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

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Abstract

This paper examines the predictability of pairs of stocks, using a comprehensive set of accounting variables to capture the relative degree of limits to arbitrage. We find that ten accounting variables, including abnormal accruals, earnings smoothness, book-to-market, firm age, leverage, abnormal capital investment, investment growth, return on equity, firm size and stock volatility, provide useful information for predicting the cross-section of stock returns after controlling for time and industry fixed effects. We further show that the predictability varies over time due to liquidity funding and market sentiment. Overall, the results are consistent with the intuition that individual stocks reflect the information at different speeds, leading to the cross-stock lead-lag return predictability.

JEL Classification: G11, G14, M41
Keywords: Limits to Arbitrage, Information Diffusion, Cross-asset Predictability

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Abstract

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1. Introduction

For decades, predicting future stock returns remains one of the most active areas of research in accounting and finance.[1] A large body of studies have shown evidence for return predictability at country, industry, and supply chain levels (see, for example, Cohen and Frazzini (2008), Cohen and Lou (2012), Rapach, Strauss, and Zhou (2013), Chinco, Clark-Joseph, and Ye (2019), Han, Rapach, and Zhou (2019)). However, whether a stock's return can predict other stocks' performance remains under-investigated. This study fills this void by studying the predictability of pairs of stocks and using accounting variables as proxies for the relative degree of limits to arbitrage.

Our focus on the return predictability of pairs of stocks is motivated by a growing body of research that documents the impacts of information processing procedure on stock return predictability. Lo and MacKinlay (1990), for example, find that returns on large stocks lead returns on small stocks and suggest the gradual information diffusion explanation for the lead-lag effect observed in the stock markets. Hou and Moskowitz (2005) document that some firms' stock prices show a delayed reaction to the price innovation of others. Cohen and Frazzini (2008), Shahrur, Becker, and Rosenfeld (2009), and Menzly and Ozbas (2010) show evidence of the slow diffusion of information along the supply chain, causing individual customers' returns predicting their suppliers' returns. Rizova (2010) presents a two-country, Lucas-tree framework with gradual information diffusion which drives the cross-country return predictability between one country and another trading-partner country. More recently, Cohen and Lou (2012) show returns on easy-to-analyze firms predict returns of their more complicated peers and Rapach et al. (2013) find a cross-country return predictability with the U.S returns lead other industrialized countries. Consistent with these studies, we argue that individual stocks reflect and react to new information at different speeds which may result in the cross-stock lead-lag return predictability.

Although some controversy remains, the relevance of accounting information in predicting asset returns appears well established.[2] Holthausen and Larcker (1992) and Lewellen (2004), for instance, suggest that accounting data has a strong predictive power in forecasting stock returns. More recent studies, such as Garlappi and Yan (2011), Bhattacharya, Desai, and Venkataraman (2013), Kogan and Papanikolaou (2013), Babenko, Boguth, and Tserlukevich

[1] See Lettau and Van Nieuwerburgh (2007) and Lewellen (2010) for excellent reviews.

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

(2016), Harvey, Liu, and Zhu (2016), McLean and Pontiff (2016), Hou, Xue, and Zhang (2019), have confirmed the informative roles of various attributes of accounting information in return predictability. In this study, we utilise the informative roles accounting data in capturing the relative degree of limits to arbitrage and examine the association between the information environment and cross-stock return predictability. We examine whether, and to what extent, variations in return predictability across different pairs of stocks are associated with the relative degree of limits to arbitrage between stocks.

Using a large sample of the U.S commons stocks covering an 86-year period from January 1931 to December 2016, we create a Cartesian product to match the predictability of pairs of stocks from 500 randomly selected stocks and use seventeen accounting variables as proxies to capture the relative degree of limits to arbitrage. We find 10 out of 17 of accounting proxies, including abnormal accruals, earnings smoothness, book-to-market, firm age, leverage, abnormal capital investment, investment growth, return on equity, firm size and stock volatility, provide useful information for predicting the cross-section of stock returns after controlling for time and industry fixed effects. We further show that the predictability varies over time due to liquidity funding and market sentiment. We consider a battery of sensitivity analyses and find that our findings are robust to different model specifications (i.e., OLS, probit, and logit models) or alternative proxies for market stage variables. Our findings also hold when we consider the predictability power based on the R^2 difference. Overall, our findings are aligned with recent theories about gradual information diffusion in asset markets[3]

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

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

The rest of this study is organized as follows. Section 2 provides an in-depth review of the related literature. Sections 3 and 4 describe data and methodology used in this research. Section 5 presents main findings and Section 6 concludes the paper.

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 DeLong, Shleifer, Summers, and Waldmann (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, Khan, and Lu 2013). These factors include return reversals (Jegadeesh 1990), information diffusion (Hong et al. 2000), information asymmetry (Easley, Hvidkjaer, and O'Hara 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. (2013) 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, Huang, and Mian (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, Hand, and Zhang (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, Fisher, and Giammarino 2004; Zhang 2005), leverage (e.g, Garlappi and Yan 2011), the price-earnings ratio (e.g., Kogan and Papanikolaou 2013), size (e.g., Gomes, Kogan, and Zhang 2003; Carlson 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, Chung, and Kim (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, Duzakin, and Kilic (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, Ibrahim, and Nor (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, Pouraghajan, Tabari, Haghparast, and Shirsavar (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, Ge, and Schrand (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, Lafond, Olsson, and Schipper (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, Chan, Jegadeesh, and Lakonishok (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[4]. 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 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, Titman, and Wei (2010).

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

[4] (See, for example, Barberis, Shleifer, and Vishny (1998), Wurgler and Zhuravaskaya (2002), Kurov (2010, 2012), Stambaugh, Yu, and Yuan (2012, 2014), Lutz (2015) and Shen, Yu, and Zhao (2017))

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, Glosten, and Jagannathan (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, Barras, and Kosowski (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 Variables

3.1. Data

Our sample consists of all listed companies on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the NASDAQ and covers an 86-year period from January 1931 to December 2016. We collect data and construct variables from conventional data sources. Specifically, we obtain daily and monthly stock returns from the Center for Research in Security Prices (CRSP) and source annual and quarterly accounting information from Compustat. We obtain Fama and French (1993)'s three factors from Kenneth French's website[5] and considered only common stocks (CRSP share code of 10 or 11). To examine whether the cross-sectional return predictability varies over time, we use several market stage variables, including the average percentage of TED from the Federal Reserve Bank of St. Louis, the investor sentiment data from Baker and Wurgler (2006, 2007), the University of Michigan Consumer Sentiment Index from the University of Michigan's website, and Volatility Index from the Global Financial Data's website.[6] We exclude financial institutions and banks (one-digit SIC code of 6) and non-classifiable firms (SIC code of 9999) as these firms have different accounting practices compared to other firms. We randomly select 500

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

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

stocks that have at least 10 years of trading data to form an average market value decile rank (i.e., 50 stocks in each decile). We also follow Vuolteenaho (2002) and require firms having a December fiscal year-end as these firms account for a majority of the sample firms and our sample is, therefore, an unbiased representation of the sample. We match data from Compustat for the fiscal year ending in year $t - 1$ with CRSP from July of year t to June of year $t + 1$. Finally, we remove observations with negative book-to-equity values and winsorize the extreme observations to one percentile to mitigate the influence of outliers.

3.2. Variables and Descriptive Statistics

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

We also employ four market stage variables to examine whether cross-stock predictability varies over time. They are TED spread (*TED*), market sentiment (*SENT* and *SENT_6*), consumer sentiment (*ICS*), and volatility index (*VIX*). We provide the description for each variable in the Appendix and descriptive statistics and correlation matrix of the variables in Table 1.

{ENTER TABLE 1}

According to Table 1's Panel A, earnings quality attributes, firm characteristics, and market-based variables are all positively skewed (as the mean is higher than the median) while growth- and profit-related characteristic variables (e.g., *IA*, *NOA* and *ROA*) are negatively skewed. The standard deviation of the determinants ranges from 0.026% for *VOL* to 8.364% for *AGE.* Panels B and C of Table 1 shows a Pearson correlation matrix of accounting and market stage variables. *AGE,* for example, has a positive correlation with *EP* (ρ*AGE*, *EP* =

0.01) while it is inversely related to *AA* (ρ*AGE, AA* = -0.03), suggesting a positive (negative) association between the age of a firm and its earnings quality (abnormal accruals). *SIZE* is positively related to *ROA* and *ROE* (ρ*SIZE*, *ROA* = 0.27 and ρ*SIZE*, *ROE* = 0.15) and negatively associated with *AA*, *BTM*, and *VOL* (ρ*SIZE*, *AA* = -0.17, ρ*SIZE*, *BTM* = -0.32 and ρ*SIZE*, *VOL* = -0.37), which is highly consistent with findings of Nagel (2004). Panel C's results suggest that four market stage variables capture different dimensions of the market information. The correlation between *ICS* and *VIX* or *TED* is negative (ρ*ICS*, *VIX* = -0.21) or (ρ*ICS*, *TED* = -0.13), which is consistent with findings of Lashgari (2000). *TED* and *VIX* have a positive and moderately high correlation (ρ*TED*, *VIX* = 0.56), suggesting a positive association between the systematic risk and changes in market uncertainty.[7]

4. Methodology

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

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

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.

The significant results and R^2 of Equation (1) is employed as a dependent variable of our model estimations.[8] We calculate the independent variables, which are the level of difference in determinants between firms *j* and *i*, scaled by the mean value of firm *j* and *i*. We use seventeen accounting variables as proxies to capture the relative degree of limits to arbitrage. We first examine whether the difference in the sources of variables increases the probability of cross-stock return predictability. We follow Pedersen (2009) and estimate the OLS regressions with standard errors clustered by pairs of stocks to obtain unbiased standard

[7] We also consider the Spearman correlations between all variables and find results (untabulated for brevity and available upon request) are consistent with the Pearson correlation results.
[8] We report the descriptive statistic of pairwise regression in Tables A1 and A2 in the Online Appendix.

errors of OLS coefficients under a specific kind of heteroscedasticity. We also control for time (year) and industry fixed effects (the first digit SIC code) in all regression models.

The first model estimation is as follows:

$$Sig = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, Year + \beta_3\, Industry + \varepsilon_t \qquad (2)$$

The dependent variable in Equation (2), *Sig* is a dummy variable that takes the value of 1 if the value(s) from the regression results of Equation (1) is positive and significant at 0.05 level and 0 otherwise.

The independent variables are the differences in determinants between firms *j* and *i* including 17 accounting variables scaled with the mean values of firms *j* and *i* ($DIFF_{j,i}$) 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 include year- and industry-fixed effects to account for time- and industry-invariant factors, respectively, that could be associated with return predictability.

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

$$(R^2_1 - R^2_0) / R^2_0 = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, Year + \beta_3\, Industry + \varepsilon_t \qquad (3)$$

The dependent variable in equation (3), $(R^2_1 - R^2_0)/ R^2_0$ is a proxy for change in the R^2, where R^2_1 is R^2 of the 5-year rolling window regression from equation (1) which is R^2 of return predictability across firms; R^2_0 is R^2 of the 5-year rolling window regression which is no predictability across firms as follows:

$$R_{i,t} = \alpha + \beta_i\, R_{i,t-1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t \qquad (4)$$

Higher (lower) change in the R^2 represents higher (lower) degree of predictive power across firms. We then employ the interaction terms of five well-known market stage variables (as described in Table 1) to examine whether the cross-sectional predictability varies over time. Our model is as follows:

$$Sig = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, MKTV + \beta_3\, DIFF_{j,i} * MKTV + \beta_4\, Year + \beta_5\, Industry + \varepsilon_t \qquad (5)$$

$$(R^2_1 - R^2_0)/ R^2_0 = \alpha + \beta_1\, DIFF_{j,i} + \beta_2\, MKTV + \beta_3\, DIFF_{j,i} * MKTV + \beta_4\, Year + \beta_5\, Industry + \varepsilon_t \qquad (6)$$

Other independent variables are the market stage variables (*MKTV)*, including TED spread, investor sentiment, the index of consumer sentiment, and the volatility index.

Furthermore, we consider two additional sensitivity analyses. First, we use logit and probit regressions for equations (2) and (5) because the dependent variable in these two equations is binomial. Second, we use the dependent variable, (R^2_1 - R^2_0) which is the difference in R^2 as a robustness test for equations (3) and (6). We report results for these tests in the following section

5. Empirical Results

We examine whether a stock's return can predict other stocks' performance by studying the predictability of pairs of stocks and using accounting variables as proxies to capture the relative degree of limits to arbitrage. Our approach is based on the intuition that stock reflects the information at different speeds, leading to the cross-stock lead-lag effect. We begin with the estimation of the significance of pairwise across-firm returns' predictability using the Fama-French three-factor model (Fama and French 1993) in equation 5. We then obtain the results from Equation (1) that takes the value of 1 if the value(s) is positive and significant at 0.05 level and 0 otherwise as a dependent variable (*Sig*) and examine whether the difference in the source of variables is associated with the likelihood of predictability. In addition, we estimate another model using R^2 difference ($R^2{}_1$ - $R^2{}_0$/ $R^2{}_0$) in Equations (6) and (7,) which represents the degree of predictive power as a dependent variable in Equation (2), to examine whether the difference in the source of variables is associated with the predictability power. The independent variables are the differences in determinants between firms *j* and *i* including 17 accounting variables *($DIFF_{j,i}$).* We estimate the OLS regression of Equations (1) and (2) and use clustered standard errors to obtain unbiased standard errors of OLS coefficients. Finally, we include year- and industry-fixed effects to control for time- and industry-invariant factors that could be associated with return predictability.

We report results for the determinants of cross-stock returns predictability in Table 2. We first consider whether the difference in the source of the accounting variables is related to the likelihood of predictability. The dependent variable in Column (1) is *Sig*. We find that 11 out of 17 accounting variables contain valuable information about cross-stock returns' predictability. They include: abnormal accruals (*AA*), book-to-market ratio (*BTM*), firm age (*AGE*), return on equity (*ROE*), firm size (*SIZE*), stock return volatility (*VOL*), earnings smoothness (*ES*), investment growth (*IG*), net operating assets (*NOA*), leverage (*LEV*), and capital investments (*CI*). The results suggest a strong evidence of cross-stock return predictability. The results also indicate an economic significance. For example, differences in abnormal accruals (*AA*) and earnings smoothness (*ES*) predict cross-firm returns with coefficients of 0.292 (*t*-statistics of 5.96) and 0.105 (*t*-statistics of 2.40), respectively, suggesting that one standard deviation increase in the differences in *AA* and *ES* between firms *j* and *i*, increases the likelihood that firm *j* is able to predict firm *i* by 0.30% (i.e., 0.292*1.016) and 0.10% (i.e., 0.105*0.965), respectively. These results are aligned with findings of Francis *et al.* (2004) and Dechow *et al.* (2010) which suggest that firms with higher earnings quality generally provide more information about the future of their financial performance and thus, are more predictable in their capital valuation.

We consider several sensitivity analyses to ensure that our results are robust. Specifically, we employ logistic and probit models instead of OLS models, and results from these tests, reported in Table A7 in the Online Appendix, suggest that our results hold once logistic regressions are employed.

Second, we consider whether the difference in the source of variables is associated with the predictability power based on the R^2 difference. We report results for these tests in Column (2) of Table 2. The dependent variable of interest is the change in the R^2. The results suggest that the coefficients of difference in the source of variables between firms *j* and *i* ($DIFF_{j,i}$) are statistically significant at the 10 % level or better for 12 (out of 17) accounting variables, including *AA*, *BTM*, *AGE*, *IA*, *IG*, *IK*, *ROE*, *SIZE*, *VOL*, *ES*, *LEV*, *IK*, and *CI*. These results are also economically significant. For example, the coefficient on *SIZE* enters is 15.27 (*t*-statistics of 85.28) suggests that one standard deviation increase in the difference in *SIZE* between firm *j* and firm *i* would increase the ability that firm *j* can predict the performance of firm *i* by 3.50% (i.e.,15.27*0.229). In other words, the result indicates that, when firm *j*'s size is bigger (smaller) compared to firm *i*, it would increase (decrease) the power of prediction that firm *j* is able to wield over firm *i*. This finding is highly consistent with Lo and MacKinlay (1990), Drakos, Diamandis, and Kouretas (2015) and Hou (2007) which suggest that there is a lead-lag relation in information processing procedure between large and small firms in stock markets. The larger capitalization portfolio stock returns lead while the smaller ones mostly merely follow. Interestingly, 10 accounting variables from four groups, including *AA*, *ES*, *BTM*, *AGE*, *LEV*, *CI*, *IG*, *ROE*, *SIZE*, and *VOL* are strong and consistent predictors of returns across firms (i.e., these variables not only increase the probability of predictability in Column (1) but also increase the power of cross-stock returns' prediction in Column (2)). The results also indicate that the market is slow to aggregate the information contained in firm connections, which is aligned with recent theories of gradual information diffusion in financial markets.[9]

{ENTER TABLE 2}

We now introduce the interaction terms of four well-known market variables to examine (i) whether the stock return predictability varies across time and (ii) whether market variables matter for the predictability. These market variables include TED spread (*TED*), investor sentiment (*SENT* and *SENT_6*), the Index of Consumer Sentiment (*ICS*), and the Volatility Index (*VIX*). We estimate the OLS regression specified in Equations (3) and (4) and use clustered standard errors. Consistent with previous sections, we include in our model year- and industry-fixed effects. We estimate Equations (3) and (4) jointly across firms and present the regression results in Tables 3 to 6.

First, we use TED spread as a market variable to examine whether funding liquidity matters for cross-stock return predictability. As Guta and Subrahmanyam (2000) and Campbell and Taksler (2003) note, the TED spread is a widely-employed measure of funding liquidity in the market. The dependent variable is *Sig* and the independent variable of interest is the interaction term of *TED* and $DIFF_{j,i}$. Results of Panel A of Table 3 suggest that an increase in TED spread leads to an increase in the probability of cross-firm return predictability by *LEV*, *IK*, *ROA* and *CP*. In contrast, the coefficients on the interaction terms of 7 accounting variables, including *ES*, *BTM*, *IG*, *SIZE*, *VOL*, and *AG*, are negative and significant at the 10% level or better, suggesting that an increase in TED spread results in a reduction in the likelihood of prediction by *ES*, *BTM*, *IG*, *SIZE*, *VOL*, and *AG*.

In Panel B of Table 3, the dependent variable is the change in the R^2. Panel B's results suggest a positive relation between *TED* and the power of cross-firm predictability based on five accounting variables, including *AA*, *LEV*, *IK*, *NOA*, *SIZE*, and *VOL*. The results indicate that an increase in TED spread lead to an increased power of predictability that firm *j* can predict the performance of firm *i*, using these five accounting variables. In contrast, an increase in TED spread results in a reduction in the power of predictability by *BTM* and *ROA*.[10] Table

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

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

3's results are consistent with findings of Pontiff (1996) which suggests that an increase (decrease) in TED spread leads to an increase (reduction) in the cost of funding, which then facilitates (impedes) informed investors' ability to trade against such mispricing. Consequently, the limits to arbitrage are higher (lower), leading to an increasing (decreasing) predictability.

{ENTER TABLE 3}

Another important market-based measure is market sentiment. Baker and Wurgler (2006, 2007) show that the impact of investment sentiment on stocks return is more pronounced among stocks that are more difficult to arbitrage. We therefore employ investor sentiment as a market-based information to examine whether the cross-stock predictability varies over time. We report results for these tests in Table 4.

According to Table 4's results, a standard deviation increase in *SENT* leads to a 0.20% (i.e., -1.143*0.174) and 0.12% (i.e., -0.697*0.174) decrease in the probability and power of cross-firm return prediction by *SIZE*, respectively. Regarding the cross-stock return predictability by *VOL*, these numbers are 0.25% (-0.530*0.469) and 0.56% (-1.194*0.469), respectively. In contrast, 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 by *ROA* by 0.07% (0.016*4.07) and 0.09% (0.022*4.07). We also adopt *SENT_6*[11] and *ICS* as alternative measures for investor sentiment and report results for these robustness checks Tables A6 and A7 in the Online Appendix. We find our findings are robust after considering alternative measures of investor sentiment.

{ENTER TABLE 4}

{ENTER TABLE 5}

Furthermore, our final measure of market-based funding liquidity is the market volatility index (*VIX*), which captures the implied volatility of the stock market. We employ the market volatility index to examine whether the predictability across different pairs of stocks

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

varied over time, based on changes in the market uncertainty. We report the results for this test in Table 6.

According to Table 6's results, a positive and significant coefficient on interaction term of *VIX* and the difference in *LEV* between firms *j* and *i* suggest that when the *VIX* increases, the probability and power of cross-stock prediction increases by 0.17% (0.011*15.418) and 0.23% (0.015*15.418), respectively. In addition, an increase in *VIX* leads to a decrease in the likelihood and power of cross-firm return predictability by *ES* and by *SIZE*. These results are consistent with findings of Shleifer and Vishny (1997) which show that, an increase in market volatility is related to greater mispricing due to noise traders' sentiment, leading to higher probability of losses for arbitrageurs and hence, the need for portfolio liquidation under investors' expectations. As a consequence, the higher limits to arbitrage can lead to an increase in predictability.

We also consider two additional robustness tests to ensure that our results are robust and not driven by alternative explanations. Specifically, first, we use the difference in R^2 (R^2_1 - R^2_0) as an alternative dependent variable for Equations (2) and (4) and report the OLS regression results in Tables A3 to A8 in the Online Appendix. Second, we use the logit and probit regressions instead of the OLS model for Equations (1) and (2) and report results for these tests in Tables A9 to A13 in the Online Appendix. Overall, results from Tables A4 to A14 are highly consistent with our findings.

{ENTER TABLE 6}

6. Conclusion

We study whether variations in predictability across different pairs of stocks are associated with the degree of limits to arbitrage between the stocks. Our findings suggest a clear "Yes". We find that ten out of seventeen accounting variables are strong predictors of stock returns across firms, evidenced by the likelihood and the power of cross-stock returns predictability. We also find the predictability varies over time due to the funding of liquidity and market sentiment. Our findings are consistent with the gradual information diffusion theory, which suggest that a single stock can gradually diffuse information among other stocks, leading to a lead-lag effect in the stock markets.

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Appendix: Variable description

Variables	Description	Predicted Sign	Definition	Rationale
EP	Earnings persistence	(+)	The slope coefficient between current period earnings regressed scaled by total assets (data 6) over previous period earnings, estimated based on the Kormendi and Lipe (1987) regression model using a five-year rolling window.	Kormendi and Lipe (1987), Collins and Kothari (1989) and Easton and Zmijewski (1989) find more persistent earnings have a higher security price response and positive stock market returns. A higher β represents a highly persistent earnings stream (higher earnings quality). Firms which have more *earnings persistence* show a higher "sustainable" earnings/cash flow stream, providing 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.
AA	Abnormal accruals	(-)	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) measure earnings quality by capturing the uncertainty arising from estimation errors in the mapping of working capital accruals to operating cash flow realizations. Firms with 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) show that some investors are unable to incorporate completely the mean reverting of the accruals of high accrual firms. The literature suggests that there is a negative relationship between earnings quality (proxied by accruals) and the degree of information asymmetry as high accruals result in a low quality of earnings and thus a higher degree of information asymmetry.
ES	Earnings Smoothness	(+)	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, Rajgopal, and Venkatachalam (2008) over the five years *t-5* to *t-1*.	Tucker and Zarowin (2006) find that smoothness enhances earnings informativeness. Firms with higher (lower) values of earnings smoothness indicate more (less) smoothing of the earnings stream relative to cash flow and accounting discretion.
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, Lakonishok, Shleifer, and Vishny (1997) and Skinner and Sloan (2002) show that market participants underestimate future earnings for high book-to-market ratio and overestimate future earnings for low book-to-market stocks. Thus, firms, which have larger book-to-market ratios, tend to have higher information transparency.
CP	Cash flow to price ratio	(+)	$CP = (IB+EDP+TXDI)/ME$	As Chan, Hamao, and Lakonishok (1991), Fama and French (1992) and Lakonishok *et al.* (1994) note, stock returns have a positively association

			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). $EDP=ME/(ME+AT-BE)*DP$ 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.	with the cash flow-to-price ratio. The results are consistent with Lau, Lee, and McInish (2002) who find that the cash flow-to-price ratio is positively related to stock returns in Japan. The results imply that a 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) find firms with a long history (age) have more information available to the market, which leads to capturing more information in predicting future returns. Barinov, Shawn, and Celim (2018) show that firms with a lower age are associated with weaker incorporation of information into their stock prices. Thus, older firms tend to have higher information transparency.
LEV	Leverage	(+)	The ratio of total debt (data 181) to total assets (data 6).	Hanifa and Rashid (2005) find a positive association between information transparency and firm leverage in the emerging markets, indicating 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, Gulen, and Schill (2008) document that there is a strong negative association between a firm's asset growth and the future stock returns, suggesting that firms with lower total asset growth tend to have higher information transparency.
CI	Abnormal capital investments	(-)	$CI_t = [CE_{t-1} / (CE_{t-2} + CE_{t-3} + CE_{t-4}) / 3] -1$ where CE_t is the firm's capital expenditure (data 128) divided by net sales (data 12).	Studies by Titman, Wei, and Xie (2004) find that an investment anomaly is the tendency of firms which recently experienced high capital investments to have low expected returns, suggesting that lower abnormal capital investments tend to have higher information transparency.
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) document the negative relation between investment and expected returns, suggesting that firms increasing capital tend to have a higher investment-to-assets ratio and have lower expected returns whereas firms distributing capital tend to have a lower investment-to-assets ratio and have higher expected returns. Thus, firms with a lower investment-to-assets ratio tend to have higher information transparency.
IG	Investment growth	(-)	The annual change in capital expenditures $_t$ and $_{t-1}$ (data 128) divided by capital expenditures $_{t-1}$ (data 128).	Xing (2008) show that 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, implying 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) shows 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 suggest a negative relationship between capital investment and future stock returns. Xing (2008) also documents that stocks with the lowest (highest) investment-to-capital ratios have the highest (lowest) returns, indicating that firms with a lower investment-to-capital ratio tend to have higher information transparency.
NOA	Net operating assets	(+)	*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, Hou, Teoh, and Zhang, (2004) suggest that net operating assets are positively associated with future stock returns. This study implies that firms having 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, Liu, and Wang (2011) find that portfolios with higher cumulative abnormal returns have a positive association with ROA, suggesting that a higher return on assets tends to have higher information transparency.
ROE	Return on equity	(+)	*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.	Claus and Thomas (2001) show that there is a positive association between ROE and abnormal earnings. This study implies 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) find that larger capitalization portfolio stock returns lead while smaller ones mostly merely follow. Hou (2007) also show that the lead-lag relationship in information between large and small firms is predominantly an intra-industry phenomenon. That is, stock returns in small firms 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, Carlos and Pinho (2015) find that there is a negative relation between information transparency scores and the stock price volatility, which is contrary to the findings of Ding, Hope, and Schadewitz (2008).

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) document that a declining TED spread may result in improvements in the value of stocks. Lashgari (2000) also show that there is a negative relationship between TED spread and stock prices. These studies imply that a low TED spread has higher information transparency.
SENT	Sentiment index	(-)	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_6	(-)	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/.	Chui et al. (2010) and Schmeling (2009) show that sentiment negatively predicts aggregate stock exchange returns. These studies imply that a low sentiment index has higher information transparency.
ICS	Index of consumer sentiment	(-)	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) find that the VIX index is negatively associated with investment returns, suggesting that a low VIX index has higher information transparency.

Table 1. Descriptive statistics of accounting and market stage variables

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

Panel A: Descriptive statistics

Variable	N	Min	Median	Max	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
TED	31	0.192	0.495	1.548	0.588	0.372	1.141	0.660
SENT	50	-1.960	-0.025	2.990	0.018	1.042	0.399	0.494
SENT_6	50	-2.190	0.070	3.060	0.020	1.047	0.193	0.862
ICS	38	60.100	91.000	105.400	86.287	12.180	-0.709	-0.692
VIX	31	11.460	18.710	40.000	20.582	7.387	1.123	1.191

Panel B: Pearson correlations among accounting 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

Panel C: Pearson correlations among market stage variables

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

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

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

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

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

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

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

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

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

Table 3. Determinants of time-varying return predictability based on the TED spread

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

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

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

Panel A: OLS regression using Sig

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

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

Variables	$\boldsymbol{DIFF_{j,i}}$	***TED***	$\boldsymbol{DIFF_{j,i}}$ **** TED***	$\boldsymbol{R^2}$	***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

Table 4. Determinants of time-varying return predictability based on the sentiment index

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

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

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)*. Year fixed effect and industry fixed effects are included in all regressions. We provide a description of each variable in the Appendix. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1 %, 5%, and 10% level, respectively.

Panel A: OLS regression using Sig

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

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

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

Table 5. Determinants of time-varying return predictability based on the Index of Consumer Sentiment

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

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

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

Panel A: OLS regression using Sig

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

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

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

Table 6. Determinants of time-varying return predictability based on the Volatility Index

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

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

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

Panel A: OLS regression using Sig

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

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

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

Online Appendix:
"Do Accounting Information and Market Environment Matter for Cross-Asset Predictability?"

Content

Table A1. Descriptive statistics for pairwise regression sample

This table presents the descriptive statistics 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. 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}, *SMB*, *HML* are Fama and French (1993)'s three factors. We source returns data from CRSP and factors from Kenneth French's website.

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

Figure 1: The proportions of positive and negative coefficient from pairwise regression

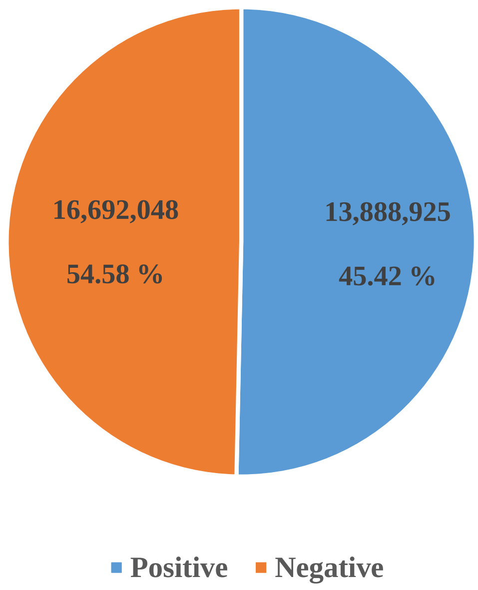

Table A2. The proportions of positive and negative significances from pairwise regression

This table presents the descriptive statistics 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. 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}, SMB, HML are Fama and French (1993)'s three factors. We source returns data from CRSP and factors from Kenneth French's website.

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

Figure 2: The proportions of positive and negative significance from pairwise regression

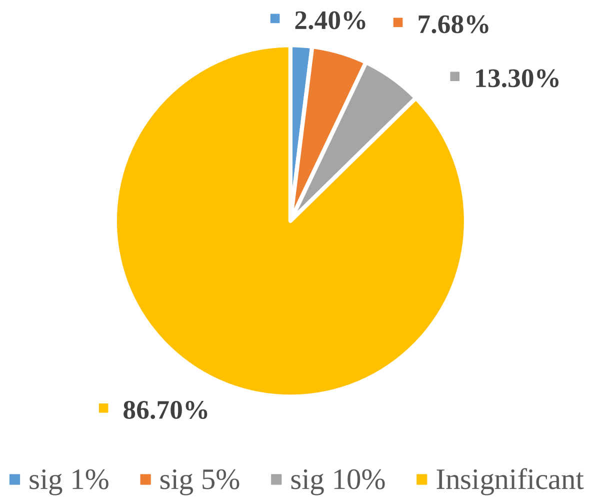

Table A3. Determinants of return predictability using *Sig* and R^2_1 - R^2_0

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 and significant at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_j R_{j,t-1} + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t.$

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

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

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

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

Table A4. Determinants of of time varying return predictability based on the TED spread using $(R^2_1 - R^2_0)/ R^2_0$

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

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

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

Table A5. Determinants of time varying return predictability based on the sentiment index using $(R^2_1 - R^2_0)/ R^2_0$

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

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

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

Table A6. Determinants of time varying return predictability based on the sentiment index

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

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

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

The explanatory variables are the differences in determinants between firms *j* and *i* ($DIFF_{j,i}$) and the Sentiment Index in Baker and Wurgler (2006) (denoted as *SENT_6*) constructed based on the first principal component of five (standardized) sentiment proxies where each of the proxies has first been orthogonalized with respect to a set of six macroeconomic factors. Year fixed effect and industry fixed effects are included in all regressions. We provide a description of each variable in the Appendix. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A: OLS regression using Sig

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

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

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

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

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

Table A7. Determinants of time varying return predictability based on the Index of Consumer Sentiment using R^2_1 - R^2_0

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 $R_{i,t} = \alpha + \beta_j R_{j,t-1} + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$. The explanatory variables are the differences in determinants between firms *j* and *i* *($DIFF_{j,i}$)* and the Index of Consumer Sentiment *(ICS)*. Year fixed effect and industry fixed effects are included in all regressions. We provide a description of each variable in the Appendix. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

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

Table A8. Determinants of time varying return predictability based on the Volatility Index using R^2_1 - R^2_0

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 $R_{i,t} = \alpha + \beta_j R_{j,t-1} + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$ and R^2_0 is R^2 of the 5-year rolling window regression $R_{i,t} = \alpha + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$. The explanatory variables are the differences in determinants between firms *j* and *i* (*DIFF*$_{j,i}$) and the Volatility Index *(VIX)*. Year fixed effect and industry fixed effects are included in all regressions. We provide a description of each variable in the Appendix. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

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

Table A9. Determinants of return predictability by logistic regressions using *Sig* and $(R^2_1 - R^2_0)/R^2_0$

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

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

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 $R_{i,\,t} = \alpha + \beta_j\, R_{j,\,t-1} + \beta_i\, R_{i,\,t-1} + \beta_{MKT}\, R_{MKTt} + \beta_S\, SMB_t + \beta_v\, HML_t + \varepsilon_t$. The explanatory variable is the difference in determinants between firms *j* and *i* ($DIFF_{j,\,i}$). Year fixed effect and industry fixed effects are included in all regressions. We provide a description of each variable in the Appendix. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

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

Table A10. Determinants of time varying return predictability based on the TED spread by logistic regressions using *Sig*

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 and significant at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_j R_{j,t-1} + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$. The explanatory variables are the differences in determinants between firms *j* and *i* *($DIFF_{j,i}$)* and the average percentage of TED Spread *(TED)*. Year fixed effect and industry fixed effects are included in all regressions. We provide a description of each variable in the Appendix. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

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

Table A11. Determinants of time varying return predictability based on the sentiment index by logistic regressions using *Sig*

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 and significant at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_j R_{j,t-1} + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_{t.}$ The explanatory variables are the differences in determinants between firms *j* and *i* ($DIFF_{j,i}$) and the Sentiment Index in Baker and Wurgler (2006) (denoted *SENT*) constructed based on the first principal component of five (standardized) sentiment proxies. Year fixed effect and industry fixed effects are included in all regressions. We provide a description of each variable in the Appendix. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

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

Table A12. Determinants of time varying return predictability based on Index of Consumer Sentiment by logistic regressions using *Sig*

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 and significant at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_j R_{j,t-1} + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$. The explanatory variables are the differences in determinants between firms *j* and *i* ($DIFF_{j,i}$) and the Index of Consumer Sentiment *(ICS)*. Year fixed effect and industry fixed effects are included in all regressions. We provide a description of each variable in the Appendix. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

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

Table A13. Determinants of time varying return predictability based on the Volatility Index by logistic regressions using *Sig*

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 and significant at 0.05 level and 0 = otherwise of the 5-year rolling window regression results $R_{i,t} = \alpha + \beta_j R_{j,t-1} + \beta_i R_{i,t-1} + \beta_{MKT} R_{MKTt} + \beta_S SMB_t + \beta_v HML_t + \varepsilon_t$. The explanatory variables are the differences in determinants between firms *j* and *i* *(DIFF $_{j,i}$)* and the Volatility Index *(VIX).* Year fixed effect and industry fixed effects are included in all regressions. We provide a description of each variable in the Appendix. The coefficient is scaled by 10^{-2}. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

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