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

Narongdech Thakerngkiat [a], Nuttawat Visaltanachoti [b],
Nick Nguyen [c], Harvey Nguyen [d]

[a]School of Economics and Finance, Massey University, New Zealand,
E-mail: N.Thakerngkiat@massey.ac.nz
[b]School of Economics and Finance, Massey University, New Zealand,
E-mail: N.Visaltanachoti@massey.ac.nz
[c]Finance Department, Auckland University of Technology, New Zealand,
E-mail: Nhut.Nguyen@aut.ac.nz
[d]School of Economics and Finance, Massey University, New Zealand,
E-mail: H.Nguyen3@massey.ac.nz

Abstract

This study examines the predictability of pairs of stocks, using several accounting variables as proxies to capture the relative degree of limits to arbitrage. We also include market stage variables to examine whether their relation or predictability vary over time, thus generating the return predictability across assets. We find that ten out of seventeen selected accounting proxies, namely, abnormal accruals, earnings smoothness, book-to-market, firm age, leverage, abnormal capital investment, investment growth, return on equity, firm size and stock volatility, provide strongly reliable information that is useful for predicting the cross-section of returns after controlling the firm and year fixed effects. We further show that the predictability varies over time due to liquidity funding and market sentiment. The level of predictive power can then be explained by the interaction terms of selected accounting information across stock and funding proxies.

JEL Classification: G11 G14 M41

Keywords: return predictability, limits to arbitrage, information diffusion, accounting information.

1. Introduction

The majority of the literature reports a variation in how different stocks reflect and react to new information at different speeds. One of the paramount concerns, according to Lo and MacKinlay (1990), is a lead-lag effect in the stock markets, which causes some stocks to reflect information faster than others. It is typical of this phenomenon that large stocks tend to lead small stocks. Studies by Hou and Moskowitz (2005) similarly showed that some firms' stock prices show a delayed reaction to the price innovation of others. These studies indeed seem to suggest an explanation for some of the causes of return predictability factors and anomalies in the markets. As a result, it could be useful to use individual stock returns as a leading indicator to predict the returns of other stocks. Several empirical studies have also focused on accounting information and the quality of such information. They documented that there is in fact a predictive value to accounting information in the stock markets. Prior studies, such as Garlappi and Yan (2011), Kogan and Papanikolaou (2013) and Babenko *et al.* (2016), showed evidence of the ability of various attributes of accounting information to be useful for return predictability. The lead-lag effect and the accounting information literature, as shaped by growing empirical and theoretical research over the past few decades, are indicative of their significant role in the predictability of stock returns. In this study, we examine the variation in predictability across different pairs of stocks, depending on the relative degree of limits to arbitrage between stocks. This is achieved by using a broad set of accounting variables as a proxy. Furthermore, we also examine whether this varies over time, based on the proxies for funding and investor sentiments.

There have been several previous studies in recent years on the determinants of the diffusion of information and stock return predictability of the equity market. A growing body of studies has shown evidence that stock return forecasting tends to align itself with cross-asset return predictability. Due to the fact that information travels slowly, the information that originates from one asset reaches investors in other assets only after a lag, as confirmed by the findings of Lo and MacKinlay (1990) and Chan (1993). These studies showed that there is an information flow across and between firms with large market capitalization and those with small market capitalization. Prior researches revealed that larger firms' stocks lead and reflect information earlier than small firms' stocks do but interestingly not vice-versa.[1] This is also

[1] Several empirical researches followed, attempting to rationalize this finding on the diffusion of information (e.g., Brennan *et al.* (1993), Badrinath *et al.* (1995), Jegadeesh and Titman (1995), Chordia and Swaminathan (2000), Huberman and Regev (2001), Hou and Moskowitz (2005), Hirshleifer *et al.* (2009), Hou (2007), Cohen and Frazzini (2008), Loh (2008), Peress (2008), DellaVigna and Pollet (2009) and Menzly and Ozbas (2010).

true for specific industries or even for specific links within or across industries. For example, Cohen and Frazzini (2008), Shahrur *et al.* (2009) and Menzly and Ozbas (2010) showed evidence of cross-predictability on the slow diffusion of information along the supply chain, so much so that individual customer returns can predict future suppliers' returns. Rizova (2010) presented evidence that a two-country, Lucas-tree framework with gradual information diffusion can cause cross-country return predictability between one country and another trading-partner country.

Specifically, one of the most significant determinants of return predictability is financial and accounting information. Several studies have shown how the wide variety of accounting information and of firm characteristics contains information about firms' future stock returns (Bhattacharya *et al.* 2013). Likewise, Holthausen and Larcker (1992) and Lewellen (2004) provided evidence that, when using a large amount of accounting data in testing stock returns, forecasting is a useful indicator, which in turn leads to strong predictive power in stock return forecasting.

Inspired by all these researches, this study is motivated by cross-asset return predictability, namely, the predictive power of the determinants of single stocks to be able to predict the performance of other stocks in the equity market. We therefore employ a set of accounting data and firm characteristics to calculate the relative degree of limits to arbitrage and to examine the association between the information environment and cross-stock return predictability. Moreover, we also propose a methodology to examine the predictive power of this determinant for forecasting a given pair of stock returns. We investigate whether, and to what extent, the predictability of stocks is influenced by the determinants of the information environment and whether they vary over time, based on the proxies for funding and investor sentiments.

Most importantly, this study examines whether a single stock can produce a gradual diffusion of information across other stocks, thereby leading to cross-asset return predictability. This study is in fact the first to use seventeen publicly available accounting indicators as proxies to capture the relative degree of limits. This is achieved by employing four market-based variables, such as TED spread, market sentiment and market volatility, for testing the cross-asset return predictability and then assessing whether they vary over time. Using data from 1931 until 2016 from NYSE, AMEX and NASDAQ, we created a cartesian product to match the pairs of stocks' predictability and to estimate the stock pairs by using the Clustered Standard Errors to obtain unbiased standard errors of OLS coefficients under a specific kind of heteroscedasticity. We also control for time (year) and industry fixed effects. Our main results showed that 10 out of 17 of the selected accounting proxies, namely, abnormal accruals, earnings smoothness, book-to-market, firm age, leverage, abnormal capital investment, investment growth, return on equity, firm size and stock volatility, contain reliable and statistically significant information that is useful for predicting the cross-section stock pair returns and ascertaining the relative degree of the limits to arbitrage. The results also suggest that the market is slow to aggregate the information contained in a firm's connections. This is in line with recent theories about gradual information diffusion in asset markets. Further findings suggested that the level of the cross-asset return predictability power can be explained by the interaction of different characteristics across stock and funding liquidity proxies.

The novelty of this research lies in its contribution to the burgeoning accounting and financial literature on slow information diffusion in the equity market. We specifically provide an analysis of the variation in predictability across different pairs of stocks, based on several accounting variables in the US stock market, and how it contains information about future stock returns and determines the relative degree of limits to arbitrage. This paper specifically employs market stage variables to test whether their relation or predictability vary over time and thus provides a new approach for predicting stock returns but also enabling a more comprehensive understanding of return predictability at an individual stock level.

The rest of this study is organized as follows: the second section comprises an in-depth review of the related literature, while also highlighting the research gap and developing a hypothesis. Section 3 describes the data and methodology used in this research. Section 4 presents the empirical results and the analysis whilst the conclusions and implications are provided in Section 5.

2. Literature Review

2.1 The Limits of Arbitrage and Return Predictability

In an efficient equity market, it is generally believed that the capital market efficiently reflects all the available information about individual stocks while share prices fully reflect any new information on the market and are an accurate indicator of resource allocation. This further implies that prices are a reflection of the fundamental value of stocks, as claimed in the Efficient Markets Hypothesis (EMH). The EMH suggests that agents have a rational preference and comprehend Bayes' law while there is no real investment strategy for earning excess risk-adjusted average returns. Again, investors are able to select stocks that represent firms' performances, based on the assumption that their share prices fully reflect all the available information (Fama, 1970).

Nevertheless, one of the most significant questions associated with the degree of market efficiency concerns the limits of arbitrage. Arbitrage is a crucial part in terms of the analysis of stock markets since its effect is to transform the prices into fundamental values. Market anomalies are frequently seen as evidence against market efficiency. However, the existence of anomalies that are able to be profitable to trade nevertheless provides strong evidence of market efficiency. Arbitrage forces help to preserve market efficiency while anomalies do not affect arbitrage capital if they are not in fact profitably traded. Shleifer and Vishny (1997) provided an approach to understand anomalies by investigating arbitrage and its effectiveness in achieving market efficiency. They explained why practitioners of arbitrage might possibly be unsuccessful in closing the arbitrage opportunity. They indicated that specialized performance-based arbitrage may not be fully effective in turning stock prices into fundamental values, specifically in extreme circumstances. This is due to fund withdrawals by creditors and equity investors. Another point to consider is the agency problem in arbitrage organization, if the management is not confident about the potential of the subordinate investment. The management will then liquidate the position before the suspected uncertainty happens. In addition, professional arbitrageurs possibly deliberately avoid extremely volatile arbitrage positions that offer high returns. High volatility is perhaps related to greater mispricing due to loud-mouthed traders' sentiments. Such volatility reveals the probability of losses for arbitrageurs and the portfolio liquidation is then below investors' expectations. High volatility is therefore closely associated with less attractive opportunities for arbitrage.

The studies of Long *et al.* (1990) also show that noisy traders' risk in the financial market is an important determinant of arbitrageurs liquidating their position beforehand, causing them potentially sudden losses. They indicate that the unpredictability of irrational investors' perspectives leads to a reduction in attractiveness as far as arbitrage is concerned. Arbitrageurs trade against irrational investors in the market, and this is the cause of stock prices becoming closer to their fundamental values. Furthermore, in the process of trading, noise traders' judgements are sufficiently mistaken to affect the share price, thereby losing money to arbitrageurs and finally disappearing from the stock market. The main results show that arbitrage does not get rid of the effects of the noisy trader since noise itself generates risk.

Pontiff (1996) indicates that transaction costs, such as bid-ask spreads, brokerage fees and market impact costs, are important barriers to arbitrage. Transaction costs show essential cross-sectional variation, which decreases rational traders' ability to trade against any mispricing. To maintain equilibrium, arbitrage trades should earn the same net return, irrespective of transaction costs. For stocks with higher transaction costs, arbitrage constraint will occur with higher magnitudes of mispricing in equilibrium than for stocks with lower transaction costs.

Moreover, previous studies have been concerned with the link between mispricing and academic publications. For example, Jegadeesh and Titman (2001) revealed that the relationship between stock returns and high momentum stocks rose after the publication of their paper in 1993. Likewise, McLean and Pontiff (2016) provided evidence that certain stock market anomalies are in fact less anomalous after the publication of academic papers. They studied 97 anomalies and found a 26% out-of-sample decrease and a 58% post-publication reduction in anomalous returns. They also showed that long-short portfolio strategies, which are costlier (limited) for arbitrage, experience lower declines in returns after publication. This clearly shows that the relative degree of limits to arbitrage is an important focus for analysis in this context.

2.2 Delayed Information Processing

The finance literature includes a number of theoretical and empirical studies on the relevance of delayed information processing, which has been connected to information processing capacity factors (Callen *et al.* 2013). These factors include return reversals (Jegadeesh 1990), information diffusion (Hong *et al.* 2000), information asymmetry (Easley *et al.* 2002) and information transmission (Cohen and Lou 2012). All of these studies concluded that information frictions are important for understanding asset price dynamics and the slow price adjustment to new information.

According to Hirshleifer and Teoh (2003), delayed information reaction and the limited attention of investors are likely to result in the generation of expected returns. In a related paper Verrecchia (1980) and Callen *et al.* (2000) found that imperfections in information can potentially impede timely equity price discovery and thus delay any price changes in response to new information. In addition to this, there has also been considerable research into the relationship between geography and information acquisition. Coval and Moskowitz (1999) showed that the preference for geographically proximate investments can be explained by asymmetric information among regional and foreign investors. Moreover, it has also been shown in the literature that lead-lag patterns are able to serve as sources of profit for contrarian investors. For example, Hou (2007) concluded that the slow diffusion of industry information can be the main reason for the lead-lag relationship in stock returns. The results clearly indicate that the lead-lag effect in information between big and small firms is predominantly an intra-industry phenomenon. Thus, the stock returns of small firms follow the returns release of big firms within the same industry groups.

This phenomenon has not been recently extensively studied but previous studies have shown new information flows for cross-industry predictability. For example, Hong *et al.* (2007) documented that some specific industries tend to be representative of the whole equity market. Menzly and Ozbas (2010) demonstrated that information can be transferred between suppliers and customer-oriented industries. Furthermore, Cohen and Lou (2012) found evidence that there is an information flow from single-segment industry firms to multi-industry firms. Most recently, Hameed *et al*. (2015) examined intra-industry reversals in monthly returns. They showed that a strong reversal effect arises within the same industry due to reversions by companies that have diverged from their own industry peers rather than within the whole market. Specifically, intra-industry reversals are stronger following aggregate market declines and volatile times.

2.3 Return Predictability and Accounting-based Performance Measures.

There is a large and still growing sheaf of papers documenting how stock return predictability tends to be aligned with several firm characteristics. Green *et al.* (2013) conducted a vast search for "return predictive signals", based on accounting and finance literature, and found that more than 300 of them had been reported.

Several studies have extensively investigated from various aspects the predictive value of the information available in financial statements. For example, Holthausen and Larcker (1992) used a large amount of accounting data for testing returns predictability and showed that they are useful indicators for stock returns forecasting. Likewise, Lev and Thiagarajan (1993) showed that financial and accounting information is highly correlated with stock returns, after controlling for earnings innovations, firm size and macroeconomic conditions. Abarbanell and Bushee (1998) studied how the fundamental indicators, produced by accounting data, provide information for forecasting changes in future earnings in the US equity market. In a related paper, Nissim and Penman (2001) provided strong evidence of the benefit of accounting data for future streams of abnormal earnings predictability. Lewellen (2004) also showed that accounting ratios have a strong predicting power on stock returns.

Furthermore, a large amount of empirical research established theoretical links between accounting information and future returns predictability, such as the book-to-market ratio (e.g., Carlson *et al.* 2004; Zhang 2005), leverage (e.g, Garlappi and Yan 2011), the price-earnings ratio (e.g., Kogan and Papanikolaou 2013), size (e.g., Gomes *et al.* 2003; Carlson *et al.* 2004) and idiosyncratic volatility (e.g., Babenko *et al.* 2016). Prior literature showed that accounting data has a predictive value in the global equity markets. For example, Cheung *et al.* (1997) examined the association between the incremental utility of earnings-to-price, the book-to-price ratios and stock returns forecasting in the Hong Kong stock exchange. Martinez (1999) used a sample from the French stock market and investigated the relationship between financial ratios and the stock returns of 50 industries. He found that financial data are useful for stock returns prediction. Canbas *et al.* (2002) showed that financial statement information helped to enhance the quality of fundamental analysis for stock estimation in Turkey. Abekah (2005) also presented evidence of stock returns' predictability, using fundamental accounting variables in the Ghanaian equity market. Kheradyar *et al.* (2011) examined the relationship between accounting information and stock returns in the Malaysian Stock Exchange. Book-to-market value, dividend yield and earning yield were used in this research. The results clearly supported the argument that financial ratios are able to improve stock returns predictability in the stock market. More importantly, book-to-market values have a more predictive power than other variables. Furthermore, Emamgholipour *et al.* (2013) investigated the effects of performance evaluation market ratios on stock returns. Their analysis indicated that earnings per share are positively associated with stock returns while the price earnings ratio and the market-to-book value ratio are inversely related to stock returns.

In addition, the relevance of earnings quality is one of the predictive values for the financial position and performance, as provided by financial reporting. Dechow *et al.* (2010) postulated that "Higher earnings' quality provides more information about the future of a firm's financial performance and are relevant to a specific decision made by a specific decision-maker". Many studies have employed earnings quality proxies as an accounting signal of future returns, making it an ideal complement to value relevance. Previous studies on the predictability of earnings, including Penman and Zhang (2002), Francis *et al.* (2004) and Gaio (2010), used persistent earnings to explain the ability of given variables to forecast performance in an upcoming period. Their results showed that firms with higher earnings persistence are related to a more sustainable flow of earnings and are more predictable in capital valuation, due to their generating lower valuation errors.

Another important indicator of earnings quality is abnormal accruals. The accruals and the earnings quality are associated with transitory change in the operating cash flow, caused by management manipulation (Ball and Shivakumar 2005). Chan *et al.* (2006) found that the components of abnormal accruals, such as changes in current assets and liabilities, are associated with future stock returns. The existence of high accruals is likely to be of low earnings quality, as a less persistent component of earnings (Dechow *et al.,* 2010). Moreover, several empirical studies proposed that earnings smoothness is a crucial proxy for earnings quality, encouraging managers to smooth the intertemporal volatility of earnings informativeness (Biedleman 1973, Demski 1998 and Kirschenheiter and Melumad 2002). Tucker and Zarowin (2006) provided evidence that smoothing improves earnings informativeness, based on their study that divided firms into low- and high-smoothing groups. They defined the high-smoothing groups as firms that have a larger negative association between discretionary accruals and unmanaged earnings. The result showed that higher smoothing firms have greater earnings informativeness than those with lower smoothing.

2.4 Market Stage Variables

More recently, studies have assessed how market conditions could affect return predictability. Specifically, these studies have been focused on testing whether the cross-sectional predictability of returns varies over a given time.

One of the crucial financial market measures has been investment sentiment. Investor sentiment is mostly regarded as the general investors' perspective on estimated stock value that affects several fundamental and technical determinants in the exchange market. These include historical, financial and economic information, seasonal factors and national and world circumstances. A number of studies have argued that investment sentiment is a significant indicator of stock return predictability and monetary policy on stock exchanges[2]. More importantly, Baker and Wurgler (2006) studied how the effects of investment sentiment vary on a cross-section of stock returns over time. They estimate that investment sentiment has a stronger impact on stocks and determine which estimations are highly subjective and more

[2] (See, for example, Barberis *et al.* (1998), Wurgler and Zhuravaskaya (2002), Kurov (2010, 2012), Stambaugh *et al.* (2012), Lutz (2015) and Shen *et al.* (2017))

difficult to arbitrage. Their findings show 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. When sentiments are high, however, these patterns reverse. In addition, Schmeling (2009) investigated the impact of individual investor sentiment on expected stock returns in 18 industrialized countries. He provided evidence that sentiment negatively predicts aggregate stock exchange returns on average across countries. When sentiments are high, future stock returns are likely to be lower and conversely for small, value and growth stocks as well as stocks with different furcating horizons. Moreover, the findings showed that sentiment has a stronger impact on stock returns for countries which have a lower market integrity and are culturally more prone to herd-like behaviour, as argued by Chui *et al.* (2008).

In addition, studies have used a number of funding liquidity proxies to explain return predictability, such as TED spread and the market volatility index (VIX). Several financial market observers have been concerned about TED spread, which is the difference in yields between US Eurodollar deposits (effectively three-month USD LIBOR) and US Treasury-bills. TED spread represents the difference in yields between unsecured top-rated interbank and government credits. The IMF (2009) suggests that TED spread is an efficient market proxy for global systemic risk. A study by Lashgari (2000) showed a negative relationship between TED spread and investor confidence. He postulated that TED spread appears to decrease (increase) during periods of high (low) level of investor confidence.

Many empirical researches have provided evidence that TED spread has been employed as an information variable to examine asset returns predictability in the financial markets. Ferson (1989) and Breen *et al*. (1989) presented evidence on the topic of the predicting ability of US Treasury bills in forecasting the performance of the stock exchange. Tse and Booth (1996) found that TED spread changes appear to be a source of volatility for stock prices. Kawaller (1997) suggested that TED spread reflects information about interest rates in the future. That is, when the level of TED spread narrows, the interest rate possibly declines. This can be explained by the fact that a falling TED spread may result in improvements in the value of equity and fixed-income. Likewise, Lashgari (2000) examined the relationship between the rate of return on the S&P 500 index and changes in TED spread. His result is a negative significant coefficient, by means of which the narrowing in TED spread is related to the decreasing interest rate, bringing about increasing stock prices and vice-versa. Bianchi and Drew (2010) employed TED spread as a proxy for systematic risk to predict hedge fund returns.

They found that increases in TED spread lead to hedge fund managers reducing their exposure to any risk factor momentum.

The market volatility index (VIX) is also generally used as a financial indicator of investor fear. The movements of the VIX reflect stock exchange reactions. That is, when the VIX increases, stock prices are falling and investors are fearful. Conversely, the VIX declines when stock prices are increasing. The movement of the index is normally more than that of the stocks. In addition, the VIX has been used as a means for providing profits or protection for investors' investments. Prior studies have suggested that the VIX captures the implied volatility of the stock index and that there is a negative association between the VIX and the S&P 500 index. Previous studies have also provided evidence that implied volatilities are able to forecast future stocks and hedge fund returns. Avramov *et al.* (2012) investigated the variation in hedge fund returns across the movements of macro-variables. They used the VIX index to indicate changes in market uncertainty and showed that 25% of funds have a significant deviational decrease in the VIX results with an additional investment return of over 6.6% per year.

Nonetheless, most previous studies have focused on cross-industry return predictability within the same industries. In contrast, this study is motivated by cross-asset return predictability and is designed particularly to assess whether single assets (stock) are able to predict the performance of other stocks in the equity market. This paper examines the predictability of pairs of stocks, using several accounting variables as proxies to capture the relative degree of limits to arbitrage. We also introduce market stage variables to test whether their relation or predictability vary over time and thus provide a new approach for predicting stock returns while providing an inclusive understanding into return predictability at the individual stock level.

3. Data and Descriptive Statistics

3.1 Data

The sample consists of all the listed companies on NYSE, AMEX and NASDAQ and covers an 86-year period from January 1931 to December 2016, guided purely by the availability of data. Moreover, the data and the defined variables were collected from various standard and acceptable sources, consistent with the literature. Daily and monthly data, such as stock returns, market capitalization, SIC code and number of shares outstanding, were sourced from the Center for Research in Security Prices (CRSP) while annual and quarterly accounting data were sourced from the Compustat Fundamentals annual files. We employed market stage variables to test whether the cross-sectional return predictability varies over time from several sources[3], such as the average percentage of TED from the Federal Reserve Bank of St. Louis, and investment sentiment data from Jeffrey Wurgler's website. The University of Michigan Consumer Sentiment Index was sourced from the University of Michigan's website while the Volatility Index was sourced from the Global Financial Data's website.

We obtained Fama and French (1993)'s three factors from Kenneth French's website[4] and considered only common stocks (with a CRSP share code of 10 or 11). For data cleaning purposes, financial institutions and banks (with a one-digit SIC code of 6) and non-classifiable (with an SIC code of 9999) were excluded from the sample because of their peculiar accounting practices. Firms under this classification have accounting practices/policies that are significantly different from firms in other classifications/industries. We randomly selected 500 stocks that had been engaged in trading activity for 10 years to form an average market value decile rank (50 stocks in each decile). We removed observations with negative book-to-equity values and winsorized the extreme observations to one percentile to mitigate the influence of outliers. The requirement of a December fiscal year-end was adopted to support the accounting data across firms. This was because the majority of the sample firms have a December year-end, making the selection an unbiased representation of the sample (Vuolteenaho 2002). We matched data from Compustat for the fiscal year ending in year $t-1$ with CRSP from July of year t to June of year $t+1$.

3.2 Measuring Variables and Rationale.

We employed seventeen accounting variables as proxies to capture the relative degree of limits to arbitrage. Following Light *et al.* (2017), the selection of proxies was based on a consideration of key proxies that are related to prominent asset pricing anomalies. The variables were classified into four groups. The first group contained earnings quality proxies, such as earnings persistence (*EP*), abnormal accruals (*AA*) and earnings smoothness (*ES*). The second group contained firm characteristics, such as book-to-market ratio (*BTM*), cash flow-to-price ratio (*CP*), firm age (*AGE*) and leverage (*LEV*). The third group included growth- and profit-related characteristics, such as total asset growth (*AG*), abnormal capital investments (*CI*), investment-

[3] TED Spread from https://fred.stlouisfed.org/series/TEDRATE, the Sentiment Index from http://people.stern.nyu.edu/jwurgler/, the Index of Consumer Sentiment (University of Michigan) from https://data.sca.isr.umich.edu/data-archive/mine.php and the Volatility Index from https://www.globalfinancialdata.com/.

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

to-assets ratio (*IA*), investment growth (*IG*), investment-to-capital ratio (*IK*) and net operating assets (*NOA*), returns on assets (*ROA*) and returns on equity (*ROE*). The fourth group included stock return volatility (*VOL*) and firm size (*SIZE*), which are market-based variables. These are consistent with the existing literature that shows that these are significant in predicting stock market returns in a cross-sectional setting (Light *et al.* 2017). The accounting proxies were annual data. In addition, we employed four market stage variables to explain whether cross-stock predictability varies over time, namely, TED spread (*TED*), market sentiment (*SENT* and *SENT_6*), consumer sentiment (*ICS*) and volatility index (*VIX*). The definitions of and rationale for each variable are described in Table A1 (See Appendix 1). Table 1 shows the description, predicted sign, sample period and sample frequency of the variables.

Table 1 Variables Description

Variables	Description	Predicted Sign	Sample Period	Sample Frequency
EP	Earnings persistence	(+)	1984-2016	Annual
AA	Abnormal accruals	(-)	1983-2016	Annual
ES	Earnings Smoothness	(+)	1989-2016	Annual
BTM	Book-to-market ratio	(-)	1980-2016	Annual
CP	Cash flow-to-price ratio	(+)	1980-2016	Annual
AGE	Firm age	(+)	1980-2016	Annual
LEV	Leverage	(+)	1980-2016	Annual
AG	Total asset growth	(-)	1982-2016	Annual
CI	Abnormal capital investments	(-)	1984-2016	Annual
IA	Investment-to-assets ratio	(-)	1982-2016	Annual
IG	Investment growth	(-)	1981-2016	Annual
IK	Investment-to-capital ratio	(-)	1980-2016	Annual
NOA	Net operating assets	(+)	1981-2016	Annual
ROA	Return on assets	(+)	1981-2016	Annual
ROE	Return on equity	(+)	1980-2016	Annual
SIZE	Firm size	(+)	1931-2016	Annual
VOL	Stock return volatility	(-)	1931-2016	Annual
TED	TED spread	(-)	1986-2016	Annual
SENT	Sentiment index	(-)	1965-2015	Annual
SENT_6	Sentiment index	(-)	1965-2015	Annual
ICS	Index of consumer sentiment	(-)	1980-2016	Annual
VIX	Volatility index	(-)	1986-2016	Annual

3.3 Descriptive Statistics

Table 2 presents the descriptive statistics of the accounting determinants by individual stock. All earnings quality attributes, firm characteristics and market-based variables are positively skewed as the mean is higher than the median and shows a wide variation among firms. Some growth- and profit-related characteristic variables are negatively skewed, such as *IA*, *NOA* and *ROA*. However, *IA* is right-skewed but the mean is right of the median under the right skew because one tail is long but the other is heavy. The standard deviation of the determinants ranges from 0.026% for VOL to 8.364% for AGE.

Table 2 Descriptive statistics of the accounting determinants by individual stock.

Variable	N	Minimum	Median	Maximum	Mean	Std.	Skewness	Kurtosis
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
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
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
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

Note:
This table presents the descriptive statistics for the accounting variables employed in this study. The sample covers an 86-year period from January 1931 to December 2016. The sample period of each variable is guided purely by the availability of data. The accounting variables reported are obtained from COMPUSTAT and CRSP and as follows: *EP*: Earnings persistence; *AA*: Abnormal accruals; *ES*: Earnings smoothness; *BTM*: Book-to-market ratio; *CP*: Cash flow-to-price ratio; *AGE*: Firm age; *LEV*: Leverage; *AG*: Total asset growth; *CI*: capital investments; *IA*: Investment-to-assets ratio; *IG*: Investment growth; *IK*: Investment-to-capital ratio; *NOA*: Net operating assets; *ROA*: Return on assets; *ROE*: Return on equity; *SIZE*: Firm size; *VOL*: Stock return volatility. The definitions and rationale of each variable are described in Table A1 (See Appendix 1).

Table 3 shows a Pearson correlation matrix of variables. The results reveal that most firm characteristics' determinants are positively related to *EP* whereas they are negatively related to *AA*. For example, *AGE* has a positive correlation with *EP* (ρ*AGE*, *EP* = 0.01) while this is inversely related to *AA* (ρ*AGE*, *AA* = -0.03). This means firms that are of an older age tend to have higher earnings quality. Moreover, there is a positive correlation between firm age and *NOA*, *ROA* and *SIZE* (ρ*AGE*, *NOA* = 0.08, ρ*AGE*, *ROA* = 0.12 and ρ*AGE*, *SIZE* 0.41). This can be explained by the fact that older firms are associated with having a higher ability to generate earnings from investments and also tend to be bigger firms. Apart from that, *SIZE* is positively related to *ROA* and *ROE* (ρ*SIZE*, *ROA* = 0.27 and ρ*SIZE*, *ROE* = 0.15) but this is contrarily related to *AA*, *BTM* and *VOL* (ρ*SIZE*, *AA* = -0.17, ρ*SIZE*, *BTM* = -0.32 and ρ*SIZE*, *VOL* = -0.37). This is consistent with previous findings by Nagel (2004). Additionally, we calculated the Spearman correlations between variables. The results are reported in Table A4 (See Appendix 2). The results are consistent with the Pearson correlation results.

Table 3 Pearson correlations between variables

Variable	*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

Note:
This table presents a Pearson correlation matrix of the variables employed in this study. The sample covers an 86-year period from January 1931 to December 2016. The sample period of each variable is guided purely by the availability of data. The accounting variables reported are obtained from COMPUSTAT and CRSP and as follows: *EP*: Earnings persistence; *AA*: Abnormal accruals; *ES*: Earnings smoothness; *BTM*: Book-to-market ratio; *CP*: Cash flow-to-price ratio; *AGE*: Firm age; *LEV*: Leverage; *AG*: Total asset growth; *CI*: capital investments; *IA*: Investment-to-assets ratio; *IG*: Investment growth; *IK*: Investment-to-capital ratio; *NOA*: Net operating assets; *ROA*: Return on assets; *ROE*: Return on equity; *SIZE*: Firm size; *VOL*: Stock return volatility. The definitions and rationale of each variable are described in Table A1 (See Appendix 1).

4. Methodology

In order to examine whether cross-asset return predictability, particularly that of single asset (stock), is able to predict the performance of other stocks, we created a cartesian product to match the predictability of pairs of stocks from 500 randomly selected stocks. The pairs of stocks had been subject to at least a 24-month observation. Seventeen accounting variables were adopted as proxies to capture the relative degree of limits to arbitrage. In addition, four market stage variables were employed to examine whether their predictability varies over time. We calculated independent variables, which were the level of difference in determinants between firms *j* and *i* and scaled with the mean value of firm *j* and *i* because of small coefficients. The OLS regression was estimated by using the Clustered Standard Errors to obtain unbiased standard errors of OLS coefficients under a specific kind of heteroscedasticity. We also controlled for time (year) and industry fixed effects by using the first digit SIC code for all regression models. The model estimations were as follows:

$$Sig = \alpha + \beta_1 DIFF_{j,i} + \beta_2 Year + \beta_3 Industry + \varepsilon_t \quad (1)$$

We also estimated another model to test how much lag1 can predict the performance of other firms based on the difference in the R^2, which is higher different R^2 is higher return predictability as follows:

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

We employed the interaction terms of four well-known market variables, including TED spread, investor sentiment, the Index of Consumer Sentiment and the Volatility Index, to examine whether the cross-sectional predictability varies over time as follows:

$$Sig = \alpha + \beta_1 DIFF_{j,i} + \beta_2 variable + \beta_3 DIFF_{j,i} * variable + \beta_4 Year + \beta_5 Industry + \varepsilon_t \quad (3)$$

$$(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \beta_2 variable + \beta_3 DIFF_{j,i} * variable + \beta_4 Year + \beta_5 Industry + \varepsilon_t \quad (4)$$

The dependent variable in equations (1) and (3), *Sig* is a dummy variable that takes of 1, where 1= positive significance at 0.05 level and 0 =otherwise of the 5-year rolling window regression results as follows:

$$R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t \quad (5)$$

The dependent variable in equations (2) and (4), $(R^2{}_1 - R^2{}_0) / R^2{}_0$ is a proxy for change in the difference in R^2

where $R^2{}_1$ is R^2 of the 5-year rolling window regression:

$$R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t \quad (6)$$

$R^2{}_0$ is R^2 of the 5-year rolling window regression:

$$R_{i,t} = \alpha + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t \quad (7)$$

where $R_{i,t}$ is monthly returns in month t for stock i; $R_{j,t-1}$ is monthly returns in month $t-1$ for stock j; $R_{i,t-1}$ is monthly returns 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 from Kenneth French's website; and ε_t is the regression residual. We also use the dependent variable, $(R^2{}_1 - R^2{}_0)$ is the difference in R^2 as a robustness test for equations (2) and (4).

The independent variables are the differences in determinants between firms j and i including 17 accounting variables scaled with the mean value of firms j and i $(DIFF_{j,i})$ and the 5 market variables (*variable)* in Table 1. For the accounting variables, which have a negative predicted sign, we multiply the value by -1 before calculating Diff j, i. We therefore expect all accounting variables in the regression results will have a positive expected correlation, which means every variable predicts positive and increases the prediction (coefficient and t-value are positive). The dummy variables are year (*Year*) and industry (*Industry*) fixed effects. Apart from that, we use logit and probit regressions as a robustness test for equations (1) and (3).

5. Empirical Results

The main objective in this section is to explain the findings we arrived at through the regression analysis. In order to examine whether single stocks are able to predict the performance of other stocks, as first posited in Section 2 of this study, we conducted a test of the predictability of pairs of stocks, using several accounting variables as proxies to capture the relative degree of limits to arbitrage. The basic idea is a lead-lag effect across firms, since several factors that cause information to be transmitted slowly also differ substantially at the individual firm level. Stock reflects the information at different speeds. As a result, some stocks reflect information faster than other stocks. We were therefore particularly interested in investigating how the significance of the cross-stock lead-lag effect related to the firm values of the set of accounting variables that affect the speed of returns prediction at the firm level.

We first examined whether stock returns were able to predict the performance of other stocks. We began with the estimation of the significance of pairwise across-firm returns' predictability using the Fama-French three-factor model (Fama and French 1993) in equation 5. Then, we obtained the significant result as a dependent variable (*Sig*) in Equation (1) to examine whether the difference in the source of variables increased the likelihood of predictability. Second, we also estimated another model using R^2 difference (R^2_1 - R^2_0 / R^2_0) in equations 6 and 7, which represent the degree of predictive power as a dependent variable in equation 2 to show that the difference in the source of variables increases the power of predictability. The independent variables are the differences in determinants between firms *j* and *i* including 17 accounting variables *(DIFF $_{j,\ i}$)*. We estimated the OLS regression of Equations (1) and (2) by using Clustered Standard Errors to obtain unbiased standard errors of OLS coefficients under a specific kind of heteroscedasticity. Finally, we included dummy variables, namely, year (*Year*) and industry (*Industry*) fixed effects, to control for year and industry specific impact. We expected all accounting variables in the regression results to predict positive and to increase the prediction across stocks (coefficient and *t*-value are positive).

The main results concerning the determinants of cross-stock returns predictability, as reported in Table 4, can be summarized as follows. First, we considered whether the difference in the source of the accounting variables increased the likelihood of predictability. The dependent variable in Column (1) is *Sig*. The determinants that have significant coefficients in this column are denoted by asterisks. We found that there are 6 out of 17 accounting variables, including abnormal accruals (*AA*), book-to-market ratio (*BTM*), firm age (*AGE*), return on equity

(*ROE*),firm size (*SIZE*) and stock return volatility (*VOL*) that have *t*- statistics of the corresponding $DIFF_{j,\,i}$ that are higher than 2.58 in absolute value (or significant at the 1% level). Five additional variables, earnings smoothness (*ES*), investment growth (*IG*), net operating assets (*NOA*), leverage (*LEV*) and capital investments (*CI*) have *t*-statistics of 2.40, 2.24, 2.23, 1.66 and 1.89. Thus, at the 5% and 10% levels of significance respectively (or with *t*-statistics higher than 1.96 and 1.65). There is a total of 11 accounting variables that contain valuable information about cross-stock returns' predictability. They show a significant capability to predict across firm's returns predictability and capture the relative degree of limits to arbitrage.

The signs from the predictability coefficients for these 11 accounting variables also seem to make economic sense. For example, differences in abnormal accruals (*AA*) and earnings smoothness (*ES*) predict cross-firm returns with coefficients of 0.292 and 0.105 and *t*-statistics of 5.96 and 2.40 respectively. This means that a standard deviation, increasing the differences in *AA* and *ES* between firms *j* and *i,* increases the likelihood that firm *j* is able to predict firm *i* by 0.297% (0.292*1.016) and 0.101% (0.105*0.965) respectively. This could be the explanation why when firm *j*'s information environment is of a higher (lower) quality compared to the predicted firm (firm *i*), then there is higher (lower) probability that firm *j* is able to predict firm *i*. This is in line with the research findings of Francis *et al.* (2004) and Dechow *et al.* (2010) that found that firms with higher earnings quality generally provide more information about the future of their financial performance and are also more predictable in their capital valuation. To test the robustness of these results, we employed logistic regression. The results are reported in Table A9 (See Appendix 2). We found that the logit and probit model produces the same results. The 11 accounting determinants that are significant in Column (1) of Table 4 show strong statistical significance at the 1% level, once logistic regression is undertaken.

However, two variables, namely, earnings persistence (*EP*) and cash flow-to-price ratio (*CP*), show a significant negative across stocks' return prediction with a coefficient of -0.005 and -0.186 and *t*-statistics of -1.96 and -3.84 respectively. These results are not in line with the hypothesis that when firm *j*'s earnings persistence and cash flow-to-price ratio is higher (lower) than firm *i*'s, there is higher (lower) probability that firm *j* is able to predict firm *i*'s performance.

Second, in Column (2) of Table 4, we consider whether the difference in the source of variables increases the predictability and explanatory power based on the R^2 difference. The dependent variable is the change in the difference in R^2. The results show that the coefficients of difference in the source of variables between firms *j* and *i* ($DIFF_{j,i}$) are statistically significant at the 1 % level for 8 accounting variables, including *AA*, *BTM*, *AGE*, *IA*, *IG, IK*, *ROE*, *SIZE* and *VOL*. Three additional variables, *ES*, *LEV* and *IK* are statistically significant at 5% level and at the 10% for 1 variable, which is *CI*. However, of the 11 variables that are significant in Column (1), only *NOA* is no longer statistically significant. The coefficients of $DIFF_{j,i}$ for these 11 accounting variables are a positive correlation, which neatly confirms the power of prediction across stocks. For example, $DIFF_{j,i}$ in *SIZE* enters with a coefficient of 15.27 and *t*-statistics of 85.28. This means that a standard deviation enlargement in the difference in *SIZE* between firm *j* and firm *i* would increase the ability of prediction so that firm *j* can predict the performance of firm *i*. In other words, the result indicates that, when firm *j*'s size is bigger (smaller) compared to firm *i,* it would increase (decrease) the power of prediction that firm *j* is able to wield over firm *i*. This finding supports the studies of Lo and MacKinlay (1990), Drakos *et al*. (2015) and Hou (2007) that there is a lead-lag relationship in information between large and small firms in stock markets. The larger capitalization portfolio stock returns lead whereas the smaller ones mostly merely follow. Interestingly, the findings emphasize that 10 accounting variables from four groups, including *AA*, *ES*, *BTM*, *AGE*, *LEV*, *CI*, *IG*, *ROE*, *SIZE* and *VOL,* are strong predictors of returns across firms, not only increasing the probability of predictability in Column (1) but also increasing the power of cross-stock returns' prediction in Column (2). The results also suggest that the market is slow to aggregate the information contained in firm connections. This is in line with recent theories of gradual information diffusion in asset markets.

Table 4
The determinants of return predictability

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

Note:
This table reports the determinants of return predictability using the following models:
$Sig = \alpha + \beta_1 DIFF_{j,i} + \beta_2 Year + \beta_3 Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
$(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \beta_2 Year + \beta_3 Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
The explanatory variable is the difference in determinants between firms *j* and *i* $(DIFF_{j,i})$. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (See Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

The previous table demonstrated the potential for accounting variables in relation to cross-firm predictability and its predictor variables according to the degree of the limits to arbitrage. Moreover, we also introduced the interaction terms of four well-known market variables that had been previous studied in the literature; these included TED spread (*TED*), investor sentiment (*SENT* and *SENT_6*), the Index of Consumer Sentiment (*ICS*) and the Volatility Index (*VIX*). The goal was to examine whether the predictability of stocks is influenced by the determinants of the information environment and vary across time, based on the proxies for funding and investor sentiments. We estimated the OLS regression specified in Equations (3) and (4) by using Clustered Standard Errors and control for year and industry fixed effects. We estimated Equations (3) and (4) jointly across firms and present the regression results in Table 5-8.

First, we introduced TED spread as an information variable to examine whether cross-stock predictability varies over time, based on the TED spread, or not. According to Guta and Subrahmanyam (2000) and Campbell and Taksler (2003), the TED spread is an extensively used measure of funding liquidity in the market. We therefore included the interaction term of *TED* and $DIFF_{j,\,i}$ to investigate the relationship between money in the market and stock predictability. In Panel A of Table 5, the dependent variable is *Sig*. The results provide statistical evidence that the coefficients on the interaction term for 4 variables are positive and significant. *LEV* and *IK* are statistically significant at the 1% level and *ROA* and *CP* are significant at the 5% and the 10% levels, which suggests 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 6 accounting variables, namely, *ES*, *BTM, IG, SIZE* and *VOL,* are negative and highly significant at the 1% level and *AG* is significant at the 10% level, 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 5, the dependent variable is change in the difference in R^2. This allows the predictive power of accounting information to vary across different pairs of stocks with TED spread. The results show a positive relation between *TED* and the power of cross-firm predictability, based on accounting variables, including *AA*, *LEV*, *IK*, *NOA*, *SIZE* and *VOL*. The coefficients on interaction terms are positive and statistically significant at the 1% level. The results show that an increase in TED spread can cause an increased power of predictability so that firm *j* is able to predict the performance of firm *i*. In contrast to this, *BTM* and *ROA* show a negative coefficient on the interaction term and are significant at the 1% level, suggesting that an increase in TED spread brings about a decrease in the power of predictability by *BTM* and *ROA*.

More importantly, from the results it can be clearly seen that there is strong predictability across pairs of stocks for 3 accounting determinants, namely, *BTM*, *LEV* and *IK,* varying across time with the TED spread. As shown in Table 5, Panels A and B, the coefficient on the interaction term between *TED* and the difference in *BTM* between firms $_{j,}$and $_{i}$ are negative and highly significant, which suggests that when the TED spread rises (drops), the probability and power predictability across the stock decreases (increases). Meanwhile, a positive coefficient estimate for the interaction term of *TED* and the difference in *LEV* and *IK* between firms $_{j,}$and $_{i}$ would suggest that when the TED spread rises (drops), the cross-stock prediction increases (decreases). This finding is consistent with the study of Pontiff (1996) that showed that increasing (decreasing) TED spread results in the cost of funding will be higher (lower), which will then decrease (increase) informed investors' ability to trade against such mispricing. The limits to arbitrage will occur higher (lower), which leads to increasing (decreasing) predictability.

Table 5
The determinants of return predictability
Panel A:

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

Note:
This table reports the determinants of return predictability using the following models:
Panel A: $Sig = \alpha + \beta_1 DIFF_{j,i} + \beta_2 TED + \beta_3 DIFF_{j,i} * TED + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
Panel B: $(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \beta_2 TED + \beta_3 DIFF_{j,i} * TED + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
The explanatory variables are the differences in determinants between firms *j* and *i* $(DIFF_{j,i})$ and the average percentage of TED Spread *(TED)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (See Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Table 5 (Continuous)
The determinants of return predictability
Panel B:

Variables	$DIFF_{j,i}$	*TED*	$DIFF_{j,i}$ * *TED*	R^2	N
	-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
	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
	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
	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

Note:
This table reports the determinants of return predictability using the following models:
Panel A: $Sig = \alpha + \beta_1 DIFF_{j,i} + \beta_2 TED + \beta_3 DIFF_{j,i} * TED + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
Panel B: $(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \beta_2 TED + \beta_3 DIFF_{j,i} * TED + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
The explanatory variables are the differences in determinants between firms *j* and *i* $(DIFF_{j,i})$ and the average percentage of TED Spread *(TED)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (See Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Another important market-based measure is market sentiment. Baker and Wurgler (2006) found evidence that investment sentiment has a stronger impact on stocks, for which estimations are highly subjective and more difficult to arbitrage. To examine the effects of investment sentiment on a cross-section of stock returns that vary over time, we employed investor sentiment (*SENT* and *SENT_6*) and the Index of Consumer Sentiment (*ICS*) as information variables to examine whether cross-stock predictability actually does vary over time or not. As can be seen from both Panels A and B in Table 6, the results provide statistical evidence that the coefficients on the interaction term for both market-based variables, namely, *SIZE* and *VOL,* are negative and strongly significant at the 1% level, which suggests that an increase in *SENT* leads to a decrease in the probability and power of cross-firm return predictability and vice-versa. In contrast to this, the coefficients on the interaction terms of *ROA* are positive and significant, indicating that an increase in *SENT* results in the likelihood and power of prediction being enhanced. We also adopted *SENT_6*[5] as a robustness test for investor sentiment. The results of this robustness check are presented in Table A8 and demonstrate consistency with *SENT*. In addition, we found that *ICS* produces statistical evidence, which is in line with the results of *SENT* and *SENT_6*. Panels A and B in Table 7 show a negative relation of interaction terms between *ICS* and *SIZE* and *VO*L with statistical significance at 1%. The results show that an increase in *ICS* can cause a reduction in the explanatory power that firm *j* is able to predict firm *i*'s by *SIZE* and *VO*L.

All of these findings in Tables 6 and 7 present a consistent prediction that there is strong cross-stock returns predictability for *SIZE* and *VOL,* varying over time with market sentiment. It could be the explanation for, when the market sentiment decreases (is more bearish), informed investors move their funds out of the stock market. The limits to arbitrage will occur higher, which leads increasing probability and power predictability across stock. Meanwhile, these patterns can completely reverse. That is when the market sentiment increases (is more bullish) as investors enthusiastically participate in the hope of earning a profit. The limits to arbitrage will occur lower, which can cause a reduction in the capability of cross-stock returns prediction by *SIZE* and *VOL*.

[5] The Sentiment Index in Baker and Wurgler (2006); 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 with respect to a set of six macroeconomic factors from http://people.stern.nyu.edu/jwurgler/.

Table 6
The determinants of return predictability
Panel A:

Variables	$DIFF_{j,i}$	$SENT$	$DIFF_{j,i}$ * $SENT$	R^2	N
	-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
	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
	-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
	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

Note:
This table reports the determinants of return predictability, using the following models:
Panel A: $Sig = \alpha + \beta_1 DIFF_{j,i} + \beta_2 SENT + \beta_3 DIFF_{j,i} * SENT + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
Panel B: $(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \beta_2 SENT + \beta_3 DIFF_{j,i} * SENT + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
The explanatory variables are the differences in determinants between firms *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)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (See Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Table 6 (Continued)
The determinants of return predictability
Panel B:

Variables	*DIFF $_{j,i}$*	*SENT*	*DIFF $_{j,i}$ * SENT*	R^2	N
	-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
	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
	-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
	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

Note:
This table reports the determinants of return predictability using the following models:
Panel A: $Sig = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, SENT + \beta_3\, DIFF_{j,i} * SENT + \beta_4\, Year + \beta_5\, Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
Panel B: $(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, SENT + \beta_3\, DIFF_{j,i} * SENT + \beta_4\, Year + \beta_5\, Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
The explanatory variables are the differences in determinants between firms *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)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (See Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Table 7
The determinants of return predictability
Panel A:

Variables	$DIFF_{j,i}$	ICS	$DIFF_{j,i} * ICS$	R^2	N
	-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
	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
	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
	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

Note:
This table reports the determinants of return predictability, using the following models:
Panel A: $Sig = \alpha + \beta_1 DIFF_{j,i} + \beta_2 ICS + \beta_3 DIFF_{j,i} * ICS + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
Panel B: $(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \beta_2 ICS + \beta_3 DIFF_{j,i} * ICS + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
The explanatory variables are the differences in determinants between firms *j* and *i* $(DIFF_{j,i})$ and the Index of Consumer Sentiment *(ICS)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (See Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Table 7 (Continued)
The determinants of return predictability
Panel B:

Variables	$DIFF_{j,i}$	ICS	$DIFF_{j,i} * ICS$	R^2	N
	-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
	-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
	-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
	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

Note:
This table reports the determinants of return predictability, using the following models:
Panel A: $Sig = \alpha + \beta_1 DIFF_{j,i} + \beta_2 ICS + \beta_3 DIFF_{j,i} * ICS + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
Panel B: $(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \beta_2 ICS + \beta_3 DIFF_{j,i} * ICS + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
The explanatory variables are the differences in determinants between firms *j* and *i* $(DIFF_{j,i})$ and the Index of Consumer Sentiment *(ICS)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (See Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

In addition to this, the last measure of market-based funding liquidity is the market volatility index (*VIX*). The VIX index helps to captures the implied volatility of the stock market. We employed the market volatility index to examine whether the predictability across different pairs of stocks varied over time, based on changes in the market uncertainty or not. Table 8 shows that the coefficient on the interaction of $DIFF_{j,i}$ * *VIX* can be interpreted as the likelihood and power of predictability between the difference in determinants between firms $_{j,}$and $_{i}$ and *VIX*. The results in both Panels A and B of Table 8 present statistical evidence that a positive coefficient estimate for the interaction term of *VIX* and the difference in *LEV* between firms $_{j,}$and $_{i}$ would suggest that when the *VIX* rises (drops), the cross-stock prediction by *LEV* increases (decreases). Meanwhile, the coefficients on the interaction term for *ES* and *SIZE* are negative and statistically significant at the 1% level, which suggests that an increase in *VIX* leads to a decrease in the likelihood and power of cross-firm return predictability by *ES* and *SIZE* and vice-versa. These findings support the study of Shleifer and Vishny (1997) that showed that, when the level of market volatility increases (decrease) related to greater mispricing due to noise traders' sentiments, it leads to higher (lower) probability of losses for arbitrageurs and the need for portfolio liquidation under investors' expectations. This is therefore associated with less (more) attractive opportunities for arbitrage. The limits to arbitrage will occur higher (lower), leading to increasing (decreasing) predictability.

We also explored two additional robustness checks of the test in Tables 4-8 to address other potential stories. First, we employed the dependent variable, the difference in R^2 (R^2_1 - R^2_0), as a robustness test for equations (2) and (4). However, the independent variables were the same as those used in Tables 4-8. The OLS regression with robustness check results is reported in Tables A5-A10 (See Appendix 2). The results are consistent with the main outcome. Second, for a robustness check for equations (1) and (3), the logit and probit regressions were also used. The logistic results are presented in Tables A11-A16 (See Appendix 2). They produced quite similar results.

Table 8
The determinants of return predictability
Panel A:

Variables	*DIFF j,i*	*VIX*	*DIFF j,i * VIX*	R^2	N
	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
	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
	-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
	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

Note:
This table reports the determinants of return predictability using the following models:
Panel A: $Sig = \alpha + \beta_1 DIFF_{j,i} + \beta_2 VIX + \beta_3 DIFF_{j,i} * VIX + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
Panel B: $(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \beta_2 VIX + \beta_3 DIFF_{j,i} * VIX + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
The explanatory variables are the differences in determinants between firms *j* and *i* $(DIFF_{j,i})$ and the Volatility Index *(VIX)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (See Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Table 8 (Continued)
The determinants of return predictability
Panel B:

Variables	***DIFF*** $_{j,i}$	***VIX***	***DIFF*** $_{j,i}$ *** * VIX***	R^2	***N***
	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
	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
	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
	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

Note:
This table reports the determinants of return predictability, using the following models:
Panel A: $Sig = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, VIX + \beta_3\, DIFF_{j,i} * VIX + \beta_4\, Year + \beta_5\, Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_1\, R_{j,t-1} + \beta_2\, R_{i,t-1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t$.
Panel B: $(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, VIX + \beta_3\, DIFF_{j,i} * VIX + \beta_4\, Year + \beta_5\, Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1\, R_{j,t-1} + \beta_2\, R_{i,t-1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1\, R_{i,t-1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t$.
The explanatory variables are the differences in determinants between firms *j* and *i* $(DIFF_{j,i})$ and the Volatility Index *(VIX)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (See Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

In summary, it can be clearly seen that cross-stock prediction is influenced by the determinants of accounting information. Ten out of seventeen accounting variables are strong predictors of returns across firms. This shows that differences in the source of variables increase the probability and power of cross-stock returns predictability. Interestingly, we also found that the predictability varies over time due to the funding of liquidity and market sentiment. For example, *BTM*, *LEV* and *IK* vary across time with the TED spread. *SIZE* and *VOL* vary over time with market sentiment while *ES*, *LEV* and *SIZE vary* throughout time with the VIX index. However, we did find strong evidence of predictability by using earnings quality and growth-related characteristics variables, both of which proved to be powerful predictors. Our findings showed that *AA*, *CI*, *IG* and *ROE* contain information about future stock returns across pairs of stocks and do not vary across time.

6. Conclusion

We examined the variation in predictability across different pairs of stocks depending on the relative degree of limits to arbitrage between the stocks. We also examined how cross-stock returns predictability varies over time, based on the proxies for funding liquidity and investor sentiments. This study proposes a methodology derived from a set of accounting data that enabled predictive power, namely, the forecasting of the performance of a given pair of stock returns. Our findings seem most consistent with the theories of gradual information diffusion, which suggest that a single stock has the ability to gradually diffuse information across other stocks. We found that ten out of seventeen accounting variables are strong predictors of returns across firms. This shows how the difference in the source of accounting determinants increases not only the likelihood but also the power of cross-stock returns predictability. Moreover, we also found that the predictability varies over time due to the funding of liquidity and market sentiment. These findings support the studies of Pontiff (1996) and Shleifer and Vishny (1997) that when the cost of funding and market volatility are higher, informed investors' ability to trade against mispricing is decreased; a similar situation develops with mispricing that is due to noise traders' sentiments. The limits to arbitrage will then occur higher, leading to increasing predictability and vice-versa. Interestingly, our findings suggest that earnings quality and growth-related characteristics variables, namely, abnormal accruals, abnormal capital investments, investment growth and return on equity, are strong cross-stock returns predictors. They contain valuable information about future stock returns across pairs of stocks and also do not vary across time.

References

Abarbanell, A. and Bushee, T. (1998) Fundamental analysis, future earnings and stock prices. *Journal of Accounting Research*, 2, pp. 1–24.

Abekah, J. (2005) Fundamental variables and stock returns: evidence from Ghana stock market. *African Finance Journal*, 7, pp. 18–36.

Avramov, D., Barras, L. and Kosowski, R. (2012) Hedge Fund Return Predictability Under the Magnifying Glass. *Journal of Financial and Quantitative Analysis*, 48 (4), pp. 1057-1083.

Babenko, I., Boguth, O. and Tserlukevich, Y. (2016) Idiosyncratic cash flows and systematic risk. *Journal of Finance,* 71, pp. 425–456.

Badrinath, S., Kale, J. and Noe, T. (1995) Of shepherds, sheep and the cross-autocorrelations in equity returns. *Review of Financial Studies*, 8, pp. 401–430.

Baker, M. and Wurgler, J. (2006) Investor Sentiment and the Cross-Section of Stock Returns. *Journal of Finance*, 61(4), pp. 1645-1680.

Ball, R. and Shivakumar, L. (2005) Earnings quality in U.K. Private firms: comparative loss recognition timeliness. *Journal of Accounting and Economics*, 39(1), pp. 83-128.

Barinov, A., Shawn, S. P. and Celim, Y. (2014) Firm complexity and post-earnings announcement drift. *Working paper*, University of Georgia.

Barry, C. B., and Brown, S. J. (1985) Differential information and security market equilibrium. *Journal of Financial and Quantitative Analysis*, 20, pp. 407–422.

Bhattacharya, N., Desai, H. and Venkataraman, K. (2013) Does Earnings Quality Affect Information Asymmetry? Evidence from Trading Costs. *Contemporary Accounting Research*, 30(2), pp. 482-516.

Bianchi, R. J. and Drew M. E. (2010) The role of TED spread and confidence index in explaining the behavior of stock prices. Griffith University. *Department of Accounting, Finance and Economics in its series Discussion Papers in Finance* (201004), pp. 1–17.

Biedleman, C. (1973) Income smoothing: The role of management. *The Accounting Review, 48*(4), pp. 653-667.

Brennan, M. J., Jegadeesh, N. and Swaminathan, B. (1993) Investment analysis and the adjustment of stock prices to common information. *Review of Financial Studies*, 6, pp. 799–824.

Callen, J., Khan, M. and Lu, H. (2013) Accounting quality, stock price delay, and future stock returns. *Contemporary Accounting Research,* 30, pp. 269-295.

Canbas, S., Duzakin, H. and Kilic, S. (2002) Fundamental and macroeconomic information for common stock valuation: the Turkish case. *Working Paper*, Cukurova University, Adana, Turkey.

Carlson, M., Fisher A., and Giammarino R. (2004) Corporate investment and asset price dynamics: Implications for the cross-section of returns. *Journal of Finance,* 59, pp. 2577–603.

Chan, K.C., Hamao, Y. and Lakonishok, J. (1991) Economics and stock returns in Japan. *Journal of Finance*, 46, pp. 739–1764.

Chan, Louis K. C., Chan K., Jegadeesh N., and Lakonishok J. (2006) Earnings quality and stock returns. *Journal of Business*, 79, pp. 1041–1082.

Cheung, J. K., Chung, R. and Kim, J. B. (1997) The profitability of trading strategies based on book value and earnings in Hong Kong: market inefficiency versus risk premia. *Journal of International Financial Management and Accounting*, 8, pp. 204–33.

Chordia, T. and Swaminathan, B. (2000) Trading volume and cross-autocorrelations in stock returns. *Journal of Finance,* 55, pp. 913–935.

Chui, A. C. W., Titman S. and Wei K.C.J, 2010, Individualism and momentum around the world. *Journal of Finance,* 65, pp. 361–392.

Claus, J. and Thomas, J. (2001) Equity Premia as Low as Three Percent? Evidence from Analysts' Earnings Forecasts for Domestic and International Stock Markets. *Journal of Financial*, 56(5), pp. 1629-1666.

Cohen, L. and Frazzini, A. (2008) Economic links and predictable returns. *Journal of Finance,* 63, pp. 1977–2011.

Cohen, L. and Lou, D. (2012) Complicated firms. *Journal of Financial Economics*, 104, pp. 383–400.

Cooper, M. J., Gulen, H. and Schill, M. J. (2008) Asset growth and the cross-section of stock returns. *Journal of Finance*, 63, pp. 1609–51.

Coval, D. and Moskowitz, T. (1999) Home bias at home: Local equity preference in domestic portfolios. *Journal of Finance,* 54, pp. 2045–2073.

Dechow, P. and Dichev, I. (2002) The quality of accruals and earnings: the role of accrual estimation errors. *The Accounting Review*, 77, pp. 35–59.

Dechow, P., Ge, W. and Schrand, C. (2010) Understanding earnings quality: a review of the proxies, their determinants and their consequences*.* *Journal of Accounting and Economics*, 50, pp. 344-401.

DellaVigna, S. and Pollet, J. M. (2009) Investor inattention and Friday earnings announcements. *Journal of Finance*, 64, pp. 709-749.

Demski, J. (1998) Performance measure manipulation. *Contemporary Accounting Research,* 15, pp. 261–285.

Drakos, A., Diamandis, P. and Kouretas, G. (2015) Information Diffusion and the Lead-Lag Relationship between Small- and Large-Size Portfolios: Evidence from an Emerging Market. *International Journal of Economics and Finance*, 7(11), pp. 25-38.

Easley, D., Hvidkjaer, S. and O‟Hara, M. (2002) Is information risk a determinant of asset returns? *Journal of Finance*, 57(5), pp. 2185-2221.

Emamgholipour, M., Pouraghajan, A., Tabari, N. A. Y., Haghparast, M. and Shirsavar, A. A. A. (2013) The effect of performance evaluation market ratios on the stock return: evidence from the Tehran stock exchange. *International Research Journal of Applied and Basic Sciences*, 4.

Fama, Eugene F. (1970) Efficient Capital Markets: A Review of Empirical Work. *Journal of Finance*, 25(2), pp. 383–417.

Ferson W. (1989) Changes in expected security returns, risk, and the level of interest rates. *Journal of Finance*, 44(5), pp. 1191-1217.

Francis, J., Lafond, R., Olsson, P. M. and Schipper, K. (2004) Costs of equity and earnings attributes. *The Accounting Review*, 79(4), pp. 967-1010.

Gaio, C. (2010) The relative importance of firm and country characteristics for earnings quality around the world. *European Accounting Review*, 19(4), pp. 693-738.

Garlappi, L. and Yan, H. (2011) Financial distress and the cross-section of equity returns. *Journal of Finance,* 66, pp. 789–822.

Green, J., Hand J. R. M., and Zhang, X. F. (2013) The supraview of return predictive signals. *Review of Accounting Studies,* 18, pp. 692–730.

Gomes, J., Kogan, L. and Zhang L. (2003) Equilibrium cross-section of returns. *Journal of Political Economy,* 111, pp. 693–732.

Hameed, A., Huang, J. and Mian, G. M. (2015) Industries and stock return reversals. *Journal of Financial and Quantitative Analysis*, 50, pp. 89-117.

Hanifa, M. H., and Rashid, H. Ab. (2005) The determinants of voluntary disclosures in Malaysia: The case of internet financial reporting. *Unitar E-Journal*, 2, pp. 22–42.

Hirshleifer, D. and Teoh, S. (2003) Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics*, 36, pp. 337–386.

Hirshleifer, D., Hou, K., Teoh, S. H. and Zhang, Y. (2004) Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics*, 38, pp. 297–331.

Hirshleifer, D., Lim, S. and Teoh, S. H. (2009) Driven to distraction: extraneous events and underreaction to earnings news. *Journal of Finance*, 64 (5), pp. 2289-2325.

Holthausen W. and Larcker D. (1992) The Prediction of Stock Returns using Financial Statement Information. *Journal of Accounting and Economics*, 15, pp. 373- 411.

Hong, H., Lim, T. and Stein, J. (2000) Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance,* 55, pp. 265–295.

Hong, H., Tourus, W. and Valkanov, R. (2007) Do industries lead the stock market? *Journal of Financial Economics,* 83, pp. 367–396.

Hou, K. (2007) Industry information diffusion and the lead-lag effect in stock returns. *Review of Financial Studies,* 20, pp. 1113.

Hou, K. and Moskowitz, T. J. (2005) Market frictions, price delay, and the cross-section of expected returns. *Review of Financial Studies,* 18, pp. 981-1020.

Huberman, G. and Regev, T. (2001) Contagious speculation and a cure for cancer. *Journal of Finance,* 56, pp. 387-396.

International Monetary Fund (IMF) (2009) Detecting Systemic Risk, chapter 3. *IMF Global Financial Stability Report*: Responding to the Financial Crisis and Measuring Systemic Risks, April, pp. 1-39.

Jahanshad, A., Heidarpoor, F. and Valizadeh, Y. (2013) Relationship between Financial Information Transparency and Financial Performance of Listed Companies in Tehran Stock Exchange. *Research Journal of Recent Sciences*, 3(3), pp. 27-32.

Jegadeesh, N. (1990) Evidence of predictable behavior of security returns. *Journal of Finance*, 45, pp. 881-898.

Jegadeesh, N. and Titman, S. (1995) Overreaction, delayed reaction and contrarian profits. *Review of Financial Studies,* 8, pp. 973–993.

Jegadeesh, N. and Titman, S. (2001) Profitability of momentum strategies: An evaluation of alternative explanations. *Journal of Finance*, 56, pp. 699-720.

Kawaller, I. (1997) The TED Spread. *Derivative Quarterly*, pp. 541-566.

Kheradyar, S., Ibrahim, I., and Nor, F. M. (2011) Stock return predictability with financial ratios. *International Journal of Trade, Economics and Finance*, 2(5).

Kirschenheiter, M. and Melumad, N. (2002) Can ‘‘big bath’’ and earnings smoothing co-exist as equilibrium financial reporting strategies? *Journal of Accounting Research,* 40, pp. 761–796.

Kogan, L. and Papanikolaou D. (2012) Economic activity of firms and asset prices. *Annual Review of Financial Economics,* 4, pp. 361–84.

Kogan, L. and Papanikolaou, D. (2013) Firm Characteristics and Stock Returns: The Role of Investment-Specific Shocks. *Review of Financial Studies*, 26(11), pp. 2718–2759.

Kormendi, R. and Lipe, R. (1987) Earnings innovations, earnings persistence, and stock returns. *Journal of Business*, 60, pp. 323–345.

Lakonishok, J., Shleifer, A. and Vishny, R. (1994) Contrarian investment, extrapolation and risk. *Journal of Finance*, 49, pp. 1541–1578.

Lashgari, M. (2000) The Role of TED Spread and Confidence Index in Explaining the Behavior of Stock Prices. *American Business Review*, 18(2), pp. 9-11.

La Porta, R., Lakonishok, J., Shleifer, A. and Vishny, R. (1997) Good news for value stocks. *Journal of Finance*, 52, pp. 859–873.

Lau, S. T., Lee, C. T. and McInish, T. H. (2002) Stock returns and beta, firm size, E/P, CF/P, book-to-market, and sales growth: evidence from Singapore and Malaysia. *Journal of Multinational Financial Management*, 12, pp. 207–222.

Lev B. and Thiagarajan S. (1993) Fundamental Information Analysis. *Journal of Accounting Research,* 31, pp. 190-215.

Lewellen, J. (2004) Predicting returns with financial ratios. *Journal of Financial Economics*, 74, pp. 209–35.

Liao, L., Liu, B. and Wang, H. (2011) Information discovery in share lockups: Evidence from the split-share structure reform in China. *Financial Management*, 40, pp. 1001–1027.

Light, N., Maslov, D. and Rytchkov, O. (2017) Aggregation of information about the cross section of stock returns: A latent variable approach. *The Review of Financial Studies*, 30(4), pp. 1339-1381.

Lo, A. and MacKinlay, C. (1990) When are contrarian profits due to stock market overreaction? *Review of Financial Studies*, 3, pp. 175-206.

Loh, R. K. (2010) Investor inattention and the underreaction to stock recommendations. *Financial Management*, 39, pp.1223-1252.

Lyandres, E., L. Sun, and Zhang, L. (2008) The new issues puzzle: Testing the investment-based explanation. *Review of Financial Studies*, 21, pp. 2825–55.

Martinez, I. (1999) Fundamental and macroeconomic information for the security prices valuation: the French case. *Managerial Finance*, 12, pp. 17–30.

McLean, R. D. and Pontiff. J. (2015) Does academic research destroy stock return predictability? *Journal of Finance*, Forthcoming.

Menzly, L. and Ozbas, O. (2010) Market segmentation and cross-predictability of returns. *Journal of Finance*, 65, pp. 1555-1580.

Nagel, S. (2005) Short Sales, Institutional Investors and the Cross-Section of Stock Returns. *Journal of Financial Economics*, 78, pp. 277–309.

Nissim, A. and Penman, P. (2001) Ratio analysis and equity valuation: from research to practice. *Review of Accounting Studies*, 6, pp. 109–54.

Penman, S. H., and Zhang, X-J. (2002) Accounting conservatism, the quality of earnings and stock returns. *The Accounting Review*, 77(2), pp. 237-264.

Polk, C. and Sapienza, P. (2009) The stock market and corporate investment: A test of catering theory. *Review of Financial Studies*, 22, pp. 187–217.

Pontiff (1996) Costly arbitrage: Evidence from closed-end funds. *Quarterly Journal of Economics*, 111, pp. 1135–1151.

Rizova, S. (2010) Predictable trade flows and returns of trade-linked countries. *Working paper*, University of Chicago.

Schmeling, M. (2009) Investor sentiment and stock returns: Some international evidence. *Journal of Empirical Finance*, 16(3), pp. 394-408.

Shahrur, H., Becker, Y. L. and Rosenfeld, D. (2009) Return predictability along the supply chain: the international evidence. *Financial Analysts Journals*, 66(3), pp. 60-77.

Shleifer, A. and Vishny W. R. (1997) The Limits of Arbitrage. *Journal of Finance*, 52(1), pp. 35–55.

Skinner, D. and Sloan, R. (2002) Earnings surprises, growth expectations, and stock returns, or, don't let an earnings torpedo sink your portfolio. *Review of Accounting Studies*, 7, pp. 289–312.

Titman, S., Wei, K. C. J. and Xie, F. (2004) Capital investments and stock returns. *Journal of Financial and Quantitative Analysis*, 39, pp. 677–700.

Tse, Y. and Booth, G. (1996) Common volatility and volatility spillovers between US and Eurodollar interest rates: Evidence from the futures market. *Journal of Economics and Business* 48(3), pp. 299-312.

Tucker, J. and Zarowin, P. (2006) Does income smoothing improve earnings informativeness? *The Accounting Review,* 81, pp. 251–270.

Verrecchia, R. (1980) The rapidity of price adjustments to information. *Journal of Accounting and Economics*, 2, pp. 63-92.

Vieira, E., Carlos, J. and Pinho, C. (2015) Transparency and Stock Price Volatility: European Evidence. *Working paper.*

Vuolteenaho, T. (2002) What Drives Firm-Level Stock Returns. *Journal of Finance*, 56(1), pp. 233-263.

Xing,Y. (2008) Interpreting the value effect through the Q-theory: An empirical investigation. *Review of Financial Studies*, 21, pp. 1767–95.

Zhang, L. (2005) The value premium. *Journal of Finance,* 60, pp. 67–103.

	Definition	Rationale
ce	The slope coefficient between current period earnings regressed scaled by total assets (data 6) over previous period earnings, using 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) found evidence that 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) whereas lower values indicate highly transitory earnings (lower earnings quality). Firms which have more *earnings persistence* will show a higher "sustainable" earnings/cash flow stream, which will give it a more decisive beneficial input into equity valuations (Dechow *et al.* 2010). Thus, firms which have more earnings persistence represent a higher degree of information transparency.
	The standard deviation of the estimated residual over 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) measured earnings quality as capturing the uncertainty arising from estimation errors in the mapping of working capital accruals to operating cash flow realizations. Firms with 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) showed that, for example, some investors are unable to incorporate completely the mean reverting of the accruals of high accrual firms. 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.
ess	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 Bowen *et al.* (2008) over the five years *t-5* to *t-1*.	Tucker and Zarowin (2006) postulated that smoothness enhances earnings informativeness, based on their analysis, which divides the sample into a high and a low smoothing group, with the high smoothing group having stronger earnings informativeness. Firms with higher (lower) values of earnings smoothness indicate more

Table A1 Definition and Rationale of Variables (Continued)

Variables	Description	Definition	Rationale
BTM	Book-to-market ratio	The book value of equity (data 6-181) divided by the market value of equity (data 199*25).	La Porta *et al.* (1997) and Skinner and Sloan (2002) showed 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	$CP = (IB+EDP+TXDI)/ME$ where *IB* is income before extraordinary items (data 118), *EDP* is the equity's share of depreciation, *TXDI* is the deferred taxes (data 50) and *ME* is the market value of equity (common shares outstanding (data 25) * price close (data 199). $EDP=ME/(ME+AT\text{-}BE)*DP$ where *DP* is the depreciation and amortization (data 14), *AT* is the total assets (data 6) and *BE* is the book value of equity (data 6-181). Only firms with positive earnings are included in the sample.	As shown by Chan *et al.* (1991), Fama and French (1992) and Lakonishok *et al.* (1994), stock returns have a positively association with the cash flow-to-price ratio. The results are consistent with Lau *et al.* (2002) who found that the cash flow-to-price ratio is positively related to stock returns in Japan. It could be implied that higher cash flow-to-price ratio tends to have higher information transparency.
AGE	Firm age	The number of years since the firm first appeared on Compustat.	Barry and Brown (1985) found that firms with a long history (age) have more information available to the market, which leads to capturing more information in predicting future returns. Barinow *et al.* (2014) found that firms with a lower age are associated with weaker incorporation of information into their stock prices. Therefore, older firms tend to have higher information transparency.
LEV	Leverage	The ratio of total debt (data 181) to total assets (data 6).	Hanifa and Rashid (2005) found a positive association between information transparency and firm leverage in the emerging markets. This can imply that lower leverage tends to have higher information transparency.
AG	Total asset growth	The annual change in total asset $_{t-1}$ and $_{t-2}$ (data 6) divided by total assets $_{t-2}$ (data 6)	Cooper *et al.* (2008) documented that there is a strong negative association between a firm's asset growth and the future stock returns. This can imply that firms with lower total asset growth tend to have higher information transparency.
CI	Abnormal capital investments	$CI_t = [CE_{t-1}/ (CE_{t-2} + CE_{t-3} + CE_{t-4})/ 3] -1$ where CE_t is the firm's capital expenditure (data 128) divided by net sales (data 12).	Studies by Titman *et al.* (2004) found that an investment anomaly is the tendency of firms which recently experienced high capital investments to have low expected returns. It could imply that lower abnormal capital investments tend to have higher information transparency.

Table A1 Definition and Rationale of Variables (Continued)

Variables	Description	Definition	Rationale
IA	Investment-to-assets ratio	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 and Zhang (2008) documented the negative relation between investment and expected returns. That is, 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	The annual change in capital expenditures $_{t}$ and $_{t-1}$ (data 128) divided by capital expenditures $_{t-1}$ (data 128).	Xing (2008) showed that in the cross-sectional study, stocks of firms with low past investment growth rates have significantly higher average returns than those stocks of firms with high past investment growth rates. This finding implies that lower investment growth investments tend to have higher information transparency.
IK	Investment-to-capital ratio	The ratio of capital expenditures (data 128) to total net property, plant and equipment (data 8)	Zhang (2005) forecasted the value of firms and showed evidence that firms with lower capital investment have higher expected returns. This is in line with research of Xing (2008) and Polk and Sapienza (2009) that revealed a negative relationship between capital investment and future stock returns. Xing (2008) also documented that stocks with the lowest (highest) investment-to-capital ratios have the highest (lowest) returns. Thus, it could imply that firms with a lower investment-to-capital ratio tend to have higher information transparency.
NOA	Net operating assets	*NOA* = (Operating Assets $_{t-1}$ - Operating Liabilities $_{t-1}$)/ *AT* where Operating Asset $_{t}$ = *AT-CHE* Operating Liabilities $_{t}$ = *AT-DLC-DLTT-MIB-PSTK-CEQ* *AT* is total assets (data 6), *CHE* is cash and short-term investment (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) and *CEQ* is total common equity (data 60).	An empirical study by Hirshleifer *et al.* (2004) revealed that net operating assets are positively associated with future stock returns. Hence, it could be implied that firms, which have higher net operating assets tend to have higher information transparency.
ROA	Return on assets	The ratio of income before extraordinary items in quarter $_{t-1}$ (data 8) to total assets in quarter $_{t-2}$ (data 44)	Liao *et al* (2011) found that portfolios with higher cumulative abnormal returns have a positive association with ROA. This implies that a higher return on assets tends to have higher information transparency.

Table A1 Definition and Rationale of Variables (Continued)

Variables	Description	Definition	Rationale
ROE	Return on equity	*ROE* = (*IB*-*DVP*+*TXDI*)/*BE* where *IB* is income before extraordinary items (data 118), *DVP* is the preferred dividends (data 19) (if available), *TXDI* is the deferred taxes (data 50) (if available). *BE* is the book value of equity (data 6-181). Only firms with positive earnings are included in the sample.	A study by Claus and Thomas (2001) showed that there is a positive impact between ROE and abnormal earnings. It could be implied that firms that have a higher return on equity tend to have higher information transparency.
SIZE	Firm size	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) investigated the way 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. Likewise, Hou (2007) also showed 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 returns release of large firms within the same industry. Therefore, larger firms tend to have higher information transparency.
VOL	Stock return volatility	The standard deviation in the CRSP daily return over a year.	Vieira *et al.* (2015) found that there is a negative relationship between information transparency scores and the stock price volatility, contrary to the results of Ding *et al.* (2008), but only for the S&P index. It could be the explanation for why low stock return volatility tends to have higher information transparency.

Table A1 Definition and Rational of Variables (Continued)

Variables	Description	Definition	Rationale
TED	TED spread	TED spread is the difference in yields between US Eurodollar deposits (effectively three-month USD LIBOR) and US Treasury-bills. We used the average percentage of TED Spread from https://fred.stlouisfed.org/series/TEDRATE	Kawaller (1997) documented that a declining TED spread may result in improvements in the value of stocks. Lashgari (2000) also showed evidence that there is a negative relationship between TED spread and stock prices. It could be implied that a low TED spread has higher information transparency.
SENT	Sentiment index	The Sentiment Index in Baker and Wurgler (2006); 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	The Sentiment Index in Baker and Wurgler (2006); 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 with respect to a set of six macroeconomic factors from http://people.stern.nyu.edu/jwurgler/.	Studies by Chui *et al*. (2008) and Schmeling (2009) showed evidence that sentiment negatively predicts aggregate stock exchange returns. Therefore, this could imply that a low sentiment index has higher information transparency.
ICS	Index of consumer sentiment	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	The Volatility Index from https://www.globalfinancialdata.com/.	Avramov *et al.* (2012) found that the VIX index is negatively associated with investment returns. Thus, this can imply that a low VIX index has higher information transparency.

Appendix 2

Table A2 Descriptive statistic for pairwise regression sample

Variable	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

Note:
This table presents the descriptive statistic for pairwise regression using the following model: $R_{i,\,t} = \alpha + \beta_1 R_{j,\,t-1} + \beta_2 R_{i,\,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ The sample covers an 86-year period from January 1931 to December 2016. The variables reported were obtained from CRSP and Kenneth French's website as follows: R_i is 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*; R_{MKT} is The excess return on the market; *SMB* is Book-to-market; *HML*is Size.

Figure 1: The proportions of positive and negative coefficient

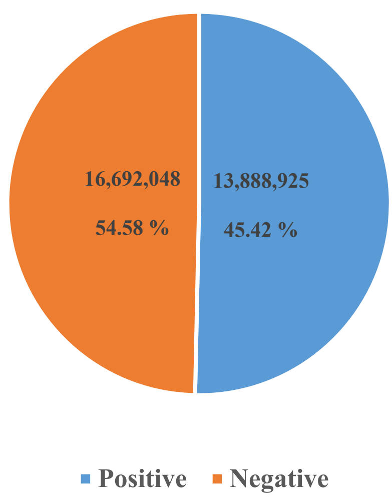

Table A3 The proportions of positive and negative significance

Significant level (%)	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

Note:
This table presents the descriptive statistic for pairwise regression using the following model: $R_{i,\,t} = \alpha + \beta_1 R_{j,\,t\text{-}1} + \beta_2 R_{i,\,t\text{-}1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ The sample covers an 86-year period from January 1931 to December 2016. The variables reported were obtained from CRSP and Kenneth French's website as follows: R_i is Monthly return of firm i; $R_{j,\,t\text{-}1}$ is The lagged monthly return of firm j; $R_{i,\,t\text{-}1}$ is The lagged monthly return of firm i; R_{MKT} is The excess return on the market; *SMB* is Book-to-market; *HML*is Size.

Figure 2: The proportions of positive and negative significance

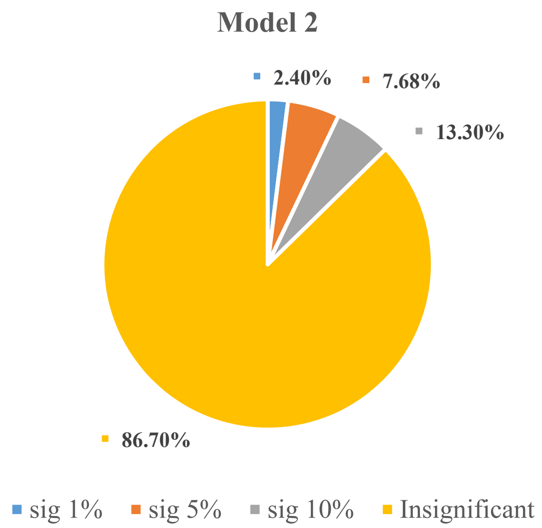

Table A4 Spearman correlations between variables

Variable	*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	0.03	-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	-0.04	0.21	-0.03	-0.29	-0.14	-0.26	-0.25	0.31	0.15	0.09	0.48	1.00					
NOA	0.09	-0.24	0.03	0.40	0.16	0.13	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	0.38	0.07	0.13	0.15	0.02	0.09	-0.03	-0.06	0.32	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

Note:
This table presents a Pearson correlation matrix of the variables employed in this study. The sample covers an 86-year period from January 1931 to December 2016. The sample period of each variable is guided purely by the availability of data. The accounting variables reported are obtained from COMPUSTAT and CRSP and as follows: *EP*: Earnings persistence; *AA*: Abnormal accruals; *ES*: Earnings smoothness; *BTM*: Book-to-market ratio; *CP*: Cash flow-to-price ratio; *AGE*: Firm age; *LEV*: Leverage; *AG*: Total asset growth; *CI*: capital investments; *IA*: Investment-to-assets ratio; *IG*: Investment growth; *IK*: Investment-to-capital ratio; *NOA*: Net operating assets; *ROA*: Return on assets; *ROE*: Return on equity; *SIZE*: Firm size; *VOL*: Stock return volatility. The definitions and rationale of each variable are described in Table A1 (See Appendix 1).

Table A5

The determinants of return predictability

Variables	*Sig*			R^2_1- R^2_0		
	DIFF $_{j,i}$	R^2	*N*	***DIFF*** $_{j,i}$	R^2	*N*
EP	-0.005** (-1.96)	0.355	632,530	-0.001* (-1.94)	0.381	632,530
AA	0.292*** (5.96)	0.262	573,204	0.045*** (7.83)	0.321	573,204
ES	0.105** (2.40)	0.306	614,082	-0.003 (-0.65)	0.180	614,082
BTM	0.354*** (7.47)	0.276	601,764	0.045*** (8.20)	0.197	601,764
CP	-0.186*** (-3.84)	0.229	334,864	-0.040*** (-7.59)	0.210	334,864
AGE	0.353*** (4.20)	0.265	644,546	0.083*** (8.31)	0.209	644,546
LEV	0.111* (1.66)	0.261	642,182	0.005 (0.67)	0.177	642,182
AG	-0.003 (-0.72)	0.186	637,694	-0.000 (-0.29)	0.219	637,694
CI	0.006* (1.89)	0.365	595,606	0.001* (1.79)	0.400	595,606
IA	0.006 (1.13)	0.203	594,426	0.001** (2.32)	0.212	594,426
IG	0.007** (2.24)	0.208	628,492	0.001*** (3.56)	0.193	628,492
IK	0.005 (0.09)	0.260	635,500	-0.011* (-1.80)	0.175	635,500
NOA	0.067** (2.23)	0.206	638,112	0.007** (2.30)	0.192	638,112
ROA	-0.007 (-1.54)	0.210	635,558	-0.001** (-2.14)	0.200	635,558
ROE	0.166*** (4.51)	0.233	335,074	0.007* (1.70)	0.180	335,074
SIZE	4.261*** (41.00)	0.355	2,376,393	0.622*** (47.58)	0.531	2,234,669
VOL	0.835*** (24.45)	0.217	2,376,397	0.092*** (21.21)	0.242	2,234,669

Note:
This table reports the determinants of return predictability using the following models:
$Sig = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, Year + \beta_3\, Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,\,t} = \alpha + \beta_1\, R_{j,\,t\text{-}1} + \beta_2\, R_{i,\,t\text{-}1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_{t.}$
$R^2_1\text{-}\ R^2_0 = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, Year + \beta_3\, Industry + \varepsilon_t$, where $R^2_1\text{-}\ R^2_0$ is the difference in R^2 $(R^2_1\text{-}\ R^2_0)$, where R^2_1 is R^2 of the 5-year rolling window regression $R_{i,\,t} = \alpha + \beta_1\, R_{j,\,t\text{-}1} + \beta_2\, R_{i,\,t\text{-}1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,\,t} = \alpha + \beta_1\, R_{i,\,t\text{-}1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t$.
The explanatory variable is the difference in determinants between firms *j* and *i* ($DIFF_{j,\,i}$). The dummy variables are year and industry fixed effects *(Year, Industry).* The definitions and rationale of each variable are described in Table A1 (see Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Table A6

The determinants of return predictability

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

Note:
This table reports the determinants of return predictability using the following models:
$R^2_1 - R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \beta_2 TED + \beta_3 DIFF_{j,i} * TED + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
The explanatory variables are the differences in determinants between firms *j* and *i* *(DIFF* $_{j,i}$*)* and the average percentage of TED Spread *(TED)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (see Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Table A7

The determinants of return predictability

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

Note:
This table reports the determinants of return predictability, using the following models:
$R^2_1 - R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \beta_2 SENT + \beta_3 DIFF_{j,i} * SENT + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
The explanatory variables are the differences in determinants between firms *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)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (See Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Table A8

The determinants of return predictability

Panel A:

Variables	*DIFF $_{j,i}$*	*SENT_6*	*DIFF $_{j,i}$ * SENT_6*	R^2	*N*
	-0.008***	-0.246***	0.006		
EP	(-2.74)	(-5.73)	(1.38)	0.326	596,958
	0.271***	-0.045	0.059		
AA	(5.08)	(-0.95)	(1.19)	0.272	542,264
	0.173***	-0.023	-0.204***		
ES	(3.59)	(-0.52)	(-3.99)	0.446	577,706
	0.349***	-0.233***	0.021		
BTM	(6.69)	(-5.25)	(0.43)	0.398	568,526
	-0.199***	-0.204***	0.027		
CP	(-3.75)	(-3.31)	(0.45)	0.354	315,392
	0.358****	-0.284***	0.005		
AGE	(3.91)	(-6.53)	(0.06)	0.400	608,164
	0.035	-0.283***	0.227***		
LEV	(0.49)	(-6.47)	(3.32)	0.397	605,800
	-0.004	0.036	-0.004		
AG	(-0.89)	(0.68)	(-0.63)	0.257	601,856
	0.005*	-0.260***	-0.004		
CI	(1.68)	(-5.81)	(-0.88)	0.335	561,342
	0.012**	0.055	-0.027***		
IA	(2.17)	(0.99)	(-3.43)	0.279	560,696
	0.007**	-0.169***	-0.001		
IG	(2.02)	(-3.35)	(-0.28)	0.315	592,654
	0.002	-0.279***	-0.023		
IK	(0.03)	(-6.26)	(-0.42)	0.395	598,854
	0.068**	-0.157***	-0.015		
NOA	(2.15)	(-3.18)	(-0.36)	0.314	602,274
	-0.009*	-0.165***	0.013*		
ROA	(-1.74)	(-3.34)	(1.85)	0.320	599,978
	0.162***	-0.203***	0.035		
ROE	(3.98)	(-3.29)	(0.71)	0.358	315,602
	4.444***	-0.144***	-0.853***		
SIZE	(40.31)	(-5.81)	(-8.75)	0.456	2,259,611
	0.952***	-0.144***	-0.495***		
VOL	(25.77)	(-5.80)	(-14.68)	0.323	2,259,615

Note:

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

Panel A: $Sig = \alpha + \beta_1 DIFF_{j,i} + \beta_2 SENT\_6 + \beta_3 DIFF_{j,i} * SENT\_6 + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.

Panel B: $(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \beta_2 SENT\_6 + \beta_3 DIFF_{j,i} * SENT\_6 + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.

Panel C: $R^2_1 - R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \beta_2 SENT\_6 + \beta_3 DIFF_{j,i} * SENT\_6 + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.

The explanatory variables are the differences in determinants between firms *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 where each of the proxies has first been orthogonalized with respect to a set of six macroeconomic factors *(SENT_6)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (See Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Table A8 (Continued)

The determinants of return predictability

Panel B:

Variables	*DIFF j,i*	*SENT_6*	*DIFF j,i * SENT_6*	R^2	*N*
EP	-0.006 (-1.43)_	1.594*** (24.80)	-0.000 (-0.01)	0.304	596,958
AA	0.925*** (14.29)	1.529*** (21.00)	-0.051 (-0.65)	0.369	542,264
ES	0.114** (2.14)	1.264*** (18.90)	-0.160** (-2.01)	0.299	577,706
BTM	0.652*** (9.57)	1.528*** (22.32)	1.131*** (14.83)	0.459	568,526
CP	-0.634*** (-9.82)	1.322*** (13.19)	-0.033 (-0.36)	0.444	315,392
AGE	2.040*** (16.98)	1.523*** (23.04)	0.100 (0.84)	0.439	608,164
LEV	0.136 (1.59)	1.518*** (22.89)	-0.175** (-1.99)	0.330	605,800
AG	-0.002 (-0.47)	1.246*** (14.86)	0.006 (0.65)	0.316	601,856
CI	0.007 (1.60)	1.565*** (23.47)	-0.001 (-0.10)	0.292	561,342
IA	0.021*** (3.49)	1.391*** (15.91)	0.019 (1.33)	0.339	560,696
IG	0.016*** (3.99)	1.484*** (18.36)	0.001 (0.13)	0.313	592,654
IK	0.227*** (3.53)	1.463*** (21.67)	-0.565*** (-6.62)	0.336	598,854
NOA	0.051 (1.37)	1.586*** (20.08)	-0.754*** (-14.11)	0.363	602,274
ROA	-0.006 (-0.97)	1.530*** (19.35)	0.020* (1.76)	0.334	599,978
ROE	0.141*** (3.08)	1.322*** (13.18)	0.386*** (5.56)	0.422	315,602
SIZE	15.113*** (84.65)	1.356*** (33.45)	-0.075 (-0.48)	1.315	2,129,537
VOL	2.940*** (48.28)	1.357*** (33.42)	-1.143*** (-18.11)	0.627	2,129,537

Note:
This table reports the determinants of return predictability using the following models:
Panel A: $Sig = \alpha + \beta_1 DIFF_{j,i} + \beta_2 SENT\_6 + \beta_3 DIFF_{j,i} * SENT\_6 + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
Panel B: $(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \beta_2 SENT\_6 + \beta_3 DIFF_{j,i} * SENT\_6 + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
Panel C: $R^2_1 - R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \beta_2 SENT\_6 + \beta_3 DIFF_{j,i} * SENT\_6 + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
The explanatory variables are the differences in determinants between firms *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 where each of the proxies has first been orthogonalized with respect to a set of six macroeconomic factors *(SENT_6)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (See Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Table A8 (Continued)

The determinants of return predictability

Panel C:

Variables	*DIFF* $_{j,i}$	*SENT_6*	*DIFF* $_{j,i}$ ** SENT_6*	R^2	N
EP	-0.001** (-2.35)	-0.002 (-0.48)	0.000 (0.93)	0.317	596,958
AA	0.045*** (7.16)	0.012** (2.34)	-0.007 (-1.22)	0.282	542,264
ES	-0.004 (-0.74)	0.001 (0.20)	-0.001 (-0.26)	0.232	577,706
BTM	0.033*** (5.61)	0.002 (0.32)	0.047*** (8.50)	0.233	568,526
CP	-0.043*** (-7.56)	0.002 (0.35)	-0.001 (-0.10)	0.225	315,392
AGE	0.090*** (8.30)	-0.005 (-1.06)	-0.029*** (-3.25)	0.249	608,164
LEV	0.001 (0.11)	-0.005 (-1.08)	0.010 (1.36)	0.215	605,800
AG	-0.000 (0.03)	0.005 (0.93)	-0.001 (-0.95)	0.213	601,856
CI	0.001* (1.84)	-0.002 (-0.34)	-0.000 (-0.86)	0.334	561,342
IA	0.002*** (3.13)	0.015*** (2.58)	-0.002** (-2.37)	0.206	560,696
IG	0.001*** (3.48)	0.005 (0.90)	-0.000 (-0.86)	0.208	592,654
IK	-0.012* (-1.85)	-0.004 (-0.93)	-0.006 (-1.02)	0.214	598,854
NOA	0.009** (2.49)	0.006 (1.10)	-0.020*** (-4.58)	0.211	602,274
ROA	-0.001** (-2.25)	0.005 (0.83)	0.002** (2.33)	0.218	599,978
ROE	0.000 (0.05)	0.003 (0.40)	0.019*** (3.55)	0.194	315,602
SIZE	0.651*** (47.31)	0.033*** (11.86)	-0.158*** (-13.31)	0.547	2,129,537
VOL	0.107*** (23.23)	0.033*** (11.85)	-0.075*** (-18.06)	0.267	2,129,537

Note:

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

Panel A: $Sig = \alpha + \beta_1 DIFF_{j,i} + \beta_2 SENT\_6 + \beta_3 DIFF_{j,i}{*}\, SENT\_6 + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.

Panel B: $(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \beta_2 SENT\_6 + \beta_3 DIFF_{j,i}{*}\, SENT\_6 + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.

Panel C: $R^2_1 - R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \beta_2 SENT\_6 + \beta_3 DIFF_{j,i}{*}\, SENT\_6 + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.

The explanatory variables are the differences in determinants between firms *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 where each of the proxies has first been orthogonalized with respect to a set of six macroeconomic *(SENT_6)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (See Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Table A9

The determinants of return predictability

Variables	$DIFF_{j,i}$	ICS	$DIFF_{j,i}$ * ICS	R^2	N
	-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
	-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
	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
	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

Note:
This table reports the determinants of return predictability using the following models:
$R^2_1 - R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \beta_2 ICS + \beta_3 DIFF_{j,i} * ICS + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$. The explanatory variables are the differences in determinants between firms *j* and *i* $(DIFF_{j,i})$ and the Index of Consumer Sentiment *(ICS)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (See Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Table A10

The determinants of return predictability

Variables	*DIFF $_{j,i}$*	*VIX*	*DIFF $_{j,i}$ * VIX*	R^2	*N*
	-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
	-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
	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
	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

Note:
This table reports the determinants of return predictability using the following models:
$R^2_1 - R^2_0 = \alpha + \beta_1 DIFF_{j,i} + \beta_2 VIX + \beta_3 DIFF_{j,i} * VIX + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, 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 $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
The explanatory variables are the differences in determinants between firms *j* and *i* $(DIFF_{j,i})$ and the Volatility Index *(VIX)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (See Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Table A11

The determinants of return predictability

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

Note:

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

$Sig = \alpha + \beta_1 DIFF_{j,i} + \beta_2 Year + \beta_3 Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$. The explanatory variable is the difference in determinants between firms *j* and *i* ($DIFF_{j,i}$). The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (see Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Table A12

The determinants of return predictability

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

Note:

This table reports the determinants of return predictability using the following model:
$Sig = \alpha + \beta_1 DIFF_{j,i} + \beta_2 TED + \beta_3 DIFF_{j,i}* TED + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
The explanatory variables are the differences in determinants between firms *j* and *i* ($DIFF_{j,i}$) and the average percentage of TED Spread *(TED)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (See Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Table A13

The determinants of return predictability

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

Note:

This table reports the determinants of return predictability, using the following model: $Sig = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, SENT + \beta_3\, DIFF_{j,i} * SENT + \beta_4\, Year + \beta_5\, Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,\,t} = \alpha + \beta_1\, R_{j,\,t-1} + \beta_2\, R_{i,\,t-1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_{t.}$

The explanatory variables are the differences in determinants between firms *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)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (see Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Table A14

The determinants of return predictability

Variables	$DIFF_{j,i}$ * $SENT\_6$		
	Logit	***Probit***	***N***
	0.117	0.052	
EP	(1.45)	(1.39)	596,958
	2.140***	0.911***	
AA	(4.42)	(3.86)	542,264
	-4.140***	-1.900***	
ES	(-17.46)	(-17.24)	577,706
	1.310**	0.512	
BTM	(1.75)	(1.28)	568,526
	0.153	0.061	
CP	(0.01)	(0.01)	315,392
	1.270	0.555	
AGE	(0.62)	(0.56)	608,164
	5.210***	2.310***	
LEV	(14.04)	(13.27)	605,800
	-0.091	-0.039	
AG	(-0.62)	(-0.44)	601,856
	-0.088	-0.043	
CI	(-0.66)	(-0.77)	561,342
	-0.578***	-0.263***	
IA	(-11.09)	(-10.91)	560,696
	-0.010	-0.004	
IG	(-0.01)	(-0.01)	592,654
	-0.363	-0.234	
IK	(-0.11)	(-0.21)	598,854
	-0.214	-0.159	
NOA	(-0.06)	(-0.16)	602,274
	0.275***	0.131***	
ROA	(3.11)	(3.44)	599,978
	1.180	0.539	
ROE	(1.20)	(1.21)	315,602
	-10.550***	-5.320***	
SIZE	(-31.12)	(-38.03)	2,259,611
	-9.560***	-4.420***	
VOL	(-183.88)	(-189.74)	2,259,615

Note:
This table reports the determinants of return predictability, using the following model: $Sig = \alpha + \beta_1 DIFF_{j,i} + \beta_2 SENT\_6 + \beta_3 DIFF_{j,i} * SENT\_6 + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
The explanatory variables are the differences in determinants between firms *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 where each of the proxies has first been orthogonalized with respect to a set of six macroeconomic factors *(SENT_6)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (see Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Table A15

The determinants of return predictability

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

Note:
This table reports the determinants of return predictability, using the following model: $Sig = \alpha + \beta_1 DIFF_{j,i} + \beta_2 ICS + \beta_3 DIFF_{j,i} * ICS + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
The explanatory variables are the differences in determinants between firms *j* and *i* (*DIFF $_{j,i}$*) and the Index of Consumer Sentiment *(ICS)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (See Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.

Table A16

The determinants of return predictability

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

Note:
This table reports the determinants of return predictability, using the following model: $Sig = \alpha + \beta_1 DIFF_{j,i} + \beta_2 VIX + \beta_3 DIFF_{j,i} * VIX + \beta_4 Year + \beta_5 Industry + \varepsilon_t$, where *Sig* is a dummy variable that takes the value of 1, where 1 = positive significance at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_1 R_{j,t-1} + \beta_2 R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$.
The explanatory variables are the differences in determinants between firms *j* and *i* ($DIFF_{j,i}$) and the Volatility Index *(VIX)*. The dummy variables are year and industry fixed effects *(Year, Industry)*. The definitions and rationale of each variable are described in Table A1 (See Appendix 1). The coefficient is scaled by 10^{-2}. *** statistically significant at 0.01 level, ** statistically significant at 0.05 level, * statistically significant at 0.10 level.