The Impacts of Dividend-Smoothing Risk, Institutional Investors and Investor Behaviour on Equity Pricing

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January 2021

University of Sussex

Thesis Submitted for the Degree of

Doctor of Philosophy in Finance

Statement

I, Yuxi Chen, 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.

Brighton

15 January 2021

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ABSTRACT

Asset pricing theory analyses the value of financial claims to uncertain future payments. In the case of a stock the financial claims are its future dividends. Prices move in response to changes in discount rates, information on future dividends reflecting profitability or changes in behavioural bias.

1. Is dividend smoothing a priced risk factor? (discount rates)

2. Do firms use smooth dividends to signal? (profitability)

3. What behaviour leads to mispricing? (behavioural bias)

I attempt to answer the first question by examining whether dividend smoothing can explain returns. More specifically, can it replace the small and value risk factors? I add a dividend smoothing factor to the CAPM and find that the smoothing factor had some explanatory power for the US stocks but not for Chinese stocks. However, this explanatory power is limited to non-large firms and does not perform well as the Fama-French three-factor model.

I attempt to answer the second question by examining the circumstances in which a smoothed dividend can convey information. Whether a smooth dividend acts as a signalling mechanism depends on its relationship with institutional investors: the type of institution, the direction of the relationship and the severity of the principal-agent problem. In the US, institutional monitors control the principal-agent problem and require dividend smoothing in exchange. In China, where the principal-agent problem is less pronounced, institutional monitors replace dividend smoothing to mitigate the minority-controlling shareholder problem. Dividend smoothing is not used as a signalling device in either case. In addition, managers in both countries pay smoothed dividends for their benefit when the colluders' institutional holdings are high.

I attempt to answer the third question by identifying the sources of momentum. I wonder whether both overreaction and underreaction to information could cause a momentum effect. I establish different momentum strategies in China only, where short selling is not allowed. I find that Chinese investors underreact to bad news and overreact to good news. Among them, institutional investors intensify their overreaction to good news in bad times.

ACKNOWLEDGEMENTS

It has been a six-year-long journey, and I could not have done it without those who helped me.

First of all, I want to thank my supervisor, Dr Xiaoxiang Zhang. His guidance helped me deeply understand the steps of academic research and the logical framework of an academic paper. I had become obsessed with details and methods and then lost the big picture in my research. Xiaoxiang taught me to reason through induction rather than deduction. I would also like to thank my advisor, Dr Xiaochun Meng, for his valuable advice on the approach to my thesis.

I want to express my deep gratitude to my two families. One lives in China and has always supported me unconditionally; the other lives in the UK. They have taken care of me and enriched my understanding of British culture. Thank you, Mum, Dad, and the McCulloch family.

I also want to thank my friends: Dr Zhicheng Wang, Dr Bingrun Xu, Dr Qing Yao, and Ningwan Zhao. Without them, my journey would have been dull.

I am fortunate to have a supportive partner who is always by my side. She is the first listener of every idea I have, and she always gives me exciting feedback. She is a great anchor for me during the most stressful times. Words can no longer express my gratitude.

Finally, and most importantly, thanks to my mentor, Dr Mike Osborne. It has been my most tremendous honour to work with him. He corrected so many pages of poorly plotted chapters and written text with amazing patience. He constantly shared with me his insightful ideas and opinions, as well as his years of research experience. All the discussions we had together during my PhD were most valuable to me. His attitude towards research has set me an excellent example.

I want to conclude by thanking myself for persevering to the end without giving up, and may my future be bright.

Table of Contents

CHAPTER 1

INTRODUCTION

"Asset pricing theory tries to understand the prices or values of claims to uncertain payments," said Cochrane (2005). It tries to describe how the financial world works so that we know why prices and returns are what they are. What went wrong with the model if the financial world did not work as the pricing model suggested? Or what went wrong in the world led to mispricing when the correct model was available?

Asset pricing theory is derived from a simple concept that price is the discounted value of expected cash flows. A financial claim comprises payment commitments at points in the future; for example, a stock is a claim on future dividends that reflect a firm's future profits. Therefore, the intrinsic value of a stock is the corporate profitability discounted by its cost of equity. Stock prices move in response to changes in discount rates, information on future dividends reflecting profitability or changes in behavioural bias.

This thesis puts forward three questions relating to equity pricing. Two questions are closely related to dividend policy because dividend policy is an important corporate decision and is a significant element of equity pricing.

1. Is dividend smoothing a priced risk factor? (discount rates)

2. Do firms use smooth dividends to signal? (profitability)

3. What behaviour leads to mispricing? (behavioural bias)

1.1 IS DIVIDEND SMOOTHING A PRICED RISK FACTOR?

1.1.1 Research Background

The most salient model for estimating the cost of equity is the Capital Asset Pricing Model (Sharpe, 1964).

$$R_i = R_f + \beta_m \cdot (R_m - R_f),$$

where R_i is expected return on a security, R_f is the risk-free rate, R_m is expected return of the market. β_m measures the volatility of a stock relative to the overall market. It is calculated by dividing the product of the covariance of stock returns and market returns by the variance of market returns. As the CAPM beta is related to the equity market risk premium, I will refer to β_m as "market beta" in the latter part of this thesis.

Following Campbell and Shiller (1988) and Campbell (1991), market returns can be decomposed into two components: news about a market's future cash flows and news about a market's future discount rates. A market beta can be regarded as the covariance of stock return and market return, scaled by the variance of the market return. In this sense, a market beta is essentially composed of a cash-flow beta and a discount-rate beta (Campbell & Mei, 1993; Campbell & Vuolteenaho, 2004; Campbell et al., 2010).

$$\beta_{cf} = \frac{\mathrm{Cov}\left(R_i, N_{cf}\right)}{\mathrm{Var}\left(R_m\right)},$$

$$\beta_{dr} = \frac{\mathrm{Cov}\left(R_i, N_{dr}\right)}{\mathrm{Var}\left(R_m\right)},$$

$$\beta_m = \beta_{cf} + \beta_{dr},$$

where N_{cf} is news about market's future cash flows, and N_{dr} is news about market's future discount rates.[1]

Campbell and Vuolteenaho (2004) and Campbell et al. (2010) argue that the cash-flow beta carries a higher risk because the changes in cash flows are more persistent than the changes in the discount rate. For example, returns are lower due to higher discount rates but can increase in the future due to a fall in discount rates.

Before 1963, the cash-flow beta was the main component of market beta, and it was evenly distributed across stocks, so CAPM estimates were effective. Campbell and Vuolteenaho (2004) find that the discount-rate beta is the main component of market beta for the vast majority of stocks after 1963. However, since not all firms'

[1] For more information on algebra, refer to Chapter 2 Appendix, on page 72.

market beta consists of discount-rate beta, which has a low premium, the CAPM underestimates the returns of stocks with cash-flow beta.

Campbell and Vuolteenaho (2004) find that cash-flow betas are concentrated in small and value stocks. Maio and Santa-Clara (2015) also find that the returns of a portfolio of small stocks or value stocks correlated with portfolio-level cash-flow information. Fama and French (1993) use size and value factors in addition to the market beta to explain abnormal returns that are not explained by market beta.

Intuitively, the excess risk for small and value firms is essentially the premium of the cash-flow beta over the discount-rate beta. Identifying a risk factor is inherently looking for places where cash-flow betas gather, i.e., stocks that correlate more strongly with the market cash flows that carry more risks. I follow Pettit and Westerfield (1972) and Campbell and Vuolteenaho (2004) in assuming that cash-flow news for stocks, rather than discount-rate news, is closely related to cash-flow news for the market.

When dividends are used as a proxy for cash flows, Chen et al. (2012) find that cash-flow news plays a more critical role than discount-rate news in price variations in the post-war period. However, in the pre-war period, the opposite is true. Chen (2009) discovers a significant increase in dividend smoothing in the post-war period compared to the pre-war period.

If a smoothed dividend disconnects dividend news from a firm's return and therefore de-links it from market cash-flow news, then it is only an unsmoothed dividend that can produce a potential cash-flow beta.

I define dividend smoothing as a phenomenon where dividend payments are determined not only by current earnings (Lintner, 1956) or perpetual earnings (Marsh & Merton, 1987) but also by past dividend payments. I measure dividend smoothing following the approach of Leary and Michaely (2011); Larkin et al. (2017) to tackle better cross-sectional differences in policies.

1.1.2 Motivation and Findings

The CAPM is an elegant model not only because it is simple to use but also because it has a solid theoretical foundation: modern portfolio theory (Markowitz, 1952). Unfortunately, the empirical record of the model became increasingly poor after 1963, and many academics are trying to identify new risk factors to explain the returns missed by the CAPM beta. The three-factor model (Fama & French, 1993) is a good example that successfully introduces size and value factors. However, there is little theoretical explanation behind it.

Beta decomposition is a good starting place to understand the mechanism of the CAPM. My goal is to find the reasons for switching between the main beta components of the CAPM by relating the behaviour of corporate dividends. My search for risk factors is derived from a combination of empirical evidence and theory, not from data mining.

I examine a possible risk factor associated with the cost of equity, namely dividend smoothing. I conduct empirical analysis in the US and China, two countries with different dividend policies. I want to know whether the size and value effects are due to the less smoothed dividends of small and value stocks, and therefore, I use the Fama and French (1993) method to construct a smoothing factor and compare it with the three-factor model. I find that dividend smoothing could explain the expected returns of the US stocks to some extent. However, it is still inferior to the three-factor model, and dividend smoothing has no explanatory power for the expected returns in the Chinese market.

1.2 DO FIRMS USE SMOOTH DIVIDENDS TO SIGNAL?

1.2.1 Research Background

Classic research shows that dividends can signal a firm's current or future profitability (Miller & Rock, 1985; John & Williams, 1985; Bhattacharya, 1979). Once a dividend is paid, managers will continue to pay the same level as before (Lintner, 1956).

Dividend smoothing only partially reveals information about a firm's profitability compared to a dividend signalling model that fully reveals information about the firm (Kumar, 1988; Kumar & Lee, 2001; Guttman et al., 2010).

Firms in the same earning range have similar characteristics such as cash flow volatility, risk factors and investment opportunities. They tend to group and separate themselves from firms outside this range. Managers in the range pay the same dividends, and investors anticipate this behaviour and price firms accordingly. Dividend is expected to be the same within the range pool that partially reveals the firm's information. In this situation, information asymmetry between shareholders and management is reduced. A smooth flow of dividends signals investors that all is well within a specific range.

Moreover, the signals of a dividend increase and reduction are asymmetric, i.e., the penalty for reducing dividends are far greater than the reward for increasing them (Allen et al., 2000; Brav et al., 2005; Guttman et al., 2010; Larkin et al., 2017). Therefore, only firms that are determined explicitly that their operational profits can support the payment of stable dividends will start to pay a dividend.

In this case, departures from a usually smoothed dividend may be true signals of underlying change in a firm's circumstances. This type of smoothing, only occasionally interrupted by meaningful signals, deliberately and conscientiously adopted by a firm, reduces the information asymmetry between investors and the firm. Dividend smoothing can effectively address principal-agent costs, i.e. it is more applicable in countries with a low equity concentration.

However, if changes in dividends are no longer relevant to the underlying condition of a firm, then smoothing is a means of information concealment. This type of smoothing appears among managers who are afraid of being fired because of poor performance (Fudenberg & Tirole, 1995; DeMarzo & Sannikov, 2016; Wu, 2018) or seek private benefits (Lambrecht & Myers, 2012; Baker et al., 2016), which increase the information asymmetry between investors and the firm. This is most common if a firm operates in a country with a low level of investor protection or/and in an environment where there is no institutional investor monitoring.

I call the institutions that actively participate in corporate governance "monitors" and institutions with close business relationships with firms "colluders" defined by previous literature (Brickley et al., 1988; Almazan et al., 2005; Cornett et al., 2007).

If managers cater to the preferences of institutional investors or rent-seeking, there will be no dividend signals. For example, monitors force managers to offer smooth dividends in return for their ability to improve corporate governance, or managers learn that there are a large number of colluders who turn a blind eye to rent-seeking behaviour.

1.2.2 Motivation and Findings

Existing research has yielded mixed findings on whether the signalling model can be used to explain dividend smoothing. More specifically, if the signalling model holds, dividend smoothing should negatively correlate with institutional investors. It is because institutional investors are seen as a proxy for information symmetry, i.e. the more institutional holdings there are, the more symmetrical the information between shareholders and managers and the less need for signalling.

However, there are several problems inherent in these claims. The first is the heterogeneity of institutional investors, meaning that not all of them contribute to reducing information asymmetries. The monitors and the colluders certainly have different motives for investing in the firm.

Second, dividend smoothing is most beneficial as a signalling tool when dealing with principal-agent problems. In other words, dividend smoothing is less helpful when information asymmetry does not arise between managers and shareholders. For example, Chinese firms have a high ownership concentration, and information asymmetry is found between controlling and minority shareholders.

Lastly, whether firms are willing to smooth their dividends or forced to do so is essential for screening signalling mechanisms. Certain institutions are powerful monitors, and they penalise firms that cut dividends, resulting in managers being forced to smooth dividends. Dividend smoothing, for this reason, is not carrying any meaningful information.

Therefore, the type of institutional investor, the firm's operating environment and the direction of the relationship between dividend smoothing and institutional shareholding are keys to understanding whether a firm uses dividends to signal.

Static and dynamic panel models are used to understand the relationship between institutions, dividend smoothing and firm value. Panel vector autoregressive model is used to determine the direction of influence.

In the US, institutional monitors control the principal-agent problem and require dividend smoothing in exchange. The net effect of dividend smoothing and institutional monitoring is positive on value. In China, institutional monitoring replaces dividend smoothing to control the minority-control shareholder problem. Dividend smoothing has no value impact on the firm, and the increase in firm value reflects the positive monitoring influence. Dividend smoothing is not used as a signalling device in either case. In addition, managers in both countries pay smoothed dividends for their benefit when the colluders' institutional holdings are high. As a result, the firm value decreases.

1.3 WHAT BEHAVIOUR LEADS TO MISPRICING?

1.3.1 Research Background

Assume that the cost of equity used as a discount rate for a firm is accurately modelled and that its profitability is highly dependent on its cash flows. If investors react incorrectly to cash-flow news, prices may deviate from their intrinsic values, leading to mispricing. The success of momentum strategies suggests that mispricing occurs. In Chapter 4, I investigate what leads to persistent winners and losers. I pick China as a test candidate because Chinese law prohibits short-selling. This constraint helps us understand the causes of mispricing by amplifying and revealing certain behaviours and their reasons. For example, the lack of investor response to the news is a primary source of the momentum effect. This underreaction can come from good news or bad news. However, in the presence of a short-selling constraint, bad news travels slowly, which intensifies the underreaction, leading to longer and stronger underreaction-type momentum.

As to the source of the momentum effect, past literature suggests that it comes from underreaction to news, i.e., the gradual information diffusion theory. It suggests that sophisticated investors with low cognitive dissonance will promote the speed of information diffusion, i.e., less severe underreaction (Hong & Stein, 1999; Antoniou et al., 2013; Daniel et al., 2021).

A less popular explanation for the source of momentum, overreaction, suggests that investors have a self-serving bias: they attribute the performance of the winners to their ability to pick stocks and that of the losers to bad luck (Daniel et al., 2021; Lee & Swaminathan, 2000; Jegadeesh & Titman, 2001; Cooper et al., 2004). This bias can lead to overconfidence in the accuracy of the signals received, pushing prices above fundamentals. The momentum created by the overreaction will eventually reverse when prices are corrected in the long run.

1.3.2 Motivation and Findings

Antoniou et al. (2013) support the underreaction explanation, while Cooper et al. (2004) support the overreaction explanation. Both provide corresponding scenarios in their explanations: cognitive dissonance slows the diffusion of information, especially for bad news among optimistic investors in the presence of short-selling constraints; the overreaction caused by investors' overconfidence in up-market states produces momentum.

Their findings, however, do not contradict each other. On the one hand, optimistic investors are more likely to be overconfident, thus causing overreaction. On the other hand, bad news in an up-market may trigger cognitive dissonance, which reduces information diffusion speed. Given that their findings support each other's inferences, what exactly is the source of momentum?

I wonder whether both overreaction and underreaction to information could cause a momentum effect, but the types of information (good or bad) involved in the two reactions are different.

I use the method of Jegadeesh and Titman (1993) to construct price and alpha momentum portfolios. I employ a heterogeneous belief model followed by Daniel et al. (2021) to examine my hypothesis.

I find that overreactions to good news and underreactions to bad news produce momentum. A strong reversal follows the overreaction-type momentum, and a weaker reversal follows the underreaction-type momentum. This is partly because short-selling constraints limit the overshoot from the momentum trader. I use different scenarios, such as up-market state and optimistic sentiment, to illustrate that overconfidence is the cause of overreaction.

On the one hand, institutional investors are sophisticated investors with low levels of cognitive dissonance. On the other hand, they tend to be overconfident in the information they possess. My findings suggest that institutions are more likely to be overconfident investors, who tend to increase their overreaction to good news in bad times.

1.4 WHY STUDY THE CHINESE MARKET?

The reason for choosing the US as the research object of asset pricing is apparent. It has the most extended trading history, sound laws and regulations, mature management and investors, and many theoretical and empirical analyses. The literature in the past provides a clear roadmap for the later research, avoiding detours. So why China?

In Chapter 2, dividend smoothing is regarded as a risk factor because it changes the correlation between the firm's cash-flow news and market cash-flow news. Although investors' preference for a smooth dividend may generate some "discounts" to compensate, this is not the critical reason that dividend smoothing may be a risk factor. The same conclusion should be obtained even in markets that adopt different dividend smoothing policies. This is because "smoothing" rather than the "cause of smoothing" makes the firm's cash-flow news less informative.

Therefore, I pick up two markets with very different dividend smoothing policies as the basis for the tests. If my hypothesis is correct, it should hold in both markets. Unfortunately, this does not prove to be the case. In my China sample, volatile dividends have not explained much about returns, and it could be because of the small sample size. The average number of continuous dividend payers in the US sample (1990 - 2018) is 580, while only 391 in the Chinese sample (2000 - 2018), around 67% of the size. Dividends are a great proxy for cash flows. Still, they are not the only proxy, especially given China's low propensity to pay dividends, so using alternative cash-flow proxies, e.g., free cash flows may yield more accurate results.

The essence of Chapter 3 is to distinguish between two different types of smooth dividend policy, signalling and garbling, to understand which signals a firm's true profitability. My approach to distinguishing them is identifying users or beneficiaries of dividend smoothing. In this way, different institutional environments and regulatory regimes, such as the US and China, are necessary to create two different usage scenarios.

Moreover, the formation path of China's institutions is also very different from the US. The Chinese capital market is developing rapidly, and the government actively supports institutional investors, especially mutual funds, the largest Chinese investment institutions. Unlike the US funds, which are driven by market demand, Chinese funds were introduced as a regulatory tool in 2001. Chapter 3 also shows that institutional investors, primarily monitors, positively affect the value of a firm regardless of dividend policy.

In Chapter 4, the main reason for China as a sample market is that short-selling constraints are helpful to highlight investors' different responses to different news. Rather than looking for a potentially unreliable short-selling proxy, I use a market where short-selling is prohibited by law: the Chinese market. Such a market provides a purer background for research.

The remainder of the thesis proceeds as follows. Chapter 2 examines whether dividend smoothing is a priced risk factor. Chapter 3 examines whether firms use smoothed dividends to signal. Chapter 4 explores asymmetric reaction to information under short-selling constraints. The final chapter concludes the thesis.

CHAPTER 2

IS DIVIDEND SMOOTHING A PRICED RISK FACTOR?

SYNOPSIS

1. CAPM beta measures risk, and CAPM beta is determined by the scaled covariance between firm returns and market returns.

2. Before 1963, returns change with news about future cash flows; this applies to all stocks, so CAPM works well.

3. After 1963, returns change with news about future discount rates rather than future cash flows. However, this shift does not apply to all stocks, so CAPM does not work as well.

4. To which stocks is the shift not applicable? The answer is small and value

stocks. Their returns continue to move with news about cash-flows, and this kind of news is more permanent than news about discount-rates, therefore such returns are riskier.

5. How do we know this? The answer is price-dividend variance decomposition (or return variation decomposition, they are the same thing). Empirical evidence says that price to dividend ratios (or to earnings, or some other divisor) move on expected future cash-flow changes (dividend changes) before 1963 and move on expected returns after 1963. This is the same as saying that current returns move on news about future cash flows before 1963, and on news about discount rates after 1963.

6. Today, most firms' CAPM betas are essentially discount-rate betas, which convey lower risk; those firms whose betas continue to possess a cash-flow component exhibit additional risk. The reasons why the returns of some firms continue to be influenced by future cash-flow news requires explanation.

7. I posit dividend smoothing as that "explanation". Smoothed dividend strategies keep some firms' returns from changing with cash-flow news, i.e., the news is filtered; this filtering/smoothing is not so evident for small companies and value companies. Hence the hypothesis that dividend smoothing is a risk factor.

2.1 INTRODUCTION

Empirical evidence shows that the Capital Asset Pricing Model (CAPM) was a good measure of risk before 1963, and therefore a good explanation for why some stocks earn higher returns than others. After 1963, however, the CAPM no longer accurately explains stock returns, and other risk factors begin to explain returns, such as size and value. The main objective of this chapter is to determine whether dividend smoothing is an influential risk factor and, in particular, to determine whether it can replace the value and size factors in the three-factor model.[1]

Before 1963, scholars generally believed that stock returns were not predictable because prices move on changes in future cash flows, i.e., dividends. Therefore, CAPM beta was derived entirely from the covariance of stock cash flows and market cash flows. Because CAPM beta measures a stock's market risk, it is also referred to as "market beta".

$$R_i = R_f + \beta_m \cdot (R_m - R_f),$$

where R_i is expected return on a security, R_f is the risk-free rate, R_m is expected return of the market, and β_m is the stock's smoothing in relation to the overall market.

In the early 1970s, Shiller (1981) found that stock price movements were too large to be justified by subsequent changes in dividends. This was followed by empirical evidence over 1963-1991 from Fama and French (1993) that market beta

[1] 1963 is the breakpoint established by empirical works (e.g., Fama & French, 1992, 1993; Campbell & Vuolteenaho, 2004; Campbell et al., 2010; Cochrane, 2011, 2005, p. 389)

can no longer accurately estimate expected returns nowadays. Some stocks have higher returns than others, e.g., small stocks and stocks with a high book-to-market ratio (value stocks). As a result, multi-factor models became popular, using non-market betas and market beta to explain expected returns.

After 1963, stock returns move on expected future returns, and prices move on changes in future discount rates. Therefore, CAPM beta is derived from the covariance of stock discount rates and market discount rates (Fama & French, 1993; Campbell & Vuolteenaho, 2004; Cochrane, 2008; Campbell et al., 2010).

Why do small and value stocks have higher returns?

Following Campbell and Shiller (1988) and Campbell (1991), unexpected returns ($\widehat{R}$) can be decomposed into two components: news about future cash flows (N_{cf}) and news about future discount rates (N_{dr}). Campbell and Vuolteenaho (2004) redefine the market beta on the basis of this decomposition:

$$\beta_{cf} = \frac{\mathrm{Cov}\left(R_i, N_{cf}\right)}{\mathrm{Var}\left(\widehat{R_m}\right)},$$
$$\beta_{dr} = \frac{\mathrm{Cov}\left(R_i, N_{dr}\right)}{\mathrm{Var}\left(\widehat{R_m}\right)},$$

where β_{cf} is market beta of news about a stock's future cash flows, β_{dr} is market beta of news about a stock's future discount rate, and hat denotes innovation. Hence, the CAPM beta (market beta) is $\beta_m = \beta_{cf} + \beta_{dr}$.

A rational long-term investor should view the risks of these two kinds of news as different. The value of a market portfolio has fallen, either because of bad news about future cash flows or because of news about higher future discount rates. However, changes in cash flows are more permanent, while changes in discount rates are relatively transient. As a result, high discount rates are unlikely to remain high for long and will fall back at some point in the future. Permanent changes are generally considered riskier changes, meaning that stock returns related to market cash-flow beta, β_{cf}, bear higher risk and, therefore, have higher returns.

The CAPM betas were predominately cash-flow betas for most firms before 1963, and most of them became discount-rate betas after 1963. However, not all stocks' CAPM betas consist of discount-rate betas, and some consist primarily of cash-flow betas. Stocks with considerably higher cash-flow betas are riskier, and small stocks and value stocks are the most typical, so they bear a higher risk.

There are two ways to improve the performance of the traditional CAPM. One approach is to use the two-beta model defined by Campbell and Vuolteenaho (2004), where a cash-flow beta and a discount-rate beta jointly explain stock returns.

Another approach is to use a multi-factor model, such as the three-factor model proposed by Fama and French (1993), which uses non-market risk factors to generalise the returns of stocks with greater cash-flow betas.

The essence of these two approaches is that the stock whose return is related to the market cash flows will take on more risk and receive a premium. I assume that the cash flows of individual stocks are related to market cash flows, and the returns of individual stocks are related to market returns. In this way, stocks whose returns are driven by cash-flow news are more likely to be sensitive to market cash flows and thus riskier. This a strong assumption following Pettit and Westerfield (1972) and Cochrane (2005).

What affects the sensitivity of individual stock returns to their cash-flow news? I use dividends as a proxy for cash flow, the most commonly used in the literature. If a firm chooses to smooth its dividends, the information contained in dividends will no longer be available, and the stock price will not adjust to changes in dividends. As a result, stock return is no longer sensitive to dividend news.

Small and value firms have higher returns because they are more sensitive to dividend news and, therefore, more closely related to market dividend news. Dividend smoothing disconnects the dividend from stock returns, and as a result, the stock with the lowest degree of dividend smoothing (volatile dividends) should have a higher return.

A company has its reasons for dividend smoothing. For example, managers may use smooth dividends as a signal to convey or mask information; they could help reduce agency costs; they may be a product of policy requirements. This chapter discusses the result of smoothing, that is, disconnecting stock returns from cash-flow news.

When a firm smooths its dividends to a certain level, most of its price movement is due to changes in future returns, as is the case with most firms today. It has a discount-rate beta that carries a lower premium than stocks with cash-flow betas. However, different corporate implications lead to different premia among all stocks with discount-rate betas. There is some noise in the measure of risk for the group of firms with the smoothest dividends.

I conducted an empirical analysis in the US and China, two countries with different dividend policies. In the US, firms with higher dividend smoothing earn lower returns than firms with lower smoothing, and this difference remains significant across size quintiles. Dividend smoothing could explain the expected returns of the US stocks to some extent. However, it is still inferior to the three-factor model.

The number of continuous dividend payers and the degree of dividend smoothing in China is much smaller than in the US. Portfolio returns do not differ significantly across dividend smoothing sorts and remain so after considering size and value. The constructed smoothing factor cannot help explain stock returns. In general, dividend smoothing is not priced into the Chinese equity market.

Although the three-factor model is the best way to explain the returns of both stock markets, the CAPM works better in China than in the US, with higher R^2 values. One possible reason for this is that Chinese firms' two types of beta are more evenly distributed. In contrast, the vast majority of companies in the US are discount-rate betas with a low-risk premium. Yet, small and value firms have cash-flow betas with a high premium, resulting in CAPM betas being significantly underestimated in this group.

My contribution in this chapter is to identify the part played by a non-market risk factor: dividend smoothing. My hypothesis is supported by a clear theoretical framework, not data mining. Although the result is not entirely satisfactory, it provides a comprehensive empirical basis for determining the direction of theoretical development.

2.2 LITERATURE REVIEW

2.2.1 Understand Equity Risk from Beta Decomposition

Campbell (1991) decompose unexpected market return into dividend news and return news; see boxed content on page 22. The decline in the value of the market portfolio is due to bad news about future dividends or higher discount rates in the future. The high discount rate is only temporary and will fall back at some point, meaning that investment opportunities will improve in the future. In contrast, the reduction in cash flows may be permanent and does not provide any future benefits. So rational investors should treat these two kinds of market news differently (Campbell & Vuolteenaho, 2004; Campbell et al., 2010).

How Dividend News and Return News Affect Equity Returns

Campbell (1991) provides a decomposition for unexpected returns.

$$r_t - E_{t-1}r_t = \underbrace{\Delta E_t \sum_{j=0}^{\infty} \rho^j \Delta d_{t+j}}_{N_{cf}} - \underbrace{\Delta E_t \sum_{j=1}^{\infty} \rho^j r_{t+j}}_{N_{dr}}, \tag{2.1}$$

where Δd is log dividend growth, r is log return, ρ is the discount factor constrained by the average log dividend yield (Fama & French, 1988), N_{cf} is news about future cash flows, i.e., expected dividends, and N_{dr} is news about future discount rates, i.e., expected returns.

Since CAPM beta (I refer to as market beta) is the scaled covariances of firm return with market return, the decompositions from Campbell and Shiller (1988) and Campbell (1991) imply that market beta depends on two factors. First is the covariance between stock and market discount rates, and second, between stock and market cash flows. Therefore, Campbell and Vuolteenaho (2004) decompose the market beta into cash-flow beta and discount-rate beta, and the former is regarded as the riskier beta.

Alternatively, dividend yield decomposition can reveal the information of cash-flow news and discount-rate news.

Prices move on the news about future dividends or news about future returns. If most variations in prices come from variations in expected future dividends, as they were before 1963, then dividends are predictable by price. [2] Prices reveal the information about expected future dividends, and prices relative to dividends (or earnings, free cash flows, book value, or other divisors) can form expectations about dividends.

Similarly, if the stock returns are not predictable, as they were not before 1963, then expected returns will not change much over time. However, this has not been the case since 1963, and returns have become predictable, and share prices move too much to be justified by subsequent dividend changes (Shiller, 1981).

Notice the type of predictability I am looking for. If dividends are smooth, they can be predicted by past dividends, but they are no longer price-related, i.e., they are not predictable by price. The box on page 24 provides a present value model that helps understand the basic concepts: what types of news hit the market and how much prices change when news hits the market.

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[2] The well-known three-factor model of Fama and French (1993) uses 1963 as a point in time to discover size and value factors. A large body of literature has subsequently used 1963 as a benchmark and found changes in price drivers from cash flows to discount rates, e.g., Campbell and Vuolteenaho (2004); Cochrane (2008); Campbell et al. (2010).

How Expected Dividends and Expected Returns Affect Prices

Campbell and Shiller (1988) provide a framework for studying expected dividends and expected returns. They developed a log-linear present value model that allows for time-varying returns.

$$p_t - d_t = E_t \sum_{j=1}^{\infty} \rho^{j-1}(\Delta d_{t+j} - r_{t+j}), \tag{2.2}$$

where p is log price, Δd is log dividend growth, r is log return, and ρ is the discount factor constrained by the average log dividend yield. Equation (2.2) suggests that the log price-dividend ratio, $p_t - d_t$, is high when dividends are expected to increase, or when returns are expected to be low. One can understand the price driver by decomposing the variance of $p_t - d_t$.

Equation (2.1) suggests that return variation comes from *current* dividends, expected future dividends and expected future returns. The latter two effects come from their effect on future price-dividend ratio, which is Equation (2.2).

To derive Equation (2.1), start with Equation (2.2) in the box on page 22, and move it back one period. Take expectation on both sides, and then put r_t to the left-hand side,

$$\begin{aligned} p_{t-1} - d_{t-1} &= E_t \sum_{j=0}^{\infty} \rho^j \left(\Delta d_{t+j} - r_{t+j}\right), \\ 0 &= (E_t - E_{t-1}) \left[\sum_{j=0}^{\infty} \rho^j \Delta d_{t+j} - \sum_{j=1}^{\infty} \rho^j r_{t+j} \right]. \end{aligned}$$

The use of dividend yield to predict excess returns on stocks began with Fama and French (1988) and Campbell and Shiller (1988). The former provides evidence that the predictive power increases over time. The latter finds that the main driver of stock price changes is the volatility of expected returns by decomposing the variance of dividend yield. [3]

If dividends and returns were predictable (by dividend yield), then expected returns and expected dividends would fluctuate over time. If they did not fluctuate, then dividend yield would be constant. The fact that the dividend yield is constantly changing means that at least one of them is volatile, i.e., predictable. Dividend yield makes price stationary by acting as a cointegration vector, and its changes must reflect variation in future returns or future dividends or both in the long run. [4] Note that much of the literature uses the dividend yield instead of the price-dividend ratio, which is just a matter of taste.

The box on pages 22 and 24 says that if future dividends affect stock prices, then current returns depend on news of future dividends. In this case, the market beta is derived from the covariance between firm-level and market-level dividends, i.e. the riskier cash-flow beta.

2.2.2 What Affects the Riskier Cash-Flow Beta

The prevailing view is that in today's US market, price movements depend on expected returns, not expected dividends (e.g. Campbell & Yogo, 2006; Cochrane,

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[3]Fama and French (1988) reported that low prices relative to dividends predict higher subsequent returns as $R_{t\to t+k} = a + b(D_t/P_t)$. Dividend yield explains less than 5% of short-term returns, and the predictive power (measured by R^2) increases with the investment horizons. The long-run predictability of dividend yield is not a surprise due to the fact that it is very persistent. If short-term returns are slightly predicted by a slowly changing variable, then this predictability will increase over time. And precisely because dividend yield is very sticky, the regression suffers from the property of near unit root. For such a time series, any statistical inference is biased.

[4]Shiller (1981) took out "trend" in price, making price stationary by finding a cointegrating vector p/d (or p/e, B/M). p/d and Δd are cointegrated, rather than p and d.

2008, 2011; Lettau & Van Nieuwerburgh, 2008; Chen, 2009; Van Binsbergen & Koijen, 2010; Koijen & Van Nieuwerburgh, 2011; Chen et al., 2012; Maio & Santa-Clara, 2015).

Some literature argues that aggregate dividend yield fails to predict expected dividends because dividends are not a good proxy for cash flows and therefore do not reflect fundamentals. Lettau and Ludvigson (2005) provide empirical evidence that post-war US dividends can be predicted by estimated consumption-wealth ratios, since the joint changes in expected returns and expected dividends make dividend yield an unreliable measure. Sadka (2007) uses accounting earnings as a proxy for cash flows and decomposes the variance of dividend yield. He points out that most of the fluctuations in aggregate dividend yield can be explained by changes in expected earnings. Larrain and Yogo (2008) argue that ordinary dividends are not a good approximation of cash flows because they account for less than 50% of the total cash distribution. Therefore, total payouts, including dividends and stock repurchases, maybe a better option. They find that most of the changes in the returns can be explained by changes in expected total payouts.

Nevertheless, Cochrane (2008, 2011) comments that using the dividend yield to predict returns is not wrong. He argues that the variance decomposition of dividend yield is utterly unaffected by the presence of the consumption-wealth ratio or other predicting variables. To alter the results of the variance decomposition of dividend yield, one needs a variable that not only predicts long-term returns but it must also predict long-term dividends. Otherwise, the dividend yield remains unchanged. Variables that only change the term structure of expected returns do not affect the variance decomposition of dividend yield. [5]

The dividend yield is a popular valuation ratio used in literature. For example, many other variables, consumption-wealth ratio and earnings-price ratio, also forecast return. However, it is essential to quote research conclusions correctly. For example, "dividends are (not) predictable." is a misquote. One must say, "dividends are (not) predictable by dividend yield." If you use other variables, it might be a completely different story.

Cochrane (2008, 2011) finds that dividend yield is a valid predictor and argues that there is nothing wrong with using dividends instead of total payouts. The price is indeed the present value of future dividends, not the present value of future dividends adjusted for the repurchases. When a repurchase occurs, nobody is forced to sell their shares.

The predictability of expected returns and expected dividends may vary over time. Chen (2009) finds that the primary source of dividend yield volatility was the change in expected dividends during the pre-war period. The source during the post-war period is the change in expected returns. Golez and Koudijs (2018) support time-varying predictability by studying three major capital markets over the past four centuries. Chen et al. (2012) notice that post-war aggregate dividends are smoother than before the war. They argue that smoothing weakens the connection between dividends and prices so that prices can no longer reveal

[5]For example, assume that the earnings-price ratio (e/p) can predict the one-period returns and one-period earnings but cannot predict dividends. When e/p increases but d/p remains unchanged, the short-term expected returns rise, and the long-term expected returns are bound to decline, resulting in no significant change in the expectation in the long run. In addition, using the one-period vector autoregression model (VAR) to infer long-term must capture the dynamics of the data generation process well. Otherwise, the model is misspecified. The long-run implications of one-period VAR, including dividend yield, dividends and returns, have been proven reliable by many scholars.

information about future dividends. It explains why post-war dividends are not as predictable as before the war. Rangvid et al. (2014) further test the claims of Chen et al. (2012) using international samples and find that in large stock markets where dividends are not predictable, dividend smoothing is more common.

Predictability in this chapter refers to time-varying expected return (or dividends), not how much ex-post is "predictable". Suppose most variations in prices come from variations in expected future dividends. In that case, dividends are predictable by price-dividend (or earnings, free cash flows, book value, or other divisors that makes price stationary). Smoothing reduces such volatility, which reduces predictability.

Hypothesis 1: Dividend smoothing is a priced risk factor.

2.2.3 Which Stocks Have the Riskier Cash-Flow Beta?

Campbell and Vuolteenaho (2004) find that small and value stocks have higher cash-flow betas than large stocks and growth stocks, which explains the value and size premium. They also find that before 1963, market betas for all stocks are primarily cash-flow betas. After 1963, most stocks have discount-rate betas with a lower premium, except for small and value stocks. It explains why the CAPM is not effective after 1963, and the CAPM alphas of growth stocks are negative.

It is also consistent with the previous research results, i.e., pre-war stock prices fluctuate with future dividends, and post-war stock prices fluctuate with the future discount rates. Today, market beta is derived from the covariance of stock and market discount rates.

CAPM was a good measure of risk before 1963 because all stocks have cash-flow betas. Although the market beta of most stocks today is the discount-rate beta, this is not true for all stocks. Otherwise, CAPM works just as well. Small stocks and value stocks have significant cash-flow betas, which is why they have above-average returns.

Maio and Santa-Clara (2015) decompose the dividend yield of portfolios sorted by size and value. They find that changes in expected dividends can explain the changes in the dividend yield of small portfolios and value portfolios. Vuolteenaho (2002) decomposes returns for individual stocks, and he finds that news about future cash flows in small firms is highly correlated with returns.

The findings of Maio and Santa-Clara (2015) and Vuolteenaho (2002) suggest that returns of small firms and value firms are more connected to news about future dividends. It implies that small and value firms' market betas are derived from the covariance between firm-level and market dividends, supporting the Campbell and Vuolteenaho (2004) findings.

One assumption made in this chapter is that firm-level cash flows are correlated with market-level cash flows, and firm-level returns are correlated with market-level returns, as Pettit and Westerfield (1972) and Cochrane (2005). Therefore, market beta either comes from the covariance between the firm-level dividends and the market dividends or the covariance between the firm-level discount rates and the market discount rates. In other words, if stock returns vary with news of future dividends, then stock returns are more strongly linked to news of future cash flows in the market, i.e. they are exposed to higher systematic risk. Dividend smoothing weakens this connection. More generally, the smoothing of cash flows, e.g., dividends, earnings, book values, can make a stock's market beta switch from cash-flow beta to discount-rate beta.

Hypothesis 2: Dividend Smoothing Replaces Size and Value Effects.

Cash flow smoothing cuts the link between stock returns and cash flow news, reducing the sensitivity of stock prices to the volatility of cash flows. The result is that the stock's market beta is mainly influenced by its discount rate, which has a lower risk premium.

I use dividends as a proxy for cash flows, and one would argue that smooth dividends reduce the credibility of the dividend news, which leads to ambiguity in the cash flows. As a result, dividend smoothing should carry a positive premium.

I do not deny that dividend smoothing has its corporate finance implications, with ambiguous cash flow on one side (positive premium) and its use by management to address agency costs on the other (negative premium). Ultimately it is a question of corporate theory and empirical evidence.

However, whatever the reasons for a company's smoothing policy, the result of dividend smoothing is that share prices no longer vary in line with dividends (Chen, 2009; Chen et al., 2012; Rangvid et al., 2014). For example, unpredictable dividends (via dividend yields) carry a high risk premium in small and value stocks portfolios (Maio & Santa-Clara, 2015; Campbell & Vuolteenaho, 2004; Campbell et al., 2010).

I think it is a matter of degree. When dividends are volatile enough (low degree of smoothing), it determines the risk premium since cash-flow beta is a significant component of market beta. The corporate implication is more like noise on this background, and it does not play a determining influence.

On the other hand, most dividends are now smooth compared to decades ago. Changes in cash flows do not move stock prices; returns are a true reflection of corporate intentions to smooth dividends.

2.2.4 International Evidence on Dividend Predictability

The literature on predictability is mostly US-oriented, with relatively little international evidence. Ang and Bekaert (2007) study large stock markets, i.e., the US, the UK, France, and Germany, and conclude that changes in expected cash flows do not help explain changes in dividend yield. Engsted and Pedersen (2010) focus on four countries: the US, the UK, Denmark and Sweden. They find that large countries, e.g., the UK and the US, cannot predict dividends through dividend yield, while smaller countries, e.g., Denmark and Sweden, can predict dividends well.

China's market environment and the US are very different, which indirectly leads to different dividend policies. China's stock market is still young, with more small and growth firms than the US. As more and more firms have matured in the past decade, investors have paid more and more attention to value investing, which means that their focus has shifted from short-term profits to long-term profits. To help achieve this transformation, the China Securities Regulatory Commission (CSRC) initiated a unique dividend policy, the semi-mandatory dividend policy, in 2008. It refers to a series of regulatory policies that link the refinancing eligibility of listed firms to the level of dividend distribution. Therefore, the degree of dividend smoothing and the level of payment are expected to increase in the long term.

Different dividend policies in China and the US lead to different information carried by dividends. However, dividend smoothing motivations are not crucial in this analysis. The same conclusion should be obtained even in markets that adopt different dividend smoothing policies. This is because "*smoothing*" rather than the "*cause of smoothing*" makes the firm's cash-flow news less informative. It is interesting to test my hypothesis in two countries with different dividend smoothing policies.

2.3 Data and Methodology

2.3.1 Sample Selection

All US data are collected from CRSP/Compustat Merged Database provided by Wharton Research Data Services, including all NYSE, AMEX and NASDAQ non-financial stocks. All Chinese data are collected from China Stock Market & Accounting Research Database, including all domestic non-financial Chinese A-shares.[6] Due to the lack of reliable financial data from China prior to 1998, the Chinese sample used to calculate measures of dividend smoothing are from 1998 to 2018. It was not until 1999 that trading and financial reporting laws and regulations were more thoroughly designed and implemented. Therefore, in the subsequent factor return analysis, China's sampling period was from 2000 to 2018.[7]

For the purpose of dividend smoothing analysis, I demand that firms are dividend payers and have enough data to calculate both smoothing measures. Therefore, I remove firms that do not pay dividends. I also exclude those firms in the US that have paid dividends continuously for less than ten years and Chinese firms that have paid dividends continuously for less than five years. The final sample in the US consists of 1,011 firms from 1990 to 2018 (239,582 firm-month observations), and the final Chinese sample consists of 229 firms from 2000 to 2018 (33,846 firm-month observations). See Table 2.1 for variable definition.

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[6] The sample does not include financial firms of SIC 6000-6999 in the US, and financial firms of CSRC industry codes J and K in China.

[7] In order to maintain the sample size, I use a 10-year rolling window of (- 5, 4) instead of (- 9, 0), since the 5-year rolling regression is acceptable, e.g., there are 5 observations (1998 - 2002) in 1998 and 5 observations in 2018 (2013 - 2017).

Table 2.1: Variable Definition

Variables	Definitions	Measurements
		United States
$Size$	Market Equity	Close share price (PRCC_C) times common shares outstanding (CSHO).
	Book Equity	Shareholders' equity (SEQ) plus deferred taxes and investment (TXDITC) minus preferred stock. I use common book equity (CEQ) plus preferred stock if SEQ is unavailable. I use total assets (AT) minus total liability (LT) if CEQ is unavailable.
B/M	Book-to-Market ratio	Book equity divided by market equity.
	Dividend per Share	I use ordinary dividends (DVC) divided by common shares outstanding (CSHO) if dividend per share (DVPSP_C) is unavailable.
	Earnings per Share	I use income before extraordinary item (IB) divided by common shares outstanding (CSHO) if earnings per share (EPSPX) is unavailable.
DS	Dividend Smoothing	Calculated using dividend per share and earnings per share; see details in section Measures of Dividend Smoothing.
R_m	Excess return on market	Excess retuen on market (MKTRF) are collected from WRDS US factor.
R_f	Risk-free rate	One-month treasury bill rates are collected from WRDS US factor.
		China
$Size$	Market Equity	Annual market value (Ysmvttl) equals the total number of shares multiplied by its annual closing price (Yclsprc).
E/P	Earnings-to-Price ratio	Earnings per share divided by closing price.
	Dividend per Share	I use ordinary dividends (Numdiv) divided common shares outstanding if dividend per share before tax (Btperdiv) is unavailable.
	Earnings per Share	I use net profit (B002000000) divided by common shares outstanding if earnings per share are unavailable.
DS	Dividend Smoothing	Calculated using dividend per share and earnings per share; see details in section Measures of Dividend Smoothing.
R_m	Excess return on market	Excess retuen on market (MKTRF) are collected from WRDS China factor.
R_f	Risk-free rate	One-month treasury bill rates are collected from WRDS China factor.

2.3.2 Dividend Smoothing Measurement

The preliminary analysis begins with the model of Lintner (1956), one of the most popular models for measuring dividend smoothing in the past literature.

$$\Delta D_t = \alpha_0 + \alpha_1 \cdot E_t + \alpha_2 \cdot D_{t-1} + \epsilon_t, \tag{2.3}$$

where ΔD_t is the changes in dividends, E_t is net income before extraordinary items, and ϵ_t is the residual term. There are two logics implied in this model: firms tend to set a long-term target payout ratio based on the available positive NPV projects. The management tries to adjust the dividend payments to meet the target. The speed of adjustment (SOA), therefore, can be estimated as $-\alpha_2$ from equation.[8]

There are, however, two problems with using this model. First, since we study dividend smoothing, coefficients suffer from the classic small-sample bias in first-order autoregression models. The ordinary least squares (OLS) estimator is no longer unbiased when the sample size of a time series is not large and the autoregressive parameter is close to 1 (Hurwicz, 1950). The cross-sectional differences will be blurred when dividend series become more persistent since the small-sample bias is a proportion of the true SOA (Kendall, 1954). That is, in the case of dividend smoothing, the true SOA falls, and D_{t-1} becomes very sticky, which inflates the standard error of the SOA estimate. Since the distribution of parameter estimates is skewed in small samples, this inflated standard error increases bias.

[8]The speed of adjustment is often estimated as β_1 from $\Delta D_t = D_t - D_{t-1} = \beta_0 + \beta_1 \cdot (D_t^* - D_{t-1}) + \epsilon_t$ where D_t^* is target payout ratio times E_t, substituting this expression for D_t^* to get Equation (2.3).

Second, the modern dividend policies may not follow the two logics in the Lintner (1956) model, i.e., firms do not have a long-term target payout ratio to adjust towards. According to Brav et al. (2005) survey, the level of dividend per share has now become a more relevant target than the dividend payout ratio. If this is the case, the SOA estimates from Equation (2.3) will no longer be a reliable measure of dividend smoothing.

Leary and Michaely (2011) tackle these two problems through two new measures, which I use for the main analysis. According to the survey evidence, the level of dividend per share is a significant indicator of today's corporate dividend policy. Therefore, they used the number of common shares outstanding to scale dividends and earnings prior to estimating the SOA. Then they use a two-step process to get a more accurate SOA estimate. First, they estimate the firm's target payout ratio as a rolling median payout ratio, i.e., dividends divided by net income, over ten years (or five years for Chinese sample), and then retrieved the deviation from the target payout ratio at each period:

$$dev_{i,t} = TPR_{i,t} \cdot EPS_{i,t} - DPS_{i,t-1}, \tag{2.4}$$

where $dev_{i,t}$ is the deviation from the target payout ratio, $EPS_{i,t}$ is the earning per share, $TPR_{i,t}$ is the target payout ratio and $DPS_{i,t-1}$ is the lagged level of dividends per share. Second, they regress the changes in dividend per share on the deviation from the target payout ratio to determine the SOA.

$$\Delta DPS_{i,t} = \alpha + \beta_i \cdot dev_{i,t} + \epsilon_{i,t} \tag{2.5}$$

β_i is the SOA estimate. Unlike Equation (2.3), where SOA is estimated from D_{t-1}, Equation (2.5) estimates the SOA based on the deviation from the target. Because the change in the deviation reflects the change in earnings, which is much larger than the change in dividends, the accuracy of the estimation is almost constant with the change of the actual SOA. Leary and Michaely (2011) find that this new SOA is less affected by small-sample bias using simulation analysis.

At the same time, in the spirit of Guttman et al. (2010) definition, a smooth dividend is one in which changes in the dividends do not fully reflect all changes in the cash flows. Leary and Michaely (2011) introduce a non-parametric model-free measure, which is the change in dividend growth volatility relative to the change in earnings growth volatility. In recent years, scholars of dividend research have rapidly adopted this method (e.g., Chen et al., 2012; Rangvid et al., 2014; Larkin et al., 2017). They use the median payout ratio to scale annual earnings to control the impact of dividend level on relative volatility. Equation (2.3) multiplies current earnings by the target payout rate to achieve the purpose of scaling. They next fitted a quadratic time trend to both series of dividend per share and earnings per share.

$$\begin{aligned} DPS_{i,t} &= \alpha_1 + \beta_1 \cdot t + \beta_2 \cdot t^2 + \epsilon_{i,t} \\ TPR_i \cdot EPS_{i,t} &= \alpha_2 + \gamma_1 \cdot t + \gamma \cdot t^2 + \mu_{i,t} \end{aligned} \tag{2.6}$$

The alternative measure of smoothing is defined as the ratio of the root mean squared errors, $\sigma(\epsilon)/\sigma(\mu)$, from Equation (2.6). They name this alternative measure "relative volatility (RelVol)". The purpose of fitting a time trend is to include different types of dividend policies, for example, some firms focus on a fixed level of dividend per share, while others aim for dividend per share growth. [9]

Table 2.2: Summary of Continuous Dividend Payers

Year	United States	China	**Year**	United States	China
1990	400		2005	746	271
1991	411		2006	778	291
1992	425		2007	769	355
1993	450		2008	698	397
1994	497		2009	688	452
1995	524		2010	731	456
1996	568		2011	703	442
1997	572		2012	670	427
1998	595		2013	640	397
1999	617		2014	594	388
2000	628	127	2015	533	398
2001	603	156	2016	511	388
2002	623	182	2017	500	357
2003	673	202	2018	467	329
2004	731	250	**Mean**	580	391

Notes: This table summarises the number of continuous dividend payers in each sample year.

The measures of dividend smoothing I have applied in my thesis are 1 - SOA, and 1 - RelVol, referred as dividend smoothing measure (DS) and alternative dividend smoothing measure (DS_{alt}). I subtracted one from these two measures just for a more intuitive expression, i.e., the higher the value of DS, the smoother the dividend, rather than the opposite expression. I trim the top and bottom 2.5% of resulting smoothing measures following Leary and Michaely (2011).

Table 2.2 summarises the number of continuous dividend payers in each sample year. The average numbers of continuous dividend payers each year in the US and China are 580 and 391, respectively. Note that the number of continuous dividend payers in both countries increases year by year until 2010 and then declines. More US firms have stopped paying continuous dividends than Chinese firms, possibly because of the growing popularity of stock repurchases. Dividend

[9] A firm's dividend per share each year will be as smooth as a firm that adds a fixed amount of dividend payments after eliminating a linear time trend. It will also have the same degree of smoothing as a firm that grows its dividend per share by the same percentage every year after further removing a quadratic time trend.

smoothing in China could be affected by the turmoil in the Chinese stock market around 2015.

2.3.3 Factor Returns

The independent variables in the time-series regressions contain the returns on a market portfolio and mimic portfolios for the size factor, value factor and smoothing factor in stock returns.

The proxy for the return on the market portfolio is the excess market return, $R_m - R_f$. R_m is the value-weight return on all NYSE, AMEX and NASDAQ stocks, or Chinese A-shares. R_f is the one-month risk-free rate. The SMB (small minus large) and HML (high minus low) portfolios attempt to mimic the risk factors associated with size and value. The valuation ratio used to construct the portfolio is book-to-market (B/M) in the US and earnings price (E/P) in China.

SMB is the average return on the three small portfolios minus the average return on the three big portfolios. HML is the average return on the two value portfolios minus the average return on the two growth portfolios. Factor returns for both countries are collected from WRDS.[10]

$$\begin{aligned}
SMB &= 1/3(Small\,Value + Small\,Neutral + Small\,Growth) \\
&\quad - 1/3(Big\,Value + Big\,Neutral + Big\,Growth) \\
HML &= 1/2(Small\,Value + Big\,Value) \\
&\quad - 1/2(Small\,Growth + Big\,Growth)
\end{aligned}$$

[10] I did not collect returns on the China factor from CSMAR because it does not define value firms well, i.e. it uses the B/M ratio to define the value factor rather than the E/P ratio, which better captures the China value effect (Liu et al., 2019).

For US data collected from WRDS, the portfolios are formed at the end of each June. They are the intersections of two portfolios formed on market equity and three on B/M ratio. The breakpoint of market equity is the median NYSE market equity, and the breakpoints of the B/M ratio are the 30$^{\text{th}}$ and 70$^{\text{th}}$ NYSE percentiles. NYSE size and B/M breakpoints are obtained from Kenneth French's website at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/`.

Judging from the Chinese data collected by CSMAR, the structure of factor returns is different from that of the US. CSMAR's portfolio is formed at the end of January each year. The smallest 20% are excluded from the sample. Big firms are the top 50% by negotiable market equity of the remaining stocks, while small firms are the bottom 50%. The remaining 80% of stocks are divided into three E/P groups, with growth and value stocks accounting for the bottom 30% and top 30% of that universe, respectively.

I constructed the size factor and value factor in China, following the latest paper by Liu et al. (2019). They find that the smallest firms in China, whose value is related to the initial public offering (IPO), has nothing to do with fundamentals. IPOs in China are heavily regulated, time-consuming and cumbersome. So private firms have found another way to go public, i.e., reverse merger. In a reverse merger, a private firm targets an already listed firm and then buys it all up to go public. This type of target is shell firms, where the smallest firms listed on the Shanghai and Shenzhen exchanges become attractive shell firms. When building size factors, they remove the smallest 30% of firms to avoid shell contamination. They also find that the E/P ratio best absorbs the value effect compared to other valuation ratios. In contrast to the value factor based on E/P, Fama and French (1993) three-factor model based on B/M left a 17% alpha.

Portfolio VMS (Volatile Minus Smooth) attempts to mimic the risk factor in returns related to dividend smoothing. It is defined as the monthly difference between the excess return on the most volatile portfolio and the excess return on the smoothest portfolio, i.e., $VMS = Low\,DS - High\,DS$. Monthly return on portfolio is value weighted.[11] The most volatile firms are the bottom tertile of DS and the smoothest firms are the top tertile of DS.

2.3.4 Regression Methods

Average Return on Portfolios Sorted by Smoothing

Stocks are first single sorted on the level of smoothing. Smoothing portfolios are formed on the calculated measures of dividend smoothing every year, which are DS and DS_{alt}. Each year I allocate firms into ten deciles based on the degree of smoothing. Finally, I calculate value-weighted monthly average and median returns for the ten constructed portfolios.

Stocks are then double sorted on smoothing and size (or value). Each year I allocate firms into three tertiles based on the degree of smoothing. Size (or value) portfolios are formed on the quintiles of market value or (B/M and E/P) every year.[12] Then, I calculate value-weighted monthly average and median returns for

[11] "True mimicking portfolios of the common risk factors in returns minimise the variance of firm-specific factors. Using value-weighted components is in the spirit of minimising variance, since return variances are negatively related to size." Fama and French (1993)

[12] The cutoff points of size and B/M for the US firms use the NYSE quintile breakpoints. AMEX and NASDAQ have a high percentage of small firms. Therefore, portfolios are formed by size and B/M based on the NYSE breakpoints to ensure that none of the portfolio is overly dominated by small-cap

the double-sorted portfolios.

Regressions on Portfolios Formed on Size and Value

Stocks are double sorted on size and value. The 25 size-value portfolios are formed from the intersections of the size and B/M (or E/P) quintiles. I calculate the value-weighted monthly excess returns, just like the method in Fama and French (1993), and they are the dependent variables in the following four time-series regressions.

- One-factor model, i.e., CAPM,

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \epsilon_t, \quad (2.7)$$

  where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates and R_t is the value-weighted monthly returns on portfolios.

- Two-factor model, i.e., Smoothing Model,

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \beta_{smooth}VMS + \epsilon_t, \quad (2.8)$$

  where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates, R_t is the value-weighted monthly returns on portfolios and VMS is smoothing factor return.

- Three-factor model, i.e., Fame-French Model,

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \beta_{size}SMB + \beta_{value}HML + \epsilon_t, \quad (2.9)$$

where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates, R_t is the value-weighted monthly returns on portfolios, SMB is size factor return and HML is value factor return.

- Finally, a four-factor model,

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \beta_{size} SMB + \beta_{value} HML + \beta_{smooth} VMS + \epsilon_t, \tag{2.10}$$

where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates, R_t is the value-weighted monthly returns on portfolios, VMS is smoothing factor return, SMB is size factor return and HML is value factor return.

In time series regression, the coefficients and R^2 provide direct evidence of whether the different risk factors capture the common changes in stock returns. If the mimicking returns VMS captures the risks that excess market return missed out, then compare to Equation (2.7), the Equation (2.8) should have a higher R^2 and a significant β_{smooth}. If the mimicking returns VMS also absorbs the size and value effects in average returns, Equation (2.8) should perform as good as Equation (2.9) in terms of higher R^2 and significant coefficients. In addition, the intercept in Equation (2.8) should be small, preferably not different from zero, if $R_{m,t} - R_{f,t}$ and VMS absorb the time-series changes in returns and explain well the cross-section of the average returns. Finally, I add four factors to the regression analysis to get a bird's-eye view of the risk loading.

2.3.5 Descriptive Statistics

Table 2.3 summarises the correlation coefficients and means for risk premia. Average VMS (VMS_{alt}) return is 0.24% (0.31%) per month in the US. VMS and VMS_{alt} are not consistent in China, with the former at -0.21% and the latter at 0.42%. In the US, the correlation between the two smoothing factor returns is 83%, while it is only -9.7% in China.

Table 2.3: Descriptive Statistics of Factor Returns

	United States					
	VMS	VMS_{alt}	SMB	HML	$R_m - R_f$	Mean
VMS	1					0.24%***
VMS_{alt}	0.830*	1				0.31%***
SMB	-0.058*	-0.109*	1			0.14%***
HML	-0.208*	-0.118*	-0.252*	1		0.16%***
$R_m - R_f$	0.199*	0.170*	0.238*	-0.136*	1	0.61%***
	China					
	VMS	VMS_{alt}	SMB	HML	$R_m - R_f$	Mean
VMS	1					-0.21%***
VMS_{alt}	-0.097*	1				0.42%***
SMB	0.095*	-0.016*	1			0.92%***
HML	-0.048*	-0.006	-0.614*	1		1.10%***
$R_m - R_f$	0.166*	-0.196*	0.156*	-0.302*	1	0.41%***

Notes: This table presents correlation coefficients among factor returns of size (SMB), value (HML), smoothing (VMS and VMS_{alt}) and market ($R_m - R_f$). The last column shows the average premium over the sample period. The symbols * indicates statistical significance at 5%. Panel A includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1990 to December 2018, 348 months. Panel B includes all domestic China A-share on CSMAR from January 2000 to December 2018, 228 months. See Section 2.3 for details in model construction and variable definition.

Size and value premia in China are much higher than in the US at 0.92% and 1.1%, respectively. High average premia usually mean that the factor returns have some potential to explain the changes in average returns.

The average market risk premium, $R_m - R_f$, in the US is higher than in China, and except for the value factor, other factors comove with the market risk premium. In the US, the correlations for non-market factors are mostly negative, e.g., -5.8% between VMS and SML, -20.8% between VMS and HML, -25.2% between

HML and SML. Of course, adding low or negative correlated factors might yield better results in terms of diversification. The size and value factors are highly correlated in China, i.e., -61.5%, which is not ideal for portfolio construction because of the reduced diversification.

Table 2.4: Descriptive Statistics for Portfolios Formed on Size and B/M (or E/P)

	B/M (or E/P)									
SIZE	Low	2	3	4	High	Low	2	3	4	High
	United States					China				
	Mean of annual averages of firm size									
Low	242	218	219	200	154	2534	2361	2605	2644	3121
2	787	774	722	659	678	4101	4282	4335	4175	4488
3	1700	1686	1654	1611	678	5943	6934	6297	6583	7028
4	4548	4234	4094	4074	4255	10951	11841	10568	10728	10428
High	42275	40319	36476	34471	31592	34697	29777	31707	36709	29307
	Mean of annual B/M (or E/P) ratios for portfolio									
Low	0.22	0.39	0.57	0.75	1.23	0.01	0.03	0.04	0.05	0.08
2	0.21	0.39	0.56	0.74	1.16	0.02	0.03	0.04	0.04	0.09
3	0.22	0.39	0.54	0.74	1.13	0.01	0.03	0.04	0.05	0.08
4	0.21	0.37	0.54	0.74	1.12	0.01	0.03	0.04	0.05	0.09
High	0.19	0.37	0.54	0.74	1.08	0.02	0.03	0.04	0.05	0.11
	Mean of annual dividend smoothing measures for portfolio									
Low	0.59	0.59	0.65	0.66	0.71	0.31	0.27	0.32	0.33	0.43
2	0.55	0.63	0.67	0.71	0.72	0.28	0.19	0.29	0.31	0.31
3	0.52	0.62	0.66	0.71	0.74	0.21	0.21	0.28	0.23	0.24
4	0.52	0.64	0.68	0.69	0.72	0.29	0.23	0.19	0.25	0.25
High	0.51	0.62	0.68	0.71	0.72	0.28	0.23	0.25	0.25	0.21

Notes: Portfolios are formed on $Size$ and B/M (or E/P). The US sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1990 to December 2018, 348 months. The Chinese Sample includes all domestic A-share on CSMAR from January 2000 to December 2018, 228 months. Descriptive statistics are calculated in June (January in China) each year when the portfolio is formed and are averaged over the entire sample period. See Section 2.3 for details in portfolio construction.

Table 2.4 shows that when B/M increases, the average annual firm size in each size quintile decreases in the US. Similarly, the average annual B/M per B/M quintile decreases when firm size increases. This implies that firm size and B/M may negatively correlate in the US.

When the B/M quintile is fixed, the smoothness of dividends does not vary much across size quintiles. This suggests that the extent of dividend smoothing for a firm at the same B/M quintile is not affected by size. In other words, dividend smoothing can absorb some of the size effects.

In comparison, the average annual size in China does not vary significantly with the quintile of the E/P, which implies that size and E/P are not highly correlated. There is no clear pattern in the degree of dividend smoothing across 25 portfolios. Note that the degree of dividend smoothing in China (0.19 - 0.43) is much smaller than in the US (0.51 - 0.74).

A potential problem arises from my sample selection as I have restricted the sample to firms that pay dividends. Since dividend payers are selected non-randomly from the population, estimating the determinants of dividend smoothing from a sub-population of dividend payers may introduce bias.

While it is essential to include firms that pay zero dividends when studying dividend levels, this is not the case in the study of dividend smoothing. Non-payers have a steady stream of dividends, i.e. zero dividend payments, which mechanically assigns them to the highest smoothing group. Their behaviour, however, is fundamentally different from those who pay stable and positive dividends.

Prior evidence suggests that the decision to pay dividends is influenced by many of the same factors associated with dividend smoothing. In this way, the selected sample is representative of the total population and thus does not give rise to the problem of estimation bias. Therefore, I exclude firms that do not pay dividends, and my conclusions apply to dividend payers.

2.4 Empirical Results

2.4.1 Preliminary Analysis

Benefiting from the long history of stock market trading in the US, I first use a vector autoregression, i.e., VAR (which requires longer time series), to examine whether the stock prices of firms of size and value from 1971 to 2018 moved with dividends or discount rates. I then analyse the dividend smoothing behaviour of size and value firms over the last 20 years and see if this behaviour is consistent with value and size effects. This chapter only makes a preliminary analysis of the US market due to insufficient observations in the Chinese market.

What Moves Prices in Small and Value Stocks

We know that the unexpected market return consists of two parts, news about market discount rates and news about market cash flows (in this case, dividends). The latter is considered to be riskier, because once it is lowered, the investors' wealth will not be reversed. In other words, if a firm's returns are more affected by news about market dividends, it will take on greater risks and correspondingly have higher returns. I assume that firm-level dividend news correlated with market-level dividend news, and firm-level return news correlated with market-level return news (Pettit & Westerfield, 1972; Cochrane, 2005). Therefore, if a firm's unexpected return is mainly caused by the firm-level dividend news, then its return will be more correlated to the market dividend news, while for long-term investors who are accustomed to risk aversion, they do not want their holdings to be sensitive to such information, so they will demand a higher premium.

Another way to consider what constitutes returns is what affects prices. Changes in returns come from changes in current dividends, expected future dividends and expected future returns. The latter two effects come from the effect on future price relative to dividends (or earnings, free cash flows, book value or other divisors). See Box on page 22. If a firm's price moves on changes in dividends, then its unexpected return is also due to news about future dividends. Therefore, I attempt to understand the source of price volatility by decomposing variance of the dividend-price ratio.

Figure 2.1 plots the fraction of two components after decomposing the dividend-price ratio according to the method of Cochrane (2008). The details of this method will be further explained in Appendix A.1, Equation (A.1.8) on Page 75.

The predictive slopes represent the proportion of changes in the current dividend-price ratio caused by variation in return and dividend growth, respectively. Panel A includes the top 30% of stocks sorted by $Size$ based on the NYSE breakpoints, while Panel B includes the bottom 30% of stocks in the same category. According to the left graph in Panel A, while changes in both returns and dividend growth affect price movements for small stocks, more than half of the dividend-price variation is caused by changes in dividend growth. The right graph in Panel A confirms that both slopes are statistically significant. In Panel B, changes in return are the dominant source of the dividend-price variation for big stocks and increase as investment horizons extend. The changes in dividend growth, however, account for a very small percentage of the change in dividend-price ratio, and the dividend growth predictive slopes are not significant neither.

This figure shows that the price movement of small firms is more affected by

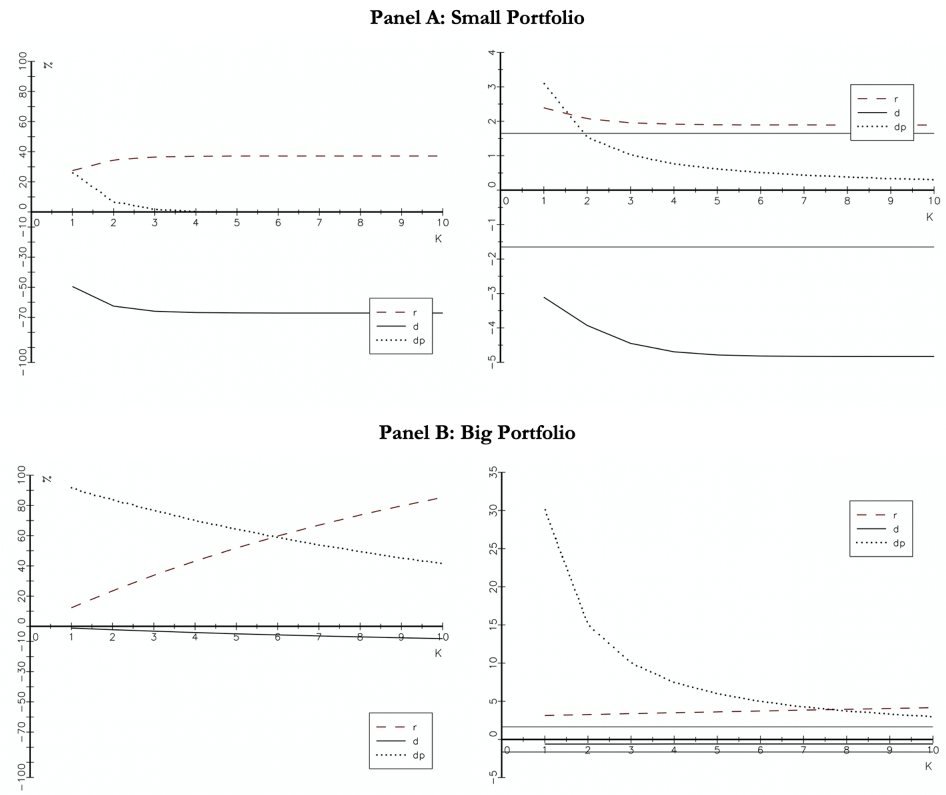
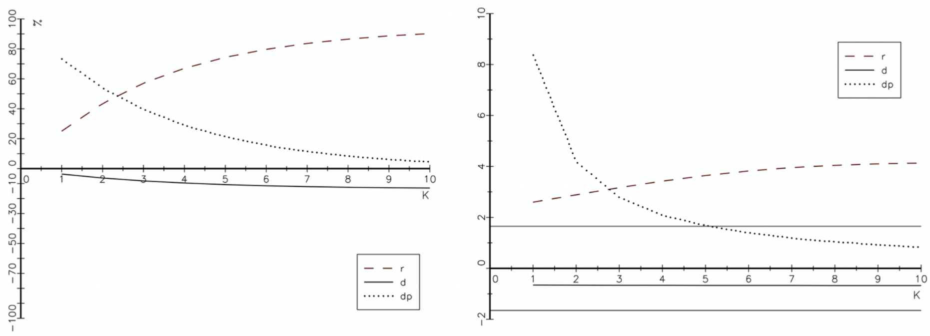


Figure 2.1: This figure plots the 10-year horizon predictive slopes (left panel) and corresponding t-value (right panel) for portfolios that formed on book equity based on the 30[th] and 70[th] NYSE percentiles. The predictive slopes are related to the expected return (r), expected dividend growth (d), and expected dividend-price (dp), taking logarithm. The horizontal line in the right panel denotes the 5% critical value. The slopes are measured in percent, and k represents the investment horizon. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP, from 1971 to 2018.

dividend fluctuations than that of large firms. It also implies that the unexpected return of small firms is more related to dividend news and therefore riskier. The black dots in the figure represent the predicted slope of the current dividend price ratio to the future dividend-price ratio (i.e., autocorrelation). Although the autocorrelation is dying out over time, the starting position is completely different for small and big portfolios. Big stocks have a much persistent log dividend-price ratio (0.9 versus 0.3) than small stocks. Note that serious dividend smoothing behaviour usually makes the dividend-price ratio very sticky.

I follow up with a similar analysis of value and growth firms. Portfolios are formed on B/M in Figure 2.2. Panel A consists of the top 30% of stocks based on the NYSE breakpoints, while Panel B includes the lowest 30% of stocks of the

Panel A: Growth Portfolio



Panel B: Value Portfolio

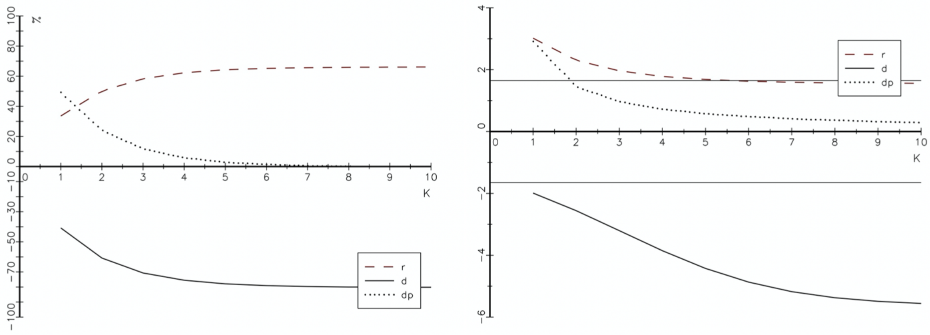


Figure 2.2: This figure plots the 10-year horizon predictive slopes (left panel) and corresponding t-value (right panel) for portfolios that formed on book-to-market ratio based on the 30th and 70th NYSE percentiles. The predictive slopes are related to the expected return (r), expected dividend growth (d), and expected dividend-price (dp), taking logarithm. The horizontal line in the right panel denotes the 5% critical value. The slopes are measured in percent, and k represents the investment horizon. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP, from 1971 to 2018.

same sort. In the case of the growth portfolio, the portion relating to the change in dividend growth never exceeds 20%, while the portion relating to the change in return approaches 80% at the 10-year horizon. The right graph in Panel A indicates that the large share of return volatility is also statistically significant. In contrast, dividend growth slopes are not significant at all horizons. Panel B plots the term structure of predictive slopes related to value portfolio. The change in the aggregate dividend-price ratio comes from the equal proportion of changes in dividend growth and return, although the return slopes are marginally significant at 5% level beyond 4-year horizons. The initial autocorrelation of dividend-price ratio of the growth portfolio is higher than that of the value portfolio (0.7 versus 0.5). All in all, value firms' share prices are more influenced by dividend news than growth firms' and therefore take on more risk.

Most previous studies on the decomposition of dividend-price ratio are based on the entire US stock market using value-weighted market index e.g., Cochrane (2008, 2011); Chen (2009); Chen et al. (2012). The prevalent view is that the variation in future return plays the most important role in driving the variation in the current aggregate market dividend-price ratio. Figure 2.1 shows that most dividend-price variation is due to the changes in return for big stocks. This is consistent with the fact that the value-weighted market index tends to have the characteristics of big firms. For the case of the value portfolio as shown in Figure 2.2, it is possible that future return variations are important in driving the dividend-price ratio because some value firms are also big. Nevertheless, dividend news can have a significant impact on price volatility in both small and value firms. Note that Figure 2.1 and Figure 2.2 replicate the work done by Maio and Santa-Clara (2015) and my results are similar to theirs.[13]

Dividend Smoothing Behaviour of Size and Value Stocks

Since my main hypothesis is to test whether dividend smoothing is related to equity pricing, a general understanding of dividend behaviour in different types of portfolios helps to solve this puzzle. First, I plot the time series of annual average of dividend smoothing DS for portfolios sorted on $Size$ and B/M from 1990 to 2018 as shown in Figure 2.3. The higher the value of DS, the smoother

[13]Despite this, my research differs from them in sampling. They use CRSP annual return with and without dividends to back out the annual dividend growth series, while I aggregate monthly dividends into annual frequencies to eliminate seasonality. The former dividends are assumed to be reinvested at a zero rate, while the latter dividends are implicitly assumed to be reinvested at cum-dividend stock market returns in the stock market. In this case, dividend growth series will inevitably behave as returns do, since dividends inherit part of annual return volatility and thus blur their characteristic.

the dividend distribution.

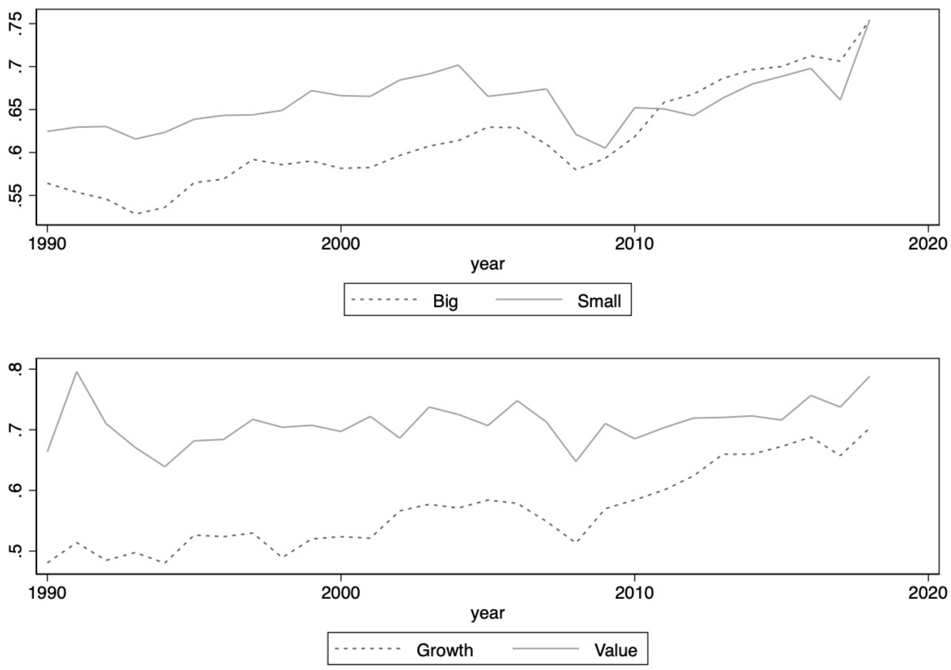


Figure 2.3: This figure plots the time series of annual average value of dividend smoothing (DS) for portfolios sorted on market equity (upper panel) and book-to-market ratio (lower panel) based on the 30^{th} and 70^{th} NYSE percentiles. DS is defined as 1 minus speed of adjustment. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP, from 1990 to 2018.

The upper panel shows the degree of dividend smoothing for portfolios formed by $Size$. The market equity breakpoints of small stocks and big stocks are the 30^{th} and 70^{th} NYSE percentiles, respectively. In the lower panel, growth stocks and value stocks are classified according to the market value based on the 30^{th} and 70^{th} percentiles of the NYSE.

Surprisingly, the dividends of small firms and value firms are smoother during the sample period, which means that dividends are less informative and have less correlation with firm returns. According to the hypothesis, if the returns of a firm is less affected by its cash flows, then its co-movement with market cash flows will be restricted, so that the firm is less exposed to systemic risks. Note that dividends in big firms are smoother around 2010 and beyond.

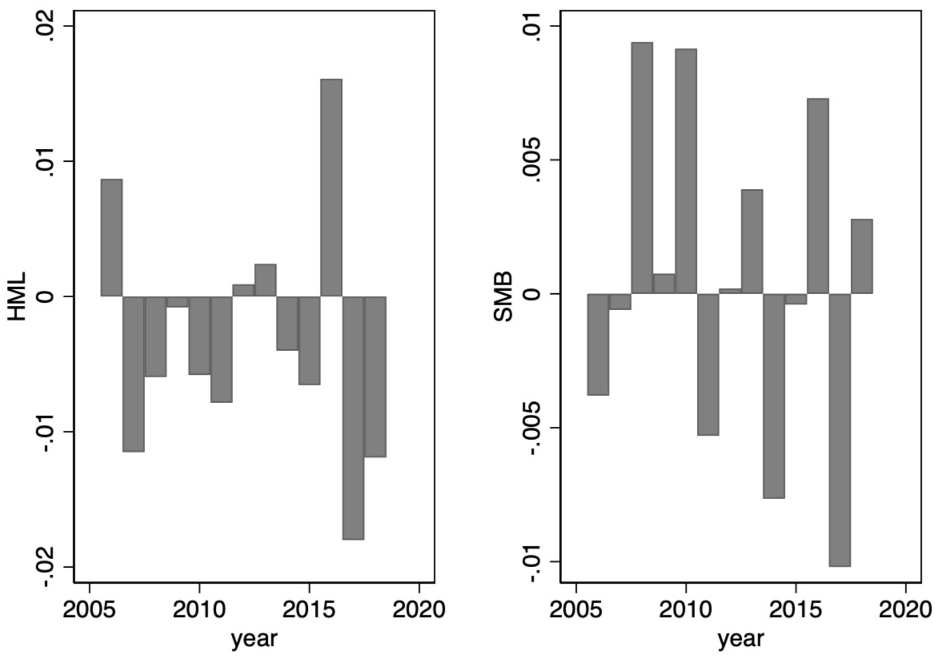


Figure 2.4: Size and value factor returns from 2006 - 2018 in the US

This is not a common feature of small firms and value firms, because their returns are usually higher than others. In order to see if the size and value effects are still the same as observed by Fama and French (1993), I compare the size (SMB) and value (HML) factor returns during the period 2006-2018. As shown in Figure 2.4, most HML and some SMB are negative, indicating a reverse value and size effect. In this way, it fits my hypothesis that firms with smooth dividends have lower returns.

Past empirical findings show that small firms and value firms have higher returns than others after 1963. I find that prices of such firms move on the changes in cash flows, i.e., dividends, by decomposing the variance of dividend-price ratio from 1971 - 2018. The size and value effects have undergone a reversal in recent years (2006 - 2018), and dividends in small firms and value firms are smoother during my sample period (1990 - 2018) in the US stock market. The purpose of this preliminary analysis is to provide some empirical basis for the subsequent construction of dividend smoothing factor.

2.4.2 Main Analysis

This part constructs a dividend smoothing factor following Fama and French (1993). I compare it with a single factor model (CAPM) and a three-factor model. Samples include all non-financial firms listed in the US and China from 1990 - 2018 and 2000 - 2018.

Table 2.5: Correlation Coefficients

	United States			
	$Size$	B/M	DS	DS_{alt}
$Size$	1			
B/M	-0.151*	1		
DS	0.005*	0.155*	1	
DS_{alt}	0.011*	0.095*	0.636*	1
	China			
	$Size$	E/P	DS	DS_{alt}
$Size$	1			
P/E	0.023*	1		
DS	-0.006	-0.020*	1	
DS_{alt}	-0.046*	-0.016*	0.383*	1

Notes: This table presents pairwise correlation among variables of market equity ($Size$), book-to-market ratio (B/M), earnings-to-price ratio (E/P), smoothing measures (DS and DS_{alt}). The symbols * indicates statistical significance at 5%. Panel A includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1990 to December 2018, 239,582 firm-month observations. Panel B includes all domestic China A-share on CSMAR from January 2000 to December 2018, 33,846 firm-month observations. See Section 2.3 for details in model construction and variable definition.

Univariate Analysis of Average Returns

Table 2.5 presents correlation coefficients among variables of size, valuation ratios and smoothing measures for the US and China. Both DS and DS_{alt} are positively correlated with $Size$ and B/M in the US, suggesting dividends in big and value firms are smoother. Compared with Figure 2.3, this is true for value firms, but only in line with the evidence of big firms after 2010. The correlation coefficient of $Size$ and B/M is -0.151, suggesting that value firms are usually small.

The degree of dividend smoothing is negatively related to both $Size$ and E/P in China. This means that dividend smoothing is more common in small and growth firms. The correlation coefficient of $Size$ and E/P is 0.023, suggesting that growth firms are usually small.

Table 2.6: Monthly Portfolio Returns Sorted by Dividend Smoothing

	United States				**China**			
	DS		DS_{alt}		DS		DS_{alt}	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Low	1.36%	1.38%	1.16%	1.47%	1.41%	1.16%	1.36%	1.45%
2	1.15%	1.39%	1.31%	1.51%	1.22%	1.08%	1.86%	2.11%
3	1.11%	1.31%	1.23%	1.45%	1.16%	1.10%	1.38%	1.02%
4	1.12%	1.46%	1.21%	1.39%	1.49%	1.40%	1.13%	1.60%
5	1.14%	1.35%	1.19%	1.30%	1.36%	1.75%	1.19%	0.43%
6	1.12%	1.42%	1.12%	1.32%	1.55%	0.80%	1.42%	1.37%
7	1.06%	1.13%	0.98%	1.22%	1.45%	1.65%	1.23%	1.34%
8	1.08%	1.21%	1.03%	1.43%	1.29%	0.63%	1.32%	1.13%
9	0.90%	1.26%	0.74%	0.91%	1.35%	1.56%	1.35%	1.31%
High	0.79%	0.99%	0.81%	0.95%	1.27%	1.63%	1.05%	0.91%
H - L	**-0.57%*****	**-0.39%*****	**-0.36%*****	**-0.53%*****	-0.14%	0.47%	-0.31%	**-0.54%****

Notes: This table reports the average and median monthly excess returns of portfolios sorted by deciles of two dividend smoothing measures (DS and DS_{alt}). US sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1990 to December 2018, 348 month. Chinese sample includes all domestic China A-share on CSMAR from January 2000 to December 2018, 228 months. See Section 2.3 for details in model construction and variable definition.

Table 2.6 reports the average and median monthly excess returns of portfolios sorted by deciles of dividend smoothing measure (DS) and its alternative (DS_{alt}). In the US, the average return on the portfolio with the lowest degree of smoothing (volatile) is 1.36%, while it is 0.79% on the portfolio with the highest degree of smoothing. Firms with the least smooth dividends receive a premium of 0.57% over those with the smoothest dividends, this premium is significantly different from zero at 1% level. Using the median or replacing the smoothing measure yield the same result, i.e., the smoother the dividends paid by the firms, the lower the returns. As for Chinese firms, except that the median return is the lowest in the least smooth portfolio measured by DS_{alt}, the differences in returns between the least and most smooth portfolios in other groups are not significant.

Table 2.7: Double Sorted Monthly Portfolio Returns (United States)

	DS				DS_{alt}			
	Low	Med	High	H - L	Low	Med	High	H - L
$Size$								
Small	1.2%	1.1%	0.9%	**-0.3%*****	1.1%	1.2%	0.8%	**-0.3%*****
2	1.2%	1.1%	0.9%	**-0.3%*****	1.2%	1.1%	0.8%	**-0.4%*****
3	1.1%	1.2%	1.0%	**-0.1%***	1.2%	1.1%	0.9%	**-0.3%*****
4	1.2%	1.2%	0.9%	**-0.3%*****	1.2%	1.1%	0.9%	**-0.3%*****
Big	1.3%	1.1%	0.9%	**-0.4%*****	1.2%	1.1%	0.8%	**-0.4%*****
B/M								
Low	1.9%	2.0%	2.1%	**0.2%*****	2.0%	2.0%	2.0%	0%
2	1.4%	1.5%	1.5%	**0.2%*****	1.5%	1.5%	1.4%	-0.1%
3	1.1%	1.2%	1.2%	0.1%	1.2%	1.2%	1.1%	-0.1%
4	0.5%	0.7%	0.7%	**0.1%*****	0.6%	0.6%	0.7%	-0.1%
High	-0.2%	-0.4%	-0.4%	**0.2%*****	-0.4%	-0.4%	-0.4%	0%

Notes: This table reports the average monthly portfolio excess returns. Portfolios are formed from the interactions of quintile of market equity ($Size$) or book-to-market ratio (B/M) and tertile of two dividend smoothing measures (DS and DS_{alt}). Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1990 to December 2018, 348 month. ***, ** and * denote the level of significance for two sample t-test at 10%, 5% and 1%, respectively. See Section 2.3 for details in model construction and variable definition.

In Table 2.7, portfolios are formed from the interactions of $Size$ (or B/M) quintile and dividend smoothing (DS and DS_{alt}) tertile in the US. The average monthly portfolio excess returns are reported from the smallest (lowest B/M) firms to the biggest (highest B/M) firms. First, when stocks are grouped by the degree of dividend smoothing, the size effect can no longer be observed. For example, the average returns of small stocks and big stocks are the same at 0.9% in the smoothest group (high DS). On one hand, the smoothness absorbs some of the size effect; on the other hand, the size effect itself is not robust in recent years, as shown in Figure 2.4. Second, in groups of different sizes, no matter what smoothing measures are adopted, the average returns of a firm with a high degree of dividend smoothing are significantly lower than that of a firm with a low degree of dividend smoothing. Third, the lower panel clearly shows the reverse value effect that firms with low B/M have higher average returns than those with high B/M, which is consistent with the negative HML in Figure 2.4. This phenomenon occurs in all dividend smoothing groups, regardless of the smoothing measure used. This suggests that dividend smoothing does not generalise the characteristics of the value effect, and not only that, the smoothing effect is contrary to expectations, but only with DS.

Table 2.8: Double Sorted Monthly Portfolio Returns (China)

	DS				DS_{alt}			
	Low	Med	High	H - L	Low	Med	High	H - L
$Size$								
Small	0.3%	0.6%	0.4%	0.1%	0.5%	0.4%	0.5%	0%
2	1.2%	0.8%	1.8%	**0.6%****	1.1%	1.0%	1.4%	0.3%
3	1.2%	2.1%	1.0%	-0.2%	1.7%	1.5%	0.8%	**-0.9%*****
4	1.7%	1.7%	1.7%	0%	1.6%	1.7%	1.6%	0%
Big	1.7%	2.3%	2.1%	0.4%	2.1%	1.7%	2.3%	0.2%
E/P								
Low	1.9%	1.4%	1.9%	0%	2.2%	1.5%	1.5%	**-0.7%****
2	1.6%	2.2%	1.5%	0.1%	2.2%	1.6%	1.6%	**-0.6%***
3	1.4%	1.2%	0.9%	**-0.5%***	1.1%	1.9%	0.5%	**-0.6%****
4	0.5%	1.2%	1.3%	**0.8%*****	1.5%	0.6%	1.1%	-0.4%
High	0.9%	1.3%	0.9%	0%	0.6%	1.0%	1.2%	**-0.6%****

Notes: This table reports the average monthly portfolio excess returns. Portfolios are formed from the interactions of quintile of market equity ($Size$) or book-to-market ratio (E/P) and tertile of two dividend smoothing measures (DS and DS_{alt}). Sample includes all domestic China A-share on CSMAR from January 2000 to December 2018, 228 months. ***, ** and * denote the level of significance for two sample t-test at 10%, 5% and 1%, respectively. See Section 2.3 for details in model construction and variable definition.

Table 2.8 presents the results for double sorted portfolios in China. Both the value and size effects are reversed and are not absorbed by dividend smoothing. If this phenomenon is true in both countries, then the nature of value and size effects has changed. The average portfolio returns are mixed in terms of different degree of dividend smoothing.

Fama-MacBeth Regression

I also use the cross-section regressions of Fama and MacBeth (1973) to further validate my hypothesis. I regress the cross-section stock returns on variables that hypothesised to explain average returns, i.e., β, $size$, B/M, E/P and DS. The time-series average of the monthly coefficients supplies standard Fama-MacBeth tests of whether the selected variables are priced on average.

Instead of using portfolios for regression as in Fama and MacBeth (1973), I use the methods of Fama and French (1992). I first estimated portfolio βs, and then allocated the portfolio βs to each stock in the portfolio. The purpose of this is to be able to use individual stocks in the Fame-MacBeth regressions.

β is calculated in two steps. First, I estimate the pre-ranking β for each stock by regressing stock excess returns on current as well as lagged market excess returns over the past 5 years (or at least 2 years of non-missing returns). The sum of the slopes is the pre-ranking β and the estimates are updated every January of year t. I sort stocks into size quintiles first. I then further divide each size quintile into β deciles, based on pre-ranking β.[14] I calculate the equal-weighted monthly returns for each size-β portfolio for the next 12 months. Lastly, I regress the monthly portfolio excess return on current as well as lagged market excess returns. The sum of the slopes is the post-ranking β used in the Fama-MacBeth analysis.[15]

In order to satisfy the normal distribution assumption, I take a logarithm on

[14]Size and β are highly correlated. Size-β treatment separates size from β effects in average returns.

[15]The estimated β is the sum of the slopes are meant to adjust for asynchronous transactions.

the $size$, B/M, and DS because they are all highly skewed to the right. I first use $\log(DS)$ alone to test whether it has an explanatory power for the average returns. Then I add $\log(size)$ and $\log(B/M)$ to the regressions to see if DS could replace them to explain the average returns on the stock. For Chinese firms, I use EP^+ when earrings-price ratio is positive, and zero otherwise.

$$R_{i,t} = \alpha_0 + \alpha_1 \log(DS)_{i,t} + \epsilon_{i,t}$$

$$R_{i,t} = \alpha_0 + \alpha_1 \beta_{i,t} + \alpha_2 \log(DS)_{i,t} + \epsilon_{i,t}$$

$$R_{i,t} = \alpha_0 + \alpha_1 \beta_{i,t} + \alpha_2 \log(DS)_{i,t} + \alpha_3 \log(size)_{i,t} + \alpha_4 \log(B/M)_{i,t} + \epsilon_{i,t}$$

$$R_{i,t} = \alpha_0 + \alpha_1 \beta_{i,t} + \alpha_2 \log(DS)_{i,t} + \alpha_3 \log(size)_{i,t} + \alpha_4 EP^+_{i,t} + \epsilon_{i,t}$$

where DS is the measure of dividend smoothing (I also used DS_{alt}), $size$ is the market equity of a firm, B/M is the book-to-market ratio, EP^+ is the positive earrings-price ratio, and zero otherwise, and β is the post-ranking beta assigned to each stock in the size-β group.

Table 2.9 represents average slopes from Fama-MacBeth regressions. First, in the US, the coefficients of both smoothing measures, $\log_{DS}$ and $\log_{DS_{alt}}$, are significantly negative and are not sensitive to the inclusion of β. A negative coefficient means that the smoother the dividends, the lower the returns.

However, when size and value variables are included in the regression, dividend smoothing loses the ability to explain returns. The negative coefficient on B/M plays a dominant role in explaining stock returns. It also confirms the reverse value effect for the US. The results are also robust, when DS_{alt} is used.

Smoothing is marginally been priced in the case of using $\log_{DS}$ alone as a risk

Table 2.9: Fama-MacBeth Regression

			United States			
$logDS$	**-0.09*** **	**-0.10*** **	0.03			
β		0.44	0.29		0.40	0.27
$\log size$			**-0.07** **			**-0.07** **
$\log B/M$			**-0.76*** **			**-0.77*** **
$\log DS_{alt}$				**-0.12*** **	**-0.12*** **	-0.02
			China			
$\log DS$	**0.12***	0.10	0.09			
β		**1.51***	0.30		1.63	0.34
$\log size$			**0.84*** **			**0.60*** **
EP^+			**-0.52*** **			**-0.25***
$\log DS_{alt}$				-0.06	-0.10	-0.06

Notes: This table represents the cross-sectional Fama-MacBeth regression results of monthly excess return on log smoothing measures ($\log DS$ and $logDS_{alt}$), post-ranking beta (β), log market equity ($\log size$), log book-to-market ratio ($\log B/M$) and EP^+, which equals the positive values of earnings-to-price ratio, and zero otherwise. The t-statistics are calculated using Newey-West (1987) standard errors with one lag. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. Panel A includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1992 to December 2018, 324 months. Panel B includes all domestic China A-share on CSMAR from January 2002 to December 2018, 204 months. On average, there are 679 US firms and 161 Chinese firms in monthly regression. See Section 2.3 for details in model construction and variable definition.

factor in China. A positive coefficient indicates firms that smooth dividends have higher returns, which is not consistent with the hypothesis. However, unlike in the US, there is a simple positive correlation between average returns and β, and $\log_{DS}$ is no longer significant. This also means that CAPM marginally performs better in China than the US. When controlling for size and value, i.e., EP^+, the relationship between β and average returns also disappears. Followed Fama and French (1992) and Liu et al. (2019), I use EP^+ as the valuation ratio for China, with EP^+ equals one when E/P is positive, and zero otherwise. Significant positive size and negative value coefficients, are consistent with the reverse effects of size and value in China.

Factor-Return Regression for Size-Value Portfolios

In this section the explanatory variables are factor returns of size (SMB), value (HML), dividend smoothing (VMS) and market risk premium ($R_m - R_f$). Table 2.10 and Table 2.11 respectively present the results of CAPM regressions for the US and China.

Table 2.10: CAPM Regressions for Size - B/M Portfolios (United States)

	B/M				
$Size$	Low	2	3	4	High
			α		
Small	2.01***	1.56***	1.02***	0.51**	-0.23
2	1.58***	1.26***	0.66***	0.32*	-0.43*
3	1.35***	0.82***	0.73***	0.24	-0.13
4	1.19***	0.67***	0.50***	0.13	-0.06
Big	0.87***	0.46***	0.46***	0.25	-0.06
			β_{market}		
Small	0.78***	0.75***	0.77***	0.73***	0.93***
2	0.78***	0.90***	0.87***	0.74***	0.90***
3	0.96***	0.85***	0.81***	0.76***	0.84***
4	0.88***	0.91***	0.89***	0.78***	0.67***
Big	0.81***	0.74***	0.81***	0.64***	0.65***
			R^2		
Small	0.202	0.290	0.375	0.403	0.268
2	0.389	0.511	0.547	0.488	0.478
3	0.652	0.607	0.569	0.543	0.475
4	0.695	0.705	0.623	0.546	0.400
Big	0.806	0.696	0.618	0.481	0.349

Notes: This table presents the regression results of monthly excess return on market risk-free returns for portfolios that formed on $Size$ and B/M.

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \epsilon_t$$

where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates, R_t is the value-weighted monthly returns on portfolios. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1990 to December 2018, 348 months. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 2.3 for details in model construction and variable definition.

Although β_{market} in both countries are all significant, they are numerically different. β_{market} in China are higher than 1, while in the US, most of them are lower than 1. This is understandable. As an emerging market, China has many small caps, so its volatility will be greater than that of the market. In big and growth portfolios, the R^2 in the US CAPM is larger, suggesting that the market risk premium does a good job of capturing the greater returns of big and growth stocks.

Table 2.11: CAPM Regressions for Size - E/P Portfolios (China)

	E/P				
$Size$	Low	2	3	4	High
			α		
Small	-0.13	0.23	-0.06	0.01	0.19
2	0.81*	0.65	0.64	0.44	-0.21
3	1.71***	1.72***	0.74**	0.58*	0.27
4	2.49***	1.49***	0.96***	0.92***	0.68**
Big	2.57***	3.54***	1.84***	1.34***	0.94***
			β_{market}		
Small	1.11***	1.00***	1.01***	0.93***	1.14***
2	1.12***	1.18***	0.92***	1.06***	1.00***
3	1.20***	1.06***	0.84***	0.97***	1.10***
4	1.07***	0.94***	0.98***	1.12***	1.02***
Big	1.12***	1.01***	1.00***	1.01***	1.03***
			R^2		
Small	0.605	0.619	0.630	0.590	0.698
2	0.631	0.664	0.579	0.691	0.585
3	0.511	0.586	0.601	0.670	0.724
4	0.532	0.537	0.698	0.733	0.792
Big	0.548	0.335	0.688	0.672	0.734

Notes: This table presents the regression results of monthly excess return on market risk-free returns for portfolios that formed on $Size$ and E/P.

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \epsilon_t$$

where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates, R_t is the value-weighted monthly returns on portfolios. Sample includes all domestic China A-share on CSMAR from January 2000 to December 2018, 228 months. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 2.3 for details in model construction and variable definition.

The average R^2 of 25 portfolios in China is higher than that of the US, but it is lower in big and growth portfolios. This shows that the overall performance of CAPM in China is better than that in the US, but the market risk premium cannot explain the higher risk in big firms and growth firms.

The two-factor model is designed to test whether the smoothing factor can capture the risk left by the market risk premium. In the US, the addition of a smoothing factor made the model R^2 slightly higher due to more explanatory variables. Except for the smallest and biggest size quintiles, most β_{smooth} are significant, regardless of the size of the portfolios. China's β_{smooth} are not at all significant, suggesting that dividend smoothing does nothing to explain the cross-sectional variation in average returns. I also use an alternative smoothing measure to construct another VMS_{alt}, and the results are shown in the Appendix.

Table 2.12: Two-Factor Regressions for Size - B/M Portfolios (United States)

	B/M				
$Size$	1	2	3	4	5
			α		
Small	1.74***	1.73***	1.29***	0.73***	-0.25
2	1.75***	1.50***	0.87***	0.57***	-0.32
3	1.55***	1.00***	0.96***	0.45**	0.06
4	1.29***	0.87***	0.66***	0.32	0.11
Big	0.82***	0.53***	0.69***	0.32*	0.10
			β_{market}		
Small	0.74***	0.77***	0.80***	0.75***	0.92***
2	0.80***	0.93***	0.90***	0.77***	0.91***
3	0.98***	0.87***	0.84***	0.79***	0.86***
4	0.90***	0.93***	0.91***	0.80***	0.69***
Big	0.80***	0.75***	0.83***	0.65***	0.67***
			β_{smooth}		
Small	1.12	-0.70	**-1.14*** **	**-0.94*** **	0.10
2	**-0.72** **	**-1.05*** **	**-0.87*** **	**-1.05*** **	-0.48
3	**-0.85** **	**-0.76** **	**-0.98*** **	**-0.88*** **	**-0.82** **
4	-0.44	**-0.85** **	**-0.70* **	**-0.80** **	**-0.91** **
Big	0.21	-0.29	**-0.98*** **	-0.30	-0.82
			R^2		
Small	0.208	0.293	0.390	0.415	0.266
2	0.394	0.523	0.556	0.507	0.480
3	0.661	0.616	0.584	0.557	0.482
4	0.698	0.717	0.629	0.557	0.411
Big	0.807	0.697	0.635	0.482	0.357

Notes: This table presents the regression results of monthly excess return on market risk-free returns and the mimicking factor return for smoothing for portfolios that formed on $Size$ and B/M.

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \beta_{smooth} VMS_t + \epsilon_t$$

where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates, R_t is the value-weighted monthly returns on portfolios. Portfolio VMS_t attempts to mimic the risk factor in returns related to dividend smoothing. The smoothing measure used here is 1 minus speed of adjustment. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1990 to December 2018, 348 months. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 2.3 for details in model construction and variable definition.

My hypothesis states that the nature of the value effect and the size effect is whether the firm chose to smooth dividends, I then test the three-factor model to see if it is better than the two-factor model.

Table 2.13: Two-Factor Regressions for Size - E/P Portfolios (China)

	E/P				
$Size$	1	2	3	4	5
			α		
Small	-0.01	0.27	-0.01	0.06	0.22
2	0.75	0.77*	0.65	0.52	-0.03
3	1.66**	1.69***	0.80**	0.59	0.3
4	2.50***	1.39***	0.86**	0.80**	0.62**
Big	2.43***	3.66***	1.69***	1.25***	0.78**
			β_{market}		
Small	1.11***	1.00***	1.01***	0.93***	1.13***
2	1.13***	1.17***	0.92***	1.05***	0.99***
3	1.20***	1.06***	0.84***	0.97***	1.10***
4	1.07***	0.94***	0.98***	1.12***	1.03***
Big	1.13***	1.01***	1.01***	1.01***	1.04***
			β_{smooth}		
Small	0.44	0.16	0.21	0.21	0.24
2	-0.23	0.44	0.03	0.34	0.60
3	-0.15	-0.12	0.22	0.05	0.11
4	0.03	-0.30	-0.36	-0.42	-0.21
Big	-0.54	0.37	-0.55	-0.34	**-0.61***
			R^2		
Small	0.60	0.62	0.63	0.59	0.70
2	0.63	0.66	0.58	0.69	0.59
3	0.51	0.58	0.60	0.67	0.72
4	0.53	0.54	0.70	0.73	0.79
Big	0.55	0.33	0.69	0.67	0.74

Notes: This table presents the regression results of monthly excess return on market risk-free returns and the mimicking factor return for smoothing for portfolios that formed on $Size$ and E/P.

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \beta_{smooth}VMS_t + \epsilon_t$$

where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates, R_t is the value-weighted monthly returns on portfolios. Portfolio VMS_t attempts to mimic the risk factor in returns related to dividend smoothing. The smoothing measure used here is 1 minus speed of adjustment. Sample includes all domestic China A-share on CSMAR from January 2000 to December 2018, 228 months. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 2.3 for details in model construction and variable definition.

Compared with CAPM, the three-factor model in the US greatly improves the R^2 of small and value firms. This improvement in explanation power exceeds the improvement of the two-factor model on CAPM.

As for China, the three-factor model explains the variation in average returns well, especially for small firms. Compared with CAPM, the three-factor β_{market} is closer to 1, which is largely due to the significant correlation between the size (or value) factor return and the market risk premium, as Table 2.3.

At last, I add all four factors to the model to see if the smoothing factor could capture something that is overlooked by the size factor and the value factor. Unfortunately, in the four-factor models, most of the β_{smooth} are not significant, even though they were significant in two-factor models. See Appendix for a summary of R^2 for models in both countries.

Factor-Return Regression for Non-Big Portfolios Sorted on B/M

Since the β_{smooth} are not previously significant in all 25 size-value portfolios in the US but concentrated in non-growth and non-big portfolios, I split the sample by size and value quintiles and then applied four models.

When portfolios are sorted by $Size$, β_{smooth} are significant, except for the largest portfolio. When I remove the largest quintile of the firms from the sample and then reform portfolios by B/M, all β_{smooth} become significant. See tabulated results in Appendix.

Note that β_{value} and β_{size} are insignificant in some portfolios before the largest portfolio is removed. Also, in Table 2.14, slopes of the fourth $Size$ quintile are not significant, where the slopes pass from positive to negative in the largest quintile. All this implies that the data structure is different among large firms. It seems that for non-big firms, the smoothing factor captures some common variation in stock returns.

Table 2.14: Three-Factor Regressions for Size - B/M Portfolios (United States)

	B/M									
$Size$	Low	2	3	4	High	Low	2	3	4	High
			α					β_{market}		
Small	1.86***	1.43***	0.85***	0.36**	-0.43	0.78***	0.68***	0.72***	0.69***	0.90***
2	1.47***	1.12***	0.52***	0.18	-0.60***	0.73***	0.86***	0.83***	0.71***	0.89***
3	1.30***	0.70***	0.59***	0.12	-0.27	0.89***	0.85***	0.83***	0.79***	0.87***
4	1.12***	0.57***	0.37***	0.03	-0.17	0.91***	0.94***	0.93***	0.83***	0.72***
Big	0.90***	0.43***	0.40***	0.16	-0.2	0.84***	0.79***	0.86***	0.71***	0.74***
			β_{size}					β_{value}		
Small	0.31*	0.78***	0.68***	0.64***	0.69***	0.49***	0.47***	0.60***	0.58***	0.79***
2	0.62***	0.61***	0.61***	0.56***	0.53***	0.41***	0.52***	0.51***	0.54***	0.66***
3	0.52***	0.31***	0.30***	0.20***	0.22***	0.16**	0.48***	0.55***	0.48***	0.56***
4	0.06	0.08	0.09	0	-0.02	0.29***	0.40***	0.50***	0.39***	0.38***
Big	-0.29***	-0.19***	-0.12*	-0.14**	-0.15*	-0.09**	0.12**	0.25***	0.37***	0.54***
			R^2							
Small	0.243	0.464	0.579	0.624	0.398					
2	0.532	0.666	0.727	0.695	0.639					
3	0.749	0.712	0.7	0.642	0.571					
4	0.727	0.764	0.708	0.608	0.464					
Big	0.858	0.735	0.657	0.582	0.491					

Notes: This table presents the regression results of monthly excess return on market risk-free returns and the mimicking factor returns for size and value for portfolios that formed on $Size$ and B/M.

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \beta_{size}SMB_t + \beta_{value}HML_t + \epsilon_t$$

where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates, R_t is the value-weighted monthly returns on portfolios. Portfolio SMB_t and HML_t attempt to mimic the risk factors in returns related to size and value. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1990 to December 2018, 348 months. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 2.3 for details in model construction and variable definition.

Table 2.15: Three-Factor Regressions for Size - E/P Portfolios (China)

	E/P									
$Size$	Low	2	3	4	High	Low	2	3	4	High
			α					β_{market}		
Small	-0.44	-0.41	-0.77**	-0.79***	-0.66	0.97***	0.90***	0.93***	0.85***	1.05***
2	0.39	0.19	0.07	-0.22	-1.26***	1.01***	1.09***	0.84***	0.99***	0.97***
3	1.34**	1.53**	0.12	-0.32	-0.51	1.11***	0.95***	0.79***	0.92***	1.06***
4	1.37***	1.16**	0.65**	0.40	0.12	1.04***	0.88***	0.93***	1.10***	1.02***
Big	2.92***	2.62***	1.37***	0.46	0.17	1.09***	1.06***	1.00***	1.05***	1.08***
			β_{size}					β_{value}		
Small	1.06***	1.01***	0.98***	1.03***	0.79***	-0.35***	-0.08	0.00	0.04	0.02
2	0.96***	0.86***	0.90***	0.87***	0.79***	-0.21*	-0.13	-0.07	0.02	0.32
3	0.81***	0.69***	0.72***	0.90***	0.72***	-0.17	-0.33	0.07	0.20*	0.19*
4	0.90***	0.55***	0.49***	0.46***	0.36***	0.33	-0.08	-0.04	0.16	0.23**
Big	-0.03	0.33	0.32***	0.35***	0.21*	-0.25	0.52	0.19	0.50***	0.48***
			R^2							
Small	0.845	0.829	0.812	0.809	0.794					
2	0.811	0.791	0.762	0.836	0.665					
3	0.603	0.707	0.723	0.815	0.802					
4	0.618	0.604	0.755	0.760	0.810					
Big	0.548	0.341	0.700	0.693	0.753					

Notes: This table presents the regression results of monthly excess return on market risk-free returns and the mimicking factor returns for size and value for portfolios that formed on $Size$ and E/P.

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \beta_{size}SMB_t + \beta_{value}HML_t + \epsilon_t$$

where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates, R_t is the value-weighted monthly returns on portfolios. Portfolio SMB_t and HML_t attempt to mimic the risk factors in returns related to size and value. Sample includes all domestic China A-share on CSMAR from January 2000 to December 2018, 228 months. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 2.3 for details in model construction and variable definition.

Table 2.16: Four-Factor Regressions for Size - B/M Portfolios (United States)

	B/M									
$Size$	Low	2	3	4	High	Low	2	3	4	High
			α					β_{market}		
Small	1.38***	1.39***	0.91***	0.37**	-0.75***	0.73***	0.67***	0.73***	0.69***	0.87***
2	1.47***	1.18***	0.54***	0.24	-0.71***	0.73***	0.87***	0.83***	0.72***	0.87***
3	1.41***	0.74***	0.67***	0.20	-0.22	0.90***	0.86***	0.84***	0.80***	0.87***
4	1.16***	0.69***	0.42**	0.15	-0.05	0.91***	0.96***	0.94***	0.84***	0.73***
Big	0.91***	0.51***	0.62***	0.17	-0.12	0.84***	0.79***	0.88***	0.71***	0.75***
			β_{size}					β_{value}		
Small	0.37***	0.78***	0.68***	0.63***	0.73***	0.58***	0.48***	0.59***	0.58***	0.85***
2	0.62***	0.60***	0.61***	0.55***	0.54***	0.41***	0.50***	0.51***	0.53***	0.68***
3	0.51***	0.31***	0.29***	0.19***	0.22***	0.14**	0.47***	0.53***	0.46***	0.55***
4	0.06	0.06	0.09	-0.01	-0.04	0.28***	0.37***	0.49***	0.36***	0.36***
Big	-0.29***	-0.20***	-0.14**	-0.14**	-0.17*	-0.10**	0.10**	0.21***	0.37***	0.52***
			β_{smooth}					R^2		
Small	1.87***	0.18	-0.24	-0.06	1.29	0.264	0.463	0.579	0.623	0.406
2	-0.00	-0.25	-0.06	-0.26	0.44	0.531	0.666	0.727	0.696	0.641
3	-0.43	-0.16	-0.33	-0.35	-0.19	0.751	0.712	0.701	0.643	0.570
4	-0.15	-0.47	-0.20	-0.48	-0.59*	0.726	0.767	0.708	0.610	0.468
Big	-0.04	-0.30	-0.87***	-0.03	-0.44	0.857	0.736	0.670	0.581	0.492

Notes: This table presents the regression results of monthly excess return on market risk-free returns and the mimicking factor returns for size and value for portfolios that formed on $Size$ and B/M.

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \beta_{size}SMB_t + \beta_{value}HML_t + \beta_{smooth}VMS_t + \epsilon_t$$

where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates, R_t is the value-weighted monthly returns on portfolios. Portfolio SMB_t, HML_t and VMS_t attempt to mimic the risk factors in returns related to size, value and smoothing. The smoothing measure used here is 1 minus speed of adjustment. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1990 to December 2018, 348 months. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 2.3 for details in model construction and variable definition.

Table 2.17: Four-Factor Regressions for Size - E/P Portfolios (China)

	E/P									
$Size$	Low	2	3	4	High	Low	2	3	4	High
			α					β_{market}		
Small	-0.43	-0.47*	-0.82**	-0.84***	-0.64	0.97***	0.91***	0.93***	0.85***	1.05***
2	0.21	0.23	-0.01	-0.21	-1.17***	1.02***	1.08***	0.84***	0.99***	0.97***
3	1.14*	1.38**	0.11	-0.40	-0.55*	1.12***	0.96***	0.79***	0.92***	1.06***
4	1.26**	0.96*	0.49	0.23	0.02	1.04***	0.89***	0.94***	1.10***	1.03***
Big	2.77***	2.71***	1.18***	0.33	-0.02	1.09***	1.06***	1.01***	1.05***	1.09***
			β_{size}					β_{value}		
Small	1.06***	1.01***	0.98***	1.04***	0.79***	-0.35***	-0.07	0.00	0.04	0.02
2	0.97***	0.86***	0.90***	0.87***	0.78***	-0.21*	-0.13	-0.06	0.02	0.31
3	0.83***	0.70***	0.72***	0.90***	0.73***	-0.16	-0.33	0.08	0.20*	0.19*
4	0.91***	0.57***	0.50***	0.47***	0.37***	0.34	-0.07	-0.03	0.16	0.24**
Big	-0.02	0.32	0.34***	0.36***	0.23**	-0.24	0.51	0.19	0.50***	0.49***
			β_{smooth}					R^2		
Small	0.04	-0.21	-0.15	-0.16	0.11	0.844	0.829	0.811	0.808	0.793
2	-0.59*	0.13	-0.30	0.03	0.25	0.812	0.790	0.762	0.835	0.664
3	-0.53	-0.47	-0.04	-0.27	-0.15	0.602	0.707	0.721	0.815	0.802
4	-0.36	-0.55	-0.55	-0.58	-0.33	0.616	0.604	0.756	0.762	0.810
Big	-0.55	0.25	-0.66	-0.43	-0.66**	0.548	0.337	0.702	0.693	0.755

Notes: This table presents the regression results of monthly excess return on market risk-free returns and the mimicking factor returns for size and value for portfolios that formed on $Size$ and E/P.

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \beta_{size}SMB_t + \beta_{value}HML_t + \beta_{smooth}VMS_t + \epsilon_t$$

where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates, R_t is the value-weighted monthly returns on portfolios. Portfolio SMB_t, HML_t and VMS_t attempt to mimic the risk factors in returns related to size, value and smoothing. The smoothing measure used here is 1 minus speed of adjustment. Sample includes all domestic China A-share on CSMAR from January 2000 to December 2018, 228 months. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 2.3 for details in model construction and variable definition.

2.5 SUMMARY

Dividend smoothing is an important risk factor in the US stock market. Firms with lower degree of dividend smoothing have higher returns, with an average monthly premium of 0.24%. I use the Fama and French (1993) method to generate a factor return of dividend smoothing, which mimics the difference in return between portfolios with the least and the most level of dividend smoothing. Two-factor models (market risk premium and dividend smooth risk premium) can explain average returns in most cases, except for large firms. The smoothing factor does not fully capture the characteristics of size and value effects. Not only that, but it can also be completely replaced by size and value factors. There are elements other than dividend smoothing that determine the unique qualities of small and value companies

Dividend smoothing has not been priced at all in the Chinese stock market. CAPM performs well with R^2 above 60% in most cases. Even so, the China version three-factor model (Liu et al., 2019) has a higher degree of fit, with average R^2 over 70%. Both countries have experienced a degree of reversal of size and value effects.

This analysis has some limitations. First of all, the method of measuring dividend smoothing may not be precise enough, especially in China, the correlation coefficients between the two measures are not high, i.e., 38.3%. Second, the sample is limited to dividend-paying firms for research purposes, so the market being studied is incomplete. Finally, the theoretical framework supporting the hypothesis of this chapter needs to be defined more carefully, such as whether the state variables used to extract the cash-flow news are reasonable in Campbell and Vuolteenaho (2004).

Future research can focus on cash-flow proxies that are not dividends, for example, income, free cash flows, book values. The advantage of this is to use the full sample when researching cash-flow smoothing, without the need to shrink the sample because of the non-payers of dividends. Finally, it is important to study the predictability of cash flows and returns from an economic point of view, not just through the variance decomposition.

APPENDIX A

SUPPLEMENTARY INFORMATION FOR CHAPTER 2

A.1 WHAT MOVES STOCK PRICES?

The algebra of this section summarises the content from book *Asset Pricing* (Cochrane, 2005, p. 396 - 401).

When stock prices are high relative to dividends (or other divisors), investors expect future dividends to grow or future returns to fall. This is an accounting identity rather than a theory. The question is which one is the main source of price volatility.

In order to relate current price to future dividends and returns, I start from the first-period present-value identity,

$$\frac{P_t}{D_t} = R_{t+1}^{-1}\left(1 + \frac{P_{t+1}}{D_{t+1}}\right)\frac{D_{t+1}}{D_t}, \tag{A.1.1}$$

where P_t is stock price at time t, D_t is dividends distributed at time t. Through forward iteration and conditional expectation, the following identity is obtained,

$$\frac{P_t}{D_t} = E_t \sum_{j=1}^{\infty}\left(\prod_{k=1}^{j} R_{t+k}^{-1}\Delta D_{t+k}\right). \tag{A.1.2}$$

Equation (A.1.2) indicates that high prices are either from high future dividend growth or low future returns. However, the nonlinearity of Equation (A.1.2) makes it difficult to use time-series models, e.g., VAR, for analysis. Campbell and Shiller (1988) solve this problem by taking logarithms. Using **lowercase** letters to indicate the logarithm, I transfer Equation (A.1.1) into,

$$p_t - d_t = -r_{t+1} + \Delta d_{t+1} + \ln\left(1 + e^{p_{t+1}-d_{t+1}}\right). \tag{A.1.3}$$

Do a first-order Taylor expansion to $\ln(1 + e^{p_{t+1}-d_{t+1}})$ around $\frac{P}{D} = e^{p_t - d_t}$, I get,

$$\begin{aligned} p_t - d_t &= -r_{t+1} + \Delta d_{t+1} + \ln\left(1 + \frac{P}{D}\right) + \frac{\frac{P}{D}}{1+\frac{P}{D}}\left[p_{t+1} - d_{t+1} - (p-d))\right] \\ &= -r_{t+1} + \Delta d_{t+1} + k + \rho\left(p_{t+1} - d_{t+1}\right), \end{aligned}$$

where $k = \ln(1+\frac{P}{D}) - \rho(p-d)$ and $\rho = \frac{\frac{P}{D}}{1+\frac{P}{D}}$. The approximate identity is obtained by iterating forward and dropping the constant,

$$p_t - d_t \approx \sum_{j=1}^{\infty}\rho^{j-1}(\Delta d_{t+j} - r_{t+j}). \tag{A.1.4}$$

Equation (A.1.2) and Equation (A.1.4) describe the same thing where a high price-dividend ratio is accompanied by high dividend growth or low returns. So how much influence do these two factors have on price movements?

To answer the question, I have to decompose the variance of price-dividend ratio, and see what causes it to fluctuate, i.e., expected returns or expected dividend growth,

$$var\left(p_t - d_t\right) = cov\left(p_t - d_t, \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j}\right) - cov\left(p_t - d_t, \sum_{j=1}^{\infty} \rho^{j-1} r_{t+j}\right). \quad \text{(A.1.5)}$$

If expected returns random walk, i.e., constant expectation, then expected dividend growth must vary, otherwise the price-dividend ratio would have to be a constant. The fact that the price-dividend ratio fluctuates means that the price must move with at least one of the two sources. Regress both side of Equation (A.1.4) on $p_t - d_t$, I have,

$$1 \approx b_d^{lr} - b_r^{lr}, \quad \text{(A.1.6)}$$

where b^{lr} denotes the long-run coefficients of following regressions,

$$\sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j} = b_d^{lr} (p_t - d_t) + \epsilon^d,$$

$$\sum_{j=1}^{\infty} \rho^{j-1} r_{t+j} = b_r^{lr} (p_t - d_t) + \epsilon^r.$$

Equation (A.1.6) is the same as variance decomposition of price-dividend ratio in Equation (A.1.5), since both terms on the right-hand side of (A.1.5) are the numerators of b^{lr}. The coefficients of b_r^{lr} and b_d^{lr} represent respectively the portion of the current price-dividend ratio variance due to future returns and future dividend growth at the infinite horizon.

For simplicity, Cochrane (2008) calculates the long-run coefficients as the implication of a first-order VAR, rather than directly. The notation was changed to **dividend yields** in his work.

$$\begin{aligned} r_{t+1} &= a_r + b_r(d_t - p_t) + \epsilon^r_{t+1}, \\ \Delta d_{t+1} &= a_d + b_d(d_t - p_t) + \epsilon^d_{t+1}, \\ d_{t+1} - p_{t+1} &= a_{dp} + \phi(d_t - p_t) + \epsilon^{dp}_{t+1}. \end{aligned} \tag{A.1.7}$$

Above coefficients of first-order VAR must obey the identity (A.1.3). Therefore, at every horizon K I have predictive coefficients implied from a first-order VAR, i.e., Equation (A.1.7),

$$\begin{aligned} 1 &= b_r^K - b_d^K + \rho^K \phi^K, \\ b_r^K &= \frac{b_r\left(1 - \rho^K \phi^K\right)}{1 - \rho\phi}, \\ b_d^K &= \frac{b_d\left(1 - \rho^K \phi^K\right)}{1 - \rho\phi}, \\ b_{dp}^K &= \rho^K \phi^K. \end{aligned} \tag{A.1.8}$$

To sum up, one can learn the source of price volatility by decomposing dividend-price ratio. The long-run predictive of coefficients provides the importance of one source relative to the other, i.e., expected return and expected dividend growth. For simplicity, one can use a first-order VAR to imply the long-run coefficients. I use this approach to determine what is driving US stock prices in my preliminary analysis.

A.2 WHAT MOVES STOCK RETURNS?

I learn the source of price variations by decomposing price-dividend ratio from Section A.1. What does this have to do with current returns? To answer it, Campbell (1991) starts with the approximation identity (A.1.4), and move it back one period,

$$p_{t-1} - d_{t-1} \approx \sum_{j=0}^{\infty} \rho^{j-1} (\Delta d_{t+j} - r_{t+j}).$$

Now, apply $E_t - E_{t-1}$ to both sides,

$$0 = (E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho^j \left(\Delta d_{t+j} - r_{t+j} \right).$$

Then, put r_t to the left-hand sides, I get the expression for unexpected returns,

$$r_t - E_{t-1} r_t = \underbrace{\Delta E_t \sum_{j=0}^{\infty} \rho^j \Delta d_{t+j}}_{N_{cf}} - \underbrace{\Delta E_t \sum_{j=1}^{\infty} \rho^j r_{t+j}}_{N_r}. \tag{A.2.1}$$

An unexpected positive return occurs either because of an increase in the current dividend, or positive news about future dividends, or negative news about future returns. Campbell (1991) finds some shares of return volatility is due to *current* dividends, because the increase in *current* dividends become return immediately, i.e., j starts from 0 for the first sum term. Therefore, if the stock price changes as a result of changes in the expected future dividend growth, then unexpected returns will change with the news of future dividends. Hence, Equation (A.2.1) can be expressed as,

$$\widehat{r_t} = r_t - E_{t-1} r_t = N_{cf,t} - N_{dr,t}, \tag{A.2.2}$$

where $N_{cf,t}$ is cash-flow (dividend) news at time t, $N_{dr,t}$ is discount-rate news at time t, and a hat indicates innovation.

First, estimating $E_{t-1}r_t$ and $(E_t - E_{t-1})\sum_{j=1}^{\infty}\rho^j r_{t+j}$, and then use the realised r_t and Equation (A.2.1) to back out the cash-flow news.[1] Campbell (1991) assumes that the data are generated by a first-order VAR,

$$z_t = \alpha + \Gamma z_{t-1} + \upsilon_t, \tag{A.2.3}$$

where z_t is the set of state vectors with r_t as its first element, α is the matrix of constants, and υ_t is the vector of shocks. Given cash-flow news and discount-rate news are linearly related to shocks, I have,

$$\begin{aligned} N_{cf,t} &= e1'\lambda\upsilon_t, \\ N_{dr,t} &= (e1' + e1'\lambda)\upsilon_t. \end{aligned} \tag{A.2.4}$$

where $e1'$ is a vector with first element (i.e., return) equals 1 and the rest elements are 0. λ was introduced by Campbell (1991) and defined as $\rho\Gamma(I - \rho\Gamma)^{-1}$, and it captures the variable persistence and arrange the VAR shocks to news.

To sum up, unexpected returns consist of cash-flow (dividend) news and discount-rate news. One can learn which is the dominant news by decomposing unexpected returns. Dividend-price decomposition is similar to the unexpected return decomposition. That is, if prices move with expected returns, then unexpected returns would be connected to the news about future returns.

[1]Most literature chooses to use indirect methods to estimate cash-flow news in order to avoid uncertain dividend policies. The choice of state variables (information set) matters to the inference.

A.3 WHICH NEWS IS RISKIER?

I understand that there are two components to unexpected returns, the cash-flow news and the discount-rate news from Section A.2. The question for this section is which news is riskier.

Beta measures risk, and it is the scaled covariances of returns with sources of risks. Therefore, it implies that beta depends on the covariance of cash-flow news and discount-rate news with sources of risks. Campbell and Mei (1993) is the first to use beta decomposition to relate a multi-factor model to fundamental analysis using the present-value identity.

Campbell and Vuolteenaho (2004) divide the beta of a stock with market index into market cash-flow beta and market discount-rate beta, which respectively reflect news about future market cash flows and future market discount rates.

The value of the market portfolio may drop because of bad future market cash-flow news or higher market discount rate news. They believe that the news of cash flows is permanent, while the news of future returns may be reversed, as investment opportunities may improve as the high discount rate falls to the mean. Therefore, Campbell and Vuolteenaho (2004) consider market cash-flow news is riskier than market discount-rate news. Accordingly, they also find that higher cash-flow betas in small firms and value firms.

$$\begin{aligned}\beta_{i,cfm} &= \frac{\mathrm{Cov}\left(\widehat{R_i}, N_{cfm}\right)}{\mathrm{Var}\left(\widehat{R_m}\right)},\\ \beta_{i,drm} &= \frac{\mathrm{Cov}\left(\widehat{R_i}, N_{drm}\right)}{\mathrm{Var}\left(\widehat{R_m}\right)},\end{aligned} \tag{A.3.1}$$

where $\beta_{i,drm}$ is market beta of news about market's future cash flows using dividends as proxy, $\beta_{i,cfm}$ is market beta of news about market's future return, and hat denotes innovation. Hence, the market beta is $\beta_{i,drm} + \beta_{i,cfm}$.

Now what about $\widehat{R_i}$? How do firm-level cash-flow news (e.g., dividend news) and discount-rate news affect the prices of individual stocks?

Vuolteenaho (2002) applies a similar analysis to individual data using different valuation ratio and cash-flow proxy. Unlike the case of market index, market return moves with news about discount rates. He finds that at the firm-level, at least half of the changes in book-to-market ratio (price) is due to cash-flow news. As a result, he believes that cash-flow news is idiosyncratic and can be largely dispersed into market portfolio.

Research about beta decomposition by Campbell and Mei (1993) is asset-specific and they decomposed market beta into $\beta_{di,m}$ and $\beta_{ri,m}$,

$$\begin{aligned} \beta_{icf,m} &= \frac{\mathrm{Cov}\left(N_{cfi}, \widehat{R_m}\right)}{\mathrm{Var}\left(\widehat{R_m}\right)}, \\ \beta_{idr,m} &= \frac{\mathrm{Cov}\left(N_{dri}, \widehat{R_m}\right)}{\mathrm{Var}\left(\widehat{R_m}\right)}, \end{aligned} \tag{A.3.2}$$

where $\beta_{di,m}$ is market beta of news about asset's future cash flows using dividends as proxy, $\beta_{ir,m}$ is market beta of new about asset's future return, and hat denotes innovation. Hence, the market beta is $\beta_{di,m} + \beta_{ri,m}$.

Based on market-level beta decomposition(Campbell & Vuolteenaho, 2004) and asset-level beta decomposition (Campbell & Mei, 1993). Campbell et al.

(2010) further decomposed market beta into 4 components,

$$\begin{aligned}
\beta_{icf,mcf} &= \frac{\mathrm{Cov}\left(N_{cfi}, N_{cfm}\right)}{\mathrm{Var}\left(\widehat{R_m}\right)}, \\
\beta_{idr,mcf} &= \frac{\mathrm{Cov}\left(N_{dri}, N_{cfm}\right)}{\mathrm{Var}\left(\widehat{R_m}\right)}, \\
\beta_{icf,mdr} &= \frac{\mathrm{Cov}\left(N_{cfi}, N_{drm}\right)}{\mathrm{Var}\left(\widehat{R_m}\right)}, \\
\beta_{idr,mdr} &= \frac{\mathrm{Cov}\left(N_{dri}, N_{drm}\right)}{\mathrm{Var}\left(\widehat{R_m}\right)},
\end{aligned} \tag{A.3.3}$$

where $\beta_{icf,mcf}$ is market beta of news about asset's future cash flows and market's future cash flows, $\beta_{idr,mdr}$ is market beta of news about asset's future discount rates and market's future discount rates. I assume that firm-level cash flows are correlated with market-level cash flows, and firm-level returns is correlated with market-level returns as Pettit and Westerfield (1972) and Cochrane (2005). That means $\beta_{icf,mdr} = \beta_{idr,mcf} = 0$

$\beta_{icf,mcf}$ can be seen as the firm-level cash-flow news is sensitive to permanent movements, driven by shocks to aggregate cash flows, while $\beta_{idr,mdr}$ as the firm-level discount-rate news is sensitive to temporary movements, driven by shocks to market discount rate. If a firm's unexpected return is mostly made up of cash-flow news, then its unexpected return is mostly likely comove with expected future market cash flows, resulting in greater systematic risks for the firm, i.e., high $\beta_{icf,mcf}$.

A.4 Additional Tables

This section provides additional tables of regressions that use the alternative smoothing measure.

Table A.4.1: Alt. Two-Factor Regressions for Size - B/M Portfolios (United States)

	B/M				
$Size$	1	2	3	4	5
			α		
Small	1.56***	1.88***	1.49***	0.86***	-0.05
2	1.72***	1.48***	0.91***	0.62***	-0.21
3	1.60***	1.04***	0.96***	0.49**	0.22
4	1.27***	0.93***	0.69***	0.40*	0.09
Big	0.76***	0.54***	0.70***	0.36*	0.09
			β_{market}		
Small	0.74***	0.78***	0.80***	0.75***	0.94***
2	0.79***	0.92***	0.89***	0.77***	0.91***
3	0.98***	0.86***	0.83***	0.78***	0.86***
4	0.89***	0.93***	0.91***	0.80***	0.68***
Big	0.80***	0.75***	0.83***	0.65***	0.66***
			β_{smooth}		
Small	1.38	**-0.98****	**-1.43*****	**-1.08*****	-0.54
2	-0.45	**-0.69***	**-0.78*****	**-0.90*****	**-0.67***
3	**-0.76*****	**-0.66****	**-0.71*****	**-0.76*****	**-1.08*****
4	-0.23	**-0.82*****	**-0.60****	**-0.83*****	**-0.54***
Big	**0.33****	-0.25	**-0.73****	-0.35	-0.51
			R^2		
Small	0.214	0.299	0.401	0.420	0.268
2	0.390	0.516	0.554	0.502	0.482
3	0.659	0.614	0.577	0.553	0.490
4	0.695	0.716	0.628	0.558	0.404
Big	0.808	0.696	0.628	0.482	0.351

Notes: This table presents the regression results of monthly excess return on market risk-free returns and the mimicking factor return for smoothing for portfolios that formed on $Size$ and B/M.

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \beta_{smooth}VMS_t + \epsilon_t$$

where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates, R_t is the value-weighted monthly returns on portfolios. Portfolio VMS_t attempts to mimic the risk factor in returns related to dividend smoothing. The smoothing measure used here is 1 minus relative volatility. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1990 to December 2018, 348 months. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 2.3 for details in model construction and variable definition.

Table A.4.2: Alt. Two-Factor Regressions for Size - E/P Portfolios (China)

	E/P				
$Size$	1	2	3	4	5
			α		
Small	-0.19	0.24	-0.12	0.08	0.38
2	0.72	0.57	0.61	0.44	-0.19
3	1.49**	1.74***	0.75**	0.54	0.24
4	2.53***	1.47***	0.84***	1.00**	0.64**
Big	2.35***	3.30***	1.71***	1.41***	1.05***
			β_{market}		
Small	1.12***	1.00***	1.02***	0.92***	1.12***
2	1.13***	1.19***	0.93***	1.06***	0.99***
3	1.21***	1.06***	0.84***	0.97***	1.10***
4	1.07***	0.94***	0.99***	1.11***	1.03***
Big	1.14***	1.04***	1.01***	1.00***	1.02***
			β_{smooth}		
Small	0.28	-0.05	0.24	-0.29	-0.54
2	0.36	0.33	0.12	-0.02	-0.07
3	0.72	-0.07	-0.05	0.17	0.12
4	-0.14	0.06	**0.49***	-0.23	0.16
Big	0.86	**0.88***	0.36	-0.26	-0.48
			R^2		
Small	0.604	0.617	0.629	0.589	0.699
2	0.631	0.663	0.577	0.690	0.583
3	0.512	0.584	0.599	0.669	0.723
4	0.530	0.535	0.700	0.732	0.791
Big	0.551	0.337	0.688	0.671	0.736

Notes: This table presents the regression results of monthly excess return on market risk-free returns and the mimicking factor return for smoothing for portfolios that formed on $Size$ and B/M.

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \beta_{smooth}VMS_t + \epsilon_t$$

where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates, R_t is the value-weighted monthly returns on portfolios. Portfolio VMS_t attempts to mimic the risk factor in returns related to dividend smoothing. The smoothing measure used here is 1 minus relative volatility. Sample includes all domestic China A-share on CSMAR from January 2000 to December 2018, 228 months. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 2.3 for details in model construction and variable definition.

Table A.4.3: Alt. Four-Factor Regressions for Size - B/M Portfolios (United States)

	B/M									
$Size$	Low	2	3	4	High	Low	2	3	4	High
			α					β_{market}		
Small	1.20***	1.49***	1.07***	0.47***	-0.55**	0.73***	0.68***	0.74***	0.70***	0.89***
2	1.39***	1.11***	0.55***	0.26*	-0.62***	0.72***	0.86***	0.83***	0.72***	0.88***
3	1.40***	0.77***	0.67***	0.25	-0.04	0.90***	0.86***	0.83***	0.80***	0.89***
4	1.14***	0.77***	0.48***	0.26	-0.04	0.91***	0.96***	0.94***	0.85***	0.73***
Big	0.88***	0.55***	0.65***	0.26	-0.07	0.84***	0.80***	0.88***	0.72***	0.75***
			β_{size}					β_{value}		
Small	0.38**	0.77***	0.66***	0.62***	0.70***	0.55***	0.46***	0.58***	0.57***	0.80***
2	0.63***	0.61***	0.61***	0.55***	0.53***	0.41***	0.52***	0.51***	0.53***	0.66***
3	0.51***	0.30***	0.29***	0.18***	0.20**	0.15**	0.47***	0.54***	0.47***	0.54***
4	0.06	0.06	0.08	-0.02	-0.04	0.29***	0.38***	0.49***	0.37***	0.37***
Big	-0.28***	-0.20***	-0.14**	-0.15**	-0.17*	-0.09**	0.11**	0.22***	0.36***	0.53***
			β_{smooth}					R^2		
Small	1.94**	-0.17	-0.66**	-0.33	0.37	0.267	0.463	0.584	0.625	0.397
2	0.23	0.02	-0.07	-0.24	0.04	0.532	0.665	0.727	0.695	0.638
3	-0.30	-0.20	-0.23	-0.40*	-0.68**	0.750	0.712	0.700	0.644	0.576
4	-0.05	-0.61***	-0.31	-0.68***	-0.42	0.726	0.769	0.709	0.615	0.465
Big	0.06	-0.36*	-0.74***	-0.29	-0.45	0.857	0.737	0.667	0.583	0.492

Notes: This table presents the regression results of monthly excess return on market risk-free returns and the mimicking factor returns for size and value for portfolios that formed on $Size$ and B/M.

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \beta_{size}SMB_t + \beta_{value}HML_t + \beta_{smooth}VMS_t + \epsilon_t$$

where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates, R_t is the value-weighted monthly returns on portfolios. Portfolio SMB_t, HML_t and VMS_t attempt to mimic the risk factors in returns related to size, value and smoothing. The smoothing measure used here is 1 minus relative volatility. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1990 to December 2018, 348 months. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 2.3 for details in model construction and variable definition.

Table A.4.4: Alt. Four-Factor Regressions for Size - E/P Portfolios (China)

	E/P									
$Size$	Low	2	3	4	High	Low	2	3	4	High
			α					β_{market}		
Small	-0.47	-0.36	-0.81**	-0.69**	-0.47	0.97***	0.90***	0.93***	0.83***	1.04***
2	0.33	0.14	0.07	-0.19	-1.23***	1.01***	1.09***	0.84***	0.98***	0.97***
3	1.13*	1.58*	0.15	-0.35	-0.53	1.12***	0.95***	0.79***	0.92***	1.06***
4	1.42***	1.16**	0.54*	0.52	0.08	1.03***	0.88***	0.94***	1.09***	1.03***
Big	2.69***	2.33***	1.25***	0.51	0.28	1.11***	1.09***	1.01***	1.04***	1.07***
			β_{size}					β_{value}		
Small	1.06***	1.01***	0.98***	1.03***	0.79***	-0.35***	-0.08	0.00	0.03	0.02
2	0.96***	0.86***	0.90***	0.87***	0.79***	-0.21*	-0.13	-0.07	0.02	0.32
3	0.82***	0.69***	0.72***	0.90***	0.72***	-0.16	-0.34	0.07	0.20*	0.19*
4	0.90***	0.55***	0.49***	0.46***	0.36***	0.33	-0.08	-0.03	0.15	0.24**
Big	-0.03	0.33	0.32***	0.35***	0.21*	-0.23	0.54	0.19	0.49***	0.47***
			β_{smooth}					R^2		
Small	0.10	-0.18	0.13	-0.40	-0.50	0.844	0.829	0.811	0.810	0.796
2	0.22	0.21	0.00	-0.11	-0.08	0.811	0.790	0.761	0.835	0.664
3	0.60	-0.18	-0.12	0.10	0.07	0.603	0.706	0.722	0.814	0.801
4	-0.17	-0.01	0.43*	-0.32	0.16	0.616	0.602	0.756	0.760	0.810
Big	0.82	0.95	0.33	-0.22	-0.42	0.552	0.343	0.700	0.692	0.754

Notes: This table presents the regression results of monthly excess return on market risk-free returns and the mimicking factor returns for size and value for portfolios that formed on $Size$ and E/P.

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \beta_{size}SMB_t + \beta_{value}HML_t + \beta_{smooth}VMS_t + \epsilon_t$$

where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates, R_t is the value-weighted monthly returns on portfolios. Portfolio SMB_t, HML_t and VMS_t attempt to mimic the risk factors in returns related to size, value and smoothing. The smoothing measure used here is 1 minus relative volatility. Sample includes all domestic China A-share on CSMAR from January 2000 to December 2018, 228 months. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 2.3 for details in model construction and variable definition.

Table A.4.5: Summary of R^2 for Factor Models (United States)

	B/M									
	CAPM					**Two-Factor**				
$Size$	Low	2	3	4	High	Low	2	3	4	High
Small	0.202	0.290	0.375	0.403	0.268	0.208	0.293	0.390	0.415	0.266
2	0.389	0.511	0.547	0.488	0.478	0.394	0.523	0.556	0.507	0.480
3	0.652	0.607	0.569	0.543	0.475	0.661	0.616	0.584	0.557	0.482
4	0.695	0.705	0.623	0.546	0.400	0.698	0.717	0.629	0.557	0.411
Big	0.806	0.696	0.618	0.481	0.349	0.807	0.697	0.635	0.482	0.357
	B/M									
	Three-Factor					**Four-Factor**				
$Size$	Low	2	3	4	High	Low	2	3	4	High
Small	0.243	0.464	0.579	0.624	0.398	0.264	0.463	0.579	0.623	0.406
2	0.532	0.666	0.727	0.695	0.639	0.531	0.666	0.727	0.696	0.641
3	0.749	0.712	0.700	0.642	0.571	0.751	0.712	0.701	0.643	0.570
4	0.727	0.764	0.708	0.608	0.464	0.726	0.767	0.708	0.610	0.468
Big	0.858	0.735	0.657	0.582	0.491	0.857	0.736	0.670	0.581	0.492

Notes: This table summarise R^2 in four factor models for the US sample.

Table A.4.6: Summary of R^2 for Factor Models (China)

	B/M									
	CAPM					**Two-Factor**				
$Size$	Low	2	3	4	High	Low	2	3	4	High
Small	0.605	0.619	0.630	0.590	0.698	0.604	0.617	0.629	0.589	0.697
2	0.631	0.664	0.579	0.691	0.585	0.630	0.663	0.577	0.691	0.585
3	0.511	0.586	0.601	0.670	0.724	0.509	0.584	0.599	0.668	0.723
4	0.532	0.537	0.698	0.733	0.792	0.530	0.536	0.698	0.733	0.791
Big	0.548	0.335	0.688	0.672	0.734	0.547	0.332	0.689	0.671	0.736
	B/M									
	Three-Factor					**Four-Factor**				
$Size$	Low	2	3	4	High	Low	2	3	4	High
Small	0.845	0.829	0.812	0.809	0.794	0.844	0.829	0.811	0.808	0.793
2	0.811	0.791	0.762	0.836	0.665	0.812	0.790	0.762	0.835	0.664
3	0.603	0.707	0.723	0.815	0.802	0.602	0.707	0.721	0.815	0.802
4	0.618	0.604	0.755	0.760	0.810	0.616	0.604	0.756	0.762	0.810
Big	0.548	0.341	0.700	0.693	0.753	0.548	0.337	0.702	0.693	0.755

Notes: This table summarise R^2 in four factor models for the Chinese sample.

Table A.4.7: Factor Regressions for Size Portfolios

	Small				2			
α	0.59***	0.78***	0.42***	0.38***	0.60***	0.80***	0.46***	0.45***
β_{market}	0.82***	0.84***	0.78***	0.77***	0.85***	0.87***	0.81***	0.81***
β_{smooth}		**-0.81*** **		0.14		**-0.84*** **		0.01
β_{size}			0.67***	0.67***			0.60***	0.60***
β_{value}			0.63***	0.64***			0.56***	0.56***
R^2	0.530	0.539	0.792	0.792	0.616	0.627	0.840	0.840
	3				4			
α	0.62***	0.81***	0.50***	0.55***	0.60***	0.75***	0.50***	0.56***
β_{market}	0.84***	0.87***	0.85***	0.86***	0.86***	0.88***	0.90***	0.91***
β_{smooth}		**-0.82*** **		-0.23		**-0.63* **		-0.23
β_{size}			0.30***	0.29***			0.06	0.05
β_{value}			0.47***	0.46***			0.41***	0.40***
R^2	0.690	0.702	0.804	0.804	0.725	0.731	0.798	0.798
	Big							
α	0.63***	0.64***	0.63***	0.67***				
β_{market}	0.79***	0.79***	0.83***	0.84***				
β_{smooth}		-0.02		-0.14				
β_{size}			-0.24***	-0.24***				
β_{value}			0.03	0.02				
R^2	0.861	0.860	0.905	0.905				

Notes: This table presents the regression results of monthly excess return on market risk-free returns and the mimicking factor returns for size, value and smoothing for portfolios that formed on size.

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \beta_{size}SMB_t + \beta_{value}HML_t + \beta_{smooth}VMS_t + \epsilon_t$$

where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates, R_t is the value-weighted monthly returns on portfolios. Portfolio SMB_t, HML_t and VMS_t attempt to mimic the risk factors in returns related to size, value and smoothing. The smoothing measure used here is 1 minus speed of sdjustment. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1990 to December 2018, 348 months. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 2.3 for details in model construction and variable definition.

Table A.4.8: Factor Regressions for B/M Portfolios

	Low				2			
α	0.90***	0.85***	0.92***	0.93***	0.49***	0.57***	0.46***	0.53***
β_{market}	0.81***	0.81***	0.85***	0.85***	0.76***	0.77***	0.80***	0.81***
β_{smooth}		0.18		-0.03		-0.34		-0.3
β_{size}			-0.26***	-0.26***			-0.15***	-0.16***
β_{value}			-0.08*	-0.08**			0.15***	0.14***
R^2	0.824	0.824	0.866	0.866	0.733	0.735	0.768	0.77
	3				4			
α	0.49***	0.71***	0.42***	0.60***	0.24*	0.35**	0.15	0.19
β_{market}	0.81***	0.83***	0.85***	0.88***	0.67***	0.69***	0.73***	0.74***
β_{smooth}		**-0.93*** **		-0.73***		-0.48		-0.18
β_{size}			-0.06	-0.09				
β_{value}			0.30***	0.27***			0.38***	0.38***
R^2	0.672	0.689	0.723	0.732	0.559	0.564	0.654	0.654
	High							
α	-0.07	0.09	-0.19	-0.13				
β_{market}	0.68***	0.70***	0.75***	0.76***				
β_{smooth}	**-0.65***		-0.22					
β_{size}			-0.03	-0.04				
β_{value}			0.51***	0.50***				
R^2	0.451	0.458	0.571	0.571				

Notes: This table presents the regression results of monthly excess return on market risk-free returns and the mimicking factor returns for size, value and smoothing for portfolios that formed on B/M.

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \beta_{size}SMB_t + \beta_{value}HML_t + \beta_{smooth}VMS_t + \epsilon_t$$

where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates, R_t is the value-weighted monthly returns on portfolios. Portfolio SMB_t, HML_t and VMS_t attempt to mimic the risk factors in returns related to size, value and smoothing. The smoothing measure used here is 1 minus speed of sdjustment. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1990 to December 2018, 348 months. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 2.3 for details in model construction and variable definition.

Table A.4.9: Factor Regressions for B/M Portfolios (Exclude the Largest)

	Low				2			
α	1.26***	1.39***	1.19***	1.24***	0.75***	0.96***	0.64***	0.74***
β_{market}	0.89***	0.91***	0.90***	0.90***	0.90***	0.92***	0.92***	0.93***
β_{smooth}		**-0.56****		-0.22		**-0.87*****		-0.41
β_{size}			0.17***	0.17***			0.17**	0.16*
β_{value}			0.28***	0.27***			0.43***	0.41***
R^2	0.743	0.748	0.78	0.78	0.717	0.73	0.792	0.794
	3				4			
α	0.58***	0.77***	0.45***	0.51***	0.19	0.39**	0.08	0.18
β_{market}	0.87***	0.89***	0.90***	0.90***	0.78***	0.80***	0.81***	0.82***
β_{smooth}		**-0.81****		-0.24		**-0.86*****		-0.4
β_{size}			0.20***	0.20***			0.14**	0.13**
β_{value}			0.52***	0.50***			0.44***	0.42***
R^2	0.663	0.674	0.771	0.771	0.62	0.634	0.708	0.71
	High							
α	-0.15	0	-0.27*	-0.24				
β_{market}	0.76***	0.77***	0.79***	0.79***				
β_{smooth}		**-0.63****		-0.12				
β_{size}			0.14**	0.14**				
β_{value}			0.48***	0.47***				
R^2	0.541	0.547	0.637	0.636				

Notes: This table presents the regression results of monthly excess return on market risk-free returns and the mimicking factor returns for size, value and smoothing for portfolios that formed on B/M. Stocks that belongs to the largest quintile are removed from the portfolio.

$$R_t - R_{f,t} = \alpha + \beta_{market}(R_{m,t} - R_{f,t}) + \beta_{size} SMB_t + \beta_{value} HML_t + \beta_{smooth} VMS_t + \epsilon_t$$

where R_m is the value-weighted monthly market returns, R_f is the one-month bill rates, R_t is the value-weighted monthly returns on portfolios. Portfolio SMB_t, HML_t and VMS_t attempt to mimic the risk factors in returns related to size, value and smoothing. The smoothing measure used here is 1 minus speed of sdjustment. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1990 to December 2018, 348 months. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 2.3 for details in model construction and variable definition.

CHAPTER 3

Do firms use smooth dividends to signal?

Synopsis

1. Managers can use a predominantly smooth dividend stream to signal investors that the business is in good shape within a given earnings range. Changes in dividends convey information about changes in the earnings range.

2. Dividend smoothing does not convey information in a truthful and meaningful way if the manager caters to the preferences of institutional investors.

3. Two types of institutional investors may influence dividend smoothing with different motivations. Independent institutional investors force firms to smooth dividends in exchange for their monitoring capabilities. In con-

trast, institutional investors with close investment business relationships with firms will tolerate rent-seeking oriented dividend smoothing to avoid unnecessary quarrels with management.

4. Equity ownership is dispersed in countries with strong legal protections, such as the US. Dividend smoothing may be used as a signalling tool to reduce information asymmetry between investors and managers. Equity ownership is concentrated in countries with weak legal protections, such as China. Dividend smoothing has little impact on reducing information asymmetry between minority and controlling shareholders. Rent-seeking oriented dividend smoothing is expected to be more prevalent in China than in the US.

3.1 INTRODUCTION

The intention of firms to smooth dividends has been a mystery since the study by Lintner (1956), and while there is extensive literature providing theoretical explanations, relevant empirical studies are scarce. The literature related to the Chinese market is even scarcer. Classic research, e.g., Lintner (1956), Miller and Rock (1985), John and Williams (1985) and Bhattacharya (1979), finds that dividends change gradually with changes in earnings, and thus they can serve as a signal about a firm's current or future profitability. Could *dividend smoothing* convey a firm's information as well?

Kumar (1988), Kumar and Lee (2001) and Guttman et al. (2010) demonstrate that the firm's management team may retain information instead of releasing all information. Firms in the same earnings range pool with each other but differentiate from firms not in this range. Firms in the same range share similar characteristics such as cash flow volatility, risk factors and investment opportunities. Managers in the range pay the same dividends, and investors anticipate this behaviour and price firms accordingly. Dividend smoothing is expected to be the same within the range pool that partially reveals the firm's information. In this situation, information asymmetry between shareholders and management is reduced. A smooth flow of dividends signals investors that all is well within a specific range. Moreover, according to survey evidence (Brav et al., 2005), the dividend policy is very conservative, and smoothing comes at a cost, so management will not initiate or increase dividends without ensuring sustainable profitability.

On the other hand, managers smooth out the distribution of dividends for their own consideration, such as managers who fear dismissal for poor performance (Fudenberg & Tirole, 1995; DeMarzo & Sannikov, 2016; Wu, 2018) or seek private benefits (Lambrecht & Myers, 2012; Baker et al., 2016). Smooth dividends, in this case, cannot reflect the underlying business, which promotes information asymmetry.

Recent empirical studies have found mixed evidence to explain the signalling theory (e.g., Leary & Michaely, 2011; Lambrecht & Myers, 2012; Javakhadze et al., 2014). That is, dividend smoothing is not more prominent in firms that suffer from information asymmetry. Authors find that institutional holdings are positively correlated with dividend smoothing, which is not comforting as high institutional holdings indicate low information asymmetry.

The use of institutional ownership as a proxy for information asymmetry implicitly assumes that institutional investors are active contributors to corporate governance as monitors. However, institutional investors are heterogeneous, and some may not be interested in governing the firm or even colluding with management.

Evidence suggests that institutional monitors independent of management, resilient to stress, and focused on long-term profits can strengthen corporate governance. In contrast, institutional colluders with close business relationships with firms, sensitive to stress and focused on short-term profits, can undermine corporate governance. See, for example, Pound (1988); Shleifer and Vishny (1997); Allen et al. (2000); Woidtke (2002); Grinstein and Michaely (2005); Cornett et al. (2007); Elyasiani and Jia (2010); Ruiz-Mallorquí and Santana-Martin (2011); Boone and White (2015).

Following the past literature, I classify institutions according to the nature of the investment business and its relationship with the invested firms (Brickley et al., 1988; Almazan et al., 2005; Cornett et al., 2007). US monitors are mutual funds and investment advisors, and Chinese monitors are mutual funds, Qualified Foreign Institutional Investors (QFIIs) and social security funds. Colluders include bank trusts and insurance companies in both countries.

The dynamics between dividend smoothing and institutional ownership depends on the **institutional type** and the **legal environment**. If dividend smoothing is considered a signalling tool to reduce information asymmetry between investors and managers, it implies the existence of a principal-agent problem.

The principal-agent problem is more pronounced where ownership is dispersed and is mitigated as ownership concentration increases. Michaely and Roberts (2012) point out that with high levels of concentration of ownership, dividends are highly sensitive to changes in investments: they decrease when cash is needed and vice versa. In other words, the controlling shareholder tolerates a cut in dividends, and therefore the degree of dividend smoothing is reduced.

Burkart and Panunzi (2006) argue that legal protection affects the expropriation of shareholder rights and the incentives of institutional investors to monitor. When legal protection facilitates monitoring incentives, it naturally reduces managerial incentives. As managerial incentives generate shareholder returns, limiting monitoring through ownership dispersion may be beneficial. This is consistent with the empirical evidence that the strength of the law is negatively correlated with the concentration of ownership (La Porta et al., 1997, 1998; Leary & Michaely, 2011; Javakhadze et al., 2014). In addition, legal shareholder protection affects the ease with which managers (possibly in collusion with institutional investors) can misappropriate corporate resources.

La Porta et al. (1997, 1998) find that legal protection for investors is generally stronger in common law countries (e.g., US) than in civil law countries (e.g., China). Therefore, dividend smoothing is more likely a signalling device in the US than in China. [1]

In an environment of strong laws, institutional monitors and dividend smoothing are alternative mechanisms for solving principal-agent problems; they are either substitutes or complements.

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[1] Although some scholars (e.g., La Porta et al., 2000) also consider dividend smoothing as an alternative to legal protection for investors. Whether it acts in practice as a substitute for the law or is replaced by institutional investors is ultimately an empirical question being examined.

The signalling model is only valid if managers are willing to pay a smooth dividend to reveal information to investors, i.e. they cannot be forced to pay. Smooth dividends either attract institutional monitors or replace them to mitigate principal-agent problems. This type of dividend smoothing reduces information asymmetry between investors and shareholders, thus increasing firm value. However, a strong monitor can penalise a manager when he cuts a dividend (Allen et al., 2000). Dividend smoothing is, therefore, a forced practice that promotes information asymmetry. It is consistent with Lin and Lee (2021) that the signalling effect of dividend smoothing on future profits is more pronounced for firms with less catering incentive to avoid dividend cuts.

Colluders are not only short-sighted, but they are also sensitive to pressure - they only want to maintain their business relationship with the firm. It does not matter whether the firm is profitable or not, so they are not concerned about smooth dividends that do not reflect the firm's prospects. As a result, dividend smoothing promotes information asymmetry.

Weak law makes collusion between management and certain types of institutional investors (colluders) easier. Managers smooth dividends for their own purposes, while colluders tolerate this behaviour because of their close business relationship with the firm. Smooth dividends that do not contain information cannot be used as signals. Weak laws also lead to higher ownership concentration, in which case the information asymmetry is between controlling and minority shareholders rather than between principals and agents. In this case, monitoring institutional investors replace dividend smoothing to reduce the agent conflict between controlling and minority shareholders. The overall institutional impact on the firm value depends on the net effect from monitors and colluders. Figure 3.1 illustrates the dynamics between dividend smoothing and institutional ownership under different legal environments.

Legal Protection	Causality	Correlation	Mechanism	Smoothing	Firm Value
Strong	Smoothing → Monitors	+	Complement	Signalling	↑
	Smoothing → Monitors	−	Substitute	Signalling	↑
	Monitors → Smoothing	+	Substitute	Garbling	~
Weak	Monitors → Smoothing	−	Substitute	No impact	↑
	Colluders → Smoothing	+	Collusion	Garbling	↓

Figure 3.1: The dynamics between dividend smoothing and institutional ownership

I apply the panel vector autoregression (PVAR) model to identify the direction of causality. I find that institutional investors influence dividend smoothing policy, not firms that smooth to cater to them. I use static and dynamic panel models to elaborate on the relationship between dividend smoothing, institutional investors and firm value.

In the US, monitors influence corporate dividend policies and firms smooth dividends to cater to their preferences, thus carrying garbling information. The interaction term between dividend smoothing and monitoring institutional holdings is positively correlated to firm value, implying that monitors who favour smooth dividends have positive impact on corporate governance.

Colluders in the US tolerate uninformative smooth dividends. Combined with the fact that they do not contribute as much to corporate governance as monitors, the interaction term between dividend smoothing and colluding institutional holdings is negatively related to firm value.

The overall institutional impact on the firm value through smooth dividends is mixed in the US. Smooth dividends alone reduce firm value because, in both cases, they do not act as a signal to reduce information asymmetry.

In China, monitors substitute smooth dividends and positively affect corporate governance by reducing agency conflicts between minority and controlling shareholders, enhancing firm performance. It is consistent with empirical evidence from China that mutual funds and Qualified Foreign Institutional Investors (QFIIs) have effectively mitigated the expropriation of minority shareholders by controlling shareholders and have played a positive role in corporate governance (Huang & Zhu, 2015; Chizema et al., 2020).

Same as in the US, colluders in China tolerate uninformative smooth dividends. The interaction term between dividend smoothing and colluding institutional holdings is negatively related to firm value. The overall institutional impact on the firm value through smooth dividends is negative, and Chinese monitors' positive influence on firm value is strong.

Previous research has demonstrated that institutions have an impact on firm value, but not through dividend policy. The past literature refers to dividend policy as omission (initiation) or reduction (increase), not dividend smoothing. This chapter explores the dynamics between dividend smoothing and institutional ownership under different legal environments. Moreover, existing research has yielded mixed findings as to whether the signalling model can be used to explain dividend smoothing. This chapter proposes a reconciliation by distinguishing real signals from garbled ones by investigating the purpose and motivation of the signaller.

3.2 Literature Review

3.2.1 Information that Smooth Dividends Convey or Disguise

Information Signalling

Lintner (1956) found that managers are reluctant to change dividends. Since then, why firms smooth dividends has remained a mystery despite an extensive literature that attempting to provide theoretical explanations.

Classic models explaining the existence of dividends involve fully revealing equilibria; the models suggest that dividends can signal a firm's current or future profitability (Miller & Rock, 1985; John & Williams, 1985; Bhattacharya, 1979).

More recent models explaining how smooth dividends signal investors involve partially revealing equilibria. Kumar (1988), Kumar and Lee (2001) and Guttman et al. (2010) demonstrate that a firm's management team may retain information instead of releasing all information. Types of firms within a specific range pool with each other but are separate from firms outside that range. Thus, the manager selects the same dividend for all earnings within the specified range, and investors anticipate this behaviour and price the firm accordingly. As a result, the pooling dividend equals last year's dividend. Smooth dividends should reveal information about cash flow volatility (Kumar, 1988), equity risk factors (Kumar & Lee, 2001), and investment opportunities (Guttman et al., 2010). They believe that firms affected by information asymmetry are more likely to conduct dividend smoothing.

Brav et al. (2005) find that dividend policies are conservative, reflected in the different market responses to dividend increases and decreases, i.e., stock prices fall much more when dividends are reduced than they rise when dividends are increased. The reluctance of payers to cut dividends and non-payers to initiate dividends implies that corporate dividend policies may be inflexible. Survey evidence shows that many executives at firms that pay dividends wish they had never paid, or at least not as much as they do now. Allen et al. (2000) argue that because dividends attract institutional investors (tax benefits), good firms are not afraid to send signals and are subject to institutional scrutiny. Poor performers are afraid to disclose their quality; the cost of imitating the behaviour of good firms can be very high. [2]

In general, firms that signal their prospects to the market through smooth dividends are confident in their ability to sustain profitability due to the conservative nature of dividend policies. Executives try to reduce the information asymmetry with investors by providing stable dividends within a specific earnings range.

Information Garbling

A smooth dividend does not always signal a firm's true profitability. Managers may worry about being fired for poor performance (Fudenberg & Tirole, 1995; DeMarzo & Sannikov, 2016; Wu, 2018) or paying dividends for their own benefit, e.g., job security, empire building (Lambrecht & Myers, 2012; Baker et al., 2016). In this situation, dividend smoothing promotes information asymmetry between investors and firms.

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[2] US dividends were taxed at a much higher rate than capital gains before 2003.

Fudenberg and Tirole (1995) point out that professional managers enjoy private benefits from operating firms. However, if firm performance is poor, large shareholders may intervene, reducing access to private benefits. Moreover, when evaluating managers, shareholders are more concerned about recent financial reports. This information decay produces income smoothing, which also leads to dividend smoothing, as dividends are the difference between reported and retained earnings. DeMarzo and Sannikov (2016) demonstrate that management and investors will learn about a firm's profitability through current cash flows, and managers will be fired when profitability is too low. Thus, managers deliberately reduce current cash flows, depositing excess money in cash reserves to deal with income shocks. When a firm has enough cash reserves, it will start paying dividends. Once it starts paying dividends, it will keep them smooth. Empirical evidence from Wu (2018) concludes that employers' own career considerations drive 39% of dividend smoothing in the US. Managers reduce investments and adjust external financing policies to accommodate this type of dividend smoothing, resulting in a 2% decrease in firm value. Lambrecht and Myers (2012) and Baker et al. (2016) show that this rent-seeking and risk-aversion behaviour of management promotes dividend smoothing. [3] Shareholders often demand regular dividend payments to reduce agency costs arising from excessive free cash flows. So as long as managers pay enough dividends to satisfy shareholders, shareholders will not have any problems with how they run their business. Rents emerge from poor corporate governance in the form of inadequate monitoring. Risk-averse

[3]Following Lambrecht and Myers (2012), rent is defined as the actual resources occupied by a broad alliance of managers and employees, including wages above the market level, job security, generous pensions and allowances.

managers are eager for rent smoothing; habit formation makes payouts and rents move in locksteps, producing dividend smoothing.

Recent empirical studies (e.g., Leary & Michaely, 2011; Lambrecht & Myers, 2012; Javakhadze et al., 2014) have attempted to test the above theories. Yet, no evidence has been found to support the signalling model. That is, dividend smoothing is not more prominent in firms suffering from information asymmetry. More specifically, high institutional ownership, as a proxy for low information asymmetry, leads to more significant dividend smoothing.

García-Feijóo et al. (2021) explain these discomforting empirical findings by linking social capital to dividend smoothing. They define social capital as a personal asset that benefits a firm. High institutional holdings and low information asymmetry are firm characteristics that are positively associated with social capital. [4] Their claim, however, does not justify why the signalling model does not work empirically. Institutional holdings are used as a proxy for information asymmetry, with the implicit assumption that their role as monitors reduces information asymmetry. What if this is not true for certain types of institutional investors?

3.2.2 Impact of Institutional Incentives on Dividend Smoothing

Institutional investors can play a dual role in corporate governance: they can be either monitors or colluders (Pound, 1988; Elyasiani & Jia, 2010; Ruiz-Mallorquí & Santana-Martin, 2011).

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[4] Information about M&A is effectively disseminated in personal networks, and such networks also reduce analysts' forecast errors (Schmidt, 2015; Ferris et al., 2017).

Institutions that monitor actively participate in corporate governance. Shleifer and Vishny (1986, 1997) discover that, with high levels of institutional ownership, the institution has incentives to monitor firm management, thereby alleviating the principal-agent problem. In addition, Allen et al. (2000) find that individual institutions having low shareholdings also exert positive influence through co-operation to improve the efficiency of corporate governance. Gillan and Starks (2000) suggest that institutions, especially public pension funds, are more likely to monitor than other investors. Boone and White (2015) find that institutions can help improve the quality of information disclosure. An institution also has more vigorous information screening and interpretative ability, and can signal the market about the firm's business status through various communication channels, thus improving information transparency.

Since institutional holding and dividend smoothing are alternative mechanisms for controlling the principal-agent problem, they can be considered substitutes (Gompers et al., 2003) or complements (La Porta et al., 2000). Moreover, Allen et al. (2000) argue that the presence of institutional investors reinforces the dividend smoothing.

If the institution is a colluder, it will side with management and undermine corporate governance (e.g., Woidtke, 2002; Grinstein & Michaely, 2005; Cornett et al., 2007; Ruiz-Mallorquí & Santana-Martin, 2011; Boone & White, 2015). In this way, it strengthens its position as a blockholder by depriving minority shareholders of their interests. Graves (1988) argues that institutional investors are short-sighted. They often focus on current profits, rather than the long-term value of the firm. When they are dissatisfied with the performance of a firm, they choose to vote with their feet in a passive way out of self-interest (Parrino et al., 2003). Short-term institutional investors may allow managers to proceed with value-reducing acquisitions or at the expense of shareholder returns in exchange for personal gain (Gaspar et al., 2005).

These institutional investors have a close business relationship with the firm and are therefore sensitive to stress. They neither care about the firm's future nor want to get into a fight with management. Improving corporate governance is the least of their concerns, so they tolerate the untruthful information that comes with smooth dividends.

Monitors and Colluders

Institutional incentives are heterogeneous, and some are inherently more willing to collude with management than others (e.g., Brickley et al., 1988; Bushee, 1998; Almazan et al., 2005; Cornett et al., 2007).

Brickley et al. (1988) describe monitoring institutional investors as 'pressure-resistant', Almazan et al. (2005) call them 'active' and Chen et al. (2007) call them 'independent'. In the US, such institutional investors are **Mutual Funds** and **Investment Advisors**. In China, they are **Mutual Funds**, **Qualified Foreign Institutional Investors (QFIIs)** and **Social Security Funds**. These institutions can gather information more effectively and have fewer potential business relationships with the firms they invest in.

Brickley et al. (1988) refer to colluding institutional investors as 'pressure-sensitive', Almazan et al. (2005) call them 'passive' and Chen et al. (2007) call them 'grey'. Colluders include **Bank Trusts** and **Insurance Companies**. The current or prospective business relationships that these types of institutional investors have with corporations tend to make this group more loyal to management and thus more likely to hold shares without reacting to management actions that do not align with the interests of shareholders. This group is more likely to collude with management to extract a share of the rent, because the cost of monitoring for them is higher.

While this classification may be flawed by its loose identification method, the data used in this study limits other classifications. For example, the investment horizon is a good criterion, as long-term institutional investors are usually active monitors. As a proxy for investment horizon, portfolio turnover is reported at the firm level in 13F Fillings rather than fund level. An institution may have several different constituent investment entities, following different strategies.

3.2.3 Impact of Legal Environments on Dividend Smoothing

Agency conflicts are the result of information asymmetry among various stakeholders. These conflicts are either between shareholders and managers (Easterbrook, 1984; Jensen, 1986; Allen et al., 2000) or between controlling and minority shareholders (Shleifer & Vishny, 1997; Faccio & Lang, 2002; Claessens et al., 2002).

Easterbrook (1984) and Jensen (1986) suggest that paying high and smooth dividends reduces excess free cash flow and forces firms to seek external capital. In this way, the firm reduces the conflict of interest between shareholders and managers by increasing its exposure to external capital market disciplines. Allen et al. (2000) argue that institutional investors have good monitoring capabilities. Given that institutional investors mostly have the tax benefits of dividends, managers will use dividends to attract them. Once institutional investors have been attracted, the investors will penalise firms that cut dividends, resulting in managers being forced to smooth dividends.

In a survey study of corporate governance, Shleifer and Vishny (1997) find that the agency problem centres on the expropriation of minority shareholders by controlling shareholders. Ownership structures exhibit relatively little concentration in the United States but not elsewhere. For example, the international empirical evidence of Shleifer and Vishny (1997), Faccio and Lang (2002) and Claessens et al. (2002) show that when the concentration of shareholding is sufficiently high, controlling shareholders take full advantage of control for personal gain at the expense of minority shareholders.

La Porta et al. (1997, 1998) were the first to study how the law and its enforcement affect corporate governance in terms of agency conflicts. Their findings suggest that legal protection for investors is generally stronger in common law countries (e.g., US) than in civil law countries (e.g., China). They also find a negative relationship between ownership concentration and investor protection in large public firms, consistent with evidence that minority shareholders are vulnerable in countries where shareholder rights are not protected.

Burkart and Panunzi (2006) suggest that legal protection affects the expropriation of shareholder rights and the incentives of institutional investors to monitor. When legal protection facilitates monitoring, strong laws strengthen the monitoring incentive and thus reduce the managerial incentive. Since managerial initiative generates shareholder returns, it may be advantageous to limit monitoring through ownership dispersion. It is consistent with previous empirical evidence

(La Porta et al., 1997, 1998; Leary & Michaely, 2011; Javakhadze et al., 2014) that the strength of law is negatively related to ownership concentration. Moreover, legal shareholder protection affects the ease with which managers (possibly in collusion with institutional investors) can misappropriate corporate resources.

While controlling shareholders may exacerbate conflicts with minority shareholders (minority-controlling shareholder problem), they will essentially reduce conflicts of interest with management (principal-agent problem) and promote an environment of information transparency among shareholders. A smooth dividend is a effective tool to reduce the principal-agent problem (e.g., Easterbrook, 1984; Jensen, 1986; Allen et al., 2000), but it does not help deal with the minority-controlling shareholder problem. Michaely and Roberts (2012) find that smooth dividends are significantly lower for private firms than for public firms because they are less attractive when information asymmetry between shareholders and managers is relatively small. Controlling shareholders might tolerate dividend cuts.

Principal-Agent Problem

As a common law country with a sound legal system, the US has a dispersed ownership structure, and the rights and interests of minority shareholders are better protected. The principal-agent problem occurs between shareholders and management. Institutional investors operating in this legal environment tend to be more motivated and able to monitor. As a result, the costs of collusion by management outweigh the benefits derived from the rents extracted.

Empirically, dividend smoothing is positively correlated with institutional ownership. It may be due to the fact that both help control the principal-agent problem. However, in order for the signalling model to work, institutional investors cannot force firms to pay smooth dividends. On the one hand, Larkin et al. (2017) find that mutual funds are positively associated with dividend smoothing and that the causal relationship is from dividend smoothing to mutual fund holdings. This implies that it is dividend smoothing that attracts mutual funds and not the other way around. On the other hand, Allen et al. (2000) and Crane et al. (2016) show that larger institutional investors ensure that firms pay higher and smoother dividends, especially for firms with higher expected agency costs.

In summary, there are three situations for the relationship between dividend smoothing and international investors in the US. In the first case, managers use smooth dividends to signal shareholders; smooth dividends are informative, reducing information asymmetry. Smooth dividends attract institutional investors (monitors), and the two have complementary effects on controlling the principal-agent problems. In the second case, managers use smooth dividends to signal shareholders as in the first case but substitute institutional investors (monitors) for controlling the principal-agent problem. For both cases, firm value increases. In the third case, institutional investors (monitors) force firms to smooth dividends; smooth dividends are uninformative, increasing information asymmetry. Institutional ownership substitutes dividend smoothing to control the principal-agent problem. As a result, the change in firm value is the net effect of dividend smoothing and institutional monitoring.

Hypothesis 1a: In the US, if the causality is from dividend smoothing to monitoring institutional holdings, and they are positively related, firm value is expected to increase.

Hypothesis 1b: In the US, if the causality is from dividend smoothing to monitoring institutional holdings, and they are negatively related, firm value is expected to increase.

Hypothesis 1c: In the US, if the causality is from monitoring institutional holdings to dividend smoothing, and they are positively related, firm value is mixed.

Minority-Controlling Shareholder Problem

As a civil law country with weaker legal systems, China has a concentrated ownership structure, and the rights and interests of minority shareholders are not safeguarded. The presence of controlling shareholders mitigates the principal-agent problem, but the agency problem between controlling and minority shareholders has increased.

In most cases, the controlling shareholders of firms in emerging countries are families and state governments. They allow dividend cuts because principal-agent problems are not prominent in a corporate environment where shareholder ownership is concentrated (Michaely & Roberts, 2012). Dividend smoothing is not an effective tool to control problems between controlling and minority shareholders; after all, the controlling shareholder determines the dividend policy.

Mutual funds and Qualified Foreign Institutional Investors (QFIIs) are the most important and influential types of monitoring institutions in China. Firth et al. (2016) find that compared to banks and insurance companies, Chinese mutual funds encourage firms to pay higher dividends in order to reduce excess free cash flow possessed by managers. However, this does not promote dividend smoothing because shareholders allow managers to cut dividends when ownership is sufficiently concentrated. Huang et al. (2011) discover that controlling shareholders in China do not force firms to initiate or increase dividends when firm earnings decline significantly. Bradford et al. (2013) also observe that as the chain of corporate control lengthens (e.g., private control), the dividends paid by Chinese firms will decrease. Chizema et al. (2020) show that mutual funds in China effectively mitigate the expropriation of minority shareholders by controlling shareholders, as long as they are not controlling shareholders. Huang and Zhu (2015) reveal that QFIIs are more immune to the influence of state-controlled firms and play a positive role in corporate governance compared to mutual funds. Furthermore, in the presence of controlling shareholders, institutional investors are unlikely to force a firm to pay smooth dividends. Thus, institutional ownership (monitoring) substitutes dividend smoothing to mitigate information asymmetry between minority and controlling shareholders.

Hypothesis 2: In China, if the causality is from monitoring institutional holdings to dividend smoothing, and they are negatively related, firm value is expected to increase.

Certain institutions that have closer business relationships (dependent and pressure-sensitive) with the firm may be more likely to collude with management or be more tolerant of inappropriate corporate resources. Weak legal shareholder protections lower the barriers to collusion. As a result, they extract rents from minority shareholders (Shleifer & Vishny, 1997; La Porta et al., 1999; Claessens et al., 2002; Ruiz-Mallorquí & Santana-Martin, 2011). Rent-seeking oriented dividend smoothing is expected to be more prevalent in China than in the US.

Hypothesis 3: If the causality is from colluding institutional holdings to dividend smoothing, and they are positively related, firm value is expected to decrease. The decline will be more significant in China than in the US.

3.3 DATA AND METHODOLOGY

3.3.1 Sample Selection

This chapter uses all firms listed on the NYSE, AMEX and NASDAQ from 1998 to 2018 as the US sample, which includes 11516 firm-year observations. I collect corporate financial information from CRSP/Compustat Merge Database provided by Wharton Research Data Service (WRDS) and obtain institutional information from the Thomson-Reuters 13F Filings through the WRDS platform. I use all A-shares listed on the Shanghai and the Shenzhen Stock Exchange from 1998 to 2018 as the Chinese sample, which includes 5400 firm-year observations. Information about corporate finance and institutions is provided by the China Stock Market & Accounting Research Database (CSMAR). This chapter removes all financial firms from both samples because of their unusual dividend distribution process and government regulatory framework. [5]

An analysis of dividend smoothing is the research objective of this chapter; therefore, the sample is limited to firms paying dividends. More precisely, it includes U.S. firms that have continuously distributed cash dividends for not less than 10 years between 1998 and 2015, and Chinese firms for not less than 5 years. This sampling method reduces the possibility of any distortion of the results in terms of dividend smoothing. A possible concern arises from such a sampling process, which limits the sample to dividend payers only. Usually, the study of dividend policy is necessary to analyse firms that do not pay dividends; how-

[5]The US sample excludes financial firms of SIC 6000-6999, and the Chinese sample excludes industry codes J and K.

ever, this is not the case when studying the dividend **smoothing** phenomenon. Nonpayers in nature behave differently from those who pay a stable and positive share of profits.

3.3.2 Variable Definition

Institutional Ownership

Institutional ownership is calculated as total shares held by the institutions, divided by the total number of shares outstanding. Following Brickley et al. (1988); Cornett et al. (2007); Chen et al. (2007), I define US $Monitor$ as mutual funds and investment advisors, while Chinese *Monitors* are mutual funds, QFIIs and social security funds. These institutions can gather information more effectively and have fewer potential business relationships with the firms they invest in. Institutions that are defined as $Colluders$ include bank trusts and insurance companies. They have close business relationships with firms. $Inst$ is the natural logarithm of one plus institutional ownership. To include a value of 0 in the analysis, I add 1 to the percentage of outstanding shares and then convert it to a logarithm to reduce the impact of positive skewness. This chapter creates an institutional dummy variable ($InsD$) equal to 1 if an institution holds more than 10% of a firm's shares, otherwise 0. The entire institutional base is further divided into monitors and colluders.

Firm Value

Tobin's Q is a common proxy used to measure firm value, which was first introduced by Kaldor (1966), and later popularised by Tobin, Brainard et al. (1976). The version I use to examine the relationship between value, dividend smoothness and institutional ownership takes the following form:

$$\text{Tobin's Q} = \frac{\text{Equity Market Value} \ + \ \text{Liabilities Book Value}}{\text{Equity Book Value} + \text{Liabilities Book Value}}$$

Although it is not a "true" Tobin Q, it is a common practice in the financial literature to calculate the ratio by comparing the market value of the equity and liabilities with their corresponding book value, given that the replacement value of the assets is difficult to estimate. More often, it is simply assumed that the market value of the liability is equal to the book value.

Dividend Smoothing Measures

This chapter uses the same method as Chapter 2 to quantify the degree of dividend smoothing. I will briefly state the steps and see Chapter 2, Section 2.3.2, on page 35 for details.

The first measure is modified Speed of Adjustment (SOA), derived from the classic partial adjustment model (Lintner, 1956), calculated using a two-step procedure. The first step is to estimate the target payout ratio for a firm as the median payout over a period of 10 years (5 years for the Chinese sample). Then I retrieve the deviation from the target payout ratio at each period. In the second step, the changes in level dividends are regressed on the deviation from the target payout ratio to determine SOA, which is the regression coefficient. The higher the SOA, the faster a firm adjusts its dividend level to respond to fluctuations in earnings, and the less smooth the dividend, relative to earnings. [6]

The second measure is model free, which captures the dividends volatility relative to the earnings volatility; Leary and Michaely (2011) name it relative volatility (RelVol). A quadratic trend is fitted to both the dividend and earnings streams for each firm during a 10- or 5-year period. Finally, RelVol is calculated by dividing the root mean square errors from the regressions of dividends per share and earnings per share respectively.[7] A higher RelVol means the change of dividend growth is in line with the earning growth volatility, indicating less smoothing of dividends. In this way, RelVol implies the fluctuations of dividend volatility despite the relationship between changes of dividends and deviations from the target payout ratios. The measures I use in this chapter are 1 - SOA and 1 - RelVol, referred to as DS and DS_{alt}, for a more intuitive expression, i.e., the higher the value of DS and DS_{alt}, the greater the degree of smoothing. I trim the top and bottom 2.5% of resulting smoothing measures, following Leary and Michaely (2011).

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[6]The first step:

$$dev_{i,t} = TPR_{i,t} \cdot EPS_{i,t} - DPS_{i,t-1},$$

where $dev_{i,t}$ is the deviation from the target payout ratio, $EPS_{i,t}$ is the earning per share, $TPR_{i,t}$ is the target payout ratio and $DPS_{i,t-1}$ is the lagged level of dividends per share.

The second step:

$$\Delta DPS_{i,t} = \alpha + \beta_i \cdot dev_{i,t} + \epsilon_{i,t},$$

where SOA is the regression coefficient, β_i.

[7]The alternative measure of smoothing is defined as the ratio of the root mean squared errors, $\sigma(\epsilon)/\sigma(\mu)$, from the following equations:

$$DPS_{i,t} = \alpha_1 + \beta_1 \cdot t + \beta_2 \cdot t^2 + \epsilon_{i,t}$$
$$TPR_i \cdot EPS_{i,t} = \alpha_2 + \gamma_1 \cdot t + \gamma \cdot t^2 + \mu_{i,t}.$$

Control Variables

This chapter includes the following control variables which can affect dividend smoothing and firm value. The size and maturity of a company is controlled by the use of total assets ($Size$) and age (Age). Sales changes are used to control growth potential ($Growth$). Tangible assets ratio (Tan) and leverage ratio (Lev) are related to smoothing, and also affect the ownership structure. Dividend yield (Dy) is used to measure the dividend level. For example, firms with high dividend yields may also tend to smooth their dividends. The Herfindahl-Hirschman Index (HHI) is introduced to control the impact of equity concentration on firm value. Finally, considering the greater weight of non-tradable shares in the Chinese market, this chapter takes the percentage of state-owned holdings ($State$) as a control variable for the Chinese sample. Table 3.3.1 summarises the definition and measurement of variables.

3.3.3 Regression Methods

Static Panel Regressions

First, a pooled ordinary least squares (OLS) regression with year- and industry-fixed effects are employed to gain a general understanding of the relationship among institutions, dividend smoothing and firm values. Then a fixed effect (FE) model is used to further eliminate the unobserved time-invariance effect. Both models adopt cluster-robust standard errors as documented by Rogers (1993). A cluster consists of all the observations of each individual at different times, and observations of the same cluster are allowed to be correlated.

$$DS_{i,t} = \alpha_0 + \alpha_1 \cdot Inst_{i,t} + \alpha_2 \cdot Control_i + \varepsilon_{i,t} \tag{3.3.1}$$

$$\begin{aligned} \Delta Value_{i,t} = &\beta_0 + \beta_1 \cdot DS_{i,t-5} + \beta_2 \cdot InsD_{i,t-5} \\ &+ \beta_3 \cdot DS_{i,t-5} \cdot InsD_{i,t-5} + \beta_4 \cdot Control_i + \mu_{i,t-5} \end{aligned} \tag{3.3.2}$$

I use changes in value, $\Delta Value_{i,t} = TobinQ_{i,t} - TobinQ_{i,t-5}$, at a 5-year investment horizon rather than the value itself because it inevitably reflects the firm's future growth potential through its market value. The empirical results show that firms with more growth opportunities have a weaker tendency to smooth dividends (Leary & Michaely, 2011). I control the within-firm changes in investment opportunities over the past five years, as well as the level and size of dividends from five years ago, since the different initial size and dividend level will generate a different growth path. So the full set of control variables in Equation (3.3.2) is $\Delta Growh_{i,t-5}$, $\Delta Size_{i,t-5}$, $\Delta Tan_{i,t-5}$, $\Delta Lev_{i,t-5}$, $\Delta Dy_{i,t-5}$, Dy_{t-5} and $Size_{t-5}$.

Dynamic Panel Regressions

One advantage of using panel data is that the dynamic behaviour of individuals can be modelled, however, traditional FE estimations are biased for dynamic panel data (Nickell, 1981).[8] Although the FE model deals with the problem of omitted variables (individual heterogeneity) to some extent, instrumental variables (IV) are needed if the regression model itself contains endogenous ex-

[8]For long panels, i.e. "large T small N", dynamic panel bias is small, which can be corrected by least-squares dummy (LSDV) to to obtain a consistent estimate. For short panels, i.e., "large N small T", like the data structure of this chapter, system GMM is a more efficient and unbiased approach.

planatory variables. Anderson and Hsiao (1981) first make a first-order difference to remove the individual effect, then use the lagged term of the explained variable as the IV, and finally perform the two-stage least squares (2SLS) estimation. Arellano and Bond (1991) find that a higher lag order is also a valid IV, and thus they use all possible lagged IV to estimate. When the number of IV exceeds the number of endogenous explanatory variables, generalised method of moments (GMM) estimation of panel data is more efficient, known as difference GMM. However, Blundell and Bond (1998) have pointed out that when explained variables have strong persistence, i.e., the first-order autoregression coefficient is close to 1, the relationship between IV and exogenous variables is weakened, and the first-order difference GMM estimation is biased. To overcome the effects of weak IV, Arellano and Bover (1995) and Blundell and Bond (1998) propose another, more effective method, the system GMM estimation method. This is done by combining level equations with difference equations, in which the lagged level estimator is used as an IV of the first-order difference equation, and the first-order difference estimator is used as an IV of the level equations. System GMM assumes that first differences of IVs are uncorrelated with the fixed effects, and it takes the form of:

$$DS_{i,t} = \alpha_0 + \alpha_1 \cdot DS_{i,t-1} + \alpha_2 \cdot Inst_{i,t} + \alpha_3 \cdot Control_i + \varepsilon_{i,t} \tag{3.3.3}$$

$$\begin{aligned} \Delta Value_{i,t} = \beta_0 + \beta_1 \cdot \Delta Value_{i,t-1} + \beta_2 \cdot DS_{i,t-5} + \beta_3 \cdot InsD_{i,t-5} \\ + \beta_4 \cdot DS_{i,t-5} \cdot InsD_{i,t-5} + \beta_5 \cdot Control_i + \mu_{i,t-5} \end{aligned} \tag{3.3.4}$$

Windmeijer (2005) finds that the two-step GMM has better performance in estimating coefficients than the one-step GMM, with lower bias and standard error. This chapter uses two-step estimation and reports the Windmeijer-corrected standard errors. Hansen (1982) J test statistic for over-identifying restrictions is reported in each Tables. Arellano-Bond test is used to detect the autocorrelation. If the first-order lag dependent variable is chosen as the independent variable, then AR (1) is expected to be significant, while AR (2) is not. However, if the first two lag terms of dependent variable are chosen as the independent variables, then AR (1) and AR (2) are expected to be significant, while AR (3) is not.

Panel Vector Autoregression

The dynamic panel model described above assumes that the status of exogenous and endogenous variables is known, either empirically or on a theoretical basis. For example, based on past literature, I believe that institutional investors can change a firm's value by influencing dividend smoothing policy. This suggests that the institutional ownership is an exogenous variable of the system, placed on the right hand-side of the equation.

However, if the relationship between several related variables is uncertain, they can be put together in a system to predict. All the variables in the system are treated as endogenous. Then, we study how the impact of one variable affects other variables in the system. The vector autoregression (VAR) proposed by Sims (1980) is such a method. Combined with the causality test of Granger (1969), one can preliminarily learn the "causality" of the system. However, Granger causality is not a causal relationship in the traditional sense, it is rather a dynamic correlation, indicating whether a variable has predictability to another.

VAR is a time-series model, typically used to capture the relationships between

Table 3.3.1: Variable Definition

Variables	**Definitions**	**Measurements**
Ins	Institutional Ownership	One plus the institutional holdings, the sum of which is taken as the natural logarithm
Ins_M	Monitoring Ownership	Institutional ownership of mutual funds and independent investment advisors (in the case of China, mutual funds, QFIIs and social security funds)
Ins_C	Colluding Ownership	Institutional ownership of banks and insurance firms
DS	Dividend Smoothing	Modified speed of adjustment, see Methodology section
DS_{alt}	Alternative DS	Relative volatility to earnings, see Methodology section
TS	Total Payout Smoothing	Same as DS including stock repurchases
TS_{alt}	Alternative TS	Same as DS_{alt} including stock repurchases
$InsD$	Institutional Dummy	The $InstD$ is one if an institution holds more than 10% of the firm's shares and zero otherwise, where the $InstD$ is subdivided into monitors and colluders
$\Delta Value$	Changes in Value	Change in Tobin's Q over five years
$Growth$	Sales Growth	The difference between the net sales of the current year and the prior year divided by the net sales of the prior year
$Size$	Firm Size	The natural logarithm of total assets
Age	Firm Age	The natural logarithm of the number of years since the firm appeared in the database
Tan	Tangibility	Property, plant, and equipment scaled by total assets
Lev	Leverage	Total liabilities divided by total assets
Dy	Dividend Yield	Common dividends scaled by the market capitalisation
HHI	Ownership Concentration	Herfindahl-Hirschman Index
$State$	State Ownership	Outstanding shares owned by the state government

multiple variables over time, and to study the dynamic impacts of random disturbances on variable systems. Holtz-Eakin et al. (1988) extend the VAR model to the application of panel data and propose a panel vector autoregression (PVAR) model, which is relaxed for the length of time of the data.

The PVAR model is a dynamic panel model with fixed effects, and thus data has to be Helmert-transformed (Holtz-Eakin et al., 1988) prior to GMM estimation in order to remove the fixed effects. Once the GMM estimation has been fitted, the impulse response function (IRF) analysis is carried out next to study how the system reacts over time to exogenous impulses, i.e., shocks. Finally, the forecast-error variance decomposition (FEVD) is used to measure the information contribution of each variable in autoregression to other variables, i.e., how much of the forecast error variance of each variable can be explained by shocks to the others. I use the lowest value of Akaike Information criterion (AIC), Bayesian Information criterion (BIC) and Hannan-Quinn information criterion (HQIC) to determine the lag order.

I specify a PVAR model as follows:

$$z_{i,t} = \Gamma_0 + \sum_{j=1}^{p} \Gamma_j \cdot z_{i,t-j} + e_t \tag{3.3.5}$$

where j is the lag order; $z_{i,t}$ is a three-variable vector, including institutional ownership, dividend smoothing and changes in firm value. One drawback of using IFR and FEVD is that order of variable in the VAR system matters. The contemporaneous and lag terms of a variable appearing earlier in the order will influence the variable appearing later, while the later variable only has its lag term affecting the variable appearing earlier. That is to say, the variables that appear earlier in the systems are more exogenous, while the variables that appear later are more endogenous. Since the hypothesis of this chapter is that institutions affect firm value though dividend smoothing policy, the order of variables in the vector is set to $Inst, Smooth, \Delta Value$.

Summary Statistics

Table 3.3.2 summarises cross-sectional means and standard deviations for defined periods. C and M represent 10% of the firm shares in the group being held by colluders or monitors, respectively. For example, DS_M represents the degree of dividend smoothing in a group that monitors hold 10% of the shares. Mutual funds were introduced to China in 2000, followed by QFII in 2002, and other institutional investors remained small until 2003. Therefore, for the period 1998 to 2002, only monitor groups are listed for all variables in China.

In the US, dividend smoothing tends to increase over time and does not differ vastly between the monitor (DS_M) and colluder (DS_C) groups (0.689 vs 0.662). In contrast, the upward trend in dividend smoothing in China in the colluder group is visibly larger than the monitor group (0.281 vs 0.346). This is consistent with the hypothesis that monitors in China substitute dividend smoothing to control agency problems, so dividend smoothing is at a lower level and increases slowly over time. Furthermore, the overall degree of dividend smoothing for Chinese firms is much lower than that of the US.

The two countries also show very different levels of dividend payments, as measured by the dividend yield (Dy). In the US, there is no significant difference in the level of dividend payments between the monitor (Dy_M) and colluder (Dy_C) groups, both of which fluctuate upwards. In China, on the other hand, the level of dividend payments for both groups is not only smaller than in the US but has declined over time.

While the level of dividend smoothing and payout in the US has increased over time, it appears that in China, the level of dividend smoothing has increased over time, but dividend payout has decreased. This phenomenon has something to do with China's large base of retail investors. Firms attempt to reduce the information asymmetry between retail and institutional investors through stable and small (to minimise tax cost) dividends.

Although China's ownership concentration (HHI) is much higher than the US average, both countries have seen a period-on-period decline in ownership concentration. This is consistent with theoretical and empirical evidence that weak legal protection tends to have dispersed ownership and that the ownership concentration decreases as the legal system improves.

Table 3.3.3 and Table 3.3.4 present correlation coefficients for the variables in the US and China, respectively. The correlations between the dividend smoothing measure and its alternative are 0.65 and 0.38, respectively, in the US and China. The total payout smoothing measure is 0.40% correlated to its alternative. It preliminarily validates the alternative variables, except that the correlation between the dividend smoothing measure and its alternative in the US is almost twice as high as in China. In addition, in the US, the correlation between the total payout and dividend smoothing measures is 0.25, while it is only 0.15 between the two alternative measures. The relatively small correlation also indicates that the volatility of stock repurchase is relatively large.

For both equity markets, dividend smoothing is negatively correlated with equity concentration, consistent with the empirical evidence. In China, dividend smoothing is negatively (-0.04) related to the payout level, while in the US, the relationship is positive (0.02), consistent with the evidence shown in Table 3.3.2.

Table 3.3.2: Descriptive Statistics

Sample Period	1998 - 2002		2003 - 2007		2008 - 2012		2013 - 2018		1998 - 2018	
	Mean	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
	United States									
DS_M	0.654	0.309	0.696	0.303	0.658	0.327	0.725	0.320	0.689	0.320
DS_C	0.620	0.316	0.672	0.298	0.694	0.305	0.786	0.272	0.662	0.306
Growth_M	0.121	0.244	0.119	0.172	0.057	0.168	0.047	0.192	0.067	0.187
Growth_C	0.071	0.279	0.127	0.155	0.073	0.150	0.056	0.098	0.098	0.207
Size_M	6.963	1.657	7.660	1.570	8.070	1.758	8.336	1.732	7.985	1.763
Size_C	8.014	1.627	8.533	1.627	8.881	1.555	9.056	1.605	8.400	1.654
Age_M	3.684	0.328	3.540	0.418	3.563	0.440	3.546	0.462	3.567	0.436
Age_C	3.766	0.328	3.716	0.364	3.755	0.436	3.756	0.392	3.739	0.359
Tan_M	0.361	0.226	0.342	0.239	0.339	0.247	0.325	0.254	0.336	0.246
Tan_C	0.363	0.207	0.330	0.216	0.313	0.207	0.321	0.240	0.341	0.215
Lev_M	0.509	0.177	0.516	0.177	0.528	0.183	0.557	0.179	0.535	0.181
Lev_C	0.565	0.165	0.549	0.167	0.595	0.167	0.620	0.155	0.563	0.166
Dy_M	0.018	0.015	0.018	0.022	0.024	0.021	0.020	0.014	0.021	0.019
Dy_C	0.019	0.015	0.017	0.019	0.027	0.013	0.028	0.018	0.019	0.017
HHI_M	0.077	0.085	0.052	0.034	0.050	0.039	0.049	0.023	0.053	0.043
HHI_C	0.065	0.070	0.046	0.032	0.055	0.035	0.051	0.019	0.054	0.050
	China									
DS_M	0.270	0.262	0.253	0.296	0.287	0.319	0.295	0.336	0.281	0.318
DS_C			0.280	0.389	0.340	0.353	0.358	0.359	0.346	0.360
Growth_M	0.536	0.230	0.430	0.777	0.237	0.297	0.182	0.245	0.267	0.454
Growth_C			0.514	1.083	0.306	0.556	0.134	0.315	0.211	0.527
Size_M	21.49	0.278	22.02	1.071	22.40	1.155	22.798	1.089	22.41	1.150
Size_C			21.71	1.823	22.33	0.901	23.561	1.251	23.10	1.469
Age_M	1.202	0.653	1.854	0.595	2.207	0.579	2.626	0.376	2.230	0.607
Age_C			1.779	0.499	2.405	0.289	2.775	0.347	2.577	0.498
Tan_M	0.475	0.134	0.489	0.176	0.395	0.161	0.355	0.162	0.407	0.172
Tan_C			0.530	0.177	0.366	0.198	0.369	0.201	0.390	0.204
Lev_M	0.319	0.067	0.453	0.177	0.446	0.194	0.422	0.181	0.441	0.187
Lev_C			0.412	0.134	0.482	0.143	0.492	0.186	0.480	0.174
Dy_M	0.023	0.014	0.016	0.016	0.013	0.012	0.011	0.014	0.013	0.014
Dy_C			0.021	0.022	0.011	0.007	0.009	0.009	0.011	0.012
HHI_M	0.178	0.101	0.217	0.132	0.171	0.112	0.140	0.094	0.174	0.116
HHI_C			0.205	0.102	0.170	0.076	0.146	0.113	0.158	0.108
State_M	0.714	0.488	0.739	0.440	0.330	0.470	0.198	0.399	0.393	0.489
State_C			0.800	0.408	0.394	0.496	0.287	0.454	0.374	0.485

Notes: Cross-sectional means and standard deviations are reported for defined periods. C and M represent 10% of the firm shares being held by colluders or monitors, respectively. Variable definition see Table 3.3.1.

Table 3.3.3: Correlation Coefficients (US)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
DS	1	1.00													
DS_{alt}	2	0.65***	1.00												
TS	3	0.25***	0.16***	1.00											
TS_{alt}	4	0.03***	0.15***	0.40***	1.00										
Base	5	0.19***	0.17***	-0.11***	-0.16***	1.00									
Monitor	6	0.14***	0.12***	-0.06***	-0.10***	0.72***	1.00								
Colluder	7	0.13***	0.15***	-0.12***	-0.11***	0.71***	0.45***	1.00							
Growth	8	-0.03**	-0.02**	0.01	0.01	-0.02**	-0.08***	-0.04***	1.00						
Size	9	0.06***	0.07***	-0.00	0.06***	-0.04***	-0.01	0.12***	0.00	1.00					
Age	10	0.08***	0.12***	0.00	0.03***	0.25***	0.10***	0.36***	-0.08***	0.05***	1.00				
Tan	11	0.01	0.03***	0.08***	0.10***	-0.15***	-0.13***	-0.08***	0.03**	0.16***	-0.05***	1.00			
Lev	12	0.11***	0.15***	0.01	0.05***	0.10***	0.07***	0.18***	-0.02	0.43***	0.13***	0.19***	1.00		
Dy	13	0.02*	0.01	0.08***	0.06***	-0.22***	-0.13***	-0.13***	-0.11***	-0.03**	-0.01	0.20***	0.14***	1.00	
HHI	14	-0.07***	-0.08***	0.07***	0.05***	-0.51***	-0.38***	-0.40***	0.01	-0.26***	-0.18***	0.05***	-0.18***	0.14***	1.00

Notes: Variables are defined in Section 3.3. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively.

Table 3.3.4: Correlation Coefficients (China)

		1	2	3	4	5	6	7	8	9	10	11	12	13
DS	1	1.00												
DS_{alt}	2	0.38***	1.00											
Base	3	0.05***	-0.08***	1.00										
Monitor	4	0.04***	-0.09***	0.94***	1.00									
Colluder	5	0.02*	0.01	0.30***	-0.04***	1.00								
Growth	6	0.01	0.00	0.02*	0.03**	-0.02	1.00							
Size	7	0.01	0.04***	-0.01	-0.05***	0.12***	0.03**	1.00						
Age	8	0.03*	0.03**	0.04***	-0.02	0.17***	-0.05***	0.34***	1.00					
Tan	9	-0.02	0.03**	-0.05***	-0.04***	-0.03**	0.01	0.08***	-0.05***	1.00				
Lev	10	0.05***	0.06***	0.03**	0.01	0.06***	0.06***	0.47***	0.16***	0.17***	1.00			
Dy	11	-0.04***	0.01	-0.10***	-0.08***	-0.08***	-0.01	0.12***	-0.07***	0.14***	-0.04***	1.00		
HHI	12	-0.04***	-0.06***	-0.23***	-0.20***	-0.14***	0.08***	0.27***	-0.18***	0.15***	0.02	0.16***	1.00	
State	13	-0.03**	-0.02	-0.00	0.01	-0.03**	0.07***	0.02	-0.18***	0.18***	0.05***	0.14***	0.23***	1.00

Notes: Variables are defined in Section 3.3. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively.

3.4 Empirical Results

3.4.1 Causality Analysis

According to my hypothesis, institutional investors can influence a firm's dividend smoothing policy, i.e., encourage dividend smoothing. Firms can use dividend smoothing in one of two ways. They can use it either to signal (if the signal continues, then all is well, but if the signal stops or changes, something important is happening) or to confuse (the signal is in-accurate, i.e., garbling). In short, dividend smoothing firms are either signallers or garblers. Different kinds of signals have different effects on the information asymmetry between the market and the firms, and thus on the value of the firms.

Therefore, the causality is expected to run from institutional ownership to dividend smoothing and firm value. In this section, I perform a panel vector autoregression (PVAR) among institutional ownership, dividend smoothing, and value changes to check the exact causal relationship. Note that the following analysis only uses the main dividend smoothing measure (DS), not total payout smoothing measure (TS) or the alternative dividend smoothing measure (DS_{alt}).

The PVAR model is essentially a dynamic panel model with fixed effects. Researchers usually know the exact causality based on theoretical or empirical evidence for studies using a system GMM model (Arellano & Bover, 1995; Blundell & Bond, 1998). However, if there is no economic theory (or theories that are still being debated) to determine a clear causal relationship, especially if multiple factors are interrelated, e.g., smoothing, value and institutional ownership, then PVAR is a sensible choice because it examines the dynamic interaction between multiple variables without a theoretical basis.

Table 3.4.1 and Table 3.4.2 present the forecast-error variance decomposition (FEVD) from a PVAR system among dividend smoothing, changes in value and institutional ownership in the US. The decomposition values that pass the Granger causality test are shown in bold, indicating that a significant causal relationship has been established. Positive and negative signs reflect the direction of the impact, according to the impulse response function (IRF). IRF diagrams are shown in Appendix B.2 on page 154. IRF diagrams reflect the dynamic impact on other variables in the VAR system when one variable is subjected to an "external shock". The impulse responses are plotted based on the dynamics of these variables over ten years following the impact.

Table 3.4.1: Forecast-Error Variance Decomposition (US)

	Entire Base	Monitor	Colluder
Variation in institutional ownership due to (in %, 10 period ahead):			
Dividend Smoothing	0.1	**+ 0.2***	0.1
Changes in Value	0.1	**+ 0.3***	0
Institutional Ownership	99.9	99.5	99.9
Variation in dividend smoothing due to (in %, 10 period ahead):			
Institutional Ownership	**+ 9.2***	**+ 6.7***	**+ 1.7***
Changes in Value	0.1	0.2	0.2
Dividend Smoothing	90.7	93.1	98.1
Variation in changes in value due to (in %, 10 period ahead):			
Institutional Ownership	**+ 11.7***	**+ 35.2***	**+ 1.7***
Dividend Smoothing	**- 0.5***	**- 5.1***	0
Changes in Value	87.7	59.8	98.3

Notes: This table presents the forecast-error variance decomposition of a panel vector autoregressive system between dividend smoothing, value changes, and US's institutional ownership. Institutional ownership is further classified into supervisors and colluders according to the nature of their business. According to the impulse response graphs, the decomposition values that passed the Granger causality test are denoted by *, where the positive and negative signs reflect the direction of the impact. See Table 3.3.1 for variable definition.

The FEVDs should be viewed in conjunction with the IRF diagrams. On page 154 of Appendix B.2, I explain how to interpret the results. Combined with the IRF (in the Appendix) and Granger causality tests (unreported), Table 3.4.1 and Table 3.4.2 summarise the size and direction of the variable that have a significant impact on the system in a decade's time.

The upper panel of Table 3.4.1 shows the sources of the percentage changes in institutional ownership over 10 years. More than 99% of the change in institutional ownership comes from its past self. Although some of the changes in monitor ownership are from changes in firm value and smooth dividends, they are small enough to be negligible (0.2% and 0.3% after ten years). It is safe to say that institutional investors are the exogenous factors of firm value and dividend smoothing policy in the US.

Institutional investors have a positive impact on the use of dividend smoothing. Ten years after the shock, 9.2% of the volatility of dividend smoothing is due to shocks to institutional investors. Monitors explain 6.7% of changes in dividend smoothing after ten years, while colluders explain its 1.7%.

Regardless of which type, institutional investors in the US have positive impacts on firm value, with monitors explaining 35.2% and colluders explaining 1.7% of the total variation in firm value. The firm value increases in response to an institutional ownership shock, while it decreases to dividend smoothing shock.

It can be seen from the top panel of Table 3.4.2 that institutional investors in China, regardless of which type, are neither affected by dividend smoothing policy nor changes in firm value, and their changes are almost entirely dependent on themselves. It also confirms that institutional investors are exogenous variables in this VAR system.

The percentage of variation in dividend smoothing due to changes in institutional investors is 6.4%, of which 5.7% is due to monitors. The IRF diagrams show that both effects are negative. Institutional investors (monitors) positively impact firm value, with 14.6% (15.3%) of the forecast variance of value coming from them.

Table 3.4.2: Forecast-Error Variance Decomposition (China)

	Entire Base	Monitor	Colluder
Variation in institutional ownership due to (in %, 10 period ahead):			
Dividend Smoothing	0	0.1	2
Changes in Value	0.1	0	0
Institutional Ownership	99.9	99.8	98.0
Variation in dividend smoothing due to (in %, 10 period ahead):			
Institutional Ownership	**- 6.4***	**- 5.7***	0.1
Changes in Value	0	0	0.1
Dividend Smoothing	93.6	94.3	99.8
Variation in changes in value due to (in %, 10 period ahead):			
Institutional Ownership	**+ 14.6***	**+ 15.3***	0.3
Dividend Smoothing	0.1	0.1	0.1
Changes in Value	85.3	84.6	99.6

Notes: This table presents the forecast-error variance decomposition of a panel vector autoregressive system between dividend smoothing, value changes, and China's institutional ownership. Institutional ownership is further classified into supervisors and colluders according to the nature of their business. According to the impulse response graphs, the decomposition values that passed the Granger causality test are denoted by *, where the positive and negative signs reflect the direction of the impact. See Table 3.3.1 for variable definition.

The primary purpose of PVAR is to identify the causal relationship among three variables, institutional ownership, dividend smoothing and changes in firm value. The structure of the single equation in the system is simple, i.e., the independent variables are the other two variables in the system. There are neither control variables nor interactions between the other two variables (therefore, one cannot conclude that institutional investors affect firm value through dividend smoothing). In more complex models, the impact of shocks in PVAR may become less significant. Therefore, I use the regression results of dynamic panel models as a benchmark.

The causal relationship summarised in Table 3.4.1 and Table 3.4.2 is that institutional ownership is the most exogenous variable in the system, institutional investors ($Inst$), changes in value ($Value$) and dividend smoothing ($Smooth$), for both countries.

In the US, institutional investors encourage the use of dividend smoothing policies ($Inst \xrightarrow{+} Smooth$), while in China, institutional investors discourage such dividend policies ($Inst \xrightarrow{-} Smooth$). Institutional investors have a positive impact on firm value for both countries ($Inst \xrightarrow{+} Value$). Dividend smoothing has a negative impact on the value of the US firms ($Smooth \xrightarrow{-} Value$) and has no impact on the value of Chinese firms ($Smoot \nrightarrow Value$).

3.4.2 Can Institutional Investors Affect Dividend Smoothing?

To determine whether institutional investors can affect a firm's dividend smoothing policy, I perform three types of regressions of dividend smoothness on institutional ownership and control the firm-specific characteristics, dividend level and ownership concentration. The first type of regression is ordinary least squares (OLS) fixed year- and industry-effects to eliminate the impact of the time-invariant effect. The second type of regression is fixed effects (FE), removing all unobserved time-invariant effects. The third type of regression is based on Arellano and Bover (1995) and Blundell and Bond (1998); they estimate using the generalized system method of moments (GMM). This type of estimation deals with time-varying unobserved variables associated with explanatory variables or residuals. Since the system GMM model can handle the correlation between regressors and residuals better than the OLS and FE models, when there is a conflict between the three models, I trust the regression results of the system GMM model more.

For the convenience of discussion and reference, I merge the main results of Table B.1.1, Table B.1.2, Table B.1.3 and Table B.1.4 into Table 3.4.3 for better display. The exact process is used for the following tables, and each table's specific statistics can be found in the Appendix B.1 on page B.1. *DS* and *TS* are smoothing of dividends and total payout, and the latter is dividends plus stock repurchase. The smoothing measure is calculated using the speed of adjustment, where its alternative is derived from relative volatility. See Section 3.3 for a detailed methodology discussion. *Inst* in the Appendix tables stands for institutional ownership, measured by the percentage of outstanding shares owned by institutional investors, in which mutual funds and independent investment advisors (in the case of China, mutual funds, QFIIs and social security funds) are defined as monitors, while banks and insurance companies are defined as colluders. To include a value of 0 in the analysis, I added 1 to the percentage of outstanding shares and then converted it to a logarithm to reduce the impact of positive skewness.

The positive slope of 0.339 in OLS time-and industry fixed effect regression shows that institutional investors and dividend smoothing are significantly and positively correlated. The result remains valid after removing all time-invariant effects in the FE model, in which case the slope is 0.160, which is significant at the 5% level. Both OLS and FE are static models, which can better capture the time-invariant effect. On the other hand, the dynamic model is superior in solving the endogeneity caused by individual time-varying effects. It takes into account the path-dependent effect of the development of events. It uses the lagged term of the dependent variable as an instrumental variable to explain the current level of the dependent variable. It also rules out the possibility of reverse causality to some extent. The regression coefficient under the system GMM model is 0.141 (significant at the 5% level), which indicates that institutional investors have a robust positive influence on the use of dividend smoothing policy.

Table 3.4.3: Regression Results of Institutional Ownership on Payout Smoothing (US)

		DS			TS	
	OLS	**FE**	**GMM**	**OLS**	**FE**	**GMM**
Ins	**0.339***	**0.160**	**0.141**	**-0.114**	0.028	**0.082***
Ins_M	**0.604***	**0.198**	0.054	**-0.256**	0.002	0.020
Ins_C	**0.648***	0.171	**0.249***	**-0.479***	0.102	**0.243***
Control	Partial	Full		Partial	Full	
		DS_{alt}			TS_{alt}	
	OLS	**FE**	**GMM**	**OLS**	**FE**	**GMM**
Ins	**0.517***	0.150	0.038	**-1.454***	0.398	-0.213
Ins_M	**1.005***	**0.363**	0.376	**-2.966***	0.136	-0.84
Ins_C	**1.244***	0.043	0.160	**-4.457***	0.270	-0.896
Control	Partial	Full		Partial	Full	

Notes: This table reports three types of regression results of institutional ownership on payout smoothing in the US. Ordinary least-squares (OLS) includes year and industry fixed effect, fixed-effect (FE) includes all unobserved time-invariant effects and system generalised method of moments (GMM) is used for dynamic panel analysis. DS and DS_{alt} are dividend smoothing and its alternative measure, respectively. TS and TS_{alt} are total payout smoothing and its alternative measure, respectively. Ins is one plus the percentage of outstanding shares owned by institutional investors, the sum of which is taken as the natural logarithm. Ins_M is institutional ownership of mutual funds and independent investment advisors. Ins_C is institutional ownership of banks and insurance firms. Control variables are $Growth$, $Size$, Age, Tan, Lev, Dy, and HHI are defined in Section 3.3. See Appendix for corresponding Table B.1.1, Table B.1.2, Table B.1.3 and Table B.1.4.

If the slope coefficient is statistically significant at the 10% level, it is indicated in bold. I am particularly concerned with the GMM model as it produces the most vigorous results of all dynamic panel models. The regression results of the static model (OLS and FE) are used to refer to the nature of unobserved individual effects (year- and industry-fixed effect, time-invariant effect, and time-varying effect) affecting the explained variables. Note that the GMM model is better used to describe the impact of short-term fluctuations on the explained variables.

The above discussion pertains to all institutional investors. What happens if all institutional investors are divided into independent institutional investors with monitoring capabilities (monitors) and institutional investors with business relationships with the firms and may seek rent together (colluders)?

The static models show that the monitors are positively associated with dividend smoothing. The coefficient in the GMM model is not significant, which may be due to reverse causality or the possibility that the relationship detected in OLS and FE does not exist after removing the time-invariant effects. From the results of OLS and GMM, the colluders positively influence dividend smoothing policy.

Since 1990, stock repurchases in the US have gradually become mainstream; this development may affect a firm's cash dividend smoothing policy. To check whether the smoothing policy takes stock repurchases into account, I repeat the previous regression but this time using total payout smoothing (*TS*) instead of dividend smoothing (*DS*).

For the entire institutional base, and the colluders, when *TS* is used as a dependent variable, the coefficients of the GMM model are not consistent with the sign of the OLS model. In this case, I only consider the GMM specification because, in the presence of endogeneity, the results of OLS are biased. The GMM results of both groups are marginally consistent with the results using *DS* as the dependent variable. Institutional investors, especially the colluders, positively affect the smoothing decision, including stock repurchases. However, when using alternative measures of *DS* and *TS*, only the results of the OLS models are significant, indicating that the conclusions are sensitive to the choice of smoothing measures.

Table 3.4.4 shows the impact of Chinese institutional investors on the dividend smoothing policy. The only reliable and significant model specification is GMM using DS as the dependent variable in the monitor group. The coefficient of -0.210 at the 5% level means that monitors in China tend to decrease the degree of dividend smoothing. Using the OLS model, the entire base and monitor groups have negative slopes (-1.169 and -1.383) on the alternative smoothing measures at the 1% level.

Table 3.4.4: Regression Results of Institutional Ownership on Payout Smoothing (China)

		DS			DS_{alt}	
	OLS	**FE**	**GMM**	**OLS**	**FE**	**GMM**
Ins	0.018	-0.059	-0.037	**-1.169*** **	-0.029	0.294
Ins_M	-0.027	-0.079	**-0.210** **	**-1.383*** **	-0.140	0.402
Ins_C	0.313	0.074	-0.357	0.562	0.509	0.342
Control	Partial	Full		Partial	Full	

Notes: This table reports three types of regression results of institutional ownership on dividend smoothing in China. Ordinary least-squares (OLS) includes year and industry fixed effect, fixed-effect (FE) includes all unobserved time-invariant effects and system generalised method of moments (GMM) is used for dynamic panel analysis. DS and DS_{alt} are dividend smoothing and its alternative measure, respectively. Ins is one plus the percentage of outstanding shares owned by institutional investors, the sum of which is taken as the natural logarithm. Ins_M is institutional ownership of mutual funds, QFIIs and social security funds. Ins_C is institutional ownership of banks and insurance firms. Control variables are $Growth$, $Size$, Age, Tan, Lev, Dy, HHI and $State$ are defined in Section 3.3. See Appendix for corresponding Table B.1.5 and Table B.1.6.

Table 3.4.1 and Table 3.4.3 are consistent with Hypothesis 1c that institutional investors (monitors) force firms to smooth dividends in the US. Smooth dividends are uninformative, increasing information asymmetry, and institutional ownership substitutes dividend smoothing to control the principal-agent problem.

Table 3.4.2 and Table 3.4.4 are consistent with Hypothesis 2 that China's institutional ownership (monitoring) substitutes dividend smoothing to control the minority-controlling shareholder problem. Dividend smoothing has no value impact.

Results are partly in line with Hypothesis c since rent-seeking oriented dividend smoothing is positively correlated with dependent and pressure-sensitive institutional ownership (colluding). However, I would expect this to be the case in the Chinese stock market, where laws and regulations are weaker. The empirical results show that colluders in the US are incentivised to influence managers to engage in smoothing. Yet, no significant relationship was found between colluders and dividend smoothing in China.

3.4.3 Can Institutional Investors Affect Firm Value through Dividend Smoothing?

This section examines whether institutional investors change a firm's value by influencing dividend policy. Tobin's Q is used as a value measure; however, I use changes in value instead of the valuation ratios themselves. Because most valuation ratios inevitably capture the firm's future growth opportunities, which are embedded in the prices, e.g., book-to-market. In the meantime, the growth opportunity is closely related to the degree of dividend smoothing. Therefore, through the changes in Tobin's Q, I can compare firms' values under different dividend policies while keeping growth opportunities unchanged.

In Table 3.4.5, when dividend smoothing is the only explanatory variable, i.e., the first three columns, dividend smoothing is negatively correlated with firm value in the US. Coefficients (-0.155, -0.143 and -0.256) are significant under OLS, FE and GMM at the conventional level. The conclusion remains valid when replacing dividends with total dividends, i.e., dividends plus stock repurchases. Alternative measures fail to detect any relationship between firm value and dividend (or total payout) smoothing in an endogeneity free manner (GMM models).

The rest of the statistics in this table include the effect of institutional investors, dividend smoothing and the interaction results between institutional investors and smoothing measures on firm value. I generate a dummy (*InsD*) to identify the types of institutional investors (entire base, monitors or colluders). *InsD* is equal to 1 if the firm is held by the corresponding institutional type; otherwise, it is 0.

Note that when the institutional dummy and its interaction terms are added to the regressions, the statistically significant and negative correlation between smoothing measures and firm value becomes insignificant. The main reason for this is caused mainly by the interaction item because they are highly correlated to the main item, which leads to the problem of multicollinearity. In fact, the variance inflation factor (VIF) of the main items without an interaction item are less than 5, and VIF is greater than 5 and less than 10 when interacting (results unreported). However, Balli and Sørensen (2013) believe that multicollinearity caused by interaction terms is not a serious problem. According to the hierarchy principle in statistics, if the model contains interactions, it must contain the main effects even if they are insignificant because there is little risk of containing irrelevant effects (James et al., 2013).

Monitors in the US have a positive impact (0.092 in OLS and 0.223 in GMM) on the firm value at the 10% level by interacting with dividend smoothing. Dividend smoothing has a significant negative relationship with firm value, consistent with the PVAR results in Table 3.4.1. However, this negative relationship

Table 3.4.5: Interaction Results between Institutional Investors and Payout Smoothing on Firm Value (US)

	$\Delta Value$					
	Entire Base (N = 11,936)					
	OLS	**FE**	**GMM**	**OLS**	**FE**	**GMM**
DS	**-0.155****	**-0.143***	**-0.256***	-0.126	-0.260	0.201
$InsD$				**0.283****	-0.188	-0.144
$InsD \cdot DS$				-0.064	0.131	-0.286
TS	**-0.087***	-0.050	**-0.135***	-0.052	**-0.386***	-0.326
$InsD$				0.155	-0.148	-0.214
$InsD \cdot TS$				-0.034	0.368	0.217
DS_{alt}	**-0.069*****	**-0.098*****	-0.024	-0.068	**-0.117***	-0.038
$InsD$				**0.216****	**-0.442***	0.067
$InsD \cdot DS_{alt}$				-0.013	0.023	0.010
TS_{alt}	-0.006	0.005	0.006	-0.046	-0.005	0.020
$InsD$				0.154	-0.366	-0.033
$InsD \cdot TS_{alt}$				0.043	0.011	-0.013
Control	Partial	Full		Partial	Full	
	$\Delta Value$					
	Monitor (N = 7,145)			Colluder (N = 2036)		
	OLS	**FE**	**GMM**	**OLS**	**FE**	**GMM**
DS	**-0.232*****	**-0.191****	-0.137	**-0.147****	-0.120	-0.070
$InsD$	0.394	-0.161	0.106	**1.333*****	**1.236****	**1.534***
$InsD \cdot DS$	**0.092***	0.082	**0.223***	**-0.265*****	**-0.222*****	**-0.207***
TS	-0.084	-0.121	-0.100	-0.066	-0.037	0.025
$InsD$	0.316	-0.261	-0.224	0.516	0.599	-0.440
$InsD \cdot TS$	0.000	0.110	0.016	-0.148	-0.126	-0.036
DS_{alt}	-0.083**	**-0.092****	-0.071	**-0.067*****	**-0.093*****	0.018
$InsD$	**0.537****	-0.130	-0.180	**0.868*****	0.275	-0.601
$InsD \cdot DS_{alt}$	0.009	-0.010	0.066	-0.119*	-0.051	-0.127
TS_{alt}	-0.003	0.009	**0.030***	-0.009	0.003	0.002
$InsD$	0.262	-0.310	-0.381	**0.555***	0.342	-0.586
$InsD \cdot TS_{alt}$	-0.003	-0.006	-0.032	0.030	0.014	-0.018
Control	Partial	Full		Partial	Full	

Notes: This table reports three types of interaction results between institutional investors and payout smoothing on firm value in the US. Ordinary least-squares (OLS) includes year and industry fixed effect, fixed-effect (FE) includes all unobserved time-invariant effects and system generalised method of moments (GMM) is used for dynamic panel analysis. DS and DS_{alt} are dividend smoothing and alternative dividend smoothing, respectively. TS and TS_{alt} are total payout smoothing and alternative total payout smoothing, respectively. $\Delta Value$ is the change in Tobin's Q over five years. $InsD$ is one if an institution holds more than 10% of the company's shares and zero otherwise, where the $InstD$ is subdivided into monitors and colluders. Control variables are $Growth$, $Size$, Age, Tan, Lev, Dy and HHI are defined in Section 3.3. See Appendix for corresponding Table B.1.7, Table B.1.8, Table B.1.9 and Table B.1.10.

is only significant under the static panel models (-0.232 and -0.191). The US colluders positively affect company value, but this effect becomes negative through dividend smoothing.

The regression results in Table 3.4.3 and Table 3.4.5 suggest that institutional investors in the US encourage dividend smoothing, with the colluders particularly prominent. The interaction term between dividend smoothing and colluders is negatively associated with firm value, and it implies ’garbling’ by colluders. The interaction term between dividend smoothing and monitor is positively associated with firm value.

Table 3.4.6: Interaction Results between Institutional Investors and Payout Smoothing on Firm Value (China)

	$\Delta Value$					
	Entire Base (N = 11,936)					
	OLS	**FE**	**GMM**	**OLS**	**FE**	**GMM**
DS	**0.174***	0.138	0.121	**0.271*****	**0.252***	0.008
$InsD$				**4.308*****	**6.827*****	**3.613*****
$InsD \cdot DS$				**-0.344***	**-0.360***	**-0.715***
DS_{alt}	0.026	0.088	-0.083	0.055	0.099*	-0.137
$InsD$				**3.941*****	**6.181*****	**2.521*****
$InsD \cdot DS_{alt}$				-0.034	-0.110	0.083
Control	Partial	Full		Partial	Full	
	$\Delta Value$					
	Monitor (N = 1,575)			Colluder (N = 187)		
	OLS	**FE**	**GMM**	**OLS**	**FE**	**GMM**
DS	**0.213****	0.201	-0.100	**0.188***	0.161	0.174
$InsD$	**4.726*****	**7.544*****	**3.467*****	-0.464	-0.900	4.440
$InsD \cdot DS$	-0.219	-0.284	-0.228	-0.247	-0.427	**-1.613***
DS_{alt}	**0.071***	**0.085***	-0.128	0.035	**0.102***	-0.157
$InsD$	**4.528*****	**6.953*****	**3.007*****	-0.943	**-1.713***	**-4.361****
$InsD \cdot DS_{alt}$	-0.083	-0.097	0.074	**-0.262*****	**-0.318****	0.216
Control	Partial	Full		Partial	Full	

Notes: This table reports three types of interaction results between institutional investors and dividend smoothing on firm value in China. Ordinary least-squares (OLS) includes year and industry fixed effect, fixed-effect (FE) includes all unobserved time-invariant effects and system generalised method of moments (GMM) is used for dynamic panel analysis. DS and DS_{alt} are dividend smoothing and alternative dividend smoothing, respectively. $\Delta Value$ is the change in Tobin’s Q over five years. $InsD$ is one if an institution holds more than 10% of the company’s shares and zero otherwise, where the $InstD$ is subdivided into monitors and colluders. Control variables are $Growth$, $Size$, Age, Tan, Lev, Dy, HHI and $State$ are defined in Section 3.3. See Appendix for corresponding Table B.1.11 and Table B.1.12.

Since the causality runs from the monitor to the dividend smoothing, as shown in Table 3.4.1, the dividend smoothing carries garbling information. A positive relationship between interaction terms and value is more likely to come from the good corporate governance of the monitors. Dividend smoothing is not used as a signalling device when interacting with these two types of institutional investors and therefore had a negative impact on firm value across the entire base. Evidence is consistent with Hypothesis 1c and Hypothesis 3.

Table 3.4.6 shows that there is no relationship between dividend smoothing and firm value in China, at least not in the GMM models. Institutional investors as a whole have a positive impact on firm value, which mainly comes from monitors. However, after interacting with the dividend smoothing, institutional investors hurt firm value (-0.715 at the 10% level) and mainly come from the interaction items of the colluders (-1.613 at the 10% level), consistent with Hypothesis 3.

The monitors positively affect the firm value, and the impact is strong economically and statistically (4.528, 6.953 and 3.007 at the 1% level). The interaction term between monitoring institutional investors and smoothed dividends has no explanatory power for firm value, implying that monitors replace smoothed dividends to control principal-agent problems, consistent with Hypothesis 2.

The conclusions are sensitive to the choice of smoothing measures for both countries. All inferences are mainly from the primary smoothing measure, DS.

3.5 SUMMARY

This chapter examines the relationship between dividend smoothing and different institutional investors and how firm value responds to corresponding dynamics.

If a firm is unlikely to cater to the preferences of institutional investors, then it is likely to signal to investors with a smoothed dividend. Such behaviour reduces information asymmetry between investors and firms, increasing firm value. If institutional investors can influence a firm's dividend policy, then dividend smoothing is not a signal for a firm's underlying health. For example, monitors (mutual funds and independent investment advisers) can force managers to pay smooth dividends; significant colluder holdings (banks and insurance companies) can induce managers to seek rents.

I use a panel vector autoregression (PVAR) model to identify a causal relationship between dividend smoothing, institutions and value. I find that, in both countries, causality runs from institutional ownership to dividend smoothing, meaning that signalling did not work in this case.

I employ static and dynamic panel models to comprehensively study their relationships. Some results are presented in one model but not in the other. I use the results of the dynamic panel as a benchmark because they are statistically more rigorous for a single equation. My findings are sensitive to the smoothing measures I use, and most alternatives are not significant for both countries.

In the US, institutional monitors ensure that firms pay smooth dividends. Monitors control the principal-agent problem, and receiving a smooth dividend is purely their preference and harms firm value. The net effect of dividend smoothing and institutional oversight is positive for value.

In China, institutional monitors replace dividend smoothing to control the minority-controlling shareholder problem. In this case, dividend smoothing has no value impact on the firm, and the increase in firm value reflects the positive institutional influence from monitors.

The interaction term between colluders and dividend smoothing is negatively related to firm value in both countries. This means that when the institutional holdings from the colluders are high, the manager pays a smooth dividend for his own benefit. As a result, the firm value decreases.

There are two limitations in this chapter. First, I try to distinguish between the two dividend smoothing strategies and their subsequent impact on value by identifying potential users of the strategies. Different types of institutional investors largely depend on the established literature, and any alteration of the definitions may hinder the capture of institutional investors' motivations to influence dividend smoothing policy.

Second, although I use the within-firm changes in the value of 5 years to control the potential growth implied in the valuation ratios, the life cycle of firms varies. The growth profile of a new firm is undoubtedly different from that of a mature firm. Future studies may consider controlling the life cycle of firms to use valuation ratios or consider the cost of capital as a proxy for value.

APPENDIX B

SUPPLEMENTARY INFORMATION FOR CHAPTER 3

B.1 STATIC AND DYNAMIC PANEL ANALYSIS

Table B.1.1, Table B.1.2, Table B.1.3 and Table B.1.4 represent the main regression results of payout smoothing on the US institutional ownership, corresponding to Table 3.4.3. Table B.1.5 and Table B.1.6 represent the main regression results of payout smoothing on Chinese institutional ownership, corresponding to Table 3.4.4. Table B.1.7, Table B.1.8, Table B.1.9 and Table B.1.10 represent the interaction results between payout smoothing and the US institutional ownership on firm value, corresponding to Table 3.4.5. Table B.1.11 and Table B.1.12 represent the interaction results between payout smoothing and Chinese institutional ownership on firm value, corresponding to Table 3.4.6.

Table B.1.1: Regressions of Dividend Smoothing on Institutional Holdings (United States)

	Dividend Smoothing								
	Entire Base			Monitor			Colluder		
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
Inst	**0.339*****	**0.160****	**0.141****	**0.604*****	**0.198****	0.054	**0.648*****	0.171	**0.249***
	(0.00)	(0.02)	(0.01)	(0.00)	(0.02)	(0.35)	(0.00)	(0.23)	(0.06)
Growth	-0.020	-0.011	0.007	-0.017	-0.012	0.051**	-0.015	-0.011	0.006
	(0.17)	(0.28)	(0.80)	(0.30)	(0.27)	(0.03)	(0.37)	(0.28)	(0.83)
Size	**0.013*****	**0.044*****	0.011	**0.011****	**0.046*****	0.002	0.004	**0.047*****	-0.012
	(0.01)	(0.01)	(0.21)	(0.04)	(0.01)	(0.66)	(0.46)	(0.01)	(0.50)
Age	-0.003	-0.087	-0.077	0.013	-0.087	-0.013	0.002	-0.088	-0.010
	(0.88)	(0.18)	(0.10)	(0.49)	(0.20)	(0.45)	(0.93)	(0.22)	(0.88)
Tan	0.011	-0.038	-0.102	0.004	-0.032	-0.020	-0.004	-0.044	0.011
	(0.83)	(0.64)	(0.25)	(0.93)	(0.69)	(0.70)	(0.93)	(0.59)	(0.94)
Lev	**0.120****	**0.100***	-0.042	**0.138****	**0.097***	0.010	**0.151*****	**0.098***	0.171
	(0.03)	(0.09)	(0.60)	(0.01)	(0.10)	(0.81)	(0.01)	(0.10)	(0.18)
Dy	0.449	0.164	0.382	0.322	0.146	0.127	0.106	0.140	0.407
	(0.23)	(0.52)	(0.32)	(0.37)	(0.56)	(0.59)	(0.76)	(0.58)	(0.39)
HHI	0.267***	0.079	0.117	0.105	0.053	0.057	0.047	0.055	0.179
	(0.00)	(0.22)	(0.37)	(0.21)	(0.41)	(0.22)	(0.59)	(0.40)	(0.26)
DS_{t-1}			**0.856*****			**0.870*****			**0.846*****
			(0.00)			(0.00)			(0.00)
No. Obs.	11508	11508	11424	11508	11508	11424	11508	11508	11424
No. Firms	875	875	873	875	875	873	875	875	873
No. Instruments			693			802			631
AR(1)			0.000			0.000			0.000
AR(2)			0.684			0.681			0.687
Hansen			0.307			0.321			0.229

Notes: This table presents the regression results of dividend smoothing on institutional holdings, i.e., entire base, monitors and colluders. Ordinary least-squares (OLS) regression includes year and industry fixed effects. Fixed-effect (FE) regression includes all unobserved time-invariant effects. Rogers standard errors adjusted for firm clustering are reported in parentheses for both models. System generalised method of moments (GMM) is used for dynamic panel analysis, Windmeijer-corrected cluster–robust errors are reported in parentheses. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1998 to 2018. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 3.3 for details in model construction and variable definition.

Table B.1.2: Regressions of Alternative Dividend Smoothing on Institutional Holdings (United States)

	Alternative Dividend Smoothing								
	Entire Base			Monitor			Colluder		
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
Inst	**0.517*****	0.150	0.038	**1.005*****	**0.363****	0.376	**1.244*****	0.043	0.160
	(0.00)	(0.29)	(0.92)	(0.00)	(0.04)	(0.31)	(0.00)	(0.87)	(0.72)
Growth	-0.032	0.001	-0.057	-0.027	0.000	-0.077	-0.023	0.001	-0.117
	(0.28)	(0.97)	(0.57)	(0.39)	(1.00)	(0.43)	(0.45)	(0.96)	(0.22)
Size	**0.019***	0.023	**0.195****	0.016	0.023	0.128	0.004	0.026	0.139
	(0.07)	(0.53)	(0.03)	(0.13)	(0.53)	(0.15)	(0.69)	(0.47)	(0.13)
Age	0.059	0.075	1.803	**0.081****	0.078	1.509	0.057	0.075	0.606
	(0.11)	(0.71)	(0.65)	(0.03)	(0.70)	(0.54)	(0.13)	(0.71)	(0.84)
Tan	0.089	**0.397****	-0.136	0.080	**0.411****	-0.041	0.067	**0.392****	0.006
	(0.30)	(0.02)	(0.79)	(0.35)	(0.02)	(0.94)	(0.44)	(0.03)	(0.99)
Lev	**0.376*****	0.173	-0.128	**0.398*****	0.170	-0.048	**0.413*****	0.169	-0.096
	(0.00)	(0.17)	(0.61)	(0.00)	(0.18)	(0.83)	(0.00)	(0.18)	(0.64)
Dy	-0.170	-0.459	-0.850	-0.363	-0.478	-1.107	-0.687	-0.491	-0.695
	(0.82)	(0.46)	(0.57)	(0.62)	(0.45)	(0.44)	(0.34)	(0.43)	(0.64)
HHI	0.302*	0.069	0.252	0.084	0.047	0.304	0.013	0.045	0.203
	(0.07)	(0.58)	(0.21)	(0.63)	(0.70)	(0.13)	(0.94)	(0.72)	(0.31)
$DS_{alt,t-1}$			**0.822*****			**0.821*****			**0.820*****
			(0.00)			(0.00)			(0.00)
No. Obs.	11516	11516	11458	11516	11516	11458	11516	11516	11458
No. Firms	875	875	875	875	875	875	875	875	875
No. Instruments			209			209			209
AR(1)			0.000			0.000			0.000
AR(2)			0.781			0.758			0.801
Hansen			0.292			0.341			0.370

Notes: This table presents the regression results of alternative dividend smoothing on institutional holdings, i.e., entire base, monitors and colluders. Ordinary least-squares (OLS) regression includes year and industry fixed effects. Fixed-effect (FE) regression includes all unobserved time-invariant effects. Rogers standard errors adjusted for firm clustering are reported in parentheses for both models. System generalised method of moments (GMM) is used for dynamic panel analysis, Windmeijer-corrected cluster–robust errors are reported in parentheses. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1998 to 2018. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 3.3 for details in model construction and variable definition.

Table B.1.3: Regressions of Total Payout Smoothing on Institutional Holdings (United States)

	Total Payout Smoothing								
	Entire Base			Monitor			Colluder		
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
Inst	**-0.114****	0.028	**0.082***	**-0.256****	0.002	0.020	**-0.479*****	0.102	**0.243***
	(0.05)	(0.75)	(0.05)	(0.03)	(0.98)	(0.78)	(0.01)	(0.54)	(0.09)
Growth	**0.033***	0.010	-0.004	**0.033***	0.011	0.013	**0.032***	0.010	-0.022
	(0.07)	(0.42)	(0.88)	(0.07)	(0.41)	(0.58)	(0.08)	(0.42)	(0.44)
Size	-0.005	0.020	-0.001	-0.004	0.021	0.002	-0.002	0.020	-0.002
	(0.50)	(0.38)	(0.86)	(0.53)	(0.36)	(0.69)	(0.82)	(0.38)	(0.75)
Age	0.017	0.105	**-0.046****	0.013	0.105	-0.032	0.024	0.105	**-0.052****
	(0.49)	(0.21)	(0.03)	(0.61)	(0.21)	(0.13)	(0.34)	(0.21)	(0.02)
Tan	0.057	0.163	-0.032	0.057	0.162	-0.012	0.059	0.161	-0.011
	(0.29)	(0.14)	(0.59)	(0.28)	(0.14)	(0.82)	(0.27)	(0.14)	(0.85)
Lev	0.056	0.081	-0.016	0.053	0.081	-0.055	0.054	0.081	-0.015
	(0.38)	(0.28)	(0.79)	(0.40)	(0.29)	(0.33)	(0.40)	(0.28)	(0.81)
Dy	-0.009	0.138	0.388	0.015	0.134	0.004	0.064	0.137	0.296
	(0.98)	(0.52)	(0.19)	(0.96)	(0.53)	(0.99)	(0.85)	(0.53)	(0.28)
HHI	0.099	-0.098	-0.065	0.141	-0.103	-0.072	0.129	-0.101	-0.080
	(0.32)	(0.20)	(0.34)	(0.10)	(0.17)	(0.13)	(0.13)	(0.18)	(0.24)
TS_{t-1}			**0.665*****			**0.677*****			**0.673*****
			(0.00)			(0.00)			(0.00)
TS_{t-2}			**0.218*****			**0.223*****			**0.223*****
			(0.00)			(0.00)			(0.00)
No. Obs	9439	9439	8028	9439	9439	8028	9439	9439	8028
No. Firms	807	807	788	807	807	788	807	807	788
No. Instruments			658			667			658
AR(1)			0.000			0.000			0.000
AR(2)			0.024			0.025			0.027
AR(3)			0.525			0.502			0.562
Hansen			0.576			0.528			0.381

Notes: This table presents the regression results of total payout smoothing on institutional holdings, i.e., entire base, monitors and colluders. Ordinary least-squares (OLS) regression includes year and industry fixed effects. Fixed-effect (FE) regression includes all unobserved time-invariant effects. Rogers standard errors adjusted for firm clustering are reported in parentheses for both models. System generalised method of moments (GMM) is used for dynamic panel analysis, Windmeijer-corrected cluster–robust errors are reported in parentheses. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1998 to 2018. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 3.3 for details in model construction and variable definition.

Table B.1.4: Regressions of Alternative Total Payout Smoothing on Institutional Holdings (United States)

	Total Payout Smoothing								
	Entire Base			Monitor			Colluder		
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
Inst	**-1.454*****	0.398	-0.213	**-2.966*****	0.136	-0.84	**-4.457*****	0.270	-0.896
	(0.00)	(0.50)	(0.59)	0	-0.88	-0.4	(0.00)	(0.81)	(0.43)
Growh	0.188	0.117	0.090	0.188	0.117	0.105	0.175	0.117	-0.030
	(0.12)	(0.14)	(0.58)	-0.12	-0.14	-0.71	(0.15)	(0.14)	(0.86)
Size	0.054	0.047	-0.047	**0.062***	0.055	-0.323	**0.094*****	0.054	-0.027
	(0.16)	(0.73)	(0.23)	-0.1	-0.68	-0.29	(0.01)	(0.69)	(0.54)
Age	0.202	0.303	0.153	0.141	0.296	3.03	0.237	0.295	-0.122
	(0.15)	(0.19)	(0.48)	-0.31	-0.16	-0.4	(0.11)	(0.15)	(0.51)
Tan	0.444	0.547	-0.266	0.455	0.539	0.147	0.477	0.530	-0.338
	(0.17)	(0.43)	(0.54)	-0.16	-0.43	-0.93	(0.14)	(0.44)	(0.42)
Lev	0.590	0.415	**1.417*****	0.53	0.411	-0.125	0.505	0.411	**1.013****
	(0.13)	(0.43)	(0.00)	-0.16	-0.44	-0.87	(0.19)	(0.44)	(0.01)
Dy	-2.678	-2.151	1.074	-2.178	-2.225	0.278	-1.438	-2.222	2.660
	(0.39)	(0.27)	(0.68)	-0.48	-0.26	-0.96	(0.64)	(0.26)	(0.26)
HHI	-0.196	-0.460	0.517	0.429	-0.531	0.591	0.500	-0.528	0.150
	(0.68)	(0.33)	(0.38)	-0.35	-0.27	-0.35	(0.27)	(0.27)	(0.74)
$TS_{alt,t-1}$			**0.793*****			**0.746*****			**0.834*****
			(0.00)			(0.00)			(0.00)
No. Obs.	9483	9483	9280	9483	9483	9280	9483	9483	9280
No. Firms	815	815	812	815	815	812	815	815	812
No. Instruments			756			209			802
AR(1)			0.000			0.000			0.000
AR(2)			0.661			0.707			0.648
Hansen			0.371			0.331			0.594

Notes:This table presents the regression results of alternative total smoothing on institutional holdings, i.e., entire base, monitors and colluders. Ordinary least-squares (OLS) regression includes year and industry fixed effects. Fixed-effect (FE) regression includes all unobserved time-invariant effects. Rogers standard errors adjusted for firm clustering are reported in parentheses for both models. System generalised method of moments (GMM) is used for dynamic panel analysis, Windmeijer-corrected cluster–robust errors are reported in parentheses. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1998 to 2018. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 3.3 for details in model construction and variable definition.

Table B.1.5: Regressions of Dividend Smoothing on Institutional Holdings (China)

	Dividend Smoothing								
	Entire Base			Monitor			Colluder		
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
Inst	0.018	-0.059	-0.037	-0.027	-0.079	**-0.210****	0.313	0.074	-0.357
	(0.88)	(0.44)	(0.57)	(0.82)	(0.32)	(0.05)	(0.23)	(0.69)	(0.40)
Growth	0.004	-0.003	0.005	0.004	-0.003	-0.000	0.004	-0.003	0.035
	(0.53)	(0.23)	(0.30)	(0.52)	(0.25)	(0.93)	(0.52)	(0.20)	(0.34)
Size	0.010	0.004	**0.018****	0.010	0.003	**-0.078****	0.009	0.003	**-0.113***
	(0.43)	(0.87)	(0.04)	(0.40)	(0.89)	(0.02)	(0.46)	(0.88)	(0.06)
Age	0.027	0.058	-0.009	0.028	0.059	0.008	0.027	0.057	0.019
	(0.27)	(0.18)	(0.43)	(0.26)	(0.17)	(0.73)	(0.28)	(0.18)	(0.68)
Tan	-0.022	-0.062	-0.021	-0.023	-0.063	0.081	-0.024	-0.062	0.001
	(0.73)	(0.37)	(0.68)	(0.72)	(0.37)	(0.37)	(0.70)	(0.37)	(1.00)
Lev	0.016	-0.019	-0.050	0.015	-0.019	0.024	0.017	-0.017	0.041
	(0.81)	(0.80)	(0.35)	(0.83)	(0.81)	(0.81)	(0.80)	(0.82)	(0.78)
Dy	-0.742	**-0.964****	-0.239	-0.762	**-0.973****	-0.387	-0.721	**-0.928****	-1.058
	(0.21)	(0.02)	(0.50)	(0.20)	(0.02)	(0.36)	(0.22)	(0.02)	(0.20)
HHI	-0.077	0.097	-0.110	-0.082	0.097	0.017	-0.070	0.109	-0.240
	(0.44)	(0.41)	(0.17)	(0.41)	(0.41)	(0.91)	(0.48)	(0.36)	(0.50)
State	-0.010	-0.019	0.015	-0.010	-0.019	-0.003	-0.012	-0.019	-0.001
	(0.61)	(0.22)	(0.24)	(0.61)	(0.21)	(0.83)	(0.56)	(0.20)	(0.98)
DS_{t-1}			**0.914*****			**0.743*****			**0.764*****
			(0.00)			(0.00)			(0.00)
No. Obs.	5400	5400	5306	5400	5400	5306	5400	5400	5306
No. Firms	501	501	499	501	501	499	501	501	499
No. Instruments			323			213			191
AR(1)			0.000			0.000			0.000
AR(2)			0.764			0.944			0.733
Hansen			0.374			0.602			0.478

Notes: This table presents the regression results of dividend smoothing on institutional holdings, i.e., entire base, monitors and colluders. Ordinary least-squares (OLS) regression includes year and industry fixed effects. Fixed-effect (FE) regression includes all unobserved time-invariant effects. Rogers standard errors adjusted for firm clustering are reported in parentheses for both models. System generalised method of moments (GMM) is used for dynamic panel analysis, Windmeijer-corrected cluster–robust errors are reported in parentheses. Sample includes all domestic China A-share on CSMAR from 1998 to 2018. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 3.3 for details in model construction and variable definition.

Table B.1.6: Regressions of Alternative Dividend Smoothing on Institutional Holdings (China)

	Alternative Dividend Smoothing								
	Entire Base			Monitor			Colluder		
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
Inst	**-1.169*****	-0.029	0.294	**-1.383*****	-0.140	0.402	0.562	0.509	0.342
	(0.00)	(0.89)	(0.31)	(0.00)	(0.52)	(0.38)	(0.33)	(0.29)	(0.55)
Growth	**0.014****	-0.002	0.010	**0.015****	-0.002	0.013	0.011	-0.002	0.011
	(0.04)	(0.69)	(0.36)	(0.03)	(0.74)	(0.65)	(0.16)	(0.72)	(0.15)
Size	0.033	0.063	0.170	0.033	0.062	**0.313***	0.018	0.060	**0.260***
	(0.18)	(0.19)	(0.23)	(0.18)	(0.20)	(0.08)	(0.48)	(0.22)	(0.06)
Age	0.058	**0.202****	0.024	0.058	**0.205****	-0.029	0.046	**0.203****	0.049
	(0.27)	(0.03)	(0.81)	(0.26)	(0.03)	(0.85)	(0.39)	(0.03)	(0.64)
Tan	0.044	**-0.257***	0.166	0.031	**-0.260***	0.189	0.062	**-0.262***	-0.072
	(0.78)	(0.09)	(0.58)	(0.84)	(0.09)	(0.63)	(0.70)	(0.08)	(0.83)
Lev	0.043	-0.113	-0.022	0.042	-0.113	-0.311	0.084	-0.103	0.016
	(0.78)	(0.48)	(0.94)	(0.79)	(0.47)	(0.30)	(0.61)	(0.52)	(0.96)
Dy	0.440	-0.885	0.218	0.461	-0.940	0.329	1.043	-0.851	0.380
	(0.72)	(0.38)	(0.89)	(0.71)	(0.36)	(0.92)	(0.42)	(0.39)	(0.79)
HHI	**-0.763*****	-0.055	0.165	**-0.756*****	-0.068	0.031	**-0.582****	-0.038	0.152
	(0.00)	(0.84)	(0.76)	(0.00)	(0.80)	(0.98)	(0.01)	(0.89)	(0.78)
State	-0.009	-0.039	0.046	-0.014	-0.039	0.039	-0.017	-0.042	0.021
	(0.84)	(0.26)	(0.26)	(0.75)	(0.26)	(0.55)	(0.72)	(0.22)	(0.60)
$DS_{alt,t-1}$			**0.686*****			**0.659*****			**0.465*****
			(0.00)			(0.00)			(0.00)
$DS_{alt,t-2}$			-0.020			-0.027			**0.150*****
			(0.46)			(0.34)			(0.01)
No. Obs.	5388	5388	4822	5388	5388	4822	5388	5388	4822
No. Firms	501	501	499	501	501	499	501	501	499
No. Instruments			213			204			208
AR(1)			0.000			0.000			0.000
AR(2)			0.019			0.028			0.000
AR(3)			0.423			0.387			0.706
Hansen			0.138			0.122			0.225

Notes: This table presents the regression results of alternative dividend smoothing on institutional holdings, i.e., entire base, monitors and colluders. Ordinary least-squares (OLS) regression includes year and industry fixed effects. Fixed-effect (FE) regression includes all unobserved time-invariant effects. Rogers standard errors adjusted for firm clustering are reported in parentheses for both models. System generalised method of moments (GMM) is used for dynamic panel analysis, Windmeijer-corrected cluster–robust errors are reported in parentheses. Sample includes all domestic China A-share on CSMAR from 1998 to 2018. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 3.3 for details in model construction and variable definition.

Table B.1.7: Regressions of Changes in Value on Dividend Smoothing and Institutional Holdings (United States)

	Changes in Value											
				Entire Base			Monitor			Colluder		
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
DS	**-0.155****	**-0.143***	**-0.256***	-0.126	-0.260	0.201	**-0.232*****	**-0.191****	-0.137	**-0.147****	-0.120	-0.070
	(0.01)	(0.06)	(0.05)	(0.41)	(0.16)	(0.54)	(0.00)	(0.03)	-0.35	(0.01)	(0.11)	(0.57)
InsD				**0.283****	-0.188	-0.144	0.394	-0.161	0.106	**1.333*****	**1.236****	**1.534***
				(0.04)	(0.56)	(0.80)	(0.21)	(0.63)	-0.82	(0.00)	(0.03)	(0.08)
InsD×DS				-0.064	0.131	-0.286	**0.092***	0.082	**0.223***	**-0.256*****	**-0.222*****	**-0.207***
				(0.65)	(0.47)	(0.39)	(0.09)	(0.15)	-0.08	(0.00)	(0.00)	(0.07)
ΔGrowth	**0.829*****	**0.838*****	**1.334*****	**0.838*****	**0.837*****	**1.147*****	**0.832*****	**0.837*****	**1.085*****	**0.839*****	**0.836*****	**1.290*****
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	0	(0.00)	(0.00)	(0.00)
ΔSize	**-1.221*****	**-1.355*****	**-2.560*****	**-1.224*****	**-1.349*****	**-1.758*****	**-1.219*****	**-1.353*****	**-1.804*****	**-1.224*****	**-1.354*****	**-2.123*****
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	0	(0.00)	(0.00)	(0.00)
ΔTan	**-0.683****	**-1.192*****	**-4.710*****	**-0.671****	**-1.195*****	**-3.833*****	**-0.665****	**-1.191*****	**-2.752*****	**-0.688*****	**-1.196*****	**-3.356*****
	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	0	(0.01)	(0.01)	(0.00)
ΔLev	-0.193	-0.112	0.078	-0.202	-0.115	-0.415	-0.209	-0.107	-0.337	-0.213	-0.115	-0.050
	(0.27)	(0.59)	(0.89)	(0.25)	(0.58)	(0.41)	(0.23)	(0.60)	-0.47	(0.22)	(0.57)	(0.92)
ΔDy	**-6.668*****	**-5.845*****	**-5.501***	**-6.340*****	**-5.869*****	**-6.633****	**-6.318*****	**-5.839*****	**-5.034***	**-6.345*****	**-5.787*****	**-6.137****
	(0.00)	(0.00)	(0.07)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	-0.08	(0.00)	(0.00)	(0.02)
Dy_{t-5}	-1.120	-0.522	7.164	-0.413	-0.581	1.552	-0.423	-0.487	9.326	-0.545	-0.489	8.075
	(0.26)	(0.79)	(0.16)	(0.70)	(0.77)	(0.75)	(0.69)	(0.80)	-0.11	(0.60)	(0.80)	(0.16)
$Size_{t-5}$	**-0.051*****	**-0.211****	0.030	**-0.050*****	**-0.206****	-0.014	**-0.047*****	**-0.206****	0.015	**-0.053*****	**-0.208****	-0.014
	(0.00)	(0.01)	(0.63)	(0.00)	(0.01)	(0.79)	(0.00)	(0.01)	-0.84	(0.00)	(0.01)	(0.82)
$\Delta Value_{t-1}$			**0.517*****			**0.517*****			**0.508*****			**0.507*****
			(0.00)			(0.00)			(0.00)			(0.00)
No. Obs.	8349	8349	7924	8349	8349	7924	8349	8349	7924	8349	8349	7924
No. Firms	827	827	819	827	827	819	827	827	819	827	827	819
No. Instruments			760			757			757			757
AR(1)			0.000			0.000			0.000			0.000
AR(2)			0.951			0.892			0.947			0.927
Hansen			0.765			0.697			0.253			0.316

Notes: This table presents the regression results of changes in value on the interaction term of dividend smoothing and institutional holdings, i.e., entire base, monitors and colluders. Ordinary least-squares (OLS) regression includes year and industry fixed effects. Fixed-effect (FE) regression includes all unobserved time-invariant effects. Rogers standard errors adjusted for firm clustering are reported in parentheses for both models. System generalised method of moments (GMM) is used for dynamic panel analysis, Windmeijer-corrected cluster–robust errors are reported in parentheses. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1998 to 2018. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 3.3 for details in model construction and variable definition.

Table B.1.8: Regressions of Changes in Value on Alternative Dividend Smoothing and Institutional Holdings (United States)

	Changes in Value											
				Entire Base			Monitor			Colluder		
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
DS_{alt}	**-0.069*****	**-0.098*****	-0.024	-0.068	**-0.117***	-0.038	**-0.083****	**-0.092****	-0.071	**-0.067*****	**-0.093*****	0.018
	(0.00)	(0.00)	(0.52)	(0.25)	(0.05)	(0.66)	(0.02)	(0.03)	(0.27)	(0.00)	(0.01)	(0.63)
InsD				**0.216****	**-0.442***	0.067	**0.537****	-0.130	-0.180	**0.868*****	0.275	-0.601
				(0.05)	(0.07)	(0.79)	(0.04)	(0.68)	(0.64)	(0.01)	(0.62)	(0.31)
$InsD \times DS_{alt}$				-0.013	0.023	0.010	0.009	-0.010	0.066	**-0.119***	-0.051	-0.127
				(0.84)	(0.75)	(0.92)	(0.84)	(0.83)	(0.39)	(0.05)	(0.45)	(0.23)
ΔGrowth	**0.832*****	**0.859*****	**0.632*****	**0.840*****	**0.857*****	**0.634*****	**0.836*****	**0.860*****	**0.569*****	**0.840*****	**0.859*****	**0.252*****
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ΔSize	**-1.248*****	**-1.429*****	**-1.184*****	**-1.250*****	**-1.419*****	**-1.125*****	**-1.246*****	**-1.429*****	**-1.105*****	**-1.252*****	**-1.430*****	**-0.724*****
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ΔTan	**-0.666****	**-1.196*****	**-1.247*****	**-0.657****	**-1.207*****	**-1.366*****	**-0.652****	**-1.197*****	**-1.542*****	**-0.664****	**-1.195*****	**-1.388*****
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
ΔLev	-0.180	-0.165	0.002	-0.189	-0.174	-0.150	-0.194	-0.165	0.066	-0.189	-0.164	0.163
	(0.31)	(0.40)	(0.99)	(0.29)	(0.38)	(0.57)	(0.27)	(0.40)	(0.79)	(0.29)	(0.41)	(0.47)
ΔDy	**-8.948*****	**-8.579*****	**-9.730*****	**-8.616*****	**-8.692*****	**-11.087*****	**-8.617*****	**-8.590*****	**-10.266*****	**-8.715*****	**-8.569*****	**-8.970*****
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Dy_{t-5}	**-2.644****	-2.706	-5.339**	**-1.997***	-2.917	**-6.894*****	**-2.021***	-2.726	**-5.305*****	**-2.271****	-2.714	**-6.630*****
	(0.02)	(0.20)	(0.03)	(0.09)	(0.17)	(0.00)	(0.08)	(0.20)	(0.01)	(0.05)	(0.20)	(0.00)
$Size_{t-5}$	**-0.054*****	**-0.268*****	-0.045	**-0.052*****	**-0.258*****	-0.028	**-0.051*****	**-0.266*****	-0.031	**-0.057*****	**-0.267*****	-0.014
	(0.00)	(0.00)	(0.14)	(0.00)	(0.00)	(0.28)	(0.00)	(0.00)	(0.19)	(0.00)	(0.00)	(0.53)
$\Delta Value_{t-1}$			**0.551*****			**0.559*****			**0.596*****			**0.747*****
			(0.00)			(0.00)			(0.00)			(0.00)
No. Obs.	8363	8363	7912	8363	8363	7912	8363	8363	7912	8363	8363	7912
No. Firms	829	829	819	829	829	819	829	829	819	829	829	819
No. Instruments			681			750			789			648
AR(1)			0.000			0.000			0.000			0.000
AR(2)			0.700			0.681			0.656			0.422
Hansen			0.289			0.180			0.347			0.149

Notes:This table presents the regression results of changes in value on the interaction term of alternative dividend smoothing and institutional holdings, i.e., entire base, monitors and colluders. Ordinary least-squares (OLS) regression includes year and industry fixed effects. Fixed-effect (FE) regression includes all unobserved time-invariant effects. Rogers standard errors adjusted for firm clustering are reported in parentheses for both models. System generalised method of moments (GMM) is used for dynamic panel analysis, Windmeijer-corrected cluster–robust errors are reported in parentheses. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1998 to 2018. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 3.3 for details in model construction and variable definition.

Table B.1.9: Regressions of Changes in Value on Total Payout Smoothing and Institutional Holdings (United States)

	Changes in Value											
				Entire Base			Monitor			Colluder		
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
TS	**-0.087***	-0.050	**-0.135***	-0.052	**-0.385***	-0.321	-0.083	-0.121	-0.093	-0.066	-0.037	0.023
	(0.07)	(0.39)	(0.05)	(0.76)	(0.09)	(0.16)	(0.39)	(0.14)	(0.39)	(0.19)	(0.54)	(0.72)
InsD				0.155	-0.151	-0.230	0.316	-0.272	-0.248	0.507	0.561	-0.515
				(0.29)	(0.66)	(0.21)	(0.35)	(0.41)	(0.43)	(0.15)	(0.33)	(0.44)
InsD×TS				-0.034	0.367	0.220	-0.001	0.109	0.016	-0.146	-0.124	-0.034
				(0.84)	(0.13)	(0.36)	(0.99)	(0.21)	(0.89)	(0.21)	(0.25)	(0.85)
ΔGrowth	**0.767*****	**0.797*****	**0.627*****	**0.773*****	**0.789*****	**0.429*****	**0.771*****	**0.796*****	**0.410*****	**0.771*****	**0.796*****	**0.408*****
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ΔSize	**-1.117*****	**-1.227*****	**-0.993*****	**-1.122*****	**-1.223*****	**-0.695*****	**-1.119*****	**-1.225*****	**-0.683*****	**-1.119*****	**-1.230*****	**-0.783*****
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ΔTan	**-0.696****	**-1.251*****	**-1.270*****	**-0.685****	**-1.267*****	**-1.348*****	**-0.685****	**-1.255*****	**-1.290*****	**-0.692****	**-1.251*****	**-1.172*****
	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)
ΔLev	**-0.529****	**-0.394***	-0.388	**-0.531****	**-0.394***	**-0.454***	**-0.534*****	**-0.386***	-0.354	**-0.528****	**-0.393***	**-0.416***
	(0.01)	(0.09)	(0.12)	(0.01)	(0.09)	(0.08)	(0.01)	(0.09)	(0.15)	(0.01)	(0.09)	(0.10)
ΔDy	**-4.381*****	**-3.714*****	**-4.085****	**-4.191*****	**-3.712*****	**-4.962****	**-4.221*****	**-3.709*****	**-4.122****	**-4.279*****	**-3.693*****	**-5.587****
	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.01)
Dy$_{t-5}$	-0.277	-0.122	**-2.885***	0.126	-0.114	**-4.728****	0.036	-0.093	**-4.360****	-0.097	-0.105	**-4.937*****
	(0.73)	(0.94)	(0.05)	(0.89)	(0.94)	(0.01)	(0.97)	(0.95)	(0.02)	(0.91)	(0.95)	(0.00)
Size$_{t-5}$	**-0.056*****	**-0.190***	-0.006	**-0.056*****	**-0.188***	0.002	**-0.055*****	**-0.186***	0.011	**-0.058*****	**-0.193***	-0.023
	(0.00)	(0.09)	(0.85)	(0.00)	(0.08)	(0.94)	(0.00)	(0.10)	(0.63)	(0.00)	(0.08)	(0.32)
ΔValue$_{t-1}$			**0.616*****			**0.723*****			**0.743*****			**0.735*****
			(0.00)			(0.00)			(0.00)			(0.00)
No. Obs.	6701	6701	6375	6701	6701	6375	6701	6701	6375	6701	6701	6375
No. Firms	738	738	729	738	738	729	738	738	729	738	738	729
No. Instruments			662			676			676			648
AR(1)			0.000			0.000			0.000			0.000
AR(2)			0.558			0.439			0.398			0.435
Hansen			0.293			0.241			0.277			0.393

Notes:This table presents the regression results of changes in value on the interaction term of total payout smoothing and institutional holdings, i.e., entire base, monitors and colluders. Ordinary least-squares (OLS) regression includes year and industry fixed effects. Fixed-effect (FE) regression includes all unobserved time-invariant effects. Rogers standard errors adjusted for firm clustering are reported in parentheses for both models. System generalised method of moments (GMM) is used for dynamic panel analysis, Windmeijer-corrected cluster–robust errors are reported in parentheses. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1998 to 2018. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 3.3 for details in model construction and variable definition.

Table B.1.10: Regressions of Changes in Value on Alternative Total Payout Smoothing and Institutional Holdings (United States)

	Changes in Value											
				Entire Base			Monitor			Colluder		
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
TS_{alt}	-0.006	0.005	0.006	-0.046	-0.005	0.018	-0.003	0.009	**0.030***	-0.009	0.003	0.002
	(0.34)	(0.52)	(0.62)	(0.12)	(0.91)	(0.71)	(0.77)	(0.45)	(0.06)	(0.15)	(0.72)	(0.87)
InsD				0.154	-0.379	-0.038	0.260	-0.321	-0.392	0.547	0.303	-0.579
				(0.15)	(0.13)	(0.86)	(0.30)	(0.32)	(0.24)	(0.10)	(0.60)	(0.32)
InsD$\times TS_{alt}$				0.043	0.011	-0.011	-0.003	-0.006	-0.032	0.030	0.014	-0.018
				(0.16)	(0.82)	(0.83)	(0.79)	(0.64)	(0.12)	(0.11)	(0.46)	(0.50)
ΔGrowth	**0.787*****	**0.833*****	**0.702*****	**0.795*****	**0.833*****	**0.457*****	**0.790*****	**0.836*****	**0.427*****	**0.793*****	**0.832*****	**0.388*****
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ΔSize	**-1.115*****	**-1.275*****	**-1.184*****	**-1.122*****	**-1.266*****	**-0.809*****	**-1.116*****	**-1.274*****	**-0.739*****	**-1.117*****	**-1.276*****	**-0.731*****
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ΔTan	**-0.632****	**-1.200****	**-1.371*****	**-0.649****	**-1.210*****	**-1.078*****	**-0.622****	**-1.202*****	**-0.974*****	**-0.619****	**-1.195****	**-0.914****
	(0.03)	(0.01)	(0.00)	(0.03)	(0.01)	(0.00)	(0.04)	(0.01)	(0.01)	(0.04)	(0.01)	(0.02)
ΔLev	**-0.571*****	**-0.473****	-0.186	**-0.561*****	**-0.476****	-0.186	**-0.574*****	**-0.472****	-0.112	**-0.572*****	**-0.474****	-0.158
	(0.01)	(0.03)	(0.45)	(0.01)	(0.03)	(0.48)	(0.00)	(0.03)	(0.66)	(0.01)	(0.03)	(0.54)
ΔDy	**-6.307*****	**-6.217*****	**-5.369*****	**-6.293*****	**-6.335*****	**-4.624****	**-6.111*****	**-6.231*****	**-3.053***	**-6.214*****	**-6.231*****	**-5.847*****
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.07)	(0.00)	(0.00)	(0.00)
Dy_{t-5}	**-1.699***	-2.648	**-3.011****	-1.520	-2.824	**-4.553*****	-1.383	-2.677	**-3.149****	-1.529	-2.666	**-4.931*****
	(0.08)	(0.15)	(0.04)	(0.16)	(0.12)	(0.00)	(0.18)	(0.15)	(0.03)	(0.13)	(0.15)	(0.00)
$Size_{t-5}$	**-0.053*****	**-0.221****	-0.047	**-0.053*****	**-0.211****	-0.010	**-0.052*****	**-0.215****	0.003	**-0.055*****	**-0.225****	-0.017
	(0.00)	(0.04)	(0.13)	(0.00)	(0.05)	(0.61)	(0.00)	(0.05)	(0.88)	(0.00)	(0.04)	(0.39)
$\Delta Value_{t-1}$			**0.588*****			**0.725*****			**0.744*****			**0.759*****
			(0.00)			(0.00)			(0.00)			(0.00)
No. Obs.	6727	6727	6374	6727	6727	6374	6727	6727	6374	6727	6727	6374
No. Firms	740	740	728	740	740	728	740	740	728	740	740	728
No. Instruments			627			676			676			648
AR(1)			0.000			0.000			0.000			0.000
AR(2)			0.531			0.371			0.344			0.382
Hansen			0.233			0.351			0.344			0.213

Notes:This table presents the regression results of changes in value on the interaction term of alternative total payout smoothing and institutional holdings, i.e., entire base, monitors and colluders. Ordinary least-squares (OLS) regression includes year and industry fixed effects. Fixed-effect (FE) regression includes all unobserved time-invariant effects. Rogers standard errors adjusted for firm clustering are reported in parentheses for both models. System generalised method of moments (GMM) is used for dynamic panel analysis, Windmeijer-corrected cluster–robust errors are reported in parentheses. Sample includes all NYSE, AMEX and NASDAQ stocks on CRSP from January 1998 to 2018. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 3.3 for details in model construction and variable definition.

Table B.1.11: Regressions of Changes in Value on Dividend Smoothing and Institutional Holdings (China)

	Changes in Value											
				Entire Base			Monitor			Colluder		
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
DS	**0.174***	0.138	0.121	**0.271*****	**0.252***	0.008	**0.213****	0.201	-0.100	**0.188***	0.161	0.174
	(0.07)	(0.47)	(0.60)	(0.00)	(0.09)	(0.97)	(0.01)	(0.19)	(0.59)	(0.05)	(0.40)	(0.44)
InsD				**4.308*****	**6.827*****	**3.613*****	**4.726*****	**7.544*****	**3.467*****	-0.464	-0.900	4.440
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.60)	(0.47)	(0.14)
InsD×DS				**-0.344***	**-0.360***	**-0.715***	-0.219	-0.284	-0.228	-0.247	-0.427	**-1.613***
				(0.05)	(0.10)	(0.07)	(0.37)	(0.34)	(0.49)	(0.34)	(0.23)	(0.05)
ΔGrowth	**0.571*****	**0.698*****	**0.351****	**0.487*****	**0.591*****	**0.504*****	**0.467*****	**0.557*****	**0.565*****	**0.569*****	**0.694*****	**0.874*****
	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ΔSize	**-0.968*****	**-1.347*****	**-0.714*****	**-1.045*****	**-1.256*****	**-1.004*****	**-1.031*****	**-1.203*****	**-0.987*****	**-0.959*****	**-1.330*****	**-1.193*****
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ΔTan	**-0.862*****	**-0.849*****	**0.298**	**-0.828*****	**-0.730*****	-0.463	**-0.818*****	**-0.714*****	-0.304	**-0.861*****	**-0.849*****	-0.274
	(0.00)	(0.00)	(0.45)	(0.00)	(0.00)	(0.24)	(0.00)	(0.00)	(0.35)	(0.00)	(0.00)	(0.60)
ΔLev	**-0.925*****	**-0.873*****	-0.165	**-0.588*****	**-0.558****	0.137	**-0.575*****	**-0.573****	0.144	**-0.935*****	**-0.895*****	-0.522
	(0.00)	(0.00)	(0.68)	(0.00)	(0.02)	(0.74)	(0.00)	(0.02)	(0.69)	(0.00)	(0.00)	(0.30)
ΔDy	**-11.655*****	**-11.104*****	**-10.392*****	**-10.267*****	**-7.647*****	**-12.764*****	**-10.181*****	**-7.001*****	**-15.141*****	**-11.718*****	**-11.146*****	**-16.306*****
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Dy_{t-5}	-1.698	-3.320	-2.376	-0.086	0.610	-5.084	-0.266	1.347	-3.651	-1.804	-3.392	-5.203
	(0.44)	(0.31)	(0.59)	(0.97)	(0.84)	(0.26)	(0.90)	(0.65)	(0.49)	(0.41)	(0.30)	(0.47)
$Size_{t-5}$	**-0.075*****	**-0.628*****	0.061	**-0.086*****	**-0.428*****	0.012	**-0.079*****	**-0.363****	-0.062	**-0.073*****	**-0.609*****	-0.043
	(0.00)	(0.00)	(0.41)	(0.00)	(0.01)	(0.86)	(0.00)	(0.02)	(0.32)	(0.00)	(0.00)	(0.46)
State	0.068	0.189*	0.142	0.072	0.132	0.230	0.089	**0.161***	0.183	0.070	**0.195****	0.003
	(0.33)	(0.06)	(0.37)	(0.29)	(0.16)	(0.15)	(0.19)	(0.09)	(0.11)	(0.31)	(0.05)	(0.99)
$\Delta Value_{t-1}$			**0.466*****			**0.451*****			**0.434*****			**0.442*****
			(0.00)			(0.00)			(0.00)			(0.00)
$\Delta Value_{t-2}$						0.016			0.015			
						(0.57)			(0.59)			
No. Obs.	3826	3826	3489	3826	3826	3168	3826	3826	3168	3826	3826	3489
No. Firms	498	498	496	498	498	490	498	498	490	498	498	496
No. Instruments			402			483			500			315
AR(1)			0.000			0.000			0.000			0.000
AR(2)			0.058			0.041			0.041			0.065
AR(3)						0.055			0.056			
Hansen			0.567			0.581			0.475			0.463

Notes:This table presents the regression results of changes in value on the interaction term of dividend smoothing and institutional holdings, i.e., entire base, monitors and colluders. Ordinary least-squares (OLS) regression includes year and industry fixed effects. Fixed-effect (FE) regression includes all unobserved time-invariant effects. Rogers standard errors adjusted for firm clustering are reported in parentheses for both models. System generalised method of moments (GMM) is used for dynamic panel analysis, Windmeijer-corrected cluster–robust errors are reported in parentheses. Sample includes all domestic China A-share on CSMAR from 1998 to 2018. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 3.3 for details in model construction and variable definition.

Table B.1.12: Regressions of Changes in Value on Alternative Dividend Smoothing and Institutional Holdings (China)

	Changes in Value											
				Entire Base			Monitor			Colluder		
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
DS_{alt}	0.026	0.088	-0.083	0.055	**0.099***	-0.137	**0.071***	**0.085***	-0.128	0.035	**0.102***	-0.157
	(0.53)	(0.13)	(0.49)	(0.20)	(0.07)	(0.23)	(0.07)	(0.10)	(0.14)	(0.41)	(0.09)	(0.15)
InsD				**3.941*****	**6.181*****	**2.521*****	**4.528*****	**6.953*****	**3.007*****	-0.943	**-1.713***	**-4.361****
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.15)	(0.07)	(0.05)
$InsD \times DS_{alt}$				-0.034	-0.110	0.083	-0.083	-0.097	0.074	**-0.262*****	**-0.318****	0.216
				(0.60)	(0.13)	(0.58)	(0.35)	(0.28)	(0.66)	(0.01)	(0.04)	(0.61)
ΔGrowth	**0.589*****	**0.658*****	**0.257***	**0.501*****	**0.563*****	**0.338****	**0.477*****	**0.524*****	**0.387****	**0.587*****	**0.648*****	**0.260***
	(0.00)	(0.00)	(0.10)	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.10)
ΔSize	**-0.943*****	**-1.281*****	**-0.712*****	**-1.028*****	**-1.211*****	**-0.830*****	**-1.005*****	**-1.146*****	**-0.867*****	**-0.936*****	**-1.271*****	**-0.707*****
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ΔTan	**-0.820*****	**-0.799*****	**0.439**	**-0.794*****	**-0.730*****	0.553	**-0.775*****	**-0.708*****	0.212	**-0.819*****	**-0.795*****	0.628
	(0.00)	(0.00)	(0.33)	(0.00)	(0.00)	(0.26)	(0.00)	(0.00)	(0.67)	(0.00)	(0.00)	(0.27)
ΔLev	**-0.991*****	**-0.907*****	0.300	**-0.628*****	**-0.569****	0.510	**-0.627*****	**-0.601****	0.613	**-0.997*****	**-0.927*****	0.746
	(0.00)	(0.00)	(0.55)	(0.00)	(0.02)	(0.29)	(0.00)	(0.01)	(0.24)	(0.00)	(0.00)	(0.11)
ΔDy	**-11.356*****	**-10.792*****	**-9.768****	**-9.643*****	**-7.176*****	**-12.244*****	**-9.555*****	**-6.586*****	**-12.582*****	**-11.359*****	**-10.732*****	**-16.011*****
	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Dy_{t-5}	-1.891	-3.085	-4.736	-0.212	0.849	-2.994	-0.369	1.488	-4.386	-1.939	-3.009	-8.812
	(0.42)	(0.35)	(0.39)	(0.93)	(0.78)	(0.56)	(0.88)	(0.62)	(0.41)	(0.42)	(0.36)	(0.10)
$Size_{t-5}$	**-0.068*****	**-0.547*****	0.082	**-0.081*****	**-0.368*****	-0.008	**-0.070*****	**-0.298****	0.015	**-0.066****	**-0.545*****	**0.106***
	(0.01)	(0.00)	(0.22)	(0.00)	(0.01)	(0.91)	(0.01)	(0.03)	(0.83)	(0.01)	(0.00)	(0.09)
State	0.062	**0.186****	0.221	0.063	0.125	**0.327***	0.085	**0.159***	0.297	0.067	**0.198****	**0.313***
	(0.36)	(0.05)	(0.20)	(0.33)	(0.16)	(0.07)	(0.19)	(0.07)	(0.11)	(0.33)	(0.04)	(0.08)
$\Delta Value_{t-1}$			**0.306*****			**0.283*****			**0.295*****			**0.285*****
			(0.00)			(0.00)			(0.00)			(0.00)
$\Delta Value_{t-2}$			**0.121*****			**0.085****			**0.079****			**0.112*****
			(0.00)			(0.02)			(0.03)			(0.00)
$\Delta Value_{t-3}$			0.040			0.006			0.002			0.007
			(0.19)			(0.86)			(0.95)			(0.82)
No. Obs.	3807	3807	2821	3807	3807	2821	3807	3807	2821	3807	3807	2821
No. Firms	497	497	471	497	497	471	497	497	471	497	497	471
No. Instruments			397			332			332			327
AR(1)			0.000			0.000			0			0.000
AR(2)			0.012			0.010			0.01			0.004
AR(3)			0.028			0.018			0.018			0.010
AR(4)			0.385			0.474			0.474			0.526
Hansen			0.335			0.354			0.354			0.430

Notes:This table presents the regression results of changes in value on the interaction term of alternative dividend smoothing and institutional holdings, i.e., entire base, monitors and colluders. Ordinary least-squares (OLS) regression includes year and industry fixed effects. Fixed-effect (FE) regression includes all unobserved time-invariant effects. Rogers standard errors adjusted for firm clustering are reported in parentheses for both models. System generalised method of moments (GMM) is used for dynamic panel analysis, Windmeijer-corrected cluster–robust errors are reported in parentheses. Sample includes all domestic China A-share on CSMAR from 1998 to 2018. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively. See Section 3.3 for details in model construction and variable definition.

B.2 Impulse Response Function Diagrams

Figure B.2.1 to Figure B.2.6 are impulse response function (IRF) diagrams, which serve as supplementary information for the direction of impacts from forecast-error variance decomposition (FEVD) in Tables 3.4.1 and Tables 3.4.2.

The FEVDs should be viewed in conjunction with the IRF diagrams. For example, Figure B.2.1 has 9 small diagrams, each with the title of "IFR of **Impulse Variable** to **Response Variable**" in turn. The three small diagrams in the first column all use Base as the impulse variable to describe the dynamic effects from the Base to Base, Smooth and Value, respectively. The three small diagrams in the last row all use Value as the response variable to describe the dynamic effects from the Base (Monitor and Colluder), Smooth and Value to Value, respectively. Base, Smooth and Value represent entire institutional (monitorial and colluding) ownership, dividend smoothing (DS) and changes in firm value.

I explain the last diagram of the second row in Figure B.2.1 that have passed the Granger causality test as an example, i.e., IRF of Smooth to Value. A shock to a firm's smooth dividend would cause its value to decline, reaching a nadir within three years, and then the effect of the changes in dividend smoothing on firm value gradually diminish over time. This is also consistent with negative coefficient at -0.256 in Table 3.4.5. In Table 3.4.1, even after a decade, a smooth dividend would explain only 0.5% of a firm's value. In other words, a dividend smoothing policy has only a small negative effect on a firm's value.

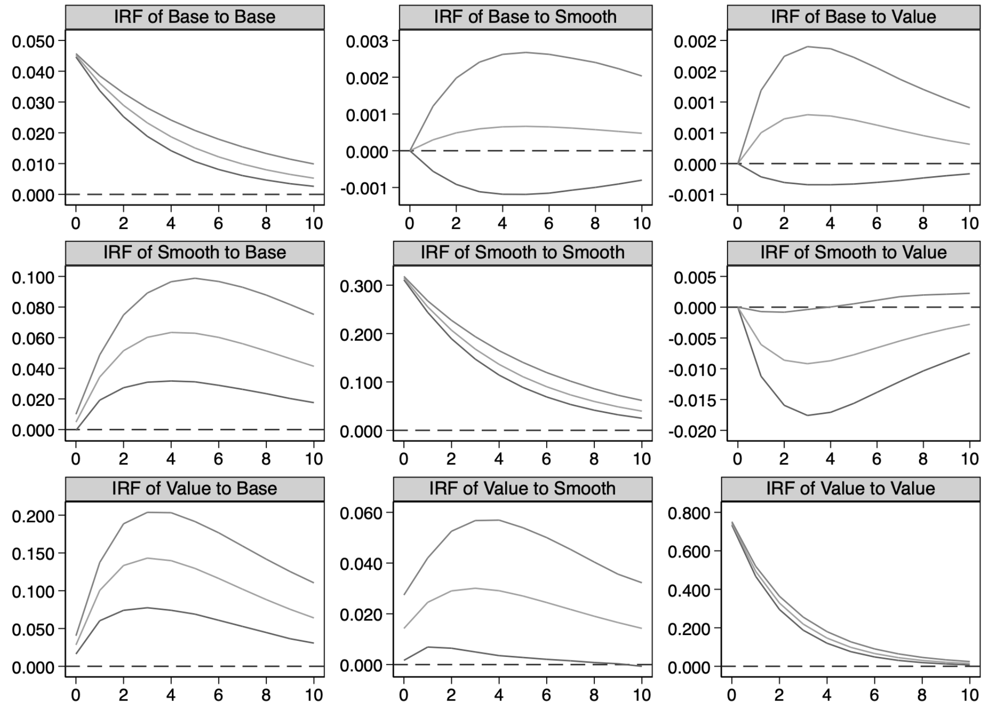

Figure B.2.1: This figure plots the impulse responses for VAR(1) of dividend smoothing (Smooth), changes in value (Value) and overall institutional ownership (Base) in the US. The middle line represents the estimates, and the top and bottom lines indicate the five standard error confidence interval around the estimates. Errors are 5% on each side generated by Monte-Carlo with 1000 repetitions. AIC, BIC and HQIC are used for the selection of VAR lag.

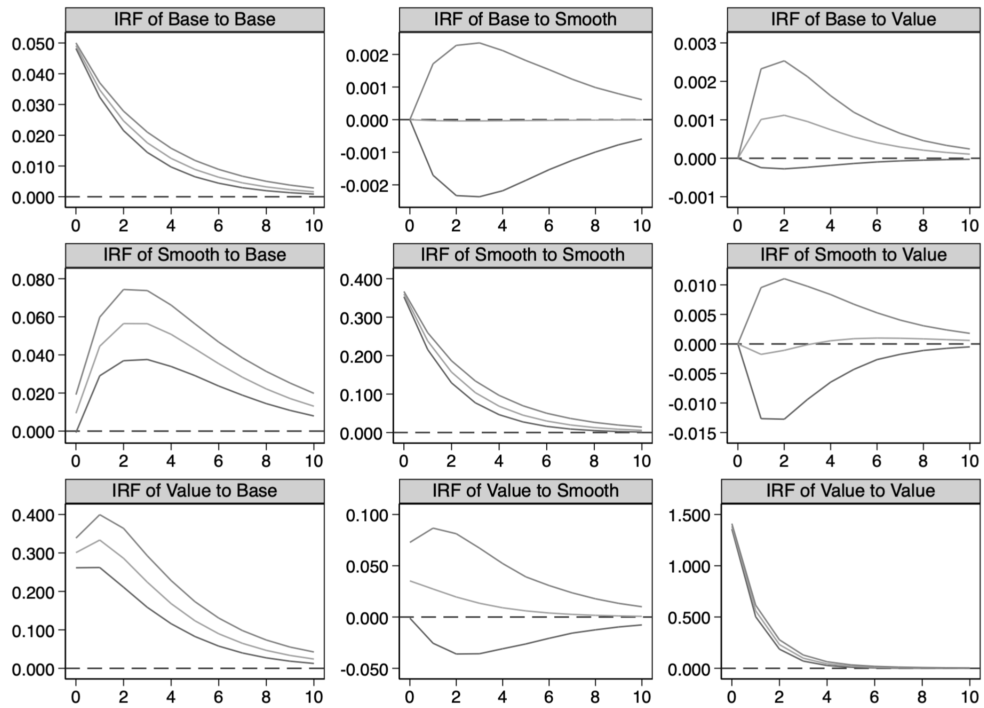

Figure B.2.2: This figure plots the impulse responses for VAR(1) of dividend smoothing (Smooth), changes in value (Value) and overall institutional ownership (Base) in China. The middle line represents the estimates, and the top and bottom lines indicate the five standard error confidence interval around the estimates. Errors are 5% on each side generated by Monte-Carlo with 1000 repetitions. AIC, BIC and HQIC are used for the selection of VAR lag.

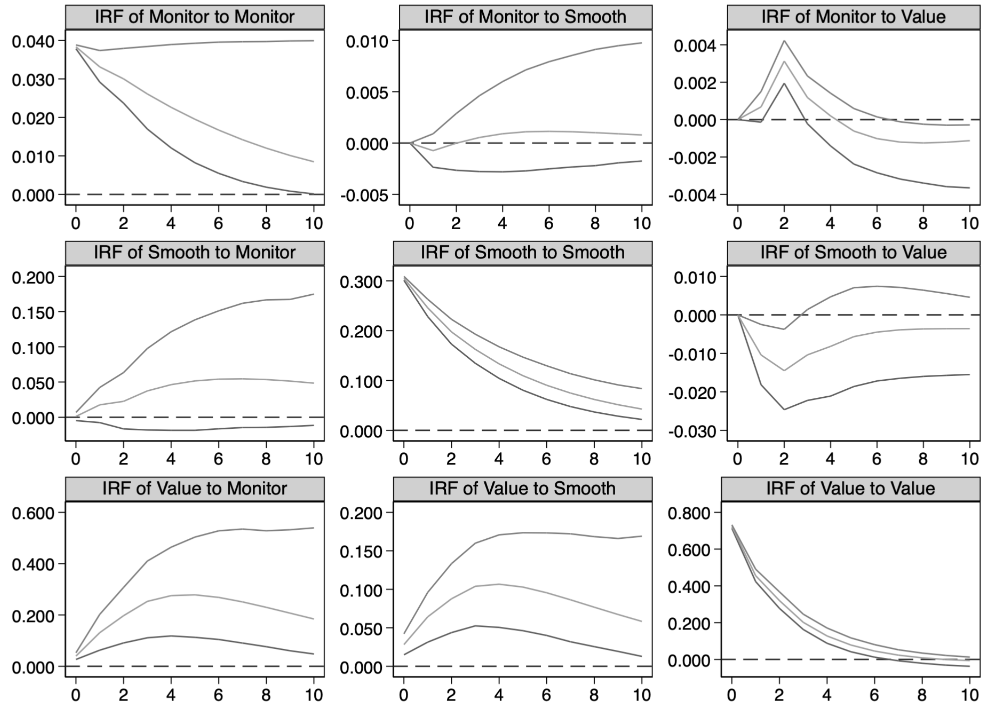

Figure B.2.3: This figure plots the impulse responses for VAR(3) of dividend smoothing (Smooth), changes in value (Value) and monitorial institutional ownership (Monitor) in the US. The middle line represents the estimates, and the top and bottom lines indicate the five standard error confidence interval around the estimates. Errors are 5% on each side generated by Monte-Carlo with 1000 repetitions. AIC, BIC and HQIC are used for the selection of VAR lag.

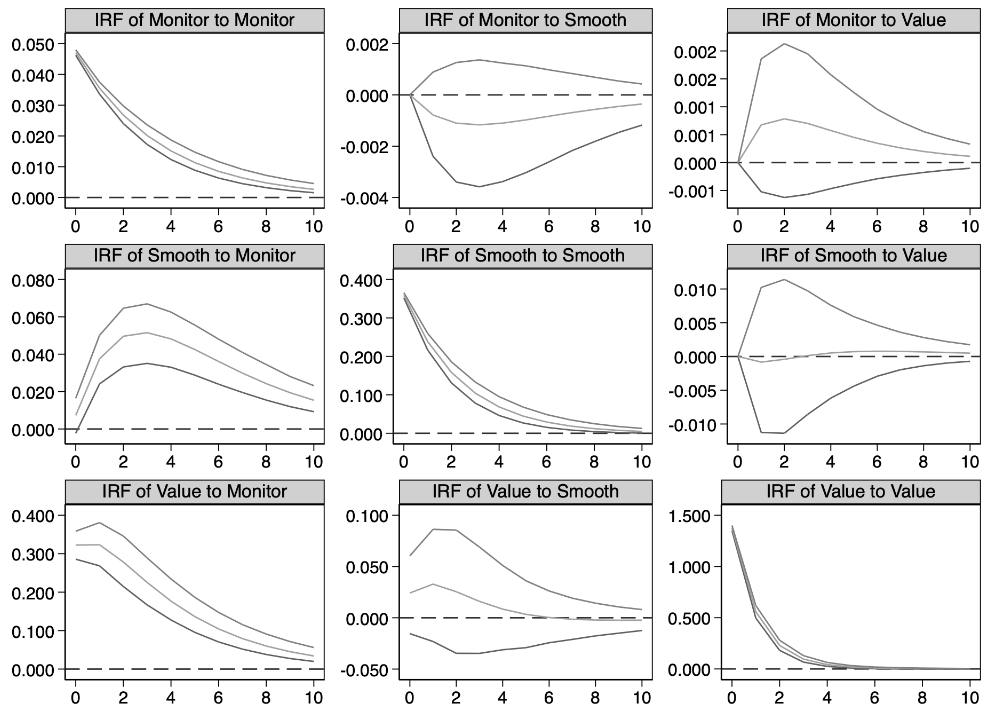

Figure B.2.4: This figure plots the impulse responses for VAR(1) of dividend smoothing (Smooth), changes in value (Value) and monitorial institutional ownership (Monitor) in China. The middle line represents the estimates, and the top and bottom lines indicate the five standard error confidence interval around the estimates. Errors are 5% on each side generated by Monte-Carlo with 1000 repetitions. AIC, BIC and HQIC are used for the selection of VAR lag.

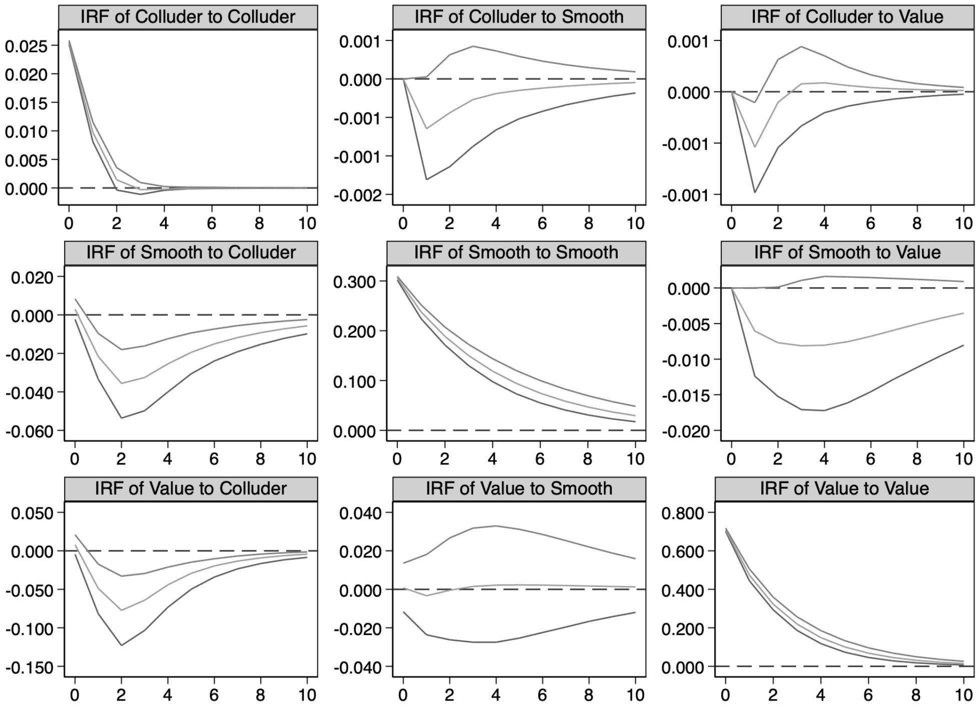

Figure B.2.5: This figure plots the impulse responses for VAR(2) of dividend smoothing (Smooth), changes in value (Value) and colluding institutional ownership (Colluder) in the US. The middle line represents the estimates, and the top and bottom lines indicate the five standard error confidence interval around the estimates. Errors are 5% on each side generated by Monte-Carlo with 1000 repetitions. AIC, BIC and HQIC are used for the selection of VAR lag.

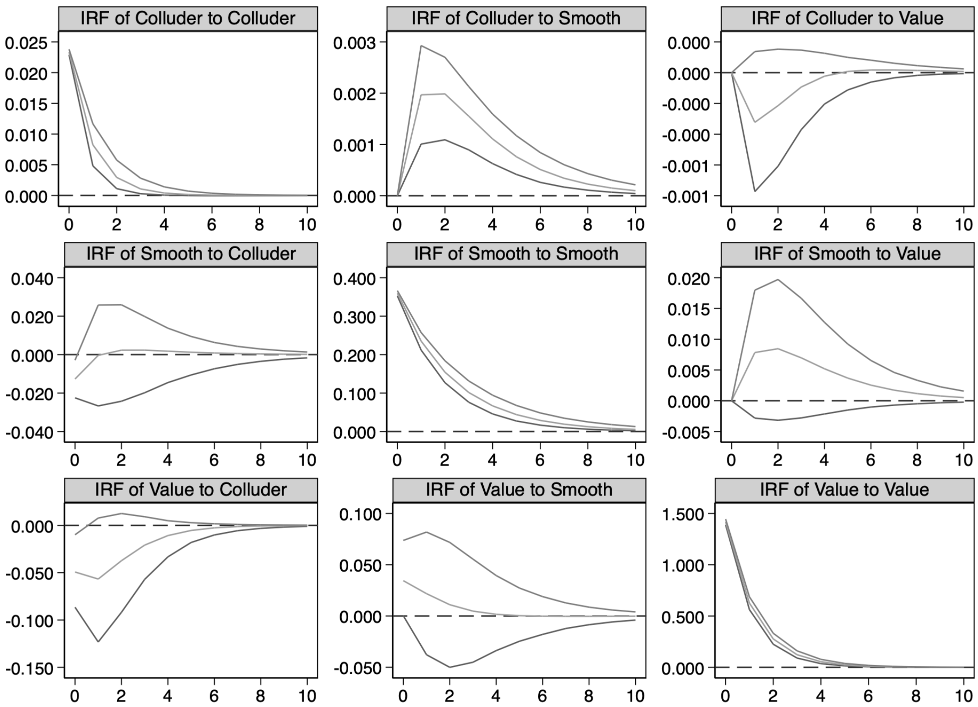

Figure B.2.6: This figure plots the impulse responses for VAR(1) of dividend smoothing (Smooth), changes in value (Value) and colluding institutional ownership (Colluder) in China. The middle line represents the estimates, and the top and bottom lines indicate the five standard error confidence interval around the estimates. Errors are 5% on each side generated by Monte-Carlo with 1000 repetitions. AIC, BIC and HQIC are used for the selection of VAR lag.

CHAPTER 4

WHAT BEHAVIOUR LEADS TO MISPRICING?

SYNOPSIS

1. 'Newswatchers' see new information about fundamentals and ignore information about prices. Such news diffuses slowly through the population of newswatchers, cause prices to underreact in the short run. Since newswatchers ignore the information content of prices, they cannot learn from prices changes either. As long as information has not fully diffused to the market, there will be momentum. I label this type of momentum as underreaction-momentum. It is prevalent in strong cognitive dissonance where a person's behaviours and beliefs do not align. For example, investors receive good news when their investment sentiment is low.

2. 'Informed agents' possess private information. Their overconfidence and self-serving bias made them put too much weight on such information, cause prices to overreact in the short run. As long as overconfidence in information persists, there will be momentum. I label this type of momentum as overreaction-momentum, and the resolution of overconfidence explains longer-term reversal effects. Overreaction-momentum is prevalent in periods of market upturns and optimism when overconfidence is common.

3. 'Momentum traders' see information about prices and ignore public information about fundamentals, thus can profit by trend-chasing. In the case of underreaction-momentum, momentum traders often cause price overshoots its fundamental value. In the case of overreaction-momentum, they further increase the scale of momentum.

4. Momentum does not come from a single source (either an overreaction or an underreaction to information); it can come from both. In the presence of short-selling constraints, momentum is expected from the overreaction to good news and underreaction to bad news. Institutional investors are expected to be either skilful newswatchers who reduce underreaction-momentum or informed agents who increase overreaction-momentum, or both.

4.1 INTRODUCTION

If the stock market is efficient, then prices reflect all available information. If efficiency were true, there would be no consistent winners or losers in the stock market. However, over the past few decades, a great deal of empirical work has demonstrated two types of return phenomena in global stock markets. One is that return shows continuity in the short- and medium-term; the other is that return reverses in the long run.

Two strands of literature attempt to provide explanations for these anomalies. On the one hand, behavioural finance literature attributes this anomaly to a behaviour bias in the way investors interpret information (Barberis et al., 1998; Daniel et al., 1998; Hong & Stein, 1999; Hong et al., 2000; Hong & Stein, 2007; Antoniou et al., 2013; Daniel et al., 2021). On the other hand, the efficient market hypothesis does not reject rational models and suggests that momentum (reversal) profits can be a compensation for risks (Carhart, 1997; Grundy & Martin, 2001; Fama & French, 2012). This chapter focuses on behavioural explanations.

The prevailing explanation of momentum is the theory of gradual diffusion of information due to Hong and Stein (1999). They simulate a market consisting of two groups of agents with bounded rationality. "Newswatchers", who trade based on public information about fundamentals that gradually diffuses among them. They are creating an initial underreaction that generates momentum. "Momentum traders", who ignore information about fundamentals, chase price trends and profit from them. However, their arbitrage efforts can lead to the wrong result, i.e., the positive feedback trading overshoots stock prices, resulting in an overreaction to any news.

Stocks with slower information diffusion are expected to have more momentum. The sophistication of the investor base is an important factor affecting the speed of information diffusion. The more skilled the investor is, the stronger the information gathering ability and corresponding information processing efficiency.

Another important factor affecting the speed of information diffusion is the degree of cognitive dissonance of investors. Antoniou et al. (2013) posit that news contradicting investor sentiment leads to cognitive dissonance, slowing the spread of such news. It means that bad news travels more slowly among losers, especially when investors are optimistic. On the other hand, good news travels more slowly among winners, especially when investors are pessimistic.

Some scholars provide an interesting explanation for the source of momentum. That is, a delayed overreaction can also cause momentum to information, see Daniel et al. (1998); Lee and Swaminathan (2000); Jegadeesh and Titman (2001); Cooper et al. (2004). Daniel et al. (1998) show that overreaction is caused by investor overconfidence and self-attribution bias. Overconfident investors value private information more than public information. Moreover, due to self-attribution bias, their confidence will be further enhanced if public information confirms private information. However, their confidence will only be slightly lower if private information is not confirmed by public information. Cooper et al. (2004) find that investors increase overconfidence and reduce risk aversion in an up-market state, which leads to more significant delayed overreaction. Aggregate overconfidence will increase following market gains, and this growing overconfidence will lead to short-term momentum profits.

What is the source of this momentum? Is it an underreaction to the news or an overreaction to the news?

This problem is not easy to solve in a market without short-selling constraints. Investors' reactions are symmetrical to good and bad news, momentum can come from either overreaction or underreaction, and there is no way to tell the source. Empirical evidence, however, suggests that investors overreact to good news and underreact to bad news in the presence of short-selling constraints.

Some (Hong et al., 2000; Nagel, 2005) argue that short-selling constraints keep negative views away from the market, while others (Miller, 1977; Daniel et al., 2021) argue that such constraints silence pessimists. Either way, the underreaction is only for the bad news. Therefore, if there is a persistent winner momentum, it has to come from the overreaction to good news.

In the same spirit, Daniel et al. (2021) explore the source of momentum in the presence of short-selling constraints. They include "informed agents" into the heterogeneous belief model of Hong and Stein (1999) and exclude momentum traders in their model. Informed investors are overconfident about the accuracy and strength of the private signals they receive and therefore overreact to them. They find no winner momentum; therefore, they reject the assumption that momentum is from overreaction to news.[1] In the meantime, they suggest that reversals are not caused by excessive trading from momentum traders but by the overconfidence of informed agents. Figure 4.1.1 summarises the sources of momentum and reversal effects found in the literature.

[1] The lack of coordination among rational investors is noteworthy. Even if investors are informed and not overconfident, their unsynchronised responses to signals can also lead to overreaction (Abreu & Brunnermeier, 2003).

Cooper et al. (2004) and Daniel et al. (1998) adopt homogeneous belief models in which investors treat good and bad news equally. Therefore, what they observe is the net effect of overreaction and underreaction to information. Empirical evidence of asymmetric market responses to good and bad news in the presence of short-selling constraints suggests a heterogeneous belief framework (Miller, 1977; Hong et al., 2000; Nagel, 2005; Antoniou et al., 2013; Daniel et al., 2021). In the absence of disagreement, the introduction of short-selling constraints would not cause any change in prices or returns. With disagreement, prices are set by the most optimistic investors, while pessimists are sidelined (Miller, 1977). As a result, markets overreact to good news and underreact to bad news.

Literature	**Momentum Source**	**Reversal Source**	**Heterogeneous Belief**
Daniel et al. (1998)	Overreaction	Correct Overreaction	No
Cooper et al. (2004)	Overreaction (Market State)	Correct Overreaction	No
Hong and Stein (1999)	Underreaction from Newswatchers	Correct Overreaction from Momentum Traders	Newswatchers Momentum Traders
Antoniou et al. (2013)	Underreaction from Newswatchers (Cognitive Dissonance)	Correct Overreaction from Momentum Traders	Newswatchers Momentum Traders
Daniel et al. (2021)	Underreaction from Newswatchers	Correct Overreaction from Informed Agents	Newswatchers Informed Agents

Figure 4.1.1: Key Models. Summary of the momentum and reversal sources.

In the Daniel et al. (2021) model, informed overconfident agents overreact to good news from the beginning. The authors believe that in a short-selling constrained market, the winner momentum is unlikely to emerge because the source of momentum, i.e., uninformed newswatchers, cannot "see" the complete information at the time and thus are relatively pessimistic, thus sidelined.

Observations on the Literature

I think there are two reasons why Daniel et al. (2021) did not observe the momentum of winners: one is that the frequency of the momentum strategy they used may be too low to capture it, and the other is that the sample environment is not ideal, i.e., overconfident enough, to trigger winner momentum. Therefore, I believe that delayed overreaction is still a potential source of momentum; see, for example, Daniel et al. (1998); Lee and Swaminathan (2000); Jegadeesh and Titman (2001); Cooper et al. (2004). However, unlike them, I follow the heterogeneous belief model, which implies that the impacts on momentum from good and bad news can differ.

I hypothesise that momentum can come either from overreaction or underreaction to information. More specifically, investors underreact to bad news and overreact to good news, given short-selling constraints. I think the momentum that comes from overreaction to good news is transient and high frequency. It is concentrated in places where investors are most prone to overconfidence: in times of optimistic investor sentiment or up-markets.

My model includes "newswatcher", "momentum trader", and "informed agent". Previous literature defines them as follows: newswatchers only know the publicly available fundamental information; momentum traders only know the past price information; informed agents possess private information and are overconfident because of it.

Newswatchers create momentum due to underreaction to bad news and informed agents create momentum due to overreaction to good news. Momentum traders push winners who have already deviated from fundamentals further away. They follow the price trend, trading the overvalued losers until prices fall below fundamentals. However, in the presence of short-selling constraints, the loser momentum overshoot is limited.

I create short-term and long-term strategies using the methodology of Jegadeesh and Titman (1993). I find that the momentum of short-term strategies is more distributed among winners (overreaction to good news) than losers (underreaction to bad news).

Winner momentum is highlighted in cases prone to overconfidence: in times of optimistic investor sentiment or up-markets. Loser momentum is also pronounced among optimistic investors or up-market due to cognitive dissonance (the nature of the news goes against the sentiment).

In contrast, only winner momentum exists during pessimistic investor sentiment or down-markets. Moreover, it is much weaker than in optimistic investor sentiment or up-markets since it is less subject to overconfidence. Loser momentum is not noticeable since bad news receives in a pessimistic period or down market is less counter-intuitive, i.e. cognitive coherence. As a result, information diffuses faster, creating little momentum.

There is no momentum effect for long-term strategies, i.e., reversal effect only. Most reversal effect comes from winners, which aligns with the empirical evidence, i.e., winner momentum is more pronounced for short-term strategies. In addition, momentum traders are less likely to chase trends to the point where prices exceed fundamentals in the presence of short-selling constraints.

Finally, I categorise institutional investors as skilled newswatchers and/or informed overconfident agents. I aim to identify which role dominates their behaviour overall. I find that institutional investors have no impact on reducing the underreaction of bad news in any case. They overreact to good news in long-term momentum strategies, especially in down-markets or pessimistic periods. In bad times, they seem to value information accuracy and their competence than retail investors, and they are prone to overconfidence and overreacting to good news. Institutional investors also intensify overconfidence about information for short-term strategies, regardless of market states and investor sentiments.

By exploring a return anomaly, i.e., momentum, I find that investors react asymmetrically to information in markets where short-selling is restricted. This inappropriate reaction causes stock prices to deviate from fair values, and therefore, reject the efficient market hypothesis in China.[2]

[2]This chapter rejects the efficient market hypothesis by finding support for the behaviour bias of investors. However, the risk interpretation of the momentum effect is open to discussion.

4.2 LITERATURE REVIEW

4.2.1 The Source of Momentum and Reversal

When is a stock fairly valued? In the weak-form of the efficient market hypothesis, the answer is when stock prices incorporate and reflect information from all past prices.

However, this is often not the case in reality. The average return for a "buy-and-hold" strategy shows a remarkable pattern: well-performing stocks (winners) continue to outperform poorly performing stocks (losers), a phenomenon known as the momentum effect, which disappears after a short period. Subsequently, winners underperform the losers for a more extended period, i.e., reversal, and the better the winner has performed in the past, the stronger the reversal.

The profitability of momentum and reversal strategies has become a notable asset pricing phenomenon since Jegadeesh and Titman (1993) first documented it for the US stock market in 1993. While some scholars have attempted to provide risk-based explanations (Carhart, 1997; Grundy & Martin, 2001; Fama & French, 2012), many have focused on investor behaviour (Barberis et al., 1998; Daniel et al., 1998; Hong & Stein, 1999; Hong et al., 2000; Hong & Stein, 2007; Antoniou et al., 2013; Daniel et al., 2021). I try to find whether the cause of the anomaly is investor behaviour bias by studying investor reactions to information.

1st Momentum Source: Underreaction to News

The prevailing view holds that the momentum effect stems from underreaction to fundamental information, while the root of the reversal effect is an overreaction to fundamental information.

The explanation for underreaction is the theory of gradual information diffusion. Hong and Stein (1999) posit that there are two kinds of boundedly rational market participants. One kind is the "newswatcher", who only sees fundamental public information and ignores prices. Authors argue that momentum arises from the gradual diffusion of information among newswatchers. The slower the diffusion is, the greater the momentum effect. The other kind is the "momentum trader", who only sees the past price information and does not care about fundamentals. Momentum traders chase the stock price trend to profit until the price overshoots its fundamental value, and then the reversal occurs.

If momentum comes from a lack of response to the news as information spreads, an obvious question is what slows the diffusion of information. Mature investors with excellent information collection and processing capabilities are better than naive investors who cannot interpret the information efficiently. Empirical evidence shows that firms with fewer analysts have more significant momentum effects (Hong et al., 2000; Cooper et al., 2004; Nagel, 2005). Inconsistency between what investors think and what they see happening in the market, i.e., cognitive dissonance, is another reason why investors may not understand and disseminate information rapidly. Scholars take investor sentiments (Antoniou et al., 2013) and aggregate cash-flow news status (Celiker et al., 2016) as examples to illustrate that good (bad) news spreads slowly in bad (good) times.

2nd Momentum Source: Overreaction to News

A less popular explanation for the source of momentum, overreaction, suggests that investors have a self-serving bias: they attribute the performance of the winners to their ability to pick stocks and that of the losers to bad luck (Daniel et al., 1998; Lee & Swaminathan, 2000; Jegadeesh & Titman, 2001; Cooper et al., 2004). This bias can lead to overconfidence in the accuracy of the signals received, pushing prices above fundamentals. The momentum created by the delayed overreaction will eventually reverse when prices are corrected in the long run. Findings from Cooper et al. (2004) support this explanation that momentum only appears in up-markets.

Confusion

Antoniou et al. (2013) support the underreaction explanation, while Cooper et al. (2004) support the overreaction explanation. Both provide corresponding scenarios in their explanations: cognitive dissonance slows the diffusion of information, especially for bad news among optimistic investors in the presence of short-selling constraints; the overreaction caused by investors' overconfidence in up-market states produces momentum.

Their findings, however, do not contradict each other. On the one hand, optimistic investors are more likely to be overconfident, thus causing overreaction. On the other hand, bad news in an up-market may trigger cognitive dissonance, which reduces information diffusion speed. Given that their findings support each other's inferences, what exactly is the source of momentum?

4.2.2 Investor Reaction to News in a Short-Selling Constrained Market

This chapter examines the stock market constrained by short-selling as the research background to identify the source of the momentum effect. Without short-selling constraints, the inappropriate response to good news and bad news is the same. Therefore, it is difficult to distinguish between the overreaction and underreaction types of momentum. What we observe is the net effect of these two types.

The gradual diffusion of information refers to investors underreact to both positive and negative news. In the presence of short-selling constraints, the impact of the two kinds of news is asymmetric. Underreaction to good news causes underpricing, while underreaction to bad news causes overpricing. Arbitrage can correct underpricing. Overpricing, however, persists since bad news is held back by short-selling constraints, creating more momentum. In addition, investor cognitive dissonance impedes diffusion because bad news cannot be arbitraged away, and thus momentum is emphasised during optimistic periods.

By the same token, overconfidence is more severe in an environment where bad news is blocked, leading to an overreaction to good news. This situation is magnified in up-markets. To sum up, in a short-selling constrained market, investors tend to overreact to good news and underreact to bad news.

It prepares a good research background to find the source of momentum. For example, if there are persistent winners, the source of this *winner* momentum can only be an overreaction type because the underreacted news is *bad* news.

Note that the existing behavioural literature has very different assumptions about the formation of beliefs. For example, the behaviour models proposed by Barberis et al. (1998) and Daniel et al. (1998) assume that investors have the same beliefs, while models of Hong and Stein (1999) and Daniel et al. (2021) assume that beliefs are heterogeneous.

The introduction of short-selling constraints means that differences between investors will be highlighted. Miller (1977) provides an explanation for underperforming firms that are subject to short-selling constraints. He believes that in the presence of disagreements, prices only reflect the views of optimists because pessimists are sidelined due to short-selling constraints. Empirical evidence also shows that higher heterogeneity among investors implies greater momentum (Hong & Stein, 1999; Verardo, 2009; Hong & Stein, 2007; Daniel et al., 2021).

The types of investors with heterogeneous beliefs in Hong and Stein (1999) are newswatchers and momentum traders, who are uninformed. Daniel et al. (2021) discuss another type of investor: "informed agents".

Model Framework

I augment the Hong and Stein (1999) model with the Daniel et al. (2021) model by including "newswatchers", "momentum traders", and "informed agents". I will use Figure 4.2.1 to illustrate my theoretical framework.

The left part of Figure 4.2.1 (investor reacts to bad news) describes the Hong and Stein (1999) model. Newswatchers underreact to bad news due to gradual information diffusion, creating initial momentum. Momentum traders chase the price trend and eventually overshoot the fundamental value. Note that this overshoot is much less severe than it would have been without short-selling constraints. The momentum or slight loser reversal effect will gradually disappear when the information is ultimately released.

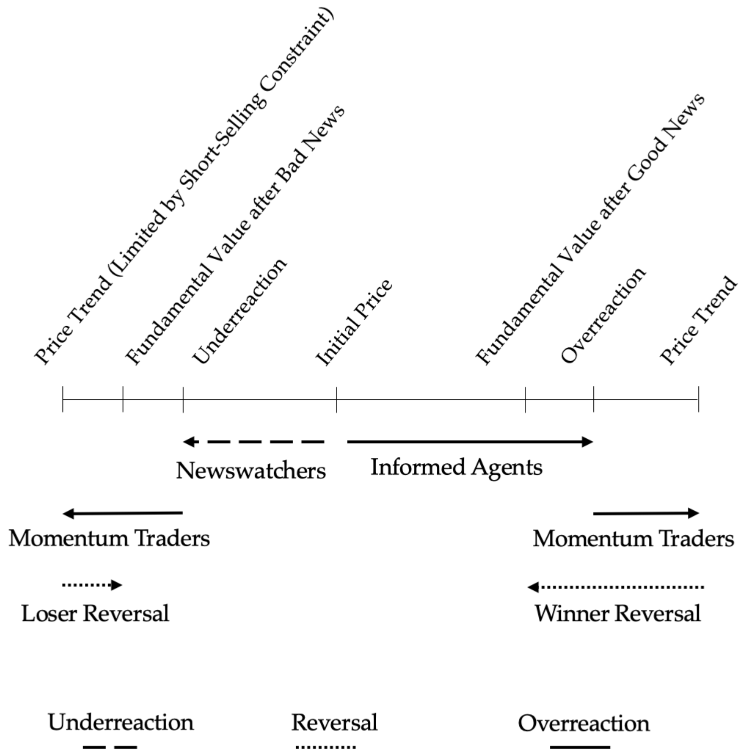

Figure 4.2.1: The formation of momentum (reversal) in the presence of short-selling constraints

Informed agents want to sell short when receiving negative private information, but the constraint prevents them from doing so, i.e., sidelined. Nor will their leanings affect share prices because they are not involved in the market and therefore do not generate momentum. Newswatchers at this moment cannot "see" the complete information, so they are relatively optimistic about this "bad news" comparing to informed agents. Hong and Stein (1999) model successfully explains investor reaction to bad news because informed agents are sidelined; in this case, newswatchers are setting the price.

The right part of Figure 4.2.1 (investor reacts to good news) partially reflects the Daniel et al. (2021) model where informed agents overreact to good news due to overconfidence. However, they do not detect any (winner) momentum based on the empirical evidence; thus, they exclude momentum traders in their model. They find that informed agents immediately made price overshoot the fundamental value. A long-term reversal effect followed until overconfidence fade away over time.

However, unlike Daniel et al. (2021) model, the right part of Figure 4.2.1 includes momentum traders. I think they fail to find the winner momentum because the situation that triggered overconfidence (the source of the winner momentum) is not ideal. Cooper et al. (2004) argue that overconfidence is at its worst when the market rises. Celiker et al. (2016) also find that momentum profits reverse following good cash-flow news, in line with the overconfidence theory. Daniel et al. (2021) empirical research does not explicitly consider the state that most triggers investors' overconfidence, i.e., up-market state.

Newswatchers want to sell short when receiving positive private information, but the constraint prevents them from doing so. Applied the same logic, newswatchers at this moment cannot "see" the complete information, so they are relatively pessimistic about this "bad news" comparing to informed agents. Moreover, investors are sceptical about the ability of others. Those who are yet to receive information believe that the informed have learned little (Luo et al., 2019). As a result, newswatchers fail to infer informed agents' signals from prices; informed agents are setting the price.

Although both sources are possible, their implications are different. Underreaction to good news assumes that the winner is underestimated, while delayed overreaction to good news assumes that the winner is overestimated. This latter winner momentum requires investors to trade with caution, as following trends will push share prices further away from fundamentals. Understanding the applicable theories has essential practical and theoretical significance for strategic trading and equity pricing.

Market Participants with Heterogeneous Beliefs

Based on previous literature, I proposed that certain market status and investor sentiment share similarities. For example, overconfidence is expected to be greater following market gains (Cooper et al., 2004; Celiker et al., 2016). It can be partly attributed to the possibility of more lucky events in the up-market state, leading to overconfidence (Gao et al., 2021). Moreover, the stock market performs well in periods when investor sentiment is optimistic (Chuang & Susmel, 2011). It suggests that overconfidence could be regarded as a psychological bias that reflects optimism.

Table 4.2.1: Market Participants with Heterogeneous Beliefs

	Up - Market / Optimistic Sentiment	
	Bad News	Good News
Newswatchers	**Cognitive Dissonance**	Sidelined Investors
Informed Agents	Sidelined Investors	**Overconfidence**
Momentum Traders	Price Trend Followers (Limited)	Price Trend Followers
	Down - Market / Pessimistic Sentiment	
	Bad News	Good News
Newswatchers	No Cognitive Dissonance	Sidelined Investors
Informed Agents	Sidelined Investors	Weak Overconfidence
Momentum Traders	Price Trend Followers (Limited)	Price trend followers

Notes: This table illustrates how different market participants react to information in the context of different market conditions and investor sentiment. The source of the potential momentum is expressed in bold.

There are two types of market states, and investor sentiment is related to the corresponding state. Regardless of the market state, informed agents are always sidelined when receiving bad news, while newswatchers are sidelined when receiving bad news. Momentum traders are trend followers and thus aggravate momentum. However, their capability is limited towards bad news in the presence of short-sell constraints.

Table 4.2.1 illustrates the reaction of three types of traders under two different market conditions (or sentiments) when they receive good news and bad news.

In an up-market state with bad news, newswatchers are the ones who set the prices. Therefore, the source of momentum is the gradual diffusion of information emphasised by cognitive dissonance. In this case, the loser momentum is more pronounced because it results from underreaction to bad news.

In an up-market state with good news, informed agents are the ones who set the prices. Therefore, the source of momentum is overconfidence. In this case, the winner momentum is more pronounced because it results from overreaction to good news.

In a down-market state, things are less interesting because, in these cases, neither cognitive dissonance nor overconfidence is apparent. Therefore, no significant momentum effect is expected. The same logic applies in terms of investor sentiments.

Hypothesis 1a: In the presence of short-selling constraints, when the market is up or investor sentiment is optimistic, newswatchers' underreaction to bad news can lead to a loser momentum, while informed agents' overreaction to good news can lead to a winner momentum.

Hypothesis 1b: In the presence of short-selling constraints, when the market is down or investor sentiment is pessimistic, neither winner nor loser momentum is significant.

4.2.3 Roles Played by Institutions

If momentum formation is related to the diffusion rate of information among newswatchers, then the heterogeneity of different newswatchers is worth discussing. The speed of information diffusion is closely related to the newswatchers' information collection efficiency and analysis ability. The degree of cognitive dissonance also depends on their level of sophistication.

The existing literature summarises the outstanding stock selection ability of institutional investors, which is mainly reflected in their positive correlation with firm value (Coval & Moskowitz, 2001; Parrino et al., 2003; Gibson et al., 2004; Yuan et al., 2008, 2009; Firth et al., 2010; Altı & Sulaeman, 2012; Firth et al., 2016).

More specifically, Cohen et al. (2002) point out that institutional investors can be momentum traders. However, they would not just follow price trends. They care about the fundamentals reflected in the cash-flow news and only trade momentum that is not out of touch with the fundamentals. Nagel (2005) believes that institutional investors are more sophisticated, and their investment decisions are less affected by sentiments, leading to a lower degree of cognitive dissonance. D'Souza et al. (2010) find that institutional investors disseminate accounting information faster because accounting information can serve as a low-cost monitoring mechanism and provide an information-rich environment for institutional investors to develop trading strategies. Ye (2012) notices that active institutional investors can reduce anomalies in the stock market, thereby improving market efficiency.

As a group of experienced and sophisticated investors, institutions can effectively accelerate the speed of information dissemination through their excellent information collection and processing capabilities, thereby reducing the degree of mispricing. As a result, the strength and length of momentum are also decreased.

Yet more information does not necessarily make a market more efficient. Institutional investors with more information are more likely to be overconfident, tend to overestimate the accuracy of the information and engage in aggressive trading, which further deviates prices from fundamentals (Barber & Odean, 2001; Scheinkman et al., 2003; Daniel & Hirshleifer, 2015).

Moreover, Abreu and Brunnermeier (2003) argue that there can be persistent bubbles in assets even among rational investors, especially if irrational investors lead to mispricing. The successful correction of mispricing requires rational investors to synchronise and coordinate information collectively. Otherwise, overreaction will occur.

This chapter discusses the heterogeneity of beliefs by assigning institutional investors to skilled "newswatchers" and "informed agents". As a sophisticated group of newswatchers, institutional investors are expected to reduce the level of underreaction to information. They are also considered overconfident because they have access to private information, which will lead to an increase in overreaction.

Hypothesis 2a: Institutional investors play a positive role in alleviating the underreaction to bad news (i.e., loser momentum) as skilled and experienced newswatchers.

Hypothesis 2b: Institutional investors play a negative role in exacerbating the overreaction to good news (i.e., winner momentum) as informed and overconfident agents.

4.2.4 Why the Chinese Stock Market?

First, the Chinese stock market is very young (it only appeared in 1990), the laws and regulations to protect investors are flawed, leading to a lot of speculation. Institutional investors were only introduced after 2000, and international investors (Qualified Foreign Institutional Investors) appeared even later (in 2002) with the high entry cost. Retail investors dominate the Chinese stock market. My motivation is that if I want to focus on the non-risk explanation of momentum effects, it makes sense to study a market with a lower degree of rationality and regulation, such as China.

Secondly, the behaviour model I adopt, i.e., Hong and Stein (1999) and Daniel et al. (2021), emphasizes differences between investors, and short-selling constraints amplify the impact of differences in beliefs on prices. The presence of a short-selling constraint makes bad news travel more slowly, resulting in an even more inadequate response to prices. Not allowing short-selling also sidelines pessimistic investors.

Although markets with short-selling constraints have been studied in developed markets, such as the United States, finding appropriate proxies for such constraints has not been easy. Early literature used short interests to measure constraints (Dechow et al., 2001; Figlewski, 1981; Desai et al., 2002), however, Chen et al. (2002) question this proxy, especially for stocks with high short interest but sufficient loan supply. Chen et al. (2002) use mutual fund ownership, while Nagel (2005) used institutional ownership scaled by firm size as proxies for short-selling constraints. They argue that low institutional ownership implies high short-selling costs for the firm. Nevertheless, this proxy presents similar problems, for example, firms have few institutional investors, but very low short interest. Finding a proxy for the constraint is not a problem for China, where short-selling is prohibited by law.

Finally, since the Chinese stock market is dominated by retail investors, investor sentiment as a mispricing factor should not be underestimated. It has been found in the literature that investor sentiment is very helpful in predicting momentum in China (Chen et al., 2014; Han & Li, 2017). This makes China a good candidate for testing cognitive dissonance in information diffusion.

My chapter extends the literature on behavioural explanations of return anomalies by discovering a source of momentum. Using the conditions offered by short-selling constraints, I find those competing theories about the source of momentum are both valid. My chapter contributes to the relevant literature by studying the impact of institutional investors in different roles on stock returns.

4.3 Data and Methodology

I use all Chinese A-shares listed in the Shanghai and the Shenzhen Stock Exchange (SSE and SZSE, respectively) from China Stock Market & Accounting Research Database (CSMAR).[3] Following Cooper et al. (2004), I use the market return 36 months before the start of the strategy holding period to define market states. If the past cumulative return is positive (negative), then the market state is classified as up (down). I measure investor sentiment using the China Investor Composite Sentiment Index (CICSI) constructed by Yi and Mao (2009). This index is based on the Baker and Wurgler (2006) investor sentiment index. It includes the characteristics of investor sentiment in the Chinese stock market while controlling for the impact of the macro-economic cycle.[4] I obtain it from CSMAR and use the median value as the cut-off point between pessimistic and optimistic investors.

4.3.1 Momentum Strategy

Price Momentum

I construct a momentum portfolio using the methodology of Jegadeesh and Titman (1993). In each period t, the stocks are sorted from top to bottom according to the return of the past J-period. Then form 9 equally weighted portfolios based

[3] A-shares is common shares issued by Chinese registered companies, listed in mainland China and denominated in Chinese renminbi (RMB).

[4] Baker and Wurgler (2006) finds that investor sentiment is sensitive to the changes in macroeconomic conditions. Therefore, in the process of investor sentiment measurement, Yi and Mao (2009) have constructed an index to address this problem, taking into account six characteristics of the Chinese stock market in a weighted average way: closed-end funds discount, trading volume, IPOs, the average first-day returns on IPOs, consumer confidence index, and new A-share investor accounts.

on this ranking and name the top rank "winner" and the bottom rank "loser". Each period t, I create a long winner and short loser strategy, held for K-periods. The construction of the portfolios is overlapped to reinforce statistical power. In order to avoid the deviation of the microstructure, I leave a period before and after the formation period. For example, in January 2000, a 3-month formation & 6-month holding strategy ($J = 3, K = 6$) is constructed as follows. In January 2000 (t), the winner portfolio is comprised of winners from October, November and December of 1999 ($t - 3$ to $t - 1$), and correspondingly for the loser portfolio. The cumulative return over the holding period is the sum of monthly raw returns from February to July of 2000 ($t + 1$ to $t + 6$).

Alpha Momentum

To test whether the price momentum strategy is strongly dependent on the realisation of factor-related returns, I also form the CAPM and Fama-French (1993) risk-adjusted momentum return, i.e., alpha momentum strategy.

I have not changed their ranking, i.e., all stocks are still ranked by cumulative returns rather than risk-adjust cumulative returns. Empirical evidence shows that the estimate errors of factor exposures during the stock formation period are independent of the stock's cumulative returns during the formation period (Grundy & Martin, 2001; Cooper et al., 2004; Antoniou et al., 2013; Celiker et al., 2016).

I first form a time-series of raw excess portfolio returns corresponding to each holding period week. Then, I regress excess portfolio returns on risk factors of CAPM or Fama-French (1993). In this way, I obtain the estimated factor loadings ($\hat{\beta}$) of each portfolio and holding period, which I use to derive the following alphas:

$$R_{kt}^{\text{adj}} = R_{kt} - \sum_i \hat{\beta}_i F_{it} \tag{4.3.1}$$

where R_{kt} is the raw excess portfolio return in holding period time (week or day) k at calendar time (week or day) t, F_{it} is the risk factor i at calendar time t, $\hat{\beta}_i$ is the estimated loading on risk factor i. As for risk factors, I use the value-weighted market index over the weekly and daily risk-free interest rate, the return differential between small and big firms, and the return differential between high and low book-to-market firms. Finally, the average weekly or daily risk-adjusted returns are calculated over the holding period.

Since the portfolio returns used to form price and alpha momentum overlap, I apply heteroscedasticity and autocorrelation adjustments to standard errors (Newey & West, 1987) and set the number of lags to the number of overlapping months in the holding-period window, i.e., K - 1.

4.3.2 Type of News

Ranking by Returns

To take a closer look at the impact of institutions on different types of news, I use the 5$^{\text{th}}$ of the 9 ranks as the middle point, i.e., neutral (N) portfolios that show no momentum, to distinguish between the momentum of the winners (W) and the losers (L) from the overall momentum (W - L). The winner momentum strategy is to short the neutral portfolio and long the past winner (W - N). The loser momentum strategy shorts the past losers and longs the neutral portfolio

(N - L).

The advantage of this classification is that I know where the bad and good news are located. I assume the good news creates "winners" and the bad news creates "losers". For short-selling constrained stocks, winner momentum captures the stocks that overreact most to good news, while loser momentum captures the stocks that underreact most to bad news. Doing so can identify the source of the momentum or reversal effect, as it is the net result of underreaction to bad news and overreaction to good news.

Ranking by News

The return ranking is not based on the nature of news but on returns that may result from receiving such news. The most intuitive classification is by the nature of the information. Following Vuolteenaho (2002), I decompose unexpected market returns into cash-flow news and discount-rate news:

$$r_t - E_{t-1}r_t = \underbrace{\epsilon_t + \Delta E_t \sum_{j=0}^{\infty} \rho^j e_{t+j}}_{N_{cf}} - \underbrace{\Delta E_t \sum_{j=1}^{\infty} \rho^j r_{t+j}}_{N_r} \tag{4.3.2}$$

where ΔE_t denotes the changes in expectation, r_t is firm-level log return, e_t is the log clean-surplus accounting return on equity (ROE), ϵ_t is the approximation error, and ρ is set to 0.97.[5] A vector autoregressive model (VAR) is used to predict future returns, which provides a way to calculate return news, N_r, as in Equation (4.3.2). Cash-flow news, N_cf, can then be defined as the residual via

[5]As long as some dividends are paid, the discount coefficient satisfies $\rho < 1$; the optimal value in the sample of Vuolteenaho (2002) is 0.967. However, the exact value appears to have little impact on the results with the range between 0.95 and 1.

$r_t - E_{t-1}r_t + N_{r,t}$. I assume a first-order VAR:

$$z_{i,t} = \Gamma z_{i,t-1} + u_{i,t} \tag{4.3.3}$$

where $z_{i,t}$ is the vector of state variables, Γ is the transition matrix and assumed to be constant. The first ($e1$), second ($e2$) and third ($e3$) element of the the firm-level state vector ($z_{i,t}$) are log return, log return to equity and log book-to-market ratio, respectively.

Cash-flow news can be calculated as $N_{cf,t} = (e2'(I - \rho\Gamma)^{-1})\, u_{i,t}$, and expected return news can be calculated as $N_{r,t} = e1'\rho\Gamma(I - \rho\Gamma)^{-1}u_{i,t}$. Alternatively, cash-flow news can be back out indirectly via Equation (4.3.2). The advantage of backing out cash-flow news is that one does not need to understand the short-run dynamics of dividends. Cohen et al. (2002) define market reactions to the relevant cash-flow news by:

$$\tilde{r}_t = a + b\tilde{N}_{\mathrm{cf},t} + w_t \tag{4.3.4}$$

where over-, correct- and underreaction are defined as $b < 1$, $b = 1$ and $b > 1$, respectively.

I do not use the cash-flow news classification as a benchmark because the estimates of cash-flow news are susceptible to state variables. The state variables used here are log return, log return on equity, and log book-to-market; any alteration to this set-up may yield different results.

Residual Institutional Ownership

To examine the role of institutional investors, I use the Nagel (2005) approach to obtain a size-controlled measure of institutional ownership. He first performs a logit transformation, limiting the institutional ownership (INST) to between 0 and 1:

$$\mathrm{logit}(\mathrm{INST}) = \log\left(\frac{\mathrm{INST}}{1-\mathrm{INST}}\right) \tag{4.3.5}$$

Then, he regresses $\mathrm{logit}(\mathrm{INST})$ on log total assets and squared log total assets. Regressions are run annually, and the residuals are referred to as residual institutional ownership (RI).

4.3.3 Summary Statistics

Table 4.3.1 reports the average, standard deviation, 1st and 99th percentile of variables. The momentum strategy ranked by the returns uses daily return data from 2003 to 2018. The momentum strategy ranked by the cash-flow news uses monthly data from 2000 to 2018.

Table 4.3.1: Summary Statistics

	Mean	Std. Dev.	Median	1st Perc.	99th Perc.
Monthly Return	1.3%	14.6%	0.3%	-32.4%	45.0%
Daily Return	0.1%	4.0%	0.1%	-9.9%	10.0%
Cumulative Market Return	34%	44%	42%	-36%	156%
Investor Sentiment Index	58.1	25.0	53.8	24.4	137.9
Residual Institutional Ownership	0.02	1.92	0.37	-6.72	3.15

Notes: This table reports mean, standard deviation, median, top and bottom 1% percentile statistics of monthly return, daily return, cumulative market return, residual institutional ownership (RI) and investor sentiment index (ISI). Monthly stock return spans between 2000 and 2018 and daily stock return data spans between 2003 and 2018. The cumulative market return is the return over the past 36 months. ISI is obtained from CSMAR. RI is defined as the regression residuals of transformed institutional ownership on log size and squared log size.

4.4 EMPIRICAL RESULTS

4.4.1 Momentum Strategies

Table 4.4.1 reports the profitable trading strategies following the methodology of Jegadeesh and Titman (1993). I focus on two different investment horizons since momentum and reversal occur at different times for different reasons. On a short-term basis, I formulate five investment strategies based on the average cumulative returns of the previous 1 to 5 days (J = 1, 2, 3, 4, 5) and the holding period of 5 days (K = 5). On a long-term basis, I formulate four investment strategies based on the average cumulative returns of the previous 1 to 4 weeks (J = 5, 10, 15, 20) and the holding period of 4 weeks (K = 20). [6]

Table 4.4.1: Price Momentum Strategies

	J = 5					J = 20			
K	**1**	**2**	**3**	**4**	**5**	**5**	**10**	**15**	**20**
Loser	0.02%	0.01%	0.04%	0.01%	0.02%	0.56%	0.57%	0.58%	0.58%
2	0.01%	0.03%	0.03%	0.05%	0.06%	0.50%	0.50%	0.51%	0.51%
3	0.03%	0.03%	0.05%	0.06%	0.06%	0.47%	0.48%	0.49%	0.49%
4	0.04%	0.04%	0.06%	0.06%	0.05%	0.46%	0.46%	0.47%	0.47%
5	0.04%	0.03%	0.05%	0.04%	0.05%	0.44%	0.44%	0.46%	0.46%
6	0.04%	0.02%	0.05%	0.03%	0.03%	0.34%	0.34%	0.35%	0.35%
7	0.01%	0.01%	0.09%	0.02%	0.02%	0.30%	0.30%	0.31%	0.31%
8	0.07%	0.03%	0.08%	0.01%	0.01%	0.19%	0.18%	0.20%	0.19%
Winner	0.08%	0.06%	0.12%	0.10%	0.09%	0.01%	0.02%	0.04%	0.04%
W - L	0.06%***	0.05%***	0.08%***	0.09%***	0.07%***	-0.55%**	-0.55%***	-0.54%***	-0.54%***

Notes: This table reports the average returns of momentum strategies in percentage. J indicates that the portfolios are formed according to the past J-day return, and K indicates that the portfolios will be held for K days. Sample includes all domestic China A-share on CSMAR from the first day in 2003 to the last day in 2018. The t-statistics are calculated using Newey-West (1987) standard errors with lags of K-1. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively.

On a long-term basis, all strategies are profitable by buying losers and selling winners, i.e., reversal. All four strategies are statistically significant. On a short-term basis, all five strategies now present with significant momentum. I use J =

[6] The long-term strategies are weekly strategies, in which there are 5 trading days in a week. I also tried other holding periods, for example, K = 1, 2, 3, 4, 5, 10, 15, 20, and all the strategy combinations are significant.

5, K = 5 as the benchmark short-term strategy, J = 20, K = 20 as the benchmark long-term strategy for the rest of the analysis. These are the common strategy choices in the literature, and both strategies are significant at 1% level using my data.

4.4.2 Momentum Conditional on Institutional Ownership

Table 4.4.2 reports the mean returns of short-term and long-term momentum strategies conditional on residual institutional ownership (RI) in percentages. Momentum (W - L) profits across all RI quintiles are negative (reversal) in the short term and positive (momentum) in the long term.

In the long term, reversal is between 3.75% and 3.85% across RI deciles, of which about 25% comes from the loser group (e.g., 0.86% out of 3.75%), and 75% comes from the winner group (e.g., 2.89% out of 3.75%). All strategy returns are significant at the conventional level regardless of which type. The reversal effect is weaker in the loser group than in the winner group, probably because the short-selling constraint limits the trade chasing from the momentum traders in the earlier stage.

The winner group strategic returns are significant at the 1% level in all RI groups, from -2.89% in the lowest group to -2.99% in the highest group. The difference of -0.1% is significantly different from zero at the 5% level (t-statistics -2.50). The group with a larger proportion of institutional investors has a more significant reversal effect for the winner group. It implies that there may be a corresponding momentum effect in earlier times caused by the overreaction of good news due to the overconfidence of the information held by institutional investors.

Table 4.4.2: Price Momentum Conditional on Residual Institutional Ownership

Long-Term	Residual Institutional Ownership					
	Low	2	3	4	High	H - L
Loser	3.80%	3.80%	3.79%	3.73%	3.65%	
2	3.28%	3.28%	3.26%	3.27%	3.18%	
3	3.17%	3.23%	3.18%	3.15%	3.10%	
4	2.97%	2.98%	3.00%	2.94%	2.87%	
Neutral	2.94%	2.94%	2.93%	2.86%	2.84%	
6	2.27%	2.26%	2.24%	2.20%	2.11%	
7	1.85%	1.86%	1.80%	1.75%	1.69%	
8	1.03%	1.02%	0.95%	0.90%	0.87%	
Winner	0.05%	0.00%	-0.05%	-0.12%	-0.15%	
N	802	802	802	802	802	802
W - L	-3.75%***	-3.80%***	-3.84%***	-3.85%***	-3.81%***	-0.06%
	(-6.67)	(-6.76)	(-6.80)	(-6.78)	(-6.76)	(-1.27)
N - L	-0.86%**	-0.86%**	-0.86%**	-0.87%**	-0.82%**	0.04%
	(-2.29)	(-2.30)	(-2.28)	(-2.33)	(-2.20)	(1.23)
W - N	-2.89%***	-2.94%***	-2.98%***	-2.98%***	-2.99%***	**-0.10%****
	(-7.30)	(-7.50)	(-7.51)	(-7.55)	(-7.49)	(-2.50)
Short-Term						
	Low	2	3	4	High	H - L
Loser	0.23%	0.24%	0.23%	0.23%	0.22%	
2	0.39%	0.39%	0.40%	0.39%	0.38%	
3	0.42%	0.42%	0.42%	0.42%	0.42%	
4	0.36%	0.36%	0.36%	0.35%	0.35%	
Neutral	0.33%	0.33%	0.33%	0.33%	0.33%	
6	0.24%	0.24%	0.24%	0.23%	0.23%	
7	0.16%	0.16%	0.16%	0.16%	0.15%	
8	0.11%	0.11%	0.10%	0.09%	0.09%	
Winner	0.59%	0.60%	0.60%	0.60%	0.59%	
N	3842	3842	3842	3842	3842	
W - L	0.36%***	0.37%***	0.37%***	0.37%***	0.37%***	0.01%
	(4.55)	(4.63)	(4.62)	(4.60)	(4.55)	(1.05)
N - L	0.10%**	0.10%**	0.10%**	0.10%**	0.10%**	0.00%
	(2.21)	(2.17)	(2.21)	(2.26)	(2.26)	(0.82)
W - N	0.26%***	0.27%***	0.27%***	0.26%***	0.26%***	0.00%
	(4.20)	(4.31)	(4.27)	(4.19)	(4.12)	(0.39)

Notes: This table reports the average returns of short- and long-term momentum strategies conditional on residual institutional ownership (RI) in percentage. RI is defined as the regression residuals of logit transformed institutional ownership on log size and squared log size. The number of days for short-term momentum strategy in the pre- and post-formation periods are J = 5, K = 5. The number of days for long-term momentum strategy in the pre- and post-formation periods are J = 20, K = 20. The t-statistics (reported in parentheses) are calculated using Newey-West (1987) standard errors, where lag is set to K - 1. Sample includes all domestic China A-share on CSMAR. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively.

In the short term, positive momentum profits are presented in all RI groups and are significant at the 1% level. The momentum from winners (e.g., 0.26% out of 0.36%) is twice that from losers (e.g., 0.10% out of 0.36%). Institutional investors do not influence the momentum effect. The difference between the high-RI group low-RI group is not different from zero in the economic and statistical sense.

Informed agents tend to be overconfident. The short-term momentum effect of the winners suggests the presence of these overconfident agents. However, the impact of institutional investors (potential candidates for informed agents) is not reflected in the chosen short-term strategy. The strategies constructed under different investment horizons may reflect different perspectives of institutional investors.

Again, the momentum from winners and losers implies different behaviours: the winner momentum is from delayed overreaction due to overconfidence. The loser momentum is from underreaction due to the slow diffusion of information.

4.4.3 Momentum Conditional on Institutional Ownership, Market State and Investor Sentiment

Table 4.4.3 and Table 4.4.4 repeat the above analysis by considering the impact on different market states.

First, I look at the results of short-term momentum in Table 4.4.3. From an economic and statistical point of view, the momentum profit of the up-market is much larger than the momentum profit of the down-market. For example, in the case of Low RI, momentum profit is 0.76% (t-statistic 6.04) in the up-market; momentum profit is -0.14% (t-statistics -1.59) in the down-market. This is consistent with Table 4.2.1.

Table 4.4.3: Short-Term Price Momentum Conditional on Residual Institutional Ownership and Market State

Up Market State	Residual Institutional Ownership					
	Low	2	3	4	High	H - L
Loser	0.25%	0.26%	0.26%	0.25%	0.24%	
2	0.47%	0.47%	0.48%	0.47%	0.46%	
3	0.54%	0.55%	0.54%	0.54%	0.55%	
4	0.45%	0.45%	0.46%	0.45%	0.44%	
Neutral	0.47%	0.47%	0.47%	0.47%	0.47%	
6	0.34%	0.35%	0.35%	0.34%	0.34%	
7	0.26%	0.27%	0.26%	0.26%	0.25%	
8	0.25%	0.25%	0.24%	0.24%	0.23%	
Winner	1.01%	1.04%	1.04%	1.04%	1.03%	
N	2234	2234	2234	2234	2234	
W - L	0.76%***	0.78%***	0.78%***	0.79%***	0.79%***	**0.03%*** **
	(6.04)	(6.14)	(6.16)	(6.17)	(6.13)	(2.87)
N - L	0.21%**	0.21%**	0.22%**	0.22%**	0.23%**	0.01%
	(2.55)	(2.50)	(2.57)	(2.62)	(2.64)	(1.37)
W - N	0.55%***	0.57%***	0.57%***	0.57%***	0.56%***	**0.02%* **
	(5.76)	(5.91)	(5.87)	(5.83)	(5.76)	(1.90)
Down Market State						
	Low	2	3	4	High	H - L
Loser	0.15%	0.15%	0.15%	0.14%	0.14%	
2	0.27%	0.28%	0.28%	0.28%	0.27%	
3	0.24%	0.25%	0.25%	0.25%	0.24%	
4	0.23%	0.22%	0.23%	0.22%	0.22%	
Neutral	0.14%	0.14%	0.14%	0.14%	0.13%	
6	0.08%	0.09%	0.09%	0.08%	0.08%	
7	0.02%	0.02%	0.02%	0.01%	0.00%	
8	-0.09%	-0.09%	-0.09%	-0.10%	-0.11%	
Winner	0.00%	0.00%	0.00%	-0.02%	-0.03%	
N	1608	1608	1608	1608	1608	
W - L	-0.14%	-0.15%*	-0.15%*	-0.16%*	-0.17%*	**-0.02%*** **
	(-1.59)	(-1.65)	(-1.69)	(-1.80)	(-1.86)	(-3.55)
N - L	-0.01%	-0.01%	-0.01%	-0.01%	-0.01%	-0.01%
	(-0.09)	(-0.09)	(-0.11)	(-0.13)	(-0.18)	(-0.98)
W - N	-0.14%**	-0.14%**	-0.15%**	-0.15%**	-0.16%**	**-0.02%*** **
	(-2.27)	(-2.35)	(-2.40)	(-2.53)	(-2.56)	(-3.44)

Notes: This table reports the average returns of short-term momentum strategies conditional on residual institutional ownership (RI) and market state in percentage. RI is defined as the regression residuals of logit transformed institutional ownership on log size and squared log size. Market state is the return of the value weighted market index including dividends 36 months prior to the beginning of holding period. Non-negative (negative) returns are defined as up (down) market state. The t-statistics (reported in parentheses) are calculated using Newey-West (1987) standard errors, where lag is set to K - 1. The number of days in the pre- and post-formation periods are J = 5, K = 5. Sample includes all domestic China A-share on CSMAR from 2003 to 2018. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively.

In up-markets, momentum comes from both winners and losers. Winner momentum aligns with Cooper et al. (2004) and Daniel et al. (1998), which means that investors are more overconfident and less risk-averse following market gains. Loser momentum is in line with Hong and Stein (1999), which means that investors underreact to bad news because of slow information diffusion.

In down-markets, informed agents' confidence in the accuracy of information is much lower than in up-markets. Although the momentum for winners generated by overconfidence is weak, it is still significantly different from zero. Lastly, regardless of the state of the market, institutional investors will increase the degree of momentum.

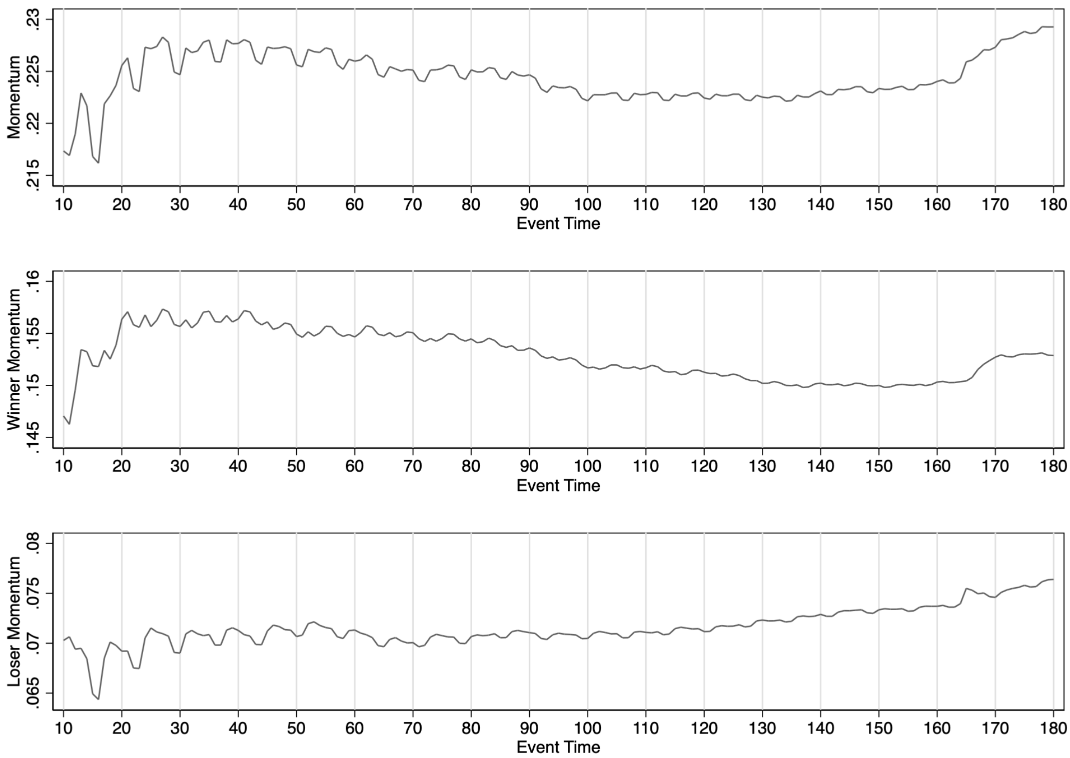

Figure 4.4.1: Cumulative momentum returns in up market state. The cumulative average daily profits over the days $t + 1$ to $t + 180$ are plotted for the 30-day momentum strategy from 2014 to 2018 following 3-year positive cumulative market returns.

In the long run, the reversal effect dominates, see Table 4.4.4. Most, if not all,

Table 4.4.4: Long-Term Price Momentum Conditional on Residual Institutional Ownership and Market State

Up Market State	Residual Institutional Ownership					
	Low	2	3	4	High	H - L
Loser	5.09%	5.04%	5.01%	4.96%	4.89%	
2	3.91%	3.92%	3.88%	3.88%	3.83%	
3	3.89%	3.96%	3.90%	3.86%	3.82%	
4	3.79%	3.78%	3.82%	3.76%	3.66%	
Neutral	3.88%	3.85%	3.86%	3.78%	3.74%	
6	2.56%	2.54%	2.54%	2.51%	2.40%	
7	2.19%	2.20%	2.15%	2.09%	2.03%	
8	1.25%	1.28%	1.16%	1.11%	1.08%	
Winner	-0.09%	-0.14%	-0.21%	-0.27%	-0.29%	
N	467	467	467	467	467	467
W - L	-5.18%***	-5.19%***	-5.22%***	-5.22%***	-5.18%***	-0.01%
	(-6.07)	(-6.06)	(-6.07)	(-6.03)	(-6.04)	(-0.10)
N - L	-1.21%**	-1.19%**	-1.15%*	-1.18%**	-1.15%**	0.06%
	(-2.05)	(-2.01)	(-1.94)	(-2.00)	(-1.97)	(1.11)
W - N	-3.97%***	-4.00%***	-4.07%***	-4.04%***	-4.03%***	-0.06%
	(-6.83)	(-6.95)	(-6.99)	(-6.96)	(-6.86)	(-1.10)
Down Market State						
	Low	2	3	4	High	H - L
Loser	1.97%	2.01%	2.05%	1.99%	1.93%	
2	2.35%	2.32%	2.33%	2.33%	2.26%	
3	2.05%	2.09%	2.05%	2.02%	2.05%	
4	1.71%	1.71%	1.71%	1.67%	1.72%	
Neutral	1.61%	1.62%	1.60%	1.55%	1.57%	
6	1.82%	1.80%	1.75%	1.70%	1.70%	
7	1.36%	1.32%	1.25%	1.22%	1.22%	
8	0.68%	0.59%	0.58%	0.53%	0.55%	
Winner	0.20%	0.14%	0.13%	0.03%	0.03%	
N	337	336	336	336	335	335
W - L	-1.78%***	-1.87%***	-1.92%***	-1.96%***	-1.90%***	**-0.12%****
	(-3.30)	(-3.49)	(-3.55)	(-3.61)	(-3.51)	(-2.04)
N - L	-0.37%	-0.40%	-0.45%	-0.44%	-0.35%	0.02%
	(-1.15)	(-1.27)	(-1.38)	(-1.38)	(-1.11)	(0.57)
W - N	-1.41%***	-1.47%***	-1.47%***	-1.52%***	-1.54%***	**-0.13%*****
	(-3.27)	(-3.44)	(-3.39)	(-3.51)	(-3.52)	(-2.67)

Notes: This table reports the average returns of long-term momentum strategies conditional on residual institutional ownership (RI) and market state in percentage. RI is defined as the regression residuals of logit transformed institutional ownership on log size and squared log size. Market state is the return of the value weighted market index including dividends 36 months prior to the beginning of holding period. Non-negative (negative) returns are defined as up (down) market state. The t-statistics (reported in parentheses) are calculated using Newey-West (1987) standard errors, where lag is set to K - 1. The number of days in the pre- and post-formation periods are J = 20, K = 20. Sample includes all domestic China A-share on CSMAR from 2003 to 2018. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively.

reversals in both market states come from the winners. After a brief momentum effect due to overconfidence in up-markets, there is a more prolonged reversal effect for winners. There is some reversal from losers as well, possibly because of cognitive dissonance.

In down-markets, winner reversal is much weaker, and institutional investors seem to overreact to good news. The reversal effect of winner stocks with high RI is 0.13% larger than stocks with low RI and is significantly different from zero (t-statistics -2.67). The presentation of the long-term and the short-term momentum strategies complement each other.

Following the even-time methodology by Lee and Swaminathan (2000); Jegadeesh and Titman (2001); Cooper et al. (2004), I plot the cumulative price momentum using daily data in Figure 4.4.1 and Figure 4.4.2. The portfolio is formed based on the returns of the past 30 days. Cumulative equal-weighted momentum returns are calculated for 10 to 180 days after portfolio formation. Following the exact definition of winner and loser as before, the strategies of buying winners and selling losers in the up and down markets are established, respectively.

In Figure 4.4.1, winner momentum (overreaction type of momentum) profits decrease over time, which is a sign of transient momentum. Loser momentum grows over time, possibly because market upturns are correlated to high sentiment, leading to cognitive dissonance, slowing the spread of information. As a result, total momentum profits fluctuate between 0.215% and 0.23%.

In Figure 4.4.2, down-markets have little momentum effect, with values ranging from -0.04% to -0.01%, i.e., little economic significance. All the evidence suggests that the momentum effect in the up-markets is attributable to both winners

Table 4.4.5: Short-Term Price Momentum Conditional on Residual Institutional Ownership and Sentiment

Optimistic	Residual Institutional Ownership					
	Low	2	3	4	High	H - L
Loser	0.37%	0.38%	0.38%	0.36%	0.36%	
2	0.52%	0.52%	0.53%	0.51%	0.51%	
3	0.63%	0.65%	0.64%	0.64%	0.65%	
4	0.52%	0.53%	0.53%	0.52%	0.52%	
Neutral	0.54%	0.55%	0.55%	0.55%	0.54%	
6	0.38%	0.39%	0.39%	0.38%	0.38%	
7	0.35%	0.36%	0.35%	0.35%	0.35%	
8	0.36%	0.36%	0.34%	0.34%	0.34%	
Winner	1.27%	1.31%	1.32%	1.32%	1.32%	
N	1739	1739	1739	1739	1739	1739
W - L	0.90%***	0.94%***	0.94%***	0.96%***	0.96%***	**0.06%*** **
	(5.51)	(5.69)	(5.72)	(5.77)	(5.72)	(3.86)
N - L	0.17%**	0.17%**	0.17%**	0.19%**	0.19%**	0.02%
	(2.06)	(2.03)	(2.07)	(1.99)	(2.01)	(1.25)
W - N	0.73%***	0.77%***	0.77%***	0.77%***	0.77%***	**0.04%*** **
	(5.96)	(6.19)	(6.18)	(6.12)	(6.08)	(3.13)
Pessimistic						
	Low	2	3	4	High	H - L
Loser	-0.01%	-0.01%	-0.01%	-0.01%	-0.02%	
2	0.21%	0.23%	0.23%	0.22%	0.21%	
3	0.21%	0.21%	0.21%	0.21%	0.20%	
4	0.19%	0.19%	0.19%	0.19%	0.18%	
Neutral	0.12%	0.12%	0.12%	0.12%	0.11%	
6	0.06%	0.06%	0.06%	0.06%	0.05%	
7	-0.06%	-0.05%	-0.06%	-0.07%	-0.08%	
8	-0.17%	-0.17%	-0.17%	-0.19%	-0.20%	
Winner	-0.03%	-0.04%	-0.05%	-0.06%	-0.08%	
N	2103	2103	2103	2103	2103	
W - L	-0.02%	-0.03%	-0.04%	-0.05%	-0.05%	-0.03%
	(-0.24)	(-0.34)	(-0.37)	(-0.52)	(-0.58)	(-0.33)
N - L	0.13%	0.13%	0.14%	0.13%*	0.13%	0.00%
	(1.54)	(1.50)	(1.53)	(1.66)	(1.64)	(-0.54)
W - N	-0.16%**	-0.16%**	-0.17%***	-0.18%***	-0.18%***	**-0.03%*** **
	(-2.42)	(-2.51)	(-2.65)	(-2.73)	(-2.84)	(-4.70)

Notes: This table reports the average returns of short-term momentum strategies conditional on residual institutional ownership (RI) and market state in percentage. RI is defined as the regression residuals of logit transformed institutional ownership on log size and squared log size. Sentiment measures are obtained from Investor Sentiment Index (ISI) on CSMAR. The top (bottom) 50% of ISI values are defined as optimistic (pessimistic) period. The t-statistics (reported in parentheses) are calculated using Newey-West (1987) standard errors, where lag is set to K - 1. The number of days in the pre- and post-formation periods are J = 5, K = 5. Sample includes all domestic China A-share on CSMAR from 2003 and 2018. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively.

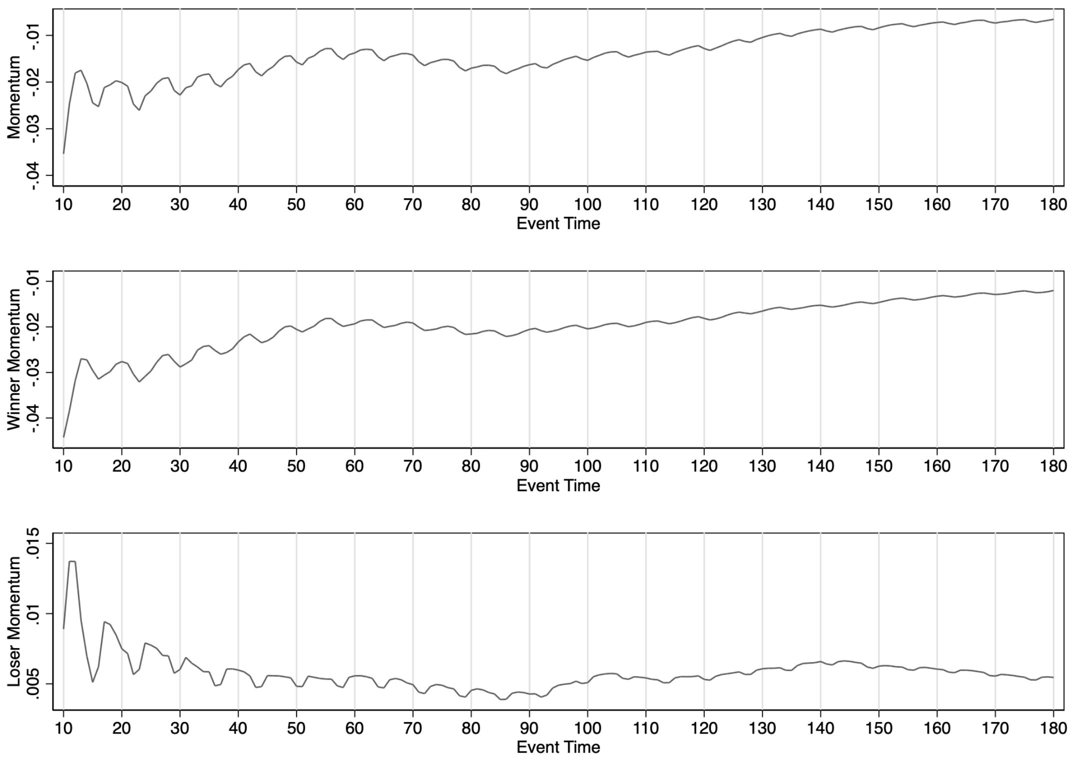

Figure 4.4.2: Cumulative momentum returns in down market state. The cumulative average daily profits over the days $t + 1$ to $t + 180$ are plotted for the 30-day momentum strategy from 2014 to 2018 following 3-year negative cumulative market returns.

and losers, consistent with hypotheses 1a and 1b.

Table 4.4.5 and Table 4.4.6 report the results by taking into account the impact on different investor sentiment. In the short run, during the period of optimistic sentiment, the results are very similar as in up-markets, see Table 4.4.3. Overreaction by winners and underreaction by losers are sources of momentum, and winners are the main contributors. Momentum is relatively weaker in the period of pessimistic sentiment, and it is from winners only. Again, this may be due to weak but still existed overconfidence from informed agents. Regardless of the investor sentiment, institutional investors will increase the degree of momentum.

In the long run, a strong reversal effect appears in both sentiments. The main source of reversals is winners, and the magnitude of reversals among the losers is small, both economically and statistically. Optimistic past winners have stronger reversals due to greater overconfidence. Institutional investors overreact to good news when the market is pessimistic. The high-RI winner group underperform their low-RI counterpart by 0.1% (t-statistics 2.97).

Combined with the empirical evidence of market conditions observed earlier, institutional investors' response to information presents a typical pattern. In the short run, institutional investors will increase the degree of momentum, regardless of the market state and investor sentiment.

In the long run, institutional investors become overconfident when investor sentiment is low because they place too much weight on the accuracy of the good news they receive. In the same way, institutional investors become overconfident when they receive good news in down-markets.

4.4.4 Alpha Momentum Conditional on Institutional Ownership

Empirical evidence so far provides two pieces of information. First, momentum comes from both winners (overreaction-type) and losers (underreaction-type) using short-term and long-term strategies in the up-markets or periods of high investor sentiment, supporting **Hypothesis 1a**. Although not completely absent, the very weak presence of momentum effects does not reject **Hypothesis 1b**.

Second, as skilled newswatchers, institutional investors do not affect the loser momentum under any circumstances, thus rejecting **Hypothesis 2a**. Regardless of market state and investor sentiment, institutional investors overreact to good news in the short term. In the long run, this overreaction occurs only in periods

Table 4.4.6: Long-Term Price Momentum Conditional on Residual Institutional Ownership and Sentiment

Optimistic	Residual Institutional Ownership					
	Low	2	3	4	High	H - L
Loser	5.14%	5.06%	5.04%	4.95%	4.94%	
2	4.23%	4.19%	4.16%	4.11%	4.09%	
3	4.12%	4.15%	4.12%	4.05%	4.03%	
4	3.82%	3.75%	3.80%	3.69%	3.64%	
Neutral	3.97%	3.89%	3.92%	3.79%	3.82%	
6	2.85%	2.76%	2.77%	2.69%	2.66%	
7	2.24%	2.15%	2.12%	2.03%	2.04%	
8	1.26%	1.24%	1.18%	1.03%	1.07%	
Winner	0.48%	0.39%	0.35%	0.24%	0.35%	
N	364	361	362	362	361	361
W - L	-4.66%***	-4.67%***	-4.69%***	-4.72%***	-4.59%***	0.07%
	(-4.63)	(-4.58)	(-4.59)	(-4.59)	(-4.52)	(0.54)
N - L	-1.17%*	-1.17%*	-1.12%	-1.16%*	-1.12%	0.06%
	(-1.70)	(-1.67)	(-1.60)	(-1.68)	(-1.61)	(1.07)
W - N	-3.48%***	-3.50%***	-3.57%***	-3.56%***	-3.48%***	0.01%
	(-5.22)	(-5.22)	(-5.28)	(-5.28)	(-5.09)	(-0.36)
Pessimistic						
	Low	2	3	4	High	H - L
Loser	2.74%	2.74%	2.78%	2.69%	2.60%	
2	2.64%	2.63%	2.63%	2.63%	2.54%	
3	2.43%	2.46%	2.42%	2.38%	2.36%	
4	2.33%	2.34%	2.38%	2.31%	2.27%	
Neutral	2.15%	2.14%	2.14%	2.08%	2.05%	
6	1.85%	1.82%	1.81%	1.76%	1.68%	
7	1.57%	1.59%	1.54%	1.48%	1.43%	
8	0.67%	0.58%	0.55%	0.52%	0.56%	
Winner	-0.37%	-0.45%	-0.46%	-0.54%	-0.57%	
N	444	444	443	443	442	442
W - L	-3.11%***	-3.18%***	-3.24%***	-3.24%***	-3.17%***	**-0.06%****
	(-5.37)	(-5.54)	(-5.58)	(-5.54)	(-5.51)	(-2.30)
N - L	-0.59%	-0.60%*	-0.64%*	-0.62%*	-0.55%	0.04%
	(-1.63)	(-1.69)	(-1.74)	(-1.68)	(-1.56)	(0.67)
W - N	-2.52%***	-2.58%***	-2.60%***	-2.62%***	-2.62%***	**-0.10%*****
	(-5.55)	(-5.80)	(-5.74)	(-5.82)	(-5.91)	(-2.97)

Notes: This table reports the average returns of long-term momentum strategies conditional on residual institutional ownership (RI) and market state in percentage. RI is defined as the regression residuals of logit transformed institutional ownership on log size and squared log size. Sentiment measures are obtained from Investor Sentiment Index (ISI) on CSMAR. The top (bottom) 50% of ISI values are defined as optimistic (pessimistic) period. The t-statistics (reported in parentheses) are calculated using Newey-West (1987) standard errors, where lag is set to K - 1. The number of days in the pre- and post-formation periods are J = 20, K = 20. Sample includes all domestic China A-share on CSMAR from 2003 and 2018. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively.

of down-markets or pessimistic investor sentiment, supporting **Hypothesis 2b**.

However, I have not yet considered the impact of different risks on returns. I now address this issue by estimating risk-adjusted momentum in different RI quntiles using Fama and French (1993) model.

Table 4.4.7 gives the FF-1993 risk-adjusted momentum or reversal, and the conclusions in Table 4.4.2 remain robust after controlling for risks. In the short run, winners generate more momentum than losers, the former from overreaction and the latter from underreaction to information. Institutional investors have little impact on short-term strategies.

In the long run, the overall reversal is highly significant at the 1% level, with the vast majority coming from the winner group. Also, the winners in the high RI group perform -0.11% worse than the low RI group. This is a corroboration of institutional investors' overreaction to good news.

Table 4.4.8, Table 4.4.9, Table 4.4.10 and Table 4.4.11 attempt to verify that the findings in Table 4.4.3, Table 4.4.4, Table 4.4.5 and Table 4.4.6 are reliable after taking risks into account. Unlike the previous analysis, in the following analysis I consider both market state and investor sentiment to help understand which factor has a greater impact on the momentum or reversal effect.

In the short-run, loser momentum exists only in up-markets where investment sentiment is optimistic and does not occur in other situations. This is potentially the most easily highlighted case of cognitive dissonance, i.e. receiving bad news when the market is playing well and investment sentiment is upbeat.

Winner momentum is present in all cases. It is not surprising to see it in com-

Table 4.4.7: Alphas Momentum Conditional on Residual Institutional Ownership

Long-Term	Residual Institutional Ownership					
	Low	2	3	4	High	H - L
Loser	3.57%	3.56%	3.56%	3.50%	3.43%	
2	3.30%	3.30%	3.28%	3.29%	3.21%	
3	3.14%	3.20%	3.15%	3.12%	3.07%	
4	2.78%	2.80%	2.81%	2.76%	2.70%	
Neutral	2.52%	2.52%	2.52%	2.44%	2.42%	
6	1.84%	1.82%	1.81%	1.77%	1.68%	
7	1.45%	1.45%	1.40%	1.34%	1.29%	
8	0.33%	0.32%	0.25%	0.20%	0.17%	
Winner	-0.68%	-0.76%	-0.78%	-0.87%	-0.89%	
N	782	782	782	782	782	782
W - L	-4.25%***	-4.32%***	-4.35%***	-4.37%***	-4.32%***	-0.07%
	(-6.32)	(-6.41)	(-6.43)	(-6.42)	(-6.40)	(-1.25)
N - L	-1.05%**	-1.04%**	-1.05%**	-1.06%**	-1.01%**	0.04%
	(-2.28)	(-2.27)	(-2.26)	(-2.31)	(-2.19)	(1.48)
W - N	-3.20%***	-3.27%***	-3.30%***	-3.31%***	-3.31%***	**-0.11%*** **
	(-6.55)	(-6.72)	(-6.72)	(-6.75)	(-6.71)	(-2.66)

Short-Term						
	Low	2	3	4	High	H - L
Loser	0.01%	0.01%	0.01%	0.01%	0.01%	
2	0.08%	0.08%	0.08%	0.08%	0.08%	
3	0.09%	0.09%	0.09%	0.09%	0.09%	
4	0.08%	0.08%	0.08%	0.08%	0.08%	
Neutral	0.06%	0.06%	0.06%	0.06%	0.06%	
6	0.05%	0.05%	0.05%	0.05%	0.04%	
7	0.03%	0.03%	0.03%	0.03%	0.02%	
8	0.00%	0.00%	0.00%	0.00%	0.00%	
Winner	0.15%	0.16%	0.16%	0.15%	0.15%	
N	3842	3842	3842	3842	3842	
W - L	0.14%***	0.15%***	0.15%***	0.15%***	0.15%***	0.00%
	(5.97)	(6.06)	(6.04)	(6.01)	(5.96)	(1.05)
N - L	0.05%***	0.05%***	0.05%***	0.06%***	0.06%***	0.00%
	(3.52)	(3.51)	(3.54)	(3.61)	(3.54)	(0.75)
W - N	0.09%***	0.09%***	0.09%***	0.09%***	0.09%***	0.00%
	(4.96)	(5.08)	(5.02)	(4.94)	(4.90)	(0.46)

Notes: This table reports the risk-adjusted average returns of short- and long-term momentum strategies calculated from Fama-French (1993), and conditional on residual institutional ownership (RI). RI is defined as the regression residuals of transformed institutional ownership on log size and squared log size. The number of days for short-term momentum strategy in the pre- and post-formation periods are J = 5, K = 5. The number of days for long-term momentum strategy in the pre- and post-formation periods are J = 20, K = 20. The t-statistics (reported in parentheses) are calculated using Newey-West (1987) standard errors, where lag is set to K - 1. Sample includes all domestic China A-share on CSMAR. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively.

Table 4.4.8: Short-Term Alpha Momentum Conditional on Residual Institutional Ownership, Market State and Sentiment

			Up Market State			
Optimistic			Residual Institutional Ownership			
	Low	2	3	4	High	H - L
Loser	0.04%	0.04%	0.04%	0.04%	0.04%	
2	0.11%	0.11%	0.11%	0.11%	0.11%	
3	0.13%	0.13%	0.13%	0.13%	0.13%	
4	0.11%	0.11%	0.11%	0.11%	0.11%	
Neutral	0.11%	0.10%	0.11%	0.11%	0.11%	
6	0.08%	0.08%	0.08%	0.08%	0.08%	
7	0.07%	0.07%	0.07%	0.07%	0.07%	
8	0.06%	0.06%	0.06%	0.06%	0.05%	
Winner	0.40%	0.41%	0.41%	0.41%	0.41%	
N	1453	1453	1453	1453	1453	
W - L	0.36%***	0.37%***	0.37%***	0.37%***	0.38%***	
	(7.33)	(7.49)	(7.49)	(7.53)	(7.50)	(3.87)
N - L	0.07%**	0.06%**	0.07%**	0.07%**	0.07%**	0.00%
	(2.04)	(1.99)	(2.00)	(2.10)	(2.09)	(0.96)
W - N	0.29%***	0.31%***	0.30%***	0.31%***	0.31%***	**0.01%*** **
	(7.97)	(8.20)	(8.16)	(8.16)	(8.09)	(3.81)
Pessimistic						
	Low	2	3	4	High	H - L
Loser	-0.03%	-0.03%	-0.04%	-0.04%	-0.04%	
2	0.06%	0.07%	0.07%	0.07%	0.06%	
3	0.09%	0.09%	0.09%	0.09%	0.09%	
4	0.06%	0.06%	0.06%	0.06%	0.06%	
Neutral	0.06%	0.06%	0.06%	0.05%	0.05%	
6	0.05%	0.05%	0.05%	0.05%	0.05%	
7	0.00%	0.00%	0.00%	-0.01%	-0.01%	
8	-0.03%	-0.04%	-0.04%	-0.04%	-0.04%	
Winner	0.03%	0.03%	0.03%	0.03%	0.02%	
N	781	781	781	781	781	
W - L	0.07%*	0.07%*	0.07%*	0.06%	0.06%	0.00%
	(1.66)	(1.64)	(1.65)	(1.59)	(1.57)	(-1.15)
N - L	0.09%	0.09%	0.09%	0.09%	0.09%	0.00%
	(-0.87)	(-0.87)	(-0.95)	(-1.00)	(-1.04)	(1.15)
W - N	-0.02%***	-0.02%***	-0.02%***	-0.03%***	-0.03%***	**-0.01%** **
	(3.06)	(3.03)	(3.10)	(3.09)	(3.12)	(-2.33)

Notes: See Table 4.4.8.

Table 4.4.9: Short-Term Alpha Momentum Conditional on Residual Institutional Ownership, Market State and Sentiment

	Down Market State					
Optimistic	Residual Institutional Ownership					
	Low	2	3	4	High	H - L
Loser	-0.05%	-0.05%	-0.05%	-0.06%	-0.05%	
2	0.09%	0.08%	0.08%	0.08%	0.08%	
3	0.13%	0.13%	0.13%	0.13%	0.13%	
4	0.09%	0.09%	0.09%	0.09%	0.08%	
Neutral	0.07%	0.08%	0.08%	0.08%	0.08%	
6	0.05%	0.05%	0.05%	0.05%	0.06%	
7	0.05%	0.05%	0.04%	0.04%	0.04%	
8	0.01%	0.01%	0.01%	0.01%	0.01%	
Winner	0.05%	0.05%	0.05%	0.04%	0.04%	
N	286	286	286	286	286	
W - L	0.10%	0.10%	0.10%	0.10%	0.10%	0.00%
	(1.25)	(1.26)	(1.27)	(1.29)	(1.24)	(-0.01)
N - L	-0.03%	-0.03%	-0.03%	-0.03%	-0.03%	-0.01%
	(-0.67)	(-0.84)	(-0.76)	(-0.89)	(-0.82)	(-0.78)
W - N	0.13%**	0.13%**	0.13%**	0.14%**	0.13%**	0.01%
	(2.15)	(2.24)	(2.20)	(2.34)	(2.22)	(0.86)
Pessimistic						
	Low	2	3	4	High	H - L
Loser	0.01%	0.01%	0.01%	0.01%	0.01%	
2	0.05%	0.05%	0.05%	0.05%	0.05%	
3	0.04%	0.04%	0.04%	0.04%	0.04%	
4	0.06%	0.06%	0.06%	0.06%	0.06%	
Neutral	0.02%	0.02%	0.01%	0.01%	0.01%	
6	0.01%	0.01%	0.00%	0.00%	0.00%	
7	-0.01%	-0.01%	-0.01%	-0.01%	-0.02%	
8	-0.04%	-0.04%	-0.05%	-0.05%	-0.05%	
Winner	-0.03%	-0.03%	-0.03%	-0.03%	-0.04%	
N	1322	1322	1322	1322	1322	
W - L	-0.04%	-0.04%	-0.04%	-0.04%*	-0.04%*	-0.01%
	(-1.44)	(-1.52)	(-1.57)	(-1.71)	(-1.77)	(-1.39)
N - L	0.01%	0.01%	0.01%	0.00%	0.00%	0.00%
	(0.35)	(0.34)	(0.35)	(0.27)	(0.20)	(-1.19)
W - N	-0.04%**	-0.04%**	-0.05%***	-0.05%***	-0.05%***	**-0.01%***
	(-2.40)	(-2.52)	(-2.61)	(-2.74)	(-2.71)	(-3.94)

Notes: This table reports the risk-adjusted average returns of short-term momentum strategies calculated from Fama-French (1993), and conditional on residual institutional ownership (RI), market state and investors sentiment in percentage. RI is defined as the regression residuals of transformed institutional ownership on log size and squared log size. Sentiment measures are obtained from Investor Sentiment Index (ISI) on CSMAR. The top (bottom) 50% of ISI values are defined as optimistic (pessimistic) period. Market state is the return of the value weigted market index including dividends 36 months prior to the beginning of holding period. Non-negative (negative) returns are defined as up (down) market state. The t-statistics (reported in parentheses) are calculated using Newey-West (1987) standard errors, where lag is set to K - 1. The number of days in the pre- and post-formation periods are J = 5, K = 5. Sample includes all domestic China A-share on CSMAR from 2003 to 2018. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively.

Table 4.4.10: Long-Term Alpha Momentum Conditional on Residual Institutional Ownership, Market State and Sentiment

	Up Market State Residual Institutional Ownership					
Optimistic	Low	2	3	4	High	H - L
Loser	5.95%	5.90%	5.86%	5.84%	5.76%	
2	4.53%	4.53%	4.48%	4.49%	4.44%	
3	4.54%	4.63%	4.57%	4.56%	4.48%	
4	4.02%	3.98%	3.99%	3.95%	3.84%	
Neutral	4.02%	3.97%	4.00%	3.90%	3.89%	
6	2.63%	2.59%	2.59%	2.58%	2.47%	
7	1.76%	1.73%	1.70%	1.64%	1.59%	
8	0.59%	0.66%	0.53%	0.46%	0.44%	
Winner	0.18%	0.11%	0.07%	0.00%	0.07%	
N	293	293	293	293	293	293
W - L	-5.77%***	-5.79%***	-5.79%***	-5.84%***	-5.70%***	0.07%
	(-4.33)	(-4.31)	(-4.32)	(-4.32)	(-4.27)	(1.01)
N - L	-1.93%**	-1.93%**	-1.86%*	-1.94%**	-1.87%*	0.06%
	(-2.02)	(-2.00)	(-1.92)	(-2.04)	(-1.96)	(1.23)
W - N	-3.84%***	-3.86%***	-3.93%***	-3.90%***	-3.83%***	0.01%
	(-4.05)	(-4.07)	(-4.12)	(-4.10)	(-3.98)	(0.15)
Pessimistic						
	Low	2	3	4	High	H - L
Loser	2.88%	2.84%	2.84%	2.70%	2.65%	
2	2.37%	2.38%	2.36%	2.37%	2.35%	
3	1.87%	1.91%	1.84%	1.80%	1.80%	
4	2.27%	2.33%	2.39%	2.33%	2.25%	
Neutral	1.78%	1.78%	1.76%	1.70%	1.63%	
6	0.95%	0.95%	0.93%	0.90%	0.77%	
7	0.44%	0.53%	0.48%	0.37%	0.33%	
8	-0.36%	-0.43%	-0.56%	-0.55%	-0.60%	
Winner	-3.06%	-3.22%	-3.27%	-3.30%	-3.45%	
N	164	165	164	164	164	164
W - L	-5.94%***	-6.05%***	-6.11%***	-6.00%***	-6.10%***	-0.16%
	(-5.07)	(-5.12)	(-5.15)	(-5.92)	(-5.95)	(-1.28)
N - L	-1.09%	-1.06%	-1.07%	-1.00%	-1.03%	0.07%
	(-1.32)	(-1.28)	(-1.23)	(-1.20)	(-1.28)	(1.05)
W - N	-4.84%***	-4.99%***	-5.04%***	-4.99%***	-5.07%***	**-0.23%****
	(-5.64)	(-5.99)	(-5.00)	(-5.09)	(-5.87)	(-2.21)

Notes: See Table 4.4.11.

bination with an up-market or optimistic sentiment. These situations are prone to induce overconfidence in investors and thus overreact to good news. However, there is also significant winner momentum (roughly -0.05% significant at the 1% level) in down-markets and pessimistic investor sentiment. To be more precise, this is the stage where prices are correcting (negative momentum).

One explanation for this is that investors have always had varying degrees of overconfidence, only to a weaker degree and subsequently less momentum in the face of market downturns and/or negative sentiment.

Another explanation for this is that although market states and investor sentiment are highly correlated, they do not always appear simultaneously. "If excessive operationalism drives prices above intrinsic value, then periods of high sentiment should be followed by low returns as market prices revert to fundamental values." Brown and Cliff (2005) point out. Institutional investors in the short term, will overreact to good news in most cases, thereby increasing winner momentum.

In the long run, results are very similar to the short run. Winner momentum dominates all scenarios while loser momentum is only seen in up-markets and when investor sentiment is optimistic (optimistic-up group). Institutional investors overreact to good news, except in the optimistic-up group, consistent with previous findings in Table 4.4.4 and Table 4.4.6.

In summary, there is clear winner momentum for long-term strategies with a high proportion of institutional investors compared to those with a low proportion of institutional investors. Institutional investors' overconfidence in information likely leads to an overreaction to good news, most pronounced in down-markets and pessimistic sentiment.

4.4.5 Asymmetric Reaction to Cash-Flow News

The previous analysis uses loser and winner groups to capture the good and bad news groups. This section directly uses cash-flow news to reflect the fundamental information. Table 4.4.12 shows investor reaction to cash-flow news (Ncf) conditional on RI. Panel A reports equal-weighted portfolio returns sorted on RI and Ncf directly calculated by VAR, while Ncf in Panel B is indirectly derived from a present-value identity. Details are in Section 4.3.2, Ranking by News, on page 183.

Both panels show strong cash flow momentum, i.e., the lowest cash-flow news category (bad) has a lower return on each RI quintile than the highest cash-flow news category (good) of the stock. In Panel A, the cash-flow momentum for the lowest RI category is 2.35%. For comparison, the momentum for the highest RI category is 2.98%. The difference in the underperformance of cash-flow losers between high RI and low RI is not significantly different from zero in both panels.

As for the source of this cash-flow momentum, the last two rows of each panel reveal the answer in part. Following Cohen et al. (2002) and Vuolteenaho (2002), I define the market's overreaction and underreaction as b > 1 and b < 1, respectively, and b+ and b represent positive and negative news, respectively. They are regression coefficients of market-adjusted returns on cash-flow news, reflecting the market's response to the information.

Table 4.4.11: Long-Term Alpha Momentum Conditional on Residual Institutional Ownership, Market State and Sentiment

	Down Market State					
Optimistic	Residual Institutional Ownership					
	Low	2	3	4	High	H - L
Loser	-0.19%	-0.73%	-0.56%	-0.50%	-0.56%	
2	2.41%	1.88%	1.91%	2.15%	2.04%	
3	2.71%	2.15%	2.22%	2.60%	2.47%	
4	1.03%	0.53%	0.70%	0.96%	0.86%	
Neutral	1.22%	0.88%	0.95%	1.12%	1.08%	
6	1.68%	1.17%	1.19%	1.38%	1.40%	
7	1.47%	0.95%	0.92%	1.03%	1.14%	
8	-0.32%	-0.99%	-0.72%	-0.61%	-0.61%	
Winner	-3.40%	-4.14%	-3.99%	-3.74%	-3.84%	
N	60	59	59	60	60	59
W - L	-3.21%*	-3.41%*	-3.44%*	-3.24%*	-3.29%*	-0.08%
	(-1.80)	(-1.92)	(-1.98)	(-1.79)	(-1.79)	(-0.40)
N - L	1.40%	1.61%	1.50%	1.62%	1.63%	0.23%
	(1.00)	(1.08)	(0.98)	(1.08)	(1.11)	(1.42)
W - N	-4.61%***	-5.02%***	-4.94%***	-4.86%***	-4.92%***	**-0.31%***
	(-2.67)	(-2.91)	(-2.87)	(-2.76)	(-2.79)	(-1.95)
Pessimistic						
	Low	2	3	4	High	H - L
Loser	1.84%	1.91%	1.95%	1.90%	1.78%	
2	2.36%	2.34%	2.37%	2.36%	2.23%	
3	2.09%	2.16%	2.11%	2.07%	2.04%	
4	1.76%	1.80%	1.78%	1.73%	1.72%	
Neutral	1.28%	1.31%	1.29%	1.22%	1.22%	
6	1.21%	1.20%	1.16%	1.12%	1.05%	
7	1.41%	1.40%	1.34%	1.32%	1.24%	
8	0.35%	0.33%	0.31%	0.26%	0.22%	
Winner	0.24%	0.19%	0.20%	0.05%	0.04%	
N	266	266	266	266	266	266
W - L	-1.60%*	-1.71%**	-1.74%**	-1.85%**	-1.74%**	**-0.14%****
	(-1.89)	(-2.04)	(-2.07)	(-2.17)	(-2.08)	(-2.02)
N - L	-0.56%	-0.59%	-0.66%	-0.68%	-0.56%	0.00%
	(-1.18)	(-1.25)	(-1.36)	(-1.42)	(-1.16)	(0.21)
W - N	-1.05%*	-1.12%*	-1.09%*	-1.17%*	-1.19%**	**-0.14%****
	(-1.78)	(-1.90)	(-1.84)	(-1.97)	(-2.03)	(-2.33)

Notes: This table reports the risk-adjusted average returns of long-term momentum strategies calculated from Fama-French (1993), and conditional on residual institutional ownership (RI), market state and investors sentiment in percentage. RI is defined as the regression residuals of transformed institutional ownership on log size and squared log size. Sentiment measures are obtained from Investor Sentiment Index (ISI) on CSMAR. The top (bottom) 50% of ISI values are defined as optimistic (pessimistic) period. Market state is the return of the value weigted market index including dividends 36 months prior to the beginning of holding period. Non-negative (negative) returns are defined as up (down) market state. The t-statistics (reported in parentheses) are calculated using Newey-West (1987) standard errors, where lag is set to K - 1. The number of days in the pre- and post-formation periods are J = 20, K = 20. Sample includes all domestic China A-share on CSMAR from 2003 to 2018. ***, ** and * denote the level of significance at 10%, 5% and 1%, respectively.

In the upper panel, the coefficient of negative news increased from 0.08 in the lowest RI group to 0.91 in the highest RI group. $b = 1$ means that cash-flow information is entirely absorbed by investors and reflected in the price impartially. Note that stocks with higher RI significantly reduce underreaction to bad news, and this improvement is statistically significant at the 1% level. In contrast, for stocks with low RI, the positive cash-news coefficient is 1.53, and for stocks with high RI, the positive cash-news coefficient is 2.48, which is a severe overreaction. The difference is significant at the 1% level.

Table 4.4.12: Market Reaction to Cash-Flow News Conditional on Residual Institutional Ownership

Cash-Flow News - Direct						
	Residual Institutional Ownership					
	Low	2	3	4	High	High - Low
Bad	-0.23%	-0.59%	-0.03%	0.27%	0.42%	
2	0.57%	0.63%	0.70%	1.10%	1.42%	
3	1.36%	0.99%	0.81%	1.27%	1.94%	
4	1.72%	1.39%	1.67%	2.05%	2.38%	
Good	2.13%	2.36%	2.59%	2.84%	3.40%	
Good - Bad	2.35%***	2.95%***	2.61%***	2.56%***	2.98%***	0.62%
$b-$	0.08**	0.48***	0.55***	0.43***	0.91***	0.82***
$b+$	1.53***	1.72***	1.78***	1.43***	2.48***	0.95***
Cash-Flow News - Indirect						
	Low	2	3	4	High	High - Low
Bad	-1.03%	-1.26%	-1.11%	-1.04%	0.10%	
2	0.12%	0.12%	0.08%	0.32%	0.45%	
3	1.28%	0.88%	0.88%	0.91%	1.37%	
4	2.09%	2.45%	2.27%	2.29%	2.54%	
Good	3.62%	3.94%	4.06%	4.30%	4.27%	
Good - Bad	4.65%***	5.21%***	5.17%***	5.34%***	4.17%***	-0.48%
$b-$	1.00***	1.01***	1.00***	1.19***	0.97***	-0.03
$b+$	1.30***	1.26***	1.26***	1.17***	1.42***	0.12***

Notes: This table reports equal-weighted monthly portfolio returns, in which stocks are sorted annually based on residual institutional ownership (RI) and cash-flow news (Ncf). RI is defined as the regression residuals of a logit transformed institutional ownership on log size and squared log size. Ncf in upper panel is calculated directly from an annual vector autoregression system, while it is calculated indirectly from an identity as in Campbell and Shiller (1988) in lower panel. See Section 4.3.2, Ranking by News, on page 183.

This table also shows market reaction to bad and good news conditional on RI. I run the following regression and define the market reaction to cash-flow news as excessive, correct, and inadequate when $b > 1$, $b = 1$, $b < 1$, respectively. $b + (-)$ represents positive (negative) cash-flow news.

$$\tilde{r}_t = a + b\tilde{N}_{\mathrm{cf},t} + w_t$$

Sample includes all domestic China A-share on CSMAR from January 2000 to December 2018. $***$, $**$ and $*$ denote the level of Newey-West (1987) with 1 lag adjusted significance at 10%, 5% and 1%, respectively.

In the lower panel, $b-$ is floating around 1 across RI quintiles, and the difference is not significantly different from zero. This means that the bad cash-flow news estimated in this way is almost always priced correctly by the market. The mar- ket's response to the good news is the same as in Panel A, i.e., overreacting, which is magnified by institutional involvement. $b+$ is 1.3 in low-RI group, and it is 1.42 in the high-RI group. The difference is significant at the 1% level.

Severe overreaction is the primary source of momentum in upper and lower panels. This is consistent with the theory of overreaction momentum, where the market becomes overconfident and less risk-averse when it receives good news. Note that the source of momentum in the upper panel also has underreaction. So strategies developed using cash-flow news sorting are very sensitive to how cash-flows news is measured.

4.5 Summary

I document the strong short-term momentum and the long-term reversal effect in this chapter. While past winners and losers both contribute to short-term momentum / long-term reversal, the primary source is past winners. A plausible explanation is the limited ability of momentum traders in the presence of short-selling constraints.

Short-term momentum / long-term reversal is emphasised in the up-markets or optimistic investor sentiment (up-optimistic pair). It is because both overconfidence and cognitive dissonance are prevalent in this situation. The former can lead to an overreaction to good news (winners), while the latter can lead to an underreaction to bad news (losers).

Chinese institutional investors are more likely to be informed and overconfident agents than skilled newswatchers. Not only do they not help reduce underreaction to bad news, but they also exacerbate overreaction to good news. This phenomenon is particularly evident in long-term strategies, especially when good news is received in bad times.

In the presence of short-selling constraints, momentum could only come from overreaction to good news (winner momentum) and underreaction to bad news (loser momentum). A practical implication of the chapter is that the winner momentum is the overvaluation of the stock, and the loser momentum is the undervaluation of the stock. Chasing past winners in this situation is risky because the value will further deviate from fundamentals.

My chapter has some limitations. First, to retain as much data as possible, I use the median of an Investor Sentiment Index as a cut-off point. However, this may be too crude to capture the corresponding investor sentiment.

Second, this is not a one-to-one comparison with Daniel et al. (2021) because I am using Chinese data. I can only suggest that a high-frequency strategy and an environment prone to overconfidence may help capture the short-term nature of overreaction-type of momentum. Future studies may consider using data from the US market, provided there is a reliable proxy for short-selling constraints.

CHAPTER 5

CONCLUSION AND OUTLOOK

5.1 MAIN FINDINGS

Chapter 2 attempts to explain how some firms achieve above-average returns by taking on more market risk. They do this by not implementing a dividend smoothing policy, which alters the relationship between firm cash flows and market cash flows.

I find that the average returns of the US firms are related to dividend smoothing to some extent. However, dividend smoothing is flawed as a pricing factor, inferior to Fama and French (1993) value and size factors.

Dividend smoothing cannot explain average returns in China. In contrast, the single CAPM model works better in China than in the US. Nevertheless, even in

China, the three-factor model is still the best pricing model (Liu et al., 2019).

Chapter 3, by exploring dividend smoothing as a signal device, I find that institutional monitors ensure that firms pay smooth dividends in the US. Institutional monitors replace dividend smoothing to control the minority-controlling shareholder problem in China. Dividend smoothing is not used as a signalling device in either case. In addition, managers in both countries pay smoothed dividends for their benefit when the colluders' institutional holdings are high. As a result, the firm value decreases.

Chapter 4, by exploring a return anomaly, i.e., momentum, I find that investors react asymmetrically to information in markets where short-selling is restricted. This inappropriate reaction causes stock prices to deviate from fair values, so I reject China's efficient market hypothesis.

Momentum is a short-term return anomaly in the Chinese stock market, and only strategies constructed daily produce a significant momentum effect. The source of momentum is investor overreaction to good news and underreaction to bad news. Institutional investors overreact to good news in bad times. In cases where overconfidence is most likely to occur, overreaction-type momentum is emphasised. In cases where cognitive dissonance is most likely to occur, underreaction-type momentum is emphasised.

5.2 QUESTIONS

In Chapter 2, finding a suitable cash-flow proxy can be challenging. First, it should be able to reflect the firm's fundamental information. Dividend distribution in China, for example, is a practice that is neither widespread nor continuous. Other cash flow proxies (such as income or free cash flows) may reflect the firm's underlying business better than dividends. Second, cash flow proxies and prices should be cointegrated in order to perform any time series analysis, i.e. there is a stable long-term relationship between them, e.g. the price-dividend ratio is a stationary cointegration (Campbell & Shiller, 1987).

Even if we find a suitable proxy, we still have other problems. Chapter 2 assumes that only variations in cash flows of a firm are closely related to the variations in cash flows in the market. What happens if we relax this assumption? What if changes in a firm's discount rate are also closely related to changes in the market's cash flows? What economic reasons did US stock prices stop predicting cash flows after 1963? I posited smoothing, but the evidence does not fully support it.

In Chapter 3, dividend smoothing acts as an information filter to investors. Some institutional investors like trustworthy filters and others tolerate untrustworthy filters because they are colluding and have inside knowledge that benefits them. However, the parties that use these filters suggested in this chapter must be specified more thoroughly.

For example, dividing institutional investors by independence may not accurately capture their intention to use smooth dividends. The length of the investment horizon, turnover rate, or any other indicator that better reflects institutional investors' vision and forward-thinking should be considered.

Nor is it clear how easy it is to use smoothing strategies in the context of corporate governance at the national level. There are firms with weak corporate governance in the US and firms with excellent corporate governance in China.

In addition, some national policies will also affect dividend smoothing. For example, the China Securities Regulatory Commission initiated a unique dividend policy, the semi-mandatory dividend policy, in 2008. It refers to a series of regulatory policies that link the refinancing eligibility of listed firms to the level of dividend distribution. [1] As a result, the extent of dividend smoothing and payment levels are expected to increase in the longer term. Therefore, the application scenarios for dividend smoothing strategies should be handled more carefully.

In Chapter 4, I introduce short-selling constraints in order to identify the source of momentum. However, short-selling itself is an interesting topic worth discussing.

For example, people sometimes object to short-selling on moral grounds. However, this chapter shows that there is more to this issue. Short-selling impacts behaviour; it impacts price movements and smoothing we see in the markets. Is underreaction to bad news a desirable thing? Is short-selling a means of avoiding overreaction from momentum traders? In which case, short-selling may not be a bad thing.

All these questions need further exploration in future research.

[1] From October 2008 onwards, public securities offerings by listed firms should meet the prerequisite that the cumulative cash profits distributed in the last three years should not be less than 30% of the average annual distributable profits realised in the recent three years.

BIBLIOGRAPHY

Abreu, D. & Brunnermeier, M. K. (2003). Bubbles and crashes. *Econometrica*, *71*(1), 173–204.

Allen, F., Bernardo, A. E. & Welch, I. (2000). A theory of dividends based on tax clienteles. *Journal of Finance*, *55*(6), 2499–2536.

Almazan, A., Hartzell, J. C. & Starks, L. T. (2005). Active institutional shareholders and costs of monitoring: Evidence from executive compensation. *Financial Management*, *34*(4), 5–34.

Altı, A. & Sulaeman, J. (2012). When do high stock returns trigger equity issues? *Journal of Financial Economics*, *103*(1), 61–87.

Anderson, T. W. & Hsiao, C. (1981). Estimation of dynamic models with error components. *Journal of the American Statistical Association*, *76*(375), 598–606.

Ang, A. & Bekaert, G. (2007). Stock return predictability: Is it there? *Review of Financial Studies*, *20*(3), 651–707.

Antoniou, C., Doukas, J. A. & Subrahmanyam, A. (2013). Cognitive dissonance, sentiment, and momentum. *Journal of Financial and Quantitative Analysis*, 245–275.

Arellano, M. & Bond, S. (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *Review of Economic Studies*, *58*(2), 277–297.

Arellano, M. & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, *68*(1), 29–51.

Baker, M., Mendel, B. & Wurgler, J. (2016). Dividends as reference points: A behavioral signaling approach. *Review of Financial Studies*, *29*(3), 697–738.

Baker, M. & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance*, *61*(4), 1645–1680.

Balli, H. O. & Sørensen, B. E. (2013). Interaction effects in econometrics. *Empirical Economics*, *45*(1), 583–603.

Barber, B. M. & Odean, T. (2001). The internet and the investor. *Journal of Economic Perspectives*, *15*(1), 41–54.

Barberis, N., Shleifer, A. & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, *49*(3), 307–343.

Bhattacharya, S. (1979). Imperfect information, dividend policy, and" the bird in the hand" fallacy. *Bell Journal of Economics*, 259–270.

Blundell, R. & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143.

Boone, A. L. & White, J. T. (2015). The effect of institutional ownership on firm transparency and information production. *Journal of Financial Economics*, *117*(3), 508–533.

Bradford, W., Chen, C. & Zhu, S. (2013). Cash dividend policy, corporate pyramids, and ownership structure: Evidence from china. *International Review of Economics & Finance*, *27*, 445–464.

Brav, A., Graham, J. R., Harvey, C. R. & Michaely, R. (2005). Payout policy in the 21st century. *Journal of Financial Economics*, *77*(3), 483–527.

Brickley, J. A., Lease, R. C. & Smith Jr, C. W. (1988). Ownership structure and voting on antitakeover amendments. *Journal of Financial Economics*, *20*, 267–291.

Burkart, M. & Panunzi, F. (2006). Agency conflicts, ownership concentration, and legal shareholder protection. *Journal of Financial Intermediation*, *15*(1), 1–31.

Bushee, B. J. (1998). The influence of institutional investors on myopic r&d investment behavior. *Accounting Review*, 305–333.

Campbell, J. Y. (1991). A variance decomposition for stock returns. *Economic Journal*, *101*(405), 157–179.

Campbell, J. Y. & Mei, J. (1993). Where do betas come from? asset price dynamics and the sources of systematic risk. *Review of Financial Studies*, *6*(3), 567–592.

Campbell, J. Y., Polk, C. & Vuolteenaho, T. (2010). Growth or glamour? fundamentals and systematic risk in stock returns. *Review of Financial Studies*, *23*(1), 305–344.

Campbell, J. Y. & Shiller, R. J. (1987). Cointegration and tests of present value models. *Journal of Political Economy*, *95*(5), 1062–1088.

Campbell, J. Y. & Shiller, R. J. (1988). The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies*, *1*(3), 195–228.

Campbell, J. Y. & Vuolteenaho, T. (2004). Bad beta, good beta. *American Economic Review*, *94*(5), 1249–1275.

Campbell, J. Y. & Yogo, M. (2006). Efficient tests of stock return predictability. *Journal of Financial Economics*, *81*(1), 27–60.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, *52*(1), 57–82.

Celiker, U., Kayacetin, N. V., Kumar, R. & Sonaer, G. (2016). Cash flow news, discount rate news, and momentum. *Journal of Banking & Finance*, *72*, 240–254.

Chen, H., Chong, T. T. L. & She, Y. (2014). A principal component approach to measuring investor sentiment in china. *Quantitative Finance*, *14*(4), 573–579.

Chen, J., Hong, H. & Stein, J. C. (2002). Breadth of ownership and stock returns. *Journal of Financial Economics*, *66*(2-3), 171–205.

Chen, L. (2009). On the reversal of return and dividend growth predictability: A tale of two periods. *Journal of Financial Economics*, *92*(1), 128–151.

Chen, L., Da, Z. & Priestley, R. (2012). Dividend smoothing and predictability. *Management Science*, *58*(10), 1834–1853.

Chen, X., Harford, J. & Li, K. (2007). Monitoring: Which institutions matter? *Journal of Financial Economics*, *86*(2), 279–305.

Chizema, A., Jiang, W., Kuo, J.-M. & Song, X. (2020). Mutual funds, tunneling and firm performance: evidence from china. *Review of Quantitative Finance and Accounting*, *55*(1), 355–387.

Chuang, W.-I. & Susmel, R. (2011). Who is the more overconfident trader? individual vs. institutional investors. *Journal of Banking & Finance*, *35*(7), 1626–1644.

Claessens, S., Djankov, S., Fan, J. P. & Lang, L. H. (2002). Disentangling the incentive and entrenchment effects of large shareholdings. *Journal of Finance*, *57*(6), 2741–2771.

Cochrane, J. H. (2005). *Asset pricing: Revised edition*. Princeton university press.

Cochrane, J. H. (2008). The dog that did not bark: A defense of return predictability. *Review of Financial Studies*, *21*(4), 1533–1575.

Cochrane, J. H. (2011). Presidential address: Discount rates. *Journal of Finance*, *66*(4), 1047–1108.

Cohen, R. B., Gompers, P. A. & Vuolteenaho, T. (2002). Who underreacts to cash-flow news? evidence from trading between individuals and institutions. *Journal of Financial Economics*, *66*(2-3), 409–462.

Cooper, M. J., Gutierrez Jr, R. C. & Hameed, A. (2004). Market states and momentum. *Journal of Finance*, *59*(3), 1345–1365.

Cornett, M. M., Marcus, A. J., Saunders, A. & Tehranian, H. (2007). The impact of institutional ownership on corporate operating performance. *Journal of Banking & Finance*, *31*(6), 1771–1794.

Coval, J. D. & Moskowitz, T. J. (2001). The geography of investment: Informed trading and asset prices. *Journal of Political Economy*, *109*(4), 811–841.

Crane, A. D., Michenaud, S. & Weston, J. P. (2016). The effect of institutional ownership on payout policy: Evidence from index thresholds. *Review of Financial Studies*, *29*(6), 1377–1408.

Daniel, K. & Hirshleifer, D. (2015). Overconfident investors, predictable returns, and excessive trading. *Journal of Economic Perspectives*, *29*(4), 61–88.

Daniel, K., Hirshleifer, D. & Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. *Journal of Finance*, *53*(6), 1839–1885.

Daniel, K., Klos, A. & Rottke, S. (2021). *The dynamics of disagreement* (Working Paper).

Dechow, P. M., Hutton, A. P., Meulbroek, L. & Sloan, R. G. (2001). Short-sellers, fundamental analysis, and stock returns. *Journal of Financial Economics*, *61*(1), 77–106.

DeMarzo, P. M. & Sannikov, Y. (2016). Learning, termination, and payout policy in dynamic incentive contracts. *Review of Economic Studies*, *84*(1), 182–236.

Desai, H., Ramesh, K., Thiagarajan, S. R. & Balachandran, B. V. (2002). An investigation of the informational role of short interest in the nasdaq market. *Journal of Finance*, *57*(5), 2263–2287.

D'Souza, J. M., Ramesh, K. & Shen, M. (2010). The interdependence between institutional ownership and information dissemination by data aggregators. *Accounting Review*, *85*(1), 159–193.

Easterbrook, F. H. (1984). Two agency-cost explanations of dividends. *American Economic Review*, *74*(4), 650–659.

Elyasiani, E. & Jia, J. (2010). Distribution of institutional ownership and corporate firm performance. *Journal of Banking & Finance*, *34*(3), 606–620.

Engsted, T. & Pedersen, T. Q. (2010). The dividend–price ratio does predict dividend growth: International evidence. *Journal of Empirical Finance*, *17*(4), 585–605.

Faccio, M. & Lang, L. H. (2002). The ultimate ownership of western european corporations. *Journal of Financial Economics*, *65*(3), 365–395.

Fama, E. F. & French, K. R. (1988). Dividend yields and expected stock returns. *Journal of Financial Economics*, *22*(1), 3–25.

Fama, E. F. & French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance*, *47*(2), 427–465.

Fama, E. F. & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56.

Fama, E. F. & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, *105*(3), 457–472.

Fama, E. F. & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, *81*(3), 607–636.

Ferris, S. P., Javakhadze, D. & Rajkovic, T. (2017). The international effect of managerial social capital on the cost of equity. *Journal of Banking & Finance*, *74*, 69–84.

Figlewski, S. (1981). The informational effects of restrictions on short sales: Some empirical evidence. *Journal of Financial and Quantitative Analysis*, 463–476.

Firth, M., Gao, J., Shen, J. & Zhang, Y. (2016). Institutional stock ownership and firms' cash dividend policies: Evidence from china. *Journal of Banking & Finance*, *65*, 91–107.

Firth, M., Lin, C. & Zou, H. (2010). Friend or foe? the role of state and mutual fund ownership in the split share structure reform in china. *Journal of Financial and Quantitative Analysis*, 685–706.

Fudenberg, D. & Tirole, J. (1995). A theory of income and dividend smoothing based on incumbency rents. *Journal of Political Economy*, *103*(1), 75–93.

Gao, H., Shi, D. & Zhao, B. (2021). Does good luck make people overconfident? evidence from a natural experiment in the stock market. *Journal of Corporate Finance*, *68*, 101933.

García-Feijóo, L., Hossain, M. M. & Javakhadze, D. (2021). Managerial social capital and dividend smoothing. *Journal of Corporate Finance*, *66*, 101811.

Gaspar, J.-M., Massa, M. & Matos, P. (2005). Shareholder investment horizons and the market for corporate control. *Journal of Financial Economics*, *76*(1), 135–165.

Gibson, S., Safieddine, A. & Sonti, R. (2004). Smart investments by smart money:

Evidence from seasoned equity offerings. *Journal of Financial Economics*, *72*(3), 581–604.

Gillan, S. L. & Starks, L. T. (2000). Corporate governance proposals and shareholder activism: The role of institutional investors. *Journal of Financial Economics*, *57*(2), 275–305.

Golez, B. & Koudijs, P. (2018). Four centuries of return predictability. *Journal of Financial Economics*, *127*(2), 248–263.

Gompers, P., Ishii, J. & Metrick, A. (2003). Corporate governance and equity prices. *Quarterly Journal of Economics*, *118*(1), 107–156.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, 424–438.

Graves, S. B. (1988). Institutional ownership and corporate r&d in the computer industry. *Academy of Management Journal*, *31*(2), 417–428.

Grinstein, Y. & Michaely, R. (2005). Institutional holdings and payout policy. *Journal of Finance*, *60*(3), 1389–1426.

Grundy, B. D. & Martin, J. S. M. (2001). Understanding the nature of the risks and the source of the rewards to momentum investing. *Review of Financial Studies*, *14*(1), 29–78.

Guttman, I., Kadan, O. & Kandel, E. (2010). Dividend stickiness and strategic pooling. *Review of Financial Studies*, *23*(12), 4455–4495.

Han, X. & Li, Y. (2017). Can investor sentiment be a momentum time-series predictor? evidence from china. *Journal of Empirical Finance*, *42*, 212–239.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica: Journal of the Econometric Society*, 1029–1054.

Holtz-Eakin, D., Newey, W. & Rosen, H. S. (1988). Estimating vector autoregressions with panel data. *Econometrica: Journal of the Econometric Society*, 1371–1395.

Hong, H., Lim, T. & Stein, J. C. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance*, *55*(1), 265–295.

Hong, H. & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance*, *54*(6), 2143–2184.

Hong, H. & Stein, J. C. (2007). Disagreement and the stock market. *Journal of Economic Perspectives*, *21*(2), 109–128.

Huang, J., Shen, Y. & Sun, Q. (2011). Nonnegotiable shares, controlling shareholders, and dividend payments in china. *Journal of Corporate Finance*, *17*(1), 122–133.

Huang, W. & Zhu, T. (2015). Foreign institutional investors and corporate governance in emerging markets: Evidence of a split-share structure reform in china. *Journal of Corporate Finance*, *32*, 312–326.

Hurwicz, L. (1950). Least squares bias in time series. *Statistical Inference in Dynamic Economic Models*, *10*, 365–383.

James, G., Witten, D., Hastie, T. & Tibshirani, R. (2013). *An introduction to statistical learning: with applications in r*.

Javakhadze, D., Ferris, S. P. & Sen, N. (2014). An international analysis of dividend smoothing. *Journal of Corporate Finance*, *29*, 200–220.

Jegadeesh, N. & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, *48*(1), 65–91.

Jegadeesh, N. & Titman, S. (2001). Profitability of momentum strategies: An evaluation of alternative explanations. *Journal of Finance*, *56*(2), 699–720.

Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *American Economic Review*, *76*(2), 323–329.

John, K. & Williams, J. (1985). Dividends, dilution, and taxes: A signalling equilibrium. *Journal of Finance*, *40*(4), 1053–1070.

Kaldor, N. (1966). Marginal productivity and the macro-economic theories of distribution: comment on samuelson and modigliani. *Review of Economic Studies*, *33*(4), 309–319.

Kendall, M. G. (1954). Note on bias in the estimation of autocorrelation. *Biometrika*, *41*(3-4), 403–404.

Koijen, R. S. & Van Nieuwerburgh, S. (2011). Predictability of returns and cash flows. *Annual Review of Financial Economics*, *3*(1), 467–491.

Kumar, P. (1988). Shareholder-manager conflict and the information content of dividends. *Review of Financial Studies*, *1*(2), 111–136.

Kumar, P. & Lee, B.-S. (2001). Discrete dividend policy with permanent earnings. *Financial Management*, 55–76.

Lambrecht, B. M. & Myers, S. C. (2012). A lintner model of payout and managerial rents. *Journal of Finance*, *67*(5), 1761–1810.

La Porta, R., Lopez-de Silanes, F. & Shleifer, A. (1999). Corporate ownership around the world. *Journal of Finance*, *54*(2), 471–517.

La Porta, R., Lopez-de Silanes, F., Shleifer, A. & Vishny, R. W. (1997). Legal determinants of external finance. *Journal of Finance*, *52*(3), 1131–1150.

La Porta, R., Lopez-de Silanes, F., Shleifer, A. & Vishny, R. W. (1998). Law and finance. *Journal of Political Economy*, *106*(6), 1113–1155.

La Porta, R., Lopez-de Silanes, F., Shleifer, A. & Vishny, R. W. (2000). Agency problems and dividend policies around the world. *Journal of Finance*, *55*(1), 1–33.

Larkin, Y., Leary, M. T. & Michaely, R. (2017). Do investors value dividend-smoothing stocks differently? *Management Science*, *63*(12), 4114–4136.

Larrain, B. & Yogo, M. (2008). Does firm value move too much to be justified by subsequent changes in cash flow? *Journal of Financial Economics*, *87*(1), 200–226.

Leary, M. T. & Michaely, R. (2011). Determinants of dividend smoothing: Empirical evidence. *Review of Financial Studies*, *24*(10), 3197–3249.

Lee, C. M. & Swaminathan, B. (2000). Price momentum and trading volume. *Journal of Finance*, *55*(5), 2017–2069.

Lettau, M. & Ludvigson, S. C. (2005). Expected returns and expected dividend growth. *Journal of Financial Economics*, *76*(3), 583–626.

Lettau, M. & Van Nieuwerburgh, S. (2008). Reconciling the return predictability evidence: The review of financial studies: Reconciling the return predictability evidence. *Review of Financial Studies*, *21*(4), 1607–1652.

Lin, J. J. & Lee, C.-F. (2021). Does managerial reluctance of dividend cuts signal future earnings? *Review of Quantitative Finance and Accounting*, *56*(2), 453–478.

Lintner, J. (1956). Distribution of incomes of corporations among dividends, retained earnings, and taxes. *American Economic Review*, *46*(2), 97–113.

Liu, J., Stambaugh, R. F. & Yuan, Y. (2019). Size and value in china. *Journal of Financial Economics*.

Luo, J., Subrahmanyam, A. & Titman, S. (2019). *A parsimonious model of momentum and reversals in financial markets* (Working Paper).

Maio, P. & Santa-Clara, P. (2015). Dividend yields, dividend growth, and return predictability in the cross section of stocks. *Journal of Financial and Quantitative Analysis*, *50*(1-2), 33–60.

Markowitz, H. (1952). Portfolio selection. *Journal of Finance*, *7*(1), 77–91.

Marsh, T. A. & Merton, R. C. (1987). Dividend behavior for the aggregate stock market. *Journal of Business*, 1–40.

Michaely, R. & Roberts, M. R. (2012). Corporate dividend policies: Lessons from private firms. *Review of Financial Studies*, *25*(3), 711–746.

Miller, E. M. (1977). Risk, uncertainty, and divergence of opinion. *Journal of Finance*, *32*(4), 1151–1168.

Miller, M. H. & Rock, K. (1985). Dividend policy under asymmetric information. *Journal of Finance*, *40*(4), 1031–1051.

Nagel, S. (2005). Short sales, institutional investors and the cross-section of stock returns. *Journal of Financial Economics*, *78*(2), 277–309.

Newey, W. K. & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation. *Econometrica*, *55*(3), 703–708.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the Econometric Society*, 1417–1426.

Parrino, R., Sias, R. W. & Starks, L. T. (2003). Voting with their feet: Institutional ownership changes around forced ceo turnover. *Journal of Financial Economics*, *68*(1), 3–46.

Pettit, R. R. & Westerfield, R. (1972). A model of capital asset risk. *Journal of Financial and Quantitative Analysis*, *7*(2), 1649–1668.

Pound, J. (1988). Proxy contests and the efficiency of shareholder oversight. *Journal of Financial Economics*, *20*, 237–265.

Rangvid, J., Schmeling, M. & Schrimpf, A. (2014). Dividend predictability around the world. *Journal of Financial and Quantitative Analysis*, *49*(5-6), 1255–1277.

Rogers, W. (1993). Regression standard errors in clustered samples. *Stata Technical Bulletin*, *13*, 19–23.

Ruiz-Mallorquí, M. V. & Santana-Martin, D. J. (2011). Dominant institutional owners and firm value. *Journal of Banking & Finance*, *35*(1), 118–129.

Sadka, G. (2007). Understanding stock price volatility: The role of earnings. *Journal of Accounting Research*, *45*(1), 199–228.

Scheinkman, J., Xiong, W. et al. (2003). Overconfidence, short-sale constraints, and bubbles. *Journal of Political Economy*, *111*, 1183–1219.

Schmidt, B. (2015). Costs and benefits of friendly boards during mergers and acquisitions. *Journal of Financial Economics*, *117*(2), 424–447.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance*, *19*(3), 425–442.

Shiller, R. J. (1981). Do stock prices move too much to be justified by subsequent changes in dividends? *American Economic Review*, *71*(3), 421–436.

Shleifer, A. & Vishny, R. W. (1986). Large shareholders and corporate control. *Journal of Political Economy*, *94*(3), 461–488.

Shleifer, A. & Vishny, R. W. (1997). A survey of corporate governance. *Journal of Finance*, *52*(2), 737–783.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: Journal of the Econometric Society*, 1–48.

Tobin, J., Brainard, W. C. et al. (1976). *Asset markets and the cost of capital* (Tech. Rep.). Cowles Foundation for Research in Economics, Yale University.

Van Binsbergen, J. H. & Koijen, R. S. (2010). Predictive regressions: A present-value approach. *Journal of Finance*, *65*(4), 1439–1471.

Verardo, M. (2009). Heterogeneous beliefs and momentum profits. *Journal of Financial and Quantitative Analysis*, 795–822.

Vuolteenaho, T. (2002). What drives firm-level stock returns? *Journal of Finance*, *57*(1), 233–264.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step gmm estimators. *Journal of Econometrics*, *126*(1), 25–51.

Woidtke, T. (2002). Agents watching agents? evidence from pension fund ownership and firm value. *Journal of Financial Economics*, *63*(1), 99–131.

Wu, Y. (2018). What's behind smooth dividends? evidence from structural estimation. *Review of Financial Studies*, *31*(10), 3979–4016.

Ye, P. (2012). The value of active investing: Can active institutional investors remove excess comovement of stock returns? *Journal of Financial and Quantitative Analysis*, 667–688.

Yi, Z. & Mao, N. (2009). Research on the measurement of investor sentiment in chinese stock market: the cicsi's construction. *Journal of Financial Research*, *11*, 014.

Yuan, R., Xiao, J. Z., Milonas, N. & Zou, J. H. (2009). The role of financial institutions in the corporate governance of listed chinese companies. *British Journal of Management*, *20*(4), 562–580.

Yuan, R., Xiao, J. Z. & Zou, H. (2008). Mutual funds' ownership and firm performance: Evidence from china. *Journal of Banking & Finance*, *32*(8), 1552–1565.