allocation in the high-yield corporate bond market.

The limitation of this thesis is the quoted price of high-yield bonds. The trades in the Euro-denominated high-yield bond market are less transparent than those in the US high-yield bond market. Recent US corporate bond studies use transaction prices, which are available from TRACE (e.g., Nikolova et al., 2020). In comparison, quoted prices are typically used in academic studies for Euro-denominated corporate bonds (e.g., Rischen and Theissen, 2021; Aussenegg et al., 2015). Quoted prices vary according to databases (e.g., Bloomberg and Refinitiv Datastream) for two primary reasons. First, databases have different dealers who contribute quoted prices. Second, databases use their proprietary method of determining a quoted price from approved pricing providers.

If insufficient dealers provide prices, databases cannot generate a price. As a result, many high-yield bonds have missing prices, which considerably reduces the sample size. The poor transparency of trades in the Euro-denominated high-yield corporate bond market will have implications for regulatory policy. It is essential to enhance trade transparency and report prices to a governing body.

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Appendix

Table A1: Principal component analysis loadings on the illiquidity measures.

	PC1	PC2	PC3
FZR	0.60	-0.51	0.62
Roll	0.41	0.86	0.31
Bid-ask spread	0.69	-0.06	-0.73
Cumulative % explained	44.09	76.26	100.00

This table presents the PC loadings (1PC, 2PC, and 3PC), and the components' cumulative explanatory power, as attributed to three illiquidity measures. The illiquidity variables are measured on a monthly basis in the sample. The data are quoted prices for Euro-denominated high-yield corporate bonds reported by Bloomberg.

Table A2: Descriptive statistics of illiquidity measures.

Panel A: Roll measure (%).

	Mean	Median	SD	Min	Max
Sample bonds	0.24	0.11	0.86	0.00	146.53
Rating BB	0.21	0.10	0.82	0.00	146.53
Rating B	0.35	0.16	0.81	0.00	68.41
Rating CCC and below	0.75	0.29	1.60	0.00	31.47
Maturity 1-3 years	0.18	0.07	0.41	0.00	6.45
Maturity 3-5 years	0.18	0.06	0.60	0.00	16.09
Maturity 5-7 years	0.21	0.09	0.68	0.00	68.41
Maturity 7-10 years	0.24	0.10	0.55	0.00	17.66
Maturity 10+ years	0.28	0.14	1.16	0.00	146.53
Financials	0.25	0.11	0.73	0.00	68.41
Non-financials	0.23	0.10	0.92	0.00	146.53

Panel B: FZR measure (%).

	Mean	Median	SD	Min	Max
Sample bonds	10.38	0.00	24.48	0.00	100.00
Rating BB	7.78	0.00	19.83	0.00	100.00
Rating B	19.99	4.35	35.55	0.00	100.00
Rating CCC and below	31.39	4.76	41.27	0.00	100.00
Maturity 1-3 years	39.72	22.73	38.31	0.00	100.00
Maturity 3-5 years	14.41	4.35	27.30	0.00	100.00
Maturity 5-7 years	12.29	0.00	28.61	0.00	100.00
Maturity 7-10 years	11.20	0.00	25.10	0.00	100.00
Maturity 10+ years	6.17	0.00	16.32	0.00	100.00
Financials	14.62	0.00	29.92	0.00	100.00
Non-financials	7.76	0.00	19.96	0.00	100.00

Table A2 continued: Descriptive statistics of illiquidity measures.

Panel C: Bid-ask spread measure (%).

	Mean	Median	SD	Min	Max
Sample bonds	0.68	0.56	0.57	0.00	16.93
Rating BB	0.64	0.55	0.45	0.00	11.38
Rating B	0.78	0.62	0.75	0.01	16.93
Rating CCC and below	1.30	0.80	1.27	0.01	16.93
Maturity 1-3 years	0.57	0.34	0.54	0.00	2.80
Maturity 3-5 years	0.58	0.41	0.60	0.01	6.73
Maturity 5-7 years	0.52	0.42	0.43	0.00	9.28
Maturity 7-10 years	0.69	0.58	0.52	0.01	8.19
Maturity 10+ years	0.84	0.69	0.65	0.01	16.93
Financials	0.69	0.53	0.69	0.00	16.93
Non-financials	0.67	0.58	0.48	0.01	11.38

This table shows the descriptive statistics for the Roll (Panel A), FZR (Panel B), and bid-ask spread variables (Panel C) between March 2000 and December 2021 by ratings, maturities and industries. These illiquidity variables are defined in Equation 3.3, Equation 3.4, and Equation 3.5. Each category is based on market-value weighted (i.e., rating, maturity, and industry). The market value of a bond equals the amount outstanding multiplied by the quoted month-end price during that month.

Table A3: Descriptive statistics of LAMBDA.

	Mean	Median	SD	Min	Max
Sample bonds	-0.16	-0.47	0.91	-1.21	53.32
Rating BB	-0.25	-0.54	0.84	-1.21	53.32
Rating B	0.13	-0.12	1.00	-1.21	24.97
Rating CCC and below	0.54	0.40	1.25	-1.21	13.48
Maturity 1-3 years	0.35	0.40	0.80	-1.21	2.38
Maturity 3-5 years	-0.09	-0.44	0.96	-1.21	6.29
Maturity 5-7 years	-0.31	-0.64	0.87	-1.21	24.97
Maturity 7-10 years	-0.44	-0.65	0.64	-1.21	7.86
Maturity 10+ years	-0.12	-0.41	0.99	-1.17	53.32
Financials	0.02	-0.16	0.93	-1.21	24.97
Non-financials	-0.42	-0.63	0.82	-1.21	53.32

This table presents descriptive statistics for LAMBDA between March 2000 and December 2021 by ratings, maturities, and industries. LAMBDA is defined in Subsection 3.4.2. Each category is based on market-value weighted (i.e., rating, maturity, and industry). The market value of a bond equals the amount outstanding multiplied by the quoted month-end price during that month.

Table A4: Results of Fama and French 2-factor model.

Panel A: By ratings.

	Model 1 Sample bonds	Model 2 Rating BB	Model 3 Rating B	Model 4 Rating CCC and below
TERM	0.459***	0.552***	0.082	0.258***
	(0.000)	(0.000)	(0.192)	(0.002)
DEF	0.510***	0.549***	0.400***	0.390***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.220**	1.053	0.550	3.712**
	(0.046)	(0.426)	(0.663)	(0.033)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	44,341	35,372	6,029	2,940
N	1,275	1,228	333	146
Adjusted R^2	0.094	0.173	0.042	0.048

Panel B: By maturities.

	Model 5 1-3 years	Model 6 3-5 years	Model 7 5-7 years	Model 8 7-10 years	Model 9 10+ years
TERM	0.079***	0.230***	0.437***	0.542***	0.567***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DEF	0.116***	0.269***	0.465***	0.553***	0.647***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.052	0.491**	0.858	1.442**	0.692
	(0.785)	(0.039)	(0.599)	(0.020)	(0.647)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	5,478	6,256	10,380	7,835	14,392
N	311	264	291	168	241
Adjusted R^2	0.042	0.086	0.116	0.144	0.090

Table A4 continued: Results of Fama and French 2-factor model.

Panel C: By industries.

	Model 10 Financials	Model 11 Non-financials
TERM	0.420***	0.503***
	(0.000)	(0.000)
DEF	0.469***	0.554***
	(0.000)	(0.000)
Constant	-0.029	1.288*
	(0.886)	(0.056)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	26,022	18,319
N	878	397
Adjusted R^2	0.084	0.106

This table exhibits the results of the following pooled regression model for a sample period between March 2000 and December 2021 by ratings, maturities, and industries:

$$er_{i,t} = \alpha_0 + \beta_1 \, TERM_{i,t} + \beta_2 \, DEF_{i,t} + \varepsilon_{i,t}$$

where $er_{i,t}$is the monthly excess return of bond i in month t, shown in Equation 3.2. TERM denotes the term premium as the difference between the monthly return of the 10-year German government bond index and the one-month Euribor rate in the previous month. DEF denotes the default premium, measured as the difference between the monthly return of the Bloomberg Pan-European High-Yield Index and the monthly return of the 10-year German government bond. We use the market-value weighted for each group. The value in the bracket is the p-value. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A5: Results of pooled regression models for the 4 factors.

Panel A: By ratings.

	Model 1 Sample bonds	Model 2 Rating BB	Model 3 Rating B	Model 4 Rating CCC and below
TERM	0.527***	0.584***	0.122	0.612***
	(0.000)	(0.000)	(0.124)	(0.000)
DEF	0.595***	0.585***	0.547***	0.781***
	(0.000)	(0.000)	(0.000)	(0.000)
LAMBDA	0.195***	0.271***	-0.146	0.370***
	(0.000)	(0.000)	(0.130)	(0.005)
ES	0.237***	0.030	1.746***	0.613
	(0.000)	(0.470)	(0.000)	(0.285)
Constant	-0.328	-0.296	-3.611***	-14.665***
	(0.500)	(0.562)	(0.009)	(0.000)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	39,537	32,650	4,841	2,046
N	1,212	1,145	278	104
Adjusted R^2	0.119	0.196	0.065	0.114

Panel B: By maturities.

	Model 5 1-3 years	Model 6 3-5 years	Model 7 5-7 years	Model 8 7-10 years	Model 9 10+ years
TERM	0.088***	0.301***	0.535***	0.643***	0.603***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DEF	0.135***	0.355***	0.585***	0.671***	0.691***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LAMBDA	0.041*	0.132***	0.340***	-0.028	0.224***
	(0.073)	(0.000)	(0.000)	(0.675)	(0.000)
ES	0.012	0.098	0.261***	0.240**	0.221*
	(0.843)	(0.224)	(0.006)	(0.041)	(0.078)
Constant	-0.086	0.515*	-0.319	-0.282	0.582
	(0.688)	(0.060)	(0.491)	(0.781)	(0.706)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	4,651	5,487	9,219	6,899	13,281
N	298	247	276	161	230
Adjusted R^2	0.052	0.126	0.171	0.188	0.100

Table A5 continued: Results of pooled regression models for the 4 factors.

Panel C: By industries.

	Model 10 Financials	Model 11 Non-financials
TERM	0.497***	0.561***
	(0.000)	(0.000)
DEF	0.566***	0.625***
	(0.000)	(0.000)
LAMBDA	0.138***	0.330***
	(0.000)	(0.000)
ES	0.065	0.459***
	(0.337)	(0.000)
Constant	-0.006	-0.754
	(0.978)	(0.167)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	23,126	16,411
N	839	373
Adjusted R^2	0.115	0.130

This table exhibits the results of the following pooled regression model for a sample period between March 2003 and December 2021 by ratings, maturities, and industries:

$$er_{i,t} = \alpha_0 + \beta_1 \, TERM_{i,t} + \beta_2 \, DEF_{i,t} + \beta_3 \, LAMBDA_{i,t} + \beta_4 \, ES_{i,t} + \varepsilon_{i,t}$$

where $er_{i,t}$ is the monthly excess return of bond i in month t. TERM denotes the term premium as the difference between the monthly return of the 10-year German government bond index and the one-month Euribor rate in the previous month. DEF denotes the default premium, measured as the difference between the monthly return of the Bloomberg Pan-European High-Yield Index and the monthly return of the 10-year German government bond. LAMBDA is the sum of the normalised illiquidity proxies (Roll, FZR, and bid-ask spread) multiplied by their respective first principal component eigenvectors. Following Bai et al. (2019), we use 10% ES as an alternative proxy for the downside risk factor, and multiply the original 10% ES by -1 for the convenience of the interpretation. The average excess returns for each rating, maturity, and industry group are equally weighted. The value in the bracket is the p-value. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A6: Results of Markov-switching regression models for the 4 factors.

	Obs.	TERM	DEF	LAMBDA	ES	Constant	Sigma	P_{ii}
Total sample	226							
High-volatility state		0.374**	0.561***	-0.512	0.094	0.071	1.474	0.638
		(0.021)	(0.000)	(0.257)	(0.552)	(0.879)		
Low-volatility state		0.459***	0.451***	0.127*	0.043*	0.285***	0.301	0.882
		(0.000)	(0.000)	(0.051)	(0.056)	(0.000)		
Rating BB	226							
High-volatility state		0.673***	0.696***	-0.718*	0.178	-0.525	1.956	0.886
		(0.000)	(0.000)	(0.080)	(0.345)	(0.355)		
Low-volatility state		0.515***	0.479***	0.197***	0.040	0.233***	0.258	0.950
		(0.000)	(0.000)	(0.001)	(0.131)	(0.000)		
Rating B	215							
High-volatility state		0.178	0.423***	0.466	0.059	0.696	3.432	0.810
		(0.586)	(0.000)	(0.600)	(0.867)	(0.459)		
Low-volatility state		0.372***	0.432***	-0.138	0.085**	0.078	0.647	0.940
		(0.000)	(0.000)	(0.383)	(0.044)	(0.523)		
Rating CCC and below	216							
High-volatility state		0.863***	0.852***	-1.310***	-0.263	0.977**	2.525	0.767
		(0.000)	(0.000)	(0.006)	(0.143)	(0.023)		
Low-volatility state		0.012	0.007	-0.260***	-0.051*	0.645***	0.201	0.641
		(0.631)	(0.498)	(0.000)	(0.093)	(0.000)		
Maturity 1-3 years	125							
High-volatility state		0.402	0.254**	0.417	0.446**	-0.301	1.189	0.776
		(0.106)	(0.049)	(0.654)	(0.029)			
Low-volatility state		0.008	0.025*	0.077	0.040**	0.258***	0.272	0.946
		(0.760)	(0.083)	(0.236)	(0.047)			
Maturity 3-5 years	190							
High-volatility state		-0.078	0.481***	1.835*	-0.004	1.044	3.864	0.754
		(0.848)	(0.000)	(0.074)	(0.993)	(0.404)		
Low-volatility state		0.210***	0.215***	0.065	0.044	0.206***	0.357	0.928
		(0.000)	(0.000)	(0.427)	(0.134)	(0.001)		
Maturity 5-7 years	226							
High-volatility state		-0.038	0.456***	-0.088	0.167	-0.103	3.119	0.730
		(0.924)	(0.000)	(0.937)	(0.764)	(0.942)		
Low-volatility state		0.325***	0.320***	0.135	0.056**	0.267***	0.440	0.960
		(0.000)	(0.000)	(0.107)	(0.027)	(0.000)		
Maturity 7-10 years	226							
High-volatility state		0.453*	0.529***	-0.565	-0.068	0.980	2.607	0.775
		(0.072)	(0.000)	(0.319)	(0.791)	(0.179)		
Low-volatility state		0.590***	0.575***	0.111	0.006	0.276***	0.405	0.908
		(0.000)	(0.000)	(0.239)	(0.851)	(0.000)		
Maturity 10+ years	213							
High-volatility state		0.571**	0.752***	-0.534	0.277	-0.314	2.598	0.804
		(0.031)	(0.000)	(0.469)	(0.397)	(0.683)		
Low-volatility state		0.782***	0.640***	0.056	-0.026	0.329***	0.503	0.941
		(0.000)	(0.000)	(0.651)	(0.409)	(0.000)		

Table A6 continued: Results of Markov-switching regression models for the 4 factors.

	Obs.	TERM	DEF	LAMBDA	ES	Constant	Sigma	P_{ii}
Financials	201							
High-volatility state		0.298***	0.376***	0.930***	0.103*	0.550***	1.014	0.942
		(0.000)	(0.000)	(0.000)	(0.066)	(0.000)		
Low-volatility state		0.339***	0.374***	-4.056***	0.940***	-4.565***	0.261	0.471
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Non-financials	226							
High-volatility state		0.593***	0.596***	-0.633*	0.075	0.143	1.547	0.724
		(0.000)	(0.000)	(0.053)	(0.559)	(0.673)		
Low-volatility state		0.625***	0.584***	0.324***	-0.001	0.358***	0.221	0.805
		(0.000)	(0.000)	(0.000)	(0.965)	(0.000)		

The table presents the results of a two-state Markov-switching model with TERM, DEF, LAMBDA, and ES. The dependent variable is the monthly time series of average excess returns using equal weights for each portfolio (i.e., rating, maturity, and industry), denoted as $R_{k,t}$. TERM denotes the term premium as the difference between the monthly return of the 10-year German government bond index and the one-month Euribor rate in the previous month. DEF denotes the default premium, measured as the difference between the monthly return of the Bloomberg Pan-European High-Yield Index and the monthly return of the 10-year German government bond. LAMBDA is the sum of the normalised illiquidity proxies (Roll, FZR, and bid-ask spread) multiplied by their respective first principal component eigenvectors. Following Bai et al. (2019), we use 10% ES as an alternative proxy for the downside risk factor, and multiply the original 10% ES by -1 for the convenience of the interpretation. We use the following model and allow the intercepts and coefficients of factors to transit between two states.

$$R_{k,t} \ = \ \alpha_{k,0}^{S} \ + \beta_{k,1}^{S} \, TERM_t + \beta_{k,2}^{S} \, DEF_t + \beta_{k,3}^{S} \, LAMBDA_t + \beta_{k,4}^{S} \, ES_t + \varepsilon_{k,t}^{S}$$

Obs. reports the number of monthly excess returns. P_{ii} denotes the probability of remaining in the same state in the next period. The estimated standard deviation of excess return is reported as sigma. Sigma with high values refers to high-volatility periods, while sigma with low values refers to low-volatility periods. The value in the bracket is the p-value. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A7: Wald tests of equality of coefficients across states for the 4-factor model.

	TERM		DEF		LAMBDA		ES	
	Chi-sq	P-value	Chi-sq	P-value	Chi-sq	P-value	Chi-sq	P-value
Total sample	0.270	0.604	3.410	0.065	1.900	0.168	0.100	0.750
Rating BB	0.840	0.360	13.320	0.000	4.860	0.028	0.510	0.477
Rating B	0.340	0.562	0.010	0.941	0.450	0.504	0.010	0.941
Rating CCC and below	15.010	0.000	51.280	0.000	4.660	0.031	1.340	0.246
Maturity 1-3 years	2.470	0.116	3.090	0.079	0.130	0.717	3.900	0.048
Maturity 3-5 years	0.490	0.482	4.270	0.039	2.960	0.086	0.010	0.914
Maturity 5-7 years	0.830	0.362	1.330	0.249	0.040	0.841	0.040	0.842
Maturity 7-10 years	0.290	0.592	0.270	0.603	1.380	0.241	0.080	0.776
Maturity 10+ years	0.600	0.437	1.360	0.244	0.590	0.441	0.850	0.357
Financials	0.280	0.598	0.000	0.945	469.860	0.000	87.830	0.000
Non-financials	0.060	0.799	0.060	0.813	7.810	0.005	0.300	0.586

The table presents Wald tests on the equality of coefficients between the high-volatility and low-volatility states, as distributed by ratings, maturities, and industries. The null hypothesis is that the coefficients of TERM, DEF, LAMBDA, and ES are not significantly different across the two states.

Table A8: Definition of variables for Chapter 4.

Variable	**Definition**
Proxies for bookbuilding theory	
Bondswithin2Y_dummy	A categorical variable equals one if the firm issued a bond within the last two years, and zero otherwise.
IBO	A categorical variable equals one if the bond is the first bond issued by the issuer, and zero otherwise.
Proxies for signalling theory	
First rating upgraded	A categorical variable equals one if the bond has a first rating upgraded after issuance.
First rating downgraded	A categorical variable equals one if the bond has a first rating downgraded after issuance.
Proxies for underwriter reputation	
Corp_top 7_annual	A categorical variable equals one if the bond is placed by reputable underwriters, whose syndicate market share is higher than the top seventh of the underwriter's market share in the league table of the bond's pricing year, and zero otherwise. The rankings of annual league tables are based on Euro-denominated fixed corporate bonds, presented in Table 4.4.
HY_top 7_annual	It is an alternative measure of reputable underwriters. It is a categorical variable, which equals one if the average syndicate market share is higher than the top seventh of the underwriter's market share in the league table of the bond's pricing year, and zero otherwise. The rankings of annual league tables are based on Euro-denominated fixed high-yield corporate bonds, presented in Table A9 in Appendix A.
Proxies for expected secondary market liquidity	
FZR_90d	The proportion of observations with zero returns during the 90 trading days following the first market price for each bond.
Bid-ask spread_90d	The average daily bid-ask spreads during the 90 trading days following the first market price for each bond.
FZR_30d	The proportion of observations with zero returns during the 30 trading days following the first market price for each bond.
Bid-ask spread_30d	The average daily bid-ask spreads during the 30 trading days following the first market price for each bond.
Characteristics of bonds and issuers	
English	A categorical variable equals one if the bond adopts English governing law, and zero otherwise.
LNExperience	LNExperience = Ln (1 + Experience). Experience is the number of years since the same issuer issued its first bond.
Private placement	A categorical variable equals one if the bond is issued through private placement, and zero otherwise.
Private	A categorical variable equals one if the issuer has no publicly traded equity, and zero otherwise.
LNTA	The natural logarithm of the issuer's total assets in the year before the bond issuance.

The table presents the definition of key variables used in Chapter 4.

Table A9: Annual top 10 underwriters in the Euro-denominated fixed high-yield corporate bond market from 2009 to 2019.

2009			
Underwriter	Rank	Issuance volume (€ in million)	Market share
Deutsche Bank	1	3,533.53	13.76%
RBS	2	3,025.41	11.79%
BNP Paribas	3	2,383.31	9.28%
Credit Suisse	4	2,275.41	8.86%
Credit Agricole CIB	5	1,672.68	6.52%
JP Morgan	6	1,643.30	6.40%
UniCredit	7	1,232.19	4.80%
Goldman Sachs	8	1,219.16	4.75%
Citi	9	1,123.86	4.38%
Commerzbank	10	938.33	3.66%
Total market share of top 7 underwriters		61.42%	
Total number of underwriters		27	
Total issuance volume (€ in million)		25,670.60	
2010			
Underwriter	Rank	Issuance volume (€ in million)	Market share
Deutsche Bank	1	4,110.72	11.34%
BNP Paribas	2	3,113.09	8.59%
JP Morgan	3	2,687.04	7.41%
Citi	4	2,511.31	6.93%
Credit Suisse	5	2,473.74	6.82%
Barclays	6	2,344.22	6.47%
Credit Agricole CIB	7	2,280.53	6.29%
RBS	8	1,809.65	4.99%
Goldman Sachs	9	1,623.31	4.48%
Societe Generale	10	1,519.36	4.19%
Total market share of top 7 underwriters		53.84%	
Total number of underwriters		41	
Total issuance volume (€ in million)		36,258.39	
2011			
Underwriter	Rank	Issuance volume (€ in million)	Market share
Deutsche Bank	1	2,587.16	10.10%
Citi	2	2,185.80	8.54%
BNP Paribas	3	1,866.63	7.29%
Credit Agricole CIB	4	1,791.67	7.00%
RBS	5	1,728.33	6.75%
Societe Generale	6	1,507.92	5.89%
JP Morgan	7	1,493.33	5.83%
Barclays	8	1,459.58	5.70%
Credit Suisse	9	1,379.58	5.39%
Goldman Sachs	10	1,264.93	4.94%
Total market share of top 7 underwriters		51.40%	
Total number of underwriters		35	
Total issuance volume (€ in million)		25,606.40	

Table A9 continued: Annual top 10 underwriters in the Euro-denominated fixed high-yield corporate bond market from 2009 to 2019.

2012			
Underwriter	Rank	Issuance volume (€ in million)	Market share
Deutsche Bank	1	2,800.58	8.96%
BNP Paribas	2	2,341.20	7.49%
Citi	3	2,254.56	7.21%
Credit Agricole CIB	4	2,013.08	6.44%
Barclays	5	1,620.95	5.18%
Goldman Sachs	6	1,600.16	5.12%
JP Morgan	7	1,511.87	4.84%
Societe Generale	8	1,470.26	4.70%
Morgan Stanley	9	1,373.34	4.39%
RBS	10	1,309.12	4.19%
Total market share of top 7 underwriters		45.23%	
Total number of underwriters		51	
Total issuance volume (€ in million)		31,265.42	
2013			
Underwriter	Rank	Issuance volume (€ in million)	Market share
JP Morgan	1	4,909.16	9.08%
Deutsche Bank	2	4,695.34	8.68%
BNP Paribas	3	3,495.53	6.47%
UniCredit	4	3,324.44	6.15%
Citi	5	3,101.06	5.74%
Goldman Sachs	6	2,702.11	5.00%
Credit Agricole CIB	7	2,442.61	4.52%
Credit Suisse	8	2,365.45	4.38%
Natixis	9	2,165.00	4.00%
Societe Generale	10	2,157.26	3.99%
Total market share of top 7 underwriters		45.63%	
Total number of underwriters		63	
Total issuance volume (€ in million)		54,064.49	
2014			
Underwriter	Rank	Issuance volume (€ in million)	Market share
Deutsche Bank	1	6,526.23	9.96%
JP Morgan	2	4,412.78	6.73%
BNP Paribas	3	3,973.81	6.06%
Credit Suisse	4	3,749.47	5.72%
Citi	5	3,634.14	5.55%
Goldman Sachs	6	3,625.70	5.53%
Credit Agricole CIB	7	3,493.00	5.33%
Societe Generale	8	3,029.18	4.62%
Barclays	9	2,865.87	4.37%
HSBC	10	2,857.79	4.36%
Total market share of top 7 underwriters		44.88%	
Total number of underwriters		65	
Total issuance volume (€ in million)		65,536.65	

Table A9 continued: Annual top 10 underwriters in the Euro-denominated fixed high-yield corporate bond market from 2009 to 2019.

2015			
Underwriter	Rank	Issuance volume (€ in million)	Market share
JP Morgan	1	4,870.88	8.31%
Deutsche Bank	2	4,139.87	7.06%
Goldman Sachs	3	3,714.75	6.34%
BNP Paribas	4	3,308.91	5.65%
Barclays	5	3,249.20	5.54%
Credit Suisse	6	3,180.63	5.43%
UniCredit	7	3,062.18	5.23%
Citi	8	2,752.43	4.70%
HSBC	9	2,619.24	4.47%
Credit Agricole CIB	10	2,562.84	4.37%
Total market share of top 7 underwriters		43.56%	
Total number of underwriters		65	
Total issuance volume (€ in million)		58,602.90	
2016			
Underwriter	Rank	Issuance volume (€ in million)	Market share
Deutsche Bank	1	3,514.68	8.03%
JP Morgan	2	3,098.88	7.08%
BNP Paribas	3	2,559.08	5.85%
Citi	4	2,390.95	5.46%
Goldman Sachs	5	2,286.96	5.22%
Barclays	6	2,267.74	5.18%
UniCredit	7	1,929.74	4.41%
BofA Securities	8	1,877.60	4.29%
Intesa Sanpaolo	9	1,829.94	4.18%
Societe Generale	10	1,776.22	4.06%
Total market share of top 7 underwriters		41.23%	
Total number of underwriters		66	
Total issuance volume (€ in million)		43,775.03	
2017			
Underwriter	Rank	Issuance volume (€ in million)	Market share
JP Morgan	1	6,520.49	9.17%
Deutsche Bank	2	6,083.96	8.56%
Goldman Sachs	3	5,364.93	7.55%
BNP Paribas	4	4,109.93	5.78%
Morgan Stanley	5	3,632.93	5.11%
Credit Suisse	6	3,436.42	4.83%
Societe Generale	7	3,161.84	4.45%
Citi	8	3,160.85	4.45%
Barclays	9	2,944.86	4.14%
HSBC	10	2,893.34	4.07%
Total market share of top 7 underwriters		45.46%	
Total number of underwriters		65	
Total issuance volume (€ in million)		71,075.00	

Table A9 continued: Annual top 10 underwriters in the Euro-denominated fixed high-yield corporate bond market from 2009 to 2019.

2018			
Underwriter	Rank	Issuance volume (€ in million)	Market share
Deutsche Bank	1	4,419.94	8.86%
JP Morgan	2	3,464.28	6.94%
Goldman Sachs	3	3,237.03	6.49%
BNP Paribas	4	3,189.56	6.39%
BofA Securities	5	3,055.03	6.12%
Citi	6	2,693.25	5.40%
Morgan Stanley	7	2,337.78	4.69%
Barclays	8	2,240.47	4.49%
HSBC	9	2,223.73	4.46%
Credit Suisse	10	2,111.18	4.23%
Total market share of top 7 underwriters		44.90%	
Total number of underwriters		70	
Total issuance volume (€ in million)		49,883.10	
2019			
Underwriter	Rank	Issuance volume (€ in million)	Market share
JP Morgan	1	6,467.52	9.58%
Goldman Sachs	2	6,130.41	9.08%
Deutsche Bank	3	5,298.66	7.85%
Citi	4	4,975.32	7.37%
BNP Paribas	5	4,437.80	6.57%
Barclays	6	3,774.05	5.59%
Morgan Stanley	7	3,075.01	4.55%
HSBC	8	2,998.72	4.44%
BofA Securities	9	2,947.20	4.36%
Credit Agricole CIB	10	2,884.75	4.27%
Total market share of top 7 underwriters		50.59%	
Total number of underwriters		67	
Total issuance volume (€ in million)		67,527.06	

This table exhibits summary statistics for the annual 10 largest underwriters in the Euro-denominated fixed high-yield corporate bond market between 2009 and 2019, collected from Bloomberg league tables. The league table excludes self-led transactions, which means that the issuer is different from the underwriter, or the issuer's ultimate parent owns less than 50% of the underwriters. The ranking of underwriters is based on the issuance volume annually. The individual market share is the respective underwriter's issuance volume divided by the yearly total issuance volume. The total number of underwriters is the total number of underwriters listed in the Bloomberg league table in that year. The total issuance volume is the sum of all the issuance volumes in that year.