WHAT DO FIRMS' PRICE SENSITIVITY TO CREDIT MARKET SENTIMENT TELL US ABOUT THEM?

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ABSTRACT

Using the data in U.S. stock market, we measure the credit sentiment beta which is firms' sensitivity to the changes in the credit market sentiment and classify individual firms into the sentiment-prone, insensitive and sentiment-counter groups. First, we find that sentiment-prone firms tend to be smaller, financially constrained, unprofitable and more volatile which is consistent with our "Hard-to-Value, Difficult-to-Finance" Hypothesis. Interestingly, while sentiment-counter firms have many similar firm characteristics with sentiment-prone firms, they have relatively low leverage, liquidity risk and tend to be value stocks. In addition, these firms are more likely belong to the industries whose products have rigid demand or largely depend on government spending. Second, our results show that while sentiment-prone firms' financing and investment are affected by credit market sentiment, the sentiment has insignificant effects on the other two groups' financing and investment. Furthermore, sentiment-prone investment leads to poor operating performance, and their delisting probability is higher. Finally, in terms of stock performance, we find that sentiment-counter firms outperform sentiment-prone firms.

Keywords: Credit Market Sentiment, Firm Characteristics, Corporate Investment, Stock Performance

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TABLE OF CONTENTS

1. Introduction

Economic recessions that follow the extreme credit expansions have triggered a large body of research on do credit booms create risks to macroeconomic outcomes in the future especially after the recent global financial crisis in 2007-2008. A magnitude of literature has shown the severe consequences caused by credit booms on the real economy such as lower GDP growth, financial crisis (e.g. Schularick and Taylor, 2012; López-Salido, Stein, and Zakrajšek, 2017), higher bank equity crash risk and lower returns in corporate bonds (e.g. Baron and Xiong, 2017; Greenwood and Hanson, 2013). Starting with Minsky (1977), a controversial view believes that irrational expectation by economic agents due to their over-extrapolation of current economic state into future drives these boom-bust patterns in credit and business cycles. Despite the size of literature on the effect of credit-market sentiment on the aggregate economic activities, there is still a lot of uncertainty on its exact causes and effects on firm level activities, making it an interesting topic for further evaluation.

One observable fact is that firms react differently to economic fluctuations. When a credit-driven recession occurs, some firms suffer severe impacts or even go bankruptcy, but some are relatively immune to economic swings, why? What makes some firms more sensitive to credit and business cycle? Will the asymmetrical effects of credit market sentiment on firms answer these questions? In this paper, we seek to provide firm-level empirical evidences of credit sentiment effects on firms with different sentiment sensitivities.

Our study is motivated by Gilchrist and Zakrajšek (2012, hereafter GZ) and Greenwood et al. (2016) who find that high (low) credit-market sentiment drives down (up) expected returns to bearing credit risk and allows more (less) capital in credit markets which induces economic fluctuations and by Baker and Wurgler (2006, 2007) who show that investor sentiment has a significant impact on the aggregate stock market and those “Hard-to-value, Difficult-to-arbitrage” stocks are likely to be disproportionately sensitive to investor sentiment shocks. The research in this paper aims to extend behavioral credit cycles literature by investigating three questions. First, what types of firms are more sensitive to credit market sentiment? Rather than simply pointing out the effects of credit-market sentiment on the aggregate economy, we study which firms are more sensitive to credit sentiment shocks by testing what we call the "Hard-to-value, Difficult-to-finance" hypothesis (HV-DF) which states that some firms are more affected by shifts in credit-market sentiment than others due to the differences in firm characteristics. Second, we try to answer how does credit-market sentiment affect firms' performance through real activities by testing firm-level responses to credit cycles using data on the financing and investment of firms over 1975-2018. Our objective is to find whether the firms' performance differences during credit-driven recessions could be partially explained by the asymmetrical effects of credit market sentiment. Third, we assess the link between credit-market sentiment sensitivities and firms' stock performance to see whether investors anticipate the risk elevated by credit sentiment fluctuations and demand a risk premium as compensation. Could investors use a sentiment-hedging strategy to earn abnormal returns?

We begin by estimating firm's sentiment beta which reflects the sensitivity of firm stock returns to credit-market sentiment changes. First, we use excess bond premium (EBP) constructed by GZ (2012) as a starting point to measure credit-market sentiment. Indeed, GZ (2012) decompose credit spread into the predicted credit spread related to firms' default risk and bond-specific characteristics[1] which captures the usual countercyclical movements in the risk of default, and the residual component referred as excess bond premium (EBP) which captures variations in the pricing of default risk. To mitigate the possibility that the sentiment factor may also present economic factors, similar to Baker and Wurgler (2006), we

[1] Bond-specific characteristics include the bond's duration, amount outstanding, coupon rate, age of issue, and a dummy variable set to one if the bond is callable and zero otherwise.

orthogonalize EBP with respect to several variables that may be related to economic conditions[2]. Our measure of credit-market sentiment (*Credit_Sentiment*) is the orthogonalized EBP multiplying by -1, which means that the orthogonalized EBP is negative associated with credit-market sentiment. Second, the credit sentiment beta is defined as the coefficient in the time-series regressions of stock returns on changes in the credit-market sentiment after controlling for the risk factors associated with the market, size, book-to-market, momentum and liquidity.

From a behavioral and psychological perspective, investors form beliefs or tastes about firms' future creditworthiness in a non-rational manner by over-extrapolating past default, cash flows, past returns (e.g. Greenwood et al., 2016; Bordalo et al., 2018) into future which suggests that good news about fundamentals will make investors become too optimistic about future default risk. When credit-market sentiment is high, lenders may loosen their lending standards, indicating high amounts of 'cheap' credit are available in the capital market even for firms with high credit risk. Thus, we assume that change in credit market conditions may has a disproportionate effect on firms that are more difficult for them to find credit and the impact of credit sentiment is stronger for speculative and hard-to-value assets since investors are more likely to have biased expectations on these firms.

Based on the sensitivities of firms' price to credit-market sentiment shocks, we classify individual firms into the sentiment-prone, insensitive, and counter-sentiment groups. Our result shows that sentiment-prone firms tend to be highly levered, smaller, younger, unprofitable, high-volatility, financially constrained, and in competitive industries which is consistent with our "Hard-to-Value, Difficult-to-Finance" hypothesis. Interestingly, while counter-sentiment firms have many similar firm characteristics as sentiment-prone ones, they have very low liquidity risk and relatively lower leverage ratios and past 12-month returns. The monotonic

[2] These variables are the growth in industrial production, consumption of durables, non-durables, and services.

decrease of HML beta (i.e. loadings on HML factor) from sentiment-counter to sentiment-prone firms suggests that value stocks are more likely to behave countercyclical. These specific characteristics could help explain why sentiment-counter firms suffer less during credit-driven recessions. When credit market sentiment turns around 2 or 3 years subsequent to high credit market sentiment, credit supply suddenly dries up with widening credit spread and deteriorating business environment as credit investors become pessimistic and risk-averse. The low liquidity risk and leverage for sentiment-counter firms may alleviate the negative impacts of tighten funding environment such as "Flight-to-liquidity/quality".

We also find that sentiment-counter firms are more likely to belong to the industries whose products have rigid demand such as Food Product and Agriculture, or largely depend on government spending like Defense, while sentiment-prone firms have products which are considered as nonessentials such as Recreation, Entertainment, and Business Services. Therefore sentiment-counter firms may be less affected by the fluctuations in the economy.

Next, we examine firm-level responses to credit-market sentiment by using panel data on the investment and financing of U.S. public firms over 1975-2018 to see whether the performance difference between firms during economic downturns is due to the relatively poor profitability caused by firms' overreaction to previous high credit sentiment. High credit-market sentiment reflects investors' optimism about future default risk, thus, when sentiment is high, the cost of capital is relatively low and the increasing in lenders' risk-bearing capacity allows firms with higher credit risk to finance and take on more risky projects. The availability of easy money may trigger firms to borrow and invest more. As credit cycle is synchronized with business cycle, easy money alleviates firms' fund constraints and allows them to take advantage of valuable investment opportunities which may increase firm operating performance and firm value. But the easily available external funds may also result in over-borrowing and over-investment problems which would reduce investment efficiency and decline firm profitability. When credit cycle turns around (i.e., creditors become pessimism), firms that over-borrow and invest at good times may find it is difficult to earn profits and pay off the debt.

In this paper, we find that higher credit-market sentiment in year *t* significantly induces sentiment-prone firms to increase their debt financing and make excess investment for years *t+1* and *t+2,* but not for counter-sentiment firms and sentiment-insensitive firms. And high credit-market sentiment predicts the declines in the operating performance and higher excess leverage level of firms that are more exposed to sentiment changes which make sentiment-prone firms have higher delisting probability compared with firms that have negative sentiment exposure during years *t+3* and *t+4*. These findings suggest that the firms' performance differences during credit-driven recessions may be partially explained by the over-borrowing and over-investment of sentiment-prone firms caused by high credit market before the onset of recessions.

As the over-optimism of credit investors could propagate and amplify risk to firms with high sensitivity to the changes in credit market sentiment such as deleveraging risk, credit risk, and probability to be delisted from market by allowing over-borrowing and over-investment among these firms, therefore we finally test whether investors will anticipate the increasing risk and required higher expected returns.

Our finding shows that portfolio that has the most negative sentiment betas tend to outperform portfolio that has the most positive sentiment betas by 0.25% per month on a risk-adjusted basis which is mainly driven by the underperformance of firms with most positive betas during large negative sentiment shock periods. Although firms with highest sentiment betas perform well with 1.61% per month for Fama-French 5-factor alpha when credit market sentiment increases, they suffer great drop with -0.41% per month for Fama-French 5-factor alpha when credit market sentiment goes down. In contrast, firms with lowest sentiment betas perform quite better during negative shocks periods, 0.16% per month for Fama-French 5-factor alpha, and there is slight difference in the stock returns between top and bottom deciles when credit condition is good. These evidences also indicate that sentiment-prone firms are more vulnerable to the economic swings, while sentiment-counter firms are relatively immune to the business cycle fluctuations, especially during downturn periods.

Given the severe influences of credit market sentiment on the economy and limited evidence on firm level, it is important to study how firms react to sentiment shocks and the effect of credit-market sentiment on firms' operating and financial performance. The main contribution of our paper including the following aspects.

Firstly, our paper contributes to the literature by helping explain why some firms suffer severe impacts during credit-driven downturns, while others are less affected by comparing firm characteristics to find which types of firms are more sensitive to credit market sentiment shocks and investigating firm-level responses to credit cycles through financing and investment activities.

Secondly, the real effects of credit market sentiment on firms with higher sentiment exposure and dynamic of credit cycle may have important implication on why some firms get into a phenomenon named "the debt trap". When the credit cycle turns around (i.e., creditors become pessimistic), the deteriorated business environment and rising credit spread make it difficult to earn profits and pay off the existing debt for those firms that over-borrow and over-invest at good times, causing these underachieving and levered firms into indebtedness.

Thirdly, our findings on the stock returns could help explain "credit risk puzzle", a negative cross-sectional relation between credit risk and future stock returns, which is empirically documented in the literature (e.g., Avramov, 2009) and is puzzling as it seems that investors pay a premium for bearing credit risk. Results in our paper also show a negative relation between sentiment betas and stock returns which suggests that investors do not require higher expected returns for firms with higher sentiment exposure, but credit market sentiment increases risk such as credit risk for these firms. Our findings implicate that credit risk effect may be due to credit investors' irrational sentiment and poor performance caused by over-borrowing and over-investment of firms that are more sensitive to credit market shocks.

Meanwhile, the results in our paper also have implication on investment strategy for investors. When the economy is booming, investors could easily make money even if they do not choose assets carefully as the aggregate market performs well, but how could investors earn profits in times of down market? This paper provides a potential Long-Short strategy that longs firms with lowest exposure to sentiment and shorts firms with highest exposure to sentiment for investors to hedge against credit market sentiment risk.

The rest of paper is organized as follow. Section 2 presents the literature and discusses theoretical predictions. Section 3 describes the data including the estimation of credit-market sentiment beta. Section 4, 5, and 6 contain empirical results and interpretation. The last section concludes the paper.

2. Literature review and theoretical predictions

This section first reviews the literature on the "Hard-to-Value, Difficult-to-Finance" hypothesis to find which firms are more vulnerable to sentiment shocks. We then present the literature related to credit-market sentiment and firms' financial and investment decisions. Finally, we discuss about the studies on credit cycles and stock returns.

2.1 Hard-to-Value, Difficult-to-Finance Hypothesis (HV-DF)

HV-DF states that creditors' irrational sentiment may have disproportionate influences on some firms than others due to the differences in their firm characteristics. First, on the borrowers' side, from a dynamic risk management perspective, to hedge future funding risk when credit becomes tighten, better quality firms would increase their debt when credit condition is good (Rampini and Viswanathan, 2010; Mian and Santos, 2018; Froot, Scharfstein, and Stein, 1993) which suggests that higher quality firms is more pro-cyclical to credit sentiment. However, a magnitude of literature posits that capital raising for firms with lower credit quality (e.g., speculative-grade borrowers) tends to be procyclical, while for high credit quality firms, it is countercyclical as firms with higher financial constraints tend to hedge less and exhaust their debt capacity rather than conserve it for future investment opportunities.

Based on the studies on financial frictions theories, the existence of agency costs limits firms' ability to borrow and cost of capital, thus, firms' ability to access the external capital and to switch their sources of capital play an important role in the degree to which firms may affect by credit supply shocks. A large body of evidence documents that the impact of supply shocks is stronger for firms without a credit rating (i.e. access to the public debt market), with smaller firm size, speculative-grade and facing more financial constraints (e.g. Faulkender and Petersen, 2006; Leary, 2009; Lemmon and Roberts, 2010; Begenau and Salomao, 2019; Gulen et al., 2019).

When credit-market sentiment is high, abundant capital is available and expected returns to bearing credit risk are driven down (López-Salido, 2017). Lenders will loosen their lending standards which allowing firms with high credit risk and more financially constrained to borrow and lower their debt financing cost. For these firms who are more difficult to tap the credit market for capital, they may make use of this opportunities to borrow as the improvement in credit conditions disproportionately affects the financing costs faced by these low credit quality firms which is consistent with the evidence shown in Greenwood and Hanson (2013) that low-quality firms will raise more debt and corporate debt issuers' credit quality deteriorates in an overheated credit market.

Second, on the lenders' side, a line of literature explains the causes and consequences of credit sentiment from behavioral finance perspective which postulates that investors' extrapolation of past credit market outcomes drives the credit cycles (Greenwood et al. 2016;

Bordalo et al., 2018). Current good news about fundamentals influence investors' beliefs on the expectations for the future which makes them become over-optimistic about future default probabilities and neglect credit risk and this optimism drives an excessive decrease in the cost of capital and plays a role in determining the quantity and allocation of credit. Following the literature on equity investor sentiment which finds that sentiment matters more for speculative and hard-to-value assets (e.g. Baker Wurgler, 2007), we assume that firms whose values are more difficult to evaluate will also be more vulnerable to the credit sentiment shocks as investors have to rely more on their own judgements which may be subject to behavioral biases, making valuation mistakes more likely. For instance, Guo et al. (2019) posit that investor sentiment has a stronger predictability in speculative-grade bonds' future returns and Gulen et al. (2019) find that the reversal effect of credit sentiment on firms' corporate investment is more significant among firms with larger analysts' earnings forecast errors.

In addition, credit supply uncertainty may have different influences on the firms in different industries. Earlier studies have been written on that business cycle fluctuations affect industries in different ways. Cyclical industries tend to suffer more as their products are considered as nonessentials such as recreation, and culture, or highly dependent on credit which will become tighten during macroeconomic downturns, but for industries produce basic goods with rigid demand or non-substitutes such as food, housing, and health, they are more likely to behave counter-cyclical (e.g. Berman et al, 1997; Conti et al., 2020).

In sum, we hypothesize that ***more sentiment-sensitive firms are those having more difficulties in external financing and those harder for investors to assess firms' values (HV-DF); and firms in cyclical industries may also be more vulnerable to the sentiment shocks***.

2.2 Credit-market sentiment and firms' financial and investment policies

Build on behavioral theories, researchers point out that the optimistic expectations of investors due to their over-extrapolation of current economic state into future drive the behavioral credit cycles (Greenwood et al. 2016; Bordalo et al., 2018). That is, when past default rate has been low or past cash flows and returns are high, credit investors will expect that future default risks will continue to be low which make them become too optimistic and are willing to provide capital with lower interest rates. However, the systematic disappointments of these over-optimistic expectations will cause reversals in credit investors sentiment. Investors may become pessimistic, causing the widening credit spread and the onset of contraction of economy.

In Lopez-Salido et al. (2017)'s paper, they suggest that credit market sentiment is an important driver of business cycle. When credit market sentiment is high (low), expected returns to bearing credit risk are driven down (up) and more (less) capital is available in credit market which fuels (decelerates) the business activities and induces the fluctuations in the aggregate economy.

Corporate capital structure decisions will be influenced by capital market supply frictions. Begenau and Salomao (2019) document that differences in funding needs and funding capacities together determine firms' financing behaviour over business cycle. When credit-market sentiment is high, lenders may loosen their lending standards, allowing firms with high credit risk and high financial constraints to borrow at relatively lower interest rates and to invest more risky projects. Firms with lower credit quality will take advantage of easy money by financing more with debt during booms. Thus, ***when the credit-sentiment increases, we expect sentiment-sensitive firms will issue more debt***.

If firms take advantage of an over-heated credit market by raising more debt, what do they do with the money? One view is that firms may act as "cross-market arbitrageurs" by exploiting the relative valuation of equity and credit (Ma, 2019). When credit is relatively cheaper than equity, managers may increase stock buybacks by issuing more debt from credit market; conversely, when credit is relatively expensive, firms tend to substitute equity for debt.

Smaller firms tend to increase both equity and debt to finance their growth during a boom, while larger firms tend to increase debt financing to repurchase their shares when credit condition is good (Covas and Den Haan, 2011; Begenau and Salomao, 2019).

In contrast, a broad range of literature states that changes in credit supply may affect firm investment. Decrease in cost of capital and abundant capital in the market due to high credit-market sentiment may alleviate underinvestment of financially constrained firms as these firms have to abandon valuable investment projects due to the limitation of funds (e.g., Huang et al., 2016). Lemmon and Roberts (2010) show that corporate investment increases when there is a positive shock on the external supply of capital. However, the easily available external funds may exacerbate the problem of overinvestment (López-de-Foronda et al., 2019). And excessive investment triggered by credit boom may lead to a subsequently crisis and generate large boom-bust business cycle (Pintus and Wen, 2008; Hoffmann, 2010). Therefore, we hypothesize that ***the availability of easy money due to optimistic credit sentiment may lead to over-investment problem in sentiment-sensitive firms which would declines investment efficiency and lower operating performance***.

Interestingly, López-Salido et al. (2017) suggest that credit cycle is synchronized with the business cycle and a contraction in economic activities coincided with widening credit spreads will happen 2 or 3 years after the high credit-market sentiment. When the credit cycle turns around (i.e. creditors become pessimistic), the deteriorated business environment and rising credit spread make it is difficult to earn profits and pay off the existing debt for those firms that over-borrow and over-invest at good times, causing these underachieving and levered firms into indebtedness. Firms that exploit high credit-market sentiment may get into a phenomenon known as “the debt trap”. And these firms will have higher deleveraging risk, funding risk, default and bankruptcy probabilities when creditors become pessimistic. Thus, we postulate that ***sentiment-sensitive firms will have higher excess leverage and higher***

probability to be delisted from market when credit-market sentiment turns around in the future.

2.3 Investor sentiment and stock returns

There is a large body of theoretical and empirical literature emphasizing the significant effect of equity investor sentiment on stock market (e.g. Baker and Wurgler, 2006, 2007; Stambaugh, Yu and Yuan, 2012; Cen, Lu and Yang, 2013; Li and Yang, 2017). Irrational investor sentiment could cause stock price to deviate from fundamental and has predictive power on the cross-sectional stock returns. Recently, a branch of literature investigates the market sentiment beta (e.g. Glushkov, 2006; Berger and Turtle, 2012; Liang, 2016; Yang and Hu, 2021). However, the relation between stocks' exposure to investor sentiment and their future stock returns hasn't reach a unanimous conclusion. Zheng et al. (2018) find that for hedge funds that hedge against sentiment risk, they tend to outperform funds having the highest positive sentiment exposure by 0.14%-0.2% per month, while Chen et al. (2021) show that hedge funds having the highest negative sentiment exposure underperform those in the top decile ranked by sentiment beta by 0.59% per month.

Compared with the studies on equity investor sentiment, there are less researches studying on the effects of credit investor sentiment on bond and stock returns. First, some papers argue that higher credit investor sentiment leads to lower returns of corporate bonds in the future (Greenwood and Hanson, 2013; Guo et al., 2019).

Second, Fama and French (1993) and Chen (1991) prove that stocks and bonds share common risk factors and variations in the term premium for discount-rate risks and default premium would impact expected stock and bond returns. When credit sentiment is high, the over-optimism of creditors drives down credit risk premium and liquidity risk which will increase the asset prices and fuel economic activities. We assume to see ***high returns on the aggregate market during high sentiment periods***.

However, the over-optimism of credit investors induces credit boom and neglect of default risk which will trigger severe outcomes like financial distress, bank crashes, and recessions in the future during which market liquidity suddenly dries up, credit risk is largely increased and aggregate market will suffer a great drop in stock returns, especially for those sentiment-sensitive firms (i.e. "hard-to-value, difficult-to-finance"). The Psychological and behavioral factors of credit risk holders may exacerbate credit risk contagion (Jiang and Fan, 2018). As credit-market sentiment shocks could affect economy activities and financial market to a great extent even trigger a financial crisis, will investors anticipate the risk and require a risk premium as compensation and could investors construct a trading strategy to hedge against credit-market sentiment risk? According to a fundamental principle of asset pricing theories, stocks with higher risk should be compensated with higher expected returns. Thus, those firms that expose more to the credit-market sentiment shocks should earn higher expected returns. However, by doing an international analysis, Baron and Xiong (2017) posit that an increase in bank credit predicts greater crash risk but lower mean bank equity returns 1 to 3 years following credit expansions. Some other papers also show a negative association between credit expansion and stock returns. Bradshaw et al. (2006) find that external financing is negatively related to future stock returns and firms' profitability which may due to the optimism of analysts. Jeong et al. (2018) explain negative relation between credit growth and aggregate stock returns mainly from investment-based and misevaluation exploitation explanations. In this paper, we firstly simply assume that ***on average there is no significant difference in future stock returns between sentiment-sensitive firms and other firms***.

3. Data and variables

In this paper, we obtain our sample by merging firm financials from the Compustat and stock prices from the CRSP. And financial firms (SIC 6000-6999) and utility firms (SIC 4900-4999) are excluded from data. The sample period spans from 1975 to 2018 due to the availability of the EBP data[3] which we use to capture credit-market sentiment and other macroeconomic variables.

3.1 Credit-market sentiment and macro-level data

To test our hypotheses, we use excess bond premium (EBP) developed by GZ (2012) as a starting point to measure credit-market sentiment. Indeed, GZ (2012) decompose credit spread into the predicted credit spread that measure the movement in the risk of default and the residual component referred as excess bond premium (EBP) to capture variations in the pricing of default risk which could reflect the effective risk appetite of investor in credit market. A higher EBP suggests a lower credit-market sentiment.

To mitigate the possibility that the sentiment factor may present economic factors, similar to Baker and Wurgler (2006), we orthogonalize EBP with respect to several variables that may be related to economic conditions. Our measure of credit-market sentiment (*Credit_Sentiment*) is the annual average of monthly orthogonalized EBP multiplying by -1 for interpretation convenience, so that a larger value of *Credit_Sentiment* corresponds to a higher credit market sentiment.

Figure 1 plots this credit market sentiment measurement from 1975 to 2018 alongside NBER recessions (the shaded areas). Consistent with prior literature, credit cycle is synchronized with business cycle. High credit-market sentiment forecasts recessions in subsequent three to four years.

As equity investor sentiment may also affect firms financial and investment decisions, we use the sentiment index (*Equity_Sentiment*)[4] constructed by Baker and Wurgler (2006) to control the impact of equity sentiment when doing regression analysis. We find that there is no significant association between credit market sentiment and equity market sentiment which

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[3] The EBP data could be downloaded from Board of Governors of the Federal Reserve System at https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/updating-the-recession-risk-and-the-excess-bond-premium-20161006.html
[4] The sentiment index data can be obtained from Jeffrey Wurgler's website at http://people.stern.nyu.edu/jwurgler/

suggests that credit market sentiment is different from equity market sentiment. In addition, we also control for macroeconomic factors in the regressions to address the influence caused by the variations in the economy by including economic conditions (*Economic_Condition*) and macro uncertainties (*Macro_Uncertainty*), in addition to sentiment variables.

Following Bonaime et al. (2018), *Economic_Condition* is calculated as the first principle component of three variables: (1) Consumer confidence[5]; (2) National activity index[6]; (3) Expected GDP growth[7]. And *Macro_Uncertainty* is defined as the first principle component of (1) JLN uncertainty index[8], (2) CS σ past returns, and (3) CS σ past sales growth[9].

3.2 Firms' sensitivity to credit-market sentiment shock (Sentiment Beta)

In order to answer the question which firms are most sensitive to the credit-market sentiment shocks in this paper, we start with the estimation of sentiment beta (i.e. the sensitivity of firms' price to the changes in the credit-market sentiment) based on the following model:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{MKT,i} R_t^{MKT} + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + \beta_{UMD,i} UMD_t + \beta_{LIQ,i} LIQ_t + \boldsymbol{\beta_{sent,i}} \Delta Sentiment_t + \varepsilon_{i,t} \quad (1)$$

Where $R_{i,t}$ is the return of stock *i* at time *t*, $R_{f,t}$ is the risk-free rate of return at time *t*, $R_t^{MKT}, SMB_t,\ HML_t$ and UMD_t are the Fama-French factors[10] which can be downloaded from the Kenneth French website, LIQ_t is the liquidity factor constructed by Pastor and Stambaugh (2003) and $\Delta Sentiment_t$ is the change of monthly credit-market sentiment at time *t* which equals to the difference between *Credit_Sentiment* at month *t* and month *t-1*. In this paper, we use a 5-year estimation window. At the end of each year, we estimate the sentiment sensitivity

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[5] The survey-based University of Michigan index of consumer confident which is available at http://www.sca.isr.umich.edu/ .
[6] An index measures current economic activity and inflationary pressure. The data is from the Chicago Federal Reserve Board and available at https://www.chicagofed.org/research/data/cfnai/historical-data .
[7] The average one-year-ahead GDP from the Livingston Survey of Professional Forecasters. Data is available from the Philadelphia FED.
[8] Jurado, Ludvigson and Ng's (2015) monthly index of macroeconomic uncertainty.
[9] The cross-sectional standard deviation of monthly returns from the CRSP and the cross-sectional standard deviation of year-on-year sales growth from the Compustat.
[10] Market, size, book-to-market and momentum factors, respectively.

($\beta_{sent,i}$) for firm *i* by regressing the monthly excess returns on the above factors over a rolling window of the most recent 60 months.

Literature has proved that stocks and bonds share common risk factors and variations in the term premium for discount-rate risks and default premium would impact expected stock and bond returns. When credit sentiment is high, the over-optimism of creditors drives down credit risk premium which decreases interest rate and may have positive impact on the asset prices. On the other hand, irrational creditors' sentiment may drive business cycle which could amplify credit risk contagion and largely increase firms' risk such as business cycle risk in the long term. The increased business cycle risk may negatively affect stock returns. Therefore, our estimated sentiment beta would reflect the net effect of these two opposite effects. For example, a firm with a negative beta may be a defensive firm which tend to behave counter-cyclically as it may have low liquidity risk and suffer less when creditors become pessimistic and flight-to-liquidity/quality happens.

3.3 Summary statistics

Following prior literature, I also include several firm-level control variables which may influence firm capital structure and investment decisions. Table 1 presents the descriptive statistics of the market-level and firm-level variables. In Panel A, the mean of *Credit_Sentiment* is 0.01 which is close to zero and the standard deviation is 0.404. And the average of firms' sensitivities to credit-market sentiment shocks (Sentiment Beta) is 0.007 with a standard deviation of 0.091.

4. "Hard-to-Value, Difficult-to-Finance" hypothesis

4.1 Sentiment sensitivity and firm characteristics: Portfolio sorts

The impact of credit investors sentiment may vary in the cross-section. Our "Hard-to-Value, Difficult-to-Finance" hypothesis assumes that firms which have more difficulties in issuing external capital are more sensitive to the changes in the credit supply conditions and firms which are harder to be evaluated are more likely affected by investors irrational sentiment. To test this hypothesis, we start out with portfolio sorts to examine the relation between sentiment beta (i.e. sentiment sensitivity) and firm characteristics. In each year starting from 1976, we match firm characteristics to the sentiment beta estimated from a rolling window of the most recent 60 months and form ten decile portfolios based on sentiment betas. Then we calculate the average characteristics of portfolios and rebalance portfolios every year.

Table 2 reports the weighted average firm characteristics of each portfolio. Portfolio 1 contains firms with most negative betas and portfolio 10 contains firms with most positive betas. On the basis of the sign and magnitude of sentiment beta, we classify firms into three groups: sentiment-prone firms whose sentiment betas are in the top 3 deciles (i.e. most positive betas), sentiment-counter firms whose sentiment betas are in the bottom 3 deciles (i.e. most negative betas), and sentiment-insensitive firms whose betas are in the middle 40 percent.

First, we find that there is a significant difference in firm size across portfolios. Firms with higher absolute loadings on sentiment factor tend to be small firms. For example, the average size of portfolio 5 or 6 (i.e. portfolio with near-zero betas) is around 1.5 times larger than that of portfolio 10 or 1 (i.e. portfolio with largest positive betas or negative betas). Evidence on SMB loadings (*SMB beta*) also confirm this finding as it exhibits a U-shaped pattern. In order to investigate whether financial constraint plays an important role, we use four proxies to measure it including the index (*WW_Index*) of financial constraints developed by Whited and Wu (2006), an indicator variable (*No credit ratings*) that equals to 1 if firm does not have a credit rating from S&P and 0 otherwise, an indicator variable (*Speculative grade*) that equals to one if firms have credit ratings below "BBB-" (i.e. BB+ and lower grade) and 0 if firms have credit rating above "BB+" (i.e. BBB- and higher grade), and a dummy variable (*DD_dum*) which takes value of 1 if firms pay dividends during the year and 0 otherwise as prior literature posits that firms without a credit rating or with a noninvestment-grade rating may have difficulties in access to public bond markets. Results show that from portfolio 1 to portfolio 10, *WW_Index*, *No Credit ratings*, and *Speculative grade* display a clear U-shaped pattern and *DD_dum* shows an inverse U-shaped pattern across sentiment beta portfolios which suggest that firms facing higher financial constraints are more exposure to the shifts in credit market sentiment. Also, the inverse U-shaped relations are found for several characteristics such as firm age, profitability measures (*Gross margin* and *ROA*). In general, smaller and younger firms tend to have higher cost of external financing which limits their financing ability. Therefore, our findings are consistent with the idea that firms with difficulties in tapping external capital (Difficult-to-Finance) are more vulnerable to credit market sentiment shocks (e.g. smaller, younger, financially constrained and unprofitable firms).

Second, we find that firms with greater exposure (in terms of magnitude) to sentiment tend to be volatile firms with higher Tobin's Q as these firms have higher sales, net income and return volatility. Baker and Wurgler (2007) argue that small, younger, unprofitable, high volatility and growth firms are more sensitive to the large shocks in equity investor sentiment because the uncertainty makes them more difficult to be evaluated and investors tend to be more overconfident when they have to rely more on their own subjective judgments according to psychology and behavioral finance theories (e.g. Daniel and Titman, 1999). Under similar mechanism, those firms are also sensitive to the fluctuations in credit investor sentiment. When credit investors are over-optimistic, they have propensity to speculate on firms with higher uncertainties. The effects of credit-market sentiment are more pronounced among glamour firms could be further supported by the monotonic decrease of HML beta (i.e. loadings on HML factor) from 0.15 for portfolio 1 to -0.08 for portfolio 10. This strictly-monotonic relation indicates that value firms which tend to be more resilient to economic slumps are more likely to have negative sentiment betas. Thus, our results support that "Hard-to-Value" firms tend to have higher exposure to credit market sentiment.

Above findings suggest that regardless of the sign of sentiment beta, sentiment-sensitive firms tend to be smaller, younger, financially constrained, unprofitable and more volatile which is consistent with the predictions of "Hard-to-Value, Difficult-to-Finance" hypothesis.

Furthermore, when we focus on the differences between sentiment-counter firms and sentiment-prone firms, although sentiment-counter firms have many similar firm characteristics with sentiment-prone firms, we find that there is a negative monotonic relationship between sentiment betas and liquidity betas which suggests that firms with negative sentiment betas tend to have less liquidity risk than firms with positive sentiment betas and the almost monotonic increases in leverage and past equity performance (*Past 12-month returns*) from portfolio 1 to portfolio 10 indicate that firms with higher leverage and better past returns tend to be procyclical to credit cycle. One potential explanation is that some investors tend to be momentum traders – they tend to over-extrapolate past returns when forming their beliefs about future outcomes (Barberis, Greenwood, Jin and Shleifer, 2015), therefore they tend to chase for firms with better past returns when they are over-optimistic. And low leverage and low liquidity risks of firms with negative betas may make firms less affected by the severe consequences caused by deteriorated credit sentiment such as "flight-to-quality/liquidity. When credit market sentiment goes down, credit investors become pessimistic and more risk-averse which makes them unwilling to invest in risky assets and prefer to hold safer assets, causing the contraction of credit supply. Therefore, when credit market condition is bad, sentiment-prone firms which have higher leverage level and liquidity risk receive disproportionally less financing, but for sentiment-counter, the low liquidity risk alleviates the negative impacts caused by the availability of external capital. As a result, sentiment-counter firms present a countercyclical relation with credit cycle and may exhibit better performance during economic downturns compared with sentiment-prone firms. Combined with the finding that value firms which tend to be more resilient to economic slumps are more likely to have negative sentiment betas suggested by the strictly-monotonic decrease in HML betas, firm characteristics may play a role in determining firms' sensitivity to credit market sentiment and may help explain the performance differences between firms during credit-driven recessions.

4.2 Sentiment sensitivity and firm characteristics: Logit analysis

To further analyze the differences in characteristics between sentiment-prone firms (i.e. firms with most positive sentiment betas) and sentiment-counter firms (i.e. firms with most negative betas), we employ a logit analysis with a binary variable (*Low-beta*) which equals to one if it is a sentiment-counter firm and zero if it is a sentiment-prone firm as the dependent variable.

Table 3 shows us the results of logit regressions with various combinations of characteristics as the independent variables. First, we include several firm characteristics that we analyzed in Table 2 and add some alternative proxies for them. We add an index constructed by Hadlock and Pierce (2010) to measure financial constraints and use the level of dividends scaled by total assets (*Dividend*) instead of a dividend payer dummy variable in the regressions. Model (1) and (3) indicate that firms with lower leverage, larger size, higher profitability, lower financial constraints and past equity performance are more likely to be sentiment-counter firms rather than sentiment-prone firms which is consistent with our previous finding that glamour firms are more likely to be procyclical.

Second, firms in competitive industries may have higher cost of debt as they have higher credit risks caused by uncertainty in cash flows due to product market competition (e.g. Valta, 2012; Corhay, 2017), therefore we assume firms in competitive industries are more pro-cyclical to credit market sentiment. In this paper, we use two variables to proxy for intensity of competition: (1) industry concentration measured by Herfindahl index (*HHI*), i.e. sales concentration at the industry level based on segment data; and (2) firm-level competition measured by Product Market Fluidity (*Fluidity_HP*)[11] constructed by Hoberg and Phillips (2014) which assesses how intensively the product market around a firm is changing in each year. In model (2), the significant negative coefficient associated with *Fluidity_HP* suggests that firm-level competition largely increases the probability of firms to have positive exposure to credit market sentiment shocks.

Third, we include a variable to measure debt overhang whose definition is same as Alanis, Chava and Kumar (2018)[12] in the regression. High credit market sentiment lowers the cost of financing and loosens the lending standards even for firms with debt overhang problems. Coincide with good investment opportunities, the availability of easy money may alleviate firms' underinvestment problems due to debt overhang. Evidence in the last column in Table 3 suggests that firms with debt overhang problems are more likely to be sentiment-prone firms which is consistent with our prediction that high credit market sentiment may alleviate debt overhang problems by allowing firms to make use of the easy money.

In sum, results in Table 3 reinforce our conclusions that firms that are "Difficult-to-Finance" are more positive sensitive to the changes in credit market sentiment. In comparison to their positive sentiment beta counterparts, firms with negative exposure to sentiment shocks are larger, older, less difficulties in tapping external capital, greater profitability and poor past 12-month stock returns. More importantly, firms with negative sentiment exposures have low leverage and liquidity risk which may weaken the negative impacts of tighten funding environment on them when credit market sentiment goes down.

4.3 Sentiment-sensitive Industries

In addition, we want to find which industries are more sensitive to the changes in credit market sentiment. By sorting industries based on the average percentage of firms with negative

[11] Data could be downloaded from the Hoberg-Phillips Data Library at http://hobergphillips.tuck.dartmouth.edu/industryconcen.htm .

[12] We thank the authors for sharing data with us.

betas within the industries, Table 4 lists the top 10 industries that having more firms with negative betas and positive betas, respectively. Industries are classified according to Fama-French 48 industrial classifications. The results are consistent with our predictions that cyclical industries tend to be those whose products are considered as nonessentials such as Recreation, Entertainment, Precious Metals, Business Services, and etc., while for industries produce basic goods with rigid demand or non-substitutes such as Food Products, Apparel and Agriculture, they are more likely to behave counter-cyclical. When economy is stressed with the contraction of credit supply, consumers still need to buy basic necessities which guarantee relatively stable orders for these firms which make them more resilient to economic slumps. Besides, industries that are largely dependent on government spending or related to infrastructure such as Defense (e.g. Guided missiles and Ordnance), Shipbuilding and Railroad Equipment tend to negatively respond to credit cycle. These defensive sectors are less affected by the fluctuations in the economy.

5. Credit market sentiment and firms' financial and investment behavior

In this section, we present our results related to the interaction effects of credit market sentiment and sentiment beta on firms' financing and investment decisions. Our baseline regressions will take the following form:

$$Y_{i,t+\tau} = \alpha_i + \left(\beta_0 + \beta_1 Beta1_{i,t} + \beta_2 Beta2_{i,t} + \beta_3 Beta3_{i,t}\right) * Credit\_Sentiment_t + \gamma_1 Beta1_{i,t} + \gamma_2 Beta2_{i,t} + \gamma_3 Beta3_{i,t} + F_{i,t} + \varepsilon_{i,t+\tau}, \quad \tau = 1, \dots, 5 \qquad (2)$$

Where $Y_{i,t+\tau}$ are the dependent variables that measure firms financing or investment during the subsequent τ years from year t in this section. $Credit\_Sentiment_t$ is the credit market sentiment in year t. In order to test whether there are asymmetrical effects of credit market sentiment on firms with different sensitivities to the credit market shocks, we decompose sentiment beta into 3 variables to capture the interaction effects of credit market sentiment on sentiment-prone, sentiment-counter and sentiment-insensitive firms, respectively. $Beta1_{i,t}$

($Beta2_{i,t}$, $Beta3_{i,t}$) takes the value of sentiment betas if it is a sentiment-prone (sentiment-counter, sentiment-insensitive) firms and 0 otherwise. We expect β_1 to be positive because sentiment-prone firms are more likely to make use of high credit market sentiment by issuing more debt and investing more. $F_{i,t}$ is a vector of firm-level and macro-level control variables including size, Tobin's Q, leverage, ROA, sales growth, operating cash flow, cash, equity sentiment, economic conditions and macro uncertainty. We also control for firm fixed effects and cluster standard errors by firm and year in all regressions.

5.1 Credit market sentiment and firms' financial policies

We start by investigating the effects of credit market sentiment on corporate financing activities. Panel A in Table 5 reports the effect of credit market sentiment on firm financing with net debt financing as the dependent variable which is defined as long-term debt issuance minus long-term debt reduction scaled by lagged total assets.

The first two columns in Panel A show that higher credit market sentiment in year *t* is positive associated with debt financing for firms with greater positive sensitivities in years *t+1* and *t+2*. The coefficients with the interaction terms capture the interaction effects of sentiment sensitivities and credit market sentiment on net debt issuance. Firms with higher positive exposure to sentiment shocks (*Beta_Prone*) will issue more debt when credit market sentiment increases, but for firms with more negative sentiment betas (*Beta_Counter*) or near-zero sentiment betas (*Beta_Insensitive*), they display no significant sensitivity of debt financing with respect to credit market sentiment. This finding is consistent with our prediction that when credit market sentiment is high (i.e. credit investors are over-optimistic), cost of capital is driven down and lending standards are loosened, allowing firms with lower quality and higher credit risks to issue external credit. Thus, firms with greater positive to credit market sentiment shocks will take advantage of the availability of easy money when credit market is boom by issuing more debt. However, in the long term, we find that the negative relation between credit market sentiment and debt issuance is also stronger for sentiment-prone firms from year *t+3* to *t+5* which supports the findings in López-Salido et al. (2017) that credit dries up 3 years after high credit market sentiment due to investors' disappointments on their optimistic expectations on economic outputs.

In addition, in order to test whether the debt issued by firms when credit market sentiment is high is used to repurchase equity and rebalance firms' capital structure as MA (2019) states, we use equity financing as the dependent variable and rerun the regressions in Panel B. the results show that there is only little effect of credit market sentiment on firms equity issuance and similar to debt financing, firms equity financing exhibits a pro-cyclical pattern.

In sum, we find that while sentiment-prone firms' financing is affected by credit market sentiment and behaves pro-cyclical to credit cycle, the sentiment has insignificant effects on the other two groups' financing activities. The availability of easy money does not induce sentiment-counter firms to change their financial policies. Potential explanation of this finding is that sentiment-counter firms may be firms with lower credit risk and higher quality firms which always have enough funds to finance their operating and investment activities, thus the easy money is less attractive to them; or sentiment-counter firms are inclined to keep low leverage to avoid financial distress when suffer negative shocks. Another potential explanation is that firms with negative or near-zero sentiment betas indeed increase debt finance as what anecdotal evidence suggests blue-chip firms do borrow when credit is cheap to increase flexibility even if they are not financially constrained, but in contrast, they use the issued capital to retire their existing debts whose interest rates are higher. As a result, there is no significant effect between net debt issuance and credit market sentiment with sentiment-counter and sentiment-insensitive firms.

5.2 Credit market sentiment and firms' investment

We have found some evidences to show that credit market sentiment has real effects on corporate financing activities and firms with greater positive sentiment betas will increase their debt issuance when credit market sentiment increases, but the other two groups' financing activities have no obvious response to credit market sentiment. In this section, we aim to examine whether firms use the capital they issued to finance their risky projects and whether the optimism of credit investors help increase capital allocation efficiency or dampen it by inducing overinvestment problems among firms.

First, following Gulen et al. (2019), we use three proxies to capture firms' investment including total investment, investment in physical capital and investment in intangible capital in Table 6. Total investment is the percentage change in total capital which is the sum of gross PPE, goodwill, R&D and SG&A. investment in physical capital is the change in gross PPE scaled by lagged total capital and investment in intangible capital is the change in total capital excluding gross PPE scaled by lagged total capital.

Column (1) in panel A suggests that firms with higher positive sentiment betas will significantly increase total corporate investment in year *t+1* when credit market sentiment increases in year *t* with an estimated coefficient of 0.1821 (t-stat=3.24) before the interaction term of *Credit_Sentiment* and *Beta_Prone*. The results are also statistically significant at the 1% level with physical investment and 10% level with intangible investment in Panel B and C. We also find reversals in corporate investment subsequent 4 years to a credit boom which is in line with prior literature that along with the contraction of credit supply 2 or 3 years after high credit market sentiment, corporate investment will decrease. And larger magnitude of coefficients in years *t+4* and *t+5* of intangible investment compared with that of physical investment indicates that when credit market deteriorates, firms decline intangible assets first. Similar with the results of financing, we find that there are no significant patterns on the investment for the other two groups under credit cycle.

High credit market sentiment may increase investment efficiency by alleviating financial constraints for these sentiment-prone firms and allowing them to engage in valuable risky projects which they have to give up due to funding limitation previously. But easily available external capital may also trigger overinvestment problems. In the next step, we further check the relation between credit market sentiment and excess investment. Following Hoberg and Phillips (2010), we measure a firm's excess investment in year *t* as the difference between firm's capital expenditure in year *t* and a predicted investment level based on several firm characteristics[13].

Panel D in Table 6 shows that credit market sentiment exacerbates overinvestment problems within firms with greater positive exposure to the changes in credit market sentiment, indicated by the coefficients of 0.6863 with a t value of 2.58 and 0.6985 with a t value of 3.17 in years *t+1* and *t+2*, respectively. And the positive effects disappear from year *t+3* which corresponds to the cycle of debt issuance. This result implicates that the availability of easy money due to the over-optimism of credit investors contributes to the overinvestment problems in sentiment-prone firms. And there is no obvious effect of credit market sentiment on sentiment-counter and sentiment-insensitive firms financing and investment behavior. In the next section, we try to examine the consequences of credit market sentiment's effect on firms' real activities and test whether there is any difference between firms' operating performance.

5.3 Consequences of credit market sentiment

We have shown that credit cycle may induce financing and investment cycle for sentiment-prone firms that are more likely to be firms with higher credit risk and exacerbate their overinvestment problem, while there is no apparent change in corporate financial and

[13] These characteristics include firm age, the volatility of the profitability, ROE and Tobin's Q.

investment policy for the other two groups. Overinvestment will reduce investment efficiency and decline firms' operating performance. By using cash flows and ROA as the dependent variables in Table 7, we find that following significant increase in debt issuance and investment in years *t+1* and *t+2*, firms that more positively sensitive to credit market sentiment shocks experience significant declines in cash flow and ROA in years *t+3* and *t+4* compared with sentiment-counter firms.

When the credit cycle turns around (i.e. creditors become pessimistic), the deteriorated business environment and rising credit spread will make it difficult to earn profits and pay off the existing debt for those firms that over-borrow and over-invest at good times, causing these underachieving and levered firms into indebtedness. Thus, creditors' over-optimism may amplify shocks to sentiment-prone firms which exploit high credit market sentiment in the future and lead these firms to have higher credit risk, default and bankruptcy probabilities when creditors become pessimistic, but not for sentiment-counter firms.

In the subsequent section, we investigate the consequences of irrational credit sentiment on firms' excessive leverage and delisting probabilities in the long term when credit market sentiment turns around by running sub-sample regressions. In Table 8, the dependent variable *Excess Leverage* is calculated as the distance between actual leverage and the optimal leverage which is estimated by employing System Generalized Method of Moments (GMM) estimation on partial adjustment model of capital structure with the firm characteristics stated in Flannery and Rangan (2006). Results show that credit market sentiment interacts with sentiment beta significantly increase firms' excessive leverage levels in years *t+3* and *t+4*, the time when credit market sentiment turns around (López-Salido et al., 2017), among sentiment-prone firms, but not for sentiment-counter firms. This finding may have an implication for why some firms get into "the debt trap". And in Table 9, by using a logit regression with an indicator which takes value of one if the firm is delisted from the market and zero otherwise, we also find that sentiment-prone firms' probabilities to be delisted from markets largely increase in years *t+3* and *t+4* when credit market sentiment increases in year *t*, but no larger delisting probability for sentiment-counter firms.

In sum, above results indicate that credit market sentiment has real effects on firms' financing and investment for firms with greater positive sensitivities to sentiment shocks, but not for the other two groups. As a result, the over-optimism of credit investors in year *t* will lower operating performance, push sentiment-prone firms into deeper indebtedness, amplify firms' credit risk and delisting probabilities in the future. In contrast, credit market sentiment has no significant real effects on the sentiment-counter firms and no obvious negative impacts on their operating performance. The findings may help explain why some firms suffer severe impacts during credit-driven recessions, while some firms are less affected. As sentiment-prone firms significantly react to high credit market sentiment by issuing more debt and invest more which push them into worse financial situation 3 or 4 years later when credit market sentiment turns around and it may also be the time of the onset of economic downturns that driven by optimistic sentiment. Therefore, the poor operating performance, higher liabilities level, tighten credit conditions and deteriorated business environment will aggravate underperformance for sentiment-prone firms during credit-driven recessions, while sentiment-counter firms may suffer less and display relatively better performance when credit market sentiment goes down.

6. Credit market sentiment and stock returns

Credit market sentiment could propagate and amplify the shocks to economy and increase risk such as credit risk and delisting probability for firms that are more vulnerable to the fluctuations in the credit investors' sentiment. According to return-risk tradeoff principle in asset pricing theories, firms with higher risk should be compensated with higher expected returns. In this section, we try to answer the question that whether investors anticipate the higher risk caused by credit market sentiment and required higher returns for firms exposing to higher sentiment risk.

To test this question, we sort firms into deciles at the beginning of each month according to their last available sentiment betas and form 10 portfolios which will be rebalanced each month to maintain equal weights. We calculate a variety of risk-adjusted and characteristic-adjusted returns for portfolios over the 1, 3, 6, and 12 months after the portfolio formation. In Table 10, market-adjusted return is the difference between individual stock return and CRSP value-weighted market index and DGTW-adjusted return presents the difference between raw return and the benchmark portfolio return based on size, industry-adjusted book-to-market ratio and past 12-month return (Daniel et al., 1997). FF5 alpha is estimated by regressing portfolio excess returns on the Fama and French (2015) five factors.

Panel A reports returns for the ten portfolios and the differences of returns between the lowest sentiment beta portfolio (portfolio 1) and the highest sentiment beta portfolio (portfolio 10) over the full sample period. We find that portfolio 1 has an average monthly excess return of 1.14% with t-stat of 3.52, while portfolio 10 holds an average monthly excess return of 0.89% with t-stat of 2.62. A zero-net investment portfolio that long stocks with lowest sentiment sensitivity and short stocks with highest sentiment sensitivity exhibits significantly positive abnormal excess return of 0.25% (t-statistics=2.16) per month and results are robust for other three risk-adjusted returns which suggests that the high sentiment beta portfolio underperform low sentiment beta portfolio on average, thus, investors do not get a compensation for holding the stocks with higher exposure to sentiment risk. This finding is contrary to what Chen et al. (2021) find with equity investor sentiment that they show there is a positive association between portfolio returns and equity investor sentiment beta by using the data of hedge funds.

When we extend the holding periods from 1 month to 12 months, the spread between the top and bottom deciles becomes more significant and larger. For example, portfolio 1 generates average cumulative 3-month FF5 alpha of 0.84% (0.28% per month) and portfolio 10 shows average cumulative 3-month FF5 alpha of -0.23% (-0.077% per month) which leads to a spread of 1.07% (0.36% per month) with t-stat of 5.06.

Although there is no strictly-monotonic trend in returns across sentiment beta portfolios, the average return of bottom three deciles (i.e. portfolios with most negative sentiment betas) exceeds that of top three deciles (i.e. portfolios with most positive sentiment betas) which indicates that, on average, there is a negative relation between sentiment betas and stock performance.

Potential explanation for this finding from investment-based perspective is that over-investment and over-borrowing triggered by high credit market sentiment for firms with higher positive exposure to sentiment shocks make them underperformance in the future.

As these sentiment-prone firms tend to take advantage of investors' over-optimism and significantly increase their debt issuance and investment, the over-borrowing and over-investment of these firms will decline their investment efficiency and reduce their operating performance. When credit market sentiment turns around 2 or 3 years subsequent to credit boom, credit suddenly dries up and business environment deteriorates, firms that over-borrow and over-invest at good time find it difficult to earn profits and pay out outstanding debt which may push them into worse financial situation such as debt trap or even bankruptcy. Under the investment-based explanation, firms financing more capital and invest more will earn lower expected returns. Therefore, on average, firms that suffer more to credit cycle will have lower stock returns.

Then, we further divided sample period into two sub-samples: months when there is a large jump in credit market sentiment and months when there is a large drop in credit market sentiment to examine the nature of months with exceptionally sentiment shocks. We define large sentiment jump months as those in which the innovation in the monthly credit market sentiment series belongs to top 30% and large sentiment drop months as those in which the changes in credit market sentiment is in the bottom 30%. Results are shown in Panel B and C in Table 10.

First, intuitively, we find that the aggregate market performs well during large jump months and experiences great drop when suffer negative sentiment shocks which is consistent with that credit sentiment is a potential driver of business cycle as high credit market sentiment fuels economy boom and induces severe consequences such as financial crisis when sentiment turns around following credit boom.

Second, we note that the underperformance of high sentiment beta portfolios is mainly driven by portfolios' returns during large drop months as there is insignificant difference between the returns of bottom and top portfolios but a larger spread between portfolio 1 and portfolio 10 from 0.25% in Panel A to 0.57% in Panel C. Firms with highest sentiment betas (portfolio 10) perform well with 1.61% per month for FF5 alpha when credit market sentiment increases but suffer great drop with -0.41% per month for FF5 alpha when credit market sentiment goes down. In contrast, firms with lowest sentiment betas (portfolio 1) perform better during negative shocks periods, a FF5 alpha of 0.16% per month. The results in Panel B and Panel C lend support to our investment-based explanations. And in addition, flight to liquidity/quality may also play a role in explaining the difference between top and bottom deciles. When credit investors become pessimistic, they become more risk-averse and unwilling to hold risky assets which may lead to "flight-to-liquidity/quality" that even worse the funding ability of sentiment-prone firms as they may have higher liquidity risk than those sentiment-counter firms which we have found in section 4.1.

7. Conclusions

In previous literature, many studies have confirmed that investor sentiment in equity market could have significant impacts on corporate capital structure, investment decisions and cross-sectional stock returns. By trading a long-short investment portfolio, hedge funds could hedge equity sentiment risk and earn abnormal returns. However, relatively less research focus on credit market sentiment and its real effects from firm-level.

Due to the importance of debt market and severe consequences on economy of credit market sentiment, we further investigate the asymmetric effects of credit market sentiment from firm level and whether credit market sentiment could play a role in explaining the performance differences between firms during credit-driven recessions.

First, we try to answer the question: what types of firms tend to be more sensitive to the credit market sentiment shocks. Our results show that sentiment-prone firms tend to be smaller, younger, financially constrained, unprofitability and more volatile firms which are consistent with our “Hard-to-Value, Difficult-to-Finance” hypothesis. Interestingly, we find that sentiment-counter firms have many similar firm characteristics with sentiment-prone firms, but they have relatively lower leverage and liquidity risk, and poor past equity performance than sentiment-prone firms and tend to be value stock. In addition, sentiment-counter firms are more likely to belong to the industries whose products have rigid demand, or largely depend on government spending, while sentiment-prone firms have products which are considered as nonessentials. Therefore sentiment-counter firms may less affected by the fluctuations in the economy.

Second, we investigate the interaction effects of credit market sentiment and sentiment beta on firms’ financing and investment behavior. Our study suggests that while sentiment-prone firms’ financing and investment are affected by credit market sentiment, the sentiment has insignificant effects on the other two groups’ financing and investment. Furthermore, sentiment-prone over-investment leads to poor operating performance, and their delisting probability is higher. This finding may have implication for why some firms get into a phenomenon named “the debt trap” and suggests that the relatively underperformance of some firms than others during recessions is partially explained by the asymmetrical effects of credit market sentiment on firms with different exposures to sentiment through real activities.

Finally, we find a negative relation between sentiment betas and stock returns. On average, firms with most negative sentiment betas tend to outperform firms with most positive sentiment betas which suggests that investors do not get a compensation for holding the stocks with higher exposure to sentiment risk. Our findings may help explain “credit risk puzzle”- low credit risk firms realize higher returns than high credit risk firms - that credit risk effect may due to credit investors’ irrational sentiment and poor performance of firms that more sensitive to credit market shocks.

Overall, evidences in the paper indicate that firm characteristics play a role in how credit market sentiment affects firms and credit market sentiment will reduce investment efficiency and increase risk for firms that are highly sensitive to the credit market shocks in the long run, while firms with negative sentiment betas are less affected by credit market sentiment, especially when credit market sentiment goes down. The results in this paper are important for investors and regulators. Investors could employ a Long-Short strategy that long firms with lowest exposure to sentiment and short firms with highest exposure to sentiment to hedge against credit sentiment risk. As credit market sentiment may largely prompt firms’ probabilities to go bankruptcy and destabilize the financial market, market regulators should pay more attention to monitor the changes in credit investor sentiment.

References

Alanis, E., Chava, S., and Kumar, P. 2018. Shareholder bargaining power, debt overhang, and investment. *Review of Corporate Finance Studies*, 7(2), 276-318.

Avramov, D., Chordia, T., Jostova, G., and Philipov, A. 2009. Credit ratings and the cross-section of stock returns. *Journal of Financial Markets*, 12(3), 469-499.

Baker, M., and Wurgler, J. 2006. Investor sentiment and the cross-section of stock returns. *The Journal of Finance* 61, 1645-1680.

Baker, M., and Wurgler, J. 2007. Investor sentiment in the stock market. *Journal of economic perspectives*, 21(2), 129-152.

Barberis, N., Greenwood, R., Jin, L., and Shleifer, A. 2015. X-CAPM: An extrapolative capital asset pricing model. *Journal of financial economics*, 115(1), 1-24.

Baron, M., and Xiong, W. 2017. Credit expansion and neglected crash risk. *The Quarterly Journal of Economics*, 132(2), 713-764.

Begenau, J., and Salomao, J. 2019. Firm financing over the business cycle. *The Review of Financial Studies*, 32(4), 1235-1274.

Berger, D., and Turtle, H. J. 2012. Cross-sectional performance and investor sentiment in a multiple risk factor model. *Journal of Banking and Finance*, 36(4), 1107–1121.

Berman, J., and Pfleeger, J. 1997. Which industries are sensitive to business cycles. *Monthly Lab*. Rev., 120, 19.

Bonaime, A., Gulen, H., and Ion, M. 2018. Does policy uncertainty affect mergers and acquisitions?. *Journal of Financial Economics*, 129(3), 531-558.

Bordalo, P., Gennaioli, N., and Shleifer, A. 2018. Diagnostic expectations and credit cycles. *The Journal of Finance*, 73(1), 199-227.

Bradshaw, M. T., Richardson, S. A., and Sloan, R. G. 2006. The relation between corporate financing activities, analysts' forecasts and stock returns. *Journal of accounting and economics*, 42(1-2), 53-85.

Cen, L., Lu, H., and Yang, L. 2013. Investor sentiment, disagreement, and the breadth–return relationship. *Management Science*, 59(5), 1076-1091.

Chen, N. F. 1991. Financial investment opportunities and the macroeconomy. *The Journal of Finance*, 46(2), 529-554.

Chen, Y., Han, B., and Pan, J. 2021. Sentiment Trading and Hedge Fund Returns. *The Journal of Finance*. Accepted Author Manuscript. https://doi.org/10.1111/jofi.13025

Conti, C. R., Goldszmidt, R., and de Vasconcelos, F. C. 2020. Firm characteristics and capabilities that enable superior performance in recessions. *Journal of Business Research*, 119, 553-561.

Corhay, A. 2017. Industry competition, credit spreads, and levered equity returns. *Rotman School of Management working paper*, (2981793).

Covas, F., and Den Haan, W. J. 2011. The cyclical behavior of debt and equity finance. *American Economic Review*, 101(2), 877-99.

Daniel, K., Grinblatt, M., Titman, S., and Wermers, R. 1997. Measuring mutual fund performance with characteristic‐based benchmarks. *The Journal of Finance*, 52(3), 1035-1058.

Daniel, K., and Titman, S. 1999. Market efficiency in an irrational world. Financial Analysts Journal, 55(6), 28-40.

Fama, E. F., and French, K. R. 1993. Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, 33(1), 3-56.

Fama, E. F., and French, K. R. 2015. A five-factor asset pricing model. *Journal of Financial Economics*, 116(1), 1-22.

Faulkender, M., and Petersen, M. A. 2006. Does the source of capital affect capital structure?. *The Review of Financial Studies*, 19(1), 45-79.

Favara, G., Gilchrist, S., Lewis, K. F., and Zakrajšek, E. 2016. Updating the Recession Risk and the Excess Bond Premium. *FEDS Notes* 2016-10-06. Board of Governors of the Federal Reserve System (U.S.).

Flannery, M. J., and Rangan, K. P. 2006. Partial adjustment toward target capital structures. *Journal of financial economics*, 79(3), 469-506.

Froot, K. A., Scharfstein, D. S., and Stein, J. C. 1993. Risk management: Coordinating corporate investment and financing policies. *The Journal of Finance*, 48(5), 1629-1658.

Gilchrist, S., and Zakrajšek, E. 2012. Credit spreads and business cycle fluctuations. *American economic review*, 102(4), 1692-1720.

Glushkov, D. 2006. Sentiment Beta. Working Paper. University of Pennsylvania.

Greenwood, R., and Hanson, S. G. 2013. Issuer quality and corporate bond returns. *The Review of Financial Studies*, 26(6), 1483-1525.

Greenwood, R. M., Hanson, S. G., and Jin, L. J. 2016. A model of credit market sentiment. Harvard Business School working paper series# 17-015.

Gulen, H., Ion, M., and Rossi, S. 2019. Credit cycles, expectations, and corporate investment. Unpublished working paper. Purdue University.

Guo, X., Lin, H., Wu, C., and Zhou, G. 2019. Investor Sentiment and the Cross-Section of Corporate Bond Returns. Available at SSRN 3223846.

Hadlock, C. J., and Pierce, J. R. 2010. New evidence on measuring financial constraints: Moving beyond the KZ index. *The Review of Financial Studies*, 23(5), 1909-1940.

Hoberg, G., and Phillips, G. 2010. Real and financial industry booms and busts. *The Journal of Finance*, 65(1), 45-86.

Hoberg, G., Phillips, G., and Prabhala, N. 2014. Product market threats, payouts, and financial flexibility. *The Journal of Finance*, 69(1), 293-324.

Hoffmann, A. 2010. An overinvestment cycle in Central and Eastern Europe?. *Metroeconomica*, 61(4), 711-734.

Huang, H., Jin, G., and Chen, J. 2016. Investor sentiment, property nature and corporate investment efficiency. *China Finance Review International.*

Jeong, G., Kang, J., and Kim, S. 2018. Credit Expansion and Aggregate Stock Returns. *European Financial Management Association*.

Jiang, S., and Fan, H. 2018. Credit risk contagion coupling with sentiment contagion. *Physica A: Statistical Mechanics and Its Applications*, 512, 186-202.

Jurado, K., Ludvigson, S. C., and Ng, S. 2015. Measuring uncertainty. *American Economic Review*, 105(3), 1177-1216.

Leary, M. T. 2009. Bank loan supply, lender choice, and corporate capital structure. *The Journal of Finance*, 64(3), 1143-1185.

Lemmon, M., and Roberts, M. R. 2010. The response of corporate financing and investment to changes in the supply of credit. *Journal of Financial and quantitative analysis*, 555-587.

Li, J., and Yang, C. 2017. The cross-section and time-series effects of individual stock sentiment on stock prices. *Applied Economics*, 49(47), 4806-4815.

Liang, W. L. 2016. Sensitivity to investor sentiment and stock performance of open market share repurchases. *Journal of Banking & Finance,* 71, 75-94.

López-Salido, D., Stein, J. C., and Zakrajšek, E. 2017. Credit market sentiment and the business cycle. *The Quarterly Journal of Economics*, 132(3), 1373-1426.

López-de-Foronda, Ó., López-de-Silanes, F., López-Iturriaga, F. J., and Santamaría-Mariscal, M. 2019. Overinvestment, leverage and financial system liquidity: A challenging approach. *BRQ Business Research Quarterly*, 22(2), 96-104.

Ma, Y. 2019. Nonfinancial firms as cross‐market arbitrageurs. *The Journal of Finance*, 74(6), 3041-3087.

Mian, A., and Santos, J. A. 2018. Liquidity risk and maturity management over the credit cycle. *Journal of Financial Economics*, 127(2), 264-284.

McLean, R.D., and Zhao, M. 2014. The business cycle, investor sentiment, and costly external finance. *The Journal of Finance* 69, 1377-1409.

Pástor, Ľ., and Stambaugh, R. F. 2003. Liquidity risk and expected stock returns. *Journal of Political economy*, 111(3), 642-685.

Pintus, P., and Wen, Y. 2008. Leveraged financing, over investment, and boom-bust cycles. *FRB of St. Louis Working Paper No.*

Rampini, A. A., and Viswanathan, S. 2010. Collateral, risk management, and the distribution of debt capacity. *The Journal of Finance*, 65(6), 2293-2322.

Schularick, M., and Taylor, A. M. 2012. Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. *American Economic Review*, 102(2), 1029-61.

Stambaugh, R. F., Yu, J., and Yuan, Y. 2012. The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, 104(2), 288-302.

Valta, P. 2012. Competition and the cost of debt. *Journal of Financial Economics*, 105(3), 661-682.

Whited, T. M., and Wu, G. 2006. Financial constraints risk. *Review of Financial Studies*, 19(2), 531–559.

Yang, C., and Hu, X. 2021. Individual stock sentiment beta and stock returns. *The North American Journal of Economics and Finance*, 55, 101306.

Zheng, Y., Osmer, E., and Zhang, R. 2018. Sentiment hedging: How hedge funds adjust their exposure to market sentiment. *Journal of Banking & Finance*, 88, 147-160.

Appendix A: Variable definitions

Variable	Definition
Credit_Sentiment	Credit market sentiment which is calculated by orthogonalizing excess bond premium developed by GZ (2012) with respect to the growth in industrial production consumption of durables, non-durables, and services to obtain the residual. Then multiply the residual by -1 to measure the credit market sentiment.
Sentiment_Beta	Firms' price sensitivity to the changes in credit market sentiment. The coefficients in the regression of firms' monthly excess returns on changes in credit market sentiment after controlling Fama-French risk factors including market, size, book-to-market, momentum and Pastor and Stambaugh (2003)'s liquidity factor over most recent 60 months.
Equity_Sentiment	Index developed by Baker and Wurgler (2006) to capture equity investor sentiment.
Economic_Condition	The first principle component of three variables: (1) Consumer confidence; (2) National activity index; (3) Expected GDP growth.
Macro_Uncertainty	The first principle component of three variables: (1) JLN uncertainty index, (2) CS σ past returns, and (3) CS σ past sales growth.
Size	Firm size which is the natural logarithm of total assets.
Lev	Book leverage ratio which is total long-term debt divided by total assets.
Tobin's Q	Market value of equity plus the book value of assets minus book value of equity plus deferred taxes, then divided by book value of assets.
Sales_Growth	Percentage change in sales.
ROA	Return on assets which is the one of operating income before depreciation, or sales minus total operating expenses, or total revenue minus total operating expenses depending on the available of data divided by the average of total assets in most recent two years.
Operating_Cash flow	Operating income before depreciation divided by total assets.
Cash	Cash and Short-Term Investments divided by total assets.
Cash Flow	Income before extraordinary items minus the share of depreciation that can be allocated to income plus any deferred taxes, divided by total assets.
Age	Firm age calculating by using CRSP data.
Gross_margin	Sales minus cost of goods sold, then divided by sales.
Tangibility	Total property, plant and equipment divided by total assets.
WW_Index	The index of financial constraints developed by Whited and Wu (2006).
HP_Index	Index constructed by Hadlock and Pierce (2010) to measure financial constraints.
Past Return	Firms' cumulative past 12-month return.
No_credit	An indicator which takes value of one if the firm has no credit rating, and zero otherwise.
Speculative_grade	An indicator which takes value of one if the credit rating of firm is below "BBB-" (i.e. BB+ and lower grade) and zero if the credit rating is above "BB+" (i.e. BBB- and higher grade).
Overhang	Debt overhang. Same definition with Alanis, Chava and Kumar (2018).
Fluidity_HP	Product Market Fluidity constructed by Hoberg and Phillips (2014) which assesses how intensively the product market around a firm is changing in each year.
HHI	Sales concentration at the industry level based on segment data.
Dividend	Cash dividends scaled by total assets.
NI_volatility	Net income volatility. Standard deviation of quarterly net income over most recent 3 years.
Sales_volatility	Sales volatility. Standard deviation of quarterly sales over most recent 3 years.
Return volatility	Standard deviation of monthly stock returns over most recent 12 months.

Appendix B: Figures and Tables

Figure 1: Credit market sentiment over time

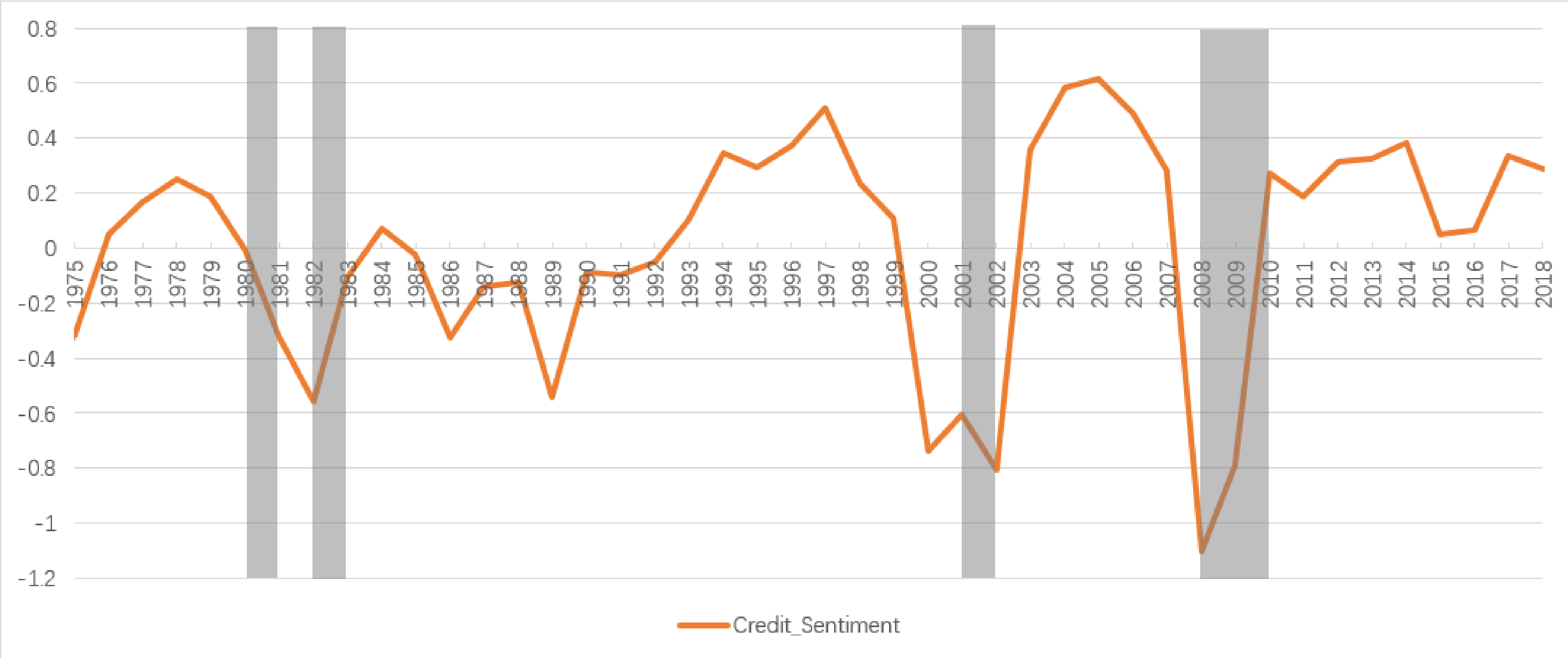

Figure 1 plots the time-variant Credit-market sentiment over 1975-2018. The shaded vertical bars present yearly NBER recession indicator which is set to one if at least 6 out of 12 months are during an economic recession defined by NBER, and zero otherwise (Mclean and Zhao, 2014).

Table 1: Summary statistics

This table lists summary statistics for the constructed Credit_Sentiment, Sentiment beta, and main control variables used in the analysis, with a sample period from 1975 to 2018. Panel A shows market level variables whose data are time series and Panel B shows firm level variables whose data are firm-year observations. All variables are defined in Appendix A and variables in Panel B are winsorized at the 1% and 99% levels.

Panel A: Market level variables				
Variable	MEAN	STD	MEDIAN	N
Credit_Sentiment	0.010	0.404	0.086	44
Equity_Sentiment	-0.027	1.358	0.450	44
Economic_Condition	0.000	1.376	-0.038	44
Macro_Uncertainty	0.000	1.060	-0.101	44
Panel B: Firm level variables				
Variable	MEAN	STD	MEDIAN	N
Sentiment beta	0.007	0.091	0.003	148,559
Lev	0.240	0.210	0.211	148,559
Size	5.278	2.260	5.110	148,559
Tobin's Q	1.777	1.505	1.298	148,559
ROA	0.082	0.192	0.110	148,559
Sales_Growth	0.140	0.459	0.080	148,559
Operating_Cashflow	0.076	0.205	0.115	148,559
Cash	0.157	0.190	0.081	148,559

Table 2: Sentiment sensitivity and firm characteristics: Portfolio sorts, 1975-2018

This Table reports the time-series averages of cross-sectional means. Each year average firm characteristics are matched to the last available Sentiment beta (Firms' price sensitivities to credit-market sentiment) estimated from Equation (1). Size is the natural logarithm of total assets. Tangibility is total property, plant and equipment scaled by total assets. DD_dum is a dummy variable which takes value of one if the firm pay dividends in current year, and zero otherwise. NI (sale/return) volatility is the standard deviation of net income (sales/stock return) series. And SMB, HML, and Liquidity beta are loadings on SMB, HML, and Liquidity factor, respectively. All variables are winsorized at 1% and 99%, and the symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Rank	*Sentiment beta*	*Leverage*	*Size*	*Age*	*ROA*	*Tobin's Q*	*Gross margin*	*Tangibility*	*WW_Index*	*DD_dum*
1 (Low)	-0.14	0.24	4.34	12.59	0.03	2.01	-0.01	0.28	-0.09	0.21
2	-0.07	0.23	5.26	16.76	0.09	1.77	0.19	0.29	-0.16	0.40
3	-0.04	0.23	5.67	19.10	0.11	1.71	0.21	0.30	-0.20	0.50
4	-0.02	0.23	5.88	20.18	0.12	1.70	0.26	0.31	-0.22	0.54
5	0.00	0.24	5.91	20.46	0.11	1.69	0.26	0.31	-0.21	0.55
6	0.01	0.24	5.85	19.87	0.11	1.70	0.25	0.31	-0.21	0.53
7	0.03	0.24	5.64	18.47	0.10	1.67	0.25	0.31	-0.19	0.49
8	0.05	0.24	5.32	16.87	0.09	1.70	0.18	0.30	-0.17	0.42
9	0.09	0.25	4.84	14.33	0.06	1.78	0.12	0.29	-0.13	0.30
10 (High)	0.18	0.26	3.99	11.32	-0.01	2.06	-0.19	0.27	-0.05	0.14
High-Low	0.319***	0.024***	-0.349***	-1.264***	-0.036***	0.053**	-0.186***	-0.007**	0.042***	-0.069***

Rank	*Past 12 months return*	*No credit ratings*	*Speculative grade*	*Debt overhang*	*NI volatility*	*Sales volatility*	*Return volatility*	*SMB beta*	*HML beta*	*Liquidity beta*
1 (Low)	0.16	0.89	0.82	0.03	0.06	0.08	0.19	1.24	0.15	-0.05
2	0.16	0.83	0.55	0.02	0.04	0.07	0.14	0.94	0.15	-0.02
3	0.14	0.79	0.42	0.01	0.03	0.06	0.13	0.82	0.16	-0.01
4	0.15	0.75	0.36	0.01	0.03	0.06	0.12	0.74	0.14	0.00
5	0.14	0.75	0.33	0.01	0.03	0.06	0.12	0.73	0.12	0.01
6	0.15	0.76	0.36	0.01	0.03	0.06	0.12	0.76	0.11	0.01
7	0.15	0.78	0.44	0.01	0.03	0.06	0.13	0.81	0.10	0.02
8	0.15	0.82	0.54	0.02	0.04	0.07	0.14	0.93	0.06	0.03
9	0.17	0.86	0.72	0.02	0.05	0.07	0.16	1.07	0.00	0.04
10 (High)	0.20	0.93	0.93	0.04	0.08	0.08	0.21	1.34	-0.08	0.08
High-Low	0.048***	0.033***	0.104***	0.010***	0.013***	0.006***	0.019***	0.105***	-0.227***	0.125***

Table 3: Sentiment sensitivity and firm characteristics: Logit analysis

This Table presents results from a Logit analysis with a dummy variable (*Low-beta*) which equals to one if firm has a negative beta which is in the bottom 3 deciles ranked by sentiment beta (i.e. sentiment-counter firms), and 0 if firm has a positive beta that is in the top 3 deciles (i.e. sentiment-prone firms) as the dependent variable. All control variables are defined in Appendix A. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent variable	*Low-beta*	*Low-beta*	*Low-beta*	*Low-beta*	*Low-beta*
Lev	-0.4256***	-0.4788***	-0.4186***	-0.4305***	-0.4273***
	(-12.53)	(-11.54)	(-12.32)	(-12.37)	(-9.76)
Size	0.0281***	0.0443***	0.0672***	0.0241***	0.0211*
	(3.38)	(3.94)	(14.19)	(2.85)	(1.92)
ROA	0.2762***	0.2237***	0.2955***	0.2695***	0.2512***
	(7.02)	(4.82)	(7.50)	(6.75)	(5.48)
Tobin's Q	0.0284***	0.0323***	0.0270***	0.0276***	0.0321***
	(5.98)	(5.96)	(5.72)	(5.70)	(5.90)
HP_Index	-0.1495***	-0.1567***		-0.1589***	-0.2077***
	(-6.08)	(-5.03)		(-6.34)	(-6.81)
Past Return	-0.0830***	-0.0855***	-0.0817***	-0.0802***	-0.0798***
	(-7.62)	(-6.64)	(-7.51)	(-7.23)	(-6.26)
Age	0.0035***	0.0015	0.0068***	0.0035***	0.0027***
	(4.36)	(1.46)	(11.53)	(4.21)	(2.88)
Dividend	2.9102***	1.9983***	2.8251***	2.8838***	2.7677***
	(7.34)	(4.05)	(7.12)	(7.11)	(5.51)
No_credit	-0.0595**	-0.0721**	-0.0355	-0.0693***	-0.0562*
	(-2.44)	(-2.42)	(-1.47)	(-2.77)	(-1.94)
Fluidity_HP		-0.0230***			
		(-8.36)			
WW_Index			-0.0675***		
			(-3.21)		
HHI				0.0438	
				(0.87)	
Overhang					-0.2871***
					(-2.66)
Constant	-0.4476***	-0.3281***	-0.2531***	-0.4597***	-0.6460***
	(-6.34)	(-4.30)	(-4.04)	(-6.38)	(-7.30)
N	87382	55074	87185	83816	65025

Table 4: Sentiment sensitivity and industries

This Table lists the top 10 industries that having more firms with negative betas or positive betas. Based on Fama-French 48 industrial classifications, all firms are assigned into one of 48 industries. Industries are sorted according to the average percentage of negative sensitivity firms within the industry. Industries listed on the left are those with highest percentage of negative-sensitive firms, while industries listed on the right are those with lowest percentage. FF48_code refers to Fama-French industry code.

	Industries with more firms having Negative betas		Industries with more firms having Positive betas	
Rank	FF48_code	Industry	FF48_code	Industry
1	24	Aircraft	28	Non-metallic and Industrial Metal Mining
2	26	Defense (e.g. guided missiles and ordnance)	27	Precious Metals
3	25	Shipbuilding, Railroad Equipment	6	Recreation (Toys)
4	29	Coal	7	Entertainment (Fun)
5	2	Food Products	35	Computers
6	10	Apparel	34	Business Services
7	8	Printing and Publishing	12	Medical Equipment
8	39	Shipping Containers	48	Almost Nothing (Sanitary Services; Steam & Air conditioning Supplies; Irrigation systems; Cogeneration-SM Power producer)
9	1	Agriculture	19	Steel Works Etc.
10	14	Chemicals	30	Petroleum and Natural Gas

Table 5: Credit market sentiment and firm financing

This table reports the interaction effects of credit market sentiment and sentiment beta on corporate financing activities. Panel A uses the debt financing as the dependent variable which is measured as long-term debt issuance minus long-term debt reduction scaled by lagged total assets. Panel B uses equity financing as the dependent variable which is defined as sale of common and preferred stock minus purchase of common and preferred stock scaled by lagged total assets. All control variables are defined in Appendix A. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Debt Financing

Dependent variable	*Debt_Finance*				
	T+1	T+2	T+3	T+4	T+5
	(1)	(2)	(3)	(4)	(5)
Credit_Sentiment	0.0098***	0.0148***	0.0121**	0.0085	0.0040
	(3.39)	(4.04)	(2.47)	(1.63)	(0.84)
Credit_Sentiment*Beta_Prone	0.0375**	0.0322*	-0.0309*	-0.0398**	-0.0408*
	(2.05)	(1.86)	(-1.81)	(-2.18)	(-1.79)
Credit_Sentiment*Beta_Counter	0.0091	-0.0024	-0.0049	0.0150	-0.0050
	(0.55)	(-0.13)	(-0.22)	(0.50)	(-0.20)
Credit_Sentiment*Beta_Insensitive	0.0598	0.0768	-0.0046	0.0117	-0.0523
	(1.33)	(1.17)	(-0.07)	(0.18)	(-1.23)
Beta_Prone	-0.0127	-0.0042	0.0141	0.0097	0.0116
	(-1.38)	(-0.38)	(1.22)	(0.73)	(0.78)
Beta_Counter	0.0410***	0.0187	0.0021	-0.0263	-0.0435***
	(4.52)	(1.58)	(0.15)	(-1.68)	(-3.13)
Beta_Insensitive	0.0159	0.0320	-0.0520	0.0158	0.0037
	(0.57)	(1.08)	(-1.64)	(0.51)	(0.11)
Size	-0.0036***	-0.0094***	-0.0122***	-0.0121***	-0.0116***
	(-3.01)	(-7.59)	(-10.11)	(-8.57)	(-8.33)
Tobin's Q	0.0091***	0.0046***	0.0019***	0.0005	-0.0007
	(10.94)	(6.53)	(3.09)	(0.84)	(-1.48)
Lev	-0.1820***	-0.1363***	-0.0946***	-0.0691***	-0.0528***
	(-24.33)	(-21.84)	(-18.44)	(-14.78)	(-11.11)
ROA	-0.0686***	-0.0124*	0.0072	0.0044	0.0120*
	(-7.79)	(-1.75)	(0.90)	(0.63)	(1.71)
Sales_Growth	0.0078***	0.0008	-0.0003	-0.0008	-0.0039***
	(6.70)	(0.57)	(-0.21)	(-0.62)	(-3.03)
Operating_Cashflow	0.0477***	0.0168**	0.0047	-0.0045	-0.0050
	(4.73)	(2.07)	(0.51)	(-0.56)	(-0.64)
Cash	-0.0508***	-0.0079*	0.0044	0.0042	-0.0030
	(-9.28)	(-1.94)	(1.05)	(0.85)	(-0.66)
Equity_Sentiment	-0.0001	-0.0006	0.0000	-0.0007	-0.0014
	(-0.15)	(-0.64)	(0.04)	(-0.66)	(-1.60)
Economic_Condition	0.0028**	-0.0017	-0.0046***	-0.0061***	-0.0073***
	(2.52)	(-1.26)	(-2.86)	(-4.19)	(-4.54)
Macro_Uncertainty	-0.0000	-0.0017	-0.0034*	-0.0034**	-0.0041**
	(-0.03)	(-0.96)	(-1.72)	(-2.14)	(-2.69)
Constant	0.0757***	0.0942***	0.1009***	0.0968***	0.0928***
	(9.31)	(11.71)	(14.13)	(11.74)	(10.96)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	128,519	118,098	109,029	99,204	90,172
R^2	0.1759	0.1546	0.1420	0.1333	0.1321

Panel B: Equity Financing

Dependent variable	*Equity_Finance*				
	T+1	T+2	T+3	T+4	T+5
	(1)	(2)	(3)	(4)	(5)
Credit_Sentiment	0.0044	-0.0029	-0.0029	0.0031	0.0068
	(0.62)	(-0.57)	(-0.46)	(0.62)	(1.30)

Credit_Sentiment*Beta_Prone	0.1193*	0.0995	0.0002	-0.0983*	-0.1119**
	(1.86)	(1.27)	(0.00)	(-2.00)	(-2.70)
Credit_Sentiment*Beta_Counter	-0.1616**	-0.1467	-0.0883	0.1036	-0.0028
	(-2.27)	(-1.64)	(-0.73)	(1.43)	(-0.05)
Credit_Sentiment*Beta_Insensitive	0.0439	0.1297	0.0221	-0.1673**	-0.0684
	(0.46)	(1.49)	(0.21)	(-2.53)	(-0.98)
Beta_Prone	0.0497	0.0461*	0.0532	0.0639**	0.0187
	(1.63)	(1.70)	(1.61)	(2.54)	(1.03)
Beta_Counter	-0.0491	-0.0630*	-0.0388	-0.0343	-0.0352
	(-1.48)	(-1.77)	(-1.21)	(-1.46)	(-1.26)
Beta_Insensitive	0.0515	0.1077**	0.0550	0.0468	0.0427
	(1.30)	(2.63)	(1.60)	(1.63)	(1.50)
Size	-0.0371***	-0.0335***	-0.0250***	-0.0198***	-0.0187***
	(-11.70)	(-9.62)	(-10.35)	(-9.47)	(-7.22)
Tobin's Q	0.0397***	0.0036**	-0.0018	0.0003	-0.0019
	(7.33)	(2.08)	(-1.49)	(0.23)	(-1.51)
Lev	0.0420***	0.0372***	0.0255***	0.0206***	0.0122*
	(5.30)	(5.62)	(2.86)	(3.16)	(1.70)
ROA	0.3173***	0.0049	-0.0000	-0.0134	0.0466***
	(5.39)	(0.18)	(-0.00)	(-0.89)	(2.79)
Sales_Growth	0.0032	-0.0020	0.0072***	0.0014	0.0004
	(1.22)	(-0.88)	(3.19)	(0.56)	(0.17)
Operating_Cashflow	-0.5389***	-0.1729***	-0.0945***	-0.0348**	-0.0717***
	(-6.81)	(-4.06)	(-3.38)	(-2.13)	(-3.71)
Cash	-0.1140***	-0.0283***	-0.0077	-0.0201**	-0.0258**
	(-7.39)	(-3.16)	(-0.80)	(-2.41)	(-2.33)
Equity_Sentiment	-0.0040	0.0010	0.0008	0.0003	0.0000
	(-1.45)	(0.66)	(0.42)	(0.19)	(0.01)
Economic_Condition	-0.0060**	-0.0063***	-0.0024	-0.0012	-0.0015
	(-2.66)	(-3.78)	(-1.24)	(-0.66)	(-0.68)
Macro_Uncertainty	0.0010	-0.0083***	-0.0043**	-0.0012	0.0018
	(0.25)	(-3.80)	(-2.34)	(-0.70)	(0.97)
Constant	0.1866***	0.2127***	0.1663***	0.1307***	0.1285***
	(10.42)	(9.82)	(10.61)	(10.36)	(7.96)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	128,519	118,098	109,029	99,204	90,172
R^2	0.4459	0.3826	0.3732	0.3773	0.3765

Table 6: Credit market sentiment and firm investment

This table shows the interaction effects of credit market sentiment and sentiment beta on corporate investment activities. Panel A uses the total investment as the dependent variable which is measured as the percentage change in total capital (the sum of gross PPE, goodwill, R&D and SG&A). Panel B uses physical investment as the dependent variable which is defined as the change in gross PPE scaled by lagged total capital. Panel C use intangible investment as the dependent variable which is calculated as the change in total capital excluding gross PPE scaled by lagged total capital. Panel D presents the effects of excessive investment whose definition is same as Hoberg and Phillips (2010). All control variables are defined in Appendix A. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Total Investment

Dependent variable	*Total_Investment*				
	T+1	T+2	T+3	T+4	T+5
	(1)	(2)	(3)	(4)	(5)
Credit_Sentiment	0.0059	0.0038	0.0062	-0.0060	-0.0037
	(0.52)	(0.29)	(0.47)	(-0.43)	(-0.33)
Credit_Sentiment*Beta_Prone	0.1821***	0.0658	-0.0256	-0.1627**	-0.2054***
	(3.24)	(0.90)	(-0.26)	(-2.62)	(-2.96)
Credit_Sentiment*Beta_Counter	-0.0264	-0.0587	-0.0187	0.0571	0.0656
	(-0.28)	(-0.57)	(-0.20)	(0.95)	(1.20)
Credit_Sentiment*Beta_Insensitive	0.2174	0.2246	-0.1255	0.0210	-0.1324
	(1.31)	(1.53)	(-0.86)	(0.20)	(-0.84)
Beta_Prone	0.0251	0.0273	0.0709***	0.1172***	0.1156***
	(0.93)	(0.89)	(2.71)	(3.50)	(4.14)
Beta_Counter	-0.0636*	-0.0673*	-0.0584**	-0.1174***	-0.1329***
	(-1.70)	(-1.75)	(-2.06)	(-3.51)	(-3.98)
Beta_Insensitive	0.0693	0.1164	0.0555	0.0566	0.0680
	(1.08)	(1.48)	(0.88)	(0.94)	(0.89)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	128,161	117,726	108,690	98,905	89,895
R^2	0.2516	0.2128	0.1984	0.1884	0.1826

Panel B: Investment in Physical Capital

Dependent variable	*Physical_Investment*				
	T+1	T+2	T+3	T+4	T+5
	(1)	(2)	(3)	(4)	(5)
Credit_Sentiment	0.0013	0.0065	0.0051	0.0014	0.0013
	(0.23)	(1.35)	(0.99)	(0.28)	(0.31)
Credit_Sentiment*Beta_Prone	**0.0603*** **	**0.0094**	**-0.0128**	**-0.0018**	**-0.0127**
	(2.95)	(0.37)	(-0.49)	(-0.07)	(-0.50)
Credit_Sentiment*Beta_Counter	-0.0274	-0.0462	-0.0244	-0.0016	0.0387
	(-0.83)	(-1.31)	(-0.70)	(-0.06)	(1.45)
Credit_Sentiment*Beta_Insensitive	0.0468	0.0607	-0.0470	-0.0727	-0.0612
	(0.72)	(1.00)	(-0.76)	(-1.43)	(-0.93)
Beta_Prone	-0.0118	-0.0133	-0.0005	0.0158	0.0182
	(-1.10)	(-0.94)	(-0.04)	(1.17)	(1.39)
Beta_Counter	-0.0108	-0.0124	-0.0188	-0.0493**	-0.0535***
	(-0.66)	(-0.73)	(-1.14)	(-2.67)	(-3.24)
Beta_Insensitive	-0.0478	-0.0030	0.0120	0.0094	0.0212
	(-1.27)	(-0.08)	(0.41)	(0.32)	(0.77)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	127,558	117,166	108,145	98,385	89,408
R^2	0.2735	0.2583	0.2449	0.2391	0.2347

Panel C: Investment in Intangible Capital					
Dependent variable	*Intangible_Investment*				
	T+1	T+2	T+3	T+4	T+5
	(1)	(2)	(3)	(4)	(5)
Credit_Sentiment	0.0065	0.0005	0.0024	-0.0055	-0.0053
	(0.98)	(0.06)	(0.28)	(-0.58)	(-0.67)
Credit_Sentiment*Beta_Prone	**0.0997***	**0.0729**	**-0.0114**	**-0.1343*****	**-0.1640*****
	(1.85)	(1.35)	(-0.15)	(-3.04)	(-3.78)
Credit_Sentiment*Beta_Counter	0.0179	0.0005	0.0171	0.0633	0.0180
	(0.29)	(0.01)	(0.28)	(1.32)	(0.46)
Credit_Sentiment*Beta_Insensitive	0.0851	0.2417*	-0.0402	0.1001	-0.0675
	(0.72)	(1.85)	(-0.43)	(1.44)	(-0.75)
Beta_Prone	0.0346*	0.0388**	0.0691***	0.1049***	0.0971***
	(1.72)	(2.24)	(4.19)	(4.40)	(5.17)
Beta_Counter	-0.0434*	-0.0451*	-0.0391**	-0.0651***	-0.0733***
	(-1.93)	(-1.80)	(-2.31)	(-2.72)	(-3.28)
Beta_Insensitive	0.1006***	0.0616	0.0374	0.0833*	0.0726
	(2.71)	(1.36)	(0.86)	(1.84)	(1.29)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	125,745	115,639	106,893	97,353	88,548
R^2	0.2342	0.1936	0.1857	0.1776	0.1733

Panel D: Excess Investment					
Dependent variable	*Excess_Investment*				
	T+1	T+2	T+3	T+4	T+5
	(1)	(2)	(3)	(4)	(5)
Credit_Sentiment	0.2089***	0.2205***	0.1442***	0.0322	-0.0208
	(5.40)	(6.61)	(3.00)	(0.66)	(-0.48)
Credit_Sentiment*Beta_Prone	**0.6863****	**0.6985*****	**0.2993**	**0.0285**	**-0.2843**
	(2.58)	(3.17)	(1.29)	(0.14)	(-1.20)
Credit_Sentiment*Beta_Counter	0.2356	-0.0311	-0.1245	0.0287	0.4226
	(1.03)	(-0.13)	(-0.48)	(0.12)	(1.46)
Credit_Sentiment*Beta_Insensitive	0.5176	0.7017	0.1080	-0.4414	-1.4643***
	(1.01)	(1.23)	(0.17)	(-0.77)	(-3.54)
Beta_Prone	-0.1832*	-0.1568	-0.0753	-0.0410	0.0270
	(-1.87)	(-1.46)	(-0.53)	(-0.29)	(0.24)
Beta_Counter	-0.1373	-0.1053	-0.0747	-0.0658	-0.1207
	(-1.31)	(-0.78)	(-0.54)	(-0.40)	(-0.78)
Beta_Insensitive	-0.0328	-0.2908	-0.1307	-0.2737	-0.1999
	(-0.12)	(-0.90)	(-0.49)	(-0.90)	(-0.71)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	117,164	105,947	96,020	87,229	79,329
R^2	0.2762	0.2719	0.2847	0.2804	0.2790

Table 7: Credit market sentiment and firm operating performance

This table presents the interaction effects of credit market sentiment and sentiment beta on corporate operating performance. All variables are defined in Appendix A. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Firm-level Cash Flow					
Dependent variable			*Cash Flow*		
	T+1	T+2	T+3	T+4	T+5
	(1)	(2)	(3)	(4)	(5)
Credit_Sentiment	0.0102*	0.0040	-0.0008	-0.0040	-0.0070
	(1.91)	(0.83)	(-0.17)	(-1.02)	(-1.63)
Credit_Sentiment*Beta_Prone	0.0586	-0.0199	-0.0745***	-0.0738**	-0.0702**
	(1.32)	(-0.46)	(-2.78)	(-2.27)	(-2.19)
Credit_Sentiment*Beta_Counter	-0.0766***	-0.0482	0.0486	0.0396	0.0403
	(-2.85)	(-0.81)	(1.23)	(1.30)	(1.34)
Credit_Sentiment*Beta_Insensitive	0.0319	0.0312	0.0524	-0.1036	-0.0943*
	(0.31)	(0.50)	(0.78)	(-1.55)	(-1.87)
Beta_Prone	-0.0334***	-0.0347*	-0.0139	0.0126	0.0121
	(-2.77)	(-1.89)	(-0.79)	(0.92)	(0.79)
Beta_Counter	-0.0044	0.0083	0.0125	-0.0061	-0.0010
	(-0.29)	(0.46)	(0.55)	(-0.33)	(-0.05)
Beta_Insensitive	-0.0209	-0.0623*	-0.0128	-0.0132	0.0173
	(-0.70)	(-1.71)	(-0.38)	(-0.50)	(0.59)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	128,414	118,152	109,141	99,289	90,245
R^2	0.5401	0.5033	0.4950	0.4965	0.4970
Panel B: Return on Assets					
Dependent variable			*ROA*		
	T+1	T+2	T+3	T+4	T+5
	(1)	(2)	(3)	(4)	(5)
Credit_Sentiment	0.0107***	0.0073*	0.0024	0.0017	0.0005
	(3.03)	(1.78)	(0.56)	(0.50)	(0.12)
Credit_Sentiment*Beta_Prone	-0.0497	-0.0674**	-0.0767***	-0.0722*	-0.0014
	(-1.35)	(-2.26)	(-2.78)	(-1.93)	(-0.04)
Credit_Sentiment*Beta_Counter	-0.0145	0.0025	0.0683*	0.0603	0.0334
	(-0.64)	(0.04)	(1.72)	(1.67)	(0.78)
Credit_Sentiment*Beta_Insensitive	-0.0039	0.0692	0.1111*	-0.0910*	-0.1340***
	(-0.08)	(0.96)	(1.84)	(-1.75)	(-2.84)
Beta_Prone	-0.0282**	-0.0251	-0.0154	-0.0024	-0.0020
	(-2.41)	(-1.56)	(-1.03)	(-0.17)	(-0.12)
Beta_Counter	0.0220*	0.0370**	0.0455**	0.0355*	0.0215
	(1.88)	(2.04)	(2.19)	(1.93)	(1.13)
Beta_Insensitive	-0.0406	-0.0563	0.0045	-0.0355	-0.0216
	(-1.53)	(-1.49)	(0.16)	(-1.42)	(-0.66)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	128,213	117,992	108,988	99,160	90,138
R^2	0.6646	0.6305	0.6200	0.6188	0.6156

Table 8: Consequence of credit market sentiment on firms' excess leverage

This table shows the results of sub-sample regressions of the interaction effects of credit market sentiment on the excessive leverage. Excess Leverage is calculated as the distance between actual leverage and the optimal leverage which is estimated by employing System Generalized Method of Moments (GMM) estimation on partial adjustment model of capital structure with the firm characteristics stated in Flannery and Rangan (2006). All control variables are defined in Appendix A. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	*Excess Leverage*					
	Sentiment-prone Firms			Sentiment-counter Firms		
	T+3	T+4	T+5	T+3	T+4	T+5
	(1)	(2)	(3)	(4)	(5)	(6)
Credit_Sentiment	-0.0069	-0.0093	-0.0003	0.0104	0.0087	0.0104
	(-0.86)	(-1.06)	(-0.04)	(1.63)	(1.20)	(1.36)
Credit_Sentiment*Sentiment_Beta	0.1221***	0.1398***	0.0671	0.0139	-0.0062	-0.0356
	(3.77)	(3.18)	(1.47)	(0.40)	(-0.16)	(-0.80)
Sentiment_Beta	0.0421*	0.0290	0.0486	-0.0012	-0.0182	-0.0526
	(1.76)	(0.96)	(1.44)	(-0.05)	(-0.64)	(-1.68)
Size	0.0018	0.0010	0.0005	0.0020	0.0033	0.0043
	(0.83)	(0.40)	(0.18)	(0.84)	(1.22)	(1.68)
Tobin's Q	0.0003	-0.0000	0.0007	0.0049***	0.0017	0.0018
	(0.23)	(-0.01)	(0.50)	(4.05)	(1.43)	(1.40)
Lev	0.2210***	0.1270***	0.0711***	0.2471***	0.1584***	0.0692***
	(12.90)	(6.96)	(3.91)	(11.98)	(7.49)	(3.52)
ROA	-0.0658***	-0.0469***	-0.0300*	-0.0191	-0.0090	0.0167
	(-3.39)	(-2.74)	(-1.89)	(-1.22)	(-0.57)	(1.07)
Sales_Growth	0.0031	0.0033	-0.0032	0.0008	0.0037	0.0004
	(1.07)	(1.23)	(-1.23)	(0.27)	(1.30)	(0.11)
Operating_Cashflow	0.0239	0.0016	0.0029	-0.0260	-0.0479***	-0.0573***
	(1.34)	(0.08)	(0.17)	(-1.44)	(-2.79)	(-2.86)
Cash	-0.0251*	-0.0226	-0.0276	-0.0078	0.0075	0.0070
	(-1.90)	(-1.39)	(-1.66)	(-0.54)	(0.60)	(0.52)
Equity_Sentiment	0.0019	0.0026*	-0.0007	-0.0003	0.0003	-0.0009
	(1.40)	(1.71)	(-0.43)	(-0.21)	(0.21)	(-0.53)
Economic_Condition	0.0050**	0.0035	-0.0004	0.0019	0.0022	-0.0009
	(2.27)	(1.53)	(-0.19)	(1.06)	(1.33)	(-0.43)
Macro_Uncertainty	-0.0001	-0.0002	-0.0016	0.0013	0.0022	0.0009
	(-0.04)	(-0.08)	(-0.56)	(0.62)	(1.19)	(0.36)
Constant	-0.1714***	-0.1466***	-0.1370***	-0.2037***	-0.1908***	-0.1820***
	(-14.20)	(-10.43)	(-9.28)	(-13.83)	(-10.72)	(-11.52)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	29,103	26,093	23,421	30,869	28,085	25,453
R^2	0.7091	0.7064	0.7077	0.7090	0.7072	0.6978

Table 9: Consequence of credit market sentiment on firms' delisting probabilities

This table reports the results of logit regression with a dummy which equals to one if the firm delist from market due to bankruptcy or acquisition and zero otherwise as the dependent variable. All control variables are defined in Appendix A. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	*Delist_Dum*					
	Sentiment-prone Firms			Sentiment-counter Firms		
	T+3	T+4	T+5	T+3	T+4	T+5
	(1)	(2)	(3)	(4)	(5)	(6)
Credit_Sentiment	-0.3887	0.0515	0.0998	0.1526	0.7495**	0.6978*
	(-1.22)	(0.16)	(0.24)	(0.46)	(2.02)	(1.71)
Credit_Sentiment*Sentiment_Beta	4.4802**	3.6428*	3.2500	1.0324	1.8462	0.1959
	(2.24)	(1.93)	(1.54)	(0.42)	(0.71)	(0.06)
Sentiment_Beta	0.7364	0.7650	1.3676	-1.9012**	-2.0946*	0.6903
	(0.87)	(0.89)	(1.44)	(-1.98)	(-1.77)	(0.48)
Size	-0.3705***	-0.3780***	-0.3307***	-0.4097***	-0.4347***	-0.3872***
	(-8.32)	(-7.81)	(-6.21)	(-7.07)	(-7.42)	(-6.85)
Tobin's Q	-0.1228**	-0.1120*	-0.0019	-0.0982*	-0.1719***	-0.2266***
	(-2.29)	(-1.77)	(-0.03)	(-1.78)	(-2.75)	(-2.93)
Lev	1.2431***	1.4754***	1.2576***	1.0462***	1.0771***	0.7993*
	(4.20)	(4.38)	(3.52)	(2.99)	(2.93)	(1.81)
ROA	-0.2350	-1.0615	-2.1606**	-1.6790**	-0.6866	-0.0734
	(-0.34)	(-1.28)	(-2.14)	(-2.56)	(-1.14)	(-0.09)
Sales_Growth	-0.0205	-0.0282	-0.0732	0.1736	0.0664	-0.1662
	(-0.14)	(-0.22)	(-0.51)	(1.50)	(0.44)	(-0.81)
Operating_Cashflow	-0.9831	0.0416	1.2036	0.0254	-0.8360	-0.9528
	(-1.58)	(0.06)	(1.31)	(0.04)	(-1.55)	(-1.31)
Cash	-0.4815	-0.4286	-0.6329	-0.4904	0.1539	0.0444
	(-1.21)	(-0.92)	(-1.27)	(-1.17)	(0.34)	(0.09)
Equity_Sentiment	-0.0139	0.1796***	0.2325***	-0.0691	0.0591	0.1799**
	(-0.23)	(2.64)	(2.73)	(-1.10)	(0.81)	(2.15)
Economic_Condition	-0.1255*	-0.1890**	-0.0724	-0.1111	-0.2482***	-0.1678*
	(-1.81)	(-2.34)	(-0.80)	(-1.52)	(-2.76)	(-1.80)
Macro_Uncertainty	-0.2795***	-0.1945**	-0.0085	-0.2833***	-0.1369	-0.1831*
	(-3.96)	(-2.44)	(-0.08)	(-3.59)	(-1.58)	(-1.88)
Constant	-3.3744***	-3.5600***	-4.0032***	-3.4760***	-3.4389***	-3.1252***
	(-14.55)	(-14.11)	(-13.54)	(-12.58)	(-11.22)	(-9.67)
N	30,516	27,313	24,511	32,158	29,121	26,401

Table 10: Sentiment sensitivity and stock returns

This table shows the returns of portfolios ranked by sentiment beta over 1, 3, 6, and 12 months holding periods. Market-adjusted return is the difference between individual stock return and CRSP value-weighted market index and DGTW-adjusted return presents the difference between raw return and the benchmark portfolio return based on size, industry-adjusted book-to-market ratio and past 12-month return (Daniel et al., 1997). FF5 alpha is estimated by regressing portfolio excess returns on the Fama and French (2015) five factors. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Full time period											
	Average returns (%/month)										
	1	2	3	4	5	6	7	8	9	10	**1-10**
Excess Return	1.14%	1.13%	0.98%	1.01%	1.03%	1.04%	1.12%	0.99%	1.13%	0.89%	0.25%
	(3.52)	(4.24)	(3.98)	(4.20)	(4.36)	(4.45)	(4.55)	(3.80)	(3.85)	(2.62)	(2.16)
Market-adjusted Return	0.53%	0.52%	0.37%	0.40%	0.42%	0.43%	0.51%	0.38%	0.52%	0.28%	0.25%
	(2.51)	(3.64)	(2.97)	(3.48)	(3.72)	(3.73)	(4.04)	(2.65)	(2.91)	(1.18)	(2.16)
DGTW-adjusted Return	0.30%	0.24%	0.12%	0.12%	0.16%	0.17%	0.23%	0.13%	0.27%	0.07%	0.23%
	(3.01)	(4.75)	(2.55)	(2.85)	(3.90)	(3.92)	(5.43)	(2.61)	(4.10)	(0.61)	(2.14)
FF5 Alpha	0.44%	0.32%	0.08%	0.08%	0.15%	0.16%	0.26%	0.17%	0.34%	0.20%	0.25%
	(2.98)	(3.62)	(0.93)	(0.93)	(1.80)	(1.92)	(2.87)	(1.59)	(2.53)	(0.89)	(1.72)
	Average cumulative 3-month returns (%)										
	1	2	3	4	5	6	7	8	9	10	**1-10**
Excess Return	3.15%	3.25%	2.90%	2.95%	2.90%	3.05%	3.25%	2.75%	3.25%	2.30%	0.85%
	(4.97)	(6.24)	(5.96)	(6.26)	(6.40)	(6.68)	(6.81)	(5.52)	(5.64)	(3.60)	(4.43)
Market-adjusted Return	1.35%	1.40%	1.05%	1.10%	1.05%	1.20%	1.40%	0.95%	1.45%	0.50%	0.85%
	(3.23)	(4.91)	(4.17)	(4.71)	(4.85)	(5.19)	(5.76)	(3.35)	(4.03)	(1.10)	(4.43)
DGTW-adjusted Return	0.65%	0.60%	0.30%	0.25%	0.30%	0.40%	0.55%	0.15%	0.70%	-0.20%	0.84%
	(3.10)	(5.65)	(2.94)	(2.99)	(3.82)	(4.53)	(6.44)	(1.73)	(4.93)	(-1.02)	(4.58)
FF5 Alpha	0.84%	0.55%	0.00%	-0.09%	0.11%	0.21%	0.50%	0.10%	0.70%	-0.23%	1.07%
	(3.32)	(3.50)	(0.01)	(-0.70)	(0.83)	(1.74)	(4.03)	(0.67)	(3.51)	(-0.90)	(5.06)
	Average cumulative 6-month returns (%)										
	1	2	3	4	5	6	7	8	9	10	**1-10**
Excess Return	6.05%	6.50%	5.90%	5.75%	5.60%	6.05%	6.50%	5.30%	6.40%	4.65%	1.42%
	(6.38)	(8.53)	(8.24)	(8.39)	(8.57)	(9.11)	(9.33)	(7.32)	(7.50)	(4.87)	(4.52)
Market-adjusted Return	2.40%	2.80%	2.20%	2.05%	1.95%	2.35%	2.80%	1.60%	2.75%	1.05%	1.39%
	(3.80)	(6.35)	(5.68)	(5.59)	(5.81)	(6.61)	(7.46)	(3.86)	(5.06)	(1.56)	(4.44)
DGTW-adjusted Return	1.15%	1.40%	0.75%	0.45%	0.55%	0.85%	1.15%	0.25%	1.45%	-0.30%	1.45%

	(3.38)	(8.41)	(5.03)	(3.41)	(4.77)	(6.25)	(9.03)	(1.86)	(6.30)	(-0.95)	(4.73)
FF5 Alpha	1.36%	0.85%	-0.16%	-0.49%	-0.14%	0.21%	0.69%	-0.20%	1.09%	-0.98%	2.34%
	(2.76)	(3.30)	(-0.67)	(-2.13)	(-0.67)	(1.13)	(3.49)	(-0.89)	(3.15)	(-2.53)	(5.91)
	Average cumulative 12-month returns (%)										
	1	2	3	4	5	6	7	8	9	10	**1-10**
Excess Return	12.20%	12.80%	12.35%	11.40%	11.10%	12.20%	13.00%	11.00%	12.95%	9.70%	2.50%
	(8.90)	(11.72)	(12.10)	(12.17)	(12.13)	(13.02)	(13.14)	(10.45)	(10.72)	(7.16)	(4.60)
Market-adjusted Return	5.00%	5.40%	4.90%	3.90%	3.65%	4.75%	5.60%	3.60%	5.65%	2.60%	2.41%
	(5.11)	(7.77)	(8.13)	(7.12)	(7.16)	(8.53)	(9.26)	(5.29)	(6.88)	(2.62)	(4.44)
DGTW-adjusted Return	2.85%	3.05%	2.25%	1.00%	1.20%	1.90%	2.70%	1.35%	3.35%	0.65%	2.18%
	(5.36)	(11.24)	(9.19)	(5.41)	(6.53)	(9.69)	(12.97)	(5.59)	(9.55)	(1.42)	(4.19)
FF5 Alpha	1.73%	0.31%	-1.10%	-1.55%	-1.43%	-0.26%	0.45%	-1.05%	0.82%	-3.42%	5.15%
	(2.01)	(0.71)	(-2.94)	(-4.33)	(-4.90)	(-0.88)	(1.29)	(-2.64)	(1.62)	(-5.66)	(6.12)
Panel B: Large credit-market sentiment Jump months (i.e. positive shocks)											
	Average returns (%/month)										
	1	2	3	4	5	6	7	8	9	10	**1-10**
Excess Return	2.55%	2.00%	1.80%	1.75%	1.90%	1.90%	2.00%	1.95%	2.45%	2.65%	-0.12%
	(3.95)	(3.75)	(3.56)	(3.55)	(3.91)	(4.01)	(3.92)	(3.64)	(4.18)	(3.67)	(-0.46)
Market-adjusted Return	1.55%	1.00%	0.80%	0.75%	0.85%	0.90%	0.95%	0.95%	1.45%	1.65%	-0.12%
	(3.62)	(3.46)	(2.99)	(3.11)	(3.76)	(3.75)	(3.72)	(3.06)	(3.89)	(3.03)	(-0.05)
DGTW-adjusted Return	0.55%	0.25%	0.10%	0.10%	0.25%	0.25%	0.25%	0.20%	0.60%	0.65%	-0.10%
	(3.21)	(2.95)	(1.13)	(1.05)	(3.24)	(2.51)	(3.14)	(2.02)	(4.89)	(2.52)	(-0.43)
FF5 Alpha	1.30%	0.72%	0.47%	0.43%	0.65%	0.67%	0.72%	0.67%	1.30%	1.61%	-0.30%
	(4.15)	(4.05)	(3.05)	(2.60)	(3.84)	(4.13)	(4.06)	(2.62)	(4.37)	(2.99)	(-0.94)
Panel C: Large credit-market sentiment Drop months (i.e. negative shocks)											
	Average returns (%/month)										
	1	2	3	4	5	6	7	8	9	10	**1-10**
Excess Return	0.45%	0.65%	0.45%	0.50%	0.55%	0.55%	0.55%	0.55%	0.50%	0.00%	0.48%
	(0.76)	(1.30)	(0.94)	(1.08)	(1.20)	(1.22)	(1.19)	(1.12)	(0.87)	(-0.00)	(2.63)
Market-adjusted Return	0.40%	0.60%	0.40%	0.45%	0.50%	0.50%	0.50%	0.50%	0.45%	-0.05%	0.48%
	(1.10)	(2.41)	(2.01)	(2.39)	(2.72)	(2.64)	(2.33)	(2.07)	(1.39)	(-0.13)	(2.63)
DGTW_adjusted Return	0.20%	0.25%	0.10%	0.15%	0.15%	0.20%	0.20%	0.25%	0.20%	-0.20%	0.41%
	(1.08)	(2.27)	(1.27)	(1.62)	(2.02)	(2.50)	(2.54)	(2.85)	(1.68)	(-1.04)	(2.36)
FF5 Alpha	0.16%	0.31%	0.03%	0.01%	0.08%	0.07%	0.10%	0.12%	0.03%	-0.41%	0.57%
	(0.72)	(2.14)	(0.30)	(0.07)	(0.69)	(0.59)	(0.80)	(0.91)	(0.19)	(-1.67)	(3.00)