Essays on Financial Accounting Information, Return Predictability, and Default Risk

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ABSTRACT

There is a growing realization of the importance of financial and accounting information on financial markets, and this is thus very much an area of focus for academics, practitioners, and regulators. This thesis consists of three essays on financial accounting information, return predictability, and default risk.

The first essay considers the impact of inconsistent financial accounting information on the cross-section of stock returns. This essay uses earnings quality and firm characteristics to capture information signals about the firm value and measure information inconsistency as the variation across the information of the same company. The findings show that returns of information-consistent firms predict the returns of information-inconsistent firms in both equal- and value-weighted portfolios. However, such predictability varies over time due to liquidity funding and investor attention. This first essay thus contributes to the growing literature documenting the cross-section of stock return predictability as a result of the varying speed of information incorporation across stocks.

The second essay examines whether the differences in accounting information between the pairs of stocks affect cross-asset return predictability. This essay uses a comprehensive set of accounting variables and market environments to capture the degree of information reflection. The results show that accounting variables such as abnormal accruals, earnings smoothness, book-to-market, firm age, leverage, abnormal capital investment, and investment growth, among others, explain the variation in predictability across pairing stocks. The cross-asset predictability varies over time and is associated with liquidity funding and market sentiment. A simple trading strategy based on our findings yields a higher mean return, lower standard deviation, and higher Sharpe ratio compared to the buy-and-hold strategy.

The final essay investigates the impact of risk aversion on default risk. While a large body of research documents various firm characteristics and market conditions that drive corporate default, whether risk aversion matters for default risk remains under-investigated. This could be attributed to endogeneity concerns, such as that the investor risk aversion is not an exogenous variable or the presence of omitted variables that drive the default risk and the simultaneity bias between the default risk and the risk aversion. To address the endogeneity challenge, we use the largest mega-terrorist event, the 9/11 terrorist attacks, as an exogenous shock to investor's risk aversion; the empirical evidence shows a significant increase in default risks at both market and firm levels following the 9/11 attacks. Terrorism causes an increase in market-wide default risk for firms located in the attacked states, as well as for those located in the non-affected states. The findings are consistent with the strand of literature suggesting that, following terrorist attacks, investors become more risk-averse and demand a higher premium for their investment, leading to increased default risk.

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CHAPTER ONE

INTRODUCTION

This chapter provides an overview of this thesis. In particular, it outlines the motivation and needs to explore the area of financial accounting and risk and return predictability and the contribution of the three essays contained in this thesis. The chapter concludes by outlining the structure for the remainder of the thesis.

1.1. Introduction

Understanding the role of financial and accounting information has been a major focus of academic research over the decades. A variety of the attributes of such information have been studied in a large and growing body of literature (see, for example, Lewellen, 2004; Dechow, Ge, and Schrand, 2010; Gaio, 2010; Garlappi and Yan, 2011; Bhattacharya, Desai, and Venkataraman, 2013; Kogan and Papanikolaou, 2013; Harvey, Liu, and Zhu, 2016; McLean and Pontiff, 2016; Hou, Xue, and Zhang, 2020). The relevance of financial accounting information in predicting asset return appears to be well-established.[1] Meanwhile, a large number of firm characteristics have been extensively documented as being drivers of corporate default risk.[2] However, whether the financial accounting information impacts cross-asset return predictability and corporate default risk at an individual stock level remains under-investigated. This thesis examines the predictability of cross-stock returns and firm default risk, using financial and accounting information as proxies to capture the informative signals about firm value.

The focus of this thesis is motivated by two strands of literature. The first is the finance and accounting literature on the information processing capacity of cross-stock return predictability, such as lead-lag effects from large to small firms (e.g., Lo and MacKinlay, 1990; Hou, 2007), asymmetric information, and incomplete information (e.g., Barry and Brown, 1984; Merton, 1987; Easley, Hvidkjaer, and O'Hara, 2002; Hou and Moskowitz, 2005; Lambert, Leuz, and Verrecchia, 2007), and information flow (e.g., Hong, Lim, and Stein, 2000; Cohen and Frazzini, 2008; Menzly and Ozbas, 2010; Cohen and Lou, 2012; Rapach, Strauss, and Zhou, 2013). This evidence suggests that imperfections in information can impede timely

[1] See, for example, Lakonishok, Shleifer, and Vishny (1994), Sloan (1996), Richardson, Sloan, Soliman, and Tuna (2005, 2006), and Dechow, Richardson, and Sloan (2008).

[2] See, for example, Vassalou and Xing (2004), Duffie, Saita, and Wang (2007), Cuadra and Sapriza (2008), and Brogaard, Li, and Xia (2017).

equity price discovery and consequently delay any price adjustment to new information. Consistent with these studies, this thesis argues that individual stocks reflect and react to new information at different speeds, leading to cross-stock lead-lag return predictability.

The second motivating literature for this thesis is the psychological and behavioural economic literature, suggesting that terrorist attacks and mass shootings have extremely negative effects on international economies and financial markets through fear, anxiety, and uncertainty (e.g., Dumont, Yzerbyt, Wigboldus, and Gordijn, 2003; Mythen and Walklate, 2006; Smelser, 2009; Choi, 2015; Dai, Rau, Stouraitis, and Tan, 2020). Burch, Emery, and Fuerst (2003) and Glaser and Weber (2005) suggest that terrorism has a strong negative impact on investor sentiment, and such negative emotions from fearful circumstances increase aggregate risk aversion, causing investors to invest in less risky assets (Levy and Galili, 2006; Wang and Young, 2020). Lizarazo (2013) finds that when international investors become more risk-averse, the economy becomes credit-constrained, resulting in higher sovereign risk because investors require an excess premium for the higher probability of default. Motivated by these studies, this thesis conjectures that the negative impact of extreme negative events influences investors' risk aversion, leading to an increased firm default risk.

This thesis consists of three essays and contributes to the literature on financial accounting return predictability and corporate default risk. The first essay examines the impact of inconsistent financial accounting information on the cross-section of stock returns. The second essay investigates whether the differences in accounting information between stocks affect cross-asset return predictability. The third essay considers the largest mega-terrorist event, namely, the 9/11 terrorist attacks, as an exogenous shock and thereby investigates the impact of investors' risk aversion on default risk.

The remainder of this chapter is organized as follows. The next sections (Sections 1.2, 1.3, and 1.4) provide an overview, including the important contribution of these dissertation findings to the existing literature, of each of the three essays. Section 1.5 presents the research outputs from this thesis, and Section 1.6 summarizes the structure of the remainder of the thesis.

1.2. Essay One

Financial accounting information has played a significant role in stock returns predictability. A growing number of studies have focused on the quality of such information (see, for example, Porta, Lakonishok, Shleifer, and Vishny, 1997; Skinner and Sloan, 2002; Richardson, Tuna, and Wysocki, 2010; Papadamou, Sidiropoulos, and Spyromitros, 2014). The first essay in this thesis examines the impact of inconsistent financial accounting information on the cross-section of stock returns by using earnings quality and firm characteristics as proxies to capture the informative signals about firm value.

Using a sample of US common stocks, covering 25 years from January 1991 to December 2015, this study measures information inconsistency as the variation across the same company's information. The findings show that returns of information-consistent firms predict one-month ahead returns of information-inconsistent firms. The essay further shows that predictability varies over time and is associated with liquidity funding and investor attention. Furthermore, this essay finds positive and statistically significant out-of-sample R^2. The encompassing tests show that the forecasts based on the model have superior information content relative to forecasts based on the historical mean. Finally, a trading strategy based on the predictability results outperforms the buy-and-hold strategy. The findings are in alignment with recent theories about information deficiencies in stock markets.

1.3. Essay Two

Cross-asset return predictability has been a large and still growing body of finance and accounting research. Recent studies have shown evidence of return predictability at the country, industry, and supply chain levels (see, for example, Cohen and Lou, 2012; Rapach, Strauss, and Zhou 2013; Han, Rapach, and Zhou, 2019). The second essay in this thesis examines predictability across different pairs of stocks by using a comprehensive set of accounting variables and market environments as proxies for the degree of information reflection.

Using a large sample of US commons stocks covering 86 years from January 1931 to December 2016, this essay finds that 10 of the 17 accounting variables, including abnormal accruals, earnings smoothness, book-to-market, firm age, leverage, abnormal capital investment, investment growth, return on equity, firm size, and stock volatility, provide useful information for predicting the cross-section of stock returns. They are strong predictors of stock returns across firms, evidenced by the likelihood and the power of cross-stock returns predictability. This essay further shows that the cross-asset predictability varies over time due to liquidity funding and market sentiment. Finally, a simple trading strategy, based on the predictability results, outperforms the buy-and-hold strategy. Interestingly, the results are consistent with recent theories about gradual information diffusion in asset markets.

1.4. Essay Three

A large body of literature documents various firm characteristics and market conditions that drive corporate default. The causal relation between risk aversion and default risk, however, remains under-investigated due to endogeneity concerns. Investors' risk aversion is not exogenous and is affected by various factors, such as sentiment, firm-specific and economic conditions (e.g., Duffie, Saita, and Wang, 2007), that could also affect the default risk. To overcome the endogeneity concern, this essay uses the largest mega-terrorist event, namely, the 9/11 terrorist attacks in 2001, as an exogenous shock to investigate the impact of investors' risk aversion on default risk.

Using the Volatility Index and the News Sentiment Index to investigate the impact of the 9/11 terrorist attacks on market sentiment, this essay finds that terrorist attacks intensely affect people's emotions, create fear, and influence stock market sentiment and future economic prospects. Moreover, this essay uses an event-study approach to measure the impact of terrorist attacks on the market and firm levels. The essay finds significantly increased default risks at both market and firm levels following the 9/11 terrorist attacks. Interestingly, terrorist attacks cause an increase in default risk in all industries. This essay employs a difference-in-difference analysis to examine the state reaction to the 9/11 attacks. The evidence shows that this mega-terrorism causes an increase in market-wide default risk for firms located in the attacked states, as well as for those located in the non-affected states.

This essay provides two important contributions to the existing literature. First, terrorist attacks impose negative and multi-dimensional externalities. This study is the first to study the impact of terrorist attacks on unfavourable events in the life of a corporation by showing the adverse consequences of these extreme negative events (e.g., Cuculiza, Antoniou, Kumar, and Maligkris, 2020; Wang and Young, 2020). Second, this essay highlights the roles of investor sentiment and risk preference in understanding various economic decisions (e.g., Kuhnen and Knutson, 2011; Guiso, Sapienza, and Zingales, 2018), suggesting that terrorist attacks influence investors' risk aversion and thus affect the default risk.

1.5. Research Outputs from the Thesis

Essay One:

Essay one has been presented at the following conferences:

Thakerngkiat, N., Nguyen, H. T., Nguyen, N. H., & Visaltanachoti, N. Inconsistent Information and the Cross-Section of Stock Returns. Proceedings of the 25th *New Zealand Finance Colloquium* (*NZFC*), *PhD Symposium*, Tauranga, New Zealand, February 2021.

Thakerngkiat, N., Nguyen, H. T., Nguyen, N. H., & Visaltanachoti, N. Inconsistent Information and the Cross-Section of Stock Returns. Proceedings of *Massey University Seminar Series*, Auckland, New Zealand, August 2017.

Essay Two:

Essay two has been published in the following journal:

Thakerngkiat, N., Nguyen, H. T., Nguyen, N. H., & Visaltanachoti, N. (2021). Do accounting information and market environment matter for cross-asset predictability?. *Accounting & Finance*.

Essay two has been presented at the following conferences:

Thakerngkiat, N., Nguyen, H. T., Nguyen, N. H., & Visaltanachoti, N. Do Accounting Information and Market Environment Matter for Cross-Asset Predictability? Proceedings of the 32nd *Australasian Finance & Banking Conference (AFBC)*, Sydney, Australia, December 2019.

Thakerngkiat, N., Nguyen, H. T., Nguyen, N. H., & Visaltanachoti, N. Do Accounting Information and Market Environment Matter for Cross-Asset Predictability? Proceedings of the 9th *New Zealand Finance Meeting* (*NZFM*), Auckland, New Zealand, December 2019.

Thakerngkiat, N., Nguyen, H. T., Nguyen, N. H., & Visaltanachoti, N. Do Accounting Information and Market Environment Matter for Cross-Asset Predictability? Proceedings of the 11th *Financial Management Association* (*FMA*) *Asia/Pacific Conference and Doctoral Student Consortium*, Ho Chi Minh City, Vietnam, July 2019.

Thakerngkiat, N., Nguyen, H. T., Nguyen, N. H., & Visaltanachoti, N. Do Accounting Information and Market Environment Matter for Cross-Asset Predictability? Proceedings of the 31st *Asian Finance Association Annual Meeting* (*Asian FA*), Ho Chi Minh City, Vietnam, July 2019.

Thakerngkiat, N., Nguyen, H. T., Nguyen, N. H., & Visaltanachoti, N. Do Accounting Information and Market Environment Matter for Cross-Asset Predictability? Proceedings of *Massey University Seminar Series*, Auckland, New Zealand, July 2019.

1.6. Structure of the Thesis

The remainder of this thesis is organized as follows. The first essay, which examines the impact of inconsistent financial accounting information on the cross-section of stock returns, is presented in Chapter 2. Chapter 3 provides the second essay, which examines whether the differences in accounting information between the stocks affect cross-asset return predictability. Chapter 4 presents the third essay, which investigates the impact of risk aversion on default risk. Chapter 5 outlines the main findings and their implications for future research directions. Supplementary information, such as variable description and the correlation matrix, is given in the Appendices.

CHAPTER TWO

ESSAY ONE

This chapter presents the first essay of this thesis, which examines the impact of inconsistent financial accounting information on the cross-section of stock returns, using earnings quality and firm characteristics to provide informative signals about firm value. A brief overview of the study is presented in Section 2.1. Section 2.2 presents an in-depth review of the related literature and hypothesis development. Sections 2.3 and 2.4 describe the data and the methodology used in this study. Section 2.5 discusses the empirical results. Section 2.6 provides the trading strategy implications, and Section 2.7 concludes this chapter. The essay's Appendix and References are presented at the end of this chapter and in the references section, respectively.

Inconsistent Information and the Cross-Section of Stock Returns

2.1. Introduction

The ability of investors and stakeholders in the financial markets to make informed decisions is mainly based on the financial and accounting information provided by companies, emphasizing the importance of such information for both market players and regulators. In an ideal economic world with complete and frictionless equity markets, rational investors have full market information while share prices immediately reflect any new information on the market. However, in reality, there are information deficiencies such as lead-lag effects and incomplete or asymmetric information (see, for example, Lo and MacKinlay, 1990; Easley, Hvidkjaer, and O "Hara, 2002; Lambert, Leuz, and Verrecchia, 2007). A large body of research documents financial and accounting information in predicting asset returns appearing to be well established.[3] However, whether the inconsistent financial accounting information impacts the cross-section of stock returns still remains under-investigated. The current study fills this void by examining the predictability of stocks and using earnings quality and firm characteristics as proxies to capture the informative signals about firm value.

Recent studies have focussed on the disclosure of all possible financial information and on the quality of such information. A significant aspect of this interest is rooted in the quality of information and the extent to which earnings (accruals) predict cash flows. Earnings indeed provide crucial input for analysts' and investors' valuation models. For example, Francis, LaFond, Olsson, and Schipper (2004) find that companies with low earnings potentially tend

[3] See, for example, Sloan (1996), Porta, Lakonishok, Shleifer, and Vishny (1997), Skinner and Sloan (2002), Gaio (2010), Richardson, Tuna, and Wysocki (2010), and Papanastasopoulos (2014).

to have higher capital costs, and those experiencing and undergoing SEC enforcement and restatement actions tend to experience an economically significant negative stock price reaction to information. Dechow and Schrand (2004) find that high earnings quality is considered to be an accurate indicator of the current operating performance of a company. More recently, Dechow, Ge, and Schrand (2010) have shown that earnings quality is a function of both how the accounting system is implemented and its ability to evaluate the fundamental performance of firms. The literature suggests that earnings quality is the informativeness of financial statement for understanding the firm performance and forms the basis for predicting future cash flow. Firms with a higher quality of information provide more earnings-information-accessing ability result in a better forecast of the earnings implication of new information than firms with low quality of information. If the low quality of financial statement hinders investor understanding of firms' financial performance and delays consensus in investor perspective about the earnings impact of the new information. When new information arrives, the high quality of information firms' stock price will respond before the low quality of information firms' stock price to new information. This study is interested in a return pattern in the cross-section of information inconsistency that has not been previously studied: cross-stock return predictability from information-consistent firms to information-inconsistent firms. We simply ask whether the returns of information-consistent firms predict the returns of information-inconsistent firms.

A growing body of studies has also shown that stock return predictability tends to align with several firm characteristics[4]. Holthausen and Larcker (1992) and Lewellen (2004) suggest that firm characteristics are a strong indicator of the predictability of stock returns with given

[4] Such as size (e.g., Berk, Green, and Naik, 1999; Carlson, Fisher, and Giammarino, 2004), book-to-market ratio (e.g., Gomes, Kogan, and Zhang, 2003; Carlson, Fisher, and Giammarino, 2004; Zhang, 2005), leverage (e.g., Garlappi and Yan, 2011), returns (e.g., Berk, Green, and Naik, 1999; Johnson, 2002; Liu and Zhang, 2014), and idiosyncratic volatility (e.g., Kogan and Papanikolaou, 2013; Babenko, Boguth, and Tserlukevich, 2016).

financial information. This poses an important question, how to aggregate the information associated with a number of firm characteristics and provide explicit stock returns predictability. In the current study, we employ earnings quality proxies and firm characteristics to examine how frictions and processing incompatibilities in the whole information environment can impact stock returns predictability. We also investigate the impact of inconsistent financial accounting information on across-section of stock returns. We propose a methodology that reveals signals that enable future stock returns to be predicted while capturing the speed of information incorporation across stocks.

Using a sample of US common stocks, covering 25 years from January 1991 to December 2015, we use a specification that involves predicting individual information-inconsistent stock returns using the portfolio return from information-consistent stocks and use earnings quality and firm characteristics as informative signals to capture the speed of information incorporation. We measure information inconsistency as the variation across the information of the same company. We find that stock returns of information-consistent firms are positive and significant in the prediction of the subsequent one-month-ahead stock returns of information-inconsistent firms in both equal- and value-weighted portfolios. We further show that predictability varies over time due to funding liquidity and investor attention. We also examine the out-of-sample predictive ability of our forecasting model.[5] We find positive and statistically significant out-of-sample R^2. Using encompassing tests, we show that forecasts based on our model have superior information content relative to forecasts based on the historical mean. Finally, we create a trading strategy based on our predictability results and find

[5] We use only information available at the time forecasting formation when calculating out-of-sample analysis, so that our forecasts do not have a "look-ahead bias".

that this strategy outperforms the buy-and-hold strategy. Overall, our findings are aligned with recent theories about information deficiencies in stock markets.[6]

The novelty of this research lies in its contribution to the accounting and finance literature on delayed information processing in stock markets. First, we advance the literature on the roles of the quality of the information in predicting asset returns with evidence for the predictability of stocks, using earnings' quality and firm characteristics as proxies to capture the informative signals about firm value. Second, we contribute to the growing strand of the literature that highlights the impact of inconsistent financial accounting information on the cross-section of stock returns.

The rest of this study is organized as follows: Section 2.2 provides an in-depth review of the related literature as well as highlighting the research gap and hypothesis development. Sections 2.3 and 2.4 describe the data and the methodology used in this research. Section 2.5 presents the empirical results. Section 2.6 provides the trading strategy implications, and Section 2.7 concludes the study.

2.2. Literature Review

2.2.1. Earnings Quality

Over the past two decades, the finance literature has theoretically and empirically emphasized the relevance of earnings quality, especially in the financial market. Dechow, Ge, and Schrand (2010) suggest that the quality of earnings is jointly determined by the relevance of underlying financial performance to the decision and by the ability of the accounting system

[6] See, for example, Lo and MacKinlay (1990), Hong and Stein (1999), Chordia and Swaminathan (2000), Hong, Lim, and Stein (2000), Easley, Hvidkjaer, and O "Hara (2002), Hong, Tourus, and Valkanov (2007), Hou (2007), Cohen and Frazzini (2008), Menzly and Ozbas (2010), Cohen and Lou (2012), and Albuquerque, Ramadoraie, and Watugala (2015).

to evaluate performance. The quality of a reported earnings number depends on whether it is informative about the firm's performance. It is, therefore, conceivable that higher earnings quality reflects more information from the financial performance aspect related to a specific decision context. One of the significant issues with studies on earnings quality is the difficulty in properly measuring it as a variable. Several empirical researchers have examined earnings quality from different angles. Various measures, such as accruals, earnings persistence, and earnings smoothness, have been employed with different dimensions of the fundamental performance of the firms.

However, one of the most important and interesting developments has been the focus on the inflexibility of earnings quality proxies, especially those measuring abnormal accruals. Abnormal accruals have been used as an earnings quality proxy in several empirical research (see, for example, Aboody, Hughes, and Liu, 2005; Francis, LaFond, Olsson, and Schipper, 2005; Bharath, Sunder, and Sunder, 2008; Chen, Dhaliwal, and Trombley, 2008; Biddle, Hilary, and Verdi, 2009). Some of the pioneering studies, for example, Healy (1985) on earnings quality, measured "abnormality" by examining the current period's total accruals. DeAngelo (1988) presents an expectation model, making use of the change in total accruals, while Jones (1991) devised a multivariate model to extract "normal" accruals. This further emphasizes the difficulty in finding the appropriate measure for earnings quality. Notwithstanding this, some quite recent studies have also modified such methods responding to their limitations. For example, DeFond and Jiambalvo (1994), Dechow, Sloan, and Sweeney (1995), Hribar and Collins (2002), Kothari, Leone, and Wasley (2005), Doyle, Ge, and McVay (2007), and Ashbaugh-Skaife, Collins, Kinney Jr, and LaFond (2008) show that firms with internal control deficiencies have lower quality accruals. Hutton, Marcus, and Tehranian (2009), on the other hand, report that a higher probability of material misstatements and restatements is related to versions of accrual quality. Their results show that accrual quality is related to low accounting quality.

Furthermore, earnings persistence has been used as a proxy for earnings quality. Prior studies, such as Kormendi and Lipe (1987), Collins and Kothari (1989), and Easton and Zmijewski (1989), have been concerned with the consequences of persistence. They find evidence that more persistent earnings have a higher security price response and positive stock market returns. Another important measure of earnings quality is the use of earnings smoothness. Such smoothness in a firm's earnings reveals a variation in the informativeness about financial performance (Dechow, Ge, and Schrand, 2010). Tucker and Zarowin (2006) postulate that smoothness enhances earnings informativeness. They divide the sample into a high and a low smoothing group and find the high smoothing group has stronger earnings informativeness. These findings highlight the fact that earnings quality proxies reflect information about the features of a firm's fundamental financial performance and also take into account a wide range of perspectives. This clearly shows that earnings quality is an important focus for analysis in this context.

2.2.2. Information Environment and Return Predictability

A considerable number of theoretical and empirical studies have been conducted on delayed information processing, which has been linked to information processing capacity factors (e.g., Callen, Khan, and Lu, 2013). These factors include slow information diffusion (e.g., Hong, Lim, and Stein, 2000), incomplete information (e.g., Merton, 1987), information asymmetry across investors (e.g., Easley, Hvidkjaer, and O "Hara, 2002), and information transmission barriers (e.g., Cohen and Lou, 2012), all of which emphasize the relevance of the elements of information frictions. The prior literature suggests these frictions are significant for the understanding of asset price dynamics and, even more so, for a slow price adjustment to new information.

2.2.2.1. Delayed Reactions to Information

Merton (1987), Hong and Stein (1999), and Hirshleifer and Teoh (2003) show that the limited attention and delayed information reaction of investors tend to lead to a generation of expected returns. This cannot, however, be completely described by traditional asset pricing models, although several empirical studies have shown that this phenomenon is in line with the models' predictions. For example, Hong, Tourus, and Valkanov (2007), Hou (2007), Barber and Odean (2008), Cohen and Frazzini (2008), and DellaVigna and Pollet (2009) find that investors will react speedily to relevant and important information, whereas they will disregard information that is less noteworthy and not in keeping with company values. Verrecchia (1980) and Callen, Khan, and Lu (2013) find that information imperfections potentially obstruct timely stock price discovery and delay any stock price changes in response to new information.

2.2.2.2. Lead-Lag Effects

Lo and MacKinlay (1990) investigated how stock market information is incorporated into stock prices and provided evidence from the New York Stock Exchange that larger capitalization portfolio stock returns lead, whereas smaller ones mostly merely follow. This finding suggests that lead-lag patterns are able to serve as sources of profit contrarianism. Hou (2007) postulates that the slow diffusion of industry information is the main reason for the lead-lag effect in equity returns. His findings show that the lead-lag relationship in information between large and small firms is predominantly an intra-industry phenomenon. That is, stock returns in small firms following the release of the returns of large firms within the same industry. Moreover, the literature shows that this effect results from a sluggish adjustment to negative information (e.g., see Lo and MacKinlay, 1990; Brennan, Jegadeesh, and Swaminathan, 1993; Badrinath, Kale, and Noe, 1995).

Recounting the causes of the lead-lag effect, prior studies such as those by Brennan, Jegadeesh, and Swaminathan (1993), Badrinath, Kale, and Noe (1995), and Chordia and Swaminathan (2000), show that the factors responsible for the lead-lag effect are not only the firm size but also analyst coverage, institutional ownership, and trading volume. Moreover, there has also been considerable research into the economic significance of geography in relation to information acquisition. For example, Bae, Stulz, and Tan (2008) provide evidence that there is a benefit when local analysts are used as they are able to make more accurate return predictions for local firms than non-local analysts are able to. Coval and Moskowitz (1999) also find that the preference for proximate geographical investments can be explained by there being asymmetric information among regional and foreign investors.

2.2.2.3. Information Transmission

Prior studies have revealed new channels for cross-firm information flows. Specifically, Hong, Torous, and Valkanov (2007) find that some particular industries tend to be leaders for the whole market. Menzly and Ozbas (2010) find that there is also information transmission between supplier- and customer-oriented industries. Albuquerque, Ramadoraie, and Watugala (2015) indicate that information travels slowly within a nation by showing that companies with high trade credit and located in producer nations have strongly predictable equity returns based on their related customer nations' returns. This gives a strong suggestion that early return announcers forecast the returns of late announcers within the same business sector. Moreover, Cohen and Frazzini (2008) show that information transfers slowly across the supply chain; in this set-up, followers within the same industry may obtain uncorrelated signals while the finding is related to the lead-lag literature, the information leaders tend to be the bigger firms.

Cohen and Lou (2012) also demonstrate that information can slowly flow from single segment industry firms to multi-industry (conglomerate) firms.

2.2.2.4. Information Asymmetry

The theory of information asymmetry is well-established, emphasizing the non-equivalent sets of information among market participants (e.g., see Lu, Chen, and Liao, 2010). This concept reveals that certain investors are more informed than other investors when making value judgments pertaining to their investments. Studies, such as Glosten and Milgrom (1985) and Diamond and Verrecchia (1991), show evidence of the presence of such information deficiencies as being in the form of incomplete or asymmetric information. They point out that higher quality disclosures result in the minimization of information asymmetry. In addition to this, Bhattacharya, Desai, and Venkataraman (2013) investigate the relationship between earnings quality and information asymmetry. They present evidence that shows less-informed investors being more likely not to be able to process earnings information compared to their more sophisticated counterparts who are able to strengthen information asymmetry. In a related paper, Sloan (1996) shows that, for example, some investors are unable to incorporate the mean-reverting of the accruals of high accrual firms completely. The literature reveals that there is a negative relationship between (accruals) earnings quality and the degree of information asymmetry as high accruals result in a low quality of earnings and thus a higher degree of information asymmetry. Nonetheless, most previous studies have focused on different characteristics, leading or lagging one another and using the above variables in the literature. By contrast, this research examines the impact of delayed and biased reactions to information on the relationship between earnings management, the information environment, and return predictability.

2.2.3. The Limits of Arbitrage and Market Environment Variables

More recently, studies have considered how market conditions affect return predictability. In particular, they focus on whether the cross-sectional predictability of returns varies over time and to what extent market environment variables for limits to arbitrage have explanatory power for the stock return predictability. The studies suggest that the investor attention effect is more pronounced in stocks with higher limits to arbitrage (e.g., Chai, Dai, Gharghori, and Hong, 2019). Besides this, prior studies document that market liquidity measures, including TED spread (e.g., see Lashgari, 2000; Brunnermeier and Pedersen, 2009; Ang, Gorovyy, and Van Inwegen, 2011; Moskowitz, Ooi, and Pedersen, 2012; Asness, Moskowitz, and Pedersen, 2013) and market liquidity factor (e.g., Amihud, 2002; Pástor and Stambaugh, 2003) explain return predictability.

This research is motivated by the significance of return predictability, particularly in the current much integrated financial market with its highly complicated information environment. This paper combines both earnings quality and firm characteristics into informative signals about a return, thus providing a novel approach for predicting stock returns while also giving a comprehensive insight into earnings management. We introduce market state variables to test whether their relation or predictability varies over time, and thus we provide a new approach for predicting stock returns. To the best of our knowledge, this study will be the first to address this very important but so far ignored aspect of the literature.

2.2.4. Hypothesis Development

Our study is motivated by two strands of literature. The first is finance literature on the delayed information processing literature, which shows cross-stock return predictability from large to small firms (Lo and Mackinlay, 1990; Hou, 2007), trading volume (Chordia and Swaminathan, 2000), geographic operational structures (Huang, 2015), supply chain levels

(Cohen and Frazzini, 2008; Menzly and Ozbas, 2010), and business homogeneity (Cohen and Lou, 2012). This evidence from the literature suggests that slow price adjustment to new non-idiosyncratic information has value relevance across stocks. The second motivating literature is the accounting literature on accounting quality and a return pattern. Dechow, Ge, and Schrand (2010) stated that firms with higher quality earnings provide more information about the features of firms' financial performance. Chen, Khan, Kogan, and Serafeim (2021) suggest that poor accounting quality is associated with poor investor understanding of firms' financial statement, then poor accounting quality stocks likely respond more slowly than good accounting quality stocks to new information. In this study, we are interested in a return pattern in the cross-section of information inconsistency that has not been previously studied: cross-stock return predictability from information-consistent firms to information-inconsistent firms. Motivated by two strands of literature, our main hypothesis is that "A more inconsistent (consistent) financial accounting information leads to a slower (faster) incorporation of information across stocks."

2.3. Data and Variables

2.3.1. Data

The sample in this research includes all the listed companies on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the NASDAQ and covers 25 years from January 1991 to December 2015. The sample period starts in 1991 because we require the availability of all financial accounting variables to calculate a measure of firm information consistency. We collect data and construct variables from various standard and acceptable sources consistent with the literature. Specifically, we obtain stock returns, prices, and the number of shares outstanding from the Center for Research in Security Prices (CRSP) and source annual accounting information from Compustat. We obtain Fama and French

(1993)'s three factors from Kenneth French's website[7] and consider only common stocks (with a CRSP share code of 10 or 11). The sample excludes financial institutions and real estate companies (with SIC codes between 6000 and 6999) since the investment and financing policies in these industries are likely to be significantly different from firms in other industries. To examine whether the cross-sectional return predictability varies over time, we use several market state variables, including the investor attention index from Chen, Tang, and Yao (2020), the market liquidity factor from Pástor and Stambaugh (2003), and the average percentage of TED from the Federal Reserve Bank of St. Louis.[8] We follow Hou (2007) and match the accounting information from Compustat for the fiscal year ending in year $t - 1$ with the stock return information from CRSP from July of year t to June of year $t + 1$. We use the annual frequency of all financial accounting variables to maintain the consistency of variables. Finally, we remove observations with negative book-to-equity values and winsorize the extreme observations to one percentile to mitigate the influence of outliers.

2.3.2. Variables and Descriptive Statistics

As signals about future stock returns, we employ eight accounting variables, including three earnings quality proxies and five firm characteristics, to incorporate the same piece of information into the stock returns. The earnings quality proxies are estimated as follows:

Earnings persistence

Consistent with Kormendi and Lipe (1987), we measure earnings persistence by using firm-level regression of the current earnings and the previous year's earnings to estimate the slope-coefficient estimate as follows:

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[7] We thank Kenneth French for making the data available through his website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[8] The investor attention index is from http://apps.olin.wustl.edu/faculty/zhou/, the market liquidity factor is from http://finance.wharton.upenn.edu/~stambaug/, and TED Spread is from https://fred.stlouisfed.org/series/TEDRATE.

$$Earnings_{j,t} = \alpha + \beta Earnings_{j,t-1} + \varepsilon_t, \tag{2.1}$$

where $Earnings_{j,\,t}$ = firm's *j* net income before extraordinary items (Compustat #18) in year *t*; and $Earnings_{j,\,t-1}$ = firm's *j* net income before extraordinary items in year $t-1$.

The slope coefficient between current periods earnings regressed scaled by total assets (Compustat #6) over previous period earnings, estimated based on the Kormendi and Lipe (1987) regression model using a five-year rolling window. The measure of earnings persistence is based on the slope coefficient estimate (β). A higher β represents a highly persistent earnings stream (higher earnings quality), whereas lower values indicate highly transitory earnings (lower earnings quality). Firms with more earnings persistence will show a higher "sustainable" earnings/cash flow stream, giving it a more decisive beneficial input into equity valuations (Dechow, Ge, and Schrand,2010).

Abnormal accruals

The abnormal accruals are shown to capture distortions induced by the application of earnings management and accounting rules that are based on the view that earnings can be matched more closely into cash flows from operations. Dechow and Dichev (2002) measured earnings quality as capturing the uncertainty arising from estimation errors in the mapping of working capital accruals to operating cash flow realizations. We follow Dechow and Dichev (2002)'s model, modified by McNichols (2002) as a measure of abnormal accruals as follows (All variables are scales by average assets (Compustat #6)):

$$TCA_{j,t} = \varphi_{0,j} + \varphi_{1,j}CFO_{j,t-1} + \varphi_{2,j}CFO_{j,t} + \varphi_{3,j}CFO_{j,t+1} + \varphi_{4,j}\,\Delta Rev_{j,t} + \varphi_{5,j}PPE_{j,t} + \nu_{j,t} \tag{2.2}$$

where $TCA_{j,t} = \Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t}$ = total current accruals in year *t*; $CFO_{j,t} = NIBE_{j;t} - TA_{j;t}$ = firm *j*'s cash flow from operations in year *t*; $NIBE_{j,t}$ = firm *j*'s net income before extraordinary items (Compustat #18) in year *t*; $TA_{\,j,t} = (\Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t} - DEPN_{j,t})$ = firm *j*'s total accruals in year *t*; $\Delta CA_{j,t}$ = firm *j*'s change in current assets (Compustat #4) between year *t-1* and year *t*; $\Delta CL_{j,t}$ = firm *j*'s change in current liabilities (Compustat #5) between year *t-1* and year *t*; $\Delta Cash_{j,t}$ = firm *j*'s change in cash (Compustat #1) between year *t-1* and year *t;* $\Delta STDEBT_{j,t}$ = firm *j*'s change in debt in current liabilities (Compustat #34) between year *t-1* and year *t*; $DEPN_{j,t}$ = firm *j*'s depreciation and amortization expense (Compustat #14) in year *t*; ΔRev_t = firm *j*'s change in revenues (Compustat #12) between year *t-1* and year *t*; and PPE_t = firm *j*'s gross value of PPE (Compustat #7) in year *t*.

We estimate the model for each of Fama-French's 48 industry groups with at least 20 observations in year *t* and save the annual cross-sectional estimations of Eq. (2.2) yield firm- and year-specific residuals. The standard deviations of each firm *j*'s residuals are calculated over the year's *t-4* to *t* as accruals and earnings quality measures. Firms with a higher (lower) standard deviation of residuals are likely to be of lower (higher) earnings quality since they demonstrate a less (more) persistent component of earnings.

Earnings Smoothness

According to the studies of Wysocki (2004) and Francis, LaFond, Olsson, and Schipper (2004), smoothness is an important desirable earnings characteristic, which is derived from the concept of managers using private information about the future earnings of their company to temper possible future earnings volatility. The benefit will be to attain close representative and comprehensively useful earnings figures. We employ the measuring smoothness of Bowen, Rajgopal, and Venkatachalam (2008), as follows:

$$\sigma(Cash\ flows_{j,t}) / \sigma(Earnings_{j,t}) \qquad (2.3)$$

where σ = firm *j*'s standard deviation; $Cash\ flows_{j,t}$ = firm *j*'s operating cash flows (Compustat #308) in year *t* and $Earnings_{j,t}$ = firm *j*'s net income before extraordinary items (Compustat #18) in year *t*.

The standard deviation of cash flows (Compustat #308) scaled by total assets (Compustat #6) divided by the standard deviation of earnings (Compustat #18) scaled by total assets (Compustat #6) over the five years *t−5* to *t−1*. This ratio captures the extent to which accrual accounting has smoothed out the underlying volatility of the firm's operations. Firms that have higher (lower) values of earnings smoothness indicate more (less) smoothing of the earnings stream relative to cash flow and accounting discretion

Firm Characteristics

We follow Light, Maslov, and Rytchkov (2017) and employ five firm characteristics to capture the speed of information transparency. They are book-to-market ratio (*BTM*), firm age (*AGE*), leverage (*LEV*), firm size (*SIZE*), and stock return volatility (*VOL*).

For the purposes of this study, firms that have more earnings persistence and earnings smoothness represent a higher degree of information transparency, while higher abnormal accruals will reduce the degree of information transparency. Moreover, larger book-to-market ratios, older firms, higher leverage, larger firms, and lower stock return volatility tend to have higher information transparency. We describe the rationale of each variable in Appendix A.1 We calculate the level of information consistency by ranking firms according to the degree of information transparency of eight financial accounting variables by year and calculating the standard deviation (SD) of eight ranks. Firms with low (high) standard deviation across information quality variables have consistent (inconsistent) signals.

Market State Variables

We also employ three market state variables to examine whether the cross-section of stock return predictability varies over time. They are the investor attention index (*IA*), market liquidity factor (*MLF*), and TED spread (*TED*). We describe each variable in Appendix A.1 and the descriptive statistics and a correlation matrix of the variables in Table 2.1.

Table 2.1. Descriptive statistics of accounting and market state variables

Panel A presents the descriptive statistics for the accounting and market state variables employed in the study. Panels B and C report a Pearson correlation matrix of these variables. The sample covers 25 years from January 1991 to December 2015. We source return and accounting variables from the Compustat and CRSP databases. *EP* refers to earnings persistence; *AA* is abnormal accruals; *ES* is earnings smoothness; *BTM* is book-to-market ratio; *AGE* is firm age; *LEV* is leverage; *SIZE* is firm size; *VOL* is stock return volatility; and *XRET* is the monthly excess return. The market state variables include investor attention index (*IA*), market liquidity factor (*MLF*), and TED spread (*TED*). We provide a description of each variable in Appendix A.1. *t*-statistics that are statistically significant at the 10% level or better are in bold.

Panel A: Descriptive statistics

Variables	**N**	**Min**	**Median**	**Max**	**Mean**	**Std.**	**Skewness**	**Kurtosis**
Accounting variables								
EP	613,452	-1.554	0.117	2.532	0.163	0.603	0.762	2.727
AA	613,452	0.004	0.051	0.540	0.080	0.089	2.787	9.431
ES	613,452	0.105	1.179	10.593	1.773	1.811	2.541	7.634
BTM	613,452	0.042	0.521	3.482	0.679	0.587	2.252	6.523
AGE	613,452	4.000	14.000	34.000	15.148	7.787	0.596	-0.434
LEV	613,452	0.055	0.475	0.937	0.468	0.214	0.029	-0.798
SIZE	613,452	7.719	12.399	17.792	12.445	2.227	0.134	-0.516
VOL	613,452	0.009	0.030	0.127	0.036	0.022	1.643	3.176
XRET	613,452	-0.371	0.000	0.564	0.009	0.146	0.715	2.442
Market state variables								
IA	300	-4.757	0.133	2.744	-0.075	1.507	-0.905	0.625
MLF	300	-0.308	-0.013	0.198	-0.023	0.065	-1.198	3.559
TED	300	0.118	0.404	3.353	0.491	0.370	2.977	14.650

Table 2.1. (Continued)

Panel B: Spearman correlations among accounting variables

Variables	***EP***	***AA***	***ES***	***BTM***	***AGE***	***LEV***	***SIZE***	***VOL***
AA	**-0.08**							
ES	**0.01**	**-0.17**						
BTM	**0.00**	**-0.10**	**0.06**					
AGE	**0.02**	**-0.09**	**0.08**	**0.04**				
LEV	**-0.02**	**-0.18**	**0.04**	**-0.01**	**0.11**			
SIZE	**0.03**	**-0.22**	**0.07**	**-0.37**	**0.32**	**0.14**		
VOL	**-0.04**	**0.32**	**-0.20**	**0.08**	**-0.38**	**-0.14**	**-0.62**	
XRET	**0.01**	**-0.03**	**0.01**	**0.02**	**0.03**	**0.01**	**0.10**	**-0.08**

Panel C: Spearman correlations among market state variables

Variables	***IA***	***MLF***
MLF	**0.19**	
TED	-0.02	-0.09

Table 2.1, Panel A, presents the descriptive statistics of the key variables. The means of earnings quality (*EP*, *AA*, and *ES*) of most firms are around 0.163, 0.080, and 1.773, respectively. Meanwhile, firm characteristics variables (*BTM*, *AGE*, *LEV*, *SIZE*, and *VOL*) are 0.679, 15.148, 0.468, 12.445, and 0.036, respectively. Most earnings quality attributes and firm characteristics variables are positively skewed as the mean is higher than the median. The standard deviation of the determinants ranges from 0.022% for *VOL* to 7.787% for *AGE*. Panels B and C of Table 2.1 show a Spearman correlation matrix of financial accounting and market state variables. *EP* has a positive correlation with *ES* ($\rho_{EP,ES}$ = 0.01) and is negatively related to *AA* ($\rho_{EP,AA}$ = -0.08), suggesting that the high values of *EP* and *ES* indicate a higher earnings quality, but the high value of *AA* suggests a lower earnings quality. *SIZE* is positively related to *EP*, *ES*, and *XRET* ($\rho_{SIZE,EP}$ = 0.03, $\rho_{SIZE,ES}$ = 0.07 and $\rho_{SIZE,XRET}$ = 0.10) and negatively associated with *AA*, *BTM*, and *VOL* ($\rho_{SIZE,AA}$ = −0.22, $\rho_{SIZE,BTM}$ = −0.37 and $\rho_{SIZE,VOL}$ = −0.62),

which is highly consistent with the findings of Nagel (2005) and Dechow, Ge, and Schrand (2010). Panel C results suggest that three market state variables capture different dimensions of the market information. The correlation between *IA* and *MLF* has a positive correlation ($\rho_{IA,MLF}$ = 0.19), suggesting a positive association between changes in investor attention and the cost of trading.

2.4. Methodology

To examine the impact of inconsistent financial accounting information on the cross-section of stock returns, we sort stocks according to earnings quality and firm characteristic values based on the level of information transparency, create quintile portfolios by using SD rank and divide them into five different groups from low to high. The SD rank represents the different outcome units of each proxy, which may, therefore, be shown to lead to an inconsistent signal from the company and to the confusion of investors. We require the availability of earnings quality and firm characteristics variables for calculating the SD rank of stocks, and our sample covers 25 years from January 1991 to December 2015. We calculate the standard deviation across all ranked values and then from the portfolio by ascending rank. The low (high) SD rank represents the consistent (inconsistent) information. We compute future realized equal- and value-weighted returns on the portfolios. The portfolio returns are generated based on the firm characteristics that are observed on an annual basis. The portfolio rebalancing frequency is on an annual basis, which is consistent with the asset pricing literature that uses the firm characteristics to construct portfolios (e.g., Fama and French, 2015).

We use a specification that involves predicting individual information-inconsistent stock returns using the portfolio return from information-consistent stocks. We estimate the OLS regression between the top (i.e., inconsistent information) and bottom (i.e., consistent information) quintile portfolios using the Fama-French three-factor model as follows:

$$R_{INCONSISTENT,i,t} = \alpha + \beta_1 R_{CONSISTENT,t-1} + \beta_2 R_{INCONSISTENT,i,t-1} + \beta_{MKT} R_{MKT,t} + \beta_S SMB_{,t} + \beta_H HML_{,t} + \varepsilon_t, \quad (2.4)$$

The dependent variable in Eq. (2.4), $R_{INCONSISTENT,i,t}$ is the excess monthly returns of the individual stock with inconsistent information in month t. The independent variable of interest is the excess monthly returns of the portfolio with consistent information in month t-1 ($R_{CONSISTENT,t-1}$). Other independent variables include the excess monthly returns of the individual stock with inconsistent information in month t-1 ($R_{INCONSISTENT,i,t-1}$) to control for the short-term reversal effect of Jegadeesh (1990); R_{MKT}, SMB, and HML are factor returns drawn from Kenneth French's website; and ε_t is the regression residual. We follow Petersen (2009) and estimate the OLS regressions with standard errors clustered by pairs of stocks to obtain unbiased standard errors of OLS coefficients under a specific kind of heteroscedasticity. We also control for time (year) and industry fixed effects (the first digit of the SIC code) in all regression models. The prediction is that the returns of information-consistent firms should be a significant and positive prediction of the returns of information-inconsistent firms after controlling for all control variables.

We also examine whether there is reverse causality in return predictability from portfolio returns of inconsistent-signalled firms.

$$R_{CONSISTENT,i,t} = \alpha + \beta_1 R_{INCONSISTENT,t-1} + \beta_2 R_{CONSISTENT,i,t-1} + \beta_{MKT} R_{MKT,t} + \beta_S SMB_{,t} + \beta_H HML_{,t} + \varepsilon_t, \quad (2.5)$$

The dependent variable in Eq. (2.5), $R_{CONSISTENT,i,t}$ is the excess monthly returns of the individual stock with consistent information in month t. The independent variable of interest is the excess monthly returns of the portfolio with inconsistent information in month t-1 ($R_{INCONSISTENT,t-1}$). We expect the returns of information-inconsistent firms do not load a significant predictor of the following month's returns of information-consistent firms.

We further employ the interaction terms of three well-known market state variables (as described in Appendix A.1) to examine whether the cross-sectional predictability varies over time and to what extent market state variables for limits to arbitrage have explanatory power for the stock return predictability. Our model is as follows:

$$R_{INCONSISTENT,i,t} = \alpha + \beta_1 R_{CONSISTENT,t-1} + \beta_2 R_{CONSISTENT,t-1} * MKT\_STATE_{,t-1} + \beta_3 MKT\_STATE_{,t-1} + \beta_4 R_{INCONSISTENT,i,t-1} + \beta_{MKT} R_{MKT,t} + \beta_S SMB_{,t} + \beta_H HML_{,t} + \varepsilon_t, \tag{2.6}$$

Other independent variables are the market state variables (*MKT_STATE*), including the investor attention index (*IA*), the market liquidity factor (*MLF*), and TED spread (*TED*). We report the results for these tests in the following section.

2.5. Empirical Results

2.5.1. In-Sample Tests

This section explains the findings we arrived at through the regression analysis. In order to test the main hypothesis, *"A more inconsistent (consistent) financial accounting information leads to a slower (faster) incorporation of information across stocks."* which is first posited in Section 2.2.4 of this study, we conduct a return predictability regressions analysis. The basic idea is that firms' information environment can potentially accentuate or mitigate the effects of inconsistent signals if earnings quality and firm characteristic variables are picking up information effects in the return predictability results. We, therefore, expect stronger return predictability from information-consistent firms with a rich information environment compared to information-inconsistent firms with a poor information environment.

We create a Cartesian product of two sets to examine the relationship between the portfolio returns with consistent information and the individual stock returns with inconsistent information. The estimated excess returns of the portfolios are derived from the market excess return, using the Fama-French three-factor model (Fama and French, 1993). We estimate the OLS regression of Eq. (2.4) and use clustered standard errors to obtain unbiased standard errors of OLS coefficients. Finally, we include year- and industry-fixed effects to control for the specific impact of time- and industry-invariant factors that could be associated with return predictability. The predictability regression analysis is in Table 2.2. The results of the equal-weighted and value-weighted stock return portfolios suggest that the portfolio returns of information-consistent firms in month *t-1* ($R_{CONSISTENT,t-1}$) are a strong statistically significant predictor of the individual stock returns of information-inconsistent firms in month *t* ($R_{INCONSISTENT,i,t}$) at the 1% level. These results are also economically significant. For example, the prediction coefficient of $R_{CONSISTENT,t-1}$ of the equal-weighted portfolio is 0.185, indicating that a one-standard-deviation increase in $R_{CONSISTENT}$ leads to a 1% (i.e., 0.185 × 0.054) increase in $R_{INCONSISTENT}$ the following month (corresponding to a 12% increase in annualized excess return). Meanwhile, the prediction coefficient of the value-weighted portfolio is 0.110, indicating that a one-standard-deviation increase in $R_{CONSISTENT}$ leads to a 0.68% (i.e., 0.110 × 0.062) increase in $R_{INCONSISTENT}$ the following month (corresponding to an 8.16% increase in annualized excess return). Our results are consistent with the general information flowing into the returns of information-inconsistent firms with a delay relative to the returns of information-consistent firms.

As excess monthly returns innately contain a large unpredictability component, the R^2 in equal- and value-weighted in Panels A and B of Table 2.2 will essentially be small. However, Campbell and Thompson (2008) argue that a monthly R^2 statistic of approximately 0.5% represents an economically significant degree of stock return predictability. The monthly R^2 statistic for the significant predictors of the equal- and value-weighted portfolios are both well above this threshold (8.40% and 8.40%, respectively).

We also consider whether there is reverse causality in return predictability from the portfolio returns with inconsistent information compared to individual stock returns with consistent information in Eq. (2.5). The dependent variable in Column 2 of Table 2.2 is the excess monthly return of individual stock with consistent information in month t ($R_{CONSISTENT,i,t}$), and the main explanatory variable of interest is the excess monthly return of a portfolio with inconsistent information in month t-1 ($R_{INCONSISTENT,t-1}$). The results show that the returns of information-inconsistent firms do not load a significant predictor of the following month's returns of information-consistent firms. Overall, these findings provide strong support for our hypothesis and show that more inconsistent (consistent) financial accounting information leads to a slower (faster) incorporation of information across stocks.

Table 2.2. Return predictability regression analysis

This table reports return predictability regression using the following models:
$R_{INCONSISTENT,i,t} = \alpha + \beta_1 R_{CONSISTENT,t-1} + \beta_2 R_{INCONSISTENT,i,t-1} + \beta_{MKT} R_{MKT,t} + \beta_S SMB_{,t} + \beta_H HML_{,t} + \varepsilon_t$,
$R_{CONSISTENT,i,t} = \alpha + \beta_1 R_{INCONSISTENT,t-1} + \beta_2 R_{CONSISTENT,i,t-1} + \beta_{MKT} R_{MKT,t} + \beta_S SMB_{,t} + \beta_H HML_{,t} + \varepsilon_t$,

The dependent variables are the excess monthly return of the individual stock with inconsistent information ($R_{INCONSISTENT,i,t}$) and the excess monthly return of the individual stock with consistent information ($R_{CONSISTENT,i,t}$). The explanatory variables are the lagged excess monthly return of the portfolio with consistent information ($R_{CONSISTENT,t-1}$) and inconsistent information ($R_{INCONSISTENT,t-1}$) and the lagged excess monthly return of the individual stock with inconsistent information ($R_{INCONSISTENT,i,t-1}$) and consistent information ($R_{CONSISTENT,i,t-1}$). R_{MKT}, *SMB*, and *HML* are Fama and French (1993)'s three factors. The quintile portfolios are equal-weighted in Panel A and value-weighted in Panel B. Year and industry fixed effects are included in all regressions. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	$R_{INCONSISTENT,i,t}$	**Variables**	$R_{CONSISTENT,i,t}$
Panel A: Equal weights			
$R_{CONSISTENT,t-1}$	0.185*** (7.22)	$R_{INCONSISTENT,t-1}$	-0.095 (-1.61)
$R_{INCONSISTENT,i,t-1}$	-0.076** (-2.55)	$R_{CONSISTENT,i,t-1}$	0.132*** (2.64)
R_{MKT}	0.874*** (52.79)	R_{MKT}	1.008*** (33.84)
SMB	0.531*** (22.47)	*SMB*	0.754*** (5.41)
HML	0.169*** (6.61)	*HML*	0.381*** (6.94)
R^2	0.084	R^2	0.147
N	121,618	*N*	123,526
Panel B: Value weights			
$R_{CONSISTENT,t-1}$	0.110*** (8.50)	$R_{INCONSISTENT,t-1}$	0.008 (0.20)
$R_{INCONSISTENT,i,t-1}$	-0.010 (-0.43)	$R_{CONSISTENT,i,t-1}$	0.044 (1.55)
R_{MKT}	0.878*** (52.86)	R_{MKT}	1.008*** (35.22)
SMB	0.519*** (21.58)	*SMB*	0.746*** (5.30)
HML	0.167*** (6.65)	*HML*	0.378*** (6.67)
R^2	0.084	R^2	0.147
N	121,618	*N*	123,526

Moreover, we follow Nguyen and Truong (2018) to consider the impact of micro stocks on our test results. We exclude from our sample those stocks that are priced below one dollar a share at the beginning of the holding period. The results are highly consistent with our findings.[9]

We further introduce the interaction terms of three well-known market variables to examine (i) whether the cross-section of stock return predictability varies across time and (ii) whether market variables matter for the predictability. These market variables include the investor attention index (*IA*), the market liquidity factor (*MLF*), and TED spread (*TED*). We estimate the OLS regression specified in Eq. (2.6) and with clustered standard errors. Consistent with previous sections, we include in our model year- and industry-fixed effects. We estimate Eq. (2.6) and present the regression results in Table 2.3.

First, we use the investor attention index (*IA*) constructed by Chen, Tang, Yao, and Zhou (2020) as a market state variable to capture investors' attention in the stock market.[10] We employ the investor attention index to examine whether the predictability across stocks varies over time, based on investor attention.

According to these results in Table 2.3, a positive and significant coefficient on the interaction term of the lagged *IA* and the lagged excess monthly return of the portfolio with consistent information suggests that an increase in *IA* leads to an increase in the predictability that the portfolio return of information-consistent firms can predict the performance of the individual stock return of information-inconsistent firms. Specifically, the results are statistically significant for the equal- and value-weighted portfolios.[11] These results are

[9] We report the results of additional robustness tests in Appendix A.2.
[10] We thank Jian Chen, Guohao Tang, Jiaquan Yao and Guofu Zhou for making the data available through their website: http://apps.olin.wustl.edu/faculty/zhou/.
[11] The results are also economically significant. For example, the coefficient on the interaction term between the lagged *IA* and the lagged excess monthly return of the portfolio with inconsistent information suggests that a one-standard-deviation increase in investor attention index increases the prediction across stocks for the equal- and value-weighted portfolio by 0.20% (i.e., 0.018 × 0.113) and 0.28% (i.e., 0.022 × 0.128), respectively.

consistent with the findings of Da, Engelberg, and Gao (2011) that high investor attention can create extra noise and, consequently, increase limits to arbitrage, leading to an increasing (decreasing) predictability.

Another important market-based measure is the market liquidity factor (*MLF*). We use the level of aggregate liquidity constructed in Pástor and Stambaugh (2003) as market-based information to capture the price impact of a trading volume. A high (low) value of *MLF* indicates low (high) aggregate liquidity. We employ the market liquidity factor to examine whether the stock predictability varies over time, based on the cost of a trade.[12]

According to these results, the coefficients on the interaction terms of the lagged *MLF* and the lagged excess monthly return of the portfolio with consistent information are positive and significant, indicating that an increase in *MLF* leads to an increase in return predictability between information-consistent and information-inconsistent stocks for the equal- and value-weighted portfolio by 0.10% (i.e., 0.197 × 0.005) and 0.21% (i.e., 0.343 × 0.006), respectively. These results are consistent with the findings of Chordia, Roll, and Subrahmanyam (2011), which suggest that with an increase (decrease) in liquidity cost, trading is likely to be more (less) costly. As a result, the limits to arbitrage increases (decreases), leading to an increasing (decreasing) predictability.

Our final measure of market-based measures is TED spread as a market variable to examine whether funding liquidity matters for stock return predictability. As Campbell and Taksler (2003) note, the TED spread is a widely employed measure of funding liquidity in the market. The results suggest that an increase in TED spread leads to an increase in the cross-section of stock return predictability.[13] The findings are consistent with the findings of Shleifer

[12] We thank Ľuboš Pástor and Robert Stambaugh for making the data available through their website: http://finance.wharton.upenn.edu/~stambaug/.

[13] The results are economically significant. For example, the coefficient on the interaction term between the lagged *TED* and the lagged excess monthly return of the portfolio with consistent information suggests that a one-

and Vishny (1997), which show that that that period of high credit risk in the market leads to tighter funding constraints, difficulties in borrowing or raising money or even fund withdrawals by investors leading to forced position unwinding. Consequently, the limits to arbitrage increases (decreases), leading to an increasing (decreasing) predictability.

standard-deviation increase in TED spread increases the prediction between information-consistent and information-inconsistent firms for the value-weighted portfolio by 0.15% (i.e., 0.027 × 0.055).

Table 2.3. Time-varying return predictability based on the market state variables

This table reports return predictability regression using the following models:
$R_{INCONSISTENT,i,t} = \alpha + \beta_1 R_{CONSISTENT,t-1} + \beta_2 R_{CONSISTENT,t-1} * MKT\_STATE_{,t-1} + \beta_3 MKT\_STATE_{,t-1} + \beta_4 R_{INCONSISTENT,i,t-1} + \beta_{MKT} R_{MKT,t} + \beta_S SMB_{,t} + \beta_H HML_{,t} + \varepsilon_t$,

The dependent variables are the excess monthly return of the individual stock with inconsistent information ($R_{INCONSISTENT,i,t}$). The explanatory variables are the lagged excess monthly return of the portfolio with consistent information ($R_{CONSISTENT,t-1}$), the lagged market state variables ($MKT\_STATE_{,t-1}$) include investor attention index (*IA*), market liquidity factor (*MLF*), and TED Spread (*TED*), and the lagged excess monthly return of the individual stock with inconsistent information ($R_{INCONSISTENT,i,t-1}$). R_{MKT}, *SMB*, and *HML* are Fama and French (1993)'s three factors. Year and industry fixed effects are included in all regressions. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	$R_{INCONSISTENT,i,t}$		
	IA	***MLF***	***TED***
Panel A: Equal weights			
$R_{CONSISTENT,t-1}$	0.205***	0.194***	0.157***
	(7.87)	(7.47)	(5.64)
$R_{CONSISTENT,t-1} * MKT\_STATE_{t-1}$	0.018***	0.197*	0.023
	(3.35)	(1.69)	(1.53)
MKT_STATE_{t-1}	0.002***	-0.029***	0.008***
	(3.39)	(-3.47)	(3.38)
$R_{INCONSISTENT,i,t-1}$	-0.093***	-0.072***	-0.058*
	(-3.13)	(-2.44)	(-1.94)
R_{MKT}	0.885***	0.876***	0.874***
	(53.08)	(52.59)	(52.54)
SMB	0.521***	0.541***	0.530***
	(22.25)	(22.93)	(22.40)
HML	0.159***	0.172***	0.180***
	(6.21)	(6.71)	(6.95)
R^2	0.085	0.084	0.084
N	121,618	121,618	121,618
Panel B: Value weights			
$R_{CONSISTENT,t-1}$	0.114***	0.131***	0.095***
	(8.85)	(9.58)	(6.52)
$R_{CONSISTENT,t-1} * MKT\_STATE_{t-1}$	0.022***	0.343***	0.027**
	(4.43)	(3.13)	(1.90)
MKT_STATE_{t-1}	0.002***	-0.035***	0.008***
	(3.50)	(-4.22)	(3.47)
$R_{INCONSISTENT,i,t-1}$	0.010	-0.014	-0.013
	(0.43)	(-0.61)	(-0.57)
R_{MKT}	0.893***	0.882***	0.876***
	(53.46)	(52.67)	(52.5)
SMB	0.501***	0.530***	0.519***
	(21.01)	(22.08)	(21.58)
HML	0.152***	0.172***	0.181***
	(5.98)	(6.80)	(7.04)
R^2	0.085	0.084	0.084
N	121,618	121,618	121,618

We also consider additional robustness tests to ensure that our results are not driven by alternative explanations. Specifically, we use the Carhart four-factor (Carhart, 1997) and Fama-French five-factor (Fama and French, 2015) instead of the Fama-French three-factor for Eqs. (2.4) to (2.6).[14] Overall, the results are highly consistent with our findings.[15]

2.5.2. Out-of-Sample Tests

We consider the robustness tests of the in-sample results. We follow Welch and Goyal (2008) and Rapach, Ringgenberg, and Zhou (2016) and examine the out-of-sample of return predictability. Specifically, Welch and Goyal (2008) show that the in-sample predictive ability of several return predictors essentially does not remain significant in out-of-sample tests. Table 2.4 shows the results for out-of-sample tests of the cross-section of stock returns predictability.

2.5.2.1. Out-of-Sample R^2

We estimate the following predictive regression forecast:

$$\hat{R}_{INCONSISTENT,t} = \hat{\alpha} + \hat{\beta}_1 R_{CONSISTENT,t\text{-}1} + \varepsilon_t, \tag{2.7}$$

where $\hat{\alpha}$ and $\hat{\beta}_1$ are the OLS estimation of α and β, respectively, in Eq. (2.4) based on data from January 2001 to November 2015.[16] The historical mean forecast, the average excess monthly return of the portfolio with inconsistent information, serves as a natural benchmark. This predictive regression forecast corresponds to the constant expected excess monthly return model in Eq. (2.4) with $\beta = 0$ and indicates that returns are unpredictable.

[14] The Carhart four-factor is from CRSP and the Fama-French five-factor is from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[15] We report the results of additional robustness tests in Appendix A.3-A.6.
[16] We use only information available from the beginning to the end of the sample when computing Eq. (2.7), so that our predictive regression forecast does not have a "look-ahead bias".

We use McCracken's (2007) F-statistic to examine whether the predictive regression forecast delivers a statistically significant improvement. We report the results of out-of-sample R^2 in Table 2.4. The out-of-sample R^2 of the equal-weighted and value-weighted stock return portfolios are positive (2.17% and 0.74%, respectively) and significant, according to the McCracken's (2007) statistic. This is especially strong in the equal-weighted stock return portfolios. Overall, our forecasting model outperforms the historical mean benchmark and clears the out-of-sample hurdle.

2.5.2.2. Forecast Encompassing Tests

Our next out-of-sample tests use forecast encompassing predictions to compare the information content of the predictive regression forecast based on our model to the predictive regression forecast based on the historical mean. We begin with forming an optimal combination forecast as a convex combination of a predictive regression forecast of the predictive regression forecast based on the historical mean and the predictive regression forecast based on our model as follows:

$$\hat{R}_t^* = (1 - \lambda)\, \bar{R}_t + \lambda\, \hat{R}_t \tag{2.8}$$

where $\hat{R}_t^*$ is a combination forecast based on the historical mean and our model, $\bar{R}_t$ is the predictive regression forecast based on the historical mean, $\hat{R}_t$ is the predictive regression forecast based on our model, and $0 \leq \lambda \leq 1$. The sample period is from January 2001 to December 2015. If $\lambda = 0$, the optimal combination forecast in Eq. (2.8) excludes the forecast based on our model, so that the predictive regression forecast based on the historical mean encompasses the predictive regression forecast based on our model; in other words, our model does not contain valuable information for predicting excess returns above information already contained in the historical mean. On the other hand, if $\lambda > 0$, the optimal combination forecast includes the forecast based on our model, so that the predictive regression forecast based on the historical mean, it does not encompass the predictive regression forecast based on our model; in other words, our forecasting model contains valuable information for predicting excess returns above the information already contained in the historical mean.

We report the estimation of λ in Eq. (2.8) and the statistical significance, using the approach of Harvey, Leybourne, and Newbold (1998), in Table 2.4. The estimate of $\hat{\lambda}$ are sizeable and significant in both equal-weighted and value-weighted portfolios. The results indicate that the forecast based on our model encompasses the forecast based on the historical mean.

Table 2.4. Out-of-sample test results

This table presents the out-of-sample test of return predictability results. The out-of-sample period is from January 2001 to December 2015. The second and third columns report the out-of-sample R^2 for a predictive regression forecast of the excess monthly returns of the portfolio with inconsistent information based on our forecasting model vis-á-vis the historical mean benchmark forecast, where statistical significance is based on the McCracken's (2007) *F*-statistic. The fourth and fifth columns report the estimated weight on the predictive regression forecast based on our model in a combination forecast that takes the form of a convex combination of a predictive regression forecast based on our model and a predictive regression forecast based on the historical mean, where statistical significance is based on the Harvey, Leybourne, and Newbold (1998) statistic.

Portfolio	Out-of-sample R^2	McCracken statistics	Encompassing tests	HLN
Equal weights	2.165%	3.983***	0.989	1.990**
Value weights	0.743%	1.347	0.604	1.371

2.6. Trading Strategy Implications

In the previous sections, we find that the information-consistent firms with a rich information environment can potentially predict information-inconsistent firms with a poor information environment. In this section, we utilize these results to construct a trading strategy and evaluate its performance. To mitigate potential idiosyncratic concerns, we employ a portfolio investment strategy to substantially minimize the variation in firm-specific information. We use the rank-based approach for the aggregation of information. We require the availability of earnings quality and firm characteristics variables for calculating the SD rank of stocks.[17] Each year, we rank stocks based on each of the selected variables and compute the SD rank across these variables for each stock. We then sort stocks into decile portfolios by using the SD ranks and compute equal- and value-weighted stock return portfolios. We estimate the following predictive regression between the top (i.e., inconsistent information) and bottom (i.e., consistent information) decile portfolios using a 10-year rolling window:

$$R_{INCONSISTENT,t} = \alpha + \beta_1 R_{CONSISTENT,t-1} + \varepsilon_t, \tag{2.9}$$

The dependent variable in Eq. (2.9), $R_{INCONSISTENT,t}$, is the excess monthly returns of the portfolio with inconsistent information in month t. The independent variable, $R_{CONSISTENT,t-1}$, is the excess monthly returns of the portfolio with consistent information in month $t-1$.

Following Campbell and Thompson (2008), Ferreira and Santa-Clara (2011), and Rapach, Ringgenberg, and Zhou (2016), we consider a mean-variance asset allocation between common stocks and Treasury bill rates using a predictive regression in Eq. (2.9). At the end of month t, the trading strategy implications involve optimally allocating the following share of the portfolio to common stocks during the following month:

$$W_t = \frac{1}{\gamma} \frac{\widehat{R}_{INCONSISTENT,t+1}}{\widehat{\sigma}^2_{INCONSISTENT,t+1}}, \tag{2.10}$$

where γ is the investor's coefficient of relative risk aversion, $\widehat{R}_{INCONSISTENT,t+1}$ is the predicted excess monthly returns of the portfolio with inconsistent information from Eq. (2.9), and $\widehat{\sigma}^2_{INCONSISTENT,t+1}$ is the historical variance of the excess monthly returns of the portfolio with inconsistent information from Eq. (2.9). We follow Rapach, Ringgenberg, and Zhou (2016)

[17] We use only information available at the time of portfolio formation, so that our forecasts do not have a "look-ahead bias".

and restrict W_t to lie between -0.5 and 1.5, which imposes realistic portfolio constraints and generates better-behaved portfolio weights, given the well- known sensitivity of mean-variance optimal weights to return forecasts.

We also calculate an average utility or certainty equivalent return (CER) for the investor who allocates using Eq. (2.10)

$$\text{CER} = \bar{R}_p - 0.5_\gamma\ \sigma_p^2\ , \tag{2.11}$$

where $\bar{R}_p$ and σ_p^2 are the mean and variance, respectively, of the portfolio return over the forecast evaluation period. We follow Rapach, Ringgenberg, and Zhou (2016) and assume a relative risk aversion coefficient (γ) of three in Eqs. (2.10) and (2.11).

We report the results for the out-of-sample performance between our trading strategy and buy-and-hold (BAH) strategy in Table 2.5. The equal- and value-weighted portfolios based on our trading strategy generates average excess monthly returns of 1.35% and 1.16%, respectively, translating into annual returns of 16.20% and 13.92%, respectively. The Sharp ratios are both positive (0.287 and 0.264, respectively). The average utility or certainty equivalent return (CER) gains of 108 and 93 basis points, respectively. Meanwhile, the equal- and value-weighted portfolios based on BAH produce lower average monthly excess returns of 0.90% and 0.78%, respectively, translating into annual returns of 10.80% and 9.36%, respectively. The Sharp ratios are lower than the trading strategy (0.227 and 0.220, respectively). The CER also gains lower (72 and 65 basis points, respectively.) Overall, the trading strategy outperforms BAH with higher average excess returns, higher efficiency with a higher Sharpe ratio, and CER in both equal- and value-weighted portfolios. This evidence confirms the usefulness of earning quality and firm characteristic information as proxies to capture the level of information transparency and to substantially improve portfolio performance relative to the cross-stock return predictability.

Table 2.5. Out-of-sample performance

This table presents the out-of-sample performance for our trading strategy and the buy-and-hold decile portfolios formed by sorting firms according to the degree of information transparency of financial accounting variables. The portfolio formation period is from January 2001 to December 2015. The portfolio rebalancing frequency is on a monthly basis. We source returns data, financial accounting variables, and risk-free rates from CRSP, Compustat, and Kenneth French's website, respectively. The decile portfolios are equal-weighted in Panel A and value-weighted in Panel B.

Portfolio returns	N	Mean	Std.	Sharpe Ratio	CER
Panel A: Equal weights					
Trading strategy	180	0.0135	0.0429	0.2873	0.0108
Buy-and-hold	180	0.0090	0.0342	0.2266	0.0072
Risk-free rate	180	0.0012	0.0015		0.0012
Panel B: Value weights					
Trading strategy	180	0.0116	0.0395	0.2641	0.0093
Buy-and-hold	180	0.0078	0.0300	0.2203	0.0065
Risk-free rate	180	0.0012	0.0015		0.0012

2.7. Conclusion

We study how frictions and processing incompatibilities in the whole information environment can detrimentally impact stock returns in a timely manner. We also examine the impact of inconsistent financial accounting information on across-section of stock returns. We propose a methodology that reveals signals that enable future stock returns to be predicted while capturing the speed of information incorporation. Our findings affirm this hypothesis. We find that the return predictability from information-consistent firms to information-inconsistent firms is consistent with the literature on delayed information processing. We also find that the predictability varies over time due to the funding of liquidity and investor attention. Our findings are consistent with the gradual information diffusion theory, which suggests that a single stock can gradually diffuse information among other stocks, leading to a lead-lag effect in stock markets.

APPENDIX A

FOR ESSAY ONE

Appendix A.1. Variable descriptions

Variables	Description	Predicted Sign	Sample Frequency	Definition	Rationale
Earnings quality proxies					
EP	Earnings persistence	(+)	Annual	The slope coefficient between current periods earnings regressed scaled by total assets (Compustat #6) over previous period earnings, estimated based on the Kormendi and Lipe (1987) regression model using a five-year rolling window.	Kormendi and Lipe (1987), Collins and Kothari (1989), and Easton and Zmijewski (1989) find more persistent earnings have a higher security price response and positive stock market returns. A higher β represents a highly persistent earnings stream (higher earnings quality). Firms that have more earnings persistence show a higher "sustainable" earnings/cash flow stream, providing a more decisive beneficial input into equity valuations (Dechow, Ge, and Schrand, 2010). Thus, firms that have more earnings persistence represent a higher degree of information transparency.
AA	Abnormal accruals	(−)	Annual	The standard deviation of the estimated residual over the years $t{-}4$ to t using Dechow and Dichev (2002)'s regression model where total current accruals are related to previous, current, and future period cash flows, revenues, and PPE for each of Fama and French (1997)'s 48 industry groups with at least 20 firms in year t and all variables are scaled by total assets (Compustat #6).	Dechow and Dichev (2002) measure earnings quality by capturing the uncertainty arising from estimation errors in the mapping of working capital accruals to operating cash flow realizations. Firms with a higher (lower) standard deviation of residuals are likely to be of lower (higher) earnings quality since they demonstrate a less (more) persistent component of earnings. Sloan (1996) shows that some investors are unable to completely incorporate the mean-reverting of the accruals of high accrual firms.

					The literature suggests that there is a negative relationship between earnings quality (proxied by accruals) and the degree of information asymmetry as high accruals result in a low quality of earnings and thus a higher degree of information asymmetry.
ES	Earnings Smoothness	(+)	Annual	The standard deviation of cash flows (Compustat #308) scaled by total assets (Compustat #6) divided by the standard deviation of earnings (Compustat #18) scaled by total assets (Compustat #6), using Bowen, Rajgopal, and Venkatachalam (2008) over the five years *t−5* to *t−1*.	Tucker and Zarowin (2006) find that smoothness enhances earnings informativeness. Firms with higher (lower) values of earnings smoothness indicate more (less) smoothing of the earnings stream relative to cash flow and accounting discretion.
Firm characteristics					
BTM	Book-to-market ratio	(+)	Annual	The book value of equity (Compustat #6 − Compustat #181) divided by the market value of equity (Compustat #199 × Compustat #25).	Porta, Lakonishok, Shleifer, and Vishny (1997) and Skinner and Sloan (2002) show that market participants underestimate future earnings for high book-to-market ratios and overestimate future earnings for low book-to-market stocks. Thus, firms, which have larger book-to-market ratios, tend to have higher information transparency.
AGE	Firm age	(+)	Annual	The number of years since the firm first appeared on Compustat.	Barry and Brown (1985) find firms with a long history (age) have more information available to the market, which leads to capturing more information in predicting future returns. Barinov, Shawn, and Celim (2019) show that firms with a lower age are associated with weaker incorporation of information into their stock prices. Thus, older firms tend to have higher information transparency.
LEV	Leverage	(+)	Annual	The ratio of total debt (Compustat #181) to total assets (Compustat #6).	Yu (2005) finds a positive association between firm leverage and information transparency, indicating that firms with higher leverage tend to have higher information transparency.

SIZE	Firm size	(+)	Annual	The natural log of the average in the CRSP monthly market capitalization of the firm (number of shares outstanding × share closing price) over a year.	Lo and MacKinlay (1990) find that larger capitalization portfolio stock returns lead while smaller ones mostly merely follow. Hou (2007) also shows that the lead-lag relationship in information between large and small firms is predominantly an intra-industry phenomenon. That is, stock returns in small firms follow the release of the returns of large firms within the same industry. Therefore, larger firms tend to have higher information transparency.
VOL	Stock return volatility	(−)	Annual	The standard deviation in the CRSP daily return over a year.	Papadamou, Sidiropoulos, and Spyromitros (2014) find that there is a negative relation between information transparency scores and stock price volatility.
Excess return					
XRET	The monthly excess return		Monthly	The CRSP monthly return minus the treasury bill from Kenneth French’s website.	
Market state variables					
IA	Investor Attention Index		Monthly	The investor attention index is the investor attention index in Chen, Tang, Yao, and Zhou (2020). It is estimated from twelve attention proxies (seven long-sample proxies and five short-sample proxies) based on the PCA approach from http://apps.olin.wustl.edu/faculty/zhou/	
MLF	Market Liquidity Factor		Monthly	Market Liquidity Factor is the Pastor-Stambaugh liquidity series in Pástor and Stambaugh (2003). We use the levels of aggregated liquidity from http://finance.wharton.upenn.edu/~stambaug/	
TED	TED spread		Monthly	TED spread is the difference in yields between US Eurodollar deposits (effectively three-month USD LIBOR) and US Treasury-bills. We use the average percentage of TED Spread from https://fred.stlouisfed.org/series/TEDRATE	

Appendix A.2. Return predictability regression analysis excluding micro stocks

This table reports return predictability regression using the following models:
$R_{INCONSISTENT,i,t} = \alpha + \beta_1 R_{CONSISTENT,t-1} + \beta_2 R_{INCONSISTENT,i,t-1} + \beta_{MKT} R_{MKT,t} + \beta_S SMB_{,t} + \beta_H HML_{,t} + \varepsilon_t$,
$R_{CONSISTENT,i,t} = \alpha + \beta_1 R_{INCONSISTENT,t-1} + \beta_2 R_{CONSISTENT,i,t-1} + \beta_{MKT} R_{MKT,t} + \beta_S SMB_{,t} + \beta_H HML_{,t} + \varepsilon_t$,

The dependent variables are the excess monthly return of the individual stock with inconsistent information ($R_{INCONSISTENT,i,t}$) and the excess monthly return of the individual stock with consistent information ($R_{CONSISTENT,i,t}$). The explanatory variables are the lagged excess monthly return of the portfolio with consistent information ($R_{CONSISTENT,t-1}$) and inconsistent information ($R_{INCONSISTENT,t-1}$) and the lagged excess monthly return of the individual stock with inconsistent information ($R_{INCONSISTENT,i,t-1}$) and consistent information ($R_{CONSISTENT,i,t-1}$). R_{MKT}, *SMB*, and *HML* are Fama and French (1993)'s three factors. The quintile portfolios are equal-weighted in Panel A and value-weighted in Panel B. Year and industry fixed effects are included in all regressions. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	$R_{INCONSISTENT,i,t}$	**Variables**	$R_{CONSISTENT,i,t}$
Panel A: Equal weights			
$R_{CONSISTENT,t-1}$	0.153***	$R_{INCONSISTENT,t-1}$	-0.110
	(5.72)		(-1.55)
$R_{INCONSISTENT,i,t-1}$	-0.055**	$R_{CONSISTENT,i,t-1}$	0.135***
	(-1.78)		(2.54)
R_{MKT}	0.918***	R_{MKT}	1.021***
	(53.14)		(20.51)
SMB	0.559***	*SMB*	0.743***
	(22.98)		(5.95)
HML	0.165***	*HML*	0.382***
	(6.34)		(5.04)
R^2	0.096	R^2	0.155
N	114,090	*N*	113,204
Panel B: Value weights			
$R_{CONSISTENT,t-1}$	0.107***	$R_{INCONSISTENT,t-1}$	-0.018
	(8.26)		(-0.80)
$R_{INCONSISTENT,i,t-1}$	-0.024	$R_{CONSISTENT,i,t-1}$	0.050**
	(-1.09)		(2.44)
R_{MKT}	0.923***	R_{MKT}	1.022***
	(53.23)		(20.79)
SMB	0.552***	*SMB*	0.735***
	(22.30)		(5.90)
HML	0.163***	*HML*	0.379***
	(6.34)		(4.81)
R^2	0.097	R^2	0.155
N	114,090	*N*	113,204

Appendix A.3. Return predictability regression analysis using the Carhart four-factor

This table reports return predictability regression using the following models:

$R_{INCONSISTENT,i,t} = \alpha + \beta_1 R_{CONSISTENT,t-1} + \beta_2 R_{INCONSISTENT,i,t-1} + \beta_{MKT} R_{MKT,t} + \beta_S SMB_{,t} + \beta_H HML_{,t} + \beta_U UMD_{,t} + \varepsilon_t,$

$R_{CONSISTENT,i,t} = \alpha + \beta_1 R_{INCONSISTENT,t-1} + \beta_2 R_{CONSISTENT,i,t-1} + \beta_{MKT} R_{MKT,t} + \beta_S SMB_{,t} + \beta_H HML_{,t} + \beta_U UMD_{,t} + \varepsilon_t,$

The dependent variables are the excess monthly return of the individual stock with inconsistent information ($R_{INCONSISTENT,i,t}$) and the excess monthly return of the individual stock with consistent information ($R_{CONSISTENT,i,t}$). The explanatory variables are the lagged excess monthly return of the portfolio with consistent information ($R_{CONSISTENT,t-1}$) and inconsistent information ($R_{INCONSISTENT,t-1}$) and the lagged excess monthly return of the individual stock with inconsistent information ($R_{INCONSISTENT,i,t-1}$) and consistent information ($R_{CONSISTENT,i,t-1}$). R_{MKT}, *SMB*, *HML* and *UMD* are Carhart (1997)'s four factors. The quintile portfolios are equal-weighted in Panel A and value-weighted in Panel B. Year and industry fixed effects are included in all regressions. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	$R_{INCONSISTENT,i,t}$	**Variables**	$R_{CONSISTENT,i,t}$
Panel A: Equal weights			
$R_{CONSISTENT,t-1}$	0.108***	$R_{INCONSISTENT,t-1}$	-0.025
	(4.24)		(-0.59)
$R_{INCONSISTENT,i,t-1}$	0.014**	$R_{CONSISTENT,i,t-1}$	0.065*
	(0.48)		(1.89)
R_{MKT}	0.818***	R_{MKT}	0.949***
	(52.27)		(26.34)
SMB	0.563***	*SMB*	0.780***
	(23.35)		(7.36)
HML	0.103***	*HML*	0.319***
	(3.97)		(6.42)
UMD	-0.183***	*UMD*	-0.178***
	(-12.86)		(-6.54)
R^2	0.087	R^2	0.151
N	121,618	*N*	123,526
Panel B: Value weights			
$R_{CONSISTENT,t-1}$	0.127***	$R_{INCONSISTENT,t-1}$	-0.044
	(9.82)		(-1.41)
$R_{INCONSISTENT,i,t-1}$	-0.077***	$R_{CONSISTENT,i,t-1}$	0.054**
	(-3.47)		(2.19)
R_{MKT}	0.815***	R_{MKT}	0.949***
	(52.53)		(25.73)
SMB	0.570***	*SMB*	0.782***
	(22.94)		(7.29)
HML	0.120***	*HML*	0.324***
	(4.72)		(6.20)
UMD	-0.183***		-0.180***
	(-12.91)		(-6.52)
R^2	0.087	R^2	0.151
N	121,618	*N*	123,526

Appendix A.4. Return predictability regression analysis using the Fama and French five-factor

This table reports return predictability regression using the following models:
$R_{INCONSISTENT,i,t} = \alpha + \beta_1 R_{CONSISTENT,t-1} + \beta_2 R_{INCONSISTENT,i,t-1} + \beta_{MKT} R_{MKT,t} + \beta_S SMB_{,t} + \beta_H HML_{,t} + \beta_R RMW_{,t} + \beta_C CMA_{,t} + \varepsilon_t$,
$R_{CONSISTENT,i,t} = \alpha + \beta_1 R_{INCONSISTENT,t-1} + \beta_2 R_{CONSISTENT,i,t-1} + \beta_{MKT} R_{MKT,t} + \beta_S SMB_{,t} + \beta_H HML_{,t} + \beta_R RMW_{,t} + \beta_C CMA_{,t} + \varepsilon_t$,

The dependent variables are the excess monthly return of the individual stock with inconsistent information ($R_{INCONSISTENT,i,t}$) and the excess monthly return of the individual stock with consistent information ($R_{CONSISTENT,i,t}$). The explanatory variables are the lagged excess monthly return of the portfolio with consistent information ($R_{CONSISTENT,t-1}$) and inconsistent information ($R_{INCONSISTENT,t-1}$) and the lagged excess monthly return of the individual stock with inconsistent information ($R_{INCONSISTENT,i,t-1}$) and consistent information ($R_{CONSISTENT,i,t-1}$). R_{MKT}, *SMB*, *HML*, *RMW* and *CMA* are Fama and French (2015)'s five factors. The quintile portfolios are equal-weighted in Panel A and value-weighted in Panel B. Year and industry fixed effects are included in all regressions. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	$R_{INCONSISTENT,i,t}$	Variables	$R_{CONSISTENT,i,t}$
Panel A: Equal weights			
$R_{CONSISTENT,t-1}$	0.192***	$R_{INCONSISTENT,t-1}$	-0.081
	(7.47)		(-1.28)
$R_{INCONSISTENT,i,t-1}$	-0.085***	$R_{CONSISTENT,i,t-1}$	0.116**
	(-2.86)		(2.31)
R_{MKT}	0.008***	R_{MKT}	0.010***
	(50.37)		(28.73)
SMB	0.005***	*SMB*	0.008***
	(22.09)		(8.01)
HML	0.001***	*HML*	0.002***
	(4.09)		(3.66)
RMW	-0.002***	*RMW*	0.001**
	(-4.66)		(2.41)
CMA	-0.000	*CMA*	-0.000
	(-0.09)		(-0.21)
R^2	0.085	R^2	0.149
N	121,618	*N*	123,526
Panel B: Value weights			
$R_{CONSISTENT,t-1}$	0.102***	$R_{INCONSISTENT,t-1}$	-0.011
	(8.01)		(-0.26)
$R_{INCONSISTENT,i,t-1}$	-0.000	$R_{CONSISTENT,i,t-1}$	0.051
	(-0.00)		(1.38)
R_{MKT}	0.008***	R_{MKT}	0.010***
	(50.83)		(28.03)
SMB	0.005***	*SMB*	0.008***
	(21.22)		(8.20)
HML	0.001***	*HML*	0.002***
	(3.94)		(3.55)
RMW	-0.002***	*RMW*	0.001**
	(-4.16)		(2.52)
CMA	0.000	*CMA*	-0.000
	(0.00)		(-0.18)
R^2	0.085	R^2	0.149
N	121,618	*N*	123,526

Appendix A.5. Time-varying return predictability based on the market state variables by the Carhart four-factor

This table reports return predictability regression using the following models:

$R_{INCONSISTENT,i,t} = \alpha + \beta_1 R_{CONSISTENT,t-1} + \beta_2 R_{CONSISTENT,t-1} * MKT\_STATE_{t-1} + \beta_3 MKT\_STATE_{t-1} + \beta_4 R_{INCONSISTENT,i,t-1} + \beta_{MKT} R_{MKT,t} + \beta_S SMB_{,t} + \beta_H HML_{,t} + \beta_U UMD_{,t} + \varepsilon_t,$

The dependent variables are the excess monthly return of the individual stock with inconsistent information ($R_{INCONSISTENT,i,t}$). The explanatory variables are the lagged excess monthly return of the portfolio with consistent information ($R_{CONSISTENT,t-1}$), the lagged market state variables ($MKT\_STATE_{,t-1}$) include investor attention index (*IA*), market liquidity factor (*MLF*), and TED Spread (*TED*), and the lagged excess monthly return of the individual stock with inconsistent information ($R_{INCONSISTENT,i,t-1}$). R_{MKT}, *SMB*, *HML* and *UMD* are Carhart (1997)'s four factors. Year and industry fixed effects are included in all regressions. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	$R_{INCONSISTENT,i,t}$		
	IA	***MLF***	***TED***
Panel A: Equal weights			
$R_{CONSISTENT,t-1}$	0.127***	0.115***	0.095***
	(4.93)	(4.45)	(3.45)
$R_{CONSISTENT,t-1} * MKT\_STATE_{t-1}$	0.022***	0.158	0.005
	(3.98)	(1.35)	(0.33)
MKT_STATE_{t-1}	0.003***	-0.015*	0.006***
	(5.22)	(-1.84)	(2.60)
$R_{INCONSISTENT,i,t-1}$	-0.006	0.016	0.26
	(-0.2)	(0.54)	(0.88)
R_{MKT}	0.830***	0.820***	0.820***
	(52.61)	(52.12)	(52.05)
SMB	0.551***	0.568***	0.563***
	(23.08)	(23.69)	(23.31)
HML	0.086***	0.105***	0.113***
	(3.29)	(4.04)	(4.31)
UMD	-0.192***	-0.181***	-0.182***
	(-13.31)	(-12.71)	(-12.78)
R^2	0.087	0.087	0.087
N	121,618	121,618	121,618
Panel B: Value weights			
$R_{CONSISTENT,t-1}$	0.125***	0.147***	0.120***
	(9.71)	(10.71)	(8.27)
$R_{CONSISTENT,t-1} * MKT\_STATE_{t-1}$	0.020***	0.359***	0.011
	(4.12)	(3.28)	(0.81)
MKT_STATE_{t-1}	0.004***	-0.023***	0.006**
	(6.10)	(-2.80)	(2.39)
$R_{INCONSISTENT,i,t-1}$	-0.064****	-0.078***	-0.077***
	(-2.82)	(-3.56)	(-3.48)
R_{MKT}	0.833***	0.821***	0.816***
	(53.28)	(52.51)	(52.22)
SMB	0.550***	0.576***	0.569***
	(22.39)	(23.31)	(22.94)
HML	0.095***	0.123***	0.130***
	(3.69)	(4.83)	(5.01)
UMD	-0.193***	-0.182***	-0.181**
	(13.46)	(-12.80)	(-12.75)
R^2	0.087	0.087	0.087
N	121,618	121,618	121,618

Appendix A.6. Time-varying return predictability based on the market state variables by the Fama and French five-factor

This table reports return predictability regression using the following models:

$R_{INCONSISTENT,i,t} = \alpha + \beta_1 R_{CONSISTENT,t-1} + \beta_2 R_{CONSISTENT,t-1} * MKT\_STATE_{t-1} + \beta_3 MKT\_STATE_{t-1} + \beta_4 R_{INCONSISTENT,i,t-1} + \beta_{MKT} R_{MKT,t} + \beta_S SMB_{,t} + \beta_H HML_{,t} + \beta_R RMW_{,t} + \beta_C CMA_{,t} + \varepsilon_t,$

The dependent variables are the excess monthly return of the individual stock with inconsistent information ($R_{INCONSISTENT,i,t}$). The explanatory variables are the lagged excess monthly return of the portfolio with consistent information ($R_{CONSISTENT,t-1}$), the lagged market state variables ($MKT\_STATE_{,t-1}$) include investor attention index (*IA*), market liquidity factor (*MLF*), and TED Spread (*TED*), and the lagged excess monthly return of the individual stock with inconsistent information ($R_{INCONSISTENT,i,t-1}$). R_{MKT}, *SMB*, *HML* , *RMW* and *CMA* are Fama and French (2015)'s five factors. Year and industry fixed effects are included in all regressions. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	$R_{INCONSISTENT,i,t}$		
	IA	***MLF***	***TED***
Panel A: Equal weights			
$R_{CONSISTENT,t-1}$	0.213***	0.201***	0.168***
	(8.16)	(7.71)	(6.00)
$R_{CONSISTENT,t-1}$* MKT_STATE_{t-1}	0.019***	0.232**	0.017
	(3.54)	(1.98)	(1.08)
MKT_STATE_{t-1}	0.002***	-0.025***	0.008***
	(3.67)	(-3.05)	(3.29)
$R_{INCONSISTENT,i,t-1}$	-0.103***	-0.080***	-0.068**
	(-3.49)	(-2.72)	(-2.27)
R_{MKT}	0.009***	0.008***	0.008***
	(51.49)	(50.16)	(50.31)
SMB	0.005***	0.005***	0.005***
	(21.77)	(22.41)	(22.04)
HML	0.001***	0.001***	0.001***
	(3.88)	(4.40)	(4.48)
RMW	-0.002***	-0.002***	-0.002***
	(-4.67)	(-4.72)	(-4.66)
CMA	-0.000	-0.000	-0.000
	(-0.19)	(-0.62)	(-0.23)
R^2	0.085	0.085	0.085
N	121,618	121,618	121,618
Panel B: Value weights			
$R_{CONSISTENT,t-1}$	0.105***	0.125***	0.089***
	(8.30)	(9.18)	(6.23)
$R_{CONSISTENT,t-1}$* MKT_STATE_{t-1}	0.022***	0.395***	0.022
	(4.46)	(3.58)	(1.53)
MKT_STATE_{t-1}	0.002***	-0.033***	0.008***
	(3.85)	(-3.87)	(3.47)
$R_{INCONSISTENT,i,t-1}$	0.019	-0.003	-0.002
	(0.83)	(-0.12)	(-0.10)
R_{MKT}	0.009***	0.009***	0.008***
	(52.30)	(50.71)	(50.66)
SMB	0.005***	0.005***	0.005***
	(20.51)	(21.61)	(21.21)
HML	0.001***	0.001***	0.001***
	(3.55)	(4.40)	(4.36)
RMW	-0.002***	-0.002***	-0.002***
	(-4.14)	(-4.25)	(-4.15)
CMA	-0.000	-0.000	-0.000
	(-0.12)	(-0.69)	(-0.08)
R^2	0.085	0.085	0.085
N	121,618	121,618	121,618

CHAPTER THREE

ESSAY TWO

This chapter presents the second essay of this thesis, which examines whether the differences in accounting information between the stocks affect cross-asset return predictability, using a comprehensive set of accounting variables and market environments as proxies to capture the degree of information adjustment. A brief overview of the study is presented in Section 3.1. Section 3.2 provides a related literature review. Sections 3.3 and 3.4 describe the data and the methodology used in this study. Section 3.5 discusses the empirical results. Section 3.6 provides the trading strategy implications, and Section 3.7 concludes this chapter. The essay's Appendix and References are presented at the end of this chapter and of the references section, respectively.

Do Accounting Information and Market Environment Matter for Cross-Asset Predictability?

3.1. Introduction

For decades, predicting future stock returns has been one of the most active areas of research in accounting and finance,[18] and the large body of literature offers evidence for return predictability at the country, industry, and supply chain levels (see, for example, Cohen and Frazzini, 2008; Cohen and Lou, 2012; Rapach, Strauss, and Zhou 2013; Chinco, Clark-Joseph, and Ye, 2019; Han, Rapach, and Zhou, 2019). However, whether a stock's return can predict other stocks' performance remains under-investigated. The current study fills this void by investigating the predictability of pairs of stocks using accounting variables as proxies for the degree of information reflection.

Our focus on the return predictability of pairs of stocks is motivated by a growing number of studies that document the impacts of information processing procedures on stock return predictability. For example, Lo and MacKinlay (1990) find that returns on large stocks lead to returns on small stocks, and they suggest a gradual information diffusion explanation for the lead-lag effect observed in the stock markets. Hou and Moskowitz (2005) document that some firms' stock prices show a delayed reaction to the price innovation of others. Cohen and Frazzini (2008), Shahrur, Becker, and Rosenfeld (2010), and Menzly and Ozbas (2010) provide evidence of the slow diffusion of information along the supply chain, causing individual customers' returns to predict their suppliers' returns. Rizova (2010) presents a two-country, Lucas-tree framework with gradual information diffusion that drives the cross-country

[18] See Lettau and Van Nieuwerburgh (2008) and Lewellen (2010) for excellent reviews.

return predictability between one country and its trading-partner country. More recently, Cohen and Lou (2012) show returns on easy-to-analyze firms predict returns of their more complicated peers, and Rapach, Strauss, and Zhou (2013) find a cross-country return predictability, with the US returns leading other industrialized countries. Consistent with these studies, we argue that individual stocks reflect and react to new information at different speeds, which may result in cross-stock lead-lag return predictability.

Although some controversy remains, the relevance of accounting information in predicting asset returns appears well established.[19] For instance, Holthausen and Larcker (1992) and Lewellen (2004) suggest that accounting data have strong predictive power in forecasting stock returns. More recent studies, such as Garlappi and Yan (2011), Bhattacharya, Desai, and Venkataraman (2013), Kogan and Papanikolaou (2013), Babenko, Boguth, and Tserlukevich (2016), Harvey, Liu, and Zhu (2016), McLean and Pontiff (2016), and Hou, Xue, and Zhang (2020), have confirmed the informative roles of various attributes of accounting information in return predictability. In the current study, we examine whether there is one month ahead return predictability of stock i based on the previous monthly return of stock j when there are differences in accounting information between the two firms and whether the return predictability varies over time under different market environments.

Using a large sample of US commons stocks covering 86 years from January 1931 to December 2016, we create a Cartesian product to match the predictability of pairs of stocks from 500 randomly selected stocks and use 17 accounting variables as proxies to capture the degree of information reflection. We find that 10 of the 17 accounting proxies; abnormal accruals, earnings smoothness, book-to-market, firm age, leverage, abnormal capital investment, investment growth, return on equity, firm size, and stock volatility; provide useful

[19] See, for example, Lakonishok, Shleifer, and Vishny (1994), Sloan (1996), Richardson, Sloan, Soliman, and Tuna (2005, 2006), and Dechow, Richardson, and Sloan (2008).

information for predicting the cross-section of stock returns after controlling for time and industry fixed effects. We further show that the predictability varies over time due to funding liquidity and market sentiment. We conduct a battery of sensitivity analyses and find that our findings are robust to different model specifications (i.e., OLS, probit, and logit models) and alternative proxies for market state variables. Our findings also hold when we consider predictability power based on the R^2 difference. Finally, we create a simple trading strategy based on our predictability results and find that this strategy outperforms the buy-and-hold strategy in both return and risk. Overall, our findings are aligned with recent theories about gradual information diffusion in asset markets.[20]

The novelty of our research lies in its contribution to the burgeoning accounting and finance literature on slow information diffusion in the equity market. First, we advance the literature on the roles of accounting information in predicting asset returns with evidence for the predictability of pairs of stocks, using accounting variables as proxies for the degree of information reflection. Second, we contribute to the growing strand of literature that highlights the impacts of the information processing procedure on return forecasting by documenting return predictability at an individual stock level.

The rest of this article is organized as follows. Section 3.2 provides an in-depth review of the related literature. Sections 3.3 and 3.4 describe the data and the methodology used in this research. Section 3.5 presents the main findings. Section 3.6 provides the trading strategy implications, and Section 3.7 concludes the paper.

[20] See, for example, Lo and MacKinlay (1990), Brennan, Jegadeesh, and Swaminathan (1993), Hong and Stein (1999), Chordia and Swaminathan (2000), Hong, Lim, and Stein (2000), Hou and Moskowitz (2005), Hong, Tourus, and Valkanov (2007), Hou (2007), Cohen and Frazzini (2008), Menzly and Ozbas (2010), Cohen and Lou (2012), and Rapach, Strauss, and Zhou (2013).

3.2. Literature Review

3.2.1. Delayed Information Processing

Extant literature suggests that information processing capacity plays a significant role in understanding asset price dynamics and price adjustment to new information (e.g., see Jegadeesh, 1990; Hong, Lim, and Stein, 2000; Easley, Hvidkjaer, and O'Hara, 2002; Cohen and Lou, 2012). Verrecchia (1980) and Callen, Khan, and Lu (2013) find that imperfections in information can impede timely equity price discovery and consequently delay any price changes in response to new information. Hirshleifer and Teoh (2003) show that investors' limited attention and information-processing power lead to abnormal returns. Hou (2007) documents the slow diffusion of industry information, resulting in a lead-lag relationship in stock returns. He finds that the lead-lag effect in information between big and small firms is predominantly an intra-industry phenomenon. Specifically, the stock returns of small firms follow the release of the returns of big firms within the same industry groups.

Previous studies suggest that information flows matter for cross-industry predictability. For example, Hong, Tourus, and Valkanov (2007) find that some specific industries tend to be representative of the whole equity market. Menzly and Ozbas (2010) show that information can be transferred between suppliers and customer-oriented industries. Cohen and Lou (2012) find evidence of information flow from single-segment industry firms to multi-industry firms. Hameed, Huang, and Mian (2015) examine intra-industry reversals in monthly returns. They show that a strong reversal effect arises within the same industry due to reversions by companies that have diverged from their industry peers rather than companies within the market overall. Motivated by these studies, we conjecture that individual stocks reflect and react to new information at different speeds, leading to cross-stock lead-lag return predictability.

3.2.2. Return Predictability and Accounting-Based Performance Measures

The predictive value of the information available in financial statements has been extensively investigated. For example, Holthausen and Larcker (1992), Lev and Thiagarajan (1993), Nissim and Penman (2001), and Lewellen (2004) use financial and accounting information to test returns predictability. They show that it provides useful indicators and offers strong predictive power for stock return forecasting. Furthermore, empirical research establishes theoretical links between accounting information and future returns predictability, such as the book-to-market ratio (e.g., Carlson, Fisher, and Giammarino, 2004; Zhang, 2005), leverage (e.g., Garlappi and Yan, 2011), the price-earnings ratio (e.g., Kogan and Papanikolaou, 2013), size (e.g., Gomes, Kogan, and Zhang, 2003; Carlson, Fisher, and Giammarino, 2004), and idiosyncratic volatility (e.g., Babenko, Boguth, and Tserlukevich, 2016).

Besides this, earnings quality is a relevant predictor of financial position and performance. Dechow, Ge, and Schrand (2010) suggest that firms with higher earnings quality provide more useful information about their future financial performance. Penman and Zhang (2002), Francis, Lafond, Olsson, and Schipper (2004), and Gaio (2010) use earnings persistence to show how given variables enable the forecasting of subsequent performance. Their results show that firms with higher earnings persistence are associated with a more sustainable flow of earnings and greater predictability in capital valuation due to their generating lower valuation errors. These findings highlight the significance of accounting and earnings quality proxies in stock returns predictability.

3.2.3. The Limits of Arbitrage and Return Predictability

In their investigation of arbitrage and its effectiveness in achieving market efficiency, Shleifer and Vishny (1997) provide an approach to understanding anomalies. They also highlight three important reasons why practitioners of arbitrage might be unsuccessful in closing an arbitrage opportunity. These reasons include specialized performance-based arbitrage, the agency problem in arbitrage organization, and high volatility. Besides this, Pontiff (1996) indicates that transaction costs are important barriers to arbitrage. Transaction costs show essential cross-sectional variation, which decreases the ability of rational traders to trade against any mispricing. For stocks with higher transaction costs, arbitrage constraints will occur with higher magnitudes of mispricing in equilibrium than for stocks with lower transaction costs. This clearly shows that the relative degree of limits to arbitrage is an important focus for analysis in this context.

3.2.4. Market Environment Variables

More recently, studies have assessed how market conditions affect return predictability. Specifically, they focus on whether the cross-sectional predictability of returns varies over time. The studies also suggest that investment sentiment is a significant indicator of stock return predictability (e.g., see Barberis, Shleifer, and Vishny, 1998; Wurgler and Zhuravaskaya, 2002; Kurov, 2010, 2012; Stambaugh, Yu, and Yuan, 2012, 2014; Shen, Yu, and Zhao, 2017). In particular, Baker and Wurgler (2006) study how the effects of investment sentiment vary on a cross-section of stock returns over time. They find that when beginning-of-period proxies for sentiment are low, the following returns are relatively high for small, younger, non-dividend-paying, high-volatility, unprofitable, distressed, and extreme growth stocks, and vice versa. Besides this, prior studies document that funding liquidity proxies, including TED spread (e.g., Lashgari, 2000) and the market volatility index (VIX) (e.g., Avramov, Barras, and Kosowski, 2013) explain return predictability.

However, most previous studies focus on return predictability at the country, industry, and supply chain levels. In contrast, our study is motivated by cross-asset return predictability and is specifically designed to assess whether single assets (i.e., stocks) assist in predicting the performance of other stocks. This paper uses several differences in accounting variables as proxies for varying degrees of information incorporation into stock prices and examines whether these differences could explain the one-month ahead return predictability of pairing stocks. We introduce market state variables to test whether their relation or predictability varies over time and, thus, we provide a new approach for predicting stock returns. We also provide an inclusive understanding of return predictability at the individual stock level.

3.3. Data and Variables

3.3.1. Data

Our sample consists of all listed companies on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the NASDAQ and covers 86 years from January 1931 to December 2016. We collect data and construct variables from conventional data sources. Specifically, we obtain daily and monthly stock returns from the Center for Research in Security Prices (CRSP) and source annual and quarterly accounting information from Compustat. We obtain Fama and French's (1993) three factors from Kenneth French's website[21] and consider only common stocks (CRSP share code of 10 or 11). To examine whether the cross-sectional return predictability varies over time, we use several market state variables, including the average percentage of TED from the Federal Reserve Bank of St. Louis, the investor sentiment data from Baker and Wurgler (2006, 2007), the University of Michigan Consumer Sentiment Index from the University of Michigan's website, and the Volatility Index from the Global Financial Data's website.[22] We exclude financial institutions

[21] We thank Kenneth French for making the data available through his website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[22] TED Spread is from https://fred.stlouisfed.org/series/TEDRATE, the Sentiment Index is from http://people.stern.nyu.edu/jwurgler/, the Index of Consumer Sentiment (University of Michigan) is from

and banks (one-digit SIC code of 6) and unclassifiable firms (SIC code of 9999) because they have different accounting practices compared with other firms. We select stocks that have at least 10 years of trading data. Following Vuolteenaho (2002), we require firms to have a December fiscal year-end because such firms account for a majority of the sample firms.

After applying the sample criteria, there are 4,022 available stocks, so there are 8,086,231 stock pairs ((4,022 × 4,021)/2). Since we use the monthly 5-year rolling window regression covering 86 years, there will be over 15.7 billion regressions (2 × 8,086,231 × ((86 × 12)-59)), and our findings will be affected by the excessive false positives. We balance the concern regarding data mining, computation time, and sufficient coverage of the analysis. We, therefore, calculate the average market value of each stock over the entire period and randomly select 500 stocks from each size decile rank (i.e., there are 50 stocks in each decile). Although we do not sample a new set of stocks over time, the selected stocks are a very good representative of all size deciles in all years. From 1931 to 2016, the mean, minimum, and maximum number of stocks across all deciles and all years are 50, 33, and 68 stocks, respectively. We provide a snapshot of the distribution of our selected stocks in each size decile over time in Appendix B.1. Following Hou (2007), we match the accounting information from Compustat for the fiscal year ending in year $t-1$ with the stock return information from CRSP from July of year t to June of year $t+1$. Finally, we remove observations with negative book-to-equity values and winsorize the extreme observations to one percentile to mitigate the influence of outliers.

https://data.sca.isr.umich.edu/data-archive/mine.php, and the Volatility Index is from https://www.globalfinancialdata.com/.

3.3.2. Variables and Descriptive Statistics

We employ 17 accounting variables to capture the cross-stock return predictability based on the differences in the past accounting information. We follow Light, Maslov, and Rytchkov (2017) and select proxies based on prominent asset pricing anomalies, grouping them into four groups. Specifically, the first group contains earnings quality proxies, such as earnings persistence (*EP*), abnormal accruals (*AA*), and earnings smoothness (*ES*). The second group consists of firm characteristics, such as book-to-market ratio (*BTM*), cash flow-to-price ratio (*CP*), firm age (*AGE*), and leverage (*LEV*). The third group includes growth-related characteristics, such as total asset growth (*AG*), abnormal capital investments (*CI*), investment-to-assets ratio (*IA*), investment growth (*IG*), investment-to-capital ratio (*IK*), and net operating assets (*NOA*), as well as profit-related characteristics, such as returns on assets (*ROA*) and returns on equity (*ROE*). The final group includes market-based variables, such as stock return volatility (*VOL*) and firm size (*SIZE*).

We also employ four market state variables to examine whether cross-stock predictability varies over time. They are TED spread (*TED*), market sentiment (*SENT* and *SENT_6*), consumer sentiment (*ICS*), and the volatility index (*VIX*). We describe each variable in Appendix B.2, and the descriptive statistics and a correlation matrix of the variables in Table 3.1.

Table 3.1. Descriptive statistics of accounting and market state variables

Panel A presents the descriptive statistics for the accounting and market state variables employed in this study, while Panels B and C report a Pearson correlation matrix of these variables. The sample covers 86 years from January 1931 to December 2016. We source return and accounting variables from the Compustat and CRSP databases. *EP* refers to earnings persistence; *AA* is abnormal accruals; *ES* is earnings smoothness; *BTM* is book-to-market ratio; *CP* refers to cash flow-to-price ratio; *AGE* is firm age; *LEV* is leverage; *AG* refers to total asset growth; *CI* is capital investments; *IA* is investment-to-assets ratio; *IG* is investment growth; *IK* refers to investment-to-capital ratio; *NOA* is net operating assets; *ROA* is a return on assets; *ROE* is a return on equity; *SIZE* is firm size; *VOL* is stock return volatility. The market state variables include TED spread (*TED*), sentiment index (*SENT* and *SENT_6*), index of consumer sentiment (*ICS*), and Volatility Index (*VIX*). We describe each variable in Appendix B.2. *t*-statistics that are statistically significant at the 10% level or better are in bold.

Panel A: Descriptive statistics

Variables	N	Min	Median	Max	Mean	Std.	Skewness	Kurtosis
Earnings quality proxies								
EP	77,221	-4.387	0.087	5.846	0.160	1.104	1.071	10.777
AA	68,999	0.003	0.054	0.917	0.101	0.141	3.449	14.314
ES	72,527	0.068	0.981	12.312	1.576	1.894	3.312	13.314
Firm characteristics								
BTM	76,777	0.029	0.528	4.450	0.727	0.709	2.660	9.321
CP	52,688	-0.006	0.070	0.579	0.094	0.089	2.807	10.677
AGE	90,244	1.000	8.000	35.000	10.393	8.364	1.052	0.417
LEV	90,002	0.043	0.526	2.926	0.568	0.403	2.830	12.846
Growth-related characteristics								
AG	80,058	-0.628	0.067	7.525	0.320	1.055	4.825	26.678
CI	62,562	-0.995	-0.107	6.531	0.093	1.037	3.638	17.569
IA	75,648	-0.811	0.037	0.493	0.038	0.155	-1.999	11.290
IG	81,715	-0.980	0.083	16.324	0.641	2.289	4.781	26.575
IK	89,722	0.001	0.220	1.065	0.291	0.232	1.309	1.327
NOA	84,127	-0.689	0.534	1.403	0.485	0.322	-0.559	1.595
ROA	78,651	-0.630	0.007	0.136	-0.025	0.108	-3.279	13.141
ROE	57,009	-0.423	0.126	1.223	0.155	0.189	2.539	12.873
Market-based variables								
SIZE	245,288	6.791	11.015	16.864	11.204	2.186	0.344	-0.352
VOL	246,466	0.007	0.030	0.150	0.037	0.026	1.964	4.734
Market state variables								
TED	31	0.192	0.495	1.548	0.588	0.372	1.141	0.660
SENT	50	-1.960	-0.025	2.990	0.018	1.042	0.399	0.494
SENT_6	50	-2.190	0.070	3.060	0.020	1.047	0.193	0.862
ICS	38	60.100	91.000	105.400	86.287	12.180	-0.709	-0.692
VIX	31	11.460	18.710	40.000	20.582	7.387	1.123	1.191

Table 3.1. (Continued)

Panel B: Pearson correlations among accounting variables

Variables	***EP***	***AA***	***ES***	***BTM***	***CP***	***AGE***	***LEV***	***AG***	***CI***	***IA***	***IG***	***IK***	***NOA***	***ROA***	***ROE***	***SIZE***	***VOL***
EP	1.00																
AA	**-0.03**	1.00															
ES	**-0.04**	**-0.12**	1.00														
BTM	**0.04**	**-0.04**	0.00	1.00													
CP	**-0.04**	**0.08**	**-0.02**	**0.54**	1.00												
AGE	**0.01**	**-0.02**	**0.02**	**-0.05**	**-0.14**	1.00											
LEV	**0.04**	**0.21**	**-0.03**	**0.02**	**0.14**	**0.05**	1.00										
AG	**-0.04**	**0.07**	**-0.03**	**-0.06**	**-0.08**	**-0.20**	**-0.11**	1.00									
CI	**0.01**	**0.01**	**0.01**	-0.00	-0.01	**0.02**	**-0.03**	**0.13**	1.00								
IA	**0.02**	**-0.14**	**0.06**	**-0.04**	**-0.08**	**-0.11**	**-0.13**	**0.23**	**0.17**	1.00							
IG	**-0.04**	**0.07**	**-0.01**	**-0.09**	**0.01**	**-0.12**	**-0.08**	**0.17**	**-0.13**	**-0.06**	1.00						
IK	**-0.03**	**0.19**	**-0.04**	**-0.21**	**-0.09**	**-0.26**	**-0.14**	**0.30**	**0.09**	**0.04**	**0.42**	1.00					
NOA	**0.10**	**-0.26**	**0.03**	**0.31**	**0.04**	**0.08**	**-0.05**	**-0.14**	**-0.02**	**0.13**	**-0.23**	**-0.37**	1.00				
ROA	**0.01**	**-0.36**	**0.18**	**0.02**	**-0.12**	**0.12**	**-0.27**	**-0.07**	**-0.02**	**0.12**	**-0.08**	**-0.08**	**0.23**	1.00			
ROE	**0.02**	**0.03**	**-0.02**	**-0.27**	**0.22**	**-0.02**	**0.05**	**-0.01**	0.00	-0.01	**0.02**	**0.09**	**-0.10**	**0.08**	1.00		
SIZE	**-0.01**	**-0.17**	**0.05**	**-0.32**	**-0.38**	**0.41**	**0.02**	-0.00	**-0.01**	**0.06**	**-0.07**	**-0.07**	**-0.06**	**0.27**	**0.15**	1.00	
VOL	**0.01**	**0.31**	**-0.18**	**0.16**	**0.14**	**-0.23**	**0.07**	**0.12**	-0.00	**-0.06**	**0.07**	**0.16**	**-0.05**	**-0.43**	**-0.06**	**-0.37**	1.00

Panel C: Pearson correlations among market state variables

Variables	***TED***	***SENT***	***SENT_6***	***ICS***	***VIX***
TED	1.00				
SENT	0.01	1.00			
SENT_6	-0.08	**0.97**	1.00		
ICS	-0.13	**0.44**	**0.45**	1.00	
VIX	**0.56**	0.01	-0.12	-0.21	1.00

According to Table 3.1, Panel A, earnings quality attributes, firm characteristics, and market-based variables are all positively skewed, while growth- and profit-related characteristic variables (e.g., *IA*, *NOA*, and *ROA*) are negatively skewed. The standard deviation of the determinants ranges from 0.026% for *VOL* to 8.364% for *AGE*. Panels B and C of Table 3.1 show a Pearson correlation matrix of accounting and market state variables. *AGE*, for example, has a positive correlation with *EP* ($\rho_{AGE,EP}$ = 0.01), while it is inversely related to *AA* ($\rho_{AGE,AA}$ = -0.03), suggesting a positive (negative) association between the age of a firm and its earnings quality (abnormal accruals). *SIZE* is positively related to *ROA* and *ROE* ($\rho_{SIZE,ROA}$ = 0.27 and $\rho_{SIZE,ROE}$ = 0.15) and negatively associated with *AA*, *BTM*, and *VOL* ($\rho_{SIZE,AA}$ = −0.17, $\rho_{SIZE,BTM}$ = −0.32 and $\rho_{SIZE,VOL}$ = −0.37), which is highly consistent with the findings of Nagel (2005). Panel C results suggest that four market state variables capture different dimensions of the market information. The correlation between *ICS* and *VIX* or *TED* is negative ($\rho_{ICS,VIX}$ = −0.21; $\rho_{ICS,TED}$ = −0.13), which is consistent with the findings of Lashgari (2000). *TED* and *VIX* have a positive and moderately high correlation ($\rho_{TED,VIX}$ = 0.56), suggesting a positive association between the systematic risk and changes in market uncertainty.[23]

3.4. Methodology

To examine whether cross-asset return predictability exists, we create a Cartesian product to match the predictability of pairs of stocks from 500 randomly selected stocks. We require the pairs of stocks to have at least 24 monthly observations. We estimate the OLS pairwise regression using the Fama-French three-factor model with a 5-year rolling window regression as follows:

[23] We also consider the Spearman correlations between all variables and find that the results are consistent with the Pearson correlation results in Appendix B.3.

$$R_{i,t} = \alpha + \beta_j R_{j,t-1} + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKT,t} + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \varepsilon_t, \quad (3.1)$$

where $R_{i,t}$ is the monthly return in month t for stock i; $R_{j,t-1}$ is the monthly return in month $t - 1$ for stock j; $R_{i,t-1}$ is the monthly return in month $t - 1$ for stock i to control for the short-term reversal effect of Jegadeesh (1990); R_{MKT}, SMB, and HML are factor returns drawn from Kenneth French's website; and ε_t is the regression residual.

The significant results and R^2 of Eq. (3.1) are employed as a dependent variable in our model estimations.[24] We use differences in 17 accounting variables to explain the return predictability across different pairs of stocks. First, we examine whether the difference in the sources of variables increases the probability of cross-stock return predictability. We follow Petersen (2009) and estimate the OLS regressions with standard errors clustered by pairs of stocks to obtain unbiased standard errors of OLS coefficients under a specific kind of heteroscedasticity. We also control for time (year) and industry fixed effects (the first digit of the SIC code) in all regression models.

The first model estimation is as follows:

$$Sig = \alpha + \beta_1 DIFF_{j,i} + \varepsilon_t, \quad (3.2)$$

The dependent variable in Eq. (3.2), *Sig* is a dummy variable that takes the value of 1 if the value(s) from the regression results of Eq. (3.1) is (are) positive and significant at the 0.05 level and 0 otherwise. The independent variables are the level of differences in determinants between firms j and i, including 17 accounting variables scaled by the mean values of firms j and i ($DIFF_{j,i}$) in Table 3.1. For the accounting variables that have a negative predicted sign, we multiply the value by −1 before calculating $DIFF_{j,i}$. We include year- and

[24] For the significant results, we consider a positive and significant cross-stock return prediction at the 0.05 level. The estimated coefficient is positive, indicating that the monthly return of stock j is a positive prediction of the next month return of stock i. We report the descriptive statistic of the pairwise regression in Appendix B.4-B.7.

industry-fixed effects of accounting for time- and industry-invariant factors, respectively, that could be associated with return predictability.

We also examine whether the difference in the sources of variables increases the power of cross-stock return predictability based on the change in the R^2. We use the following model:

$$(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1 \, DIFF_{j,i} + \varepsilon_t, \quad (3.3)$$

The dependent variable in Eq. (3.3), $(R^2_1 - R^2_0)/R^2_0$ is a proxy for change in the R^2, where R^2_1 is R^2 of the 5-year rolling window regression from Eq. (3.1), which is the R^2 of return predictability across firms; R^2_0 is R^2 of the 5-year rolling window regression, which indicates no predictability across firms, as follows:

$$R_{i,t} = \alpha + \beta_i \, R_{i,t-1} + \beta_{MKT} \, R_{MKTt} + \beta_S \, SMB_t + \beta_v \, HML_t + \varepsilon_t, \quad (3.4)$$

A higher (lower) change in the R^2 represents a higher (lower) degree of predictive power across firms. We then employ the interaction terms of five well-known market state variables (as described in Appendix B.2) to examine whether the cross-sectional predictability varies over time. Our model is as follows:

$$Sig = \alpha + \beta_1 \, DIFF_{j,i} + \beta_2 \, MKTV + \beta_3 \, DIFF_{j,i} * MKTV + \varepsilon_t, \quad (3.5)$$

$$(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1 \, DIFF_{j,i} + \beta_2 \, MKTV + \beta_3 \, DIFF_{j,i} * MKTV + \varepsilon_t, \quad (3.6)$$

Other independent variables are the market state variables (*MKTV*), including TED spread, investor sentiment, the index of consumer sentiment, and the volatility index. Furthermore, we consider two additional sensitivity analyses. First, we use logit and probit regressions for Eqs. (3.2) and (3.5) because the dependent variable in these two equations is binomial. Second, we use the dependent variable, $(R^2_1 - R^2_0)$, which is the difference in R^2, as a robustness test for Eqs. (3.3) and (3.6). We report the results for these tests in the following section.

3.5. Empirical Results

We examine whether a stock's return can be used to predict other stocks' performance by studying the predictability of pairs of stocks and using accounting variables as proxies for the varying degrees of information incorporation into stock prices to explain the cross-stock return predictability. We begin with the estimation of the significance of pairwise across-firm returns' predictability using the Fama-French three-factor model (Fama and French, 1993) in Eq. (3.1). We then obtain the results from Eq. (3.1), which takes the value of 1 if the value(s) is positive and significant at the 0.05 level and 0 otherwise, as a dependent variable (*Sig*) and examine whether the difference in the source of variables is associated with the likelihood of predictability. Besides this, we estimate another model using the R^2 difference ($R^2_1 - R^2_0 / R^2_0$) in Eqs. (3.1) and (3.4), which represents the degree of predictive power as a dependent variable in Eq. (3.3), in order to examine whether the difference in the source of variables is associated with the predictive power. The independent variables are the level of differences in determinants between firms j and i, including 17 accounting variables scaled by the mean values of firms j and i ($DIFF_{j,i}$). We estimate the OLS regression of Eqs. (3.2) and (3.3) and use clustered standard errors to obtain unbiased standard errors of OLS coefficients. Finally, we include year- and industry-fixed effects to control for time- and industry-invariant factors that could be associated with return predictability.

We report the results for the determinants of cross-stock returns' predictability in Table 3.2. We first consider whether the difference in the source of the accounting variables is related to the likelihood of predictability. The dependent variable in Column (1) is *Sig*. We find that 11 out of the 17 accounting variables contain valuable information about cross-stock returns predictability. They include abnormal accruals (*AA*), book-to-market ratio (*BTM*), firm age (*AGE*), return on equity (*ROE*), firm size (*SIZE*), stock return volatility (*VOL*), earnings smoothness (*ES*), investment growth (*IG*), net operating assets (*NOA*), leverage (*LEV*), and capital investments (*CI*). The results suggest strong evidence of cross-stock return predictability. The results also indicate economic significance. For example, differences in abnormal accruals (*AA*) and earnings smoothness (*ES*) predict cross-firm returns with coefficients of 0.292 (*t*-statistics of 5.96) and 0.105 (*t*-statistics of 2.40), respectively. This suggests that an increase of one standard deviation in the differences in *AA* and *ES* between firms *j* and *i* increases the likelihood that firm *j* can predict firm *i* by 0.30% (i.e., 0.292 × 1.016) and 0.10% (i.e., 0.105 × 0.965), respectively. These results are aligned with the findings of Francis, Lafond, Olsson, and Schipper (2004) and Dechow, Ge, and Schrand (2010), which suggest that firms with higher earnings quality generally provide more information about the future of their financial performance and, thus, are more predictable in their capital valuation.

We also consider whether the difference in the source of variables is associated with the predictability power based on the R^2 difference. We report the results for these tests in Column (2) of Table 3.2. The dependent variable of interest is the change in the R^2. The results suggest that the coefficients of difference in the source of variables between firms *j* and *i* ($DIFF_{j,i}$) are statistically significant at the 10% level or better for 12 (out of 17) accounting variables, including *AA*, *ES*, *BTM*, *AGE*, *LEV*, *CI*, *IA*, *IG*, *IK*, *ROE*, *SIZE*, and *VOL*. These results are also economically significant. For example, the coefficient of *SIZE* is 15.27 (*t*-statistic of 85.28), which suggests that a one standard deviation increase in the difference in *SIZE* between firm *j* and firm *i* would increase the ability of firm *j* to predict the performance of firm *i* by 3.50% (i.e., 15.27 × 0.229). In other words, the result indicates that when firm *j*'s size is bigger (smaller) compared with firm *i*, it will increase (decrease) the power of prediction that firm *j* has concerning firm *i*. This finding is highly consistent with the results of Lo and MacKinlay (1990) and Hou (2007), which suggest a lead-lag relation in the information-processing procedure between large and small firms in stock markets. The larger capitalization portfolio stock returns lead, while the smaller ones mostly just follow. Interestingly, 10 accounting variables from 4 groups; including *AA*, *ES*, *BTM*, *AGE*, *LEV*, *CI*, *IG*, *ROE*, *SIZE*, and *VOL*; are strong and consistent predictors of returns across firms (i.e., these variables not only increase the probability of predictability in Column (1) but also increase the power of cross-stock returns' prediction in Column (2)). The results also indicate that the market is slow to aggregate the information contained in firm connections, a finding that is aligned with recent theories of gradual information diffusion in financial markets.[25]

[25] See, for example, Lo and MacKinlay (1990), Brennan, Jegadeesh, and Swaminathan (1993), Hong and Stein (1999), Chordia and Swaminathan (2000), Hong, Lim, and Stein (2000), Hou and Moskowitz (2005), Hong, Tourus, and Valkanov (2007), Hou (2007), Cohen and Frazzini (2008), Menzly and Ozbas (2010), Cohen and Lou (2012), and Rapach, Strauss, and Zhou (2013).

Table 3.2. Determinants of return predictability using *Sig* and $(R^2_1 - R^2_0) / R^2_0$

This table reports the determinants of return predictability using the following models:

$$Sig = \alpha + \beta_1 DIFF_{j,i} + \varepsilon_t,$$

where *Sig* is a dummy variable that takes the value of 1 if the value(s) from the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j R_{j,t-1} + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ is positive and significant at 0.05 level and 0 otherwise.

$$(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \varepsilon_t,$$

where $R^2_1 - R^2_0$ is the difference in R^2 $(R^2_1 - R^2_0)$, where R^2_1 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j R_{j,t-1} + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.

The explanatory variable is the difference in determinants between firms *j* and *i* scaled by the mean values of firm *j* and *i* ($DIFF_{j,i}$). Year fixed effect and industry fixed effects are included in all regressions. We describe each variable in Appendix B.2. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	*Sig*			$(R^2_1 - R^2_0) / R^2_0$		
	$DIFF_{j,i}$	R^2	N	$DIFF_{j,i}$	R^2	N
Earnings quality proxies						
	-0.005**			-0.005		
EP	(-1.96)	0.355	632,530	(-1.15)	0.209	632,530
	0.292***			0.932***		
AA	(5.96)	0.262	573,204	(14.46)	0.300	573,204
	0.105**			0.116**		
ES	(2.40)	0.306	614,082	(2.16)	0.238	614,082
Firm characteristics						
	0.354***			0.875***		
BTM	(7.47)	0.276	601,764	(12.66)	0.326	601,764
	-0.186***			-0.586***		
CP	(-3.84)	0.229	334,864	(-9.48)	0.413	334,864
	0.353***			2.053***		
AGE	(4.20)	0.265	644,546	(16.94)	0.344	644,546
	0.111*			0.173**		
LEV	(1.66)	0.261	642,182	(2.01)	0.235	642,182
Growth-related characteristics						
	-0.003			-0.001		
AG	(-0.72)	0.186	637,694	(-0.13)	0.271	637,694
	0.006*			0.008*		
CI	(1.89)	0.365	595,606	(1.89)	0.207	595,606
	0.006			0.024***		
IA	(1.13)	0.203	594,426	(3.57)	0.296	594,426
	0.007**			0.018***		
IG	(2.24)	0.208	628,492	(4.39)	0.241	628,492
	0.005			0.163**		
IK	(0.09)	0.260	635,500	(2.50)	0.239	635,500
	0.067**			0.004		
NOA	(2.23)	0.206	638,112	(0.10)	0.250	638,112
	-0.007			-0.005		
ROA	(-1.54)	0.210	635,558	(-0.70)	0.254	635,558
	0.166***			0.238***		
ROE	(4.51)	0.233	335,074	(5.42)	0.389	335,074
Market-based variables						
	4.261***			15.27***		
SIZE	(41.00)	0.355	2,376,393	(85.28)	1.287	2,234,669
	0.835***			2.705***		
VOL	(24.45)	0.217	2,376,397	(44.07)	0.563	2,234,669

We now introduce the interaction terms of four well-known market variables to examine; (i) whether the stock return predictability varies across time and (ii) whether market variables affect the predictability. These market variables include TED spread (*TED*), investor sentiment (*SENT* and *SENT_6*), the Index of Consumer Sentiment (*ICS*), and the Volatility Index (*VIX*). We estimate the OLS regression specified in Eqs. (3.5) and (3.6) and use clustered standard errors. Consistent with previous sections, we include in our model year- and industry-fixed effects. We estimate Eqs. (3.5) and (3.6) jointly across firms and present the regression results in Tables 3.3 to 3.6.

First, we use TED spread as a market variable to examine whether funding liquidity matters for cross-stock return predictability. As Campbell and Taksler (2003) note, the TED spread is a widely employed measure of funding liquidity in the market. The dependent variable is *Sig,* and the independent variable of interest is the interaction term of *TED* and $DIFF_{j,i}$. The results in Panel A of Table 3.3 suggest that an increase in TED spread leads to an increase in the probability of cross-firm return predictability by *LEV*, *IK*, *ROA*, and *CP*. In contrast, the coefficients on the interaction terms of six accounting variables; including *ES*, *BTM*, *IG*, *SIZE*, *VOL*, and *AG*; are negative and significant at the 10% level or better, suggesting that an increase in TED spread results in a reduction in the likelihood of prediction by *ES*, *BTM*, *IG*, *SIZE*, *VOL*, and *AG*.

In Panel B of Table 3.3, the dependent variable is the change in the R^2. The results in Panel B suggest a positive relation between *TED* and the power of cross-firm predictability based on six accounting variables; *AA*, *LEV*, *IK*, *NOA*, *SIZE*, and *VOL*. The results indicate that an increase in TED spread leads to the increased power of predictability, such that firm *j* can predict the performance of firm *i* using these five accounting variables. In contrast, an increase in TED spread results in a reduction in the power of predictability by *BTM* and *ROA*.[26] The results in Table 3.3 are consistent with the findings of Pontiff (1996), which suggests that an increase (decrease) in TED spread leads to an increase (reduction) in the cost of funding, which then facilitates (impedes) informed investors' ability to trade against such mispricing. Consequently, the degree of adjustment to information decreases (increases), leading to an increasing (decreasing) predictability.

[26] The results are economically significant. For example, the coefficient on the interaction term between *TED* and the difference in *BTM* between firms *j* and *i* suggests that a one standard deviation increase in TED spread decreases the likelihood and power of prediction across stock by 0.27% (i.e., -0.504×0.535) and 0.20% (i.e., -0.367×0.535), respectively.

Table 3.3. Determinants of time-varying return predictability based on the TED spread

This table reports the determinants of return predictability using the following models:
Panel A: $Sig = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, TED + \beta_3\, DIFF_{j,i} * TED + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1 if the value(s) from the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j\, R_{j,t-1} + \beta_i\, R_{i,t-1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t$ is positive and significant at the 0.05 level, and 0 otherwise.

Panel B: $(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, TED + \beta_3\, DIFF_{j,i} * TED + \varepsilon_t$, where $R^2_1 - R^2_0$ is the difference in R^2 $(R^2_1 - R^2_0)$, where R^2_1 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j\, R_{j,t-1} + \beta_i\, R_{i,t-1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_i\, R_{i,t-1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t$.

The explanatory variables are the level of differences in determinants between firms *j* and *i* scaled by the mean values of firm *j* and *i* ($DIFF_{j,i}$) and the average percentage of TED Spread (*TED*). Year fixed effect and industry fixed effects are included in all regressions. We describe each variable in Appendix B.2. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: OLS regression using Sig

Variables	$DIFF_{j,i}$	***TED***	$DIFF_{j,i}$ **** TED***	R^2	***N***
Earnings quality proxies					
	-0.005	-1.342***	-0.000		
EP	(-1.00)	(-13.43)	(-0.02)	0.395	626,696
	0.290***	-1.01***	0.008		
AA	(3.87)	(-9.73)	(0.08)	0.283	564,920
	0.438***	0.320***	-0.711***		
ES	(5.98)	(3.00)	(-6.66)	0.317	614,082
Firm characteristics					
	0.613***	0.272**	-0.504***		
BTM	(7.96)	(2.51)	(-4.61)	0.284	586,636
	-0.308***	0.470***	0.258*		
CP	(-3.54)	(3.27)	(1.85)	0.238	321,678
	0.468***	0.333***	-0.248		
AGE	(3.57)	(3.15)	(-1.39)	0.268	629,110
	-0.109	0.337***	0.411***		
LEV	(-1.09)	(3.19)	(3.06)	0.264	626,746
Growth-related characteristics					
	0.007	-0.401***	-0.019*		
AG	(1.03)	(-4.07)	(-1.76)	0.189	626,962
	0.008	-1.376***	-0.006		
CI	(1.58)	(-13.34)	(-0.77)	0.408	589,884
	0.008	-0.360***	-0.006		
IA	(0.92)	(-3.48)	(-0.41)	0.205	583,694
	0.019***	-0.061	-0.024***		
IG	(3.42)	(-0.60)	(-2.63)	0.207	615,622
	-0.244***	0.321***	0.518***		
IK	(-3.10)	(3.03)	(4.61)	0.266	620,278
	0.072	-0.002	-0.010		
NOA	(1.54)	(-0.02)	(-0.15)	0.204	625,028
	-0.021**	-0.020	0.028**		
ROA	(-2.52)	(-0.19)	(2.07)	0.207	624,306
	0.209***	0.469***	-0.065		
ROE	(3.30)	(3.26)	(-0.67)	0.242	321,788
Market-based variables					
	5.640***	0.278***	-2.605***		
SIZE	(32.61)	(5.05)	(-11.37)	0.367	2,240,262
	0.951***	0.278***	-0.230***		
VOL	(16.73)	(5.05)	(-2.74)	0.219	2,240,266

Table 3.3. (Continued)

Panel B: OLS regression using $(R^2_1 - R^2_0) / R^2_0$

Variables	$DIFF_{j,i}$	*TED*	$DIFF_{j,i}$ * *TED*	R^2	*N*
Earnings quality proxies					
	-0.004	1.181***	-0.002		
EP	(-0.54)	(9.08)	(-0.18)	0.243	626,696
	0.371***	0.835***	1.101***		
AA	(4.31)	(5.66)	(8.15)	0.344	564,920
	0.075	-0.057	0.088		
ES	(0.96)	(-0.37)	(0.70)	0.238	614,082
Firm characteristics					
	1.077***	-0.309*	-0.367***		
BTM	(10.88)	(-1.92)	(-2.70)	0.334	586,636
	-0.624***	0.151	0.020		
CP	(-6.53)	(0.69)	(0.10)	0.445	321,678
	1.828***	-0.272*	0.485		
AGE	(11.54)	(-1.75)	(1.64)	0.358	629,110
	-0.552***	-0.292*	1.594***		
LEV	(-4.82)	(-1.88)	(8.13)	0.260	626,746
Growth-related characteristics					
	0.001	0.407***	-0.005		
AG	(0.06)	(2.78)	(-0.28)	0.297	626,962
	0.014**	1.109***	0.011		
CI	(2.25)	(8.36)	(0.94)	0.240	589,884
	0.015	0.467***	0.016		
IA	(1.45)	(2.99)	(0.96)	0.325	583,694
	0.022***	0.070	-0.008		
IG	(3.35)	(0.46)	(-0.80)	0.259	615,622
	-0.692***	-0.327**	1.873***		
IK	(-7.94)	(-2.10)	(12.35)	0.276	620,278
	-0.216***	0.0386	0.467***		
NOA	(-4.22)	(0.25)	(4.71)	0.273	625,028
	0.017*	0.066	-0.017***		
ROA	(1.67)	(0.43)	(-2.81)	0.269	624,306
	0.174***	0.154	0.132		
ROE	(2.69)	(0.70)	(0.98)	0.423	321,788
Market-based variables					
	14.553***	0.65***	2.229***		
SIZE	(55.81)	(7.40)	(6.77)	1.178	2,098,758
	2.409***	0.655***	0.617***		
VOL	(27.21)	(7.42)	(4.71)	0.430	2,098,758

Another important market-based measure is market sentiment. Baker and Wurgler (2006, 2007) show that the impact of investor sentiment varies on stock returns over time. We, therefore, employ investor sentiment as market-based information to examine whether the cross-stock predictability varies over time. We report the results for these tests in Table 3.4.

According to these results, a standard deviation increase in *SENT*[27] leads to a 0.20% (i.e., −1.143 × 0.174) and 0.12% (i.e., −0.697 × 0.174) decrease in the probability and power of cross-firm return prediction by *SIZE*, respectively. Regarding the cross-stock return predictability by *VOL*, these numbers are 0.25% (i.e., −0.530 × 0.469) and 0.56% (i.e., −1.194 × 0.469), respectively. In contrast, the coefficients on the interaction terms of *ROA* are positive and significant, indicating an increase in *SENT* results in the likelihood and power of prediction by *ROA* by 0.07% (i.e., 0.016 × 4.07) and 0.09% (i.e., 0.022 × 4.07), respectively. We also adopt *ICS* as alternative measures for investor sentiment and find that our findings in Table 3.5 are robust to these alternative measures of investor sentiment.

[27] The Sentiment Index is drawn from Baker and Wurgler (2006). It is constructed based on the first principal component of five (standardized) sentiment proxies, where each of the proxies has first been orthogonalized with respect to a set of six macroeconomic factors. We thank Malcolm Baker and Jeffrey Wurgler for making the data available through their website: http://people.stern.nyu.edu/jwurgler/.

Table 3.4. Determinants of time-varying return predictability based on the Sentiment Index

This table reports the determinants of return predictability, using the following models:
Panel A: $Sig = \alpha + \beta_1\ DIFF_{j,i} + \beta_2\ SENT + \beta_3\ DIFF_{j,i}{*}\ SENT + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1 if the value(s) from the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j\ R_{j,t-1} + \beta_i\ R_{i,t-1} + \beta_{MKT}\ R_{MKTt} + \beta_S\ SMB_t + \beta_v\ HML_t + \varepsilon_t$ is positive and significant at the 0.05 level, and 0 otherwise.

Panel B: $(R^2{}_1 - R^2{}_0) / R^2{}_0 = \alpha + \beta_1\ DIFF_{j,i} + \beta_2\ SENT + \beta_3\ DIFF_{j,i}{*}\ SENT + \varepsilon_t$, where $R^2{}_1 - R^2{}_0$ is the difference in R^2 $(R^2{}_1 - R^2{}_0)$, where $R^2{}_1$ is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j\ R_{j,t-1} + \beta_i\ R_{i,t-1} + \beta_{MKT}\ R_{MKTt} + \beta_S\ SMB_t + \beta_v\ HML_t + \varepsilon_t$ and $R^2{}_0$ is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_i\ R_{i,t-1} + \beta_{MKT}\ R_{MKTt} + \beta_S\ SMB_t + \beta_v\ HML_t + \varepsilon_t$.

The explanatory variables are the level of differences in determinants between firms *j* and *i* scaled by the mean values of firm *j* and *i* ($DIFF_{j,i}$) and the Sentiment Index in Baker and Wurgler (2006); based on the first principal component of FIVE (standardized) sentiment proxies (*SENT*). Year fixed effect and industry fixed effects are included in all regressions. We describe each variable in Appendix B.2. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1 %, 5%, and 10% levels, respectively.

Panel A: OLS regression using Sig

Variables	$DIFF_{j,i}$	*SENT*	$DIFF_{j,i}$* *SENT*	R^2	*N*
Earnings quality proxies					
	-0.008***	-0.306***	0.005		
EP	(-2.60)	(-6.85)	(1.10)	0.328	596,958
	0.279***	-0.170***	0.048		
AA	(5.40)	(-3.27)	(0.93)	0.274	542,264
	0.147***	-0.135***	-0.285***		
ES	(3.17)	(-2.92)	(-5.21)	0.450	577,706
Firm characteristics					
	0.351***	-0.334***	0.023		
BTM	(6.91)	(-7.22)	(0.46)	0.403	568,526
	-0.197***	-0.296***	0.035		
CP	(-3.84)	(-4.68)	(0.57)	0.358	315,392
	0.358***	-0.398	0.021		
AGE	(4.04)	(-8.77)	(0.25)	0.406	608,164
	0.062	-0.397***	0.333***		
LEV	(0.91)	(-8.72)	(4.56)	0.405	605,800
Growth-related characteristics					
	-0.004	-0.205***	-0.003		
AG	(-1.04)	(-3.32)	(-0.59)	0.259	601,856
	0.005	-0.315	-0.007		
CI	(1.58)	(-6.75)	(-1.37)	0.337	561,342
	0.008	-0.171***	-0.029***		
IA	(1.60)	(-2.67)	(-3.85)	0.281	560,696
	0.007**	-0.348***	-0.002		
IG	(2.07)	(-6.48)	(-0.46)	0.321	592,654
	-0.002	-0.391***	-0.014		
IK	(-0.03)	(-8.41)	(-0.24)	0.401	598,854
	0.067**	-0.339***	-0.005		
NOA	(2.31)	(-6.49)	(-0.10)	0.320	602,274
	-0.007	-0.353***	0.016**		
ROA	(-1.48)	(-6.74)	(2.33)	0.326	599,978
	0.167***	-0.296***	0.045		
ROE	(4.31)	(-4.67)	(0.89)	0.362	315,602
Market-based variables					
	4.387***	-0.284***	-1.143***		
SIZE	(40.51)	(-10.77)	(-11.07)	0.464	2,259,611
	0.904***	-0.283***	-0.530***		
VOL	(25.09)	(-10.77)	(-15.05)	0.329	2,259,615

Table 3.4. (Continued)

Panel B: OLS regression using $(R^2{}_1 - R^2{}_0) / R^2{}_0$

Variables	$DIFF_{j,i}$	*SENT*	$DIFF_{j,i}$* *SENT*	R^2	*N*
Earnings quality proxies					
	-0.006	1.719***	-0.002		
EP	(-1.37)	(25.47)	(-0.43)	0.312	596,958
	0.919***	1.751***	-0.0739		
AA	(13.77)	(21.90)	(-0.89)	0.379	542,264
	0.091	1.305***	-0.099		
ES	(1.64)	(17.69)	(-1.18)	0.299	577,706
Firm characteristics					
	0.762***	1.568***	1.262***		
BTM	(10.99)	(21.75)	(15.58)	0.478	568,526
	-0.631***	1.322***	-0.116		
CP	(-9.81)	(12.94)	(-1.28)	0.445	315,392
	2.065***	1.551***	-0.103		
AGE	(16.71)	(22.15)	(-0.81)	0.443	608,164
	0.115	1.547***	-0.234**		
LEV	(1.30)	(22.04)	(-2.49)	0.335	605,800
Growth-related characteristics					
	-0.001	1.478***	0.004		
AG	(-0.29)	(15.44)	(0.41)	0.324	601,856
	0.007	1.678***	-0.000		
CI	(1.54)	(23.88)	(-0.02)	0.298	561,342
	0.024***	1.608***	0.011		
IA	(3.67)	(16.20)	(0.78)	0.345	560,696
	0.016***	1.559***	0.000		
IG	(3.91)	(18.17)	(0.06)	0.318	592,654
	0.162**	1.494***	-0.786***		
IK	(2.44)	(20.89)	(8.77)	0.349	598,854
	-0.066*	1.656***	-0.780***		
NOA	(-1.67)	(19.80)	(-14.09)	0.371	602,274
	-0.004	1.588***	0.022*		
ROA	(-0.52)	(19.03)	(1.77)	0.338	599,978
	0.196***	1.322***	0.378***		
ROE	(4.22)	(12.93)	(5.39)	0.422	315,602
Market-based variables					
	15.177***	1.255***	-0.697***		
SIZE	(84.03)	(30.10)	(-4.25)	1.308	2,129,537
	2.831***	1.255***	-1.194***		
VOL	(45.93)	(30.05)	(-18.19)	0.621	2,129,537

Table 3.5. Determinants of time-varying return predictability based on the Index of Consumer Sentiment

This table reports the determinants of return predictability, using the following models:
Panel A: $Sig = \alpha + \beta_1\ DIFF_{j,i} + \beta_2\ ICS + \beta_3\ DIFF_{j,i}*\ ICS + \varepsilon_t$, where Sig is a dummy variable that takes the value of 1 if the value(s) from the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j\ R_{j,t-1} + \beta_i\ R_{i,t-1} + \beta_{MKT}\ R_{MKTt} + \beta_S\ SMB_t + \beta_v\ HML_t + \varepsilon_t$ is positive and significant at the 0.05 level, and 0 otherwise.

Panel B: $(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1\ DIFF_{j,i} + \beta_2\ ICS + \beta_3\ DIFF_{j,i}*\ ICS + \varepsilon_t$, where $R^2_1 - R^2_0$ is the difference in R^2 $(R^2_1 - R^2_0)$, where R^2_1 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j\ R_{j,t-1} + \beta_i\ R_{i,t-1} + \beta_{MKT}\ R_{MKTt} + \beta_S\ SMB_t + \beta_v\ HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_i\ R_{i,t-1} + \beta_{MKT}\ R_{MKTt} + \beta_S\ SMB_t + \beta_v\ HML_t + \varepsilon_t$.

The explanatory variables are the level of differences in determinants between firms *j* and *i* scaled by the mean values of firm *j* and *i* ($DIFF_{j,i}$) and the Index of Consumer Sentiment (*ICS*). Year fixed effect and industry fixed effects are included in all regressions. We describe each variable in Appendix B.2. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: OLS regression using Sig

Variables	$DIFF_{j,i}$	*ICS*	$DIFF_{j,i}$* *ICS*	R^2	*N*
Earnings quality proxies					
	-0.046**	-0.045***	0.000*		
EP	(-2.12)	(-12.37)	(1.93)	0.391	632,530
	-0.199	-0.065***	0.006		
AA	(-0.62)	(-16.49)	(1.63)	0.346	573,204
	0.957***	-0.058***	-0.010***		
ES	(2.97)	(-17.89)	(-2.79)	0.387	614,082
Firm characteristics					
	0.002	-0.054***	0.004		
BTM	(0.01)	(-15.81)	(1.11)	0.347	601,764
	-0.598	-0.045***	0.005		
CP	(-1.57)	(-10.83)	(1.11)	0.283	334,864
	1.001*	-0.062***	-0.007		
AGE	(1.70)	(-18.20)	(-1.16)	0.357	644,546
	-1.937***	-0.062***	0.024***		
LEV	(-4.40)	(-18.23)	(4.91)	0.360	642,182
Growth-related characteristics					
	0.007	-0.080***	-0.000		
AG	(0.25)	(-20.27)	(-0.35)	0.316	637,694
	0.013	-0.045***	-0.000		
CI	(0.56)	(-12.03)	(-0.32)	0.400	595,606
	0.184***	-0.080***	-0.002***		
IA	(4.45)	(-19.67)	(-4.45)	0.339	594,426
	0.004	-0.074***	0.000		
IG	(0.16)	(-19.28)	(0.12)	0.325	628,492
	0.015	-0.062***	-0.000		
IK	(0.04)	(-18.23)	(0.03)	0.353	635,500
	-0.011	-0.074***	0.001		
NOA	(-0.06)	(-19.39)	(0.43)	0.323	638,112
	-0.054	-0.073***	0.001		
ROA	(-1.48)	(-19.05)	(-1.32)	0.324	635,558
	-0.257	-0.045***	0.005		
ROE	(-0.88)	(-10.79)	(1.51)	0.287	335,074
Market-based variables					
	12.69***	-0.069***	-0.097***		
SIZE	(17.61)	(-34.38)	(-12.27)	0.475	2,302,223
	5.184***	-0.069***	-0.049***		
VOL	(20.58)	(-34.37)	(-18.01)	0.350	2,302,227

Table 3.5. (Continued)

Panel B: OLS regression using $(R^2_1 - R^2_0) / R^2_0$

Variables	***DIFF$_{j,i}$***	***ICS***	***DIFF$_{j,i}$* ICS***	***R^2***	***N***
Earnings quality proxies					
	-0.011	0.062***	0.000		
EP	(-0.40)	(14.64)	(0.21)	0.240	632,530
	2.402***	0.064***	-0.017***		
AA	(6.56)	(14.50)	(-4.07)	0.341	573,204
	-0.225	0.040***	0.004		
ES	(-0.72)	(9.74)	(1.07)	0.256	614,082
Firm characteristics					
	-4.383***	0.052***	0.061***		
BTM	(-11.88)	(12.61)	(14.04)	0.396	601,764
	0.018	0.062***	-0.007		
CP	(0.04)	(12.36)	(-1.35)	0.459	334,864
	7.857***	0.058***	-0.067***		
AGE	(10.99)	(14.26)	(-8.43)	0.400	644,546
	2.441***	0.058***	-0.026***		
LEV	(4.90)	(14.33)	(-4.65)	0.278	642,182
Growth-related characteristics					
	-0.007	0.045***	0.000		
AG	(-0.21)	(10.80)	(0.19)	0.291	637,694
	0.026	0.069***	-0.000		
CI	(0.88)	(15.77)	(-0.62)	0.245	595,606
	0.017	0.050***	0.000		
IA	(0.42)	(11.44)	(0.16)	0.320	594,426
	0.014	0.051***	0.000		
IG	(0.57)	(12.10)	(0.13)	0.269	628,492
	1.823***	0.055***	-0.019***		
IK	(4.68)	(13.58)	(-4.32)	0.277	635,500
	2.944***	0.053***	-0.035***		
NOA	(13.19)	(12.50)	(-13.37)	0.305	638,112
	-0.202***	0.052***	0.002***		
ROA	(-4.30)	(12.33)	(3.95)	0.285	635,558
	-1.904***	0.062***	0.025***		
ROE	(-6.20)	(12.38)	(7.13)	0.448	335,074
Market-based variables					
	23.906***	0. 050***	-0.095***		
SIZE	(23.12)	(19.20)	(-8.28)	1.197	2,160,499
	9.980***	0.050***	-0.082***		
VOL	(26.06)	(19.21)	(-19.32)	0.481	2,160,499

Our final measure of market-based funding liquidity is the market volatility index (*VIX*), which captures the implied volatility of the stock market. We employ the market volatility index to examine whether the predictability across different pairs of stocks varies over time, based on changes in market uncertainty. We report the results for this test in Table 3.6.

According to these results, a positive and significant coefficient on the interaction term of *VIX* and the difference in *LEV* between firms *j* and *i* suggest that when *VIX* increases, the probability and power of cross-stock prediction increases by 0.17% (i.e., 0.011 × 15.418) and 0.23% (i.e., 0.015 × 15.418), respectively. Besides this, an increase in *VIX* leads to a decrease in the likelihood and power of cross-firm return predictability by *ES* and by *SIZE*. These results are consistent with the findings of Shleifer and Vishny (1997), which show that an increase in market volatility is related to greater mispricing due to noise traders' sentiment, leading to a higher probability of losses for arbitrageurs and, hence, the need for portfolio liquidation under investors' expectations. As a consequence, a decrease in the degree of information adjustment can lead to an increase in predictability.

We also consider two additional robustness tests to ensure that our results are not driven by alternative explanations. Specifically, we first use the logit and probit regressions, instead of the OLS model, for Eqs. (3.2) and (3.5). Second, we use the difference in R^2 ($R^2_1 - R^2_0$) as an alternative dependent variable for Eqs. (3.3) and (3.6). Overall, the results are highly consistent with our findings.[28]

[28] We report the results of additional robustness tests in Appendix B.8–B.12.

Table 3.6. Determinants of time-varying return predictability based on the Volatility Index

This table reports the determinants of return predictability using the following models:
Panel A: $Sig = \alpha + \beta_1\ DIFF_{j,i} + \beta_2\ VIX + \beta_3\ DIFF_{j,i} * VIX + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1 if the value(s) from the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j\ R_{j,t-1} + \beta_i\ R_{i,t-1} + \beta_{MKT}\ R_{MKTt} + \beta_S\ SMB_t + \beta_v\ HML_t + \varepsilon_t$ is positive and significant at the 0.05 level, and 0 otherwise.

Panel B: $(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1\ DIFF_{j,i} + \beta_2\ VIX + \beta_3\ DIFF_{j,i} * VIX + \varepsilon_t$, where $R^2_1 - R^2_0$ is the difference in R^2 ($R^2_1 - R^2_0$), where R^2_1 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j\ R_{j,t-1} + \beta_i\ R_{i,t-1} + \beta_{MKT}\ R_{MKTt} + \beta_S\ SMB_t + \beta_v\ HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_i\ R_{i,t-1} + \beta_{MKT}\ R_{MKTt} + \beta_S\ SMB_t + \beta_v\ HML_t + \varepsilon_t$.

The explanatory variables are the level of differences in determinants between firms *j* and *i* scaled by the mean values of firm *j* and *i* ($DIFF_{j,i}$) and the Volatility Index (*VIX*). Year fixed effect and industry fixed effects are included in all regressions. We describe each variable in Appendix B.2. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: OLS regression using Sig

Variables	$DIFF_{j,i}$	VIX	$DIFF_{j,i}$* VIX	R^2	N
Earnings quality proxies					
	0.010	0.012***	-0.001**		
EP	(1.23)	(2.89)	(-2.01)	0.358	626,696
	0.275***	0.014***	0.001		
AA	(2.75)	(3.03)	(0.22)	0.264	564,920
	0.881***	0.005	-0.038***		
ES	(8.62)	(1.06)	(-8.74)	0.320	614,082
Firm characteristics					
	0.422***	0.002	-0.003		
BTM	(3.72)	(0.37)	(-0.59)	0.279	586,636
	-0.007	-0.000	-0.008		
CP	(-0.05)	(-0.05)	(-1.41)	0.233	321,678
	0.289	0.006	0.003		
AGE	(1.59)	(1.40)	(0.40)	0.266	629,110
	-0.145	0.006	0.011**		
LEV	(-1.07)	(1.37)	(2.06)	0.261	626,746
Growth-related characteristics					
	-0.009	0.003	0.000		
AG	(-0.79)	(0.62)	(0.61)	0.185	626,962
	0.027***	0.013***	-0.001***		
CI	(3.03)	(3.01)	(-2.64)	0.369	589,884
	0.011	0.033	-0.000		
IA	(0.74)	(0.77)	(-0.39)	0.202	583,694
	0.015	0.006	-0.000		
IG	(1.64)	(1.44)	(-0.91)	0.206	615,622
	0.013	0.007	-0.001		
IK	(0.12)	(1.70)	(-0.15)	0.260	620,278
	0.179**	0.006	-0.005*		
NOA	(2.46)	(1.39)	(-1.79)	0.205	625,028
	-0.049***	0.005	0.002***		
ROA	(-3.63)	(1.28)	(3.34)	0.208	624,306
	0.224**	-0.000	-0.002		
ROE	(2.37)	(-0.05)	(-0.54)	0.238	321,788
Market-based variables					
	4.984***	0.022***	-0.031***		
SIZE	(21.48)	(10.03)	(-3.26)	0.365	2,240,262
	0.818***	0.022***	0.001		
VOL	(10.41)	(10.03)	(0.35)	0.223	2,240,266

Table 3.6. (Continued)

Panel B: OLS regression using $(R^2_1 - R^2_0) / R^2_0$

Variables	$\boldsymbol{DIFF_{j,i}}$	***VIX***	$\boldsymbol{DIFF_{j,i}}$**** VIX***	$\boldsymbol{R^2}$	***N***
Earnings quality proxies					
	0.013	-0.039***	-0.001		
EP	(0.91)	(-7.20)	(-1.44)	0.235	626,696
	1.251***	-0.051***	-0.016***		
AA	(10.66)	(-8.04)	(-3.11)	0.336	564,920
	0.478***	0.003	-0.018***		
ES	(3.86)	(0.48)	(-3.31)	0.239	614,082
Firm characteristics					
	0.292**	0.012**	0.028***		
BTM	(2.17)	(2.23)	(4.66)	0.336	586,636
	0.090	0.011	-0.034***		
CP	(0.54)	(1.64)	(-4.37)	0.451	321,678
	1.977***	-0.002	0.004		
AGE	(9.43)	(-0.44)	(0.42)	0.357	629,110
	-0.0075	-0.002	0.015**		
LEV	(-0.46)	(-0.31)	(2.12)	0.245	626,746
Growth-related characteristics					
	0.000	0.532***	0.000		
AG	(0.02)	(29.44)	(0.09)	0.297	626,962
	0.004	-0.045***	0.000		
CI	(0.44)	(-8.17)	(0.39)	0.236	589,884
	0.000	-0.025***	0.001		
IA	(0.01)	(-4.41)	(1.23)	0.326	583,694
	0.031***	-0.005	-0.001		
IG	(2.86)	(-0.97)	(-1.29)	0.259	615,622
	0.873***	-0.005	-0.034***		
IK	(6.87)	(-0.92)	(-5.50)	0.253	620,278
	0.103	-0.005	-0.005		
NOA	(1.25)	(-0.87)	(-1.25)	0.269	625,028
	0.015	-0.005	-0.001		
ROA	(0.92)	(-0.83)	(-1.31)	0.268	624,306
	0.479***	0.011*	-0.012**		
ROE	(4.11)	(1.65)	(-2.18)	0.425	321,788
Market-based variables					
	20.500***	-0.033***	-0.217***		
SIZE	(48.91)	(-8.43)	(-13.93)	1.194	2,098,758
	5.716***	-0.033***	-0.143***		
VOL	(39.15)	(-8.37)	(-23.42)	0.463	2,098,758

3.6. Trading Strategy Implications

In the previous sections, we find that the difference in the source of accounting variables is associated with the probability and power of cross-stock returns' prediction. In particular, the results show that 10 accounting variables matter for cross-stock predictability, including *AA*, *ES*, *BTM*, *AGE*, *LEV*, *CI*, *IG*, *ROE*, *SIZE*, and *VOL*. In this section, we utilize this finding to create a simple trading strategy and assess its performance. To mitigate potential idiosyncratic concerns, we employ a portfolio investment strategy to minimize the variation in firm-specific information. We use the rank-based approach for the aggregation of accounting information. Since we require the availability of these 10 accounting variables for calculating the average rank of stocks, our sample for the trading strategy covers the period from January 1991 to December 2016. Each year, we rank stocks based on each of the selected accounting variables and compute the average rank across these variables for each stock. We then sort stocks into decile portfolios by using the average ranks and compute equal- and value-weighted stock return portfolios.[29] We estimate the following OLS regression between the bottom (i.e., lowest information transparency) and top (i.e., highest information transparency) decile portfolios using a 10-year rolling window:

$$R_{LOWt} = \alpha + \beta_1 R_{HIGHt-1} + \varepsilon_t, \tag{3.7}$$

The dependent variable in Eq. (3.7), R_{LOWt}, is the portfolio's monthly returns in month t for stocks with the lowest information transparency. The independent variable, $R_{HIGHt-1}$, is the portfolio's monthly returns in month $t-1$ for stocks with the highest information transparency.

We compare the predicted return from Eq. (3.7) to the Treasury bill rate. Our trading strategy is to buy the low transparency stock portfolio if its predicted value is higher than the

[29] We use only information available at the time of portfolio formation, so that our forecasts do not have a "look-ahead bias".

Treasury bill rate or invest in the Treasury bill otherwise. We re-estimate Eq. (3.7) and re-assess our strategy on a monthly basis using the period of 1991 – 2000 as the first estimation window. We report the results for out of sample performance between our trading strategy and the buy-and-hold strategy in Table 3.7. The equal- and value-weighted portfolios based on our trading strategy generate average monthly returns of 0.41% and 0.12%, respectively, translating into annual returns of 4.91% and 1.44%, respectively. The Sharp ratios are both positive (0.054 and 0.027, respectively). Meanwhile, the equal- and value-weighted portfolios based on the buy-and-hold (BAH) strategy produces lower average monthly returns of 0.31% and -0.47%, respectively, translating into annual returns of 3.72% and -5.64%, respectively. The BAH strategy has lower Sharp ratios and higher standard deviations than the trading strategy in both the equal- and value-weighted portfolios. Overall, the trading strategy outperforms the BAH strategy in return, risk, and Sharpe ratio. This evidence confirms the usefulness of accounting information as proxies for the level of information transparency in cross-stock return predictability and the performance of a simple trading strategy.

Table 3.7. Out of sample performance

This table presents the out of sample performance for our trading strategy and the buy-and-hold decile portfolios formed by sorting firms according to the degree of information transparency of accounting variables. The portfolio formation period is from January 2001 to November 2016. The rebalancing frequency is on a monthly basis. We source returns data, accounting variables, and risk-free rates from CRSP, Compustat, and Kenneth French's website, respectively. The decile portfolios are equal-weighted in Panel A and value-weighted in Panel B.

Portfolio returns	**N**	**Mean**	**Std.**	**Sharpe Ratio**
Panel A: Equal weights				
Our trading strategy	191	0.0041	0.0556	0.0540
Buy-and-hold	191	0.0031	0.0750	0.0267
Risk-free rate	191	0.0011	0.0014	
Panel B: Value weights				
Our trading strategy	191	0.0012	0.0280	0.0036
Buy-and-hold	191	-0.0047	0.1053	-0.0551
Risk-free rate	191	0.0011	0.0014	

3.7. Conclusion

We study whether variations in predictability across different pairs of stocks are associated with the degree of information reflection between the stocks. Our findings affirm this hypothesis. We find that 10 out of 17 accounting variables are strong predictors of stock returns across firms, evidenced by the likelihood and the power of cross-stock returns predictability. We also find that the predictability varies over time due to the funding of liquidity and market sentiment. Our findings suggest that earnings quality and growth-related characteristics' variables (abnormal accruals, abnormal capital investments, investment growth, and return on equity) are strong cross-stock returns' predictors and do not vary across time. Our findings are consistent with the gradual information diffusion theory, which suggests that a single stock can gradually diffuse information among other stocks, leading to a lead-lag effect in stock markets.

APPENDIX B

FOR ESSAY TWO

Appendix B.1. Distribution of the selected 500 stocks across size deciles over time

This table presents the distribution of the selected 500 stocks in each size decile over time. The sample covers 86 years from January 1931 to December 2016.

Year	Small	2	3	4	5	6	7	8	9	Large
1931	48	51	49	52	48	47	47	52	55	51
1941	48	53	50	54	49	48	53	40	50	55
1951	45	56	49	56	51	48	46	55	46	48
1961	47	56	46	49	41	55	59	49	43	55
1971	43	46	43	51	56	58	40	58	49	56
1981	62	44	61	55	47	44	37	57	48	45
1991	47	56	53	35	54	56	57	45	54	43
2001	53	56	58	37	44	43	53	54	45	57
2011	53	57	43	49	51	43	52	53	53	46
2016	53	42	61	46	47	46	51	50	52	52

Appendix B.2. Variable descriptions

Variables	Description	Predicted Sign	Sample Frequency	Definition	Rationale
Earnings quality proxies					
EP	Earnings persistence	(+)	Annual	The slope coefficient between current period earnings regressed scaled by total assets (data 6) over previous period earnings, estimated based on the Kormendi and Lipe (1987) regression model using a five-year rolling window.	Kormendi and Lipe (1987), Collins and Kothari (1989), and Easton and Zmijewski (1989) find more persistent earnings have a higher security price response and positive stock market returns. A higher β represents a highly persistent earnings stream (higher earnings quality). Firms that have more earnings persistence show a higher"sustainable" earnings/cash flow stream, providing a more decisive beneficial input into equity valuations (Dechow, Ge, and Schrand, 2010). Thus, firms that have more earnings persistence represent a higher degree of information transparency.
AA	Abnormal accruals	(−)	Annual	The standard deviation of the estimated residual over the years *t−4* to *t* using Dechow and Dichev (2002)'s regression model where total current accruals are related to previous, current, and future period cash flows, revenues and PPE for each of Fama and French (1997)'s 48 industry groups with at least 20 firms in year *t* and all variables are scaled by total assets (data 6).	Dechow and Dichev (2002) measure earnings quality by capturing the uncertainty arising from estimation errors in the mapping of working capital accruals to operating cash flow realizations. Firms with a higher (lower) standard deviation of residuals are likely to be of lower (higher) earnings quality since they demonstrate a less (more) persistent component of earnings. Sloan (1996) shows that some investors are unable to completely incorporate the mean-reverting of the accruals of high accrual firms. The literature suggests that there is a negative relationship between earnings quality (proxied by accruals) and the degree of information asymmetry as high accruals result in a low quality of earnings and, thus, a higher degree of information asymmetry.
ES	Earnings Smoothness	(+)	Annual	The standard deviation of cash flows (data 308) scaled by total assets (data 6) divided by the standard deviation of earnings (data18) scaled by total assets (data 6), using	Tucker and Zarowin (2006) find that smoothness enhances earnings informativeness. Firms with higher (lower) values of earnings smoothness

				Bowen, Rajgopal, and Venkatachalam (2008) is over the five years *t−5* to *t−1*.	indicate more (less) smoothing of the earnings stream relative to cash flow and accounting discretion.
Firm characteristics					
BTM	Book-to-market ratio	(+)	Annual	The book value of equity (data 6 − 181) divided by the market value of equity (data 199 × 25).	Porta, Lakonishok, Shleifer, and Vishny (1997) and Skinner and Sloan (2002) show that market participants underestimate future earnings for high book-to-market ratio and overestimate future earnings for low book-to-market stocks. Thus, firms, which have larger book-to-market ratios, tend to have higher information transparency.
CP	Cash flow to price ratio	(+)	Annual	$CP_{i,t} = \frac{IB_{i,t} + EDP_{i,t} + TXDI_{i,t}}{ME_{i,t}}$, where $IB_{i,t}$ is income before extraordinary items (data 118); $EDP_{i,t}$ is the equity's share of depreciation; $TXDI_{i,t}$ is the deferred taxes (data 50); $ME_{i,t}$ is the market value of equity (common shares outstanding (data 25) × price close (data 199). $EDP_{i,t} = \left(\frac{ME_{i,t}}{ME_{i,t} + AT_{i,t} - BE_{i,t}}\right) \times DP_{i,t}$, where $DP_{i,t}$ is the depreciation and amortization (data 14); $AT_{i,t}$ is the total assets (data 6); $BE_{i,t}$ is the book value of equity (data 6 − 181). Only firms with positive earnings are included in the sample.	As Chan, Hamao, and Lakonishok (1991), Fama and French (1992), and Lakonishok, Shleifer, and Vishny (1994) note, stock returns have a positive association with the cash flow-to-price ratio. The results are consistent with Lau, Lee, and McInish (2002), who find that the cash flow-to-price ratio is positively related to stock returns. The results imply that a higher cash flow-to-price ratio tends to have higher information transparency.
AGE	Firm age	(+)	Annual	The number of years since the firm first appeared on Compustat.	Barry and Brown (1985) find firms with a long history (age) have more information available to the market, which leads to capturing more information in predicting future returns. Barinov, Park, and Yıldızhan (2019) show that firms with a lower age are associated with weaker incorporation of information into their stock prices. Thus, older firms tend to have higher information transparency.

LEV	Leverage	(+)	Annual	The ratio of total debt (data 181) to total assets (data 6).	Yu (2005) finds a positive association between firm leverage and information transparency, indicating that firms with higher leverage tend to have higher information transparency.
Growth-related characteristics					
AG	Total asset growth	(−)	Annual	The annual change in total asset $_{t-1}$ and $_{t-2}$ (data 6) divided by total assets $_{t-2}$ (data 6).	Cooper, Gulen, and Schill (2008) document that there is a strong negative association between a firm's asset growth and the future stock returns, suggesting that firms with lower total asset growth tend to have higher information transparency.
CI	Abnormal capital investments	(−)	Annual	$CI_{i,t} = \left(\frac{CE_{i,t-1}}{\frac{CE_{i,t-2}+CE_{i,t-3}+CE_{i,t-4}}{3}}\right) - 1,$ where $CI_{i,t}$ is the firm's capital expenditure (data 128) divided by net sales (data 12).	Titman, Wei, and Xie (2004) find that an investment anomaly is the tendency of firms that recently experienced high capital investments to have low expected returns, suggesting that firms with lower abnormal capital investments tend to have higher information transparency.
IA	Investment-to-assets ratio	(−)	Annual	The annual change in inventories $_{t-1}$ and $_{t-2}$ (data 3) plus the annual change in gross property, plant, and equipment $_{t-1}$ (data 7) divided by total assets (data 6).	Lyandres, Sun, and Zhang (2008) document the negative relation between investment and expected returns, suggesting that firms increasing capital tend to have a higher investment-to-assets ratio and have lower expected returns, whereas firms distributing capital tend to have a lower investment-to-assets ratio and have higher expected returns. Thus, firms with a lower investment-to-assets ratio tend to have higher information transparency.
IG	Investment growth	(−)	Annual	The annual change in capital expenditures $_{t}$ and $_{t-1}$ (data 128) divided by capital expenditures $_{t-1}$ (data 128).	Xing (2008) shows that stocks with low past investment growth rates have significantly higher average returns than those stocks with high past investment growth rates, implying that lower investment growth rate firms tend to have higher information transparency.

IK	Investment-to-capital ratio	(−)	Annual	The ratio of capital expenditures (data 128) to total net property, plant and equipment (data 8).	Zhang (2005) shows that firms with lower capital investment have higher expected returns. This is in line with the research of Xing (2008) and Polk and Sapienza (2008) that suggest a negative relationship between capital investment and future stock returns. Xing (2008) also documents that stocks with the lowest (highest) investment-to-capital ratios have the highest (lowest) returns, indicating that firms with a lower investment-to-capital ratio tend to have higher information transparency.
NOA	Net operating assets	(+)	Annual	$NOA_{i,t} = \frac{Operating\ Assets_{i,t-1} + \ Operating\ Liability_{i,t-1}}{AT_{i,t}}$, where $Operating\ Assets_{i,t} = AT - CHE$; $Operating\ Liability_{i,t} = AT - DLC - DLTI - MIB - PSTK - CEQ$; AT is total assets (data 6); CHE is cash and short-term investments (data 1); DLC is debt in current liabilities (data 34); $DLTT$ is total long-term debt (data 9); MIB is minority interest (data 38); $PSTK$ is preferred stock (data 130); CEQ is total common equity (data 60).	Hirshleifer, Hou, Teoh, and Zhang (2004) suggest that net operating assets are positively associated with future stock returns. We imply that firms with higher net operating assets tend to have higher information transparency.
ROA	Return on assets	(+)	Annual	The ratio of income before extraordinary items in quarter $t-1$ (data 8) to total assets in quarter $t-2$ (data 44).	Liao, Liu, and Wang (2011) find that portfolios with higher cumulative abnormal returns have a positive association with ROA, suggesting that a higher return on assets tends to have higher information transparency.
ROE	Return on equity	(+)	Annual	$ROE_{i,t} = \frac{IB_{i,t} + \ DVP_{i,t} + \ TXDI_{i,t}}{BE_{i,t}}$ where $IB_{i,t}$ is income before extraordinary items (data 118); $DVP_{i,t}$ is the preferred dividends (data 19) (if available); $TXDI_{i,t}$ is the deferred taxes (data 50) (if available); $BE_{i,t}$ is the book value of equity (data 6 − 181). Only firms with positive earnings are included in the sample.	Claus and Thomas (2001) show that there is a positive association between ROE and abnormal earnings. We imply that firms that have a higher return on equity tend to have higher information transparency.

Market-based variables					
SIZE	Firm size	(+)	Annual	The natural log of the average in the CRSP monthly market capitalization of the firm (number of shares outstanding × share closing price) over a year.	Lo and MacKinlay (1990) find that larger capitalization portfolio stock returns lead, while smaller ones mostly merely follow. Hou (2007) also shows that the lead-lag relationship in information between large and small firms is predominantly an intra-industry phenomenon. That is, stock returns in small firms follow the release of the returns of large firms within the same industry. Therefore, larger firms tend to have higher information transparency.
VOL	Stock return volatility	(−)	Annual	The standard deviation in the CRSP daily return over a year.	Papadamou, Sidiropoulos, and Spyromitros (2014) find that there is a negative relation between information transparency scores and the stock price volatility, which is contrary to the findings of Ding, Hope, and Schadewitz (2009).
Market state variables					
TED	TED spread	(−)	Annual	TED spread is the difference in yields between US Eurodollar deposits (effectively three-month USD LIBOR) and US Treasury-bills. We use the average percentage of TED Spread from https://fred.stlouisfed.org/series/TEDRATE.	Lashgari (2000) shows that there is a negative relationship between TED spread and stock prices. These studies imply that a low TED spread has higher information transparency.
SENT	Sentiment index	(−)	Annual	The Sentiment Index in Baker and Wurgler (2006); the updated version of Eq. (2) in that paper; based on the first principal component of five (standardized) sentiment proxies from http://people.stern.nyu.edu/jwurgler/.	
SENT_6	Sentiment index_6	(−)	Annual	The Sentiment Index in Baker and Wurgler (2006); the updated version of Eq. (3) in that paper; based on the first principal component of five (standardized) sentiment proxies where each of the proxies has first been orthogonalized to a set of six macroeconomic factors from http://people.stern.nyu.edu/jwurgler/.	Chui, Titman, and Wei (2010) and Schmeling (2009) show that sentiment negatively predicts aggregate stock exchange returns. These studies imply that a low sentiment index has higher information transparency.

ICS	Index of consumer sentiment	(−)	Annual	The University of Michigan Consumer Sentiment Index is an index of consumer confidence provided every month by the University of Michigan on https://data.sca.isr.umich.edu/data-archive/mine.php.	
VIX	Volatility index	(−)	Annual	The Volatility Index from https://www.globalfinancialdata.com/.	Avramov, Barras, and Kosowski (2013) find that the VIX index is negatively associated with investment returns, suggesting that a low VIX index has higher information transparency.

Appendix B.3. Spearman correlations between all variables

Panels A and B report a Spearman correlation matrix of these variables. The sample covers 86 years from January 1931 to December 2016. We source return and accounting variables from the Compustat and CRSP databases. *EP* refers to earnings persistence; *AA* is abnormal accruals; *ES* is earnings smoothness; *BTM* is book-to-market ratio; *CP* refers to cash flow-to-price ratio; *AGE* is firm age; *LEV* is leverage; *AG* refers to total asset growth; *CI* is capital investments; *IA* is investment-to-assets ratio; *IG* is investment growth; *IK* refers to investment-to-capital ratio; *NOA* is net operating assets; *ROA* is a return on assets; *ROE* is a return on equity; *SIZE* is firm size; *VOL* is stock return volatility. The market state variables include TED spread (*TED*), sentiment index (*SENT* and *SENT_6*), index of consumer sentiment (*ICS*), and Volatility Index (*VIX*). We describe each variable in Appendix B.2. *t*-statistics that are statistically significant at the 10% level or better are in bold.

Panel A: Spearman correlations among accounting variables

Variables	***EP***	***AA***	***ES***	***BTM***	***CP***	***AGE***	***LEV***	***AG***	***CI***	***IA***	***IG***	***IK***	***NOA***	***ROA***	***ROE***	***SIZE***	***VOL***
EP	1.00																
AA	**-0.08**	**1.00**															
ES	**0.02**	**-0.23**	**1.00**														
BTM	**0.02**	**-0.16**	**0.04**	**1.00**													
CP	**-0.02**	**-0.09**	**0.04**	**0.51**	**1.00**												
AGE	**0.04**	0.00	**0.07**	**0.01**	**-0.17**	**1.00**											
LEV	0.00	**-0.08**	**-0.02**	**0.02**	**0.14**	**0.08**	**1.00**										
AG	**0.01**	**-0.10**	**0.14**	**-0.15**	**-0.08**	**-0.22**	**-0.14**	**1.00**									
CI	**0.03**	**-0.13**	**0.10**	**-0.01**	**-0.03**	**0.10**	-0.01	**0.22**	**1.00**								
IA	**0.05**	**-0.18**	**0.12**	0.00	**0.04**	**-0.18**	**-0.01**	**0.50**	**0.30**	**1.00**							
IG	**-0.04**	**-0.04**	**0.06**	**-0.16**	**-0.04**	**-0.10**	**-0.10**	**0.19**	**-0.22**	**-0.09**	**1.00**						
IK	**-0.03**	**0.21**	**-0.03**	**-0.28**	**-0.14**	**-0.26**	**-0.25**	**0.31**	**0.15**	**0.08**	**0.48**	**1.00**					
NOA	**0.09**	**-0.24**	**0.02**	**0.40**	**0.16**	**0.12**	**0.15**	**-0.13**	**0.01**	**0.16**	**-0.26**	**-0.39**	**1.00**				
ROA	**0.06**	**-0.24**	**0.28**	**-0.09**	0.00	**0.08**	**-0.18**	**0.30**	**0.14**	**0.14**	**0.18**	**0.12**	**-0.02**	**1.00**			
ROE	**0.06**	**-0.02**	**0.01**	**-0.42**	**0.38**	**-0.04**	**0.11**	**0.10**	**0.03**	**0.06**	**0.07**	**0.11**	**-0.13**	**0.34**	**1.00**		
SIZE	**0.03**	**-0.24**	**0.11**	**-0.28**	**-0.34**	**0.37**	**0.07**	**0.13**	**0.15**	**0.02**	**0.09**	**-0.03**	**-0.06**	**0.31**	**0.20**	**1.00**	
VOL	**-0.05**	**0.44**	**-0.26**	**-0.03**	**-0.02**	**-0.24**	**-0.11**	**-0.02**	**-0.15**	**-0.02**	**-0.06**	**0.18**	**-0.13**	**-0.40**	**-0.13**	**-0.38**	**1.00**

Appendix B.3. (Continued)

Panel B: Spearman correlations among market state variables

Variables	***TED***	***SENT***	***SENT_6***	***ICS***	***VIX***
TED	1.00				
SENT	0.14	1.00			
SENT_6	0.04	**0.95**	1.00		
ICS	-0.00	**0.42**	**0.41**	1.00	
VIX	**0.41**	0.06	-0.24	-0.11	1.00

Appendix B.4. Descriptive statistics for the pairwise regression sample

This table presents the descriptive statistics for the pairwise regression using the following model: $R_{i,t} = \alpha + \beta_j R_{j,t-1} + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$. The sample covers 86 years from January 1931 to December 2016. $R_{i,t}$ is the monthly return of firm i; $R_{j,t-1}$ is the lagged monthly return of firm j; $R_{i,t-1}$ is the lagged monthly return of firm i; and R_{MKT}, SMB, HML are Fama and French (1993)'s three factors. We source returns data from CRSP and factors from the Kenneth French website.

Variables	**N**	**Mean**	**Std.**	**Minimum**	**Maximum**
$\beta\ R_{j,t-1}$	30,580,973	0.0246	0.2135	-6.2553	6.5782
$\beta\ R_{i,t-1}$	30,580,973	-0.0519	0.1376	-1.3620	2.7428
$\beta\ R_{MKT}$	30,580,973	0.0105	0.0071	-0.0565	0.0836
$\beta\ SMB$	30,580,973	0.0079	0.0101	-0.0868	0.1299
$\beta\ HML$	30,580,973	0.0021	0.0109	-0.1482	0.1026
R^2	30,580,973	0.2762	0.1458	0.0007	0.9113
$ADJ.\ R^2$	30,580,973	0.2090	0.1593	-0.2494	0.8967

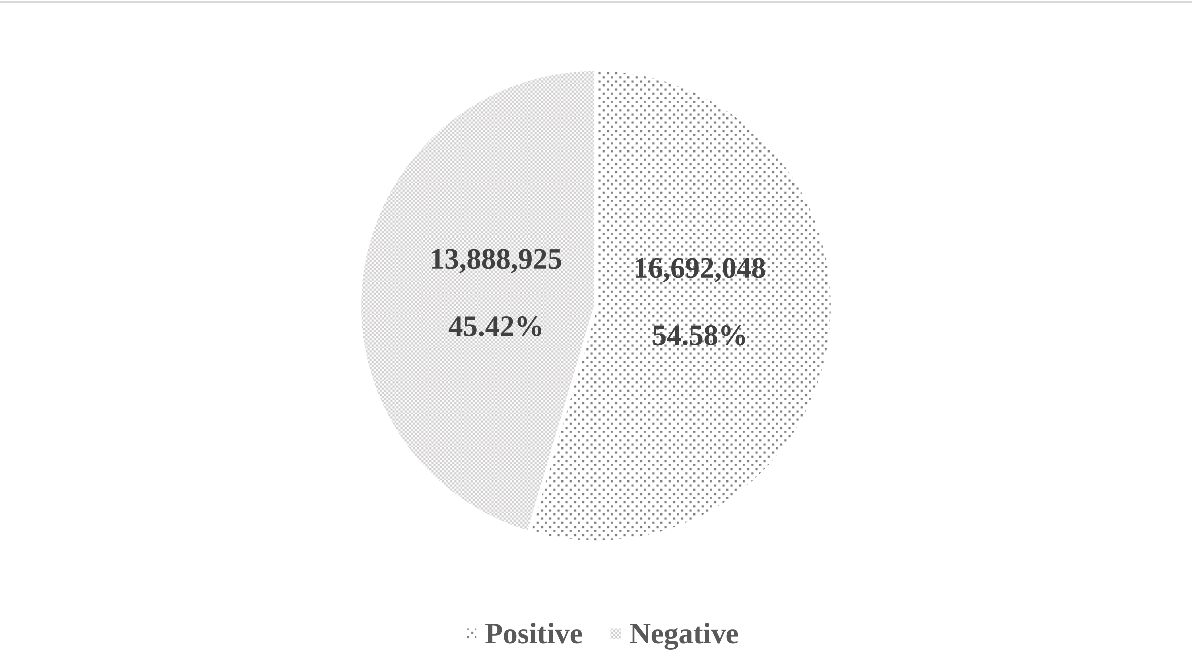
Appendix B.5. The proportions of positive and negative significances from the pairwise regression

This table presents the proportions of the positive and negative significances from the pairwise regression using the following model: $R_{i,t} = \alpha + \beta_j R_{j,t-1} + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$. The sample covers 86 years from 1931 to December 2016. $R_{i,t}$ is the monthly return of firm *i*; $R_{j,t-1}$ is the lagged monthly return of firm *j*; $R_{i,t-1}$ is the lagged monthly return of firm *i*; and R_{MKT}, *SMB*, *HML* are Fama and French (1993)'s three factors. We source returns data from CRSP and factors from the Kenneth French website.

Significance levels (%)	Positive			Negative		Total Positive & Negative	
	N	%	Z-test	N	%	N	%
1	526,561	1.72	68.09	206,131	0.67	732,692	2.40
5	1,549,822	5.07	145.84	799,318	2.61	2,349,140	7.68
10	2,578,726	8.43	198.25	1,488,275	4.87	4,067,001	13.30
Insignificant	14,113,322	46.15		12,400,650	40.55	26,513,972	86.70
Total	16,692,048	54.58		13,888,925	45.42	30,580,973	100.00

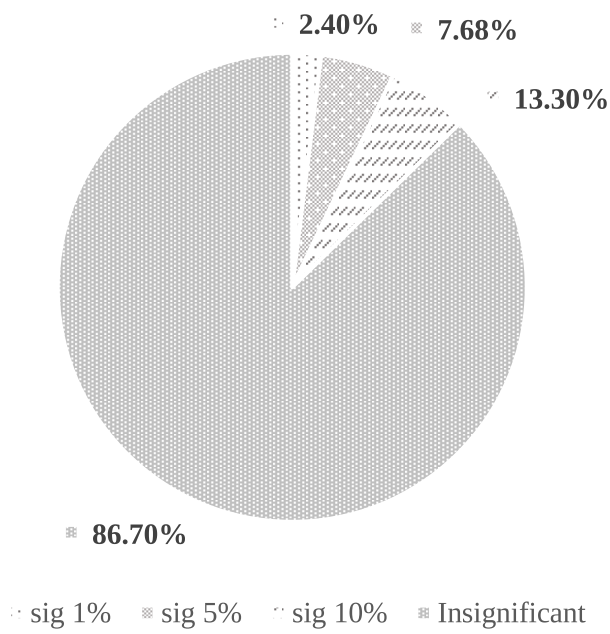
Appendix B.6. The proportions of the positive and negative coefficient from the pairwise regression

This figure presents the proportions of the positive and negative coefficient from the pairwise regression using the following model: $R_{i,t} = \alpha + \beta_j R_{j,t-1} + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$. The sample covers an 86-year period to December 2016. $R_{i,t}$ is the monthly return of firm i; $R_{j,t-1}$ is the lagged monthly return of firm j; $R_{i,t-1}$ is the lagged monthly return of firm i; and R_{MKT}, SMB, HML are Fama and French (1993)'s three factors. We source returns data from CRSP and factors from the Kenneth French website.



Appendix B.7. The proportions of the significance levels from the pairwise regression

This figure presents the proportions of the significance levels from the pairwise regression using the following model: $R_{i,t} = \alpha + \beta_j R_{j,t-1} + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$. The sample covers an 86-year period to December 2016. $R_{i,t}$ is the monthly return of firm i; $R_{j,t-1}$ is the lagged monthly return of firm j; $R_{i,t-1}$ is the lagged monthly return of firm i; and R_{MKT}, SMB, HML are Fama and French (1993)'s three factors. We source returns data from CRSP and factors from the Kenneth French website.



Appendix B.8. Determinants of return predictability by logistic regressions and R^2_1 - R^2_0

This table reports the determinants of return predictability using the following models:
Panel A: $Sig = \alpha + \beta_1 DIFF_{j,i} + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1 if the value(s) from the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j R_{j,t-1} + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ is positive and significant at 0.05 level and 0 otherwise.

Panel B: $R^2_1 - R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \varepsilon_t$, where $R^2_1 - R^2_0$ is the difference in R^2 ($R^2_1 - R^2_0$), where R^2_1 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j R_{j,t-1} + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.

The explanatory variable is the difference in determinants between firms *j* and *i* scaled by the mean values of firm *j* and *i* ($DIFF_{j,i}$). Year fixed effect and industry fixed effects are included in all regressions. We describe each variable in Appendix B.2. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Logistic regression using Sig

Variables	**$DIFF_{j,i}$**		
	Logit	***Probit***	***N***
Earnings quality proxies			
	-0.112***	-0.051***	
EP	(-4.02)	(-3.86)	632,530
	5.950***	2.800***	
AA	(84.33)	(86.62)	573,204
	2.120***	0.991***	
ES	(12.41)	(12.47)	614,082
Firm characteristics			
	7.320***	3.380***	
BTM	(116.55)	(115.71)	601,764
	-3.910***	-1.810***	
CP	(-20.47)	(-20.49)	334,864
	7.180***	3.380***	
AGE	(44.53)	(45.62)	644,546
	2.270***	1.140***	
LEV	(7.00)	(8.13)	642,182
Growth-related characteristics			
	-0.053	-0.025	
AG	(-0.52)	(-0.52)	637,694
	0.115***	0.052***	
CI	(3.42)	(3.22)	595,606
	0.115	0.051	
IA	(1.35)	(1.22)	594,426
	0.143***	0.065***	
IG	(4.95)	(4.81)	628,492
	0.090	0.132	
IK	(0.02)	(0.18)	635,500
	1.310***	0.621***	
NOA	(8.40)	(8.74)	638,112
	-0.149***	-0.068**	
ROA	(-2.63)	(-2.54)	635,558
	3.400***	1.540***	
ROE	(29.92)	(28.72)	335,074
Market-based variables			
	88.620***	40.690***	
SIZE	(4,595.60)	(4,505.86)	2,376,393
	17.300***	7.990***	
VOL	(1,294.98)	(1,290.18)	2,376,397

Appendix B.8. (Continued)

Panel B: OLS regression using R^2_1 - R^2_0

Variables	***DIFF$_{j,i}$***	***R^2***	***N***
Earnings quality proxies			
EP	-0.001* (-1.94)	0.381	632,530
AA	0.045*** (7.83)	0.321	573,204
ES	-0.003 (-0.65)	0.180	614,082
Firm characteristics			
BTM	0.045*** (8.20)	0.197	601,764
CP	-0.040*** (-7.59)	0.210	334,864
AGE	0.083*** (8.31)	0.209	644,546
LEV	0.005 (0.67)	0.177	642,182
Growth-related characteristics			
AG	-0.000 (-0.29)	0.219	637,694
CI	0.001* (1.79)	0.400	595,606
IA	0.001** (2.32)	0.212	594,426
IG	0.001*** (3.56)	0.193	628,492
IK	-0.011* (-1.80)	0.175	635,500
NOA	0.007** (2.30)	0.192	638,112
ROA	-0.001** (-2.14)	0.200	635,558
ROE	0.007* (1.70)	0.180	335,074
Market-based variables			
SIZE	0.622*** (47.58)	0.531	2,234,669
VOL	0.092*** (21.21)	0.242	2,234,669

Appendix B.9. Determinants of time-varying return predictability based on the TED spread by logistic regressions and R^2_1 - R^2_0

This table reports the determinants of return predictability using the following models:
Panel A: $Sig = \alpha + \beta_1\ DIFF_{j,i} + \beta_2\ TED + \beta_3\ DIFF_{j,i} {*}\ TED + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1 if the value(s) from the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j\ R_{j,t-1} + \beta_i\ R_{i,t-1} + \beta_{MKT}\ R_{MKTt} + \beta_S\ SMB_t + \beta_v\ HML_t + \varepsilon_t$ is positive and significant at the 0.05 level, and 0 otherwise.

Panel B: $R^2_1 - R^2_0 = \alpha + \beta_1\ DIFF_{j,i} + \beta_2\ TED + \beta_3\ DIFF_{j,i} {*}\ TED + \varepsilon_t$, where $R^2_1 - R^2_0$ is the difference in R^2 ($R^2_1 - R^2_0$), where R^2_1 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j\ R_{j,t-1} + \beta_i\ R_{i,t-1} + \beta_{MKT}\ R_{MKTt} + \beta_S\ SMB_t + \beta_v\ HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_i\ R_{i,t-1} + \beta_{MKT}\ R_{MKTt} + \beta_S\ SMB_t + \beta_v\ HML_t + \varepsilon_t$.

The explanatory variables are the level of differences in determinants between firms *j* and *i* scaled by the mean values of firm *j* and *i* ($DIFF_{j,i}$) and the average percentage of TED Spread (*TED*). Year fixed effect and industry fixed effects are included in all regressions. We describe each variable in Appendix B.2. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Logistic regression using Sig

Variables	$DIFF_{j,i}$* TED		
	Logit	***Probit***	***N***
Earnings quality proxies			
	-0.022	-0.010	
EP	(-0.02)	(-0.02)	626,696
	1.380	0.490	
AA	(0.58)	(0.35)	564,920
	-14.580***	-6.720***	
ES	(-56.69)	(-56.23)	614,082
Firm characteristics			
	-9.100***	-4.430***	
BTM	(-20.81)	(-23.05)	586,636
	4.770***	2.340***	
CP	(3.16)	(3.61)	321,678
	-3.570	-1.680	
AGE	(-1.26)	(1.30)	629,110
	8.510***	3.850***	
LEV	(12.62)	(-12.01)	626,746
Growth-related characteristics			
	-0.409***	-0.190***	
AG	(-3.41)	(-3.43)	626,962
	-0.118	-0.055	
CI	(0.42)	(-0.43)	589,884
	-0.101	-0.054	
IA	(-0.10)	(-0.13)	583,694
	-0.462***	-0.218***	
IG	(-6.08)	(-6.32)	615,622
	11.090***	5.090***	
IK	(28.05)	(27.70)	620,278
	-0.027	-0.027	
NOA	(-0.00)	(-0.00)	625,028
	0.541***	0.259***	
ROA	(3.99)	(4.25)	624,306
	-0.751	-0.379	
ROE	(-0.16)	(-0.19)	321,788
Market-based variables			
	-42.800***	-21.100***	
SIZE	(-123.58)	(-138.53)	2,240,262
	-2.230**	-1.430***	
VOL	(-2.21)	(-4.251)	2,240,266

Appendix B.9. (Continued)

Panel B: OLS regression using R^2_1 - R^2_0

Variables	$\boldsymbol{DIFF_{j,i}}$	***TED***	$\boldsymbol{DIFF_{j,i}}$**** TED***	$\boldsymbol{R^2}$	***N***
Earnings quality proxies					
	-0.001	-0.071***	0.000		
EP	(-1.17)	(-6.46)	(0.14)	0.410	626,696
	0.045***	-0.054***	0.002		
AA	(5.25)	(-4.72)	(0.15)	0.355	564,920
	0.006	0.020*	-0.019		
ES	(0.69)	(1.72)	(-1.62)	0.182	614,082
Firm characteristics					
	0.051***	-0.003	-0.012		
BTM	(5.97)	(-0.22)	(-1.06)	0.211	586,636
	-0.055***	-0.009	0.030**		
CP	(-6.09)	(-0.57)	(2.10)	0.248	321,678
	0.105***	0.005	-0.048**		
AGE	(6.88)	(0.39)	(-2.40)	0.228	629,110
	-0.060***	0.004	0.132***		
LEV	(-5.43)	(0.36)	(8.98)	0.212	626,746
Growth-related characteristics					
	0.001	-0.021**	-0.002*		
AG	(1.23)	(-1.99)	(1.70)	0.250	626,962
	0.001	-0.073***	-0.000		
CI	(1.12)	(-6.47)	(-0.19)	0.431	589,884
	0.001	-0.020*	0.000		
IA	(1.16)	(-1.76)	(0.13)	0.245	583,694
	0.002***	-0.008	-0.001		
IG	(3.12)	(-0.74)	(-1.45)	0.220	615,622
	-0.048***	0.005	0.081***		
IK	(-5.34)	(0.40)	(6.54)	0.203	620,278
	0.008	-0.005	-0.001		
NOA	(1.57)	(-0.49)	(-0.07)	0.218	625,028
	-0.001	-0.006	0.000		
ROA	(-1.27)	(-0.52)	(0.06)	0.217	624,306
	-0.006	-0.009	0.026**		
ROE	(-0.92)	(-0.58)	(2.51)	0.224	321,788
Market-based variables					
	0.724***	0.033***	-0.151***		
SIZE	(33.55)	(5.14)	(-5.55)	0.509	2,098,758
	0.092***	0.033***	0.004		
VOL	(13.03)	(5.13)	(0.39)	0.197	2,098,758

Appendix B.10. Determinants of time-varying return predictability based on the Sentiment Index by logistic regressions and R^2_1 - R^2_0

This table reports the determinants of return predictability, using the following models:
Panel A: $Sig = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, SENT + \beta_3\, DIFF_{j,i}{*}\, SENT + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1 if the value(s) from the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j\, R_{j,t-1} + \beta_i\, R_{i,t-1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t$ is positive and significant at the 0.05 level, and 0 otherwise.

Panel B: $R^2_1 - R^2_0 = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, SENT + \beta_3\, DIFF_{j,i}{*}\, SENT + \varepsilon_t$, where $R^2_1 - R^2_0$ is the difference in R^2 ($R^2_1 - R^2_0$), where R^2_1 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j\, R_{j,t-1} + \beta_i\, R_{i,t-1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_i\, R_{i,t-1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t$.

The explanatory variables are the level of differences in determinants between firms *j* and *i* scaled by the mean values of firm *j* and *i* ($DIFF_{j,i}$) and the Sentiment Index in Baker and Wurgler (2006); based on the first principal component of FIVE (standardized) sentiment proxies (*SENT*). Year fixed effect and industry fixed effects are included in all regressions. We describe each variable in Appendix B.2. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1 %, 5%, and 10% levels, respectively.

Panel A: Logistic regression using Sig

Variables	***DIFF*** $DIFF_{j,i}$* SENT		
	Logit	***Probit***	***N***
Earnings quality proxies			
	0.084	0.037	
EP	(0.75)	(0.72)	596,958
	2.230***	0.917***	
AA	(4.93)	(4.04)	542,264
	-5.830***	-2.660***	
ES	(-34.88)	(-34.33)	577,706
Firm characteristics			
	1.660***	0.630**	
BTM	(2.88)	(1.99)	568,526
	0.181	0.086	
CP	(0.02)	(0.02)	315,392
	2.060	0.893	
AGE	(1.63)	(1.47)	608,164
	7.770***	3.420***	
LEV	(31.86)	(29.73)	605,800
Growth-related characteristics			
	-0.091	-0.037	
AG	(-0.51)	(-0.41)	601,856
	-0.141**	-0.066**	
CI	(-1.71)	(-1.84)	561,342
	-0.653***	-0.291***	
IA	(-14.80)	(-14.16)	560,696
	-0.022	-0.010	
IG	(-0.05)	(-0.04)	592,654
	-0.118	-0.134	
IK	(-0.01)	(-0.07)	598,854
	0.090	0.038	
NOA	(0.01)	(0.01)	602,274
	0.352***	0.164***	
ROA	(5.14)	(5.43)	599,978
	1.580**	0.695**	
ROE	(2.17)	(2.03)	315,602
Market-based variables			
	-14.230***	-7.120***	
SIZE	(-58.43)	(-70.35)	2,259,611
	-9.810***	-4.550***	
VOL	(-200.95)	(-208.94)	2,259,615

Appendix B.10. (Continued)

Panel B: OLS regression using R^2_1 - R^2_0

Variables	***DIFF$_{j,i}$***	***SENT***	***DIFF$_{j,i}$* SENT***	***R^2***	***N***
Earnings quality proxies					
	-0.001**	-0.003	0.000		
EP	(-2.26)	(-0.53)	(0.68)	0.317	596,958
	0.044***	0.011*	-0.00		
AA	(7.21)	(1.89)	(-1.53)	0.282	542,264
	-0.004	-0.008*	-0.003		
ES	(-0.80)	(-1.68)	(-0.50)	0.232	577,706
Firm characteristics					
	0.038***	-0.002	0.054***		
BTM	(6.50)	(-0.49)	(9.11)	0.239	568,526
	-0.042***	0.003	-0.009		
CP	(-7.69)	(0.47)	(-1.31)	0.226	315,392
	0.086***	-0.011**	-0.035***		
AGE	(8.22)	(-2.15)	(-3.61)	0.251	608,164
	0.002***	-0.011**	0.023***		
LEV	(0.26)	(-2.16)	(2.84)	0.217	605,800
Growth-related characteristics					
	-0.000	-0.003	-0.001		
AG	(-0.23)	(-0.37)	(-1.21)	0.213	601,856
	0.001*	-0.002	-0.001		
CI	(1.75)	(-0.31)	(-1.17)	0.335	561,342
	0.002***	0.009	-0.002***		
IA	(2.79)	(1.33)	(-2.77)	0.205	560,696
	0.001***	-0.003	-0.000		
IG	(3.47)	(-0.56)	(-0.94)	0.208	592,654
	-0.012***	-0.010*	-0.011		
IK	(-2.02)	(-1.93)	(-1.57)	0.215	598,854
	0.005	-0.003	-0.023***		
NOA	(1.53)	(-0.48)	(-5.05)	0.212	602,274
	-0.001*	-0.006	0.002***		
ROA	(-1.90)	(-1.09)	(3.31)	0.219	599,978
	0.003	0.004	0.020***		
ROE	(0.70)	(0.51)	(3.60)	0.195	315,602
Market-based variables					
	0.642***	0.027***	-0.209***		
SIZE	(47.29)	(8.77)	(-15.86)	0.554	2,129,537
	0.101***	0.027***	-0.084***		
VOL	(22.29)	(8.75)	(-19.03)	0.270	2,129,537

Appendix B.11. Determinants of time-varying return predictability based on the Index of Consumer Sentiment by logistic regressions and R^2_1 - R^2_0

This table reports the determinants of return predictability, using the following models:
Panel A: $Sig = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, ICS + \beta_3\, DIFF_{j,i} * ICS + \varepsilon_t$, where Sig is a dummy variable that takes the value of 1 if the value(s) from the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j\, R_{j,t-1} + \beta_i\, R_{i,t-1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t$ is positive and significant at the 0.05 level, and 0 otherwise.

Panel B: $R^2_1 - R^2_0 = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, ICS + \beta_3\, DIFF_{j,i} * ICS + \varepsilon_t$, where $R^2_1 - R^2_0$ is the difference in R^2 ($R^2_1 - R^2_0$), where R^2_1 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j\, R_{j,t-1} + \beta_i\, R_{i,t-1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_i\, R_{i,t-1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t$.

The explanatory variables are the level of differences in determinants between firms *j* and *i* scaled by the mean values of firm *j* and *i* ($DIFF_{j,i}$) and the Index of Consumer Sentiment (*ICS*). Year fixed effect and industry fixed effects are included in all regressions. We describe each variable in the Appendix. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Logistic regression using Sig

Variables	$DIFF_{j,i} * ICS$		
	Logit	***Probit***	***N***
Earnings quality proxies			
	0.007***	0.004***	
EP	(2.57)	(2.86)	632,530
	0.191***	0.086***	
AA	(15.06)	(13.92)	573,204
	-0.173***	-0.080***	
ES	(-12.15)	(-11.92)	614,082
Firm characteristics			
	0.178***	0.073***	
BTM	(10.48)	(8.21)	601,764
	0.049	0.025	
CP	(0.43)	(0.53)	334,864
	-0.004	-0.006	
AGE	(-0.00)	(-0.02)	644,546
	0.484***	0.225***	
LEV	(50.17)	(49.37)	642,182
Growth-related characteristics			
	-0.003	-0.001	
AG	(-0.22)	(-0.23)	637,694
	0.000	0.000	
CI	(0.00)	(0.00)	595,606
	-0.037***	-0.017***	
IA	(-19.11)	(-18.78)	594,426
	0.003	0.001	
IG	(0.26)	(0.19)	628,492
	0.019	0.005	
IK	(0.12)	(0.04)	635,500
	0.032	0.013	
NOA	(0.78)	(0.57)	638,112
	0.008	0.004	
ROA	(1.21)	(1.43)	635,558
	0.138***	0.063***	
ROE	(6.68)	(6.50)	335,074
Market-based variables			
	-0.771***	-0.436***	
SIZE	(-52.88)	(-76.79)	2,302,223
	-0.744***	-0.363***	
VOL	(-351.19)	(-382.20)	2,302,227

Appendix B.11. (Continued)

Panel B: OLS regression using R^2_1 - R^2_0

Variables	***$DIFF_{j,i}$***	***ICS***	***$DIFF_{j,i}$* ICS***	***R^2***	***N***
Earnings quality proxies					
	-0.003	-0.001**	0.000		
EP	(-1.37)	(-2.21)	(1.14)	0.383	632,530
	0.152***	-0.002***	-0.001***		
AA	(4.29)	(-5.24)	(3.17)	0.333	573,204
	0.003	-0.003***	0.000		
ES	(0.08)	(-9.83)	(0.18)	0.205	614,082
Firm characteristics					
	-0.188***	-0.003***	0.003***		
BTM	(-5.11)	(-7.24)	(6.53)	0.227	601,764
	-0.014	-0.001***	0.000		
CP	(-0.35)	(-3.09)	(0.67)	0.214	334,864
	0.562***	-0.004***	-0.006***		
AGE	(8.10)	(-9.63)	(-7.25)	0.258	644,546
	-0.142***	-0.004***	0.002***		
LEV	(-2.95)	(-9.61)	(3.20)	0.208	642,182
Growth-related characteristics					
	0.003	-0.004***	-0.000		
AG	(0.92)	(-10.11)	(-0.97)	0.254	637,694
	0.004	-0.001*	-0.000		
CI	(1.56)	(-1.67)	(-1.35)	0.401	595,606
	0.020***	-0.004***	-0.000***		
IA	(4.68)	(-8.51)	(4.49)	0.242	594,426
	0.003	-0.004***	-0.000		
IG	(1.22)	(-10.19)	(-0.76)	0.228	628,492
	-0.106**	-0.004***	0.001**		
IK	(-2.55)	(-9.79)	(2.42)	0.206	635,500
	0.068***	-0.004***	-0.001***		
NOA	(3.36)	(-10.16)	(-3.09)	0.228	638,112
	-0.013***	-0.004***	0.000***		
ROA	(-3.34)	(-9.91)	(3.10)	0.235	635,558
	-0.063**	-0.001***	0.001**		
ROE	(-2.11)	(-2.90)	(2.42)	0.187	335,074
Market-based variables					
	1.989***	-0.003***	-0.016***		
SIZE	(22.33)	(-14.39)	(-16.07)	0.502	2,160,499
	0.579***	-0.003***	-0.006***		
VOL	(18.82)	(-14.36)	(-16.44)	0.211	2,160,499

Appendix B.12. Determinants of time-varying return predictability based on the Volatility Index by logistic regressions and R^2_1 - R^2_0

This table reports the determinants of return predictability using the following models:
Panel A: $Sig = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, VIX + \beta_3\, DIFF_{j,i} * VIX + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1 if the value(s) from the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j\, R_{j,t-1} + \beta_i\, R_{i,t-1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t$ is positive and significant at the 0.05 level, and 0 otherwise.

Panel B: $R^2_1 - R^2_0 = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, VIX + \beta_3\, DIFF_{j,i} * VIX + \varepsilon_t$, where $R^2_1 - R^2_0$ is the difference in R^2 ($R^2_1 - R^2_0$), where R^2_1 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_j\, R_{j,t-1} + \beta_i\, R_{i,t-1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_i\, R_{i,t-1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t$.

The explanatory variables are the level of differences in determinants between firms *j* and *i* scaled by the mean values of firm *j* and *i* ($DIFF_{j,i}$) and the Volatility Index (*VIX*). Year fixed effect and industry fixed effects are included in all regressions. We describe each variable in Appendix B.2. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Logistic regression using Sig

Variables	$DIFF_{j,i}$* VIX		
	Logit	***Probit***	***N***
Earnings quality proxies			
	-0.014***	-0.007***	
EP	(-3.81)	(-4.00)	626,696
	0.044	0.020	
AA	(0.30)	(0.30)	564,920
	-0.814***	-0.376***	
ES	(-88.86)	(-89.70)	614,082
Firm characteristics			
	-0.018	-0.013	
BTM	(-0.04)	(-0.09)	586,636
	-0.207***	-0.091***	
CP	(-2.84)	(-2.61)	321,678
	0.101	0.042	
AGE	(0.51)	(0.41)	629,110
	0.239***	0.107***	
LEV	(4.62)	(4.34)	626,746
Growth-related characteristics			
	0.006	0.003	
AG	(0.35)	(0.32)	626,962
	-0.019***	-0.009***	
CI	(-5.43)	(-5.95)	589,884
	-0.005	-0.002	
IA	(-0.10)	(-0.13)	583,694
	-0.007	-0.003	
IG	(-0.67)	(-0.75)	615,622
	-0.010	-0.006	
IK	(-0.01)	(-0.02)	620,278
	-0.106***	-0.050***	
NOA	(-2.82)	(-2.97)	625,028
	0.040***	0.019***	
ROA	(10.57)	(11.03)	624,306
	-0.032	-0.016	
ROE	(-0.13)	(-0.16)	321,788
Market-based variables			
	-0.646***	-0.292***	
SIZE	(-13.51)	(-12.77)	2,240,262
	0.029	0.012	
VOL	(0.20)	(0.15)	2,240,266

Appendix B.12. (Continued)

Panel B: OLS regression using R^2_1 - R^2_0

Variables	***DIFF$_{j,i}$***	***VIX***	***DIFF$_{j,i}$* VIX***	***R^2***	***N***
Earnings quality proxies					
	-0.000	0.000	-0.000		
EP	(-0.12)	(0.04)	(-0.57)	0.400	626,696
	0.062***	-0.000	-0.001*		
AA	(5.67)	(-0.08)	(-1.74)	0.350	564,920
	0.034***	0.001*	-0.002***		
ES	(3.05)	(1.90)	(-3.82)	0.184	614,082
Firm characteristics					
	-0.010	0.001	0.003***		
BTM	(-0.85)	(1.09)	(5.06)	0.216	586,636
	0.018	0.000	-0.003***		
CP	(1.23)	(0.20)	(-4.34)	0.254	321,678
	0.075***	0.001**	0.000		
AGE	(3.73)	(2.16)	(0.48)	0.228	629,110
	-0.064***	0.001**	0.003***		
LEV	(-4.45)	(2.18)	(5.64)	0.200	626,746
Growth-related characteristics					
	0.001	0.000	-0.000		
AG	(0.46)	(0.25)	(-0.58)	0.249	626,962
	0.002	0.000	-0.000		
CI	(1.63)	(0.01)	(-1.14)	0.421	589,884
	-0.001	-0.000	0.000		
IA	(-0.76)	(-0.65)	(1.63)	0.244	583,694
	0.001	0.001**	-0.000		
IG	(1.41)	(2.38)	(-0.22)	0.221	615,622
	0.024**	0.001**	-0.002***		
IK	(2.04)	(2.49)	(-3.26)	0.196	620,278
	0.039***	0.001**	-0.002***		
NOA	(5.04)	(2.32)	(-4.66)	0.223	625,028
	-0.004***	0.001**	0.000***		
ROA	(-3.15)	(2.26)	(2.58)	0.219	624,306
	0.001	0.000	0.000		
ROE	(0.14)	(0.20)	(0.56)	0.221	321,788
Market-based variables					
	0.717***	0.003***	-0.003***		
SIZE	(25.84)	(12.36)	(-2.78)	0.521	2,098,758
	0.169***	0.003***	-0.004***		
VOL	(17.64)	(12.37)	(-8.45)	0.211	2,098,758

Appendix B.13. Statement of Contribution Doctorate with Publications/Manuscripts

DRC 16

MASSEY UNIVERSITY
GRADUATE RESEARCH SCHOOL

STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of candidate:	Narongdech Thakerngkiat
Name/title of Primary Supervisor:	Professor Nuttawat Visaltanachoti
Name of Research Output and full reference:	
Thakerngkiat, N., Nguyen, H. T., Nguyen, N. H., & Visaltanachoti, N. (2020). Do Accounting Information and Market Environment Matter for Cross-Asset Predictability?. Accounting and Finance, forthcoming.	
In which Chapter is the Manuscript /Published work:	Chapter 3
Please indicate:	
• The percentage of the manuscript/Published Work that was contributed by the candidate:	
and	
• Describe the contribution that the candidate has made to the Manuscript/Published Work:	
This paper is chapter 3 in Narongdech Thakerngkiat's Ph.D. Dissertation and while his supervisors have made the contribution, which is reflected by co-authorship, the paper is essentially the work of Narongdech Thakerngkiat.	
For manuscripts intended for publication please indicate target journal:	
Candidate's Signature:	Digitally signed by Narongdech Date: 2020.12.04 13:01:49 +13'00'
Date:	4 December 2020
Primary Supervisor's Signature:	Visaltanachoti, Nuttawat Digitally signed by Visaltanachoti, Nuttawat Date: 2020.12.04 14:43:32 +13'00'
Date:	4 December 2020

(This form should appear at the end of each thesis chapter/section/appendix submitted as a manuscript/ publication or collected as an appendix at the end of the thesis)

GRS Version 4– January 2019

CHAPTER FOUR

ESSAY THREE

This chapter presents the third essay of this thesis, which uses the largest mega-terrorist event, the 9/11 terrorist attacks, as an exogenous shock to investigate the impact of investors' risk aversion on default risk. Section 4.1 presents an overview of this essay and explains the motivation behind it. Section 4.2 provides a related literature review and hypothesis development. Section 4.3 describes the data and methodology used in this study. Section 4.4 discusses the empirical findings, and Section 4.5 concludes this chapter. The essay's Appendix and References are presented at the end of this chapter and in the references section, respectively.

Does Fear Spur Default Risk?

4.1. Introduction

Default is one of the most unfavourable events in the life of the corporate world and is thus an area of focus for academics, practitioners, and regulators (e.g., Merton, 1974; Eaton and Gersovitz, 1981; Brück and Wickström, 2004; Vassalou and Xing, 2004; Bharath and Shumway, 2008).[30] A firm's inability to service its debt obligations adversely affects a range of corporate activities, the wealth and commitment of its key stakeholders, and capital allocation efficiency (see, for example, Eaton and Gersovitz, 1981; Gilson, 1997; Blomberg, Hess, and Orphanides, 2004; Arellano, 2008; Campbell, Hilscher, and Szilagyi, 2008; Eisdorfer, 2008; Brogaard, Li, and Xia, 2017). While various firm characteristics and market conditions have been found to drive corporate default in the literature[31], whether risk aversion matters for default risk remains under-investigated. The concept of risk aversion dates back hundreds of years and has been well-recognized as one of the key variables for understanding many economic decisions (Meyer, 2014; Thomas, 2016). In this paper, we ask a simple yet important question: "Does fear-induced risk aversion spur default risk?".

A challenge for researchers who aim to examine the impact of fear on default risk is that investors' risk aversion is not exogenous and can be affected by several factors that could also trigger default risks such as sentiment, firm-specific conditions, or economic conditions (e.g., Vassalou and Xing, 2004; Duffie, Saita, and Wang, 2007). To mitigate potential endogeneity concerns, we employ terrorist events as an exogenous shock to investor risk

[30] Default, generally defined as a breach of contract, occurs when a firm is unable to fulfill its debt obligations.
[31] See, for example, Vassalou and Xing (2004), Duffie, Saita, and Wang (2007), Cuadra and Sapriza (2008), and Brogaard, Li, and Xia (2017).

aversion. Our approach is intuitive for two reasons. First, evidence from psychological and behavioural economic literature suggests that terrorist attacks and mass shootings trigger fear, anxiety, and uncertainty (e.g., Dumont, Yzerbyt, Wigboldus, and Gordijn, 2003; Mythen and Walklate, 2006; Smelser, 2009), and negative emotions from terrorism increase aggregate risk aversion (Levy and Galili, 2006; Wang and Young, 2020). Second, and more importantly, terrorist attacks can also provoke increased risk aversion among investors who do not experience any loss (Guiso, Sapienza, and Zingales, 2018; Wang and Young, 2020), indicating any potential economic loss independent of changes in investors' wealth, but mainly driven by fear-induced risk aversion.

We consider the largest mega-terrorist event, namely, the 9/11 terrorist attacks[32] as an exogenous shock to investigate the impact of investors' risk aversion on default risk. We posit that as investors' risk aversion increases, they demand higher returns to compensate for their risk-taking, leading to increased default risk. Our conjecture is consistent with Lizarazo (2013), who shows that when international investors become more risk-averse, the economy becomes credit constrained, resulting in higher sovereign risk because investors command a higher return premium for the higher probability of sovereign default.

We begin our study by investigating the impact of the 9/11 terrorist attacks on market sentiment. The market risk and sentiment are captured using the Volatility Index and the News Sentiment Index. We find that terrorist attacks intensely affect people's emotions, create fear, and influence stock market sentiment and future economic prospects. We further use an event-study approach to measure the impact of terrorist attacks on the market and firm levels. Specifically, to capture the default risk, we use three measures, including the market default spreads, expected default frequency, and distance-to-default, and examine whether there is a

[32] According to the Organization for Economic Cooperation and Development (OECD), the 9/11 terrorist attacks are the largest terrorism incident in the world, causing 27.2 billion USD of economic loss and 2,996 deaths (Brück and Wickström, 2004).

causal effect between terrorism-induced risk aversion and the default risk. We find the 9/11 terrorist attacks (day 0) cause an increase in the market-wide default risk, which is strongest on day three and weakens thereafter. By the third day, the average market default risk increases by 36% compared to the day before the event. The cross-sectional average default risk across all firms rises 245% to the highest level five days after the attacks. Interestingly, terrorist attacks significantly increase the default risk in all industries. We further employ a difference-in-difference analysis to examine the state reaction to the 9/11 attacks. We find the mega-terrorism causes an increase in default risk for firms located in the attacked states, as well as for those located in the non-affected states.

Our study adds two contributions to the literature. First, terrorist attacks impose negative and multi-dimensional externalities, and the number of terrorist incidents has risen in recent decades.[33] To the best of our knowledge, we are the first to study the impact of terrorist incidents on an unwanted event in the life of the corporation: corporate default. Our paper, therefore, extends the growing literature showing the adverse consequences of these extreme negative events (e.g., Cuculiza, Antoniou, Kumar, and Maligkris, 2020; Dai, Rau, Stouraitis, and Tan, 2020; Wang and Young, 2020). Second, we contribute to a large body of studies that highlight the roles of investor sentiment and risk preference in understanding various economic decisions (e.g., Kuhnen and Knutson, 2011; Guiso, Sapienza, and Zingales, 2018). We show that risk from extreme terrorist events influences investors' risk aversion and, thus, affects the default risk in the financial market.

[33] Terrorism-related incidents increased worldwide from 930 in 1998 to nearly 17,000 in 2014; at the same time, fatalities rose from 2,261 in 1998 to 45,000 in 2014, according to the Global Terrorism Database (https://www.start.umd.edu/gtd/analysis) (retrieved on 20th June 2020).

The rest of this article is organized as follows. Section 4.2 provides relevant literature and develops the hypothesis. Sections 4.3 describes the data and the methodology used in this research. Section 4.4 presents the main empirical findings, and Section 4.5 concludes the paper.

4.2. Literature Review and Hypothesis Development

4.2.1. Background on Terrorism

Terrorism is defined as "the threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation" (Global Terrorism Database)[34]. Previous studies show that the negative impacts from terrorist attacks can substantially influence the global economy and financial markets (e.g., see Eldor and Melnick, 2004; Chesney, Reshetar, and Karaman, 2011; Shahbaz, 2013). The literature suggests that the cost associated with terrorism can be divided into two main categories: direct and indirect costs (Czinkota, Knight, Liesch, and Steen, 2010). The direct costs include loss of human life and the destruction of property, buildings, and infrastructure. However, indirect costs are likely to cause more extensive damage across the economy, with further implications for business activities. These indirect costs include, for example, decreased buyer demand (due to fear and uncertainty), increased business expenses (terrorism insurance), supply chain disruptions (shipping delays), and decreased investor confidence in corporate financial performance (higher cost of debt and lower financial capacity) (Czinkota, Knight, and Liesch, 2004; Eckstein and Tsiddon, 2004; Procasky and Ujah, 2016).

Specifically, the 9/11 terrorist attacks caused massive casualties and international economic losses. For example, Ford Motor Company temporarily shut down 5 auto plants in

[34] https://www.start.umd.edu/gtd/

the US because of the international supply chain disruptions (Siekman, 2003). Several airlines, travel, tourism, and courier companies experienced a significant financial loss due to the reduced demand in the aftermath of the 9/11 attacks (Navarro and Spencer, 2001). More recently, a growing number of studies have examined the impact of the 9/11 terrorist attacks on global stock markets. Chen and Siems (2004), Maillet and Michel (2005), Charles and Darné (2006), and Nikkinen, Omran, Sahlström, and Äijö (2008) show that the major global stock markets are negatively affected following the 9/11 terrorist events. Nikkinen, Omran, Sahlström, and Äijö (2008) examine the reaction of 53 capital markets across the 9/11 terrorist attacks. They find that increased volatility and short-run negative impacts vary across regions determined by the relative degree of integration in the international economy. Burch, Emery, and Fuerst (2003) and Glaser and Weber (2005) suggest that terrorism has a strong negative impact on investor sentiment. They find that there is a significant increase in closed-end mutual fund discounts after the 9/11 attacks. Drakos (2004) examines the reaction of airline stock returns following the 9/11 terrorist attacks, with results indicating terrorism's drastic consequences on the airline sector. Together these studies highlight that terrorist attacks have a negative impact on global economies and financial markets.

4.2.2. Risk Aversion and Default risk

The extant literature suggests that terrorist attacks have extremely negative effects on international economies and financial markets by creating fear, anxiety, and uncertainty (e.g., see Blomberg, Hess, and Orphanides, 2004; Eckstein and Tsiddon, 2004; Tavares, 2004; Crain and Crain, 2006; Blomberg, Broussard, and Hess, 2011; Choi, 2015; Dai, Rau, Stouraitis, and Tan, 2020). The immediate emotional consequences of terrorist attacks can lead to changes in risk aversion. For example, Malmendier and Nagel (2011) find that individuals become more risk-averse after experiencing macroeconomic shocks. Callen, Isaqzadeh, Long, and Sprenger

(2014) examine the link between violence and economic risk preferences in Afghanistan. They find that individuals are more risk-averse after the recollection of fearful circumstances.

More recent studies also suggest that such exogenous events negatively affect investors' risk aversion and the financial decisions of stock market participants. Glaser and Weber (2005), Kuhnen and Knutson (2011), and Guiso, Sapienza, and Zingales (2018) find a connection between negative emotions and increases in individual risk aversion. They find that negative emotions can cause the investor to take a guaranteed payoff when given the alternative of a risky asset. Wang and Young (2020) find that the level of terrorism is inversely related to the aggregate investor risk preference. They suggest that negative emotions from terrorism increase risk aversion and cause investors to invest in less risky assets.

Besides this, investors' risk aversion has a direct impact on firm default risk. Lizarazo (2013) studies the pricing of sovereign default risk and the risk aversion of international investors and finds that when investors become more risk-averse, the economy becomes credit constrained, resulting in increased default risk. Consequently, investors require an excess premium for the probability of default and compensation for investments in risky assets. Motivated by these previous studies, our hypothesis posits that the negative impact of terrorist attacks influences investors' risk aversion, leading to increased firm default risk.

4.3. Data and Methodology

Our sample consists of all US common stocks on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the NASDAQ, between 8th June and 9th November 2001. We obtain data from the Center for Research in Security Prices (CRSP) and the Compustat merged quarterly database. We consider only common stocks (CRSP share code of 10 or 11). Selected firms must have at least 60 days of trading data and non-zero trading volume. We exclude observations with returns equal to or less than -1. The final sample contains 3,078 firms. We consider the 9/11 terrorist attacks since it is the largest event that can be used to examine the effect of terrorism on stock markets. To investigate the impact of the 9/11 terrorist attacks on stock market sentiment, we use market sentiment variables, including the Volatility Index (*VIX*) from the Global Financial Data's website and the News Sentiment Index (*NEWS_SENT*) from Buckman, Shapiro, Sudhof, and Wilson (2020).[35] The market default risk is default spreads obtained from the Federal Reserve Bank of St. Louis[36]. The firm-level default risks are the expected default frequency (*EDF*) and distance-to-default (*DD*) computed following Bharath and Shumway (2008) and Brogaard, Li, and Xia (2017):

$$DD_{i,t} = \frac{\log\left(\frac{Equity_{i,t} + Debt_{i,t}}{Debt_{i,t}}\right) + \left(r_{i,t-1} - \frac{\sigma 2_{Vi,t}}{2}\right) \times T_{i,t}}{\sigma_{Vi,t} \times \sqrt{T_{i,t}}}, \tag{4.1}$$

$$\sigma_{Vi,t} = \frac{Equity_{i,t}}{Equity_{i,t} + Debt_{i,t}} \times \sigma_{Ei,t} + \frac{Debt_{i,t}}{Equity_{i,t} + Debt_{i,t}} \times \left(0.05 + 0.25 \times \sigma_{Ei,t}\right), \tag{4.2}$$

$$EDF_{i,t} = N\left(-DD_{i,t}\right), \tag{4.3}$$

where $Equity_{i,t}$ is the market value of equity computed by the number of shares outstanding × share price at the end of each day; $Debt_{i,t}$ is the face value of debt calculated from the sum of current liabilities (Compustat quarterly data 45) and one-half of long-term debt (Compustat quarterly data 51); $r_{i,t-1}$ is firm i's past annual return computed from daily stock returns over the previous year; $\sigma_{Ei,t}$ is the stock volatility calculated by the daily stock returns over the previous year; $\sigma_{Vi,t}$ is an approximation of the volatility of firm assets; $T_{i,t}$ is set to one year; $DD_{i,t}$ is the firm's daily distance-to-default; $N(.)$ is the cumulative standard normal distribution function; $EDF_{i,t}$ is the firm's daily expected default frequency.

[35] The Volatility Index is from https://fred.stlouisfed.org/series/VIXCLS and the News Sentiment Index is from https://www.frbsf.org/economic-research/indicators-data/daily-news-sentiment-index/.

[36] The market default spreads include Moody's seasoned Aaa corporate bond yield relative to yield on the 10-Year Treasury constant (*AAA10Y*); Moody's seasoned Baa corporate bond yield relative to yield on the 10-Year Treasury constant (*BAA10Y*); Moody's seasoned Aaa corporate bond minus Federal Funds rate (*AAAFF*); and Moody's seasoned Baa corporate bond minus Federal Funds rate (*BAAFF*) from https://fred.stlouisfed.org.

Table 4.1. Descriptive statistics

The table reports descriptive statistics for the key variables in this study as of 11th September 2001. *DD* refers to distance-to-default; *EDF* is expected default frequency, calculated following Bharath and Shumway (2008) and Brogaard, Li, and Xia (2017); *Equity* is the market value of equity; *Debt* is the face value of debt; r_{t-1} is the past annual return; σ_E is the stock volatility; σ_V is the volatility of firm assets; *EXRET* is excess return; *ROA* is the return on assets. The descriptions of all variables are provided in Appendix C.1.

Variables	**N**	**Mean**	**Std.**	**P25**	**Median**	**P75**
DD	3,078	4.387	2.994	2.247	3.947	5.947
EDF	3,078	0.045	0.125	0.000	0.000	0.012
Equity	3,078	2,889	15,304	40.801	192.892	940.022
Debt	3,078	1,414	15,028	9.189	51.664	252.904
r_{t-1}	3,078	0.265	0.463	0.008	0.242	0.456
σ_E	3,078	0.649	0.398	0.368	0.526	0.815
σ_V	3,078	0.527	0.331	0.296	0.430	0.671
EXRET	3,078	-0.010	0.041	-0.024	-0.007	0.004
ROA	3,078	-0.002	0.057	0.000	0.004	0.015

Table 4.1 reports the descriptive statistics of the key variables as of 11th September 2001. The average firm in our sample has *DD* and *EDF* of 4.39 and 4.5%, with median values of 3.95 and zero, respectively. The maximum *DD* and *EDF* are 24.54 and 0.95, while the standard deviations are 2.99 and 0.125, respectively. These estimates are consistent with Bharath and Shumway (2008) and Brogaard, Li, and Xia (2017). The other variables are relatively standard. For example, the average market value of equity (*Equity*) is $2.9 billion and ranges between $3 million and $59 billion. The average face value of debt (*Debt*) is $1.4 billion. The averages of the firm's past annual return (r_{t-1}) and stock return volatility (σ_E) are 26.5% and 64.8%, respectively, while the average volatility of firm assets (σ_V) is 52.7%. The average excess return (*EXRET*) is 1%, and the average return on assets (*ROA*) is -0.002.

In Equations (4.1) and (4.2), *Equity* (the market value of equity computed by the number of shares outstanding × share price at the end of each day) is the main variable of the firm-level default risks measures. During the terrorist attack, volatility increased, and the share price dropped, which may affect the default measures. To examine whether a change in share price affects the firm-level default risks, we calculate the firm-level default risks after controlling for a change in share price from day *t*-40 to day *t*+40 of the 9/11 terrorist attacks, 11th September 2001. We estimate the OLS regression as follows:

$$DEF_{i,t} = \alpha + \beta_i R_{i,t} + \varepsilon_{i,t}, \tag{4.4}$$

where $DEF_{i,t}$ is the daily firm-level default risks for stock *i*, including the firm's daily expected default frequency ($EDF_{i,t}$) and the firm's daily distance-to-default ($DD_{i,t}$); $R_{i,t}$ is the CRSP daily return for stock *i*; and ε_t is the residual for stock *i*.

The residual for stock *i* of Equation (4.4) is employed as a dependent variable in our model estimations as follows:

$$DEF^*_{i,t} = \alpha + \beta_1 After_t + \varepsilon_t, \tag{4.5}$$

The dependent variable in Equation (4.5) is $DEF^*_{i,t}$, the daily firm-level default risks after controlling for a change in share price from the residual for stock *i* of Equation (4.4), including the firm's daily expected default frequency (*EDF**) and the firm's daily distance-to-default (*DD**) after controlling for a change in share price. The independent variable is *After*, which is a dummy variable equal to one for time window (+1 to +40) and zero for (-40 to -1).

Table 4.2. Firm default risk measures after controlling for a change in stock price across the 9/11 terrorist attacks

This table shows the results of OLS regression of the daily firm-level default risks after controlling for a change in stock price across the 9/11 terrorist attacks. *EDF** is the firm's daily expected default frequency after controlling for change in stock price. *DD** refers to the firm's daily distance-to-default after controlling for change in stock price. *After* is a dummy variable equal to one for time window (+1 to +40) and zero for (-40 to -1). The descriptions of all variables are provided in Appendix C.1. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	***EDF****	***DD****
After	0.014*** (25.30)	-0.338*** (-28.76)
No. of Obs.	298,240	298,240
R^2	0.002	0.003

Table 4.2 shows the results of OLS regression of the daily firm-level default risks after controlling for a change in stock price between the pre-9/11 terrorist attacks (day-40) and the post-9/11 terrorist attacks (day+40). There are positive and negative and statistically significant in both *EDF** and *DD**, respectively. The results suggest that firm default risks after controlling for change in the stock price in the post-9/11 terrorist attacks are significantly higher than in the pre-9/11 terrorist attacks. Overall, the results indicate that our firm-level default risk measures are not entirely driven by a change in stock price.

Using the event study approach, we calculate the impact of the 9/11 terrorist attacks on default risk using the constant mean return model with an estimation period of 60 days. We define day 0 as the day of the 9/11 terrorist attacks, 11th September 2001. The event window contains only trading days. The abnormal default risk on day *t* is the difference between the percentage changes in default rates and the benchmark, which is the average percentage change in default rates from day *t*-65 to day *t*-6. The cumulative abnormal default risks for the market (*DEF_MKT*) and individual firms (*DEF_FRM* and *DD_FRM*) on day *t* are the cumulative abnormal default risks from day 1 to day *t*.

Specifically, we follow Brogaard, Li, and Xia (2017) and Dai, Rau, Stouraitis, and Tan (2020) to employ a difference-in-difference model (DID) to capture the impact of the 9/11 terrorist attacks on investors' risk aversion and firm default risk. The treatment group includes all firms located in the 9/11 attacks states[37]. The control group includes all remaining firms. The empirical models are as follow:

$$DEF\_FRM_{i,t} = \alpha + \beta_1\, Treatment_i{*}After_t + \beta_2\, Treatment_i + \beta_3\, After_t + \gamma\, Controls_{i,t} + \varepsilon_{i,t}, \qquad (4.6)$$

$$DD\_FRM_{i,t} = \alpha + \beta_1\, Treatment_i{*}After_t + \beta_2\, Treatment_i + \beta_3\, After_t + \gamma\, Controls_{i,t} + \varepsilon_{i,t}, \qquad (4.7)$$

The dependent variable in Equations (4.6) and (4.7) is *DEF_FRM*, the cumulative abnormal default risks for individual firms, and *DD_FRM*, the cumulative abnormal distance-to-default for individual firms, respectively. Our main variable of interest is *Treatment*After*, which is the interaction between *Treatment* and *After*. *Treatment* is a dummy variable equal to one if a firm is in the treatment group and zero if it is in the control group. *After* is a dummy variable equal to one for time window (+1 to +5) and zero for (-5 to -1). We follow Bharath and Shumway (2008) and Brogaard, Li, and Xia (2017) to calculate the control variables. *Ln(Equity)* is the natural log of the market value of equity at the end of each day. *Ln(Debt)* is the natural log of the face value of debt. $1/\sigma_E$ is the inverse of the annualized stock volatility. *EXRET* is the difference between daily stock returns and CRSP value-weighted returns. *ROA* is the ratio of net income to the total asset. We also control for fixed differences between the control and the treatment groups by industry fixed effects (the first digit of the SIC code). The standard errors are clustered by firm. We describe each variable in Appendix C.1.

[37] The 9/11 terrorist affected states include New York, Virginia, and Pennsylvania.

4.4. Empirical Results

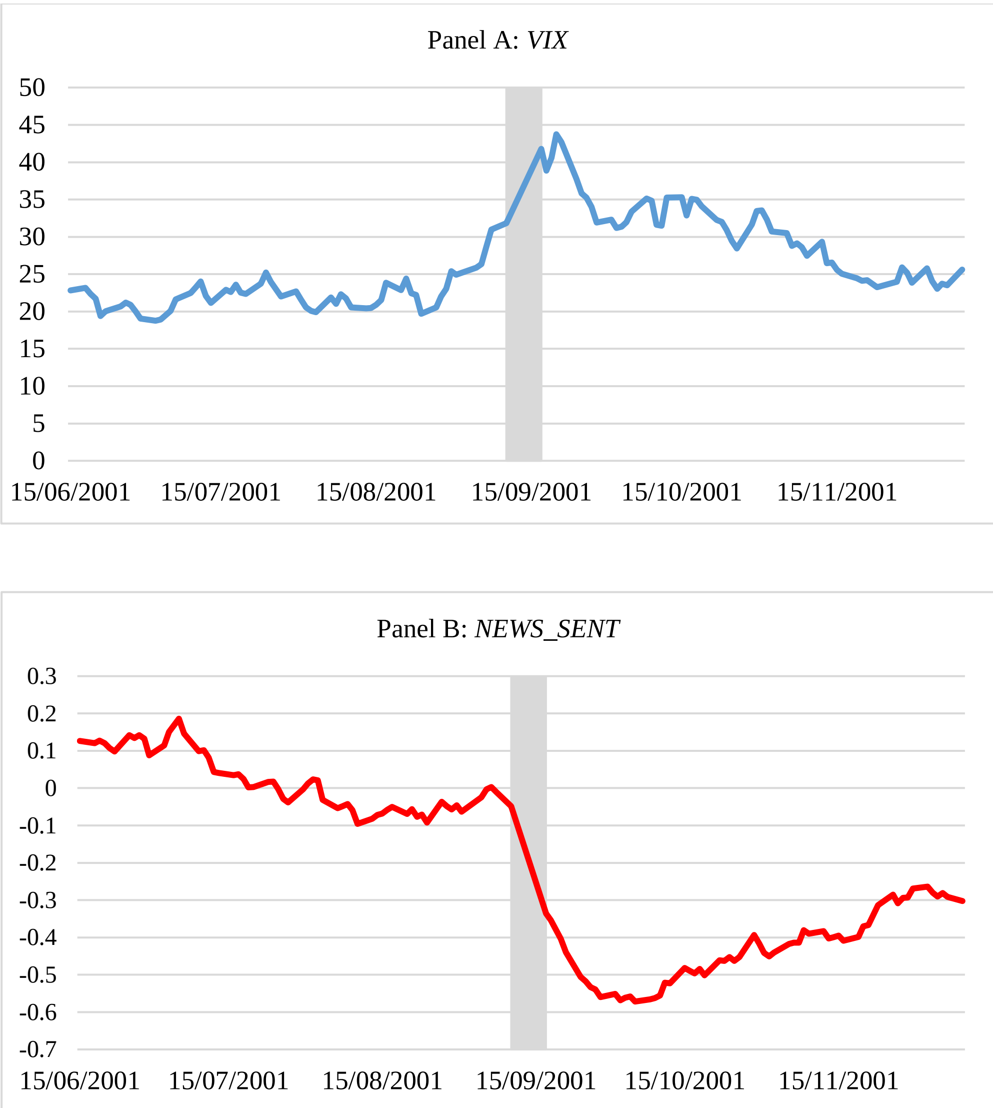
In this section, we test our hypotheses. In particular, we examine whether the negative impact of terrorist attacks influences investors' risk aversion, leading to increased firm default risk. In addition, we investigate whether the negative impact of terrorist attacks makes investors more risk-averse, increasing the default risk of firms located in the attacked states than firms located in the non-affected states.

4.4.1. Market Sentiment

To investigate the impact of the 9/11 terrorist attacks on stock market sentiment, we observe the market sentiment indices, the Volatility Index (*VIX*) and the News Sentiment Index (*NEWS_SENT*) between the pre-9/11 terrorist attacks (day-60) and the post-9/11 terrorist attacks (day+60). The indices provide measures of market risk and investors sentiment in the stock market. For *VIX,* a higher (lower) value indicates high (low) volatility resulting from increased (decreased) uncertainty, risk, and investors' fear. Meanwhile, for *NEWS_SENT,* a higher (lower) value indicates a more positive (negative) sentiment. Figure 4.1 presents the trends in the market sentiment indices during the 9/11 terrorist attacks. The *y*-axis plots *VIX* in Panel A and *NEWS_SENT* in Panel B. The *x*-axis shows the time relative to the 9/11 terrorist attacks from -60 to +60 days. The solid blue line corresponds to *VIX* and the solid red line to *NEWS_SENT*. The grey vertical bar indicates 1-day before and 1-day after 11th September 2001. The graphs in both Panels A and B of Figure 4.1 show that *VIX* begins increasing considerably on the day after the attacks, coinciding with *NEWS_SENT's* falling drastically during the weeks following the attacks. The figure indicates sharp changes, typically upward shocks of *VIX* and downward shocks of *NEWS_SENT* associated with exogenous shocks related to the 9/11 terrorist attacks. This finding suggests that extreme negative events, such as terrorist attacks, intensely affect people's emotions, creating fear and influencing stock market sentiment and future economic prospects.

Figure 4.1. Trends in the market sentiment indices during the 9/11 terrorist attacks

This figure presents the daily volatility index (*VIX*) in Panel A and the daily news sentiment index (*NEWS_SENT*) in Panel B over the 60-day before and 60-day after 11th September 2001. The *y*-axis plots *VIX* in Panel A and *NEWS_SENT* in Panel B. The *x*-axis shows the time relative to the 9/11 terrorist attacks from -60 to +60 days. The solid blue line corresponds to *VIX* and the solid red line to *NEWS_SENT*. The grey vertical bar indicates 1-day before and 1-day after 11th September 2001.



We also examine whether the market sentiment indices are statistically significant differences in the mean and median values between before and after the 9/11 terrorist attacks.

Table 4.3 shows the t-test and Wilcoxon rank-sum test of market sentiment variables between the pre-9/11 terrorist attacks (day-60) and the post-9/11 terrorist attacks (day+60). There are statistically significant differences in both *VIX* and *NEWS_SENT*'s mean and median values at a 1% level. The results suggest that *VIX* and *NEWS_SENT* in the post-9/11 terrorist attacks are significantly higher and lower than in the pre-9/11 terrorist attacks, respectively. Overall, the results indicate that terrorism has a strong adverse effect on market sentiment, suggesting that the stock market is more likely to crash in the aftermath of the 9/11 terrorist attacks.

Table 4.3. The *t*-test and Wilcoxon rank-sum test of the market sentiment indices

This table shows the *t*-test and Wilcoxon rank-sum test of market sentiment variables between the pre-9/11 terrorist attacks (day-60) and the post-9/11 terrorist attacks (day+60). The market sentiment variables include the Volatility Index (*VIX*) and the News Sentiment Index (*NEWS_SENT*). The descriptions of all variables are provided in Appendix C.1. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	**Pre-9/11**						**Post-9/11**						***t*-stat**	**Wilcoxon rank-sum test**
	N	**Min**	**Median**	**Max**	**Mean**	**Std.**	**N**	**Min**	**Median**	**Max**	**Mean**	**Std.**		
VIX	60	18.76	22.16	31.84	22.44	2.55	60	23.02	31.26	43.74	30.67	5.25	-10.91***	<0.0001***
NEWS_SENT	60	-0.10	0.003	0.19	0.02	0.08	60	-0.57	-0.42	-0.26	-0.43	0.09	28.30***	<0.0001***

4.4.2. The Event Study Analysis

We begin our analysis by examining the market reaction to the 9/11 terrorist attacks. Table 4.4 shows that the average market default spreads increase by 25.7% on the day after the attacks. The cumulative impact of the 9/11 attacks is strongest on day three and weakens afterward. The average market default risk increases by 35.6% from day one to day three. The increase in market default risk is positive and statistically significant up to 20 trading days following the 9/11 event. The results indicate that the 9/11 attacks cause an increase in the market-wide default risk.

Table 4.4. Market reaction to the 9/11 terrorist attacks

This table shows the results of the cumulative abnormal default risks for the market (*DEF_MKT*) across the 9/11 terrorist attacks over different time windows after 11th September 2001. We obtain the market default spreads from Federal Reserve Economic Data as follows: *AAA10Y* refers to Moody's seasoned Aaa corporate bond yield relative to yield on the 10-Year Treasury constant; *BAA10Y* refers to Moody's seasoned Baa corporate bond yield relative to yield on the 10-Year Treasury constant; *AAAFF* is Moody's seasoned Aaa corporate bond minus Federal Funds rate; *BAAFF* is Moody's seasoned Baa corporate bond minus Federal Funds rate. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Time windows	***DEF_MKT***			
	AAA10Y	***BAA10Y***	***AAAFF***	***BAAFF***
+1 to +1	0.189***	0.142***	0.380***	0.317***
	(12.41)	(12.65)	(12.72)	(13.45)
+1 to +2	0.199***	0.149***	0.559***	0.472***
	(9.23)	(9.40)	(13.23)	(14.15)
+1 to +3	0.213***	0.159***	0.570***	0.481***
	(8.05)	(8.19)	(11.02)	(11.79)
+1 to +4	0.207***	0.157***	0.396***	0.332***
	(6.80)	(7.03)	(6.63)	(7.04)
+1 to +5	0.213***	0.159***	0.200***	0.165***
	(6.25)	(6.34)	(2.99)	(3.12)
+1 to +10	0.167***	0.120***	0.234**	0.191**
	(3.46)	(3.39)	(2.48)	(2.56)
+1 to +20	0.099	0.079	0.298**	0.249**
	(1.45)	(1.58)	(2.23)	(2.36)
+1 to +40	0.055	0.032	0.297	0.239
	(0.57)	(0.45)	(1.57)	(1.60)

We further examine how individual firms' default risk reacts to the 9/11 terrorist attacks. Table 4.5 shows that the average firm-level default risk increases by 94.6% on the day following the attacks, and it continues to the highest level on day five, showing a total increase of 245%. After day five, the impact of terrorist attacks on default risk falls. We also use the average distance-to-default as an alternative default risk measure. The results are consistent with the average firm-level default risk. The average firms' distance-to-default has the strongest impact on day five after the event. Our results are consistent with Glaser and Weber (2005), Lizarazo (2013), and Wang and Young (2020) in that terrorist attacks cause a negative shift in investor sentiment, leading to increased investors' risk aversion. Consequently, investors demand higher compensation for their investment due to increased default risk after the 9/11 attacks.

Table 4.5. Individual firm reaction to the 9/11 terrorist attacks

This table shows the results of the cumulative abnormal default risks (*DEF_FRM*) and the cumulative abnormal distance-to-default (*DD_FRM*) for individual firms across the 9/11 terrorist attacks over different time windows after 11th September 2001. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Time windows	***DEF_FRM***	***DD_FRM***
+1 to +1	0.946***	-0.052***
	(42.36)	(-18.72)
+1 to +2	1.110***	-0.067***
	(35.12)	(-16.99)
+1 to +3	1.525***	-0.099***
	(39.42)	(-20.69)
+1 to +4	2.104***	-0.139***
	(47.08)	(-25.15)
+1 to +5	2.452***	-0.163***
	(49.08)	(-26.28)
+1 to +10	1.490***	-0.098***
	(21.09)	(-11.16)
+1 to +20	0.819***	-0.059***
	(8.20)	(-4.79)
+1 to +40	0.183	-0.025
	(1.29)	(-1.41)
No. of firms	3,078	3,078

Next, we consider the industry reaction to the 9/11 terrorist attacks. Table 4.6, Panels A and B, show that the terrorist incident significantly increases the default risk in all industries. Most of the industries exhibit the highest cumulative reaction on day five and weaken thereafter, which is consistent with the findings from the average individual firm reaction in Table 4.5. Specifically, the results are robust across different industries.

Table 4.6. Industry reaction to the 9/11 terrorist attacks

This table shows the results of the cumulative abnormal default risks (*DEF_FRM*) in Panel A and the cumulative abnormal distance-to-default (*DD_FRM*) in Panel B across the 9/11 terrorist attacks for 10 industries' portfolios over different time windows after 11th September 2001. We obtain the 10 industries from the Kenneth R. French website as follows: *NoDur* (Consumer NonDurables): Food, Tobacco, Textiles, Apparel, Leather, Toys; *Durbl* (Consumer Durables): Cars, TV's, Furniture, Household Appliances; *Manuf* (Manufacturing): Machinery, Trucks, Planes, Chemicals, Office Furniture, Paper, Commercial Printing; *Enrgy*: Oil, Gas, Coal Extraction and Products; *HiTec* (Business Equipment): Computers, Software, Electronic Equipment; *Telcm* (Telecommunications): Telephone and Television Transmission; *Shops*: Wholesale, Retail, Some Services (i.e., Laundries, Repair Shops); *Hlth*: Health Care, Medical Equipment, Drugs; *Utils* (Utilities); *Other*: Mines, Construction, Building Materials, Transportation, Hotels, Business Services, Entertainment, Finance. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: The cumulative abnormal default risks (DEF_FRM)

Time windows	***NoDur***	***Durbl***	***Manuf***	***Enrgy***	***HiTec***	***Telcm***	***Shops***	***Hlth***	***Utils***	***Other***
+1 to +1	1.114***	1.854***	1.436***	0.606***	0.417***	0.610***	1.123***	0.743***	0.616***	0.907***
	(6.87)	(15.47)	(31.50)	(5.47)	(6.62)	(11.42)	(24.83)	(8.89)	(7.94)	(23.27)
+1 to +2	1.378***	1.974***	1.671***	1.310***	0.545***	0.728***	1.249***	1.083***	0.629***	0.966***
	(6.01)	(11.65)	(25.92)	(8.37)	(6.13)	(9.64)	(19.53)	(9.16)	(5.73)	(17.53)
+1 to +3	1.952***	2.497***	2.315***	2.296***	0.779***	0.847***	1.547***	1.483***	1.001***	1.321***
	(6.95)	(12.03)	(29.32)	(11.98)	(7.15)	(9.15)	(19.75)	(10.25)	(7.45)	(19.56)
+1 to +4	2.829***	3.137***	3.038***	2.790***	1.208***	1.296***	1.990***	1.976***	1.067***	1.967***
	(8.72)	(13.09)	(33.32)	(12.61)	(9.59)	(12.12)	(22.00)	(11.82)	(6.88)	(25.22)
+1 to +5	3.536***	3.517***	3.423***	3.106***	1.340***	1.441***	2.291***	2.363***	1.683***	2.305***
	(9.75)	(13.13)	(33.58)	(12.55)	(9.52)	(12.06)	(22.65)	(12.65)	(9.70)	(26.44)
+1 to +10	2.803***	2.359***	2.257***	2.354***	0.773***	0.582***	1.550***	1.091***	0.113	1.304***
	(5.47)	(6.23)	(15.66)	(6.73)	(3.88)	(3.44)	(10.84)	(4.13)	(0.46)	(10.57)
+1 to +20	1.831**	3.303***	1.355***	0.970*	-0.642***	0.384	-0.027	-0.035	-0.918***	1.414***
	(2.52)	(6.16)	(6.65)	(1.96)	(-2.28)	(1.61)	(-0.14)	(-0.09)	(-2.64)	(8.11)
+1 to +40	1.184	3.330***	0.596**	-0.879	-1.772***	-0.207	-0.208	-0.499	-1.780***	0.901***
	(1.15)	(4.39)	(2.07)	(-1.26)	(-4.45)	(-0.61)	(-0.73)	(0.94)	(-3.63)	(3.66)
No. of firms	189	80	456	111	368	77	356	269	105	1,067

Table 4.6. (Continued)

Panel B: The cumulative abnormal distance-to-default (DD_FRM)

Time windows	***NoDur***	***Durbl***	***Manuf***	***Enrgy***	***HiTec***	***Telcm***	***Shops***	***Hlth***	***Utils***	***Other***
+1 to +1	-0.039***	-0.102***	-0.069***	-0.026***	-0.038***	-0.083***	-0.059***	-0.035***	-0.038***	-0.051***
	(-3.61)	(-6.28)	(-8.17)	(-2.81)	(-4.39)	(-4.23)	(-5.66)	(-5.47)	(-6.82)	(-11.90)
+1 to +2	-0.083***	-0.121***	-0.098***	-0.074****	-0.051***	-0.066**	-0.069***	-0.045***	-0.038***	-0.058***
	(-5.40)	(-5.29)	(-8.22)	(-5.71)	(-4.13)	(-2.36)	(-4.69)	(-4.97)	(-4.90)	(-9.50)
+1 to +3	-0.122***	-0.152***	-0.143***	-0.142***	-0.102***	-0.080**	-0.093***	-0.072***	-0.056***	-0.082***
	(-6.43)	(-5.42)	(-9.78)	(-8.91)	(-6.76)	(-2.33)	(-5.16)	(-6.47)	(-5.88)	(-10.95)
+1 to +4	-0.148***	-0.256***	-0.216***	-0.159***	-0.149***	-0.134***	-0.134***	-0.087***	-0.061***	-0.114***
	(-6.76)	(-7.92)	(-12.76)	(-8.67)	(-8.56)	(-3.41)	(-6.43)	(-6.73)	(-5.53)	(-13.24)
+1 to +5	-0.171***	-0.308***	-0.244***	-0.181***	-0.193***	-0.110**	-0.150***	-0.104***	-0.106***	-0.132***
	(-7.02)	(-8.50)	(-12.89)	(-8.80)	(-9.94)	(-2.50)	(-6.42)	(-7.22)	(-8.58)	(-9.12)
+1 to +10	-0.106***	-0.116**	-0.184***	-0.141***	-0.131***	-0.049	-0.089***	-0.046**	-0.090***	-0.063***
	(-3.06)	(-2.26)	(-6.86)	(-4.87)	(-4.79)	(-0.79)	(-2.68)	(-2.25)	(-5.16)	(-5.63)
+1 to +20	-0.034	-0.145**	-0.102***	-0.058	-0.013	-0.049	-0.010	0.000	-0.030	-0.091*
	(-0.70)	(-2.01)	(-2.68)	(-1.42)	(-0.33)	(-0.55)	(-0.22)	(0.01)	(-1.21)	(-1.86)
+1 to +40	0.019	-0.222**	-0.035	0.073	0.021	0.071	0.012	0.020	-0.034	-0.069
	(0.28)	(-2.17)	(-0.66)	(1.26)	(0.39)	(0.57)	(0.18)	(0.48)	(-0.99)	(-0.28)
No. of firms	189	80	456	111	368	77	356	269	105	1,067

Finally, we examine the state reaction to the 9/11 terrorist attacks. Table 4.7, Panel A, shows that when the 9/11 attacks take place, the cumulative impact of both firms in the attacked states and other states increase by 103% and 93%, respectively, and reach a peak of 264% and 242% on day five before decreasing afterward. Meanwhile, Panel B of Table 4.7 shows the impact of distance-to-default on the 9/11 attacks states and other states is strongest on day five, showing a total decrease of 12.4% and 17%, respectively, and weakens afterward. The results indicate that the 9/11 attacks induce a negative shock, which causes an increase in the default risk in all US states.[38]

Table 4.7. State reaction to the 9/11 terrorist attacks

This table shows the results of the cumulative abnormal default risks (*DEF_FRM*) in Panel A and the cumulative abnormal distance-to-default (*DD_FRM*) in Panel B across the 9/11 terrorist attacks. The sample consists of firms located in the 9/11 terrorist attacks states and other states over different time windows after 11th September 2001. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: The cumulative abnormal default risks (DEF_FRM)

Time windows	***9/11 states***	***Other states***
+1 to +1	1.031***	0.925***
	(20.48)	(36.68)
+1 to +2	1.198***	1.089***
	(16.84)	(30.55)
+1 to +3	1.568***	1.517***
	(17.99)	(34.73)
+1 to +4	2.187***	2.086***
	(21.73)	(41.37)
+1 to +5	2.636***	2.414***
	(23.42)	(42.82)
+1 to +10	1.611***	1.479***
	(10.13)	(18.55)
+1 to +20	0.707***	0.850***
	(3.14)	(7.54)
+1 to +40	-0.008	0.226
	(-0.03)	(1.42)
No. of firms	501	2,528

[38] We present the trends in the market, individual firm, industry, and state reactions to the 9/11 terrorist attacks in Appendix C.2-C.7.

Table 4.7. (Continued)

Panel B: The cumulative abnormal distance-to-default (DD_FRM)

Time windows	***9/11 States***	***Other States***
+1 to +1	-0.038***	-0.054***
	(-4.98)	(-18.05)
+1 to +2	-0.044***	-0.070***
	(-4.04)	(-16.63)
+1 to +3	-0.090***	-0.101***
	(-6.80)	(-19.45)
+1 to +4	-0.118***	-0.143***
	(-7.73)	(-23.92)
+1 to +5	-0.124***	-0.170***
	(-7.25)	(-25.48)
+1 to +10	-0.060**	-0.106***
	(-2.47)	(-11.17)
+1 to +20	-0.016	-0.069***
	(-0.46)	(-5.15)
+1 to +40	0.032	-0.038**
	(0.65)	(-1.98)
No. of firms	501	2,528

Overall, these findings provide strong support for our hypothesis and show that extreme terrorist attacks exogenously increase investors' risk aversion, such that they demand higher returns to compensate for their risk-taking, leading to increased firm default risk.

4.4.3. Propensity Score Matching (PSM) Analysis

We use a difference-in-difference approach (DID) to identify the impact of risk aversion on firm default risk. As Brogaard, Li, and Xia (2017) note, DID controls for the effect of omitted and unobserved variables and eliminates biases driven by time trends. We follow Brogaard, Li, and Xia (2017), Dai, Rau, Stouraitis, and Tan (2020) and construct treatment and control groups using propensity score matching. The treatment group includes firms located in the 9/11 attacks states. The control group includes all remaining firms. We estimate a probit model in which the dependent variable is one for the firms located in the attacked states and zero for firms located in other states. We use the propensity scores to match firms in the two groups with very similar firm characteristics. The matching criteria include all the variables in Equations (4.6) and (4.7), calculated in the pre-9/11 terrorist attacks (day -1). Each firm located in the attacked states is matched to a firm located in other states with the closest propensity score (within 0.01).

Table 4.8, Panel A, Column 1, reports the results of the probit regression. The dependent variable takes the value of one if a firm belongs to the treatment group and zero otherwise. The matching procedure generates 438 treatment-control pairs. We further perform diagnostic tests to verify that we do not violate the parallel trends assumption in a DID estimate. We first re-run the probit model using the matched 438 pairs. The results are shown in Table 4.8, Panel A, Column 2. All the independent variables are insignificant, while the likelihood ratio and Pseudo R^2 are less than the pre-matched results in Column 1. The p-value of X^2 is 0.919. The results explain that there is no different observable characteristic between the treatment and control groups. Second, we test the differences between the propensity scores of the treatment and control groups. Table 4.8, Panel B, presents the propensity score distribution and differences for both groups. The propensity scores are trivial. For example, the average distance between the two matched firms' propensity score is 0, while the maximum and minimum are -0.0032 and 0.0019, respectively. Overall, the diagnostic tests in Table 4.8, Panels A and B, present that the PSM procedure eliminates obvious sample selection biases, increasing the likelihood that exogenous terrorist attacks cause the risk aversion on firm default risk.

Table 4.8. Propensity Score Matching Analysis

This table shows the results of propensity score matching (PSM) analysis of the impact of risk aversion on firm default risk across the 9/11 terrorist attacks. Panel A, Column 1, presents the results of a probit model based on the pre-matched firms in the treatment and the control groups. The dependent variable equals one if the firm belongs to the treatment group (firms located in the 9/11 attacks states) and zero if the firm comes from the control group (firms located in other states). The independent variables are *Ln(Equity), Ln(Debt),* $1/\sigma_E$, *EXRET*, and *ROA* calculated in the pre-9/11 terrorist attacks (day-1). Panel A, Column 2, presents the results of the same probit model based on the post-match firms in the treatment and the control groups. Panel B presents statistical distributions of the propensity scores of the treatment and control groups and their differences. The descriptions of all variables are provided in Appendix C.1. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Probit regression with pre- and post-matched samples

Variables	**Pre-match (1)**	**Post-match (2)**
	-0.003	-0.007
Ln(Equity)	(-0.869)	(-0.799)
	0.020	0.005
Ln(Debt)	(0.220)	(0.835)
	0.044	-0.023
$1/\sigma_E$	(0.113)	(-0.602)
	0.826	1.190
EXRET	(0.219)	(0.292)
	-0.505	0.284
ROA	(0.288)	(0.698)
	-1.233***	0.093
Intercept	(-0.000)	(0.702)
No. of Obs.	3,014	876
p-value of X^2	0.082	0.919
Pseudo R^2	0.0033	0.0017
Log-likelihood	2,701.61	1,214.39

Panel B: Propensity scores distribution

Group	**N**	**Mean**	**Min**	**Median**	**Max**	**Std.**
Treatment	438	0.1682	0.0901	0.1691	0.2375	0.0220
Control	438	0.1682	0.0882	0.1691	0.2407	0.0220
Difference	438	0.0000	0.0019	0.0000	-0.0032	0.0000

We further use the PSM matched sample to examine state reaction to the 9/11 terrorist attacks. Panels A and B of Table 4.9 show that the impact of the 9/11 attacks causes a wide-spread increase in default risk across all US states. Both treatment and control groups react to the 9/11 attacks very similarly and exhibit the highest cumulative reaction on day five, weakening thereafter. The results are consistent with the state reaction in Table 4.7.[39]

Table 4.9. State reaction to the 9/11 terrorist attacks between the treatment and control groups

This table shows the results of the cumulative abnormal default risks (*DEF_FRM*) in Panel A and the cumulative abnormal distance-to-default (*DD_FRM*) in Panel B across the 9/11 terrorist attacks over different time windows after 11th September 2001. The test is based on the matched sample constructed in Table 4.7. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: The cumulative abnormal default risks (DEF_FRM)

Time windows	***Treatment***	***Control***
+1 to +1	1.051***	0.959***
	(18.83)	(14.08)
+1 to +2	1.226***	1.086***
	(15.53)	(11.28)
+1 to +3	1.573***	1.609***
	(16.27)	(13.63)
+1 to +4	2.192***	2.234***
	(19.64)	(16.40)
+1 to +5	2.666***	2.603***
	(21.36)	(17.09)
+1 to +10	1.648***	1.573***
	(9.34)	(7.30)
+1 to +20	0.717***	1.239***
	(2.87)	(4.07)
+1 to +40	0.013	0.705
	(0.04)	(1.64)
No. of firms	438	438

[39] We present the trends in state reaction to the 9/11 terrorist attacks between the treatment and control groups in Appendix C.8-C.9.

Table 4.9. (Continued)

Panel B: The cumulative abnormal distance-to-default (DD_FRM)

Time windows	***Treatment***	***Control***
+1 to +1	-0.037***	-0.046***
	(-4.71)	(-6.80)
+1 to +2	-0.044***	-0.043***
	(-3.98)	(-4.48)
+1 to +3	-0.083***	-0.059***
	(-6.17)	(-5.00)
+1 to +4	-0.110***	-0.104***
	(-7.07)	(-7.64)
+1 to +5	-0.117***	-0.136***
	(-6.74)	(-8.92)
+1 to +10	-0.058**	-0.082***
	(-2.35)	(-3.79)
+1 to +20	-0.038	-0.043
	(-1.08)	(-1.41)
+1 to +40	-0.013	-0.010
	(-0.27)	(-0.24)
No. of firms	438	438

Finally, we present the DID regression results of the impact of the 9/11 terrorist attacks on risk aversion and firm default risk. Panels A and B of Table 4.10 show that the interaction term between *Treatment* and *After* is not statistically significant. The results suggest that the strong negative exogenous shock from the 9/11 terrorist attacks cause investors to become more risk-averse, leading to increased default risk for both firms located in the attacked states and other states. The findings are consistent with the literature that the 9/11 terrorist attacks directly affect massive casualties and damage resources in the attack state, thereby indirectly affect remaining states, international economic and global financial markets (e.g., see Czinkota, Knight, Liesch, and Steen, 2010; Shahbaz, 2013; Procasky and Ujah, 2016).

Table 4.10. Difference-in-difference analysis

This table shows the results for the difference-in-differences regression based on the matched sample constructed in Table 4.7. The dependent variable is the cumulative abnormal default risks (*DEF_FRM*) in Panel A and the cumulative abnormal distance-to-default (*DD_FRM*) in Panel B. *Treatment* is a dummy variable equal to one if a firm is in the treatment group and zero if in the control group. *After* is a dummy variable equal to one for time window (+1 to +5) and zero for (-5 to -1). *Treatment*After* is the interaction between these two variables. Standard errors are clustered by the firm and are presented in parentheses. The control variables are *Ln(Equity), Ln(Debt),* $1/\sigma_E$, *EXRET*, and *ROA* calculated in the pre-9/11 terrorist attacks (day-1). The descriptions of all variables are provided in Appendix C.1. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: The cumulative abnormal default risks (DEF_FRM)

	DEF_FRM	
Variables	**(1)**	**(2)**
	0.154	0.154
*Treatment*After*	(0.300)	(0.292)
	-0.066	-0.066
Treatment	(0.212)	(0.138)
	1.792***	1.792***
After	(0.212)	(0.169)
	0.575***	0.575***
Ln(Equity)	(0.050)	(0.062)
	-0.455***	-0.455***
Ln(Debt)	(0.044)	(0.072)
	0.798***	0.798***
$1/\sigma_E$	(0.079)	(0.121)
	-8.843***	-8.843***
EXRET	(1.587)	(1.746)
	3.278**	3.278***
ROA	(1.289)	(1.182)
	-2.985***	-2.985***
Intercept	(0.449)	(0.381)
Industry fixed effects	No	Yes
No. of Obs.	1,752	1,752
R^2	0.200	0.200

Table 4.10. (Continued)

Panel B: The cumulative abnormal distance-to-default (DD_FRM)

	DD_FRM	
Variables	**(1)**	**(2)**
*Treatment*After*	0.023 (0.035)	0.023 (0.036)
Treatment	-0.004 (0.025)	-0.004 (0.016)
After	-0.091*** (0.025)	-0.091*** (0.024)
Ln(Equity)	-0.006 (0.006)	-0.006 (0.009)
Ln(Debt)	-0.005 (0.005)	-0.005 (0.007)
$1/\sigma_E$	0.010 (0.009)	0.010 (0.011)
EXRET	0.361* (0.187)	0.361 (0.381)
ROA	0.109 (0.152)	0.109 (0.139)
Intercept	0.060 (0.053)	0.060 (0.062)
Industry fixed effects	No	Yes
No. of Obs.	1,752	1,752
R^2	0.200	0.200

4.5. Conclusion

This study uses the 9/11 terrorist attacks as an exogenous shock to the investor's risk aversion and examines how it affects the default risk. First, we demonstrate that terrorist attacks intensely affect people's emotions, create fear, and influence stock market sentiment and future economic prospects. Furthermore, using an event study approach, we find terrorism elicits a strong negative shock to the stock market, which causes investors to be more risk-averse and increases the probability of a firm's default. The cumulative abnormal market-wide default risk is strongest on day three, while the cumulative reaction of firm-level default risk is highest on day five, but both weaken afterward. Terrorism significantly increases the default risk in all industries. Interestingly, a difference-in-difference analysis shows that terrorism causes an increase in the market-wide default risk for both firms located in the attacked states and other states. Our findings are consistent with the previous studies of risk aversion and default risk (Lizarazo, 2013; Wang and Young, 2020), which suggest that when terrorist attacks occur, investors become more risk-averse and hence require a higher premium due to the increased default risk.

APPENDIX C

FOR ESSAY THREE

Appendix C.1. Variable descriptions

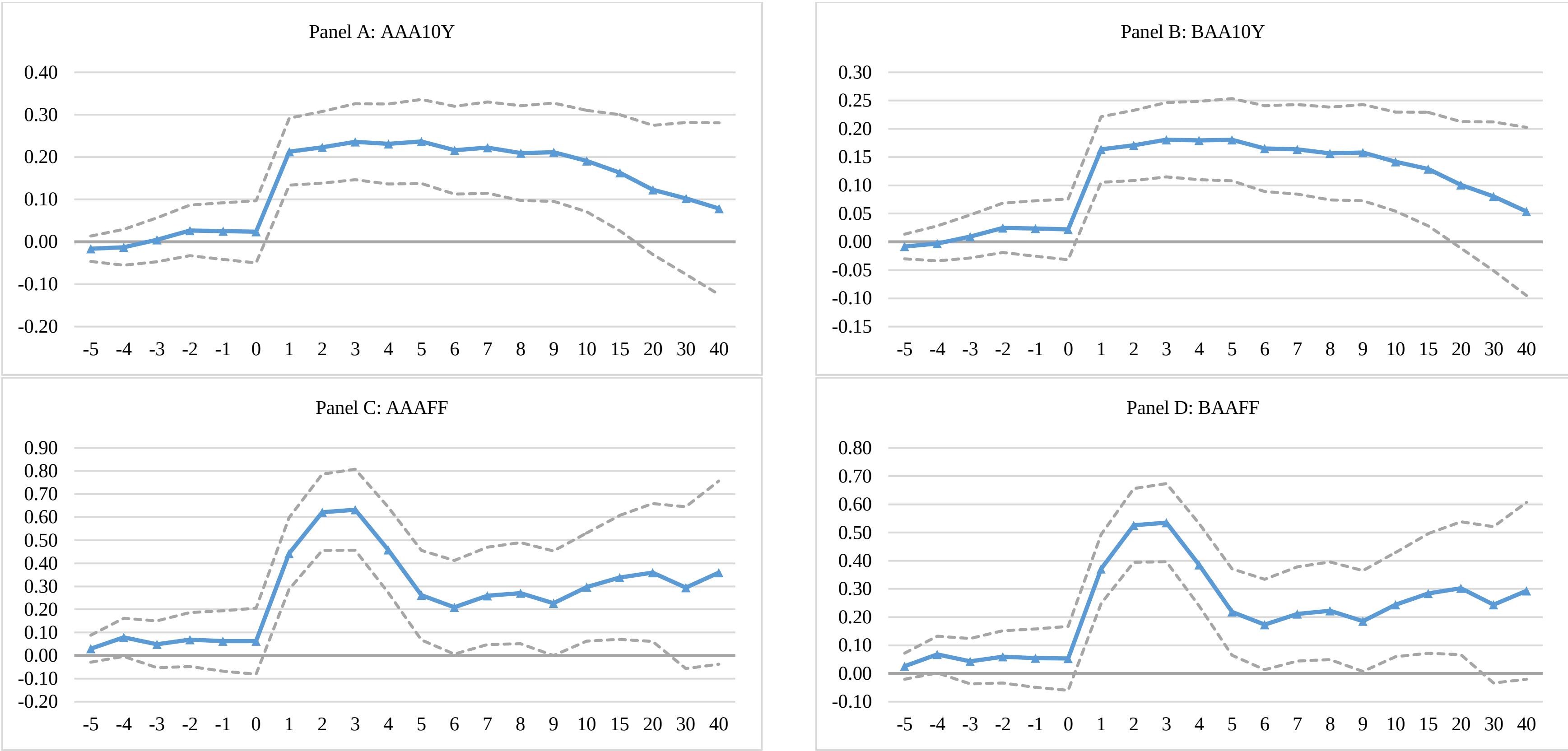
Variables	Description	Definition
DD	Distance-to-default	We follow Bharath and Shumway (2008) and Brogaard, Li, and Xia (2017).
EDF	Expected default frequency	$EDF_{i,t} = N\left(-DD_{i,t}\right)$, where $N(.)$ is the cumulative standard normal distribution function.
Equity	The market value of equity	The product of the number of shares outstanding and the share price at the end of each day (millions of dollars).
Debt	Face value of debt	The sum of current liabilities (Compustat quarterly data 45) and one-half of long-term debt (Compustat quarterly data 51) (millions of dollars).
$r_{i,t-1}$	Firm past annual return	The moving average of daily stock returns over the previous year multiplied by 252.
σ_E	The stock volatility	The moving standard deviation of daily returns over the previous year multiplied by square root 252
$\sigma_{Vi,t}$	The volatility of firm assets	An approximation of the volatility of firm assets.
EXRET	Excess Return	The difference between daily stock returns and CRSP value-weighted returns.

ROA	Return of assets	The ratio of net income (Compustat quarterly data 69) to the total asset (Compustat quarterly data 44).
DEF	The firm-level default risks	The firm's daily expected default frequency ($EDF_{i,t}$) and the firm's daily distance-to-default ($DD_{i,t}$)
*DEF**	The firm-level default risks after controlling for a change in share price	the firm's daily expected default frequency after controlling for a change in share price ($EDF^*_{i,t}$) and the firm's daily distance-to-default after controlling for a change in share price ($DD^*_{i,t}$)
*DD**	Distance-to-default after controlling for a change in share price	The residual for stock *i* of the equation as follows: $DD_{i,t} = \alpha + \beta_i R_{i,t} + \varepsilon_{i,t}$, where $DD_{i,t}$ is the daily distance-to-default for stock *i*; $R_{i,t}$ is the CRSP daily return for stock *i*; and ε_t is the residual for stock *i*.
*EDF**	Expected default frequency after controlling for a change in share price	The residual for stock *i* of the equation as follows: $EDF_{i,t} = \alpha + \beta_i R_{i,t} + \varepsilon_{i,t}$, where $EDF_{i,t}$ is the daily expected default frequency for stock *i*; $R_{i,t}$ is the CRSP daily return for stock *i*; and ε_t is the residual for stock *i*.
$R_{i,t}$	The daily stock returns	The CRSP daily stock returns
DEF_MKT	The cumulative abnormal default risks for the market	The cumulative abnormal default risks for the market from day 1 to day *t*.
DEF_FRM	The cumulative abnormal default risks for individual firms	The cumulative abnormal default risks for individual firms from day 1 to day *t*.

DD_FRM	The cumulative abnormal distance-to-default for individual firms	The cumulative abnormal distance-to-default for individual firms from day 1 to day *t*.
VIX	Volatility index	The Daily Volatility Index from https://fred.stlouisfed.org/series/VIXCLS.
NEWS_SENT	News sentiment index	The Daily News Sentiment Index in Buckman, Shapiro, Sudhof, and Wilson (2020) from https://www.frbsf.org/economic-research/indicators-data/daily-news-sentiment-index/.

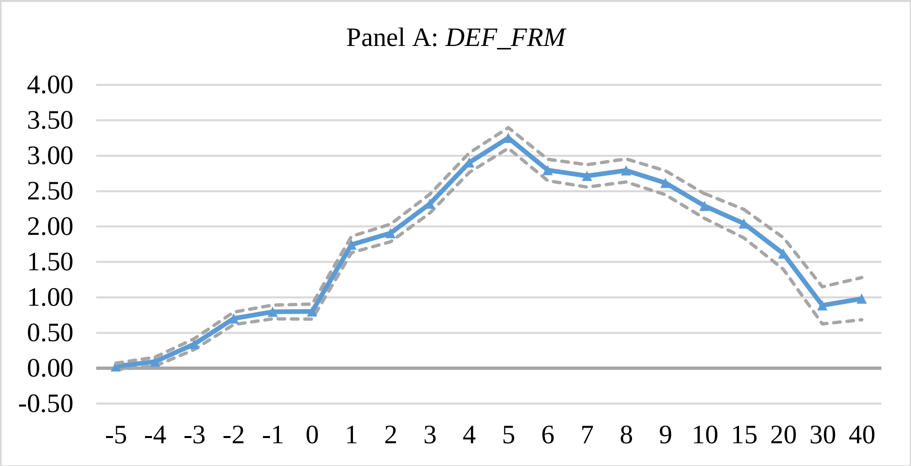
Appendix C.2. Trends in the market reaction to the 9/11 terrorist attacks

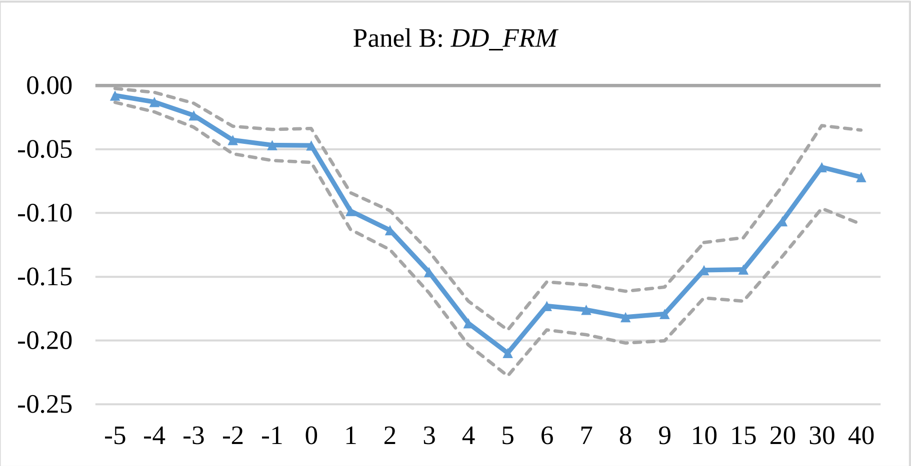
This figure presents the trends in the relation between the 9/11 terrorist attacks and the cumulative abnormal default risks for the market (*DEF_MKT*) over the 5-day before and 40-day after 11th September 2001. The *y*-axis plots the *DEF_MKT* of Moody's seasoned Aaa corporate bond yield relative to yield on the 10-Year Treasury constant (AAA10Y) in Panel A, Moody's seasoned Baa corporate bond yield relative to yield on the 10-Year Treasury constant (BAA10Y) in Panel B, Moody's seasoned Aaa corporate bond minus Federal Funds rate (AAAFF) in Panel C and Moody's seasoned Baa corporate bond minus Federal Funds rate (BAAFF) in Panel D. The *x*-axis shows the time relative to the 9/11 terrorist attacks from -5 to +40 days. The solid blue line corresponds to *DEF_MKT*. The dashed lines correspond to the 95% confidence intervals of *DEF_MKT*.



Appendix C.3. Trends in individual firm reaction to the 9/11 terrorist attacks

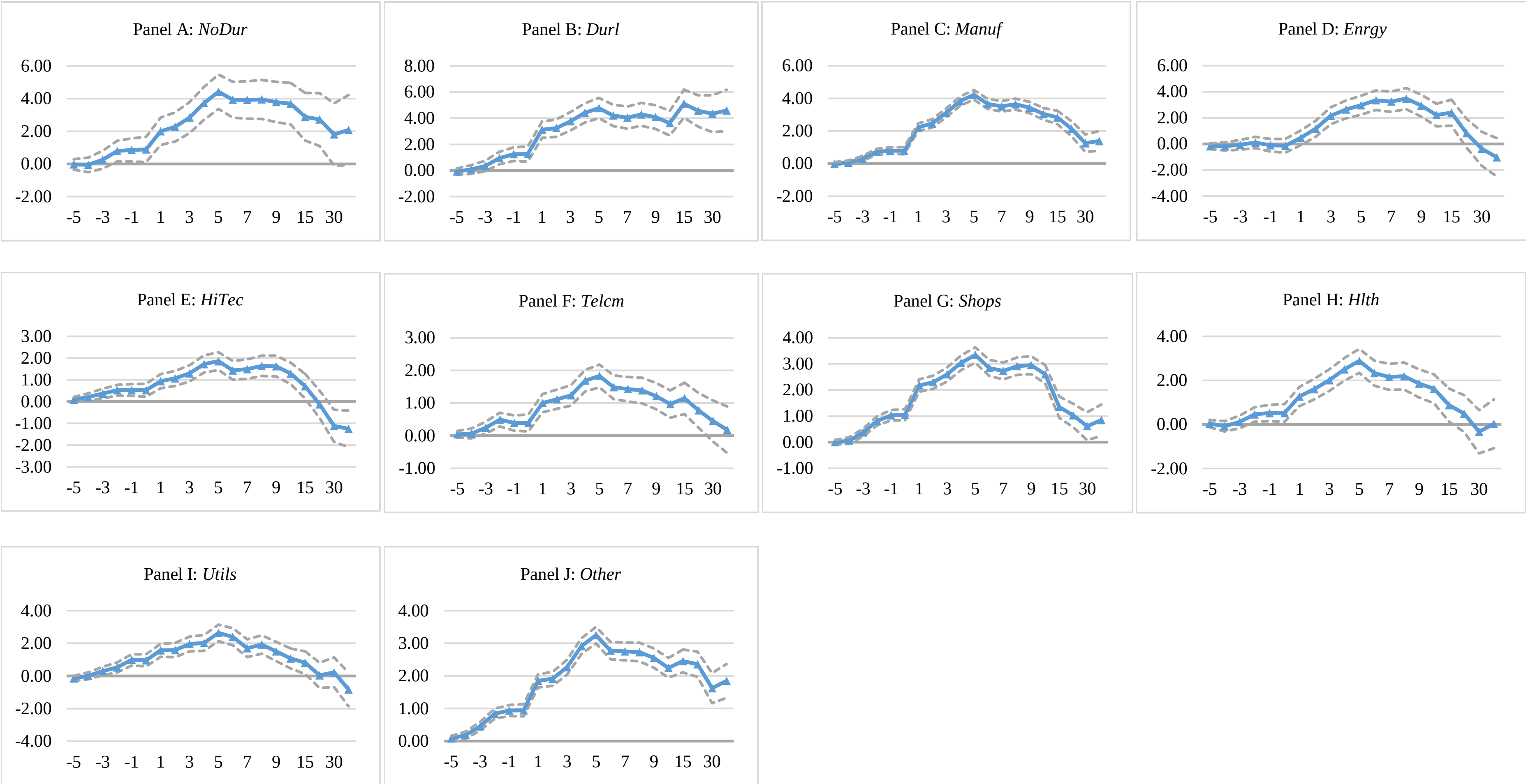
This figure presents the relation between the 9/11 terrorist attacks and the cumulative abnormal default risks (*DEF_FRM*) in Panel A and the cumulative abnormal distance-to-default (*DD_FRM*) in Panel B over the 5-day before and 40-day after 11th September 2001. The *y*-axis plots *DEF_FRM* in Panel A and *DD_FRM* in Panel B. The *x*-axis shows the time relative to the 9/11 terrorist attacks from -5 to +40 days. The solid blue line corresponds to *DEF_FRM* and *DD_FRM*. The dashed lines correspond to the 95% confidence intervals of *DEF_FRM* and *DD_FRM*.





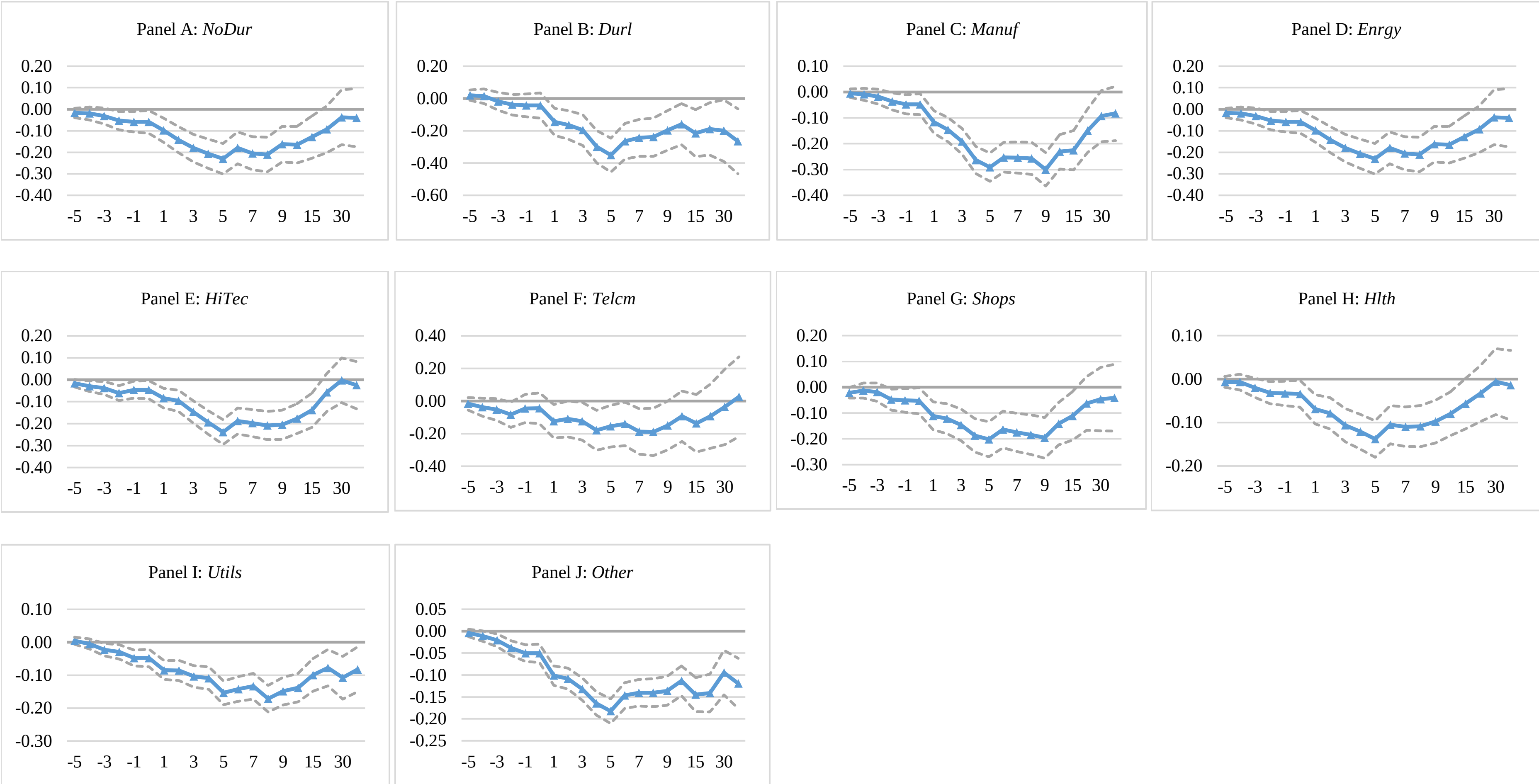
Appendix C.4. Trends in industry reaction to the 9/11 terrorist attacks using *DEF_FRM*

This figure presents the trends in the relation between the 9/11 terrorist attacks and the cumulative abnormal default risks for individual firms (*DEF_FRM*) of 10 industries from the Kenneth R. French website over the 5-day before and 40-day after 11th September 2001. The y-axis plots *DEF_FRM* for 10 industries. The *x*-axis shows the time relative to the 9/11 terrorist attacks from -5 days to +40. The solid blue line corresponds to *DEF_FRM*. The dashed lines correspond to the 95% confidence intervals of *DEF_FRM*.



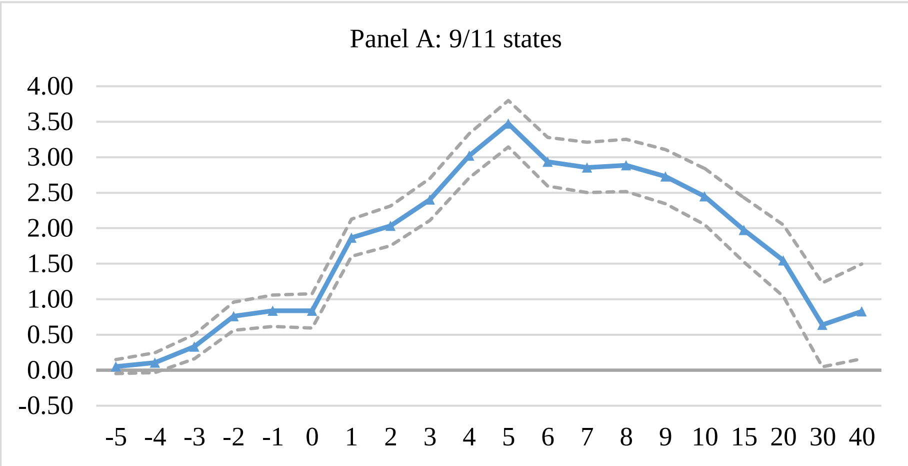
Appendix C.5. Trends in industry reaction to the 9/11 terrorist attacks using *DD_FRM*

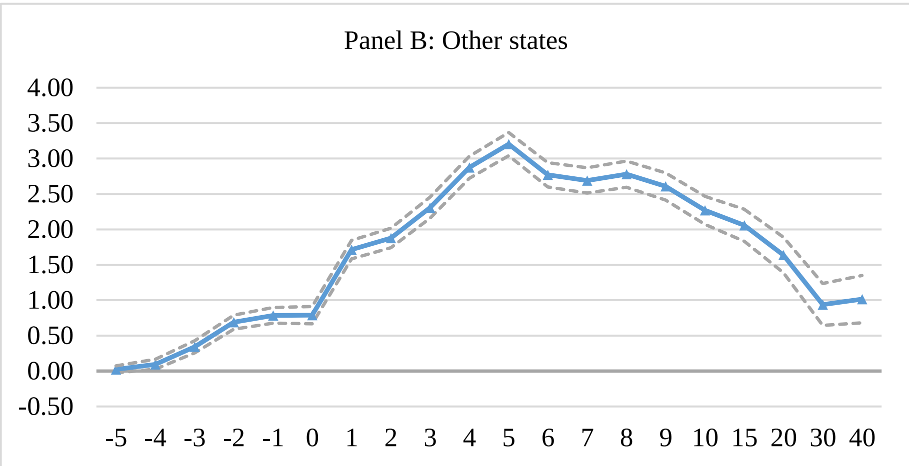
This figure presents the trends in the relation between the 9/11 terrorist attacks and the cumulative abnormal distance-to-default for individual firms (*DD_FRM*) of 10 industries from the Kenneth R. French website over the 5-day before and 40-day after 11th September 2001. The y-axis plots *DD_FRM* for 10 industries. The *x*-axis shows the time relative to the 9/11 terrorist attacks from -5 days to +40. The solid blue line corresponds to *DD_FRM*. The dashed lines correspond to the 95% confidence intervals of *DD_FRM*.



Appendix C.6. Trends in state reaction to the 9/11 terrorist attacks using *DEF_FRM*

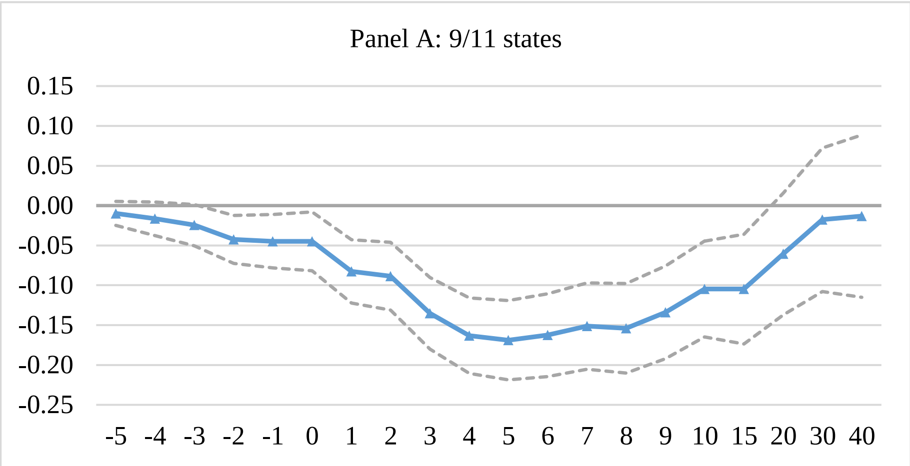
This figure presents the relation between the 9/11 terrorist attacks and the cumulative abnormal default risks for individual firms (*DEF_FRM*) over the 5-day before and 40-day after 11th September 2001. The *y*-axis plots *DEF_FRM* of firms located in the 9/11 terrorist attacks states in Panel A, and firms located in other states in Panel B. The *x*-axis shows the time relative to the 9/11 terrorist attacks from -5 to +40 days. The solid blue line corresponds to *DEF_FRM*. The dashed lines correspond to the 95% confidence intervals of *DEF_FRM*.

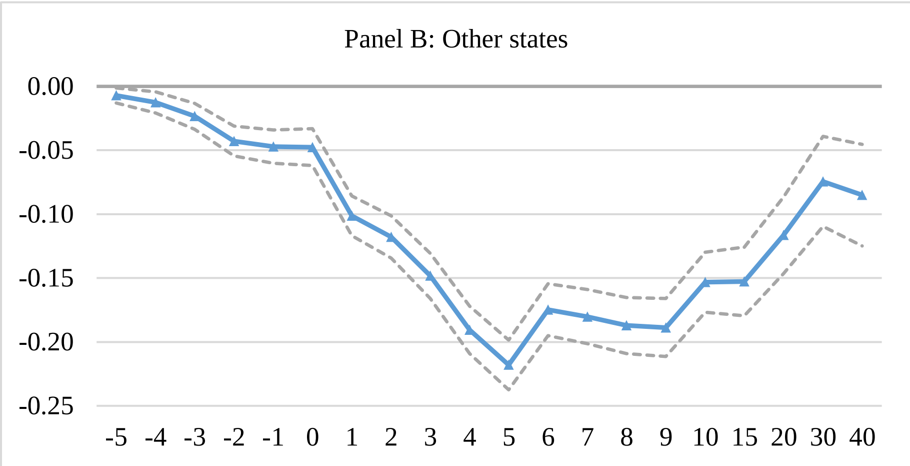




Appendix C.7. Trends in state reaction to the 9/11 terrorist attacks using *DD_FRM*

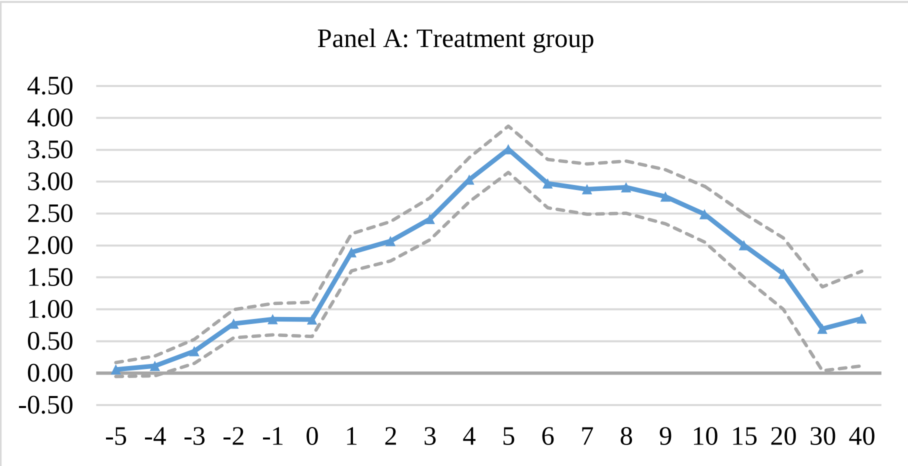
This figure presents the relation between the 9/11 terrorist attacks and the cumulative abnormal distance-to-default for individual firms (*DD_FRM*) over the 5-day before and 40-day after 11th September 2001. The *y*-axis plots *DD_FRM* of firms located in the 9/11 terrorist attacks in Panel A, and firms located in other states in Panel B. The *x*-axis shows the time relative to the 9/11 terrorist attacks from -5 to +40 days. The solid blue line corresponds to *DD_FRM*. The dashed lines correspond to the 95% confidence intervals of *DD_FRM*.

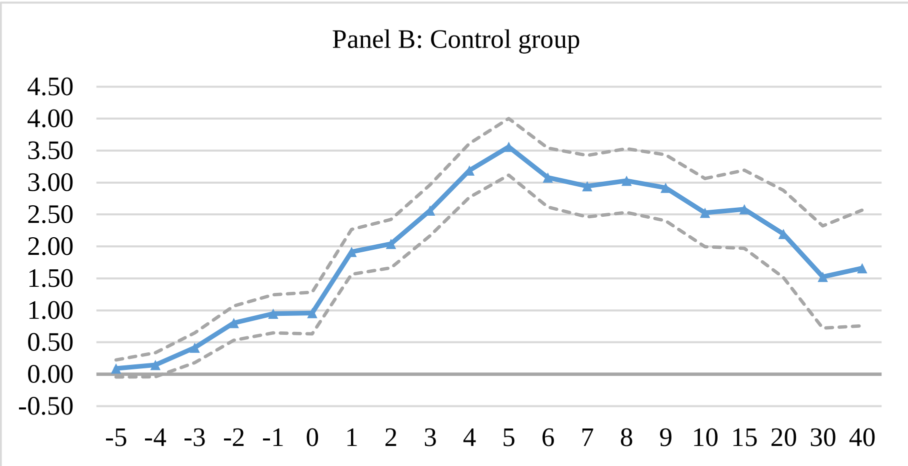




Appendix C.8. Trends in state reaction to the 9/11 terrorist attacks between the treatment and control groups using *DEF_FRM*

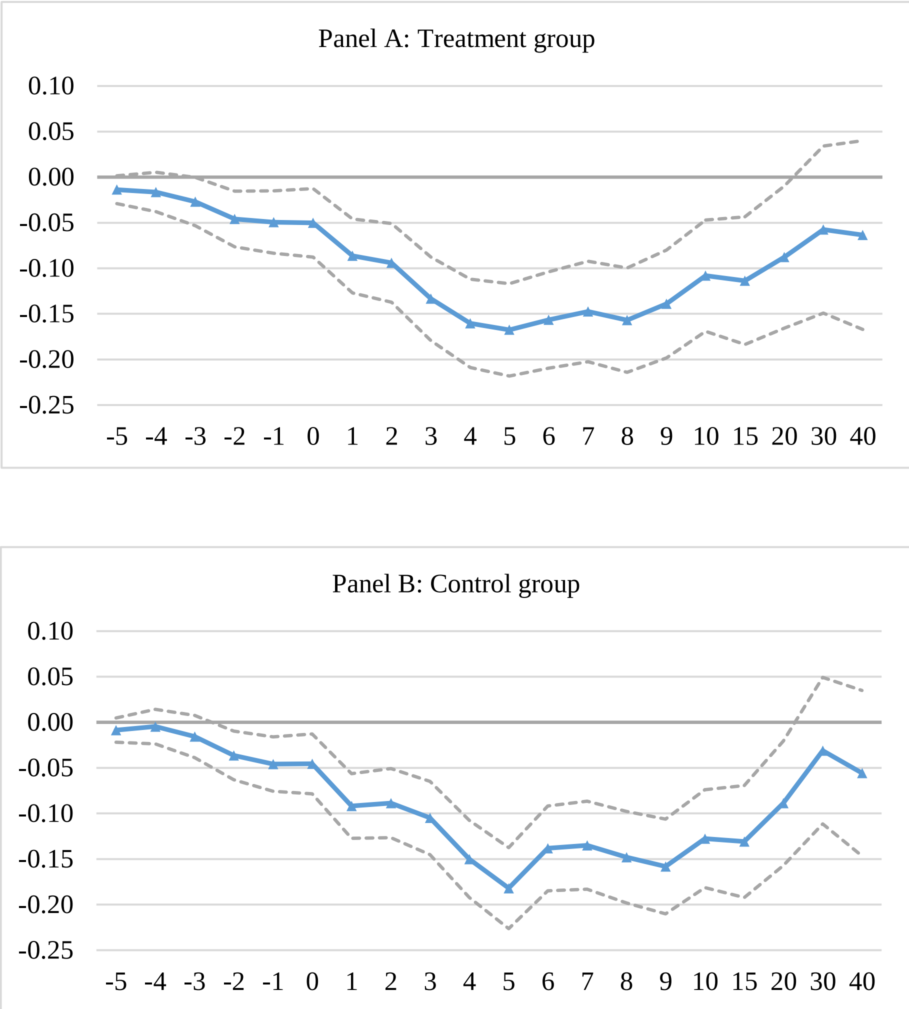
This figure presents the relation between the 9/11 terrorist attacks and the cumulative abnormal default risks for individual firms (*DEF_FRM*) over the 5-day before and 40-day after 11th September 2001. The *y*-axis plots *DEF_FRM* of the treatment group in Panel A, and the control group in Panel B. The *x*-axis shows the time relative to the 9/11 terrorist attacks from -5 to +40 days. The solid blue line corresponds to *DEF_FRM*. The dashed lines correspond to the 95% confidence intervals of *DEF_FRM*.





Appendix C.9. Trends in state reaction to the 9/11 terrorist attacks between the treatment and control groups using *DD_FRM*

This figure presents the relation between the 9/11 terrorist attacks and the cumulative abnormal distance-to-default for the individual firms (*DD_FRM*) over the 5-day before and 40-day after 11th September 2001. The *y*-axis plots *DD_FRM* of the treatment group in Panel A, and the control group in Panel B. The *x*-axis shows the time relative to the 9/11 terrorist attacks from -5 to +40 days. The solid blue line corresponds to *DD_FRM*. The dashed lines correspond to the 95% confidence intervals of *DD_FRM*.



CHAPTER FIVE

CONCLUSION

This chapter concludes the thesis by summarising the major findings for each of the three essays in Section 5.1 and by suggesting areas for future research in Section 5.2.

5.1. Major Findings and Implications

5.1.1. Essay One

The first essay examines whether inconsistent financial accounting information impacts the cross-section of stock returns by using earnings quality and firm characteristics to capture the informative signals about firm value.

This essay shows that stock returns of information-consistent firms are positive and significant in predicting the subsequent one-month-ahead stock returns of information-inconsistent firms in both equal- and value-weighted portfolios. The results also show there is no reverse causality in return predictability. The findings support the literature suggesting that firms with a higher quality of information provide more information for predicting future earnings information. The essay also shows that the cross-section of stock return predictability varies over time due to funding liquidity and investor attention. In addition, the results of out-of-sample predictive ability show a positive and statistically significant out-of-sample R^2. The encompassing tests show forecasts based on the model have superior information content relative to forecasts based on the historical mean. Finally, a trading strategy based on the predictability results outperforms the buy-and-hold strategy with higher average excess returns, greater efficiency with a higher Sharpe ratio, and certainty equivalent return.

Overall, this essay provides two important contributions to the growing strand of literature on delayed information processing in stock markets. First, this study enriches the literature on the roles of financial accounting information in predicting stock returns, using earnings quality and firm characteristics as proxies to capture firm value's informative signals. Second, the essay adds to the existing body of knowledge that highlights the impact of inconsistent financial accounting information on the cross-section of stock returns due to the different speeds of information incorporation across stocks; this is consistent with the gradual information diffusion theory. These findings provide important implications for academics, corporate insiders, and market participants with regard to the degree of information consistency and the cross-section of stock return predictability.

5.1.2. Essay Two

The second essay examines whether the differences in accounting information between the stocks affect cross-asset return predictability by using a comprehensive set of accounting variables and market environments as proxies to capture the degree of information adjustment.

The essay finds 10 of the 17 accounting proxies: abnormal accruals, earnings smoothness, book-to-market, firm age, leverage, abnormal capital investment, investment growth, return on equity, firm size, and stock volatility, thereby providing useful information for predicting the cross-section of stock returns after controlling for time and industry fixed effects. These variables not only increase the probability of predictability but also increase the power of cross-stock returns' prediction. The essay also shows that predictability varies over time due to the funding of liquidity and market sentiment. These findings suggest that earnings quality and growth-related characteristics variables (abnormal accruals, abnormal capital investments, investment growth, and return on equity) are indeed strong cross-stock returns predictors and do not vary across time. Finally, a simple trading strategy is based on the predictability results outperforming the buy-and-hold strategy in return, risk, and the Sharpe ratio, which is novel and adds to the practical value of utilizing the results for making a profit.

Overall, essay two contributes to the accounting and finance literature on slow information diffusion in the stock market (e.g., Lo and MacKinlay, 1990; Menzly and Ozbas, 2010; Cohen and Lou, 2012; Rapach, Strauss, and Zhou 2013). First, this study adds to the literature on the roles of accounting information in cross-asset returns predictability. Second, this study extends the growing strand of literature, highlighting the impacts of the information processing procedure on return predictability at an individual stock level. These findings also have implications for academics and investors, focusing on the roles of accounting information in cross-asset return predictability.

5.1.3. Essay Three

The third essay of this thesis investigates the impact of investors' risk aversion on default risk. Investors' risk aversion is not exogeneous and can be affected by various factors that could also affect the default risk. To mitigate potential the endogeneity concern, this essay employs the largest mega-terrorist event, the 9/11 terrorist attacks, as an exogenous shock.

First, the essay uses the Volatility Index and the News Sentiment Index to capture market risk and sentiment. The findings show that terrorism intensely affects people's emotions, creating fear, and influencing stock market sentiment and future economic prospects. In addition, using an event-study approach to measure the impact of terrorist attacks on the market and firm levels, the essay finds the 9/11 terrorist attacks cause an increase in the market-wide default risk, which is strongest on day three before decreasing afterward. The average market default risk increases by 36% from day one to day three. The cross-sectional average default risk across all firms rises 245% to the highest level on day five after the attacks. Interestingly, terrorist attacks significantly increase the default risk in all industries.

This essay also considers the state reaction to the 9/11 terrorist attacks. The results show that both firms' cumulative impact on the attacked states and other states increases by 103% and 93%, respectively, and reaches a peak of 264% and 242% on day five and weaken thereafter. Following Brogaard, Li, and Xia (2017), and Dai, Rau, Stouraitis, and Tan (2020), the essay employs a difference-in-difference analysis to examine the state reaction to the 9/11 terrorist attacks. The results show that mega-terrorism causes a wide-spread increase in default risk across all US states. Both firms located in the attacked states and the non-affected states react to the 9/11 attacks very similarly and show the highest cumulative reaction on day five, weakening thereafter. In addition, the DID regression results suggest that the strong negative exogenous shock from the 9/11 terrorist attacks cause investors to become more risk-averse, leading to an increased default risk for both firms located in the attacked states and those in other states.

In summary, this essay provides strong support for the strand of literature, showing that extreme terrorist attacks exogenously increase investors' risk aversion to such an extent that they demand higher returns to compensate for their risk-taking, leading to increased firm default risk. These findings provide important insights for market participants, policymakers, and regulators regarding risk aversion and default risk.

5.2. Future Areas of Research

The first essay provides empirical evidence of the impact of the inconsistency of financial accounting information on the cross-section of stock returns by using earnings quality and firm characteristics to capture the informative signals about firm value. The findings of the first essay have substantial implications for future studies. Future research could consider how the key firm stakeholders (e.g., shareholders, directors, creditors, and suppliers) respond to firms' financial accounting information inconsistency. Future research could also consider how other capital market participants value the inconsistent signal. Subsequent studies could examine whether the financial accounting information inconsistency affects financial institutions' debt contracting and underwriting fees and could also investigate the impact of inconsistent financial accounting information on the pricing of audit fees. Future studies could further examine how investors assess inconsistency when making their decisions, leading to different stock liquidity outcomes. Furthermore, stock price crashes have gradually become topics of concern owing to various accounting scandals (e.g., Kim, Li, and Li, 2014; Chang, Chen, and Zolotoy 2017).

Future research could consider the amount of information in stock prices (e.g. price non-synchronicity and probability of informed trading) as information consistency measures. Future research could employ this approach to examine the impact of inconsistent financial accounting information on stock price crashes.

The second essay of this thesis uses a comprehensive set of accounting variables and market environments to capture the degree of information reflection and documents that the differences in accounting information between the stocks affect cross-asset return predictability. The findings of the second essay provide implications for future research and investors. Future studies may employ alternative accounting information and market state variables to extend these results and expand the methodology to other future research markets. In particular, investors could further consider the accounting variables that matter for cross-stock predictability, based on the results, to create their own profitable investment strategies.

The third essay provides evidence that terrorism elicits a strong negative shock to the stock market, causing investors to be more risk-averse and increasing the probability of a firm's default. To the best of our knowledge, this essay is the first to study the impact of terrorist incidents on corporate default. The findings of the third essay have several implications for future research. Future studies could employ this approach to investigate the impact of other events that trigger investor risk-aversion on default risk. For example, examining the impact of the COVID-19 pandemic on default risk would be useful. Future studies could also employ the firm-level default risk measures to extend the investigation from a different angle, such as examining whether firm-level political risk matters for firm default risk. Future research could also consider other corporate outcomes following adverse events, such as the pricing of the cost of capital, labour costs, and stock liquidity.

To sum up, this thesis provides more insight into financial accounting information and how it is associated with cross-asset return predictability and default risk. The thesis has several implications for future academic research involving practitioners, investors, policymakers, and regulators. Corporate managers and key stakeholders could consider the inconsistency of their financial accounting information; such a move would be beneficial for their corporate valuation in terms of earnings management and future profitability. Financial institutions could consider information inconsistency for debt contracting and underwriting fees. Auditors could also take into account the quality of firms' information when determining the setting of audit fees. Investors could assess the inconsistency of information when making their investment decisions and consider the trading strategy described in this thesis for making a profit. Furthermore, this essay provides evidence of great significance for policymakers, regulators, and management to consider how best to address the adverse consequences of terrorist events.

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