TWO ESSAYS ON CORPORATE FINANCE UNDER TIME-VARYING ECONOMIC CONDITIONS

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CERTIFICATE OF ORIGINALITY

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(Signed)

SHANG LONGFEI (Name of student)

ABSTRACT

This thesis consists of two essays. The commonality of the essays is that I investigate corporate decisions under time-varying economic conditions. In the first essay, I examine how easy money may trigger competitive myopia and contribute to the investment inefficiency problem of competitive industries. The second essay investigates how economic policy uncertainty affects lobbying initiation decision.

For the first essay, studies have shown that firms in competitive industries tend to make inefficient investments, compared to their counterparts in consolidated industries. Who would finance inefficient investments? Is financing part of the investment inefficiency problem? To address these questions, I hypothesize that when credit market sentiment is high, firms in competitive industries rush to take advantage of available easy money for investing and for strengthening their current competitive positions, and overlook the developing risk of overcapacity in their industries, which leads to predictable declines in future cash flow and stock performance. Using excess bond premium to proxy for the availability of easy money, I find evidence consistent with my hypothesis. The predictable declines in cash flow are especially severe for firms that invest more during high credit market sentiment periods. Furthermore, competitive myopia triggered by easy money can explain competitive industries' booms and busts. In contrast, due to barriers to entry, consolidated industries are much less affected by easy money. In sum, my study suggests that financing is part of competitive industries' investment inefficiency problem, and that because of competitive myopia, credit market sentiment is an important

predictor for competitive industries' future cash flow, but not for consolidated industries'.

In the second essay, I find that economic policy uncertainty (EPU) raises firms' incentives to lobby and access policy information. However, I find that non-lobbying firms are less likely to initiate lobbying during periods of high EPU. I find evidence consistent with my conjecture that lobbying entry barriers increase with EPU. I verify that EPU's negative effect on lobbying initiation arises through the channels of lobbying entry expenses and returns to experience. I further identify two mechanisms regulating these channels: (1) inelastic supply of lobbying services and (2) existing lobbying firms' demand for lobbying services (which increase with EPU).

Although these two essays are independent, they both show that time-varying economic conditions significantly affect corporate decisions. I illustrate the difference in corporate behavior by comparing operation activities of competitive and consociated industries in the presence of easy money in the first essay, and lobbying firms' and non-lobbying firms' responses to economic policy uncertainty in the second essay. By studying these differences in corporate decisions under time-varying economic conditions, my essays enhance our understanding of how different types of corporations deal with time-varying economic conditions differently.

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Chapter 2 of this thesis was available online. The detailed reference is as follows:

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CHAPTER 1 EASY MONEY AND COMPETITIVE MYOPIA

1.1 Introduction

Studies have shown that firms in competitive industries tend to make inefficient investment decisions, and suffer booms and busts. [1] These studies also offer several explanations of this inefficiency, including a lack of coordination (Hoberg and Phillips, 2010), costly information gathering (Stoughton et al, 2016), biased beliefs of rivals' investment responses to common shocks (Greenwood and Hanson, 2014), and information herding (Povel et al., 2016). It remains puzzling from a financing perspective, because product market competition drives down profits, raises credit risk, and makes it difficult for firms to raise external capital (Valta, 2012; Hu, 2014; Corhay, 2017). The difficulty of obtaining external capital leaves less room for a waste of resources, and should push firms to be more efficient, rather than less efficient, in investments once they can get financing.[2] Little work, however, has been done to reconcile this inconsistency between the financing and the investment aspects of competitive industries. I do so by investigating two interrelated questions: Who would finance inefficient investments? Is financing part of the investment inefficiency problem in competitive industries?

The inefficient investment problem in competitive industries, from a holistic perspective, arises as competing firms simultaneously invest, and neglect potential development of overcapacity. I synthesize the studies on

[1] See Section 1.2 for literature review.
[2] Hovakimian (2011) studies conglomerates and support the view that capital is allocated more efficiently when it is more difficult to obtain.

the inefficient investment problem and on the difficulty of obtaining external financing, and develop a new hypothesis to show that financing is an integral part of competitive industries' investment inefficiency problem. Specifically, I hypothesize that when easy money becomes available, competitive pressure prompts firms to take advantage of easy money to invest and strengthen their current competitive positions. As competing firms would behave similarly, their managers (and investors) overlook the developing risk of overcapacity at the industry level, until overcapacity materializes and firms' profitability declines. I refer this phenomenon as competitive myopia, which seems a generic problem in competitive industries, as Xiong (2018) shows that product market competition leads to aggressive myopic investment actions.

The key testable predictions of my hypothesis are that, to the extent that easy money triggers managers' competitive myopia, easy money: (i) elevates competitive industries' investments and debt financing; (ii) leads to overcapacity as manifested by declines in sales growth and gross margin at the industry level; and (iii) can predict declines in competing firms' future cash flow and stock performance. In contrast, due to barriers to entry, consolidated industries do not have such problems associated with competitive industries, making them less affected in the presence of easy money.

I use credit market sentiment to capture the availability of easy money.[3] As Lopez-Salido et al. (2017) show, when credit market sentiment

[3] I choose not to focus on equity market because it is unclear how cost of equity financing varies with industry competition. Hou and Robinson (2006) find a positive association

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 economic activity. High credit market sentiment—reflecting credit-market investors' optimistic expectations about default probabilities—makes it easier than usual for firms in competitive industries to raise capital at a lower cost.[4] To this end, I employ excess bond premium (thereafter EBP) constructed by Gilchrist and Zakrajšek (thereafter GZ) (2012) as my measure of credit market sentiment. GZ decompose credit spread into the predicted spread related to firms' default risk and the residual component referred as EBP.[5] Consequently, EBP captures variations in the pricing of default risk, rather than movements in the risk of default. The variations in the pricing of default risk (i.e. EBP) manifest credit market sentiment and capture the availability of easy money.

Interestingly, I observe credit market sentiment and economic conditions are strongly correlated,[6] which suggests that strong economy fuels high credit market sentiment. Moreover, high credit market sentiment relaxes financing constraints of firms in competitive industries in pursuing investment opportunities that are also available at the same time.

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between competition and stock return, while Bustamante and Donangelo (2017) find the opposite. Nevertheless, I control for stock market sentiment.

[4]Greenwood et al. (2016) present a model of credit market sentiment in which investors' beliefs about future creditworthiness depend on past defaults, and beliefs affect investors' willingness to refinance debt at low interest rates.

[5] GZ uses distance to default developed by Merton (1974) and bond-specific characteristics to predict credit spread. Bond-specific characteristics include bond's duration, amounting outstanding, coupon rate, age of the issue, a dummy variable set to one if bond is callable and zero otherwise. GZ shows that EBP can better predict future GDP growth than predicted component of credit spread in terms of both economic magnitude and statistical significance.

[6] In my sample, economic condition and credit market sentiment are significantly and positively correlated at 0.51, while the correlation between economic condition and equity market sentiment is insignificant at -0.06. The weak correlation between economic condition and equity market sentiment is due to the construction of equity market sentiment that removes business cycle variation.

Consequently, for competitive industries, easy money from credit markets acts as an important catalyst for undertaking available investment opportunities for competitive industries.

Using GZ's (2012) EBP to proxy for credit market sentiment, I first investigate how credit market sentiment affects investments at the industry level. Following Hoberg and Phillips (thereafter HP) (2010), I use the previous 10 years' data to predict firm-level investments, based on firms' profitability, investment opportunities, and firm characteristics, and obtain relative investments for a given year at the firm level, and then average relative investments across all firms in an industry to obtain the industry's relative investment for that year. HP note that this industry relative investment can capture industry-wide investments acting on new opportunities, since relative investment excludes investment predicted by past information. I classify industries on the basis of three-digit SIC codes and define competitive (consolidated) industries as those in the lowest (highest) tercile sorted by Compustat HHIs. I find that high credit market sentiment in year t significantly raises competitive industries' relative investment in that year and the following two years. The investment effect of credit market sentiment is particularly large in year t+1. In contrast, I do not find a significant effect of credit market sentiment on consolidated industries' relative investment. In terms of economic significance, a one-standard-deviation increase in credit market sentiment is associated with a 9.42% increase in competitive industries' one-year-ahead relative investment, whereas there is only a 2.69% relative investment increase in consolidated industries for the same change in credit market sentiment.

The investment effect of credit market sentiment in competitive industries is robust to various industry- and macroeconomic-level controls. For industry-level controls, I consider size, Tobin's Q, leverage, ROE, sales growth, cash flow, and cash holding. My macro-level controls include Baker and Wurgler's (2006) equity market sentiment, economic conditions, and macro uncertainty. Furthermore, my findings hold when I use the fitted HHI proposed by Hoberg and Phillips (2010) as an alternative measure of industry competition.

As a robustness check, I also consider other two proxies for credit market sentiment. The first one is high-yield bond issuance used by Greenwood et al. (2016) and Lopez-Salido et al. (2017). The second proxy is the percentage of major domestic banks that report easing credit standards, which is used by Gilchrist and Zakrajsek (2012) and Greenwood et al. (2016). My results are robust for these two alternative measures of credit market sentiment. Finally, to further mitigate the concern that the effects of credit market sentiment on competitive industries' relative investments are driven by a high correlation between credit market sentiment and economic condition, I regress credit market sentiment against economic condition and take the residual component. By using the residual component of credit market sentiment, I observe similar results.

To verify channels of product competition and difficulty of raising external capital, I conduct cross-sectional analyses for competitive industries. First, I show that the effects of credit market sentiment on industry relative investments are even larger in competitive industries with higher competition. Moreover, Ortiz-Molina and Phillips (2011) and Valta

(2012) show that, for competitive industries, industry illiquidity condition is an important determinant of cost of capital. The findings indicate that firms in competitive industries with higher illiquidity face more difficulty in raising external capital. Thus, I should observe stronger effects of credit market sentiment on industry relative investments for competitive industries with higher illiquidity. The results are consistent with my conjecture.

I next examine whether firms raise more debt financing when credit market sentiment is higher. For competitive industries, I find that debt financing is significantly and positively associated with credit market sentiment, while equity financing is not. For concentrated industries, however, the effects of credit market sentiment on debt and equity financing are insignificant. My findings indicate that high credit market sentiment lessens the difficulty faced by firms in competitive industries in raising capital from the credit market, and that, during periods with high credit market sentiment, credit investors provide easy money to competitive industries.

To test whether easy money leads to competitive industries' overcapacity, I examine how credit market sentiment predicts future sales growth and gross margin at the industry level. First, I find that, for competitive industries, while industry sales growth in year t+1 is significantly and positively associated with credit market sentiment in year t, sales growth in year t+3 is significantly and negatively related to credit market sentiment in year t. Similarly, I find that competitive industries' gross margin in year t+3 is significantly and negatively related to credit market sentiment in year t. In contrast, for consolidated industries, sales growth and gross margin in years t through t+4 are largely insignificantly associated with credit market sentiment in year t. These findings, along with the investment effect of credit market sentiment, imply that, induced by high credit market sentiment in year t, competitive industries' cumulative investments over years t to t+2 lead to overcapacity in the industries, which result in the declines in the industries' sales and profitability in year t+3. The evidence is consistent with my hypothesis of competitive myopia triggered by easy money. The evidence also suggests that easy money contributes to the investment inefficiency problem of competitive industries.

To verify my findings, I investigate whether easy money can predict declines in future cash flows and stock performance at the firm level. I find that, for competitive industries, firms' operating and stock performance in year t+3 are significantly and negatively related to credit market sentiment in year t, whereas there is no such relation for consolidated industries. More importantly, I show that predictable declines in operating and stock performance are especially severe for firms that invest more during periods with high credit market sentiment, shedding further light on the detrimental effects (and thereof the inefficiency nature) of the investments made during high credit market sentiment.

In the final test, I examine whether easy money can explain competitive industries' booms and busts. First, I confirm HP's (2010) finding that industry booms (i.e., high relative valuation, high relative investment, and high new financing at the industry level) in year t+1 can predict negative changes in operating cash flow and abnormal stock returns in year t+3 for firms in competitive industries. Second, I add credit market sentiment to the regression models, and find that high credit market sentiment in year t strongly predicts negative operating cash flows and stock returns in year t+3. At the same time, the predictive power of industry booms becomes marginal or insignificant. These findings suggest that the negative effects of industry booms on firms' future operating and stock performance can be to a great extent trace back to the presence of easy money. Taken together, the results are coherently consistent with the developing risk of overcapacity in competitive industries when easy money becomes available and triggers competitive myopia.

In a related study, Gulen et al. (2018) argue that credit investors and managers similarly over-extrapolate past shocks to fundamentals, which leads to a positive relation between investments and debt issuance. However, they do not study the link between credit market sentiment and competitive industries' investment inefficiency problem. In this paper, I show that high credit market sentiment leads to competitive industries' overinvestment and predictable declines in firms' operating and stock performance. In contrast, consolidated industries do not face similar problems, due to barriers to entry.

My study contributes to the literature on competitive versus consolidated industries. Previous studies note that competitive industries suffer investment inefficiency (Hoberg and Phillips, 2010; Greenwood and Hanson, 2014; Povel et al. 2016; Stoughton et al. 2016). In this paper, I extend the literature by studying the financing side, and focus on the role of easy money in the investment inefficiency problem of competitive industries. I show that easy money triggers competitive myopia and contributes to investment inefficiency. My paper demonstrates the importance of financing side in explaining the investment inefficiency problem suffered by competitive industries. More importantly, my paper illustrates that, due to competitive myopia, credit market sentiment is useful for predicting future operating and stock performance of firms in competitive industries. But, it is not useful for consolidated industries.

This paper also contributes to the literature on time-varying financing constraints. For example, Mclean and Zhao (2014) document evidence that equity market sentiment helps relax firms' financing constraints and allows for more positive NPV projects. I complement this literature by studying the role of credit market sentiment in relaxing financing constraints. Furthermore, I show that while high credit market sentiment relaxes financing constraints, it can cause overinvestment and poor future operating and stock performance for firms in competitive industries.

Finally, my paper contributes to the literature on credit cycles. Traditional theories on credit cycles emphasize externality of leverage.[7] Recently, Lopez-Salido et al. (2017) argue that variations in credit market sentiment can better explain credit cycles, since credit market sentiment theories can better answer when and how a credit-driven downturn gets triggered by relying on extrapolative beliefs of credit investors (See also Greenwood and Hanson, 2013; Greenwood, Hanson and Jin, 2016; Bordalo et al., 2018). However, these theories cannot fully explain what causes the

[7] Specifically, when an exogenous and negative shock hits the economy, firms that have levered up to finance their investments find their net worth impaired and have to reduce borrowing and future investments. See Bernanke and Gertler (1989), Kiyotaki and Moore (1997), Eggertsson and Krugman (2012), Burnnermeier and Sannikov(2014) and Guerrieri and Lorenzoni (2017).

reversal of credit market sentiment. My study extends this strand of literature by showing there is an alternative channel through which investors' sentiment reverse. That is, due to competitive myopia, high credit market sentiment predicts declines in firms' operating and stock performance for competitive industries. As firms' cash flows and stock valuation decline, the default probability would increase, which would lead credit investors to update their beliefs, turning their optimism into pessimism. Moreover, existing empirical studies on credit market sentiment focus on macro-level analyses. I are the first to provide evidence on how the effects of credit market sentiment on business activities could vary across different industries and whether industry structure plays a role in explaining the predictability of credit market sentiment.

The remainder of this chapter is organized as follows. Section 1.2 reviews the literature and develops the hypothesis. Section 1.3 describes the data and the variables used in empirical tests. Section 1.4 investigates how easy money affects industry investments and financing activities. Section 1.5 reports that easy money leads to overcapacity at the industry level. Section 1.6 discusses how easy money affects firms' future operating and stock performance. Section 1.7 concludes.

1.2 Literature review and hypothesis development

1.2.1 Literature on investment inefficiency of competitive industries

Many studies on organizational structure compare competitive versus consolidated industries, and show that firms in competitive industries face one severe problem, namely investment inefficiency. Hoberg and

Phillips (2010) argue that since information about peers is costly to gather for competitive industries, firms rely more on public available industry-level information to conduct investment plans. Moreover, competition pressure makes firms hard to coordinate their investments. Due to the lack of coordination and reliance on public signals, firms tend to overinvest following positive industry shocks, which leads to declines in future operating performance. Indeed, they show that future cash flow and stock performance of firms in competitive industries are negatively associated with valuation and investments at the industry level. Their findings illustrate that investment inefficiency contributes to competitive industries' boom-bust cycles.

Moreover, Stoughton et al (2016) argue that, due to the difficulty of information collection, firms in competitive industries invest under incomplete information. As information about rival firms is incomplete, the investments under incomplete information are less optimal compared with the full-information case. Greenwood and Hanson (2014) argue that managers' biased expectation of peers is also important in explaining boom-bust investment cycles for competitive industries. Specifically, when managers conduct investment plans, they may underestimate their rivals' investment response and overestimate their investment skill in acting on positive shocks. As a result, firms in the same industry take similar investment strategies to positive industry shocks. Ex post, the realized investments create oversupply in the industry, leading to lower future profits. To support biased expectation hypothesis, Greenwood and Hanson (2014) use the shipping industry as an example and show that firms with high investments yield lower future returns.

Povel et al. (2016) propose an information herding theory to explain the investment inefficiency problem and the formation of boom-bust cycles in competitive industries. Specifically, Povel et al. model that since agents are not equally informed, uninformed agents infer information from decisions of informed ones. It follows that uninformed firms imitate investment decisions of informed firms. As followers have less precise information about industry shocks, such imitation leads to low performance. Indeed, Povel et al. find that hotels built during hotel construction booms have lower performance, compared to their peers.

It is understandable that the nature of competition and the organizational structure can make investment coordination and information acquisition difficult, and create investment inefficiency in competitive industries vis-à-vis consolidated industries. The question is: who would finance inefficient investments? The role of financing side in investment inefficiency of competitive industries is little discussed in the previous studies. As I will discuss below, the financing side can be part of the problem, and important in explain competitive industries' investment inefficiency.

Several studies have shown that the cost of debt tends to be higher for competitive industries than for consolidated industries. Peress (2010) note that since a lack of market power makes it hard for firms to pass shocks to customers, firms in competitive industries face difficulty in insulating profits from shocks, and suffer volatile profits. Valta (2012) further point out that since product market competition increases firms' cash flow risk, firms in competitive industries have higher default probability, compared with their counterparts in consolidated industries. Indeed, he finds that the cost of bank debt is higher for firms in competitive industries. By analyzing lines of credit contracts, Hu (2014) further shows that lenders tend to give borrowing firms from competitive industries less favorable terms, with higher loan rates, lower loan amounts, and more stringent collateral requirements.

In sum, these studies show that firms in competitive industries generally suffer costly debt financing, which suggests that these firms face severe financing constraints in making investment plans. The difficulty of obtaining debt financing should push firms to more efficiently utilize their capital and improve efficiency. For example, Shleifer and Vishny (1997) argue that product competition pressure forces firms in competitive industries to minimize costs. As a result, product market competition can serve a role of corporate governance in mitigating agency problems and increasing efficiency of these firms. Moreover, Giroud and Mueller (2010) find that, after passage of business combination laws, while firms in non-competitive industries experience a decline in operating performance, firms in competitive industries do not. Since business combination laws reduce the threat of a hostile takeover, they weaken corporate governance, and increase the opportunity of managerial slack in non-competitive industries. The findings of Giroud and Mueller (2010) support the notion that product market competition mitigates managerial slack.

To reconcile this inconsistency between the financing and the investment aspects of competitive industries, it is important to understand whether financing is part of the investment inefficiency problem in competitive industries. More specifically, when easy money is available, would firms in competitive industries rush to take advantage of easy money and invest, which leads to overcapacity?

1.2.2 Literature on credit market sentiment

Lopez-Salido et al. (2017) divide theories on credit cycles into two categories: those built on financial frictions and those based on sentiment. Financial friction based theories (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997) model that all agent have rational expectations, and that there are frictions in the debt market. These theories argue that when an exogenous and negative shock hits the economy, firms that have levered up to finance their investments find their net worth impaired and have to reduce borrowing and future investments. However, one critical part of this genre of theories is that these theories rely on exogenous and negative shocks to move the whole system. Since it is hard to model and predict the timing and frequency of exogenous shocks, these theories cannot explain when and how a credit-driven downturn gets triggered and the duration of the credit cycle.

Compared to rational arguments proposed by financial friction theories, credit market sentiment theories build on behavioral explanation. Sentiment-based theories suggest that credit investors have extrapolative beliefs (Greenwood et al., 2016; Bordalo et al., 2018). For example, Greenwood et al. model that credit investors form their beliefs about future credit default by extrapolating past defaults. When default probability has been low, credit investors extrapolate low default by forming an optimistic expectation that future default probability will continue to be low. In Bordalo et al., credit investors form their expectations about future credit defaults based on current economy state. When economic news is good, credit investors become optimistic about future default probability.

Greenwood et al. and Bordalo et al. further argue that credit investors' optimistic belief can lead to narrowing credit spreads and expanding credit supply. This makes firms easier to refinance existing debt or to issue new debt with low cost. The low cost of capital relaxes firms' financing constraints, and fuels the economic activity. However, following narrow credit spread periods, economic news generally tend to be disappointing relative to optimistic expectations of credit investors. Then, investors update their beliefs, and credit spread widens, resulting in the reversal of credit market sentiment. However, it is unclear that what may contribute to relative weaker economic conditions following high credit sentiment periods and what may trigger the reversal of credit market sentiment.

Recent studies find evidence consistent with credit market sentiment theories. Gilchrist and Zakrajsek (2012) find that a decrease in excess bond premium is associated with an increase in 12-months-adead economic activity. This finding is consistent with the prediction that for the shorter term, high credit market sentiment fuels economic activity. However, credit market sentiment theories also predict that, for the longer term, high credit market sentiment forecasts declines in economic activity. For example, Lopez-Salido et al. (2017) show that high credit market sentiment in year t is associated with a decline in economic activity in years t+2 and t+3.

However, these studies do not distinguish how credit market sentiment may have different effects on competitive industries vis-à-vis consolidated industries. Since high credit market sentiment can relax financing constraints, it should benefit more to competitive industries than consolidated industries, as firms in competitive industries tend to have more difficulty in obtaining debt financing. Based on this notion, I next develop my hypothesis.

1.2.3 Hypothesis development

As previous studies have identified that firms in competitive industries face investment inefficiency problem and have difficulty in obtaining external financing, I synthesize these two issues and develop a new hypothesis to show that financing is part of competitive industries' investment inefficiency problem. Based on the notion that the availability of easy money coincides with strong economic conditions, I hypothesize that when easy money becomes available, competitive pressure prompts firms to take advantage of easy money to invest and to strengthen their current competitive positions. As competing firms would behave similarly, their managers (and investors) overlook the developing risk of overcapacity at the industry level, until overcapacity materializes and firms' profitability declines. I refer this phenomenon as competitive myopia.

My hypothesis of competitive myopia has three key predictions. First, easy money raises competitive industries' investments and debt financing. Second, easy money leads to overcapacity in competitive industries. And, the third prediction is that high credit market sentiment can predict declines in competing firms' future cash flow and stock performance. In contrast, due to barriers to entry, consolidated industries do not have such problems associated with competitive industries, making them less affected in the presence of easy money.

1.3 Data

1.3.1 Industry classifications

Following HP (2010), I classify industries on the basis of three-digit SIC codes. I exclude financial (SIC 6000-6999) and utility (SIC 4900-4999) industries. Following HP (2010) and Li (2010), I use segment-level data to compute Compustat HHIs. Similar to Li (2010), my segment-based Compustat HHIs are from 1976 to 2015.[8] For a robustness check, I also use fitted HHI as an alternative measure of industry competition.

1.3.2 Industry-level and firm-level variable construction

Following HP (2010), I use industry-level relative investment to compare the effects of credit market sentiment on investment activities of firms in competitive and consolidated industries. HP note that this relative investment can capture industry-wide investment acting on new opportunities, since the relative investment excludes investment predicted by past information, including firms' profitability, investment opportunities, and firm characteristics.

[8] Historical segment data is available from 1976.

Specifically, I measure industry relative investment with a three-step procedure. In the first step, for each industry *j*, I run the following regression model and estimate the industry-level coefficients using data from year t-10 to t-1 for all firms in industry *j*:

$$\log(\frac{INVEST_{i,\tau}}{PPE_{i,\tau-1}}) = \alpha + bAGE_{i,\tau} + cDD_{i,\tau} + dLEV_{i,\tau} + eSIZE_{i,\tau}$$

$$+ fVOLP_{i,\tau} + gROE_{i,\tau} + hTOBINQ_{i,\tau-1} + \varepsilon_{i,\tau,}$$

$$\tau = t - 10, \dots, t - 1. \quad (1.1)$$

AGE is minus the reciprocal of one plus firm age; *DD* is a dividend dummy; *LEV* is firm leverage; *SIZE* is the log of total assets; *ROE* is earnings divided by last year's book equity; $VOLP_{i,\tau}$ is the volatility of profitability of firm *i*; *TOBINQ* is market value of equity plus book value of debt and preferred stock divided by book value of assets. I calculate $VOLP_{i,t}$ by regressing $ROE_{i,t}$ on $ROE_{i,t-1}$ for all firms in each industry *j* and taking the variance of residuals. Following Pastor and Veronesi (2003) and HP, I filter out questionable observations and winsorize extreme observations before I run the regression. That is, I filter out firms with market equity, book equity, and total assets smaller than $1 million, or market-to-book ratios outside the range of (0.01, 100), and then winsorize *VOLP* and *ROE* at one and 99 percentiles in each year.

In the second step, I apply the coefficients estimated from Equation (1.1) to calculate predicted value for each firm's investment in year t. That is, I use firm characteristics in year t and the coefficients estimated from years t-10 to t-1 to compute predicted $\log(\frac{INVEST_{i,t}}{PPE_{i,t-1}})$.

In the last step, I first calculate firm's total relative investment as follows:

$$FIRM\_RELATIVE\_INVEST_{i,t} =$$

$$\log\left(\frac{INVEST_{i,t}}{PPE_{i,t-1}}\right) - predicted \log\left(\frac{INVEST_{i,t}}{PPE_{i,t-1}}\right), \quad (1.2)$$

Next, I winsorize *FIRM_RELATIVE_INVEST* at the 1/99 percentiles within each year. Then, I obtain industry relative investment (*RELATIVE_INVEST*) by averaging the relative investments (*FIRM_RELATIVE_INVEST*) across all firms within each industry.

DEBT_FINANCE and *EQUITY_FINANCE* are the averages of firms' net debt financing and net equity financing within each industry. Firm's net debt financing is net debt issuance (long-term debt issuance minus long-term debt reduction) divided by total assets, while firm's net equity financing is net equity issuance (sale of common and preferred stock minus purchase of common and preferred stock) divided by total assets. Similarly, *SIZE*, *TOBIN'S Q*, *LEV*, *ROE*, *GROSS_MARGIN*, *SALES_GROWTH*, *CASH_FLOW*, and *CASH* are the averages of the firm-level variables within each industry.

I again follow HP (2010) and use change in operating cash flow (Δ*CASH_FLOW*) to capture a firm' operating performance and monthly abnormal stock returns (*ABNORMAL_RET*) to proxy for stock performance. Specifically, operating cash flow is operating income divided by total assets. *ABNORMAL_RET* in year t is the firm's monthly abnormal returns between July of year t-1 and June of year t. Firm *i*'s monthly abnormal return is the firm's raw monthly return minus the return of its benchmark portfolio. I follow HP and Daniel et al. (1997) to form 125 benchmark portfolios, based on firm size, book-to-market ratio, and past 12-month return. Specifically, I construct portfolios at the end of each June. I first sort firms into quintiles in each year, based on firm size.[9] Firms in each size quintile are then further sorted into quintiles based on industry-adjusted book-to-market ratios. Each portfolio is then further sorted into quintiles based on each firm's past 12-month return. *FIRM_RELATIVE_INVEST* is firm-level total relative investment defined in Equation (1.2). Δ*EBITDA* and Δ*CAPX* are the change in earnings before interest and taxes plus depreciation and the change in capital expenditures.

1.3.3 Credit market sentiment and macro variables

I use excess bond premium developed by Gilchrist and Zakrajsek (2012) to capture the availability of easy money. Specifically, GZ decompose credit spread into two components: a predicted component and a residual component. The predicted component is first obtained by regressing corporate bonds' credit spreads on the firm's default risk, including the distance to default, credit rating, and bond-specific characteristics, and then average across the predicted components of all firms. Thus, this predicted component represents systematic movements in default risk of individual firms. The residual component, which GZ refer as excess bond premium, captures variations in the pricing of default risk. GZ point out a decrease in excess bond premium reflects an increase in the effective risk-bearing capacity of financial sector. More importantly, GZ show that the residual

[9] Portfolio breakpoints are based only on NYSE/Amex firms.

component can better predict economic activity than the predicted component in terms of both economic magnitude and statistical significance, which suggests that credit spreads' information content related to economic activity largely comes from excess bond premium.

When excess bond premium is negative, current credit spread is lower than the level predicted by the model, which reflects that credit investors have optimistic beliefs about future default probability. Investors' optimistic belief drives down the expected return for bearing credit risk. Thus, during low excess bond premium periods, credit supply expands and the cost of debt is low, allowing firms to easily finance their investments. Conversely, an increase in the excess bond premium reflects an increase in risk aversion of the financial sector and, as a result, a contraction in the supply of credit, which will adversely affect firms' financing and investments. For interpretation convenience, I multiply excess bond premium with negative one and obtain *CREDIT_SENTIMENT* to proxy for credit market sentiment.

Figure 1.1 plots *CREDIT_SENTIMENT* over time, along with NBER recession periods. The figure shows two patterns. First, credit market sentiment has visible cycles and strong mean-reverting tendency. Second, credit market sentiment tends to peak three to four years before the NBER declares a recession, and tends to bottom out during the recession period.

In addition to credit market sentiment, this paper also considers other three macro-level variables to address the concern that credit market sentiment may coincide with other macro-level conditions. The three macro-level variables are equity market sentiment (*EQUITY_SENTIMENT*), economic conditions (*ECONOMIC_CONDITION*), and macro uncertainties (*MACRO_UNCERTAINTY*). To measure equity market sentiment, I use the sentiment index developed by Baker and Wurgler (2006). To obtain *MACRO_UNCERTAINTY*, I follow Bonaime et al. (2018) and use the first principle component of three variables: (i) the University of Michigan index of consumer confidence, (ii) the National Activity Index from the Chicago Federal Reserve Board, and (iii) the average one-year-ahead GDP growth forecast from the Livingston Survey of Professional Forecasters. Again following Bonaime et al. (2018), I measure *MACRO_UNCERTAINTY* as the first principle component of three macro uncertainties variables: (1) Jurado, Ludvigson, and Ng's (2015) monthly index of macroeconomic uncertainty, (2) the cross-sectional standard deviation of monthly returns from the CRSP, and (3) the cross-sectional standard deviation of year-on-year sales growth from the Compustat. All macro-level variables are measured as the averages in the same calendar year.

1.3.4 Descriptive statistics

Sorting industries by Compustat HHIs, I classify competitive industries as the ones in the lowest tercile, and consolidated industries as those in the highest tercile. Table 1.1 lists descriptive statistics for primary variables used in this study. Panel A presents the summary statistics of firm-level variables. In competitive industries, *FIRM_RELATIVE_INVEST* average -0.090, while consolidated industries have a mean of *FIRM_RELATIVE_INVEST* at -0.071. In terms of operating cash flow changes, firms in competitive industries have a mean of -0.008 and their counterparts in consolidated industries have a mean at -0.006. These numbers are similar to those in HP, -0.011 (in competitive industries) and -0.009 (in consolidated industries). Finally, abnormal stock returns are close to zero.

Panel B turns to industry-level variables. Consistent with HP, relative investments are lower in competitive industries than in consociated industries. Moreover, I observe that debt financing is higher in competitive industries than in consolidated industries. This finding is consistent with my argument that debt financing is important to business operations of competitive industries. Finally, compared with consolidated industries, competitive industries have larger size, higher sales growth and more cash holding, while their ROE, gross margin, and cash flow are lower.

In Panel C, I report market-level variables. Since excess bond premium is the residual between credit spread and predictable component of credit spread, I have a mean of *CREDIT_SENTIMENT* closed to zero. The standard deviation of *CREDIT_SENTIMENT* is high at 0.434. *EQUITY_SENTIMENT* has a mean of 0.182 and a standard deviation of 0.694.

Table 1.2 reports correlation coefficients among market-level variables. First, *CREDIT_SENTIMENT* shows a low correlation with *EQUITY_SENTIMENT* at -0.18. The low correlation is consistent with Lopez-Salido et al. (2017), who argue that sentiment in the credit market is distinct from the sentiment in the equity market. More importantly, credit market sentiment and economic conditions are highly correlated. The high correlation suggests that strong economic conditions and high credit market sentiment tend to coincide and that weak economic conditions and low credit market sentiment tend to occur together. Finally, I observe that credit market sentiment and macro-level uncertainty are insignificantly correlated.

1.4 Easy money, investment and financing activities

In this section, I first examine how credit market sentiment in year t affects industry relative investments in years t through t+4. Then, I similarly investigate how credit market sentiment affects debt and equity financing activities at the industry level in the same year and the next four years.

1.4.1 Credit market sentiment and investments

My hypothesis of competitive myopia posits that firms in competitive industries rush to take advantage of available easy money for investing and overlook the developing risk of overcapacity in their industries. Since my hypothesis emphasizes the developing risk of overcapacity at the industry level, I conduct industry-level regression analysis to investigate the effect of credit market sentiment on industry relative investment. My industry-level analysis is similar to those of Harford (2005) and Bonaime et al. (2018) in assessing M&A waves.

I model the industry-level relative investment in a given year τ as a function of credit market sentiment in year *t*, controlling for industry-, and macro-level variables. Specifically, my regression analysis is based on following model:

$$RELATIVE\_INVEST_{j,\tau} = \alpha + \beta CREDIT\_SENTIMENT_t + CONTROLS_{j,t} + \varepsilon_{j,\tau},$$

$$\tau = t, \ldots, t+4. \tag{1.3}$$

CONTROLS consist of industry-level and macro-level control variables. Industry-level controls include *SIZE, TOBIN'S Q, LEV, ROE, SALES_GROWTH, CASH_FLOW,* and *CASH.* The macro-level variables that I consider are equity market sentiment, economic conditions, and macro uncertainty, which are defined in Section 1.3.3. I also control industry fixed effects, and use standard errors clustered at the industry and year levels.

My competitive myopia hypothesis predicts that β in Equation (1.3) is positive for competitive industries. Since, compared to their counterparts in competitive industries, firms in consolidated industries face less costly external financing, they can more easily finance their investments, and so their investment decisions are less dependent on the availability of easy money. This implies that β would be less significant or insignificant for consolidated industries.

Table 1.3 reports regression results based on Equation (1.3). First, I focus on the results for competitive industries. Consistent with my hypothesis, columns (1)-(3) of Panel A show that *RELATIVE_INVEST* in years t to t+2 is indeed significantly and positively related to *CREDIT_SENTIMENT* in year t. Specifically, CREDIT_SENTIMENT shows significant effects on RELATIVE_INVEST in year t with a coefficient of 0.157 (t-value=3.18), with a coefficient of 0.217 (t-value=5.63) in year t+1, and with a coefficient of 0.150 (t-value=2.71) in year t+2. The results show that high credit market sentiment in year t raises competitive industries' relative investments in the same year as well as the next two years. Column (4) of Panel A further shows that the effect of credit market sentiment on competitive industries' relative investment turns to be insignificant. Finally, in column (5), I find that, competitive industries' relative investments in year t+4 show a negative association with credit market sentiment in year t. The findings indicate that, for competitive industries, relative investments in year t+4 tend to reverse following high credit market sentiment in year t.

Table 1.3 also shows that equity market sentiment in year t has insignificant effects on industry relative investment in year t or the subsequent years. The insignificant role of equity market sentiment is in line with the finding of Lopez-Salido et al. (2017), who conduct a horse-race test and show that credit market sentiment can subsume the effect of equity market sentiment in explaining GDP growth.

Panel B reports the effects of credit market sentiment in year t on consolidated industries' relative investments in years t to t+4. Columns (1) – (5) of Panel B shows that consolidated industries' relative investments in year t and the subsequent years are insignificantly associated with credit market sentiment in year t.

In sum, Table 1.3 shows that credit market sentiment affects industry relative investments of competitive and consolidated industries in different ways, and illustrates that easy money is more important to competitive industries than to consolidated industries. More importantly, the findings in Table 1.3 support the competitive myopia hypothesis that competitive pressure forces firms to take advantage of easy money to invest.

In a robustness check, I report firm-level evidence in APPENDIX 1.B and find similar results. Due to measurement error of Compustat HHI (HP 2010, Valta, 2012 and Keil, 2017), I alternatively use *FITTED_HHI* to define competitive and consolidated industries, and report results in APPENDIX 1.C. The results based on *FITTED_HHI* are similar with the findings in the Table 1.3.

I also consider other two proxies for credit market sentiment. The first one is high-yield bond issuance, *HYS*, proposed by Greenwood and Hanson (2013). HYS captures the dollar fraction of non-financial debt issues with high-yield ratings. Thus, when credit market sentiment is high, *HYS* is high. APPENDIX 1.D reports results based on *HYS*. Similar with the effects of credit sentiment based on *EBP*, *HYS* has significant effects on relative investments of competitive industries, but not for consolidated industries.

The second proxy for credit market sentiment is the loose of loan standards (Gilchrist and Zakrajsek, 2012; Greenwood et al, 2016). In every quarter, the Fed surveys senior loan officers of major domestic banks whether they have changed their lending standards to households and businesses. The loose of loan standards, *LOOSE*, captures the percentage of banks that have reported loosing credit standards. To proxy credit market sentiment in the annual frequency, I take the average of quarterly LOOSE. I report results based on *LOOSE* on APPENDIX 1.E and find similar results.

To mitigate the concern on the high correlation between credit market sentiment and economic conditions, I regress *CREDIT_SENTIMENT* on *ECONOMIC_CONDTION* and take the residual component of credit market sentiment, *CREDIT_SENTIMENT_RESI*. I replace *CREDIT_SENTIMENT* in Equation (1.3) by CREDIT_SENTIMENT_RESI and report results in APPENDIX 1.F. Again, I find similar results by using the residual component of credit market sentiment.

To further compare the effects of credit market sentiment on investments in competitive and consolidate industries, I estimate the effects of extremely high and low credit market sentiment in year t on relative investments in year t+1 in which year *CREDIT_SENTIMENT* has the largest effect on *RELATIVE_INVEST*. Similar to Baron and Xiong (2017), the regression model is specified as follows:

$$RELATIVE\_INVEST_{j,t+1} = \alpha + \beta CREDIT\_SENTIMENT\_HIGH_t + \varepsilon_{j,t+1,} \quad (1.4)$$

$$RELATIVE\_INVEST_{j,t+1} = \alpha + \beta CREDIT\_SENTIMENT\_LOW_t + \varepsilon_{j,t+1,} \quad (1.5)$$

Where $CREDIT\_SENTIMENT\_HIGH_t$ ($CREDIT\_SENTIMENT\_LOW_t$) is an indicator set to one if credit market sentiment in year t exceeds (falls) a given threshold and zero otherwise.

Figure 1.2 plots the coefficients of $CREDIT\_SENTIMENT\_HIGH_t$ and $CREDIT\_SENTIMENT\_LOW_t$. The figure shows that when credit market sentiment exceeds its median level, the investment effect of credit market sentiment is much larger for competitive industries than for consolidated industries. This suggests that when easy money becomes available, firms in competitive industries are eager to take advantage of available easy money and invest. Conversely, when credit market sentiment is below its median level, the investment effect of credit market sentiment is more negative for competitive industries than for consolidated industries. The figure clearly illustrates that competitive industries' investments depend on credit market sentiment much more than consolidated industries' investments.

1.4.2 Cross-sectional analyses

My competitive myopia hypothesis builds on two key premises that product market competition matters and that the firms in competitive industries face difficulty of obtaining external capital. To verify the two premises, I conduct cross-sectional analyses in this subsection. Since the findings in the Section 1.4.1 show that the effects of credit market sentiment on industry relative investments are significant for competitive industries rather than consolidated industries, my cross-sectional analyses focus on competitive industries.

Product market competition

To further support the channel of product market competition, I examine how credit market sentiment affects industry relative investments in competitive industries with different competition levels. I conjecture that the positive effect of credit market sentiment should be larger for competitive industries with higher competitions. To investigate my conjecture, I use two proxies for product market competition. The first proxy is product market fluidity proposed by Hoberg, Phillips and Prabhala

(2014), and the second one is product market similarity developed by Hoberg and Phillips (2016). Consistent with previous analyses, I use the average of firm-level competition measures to proxy for industry-level competition.

Panel A of Table 1.4 shows that the positive effect of credit market sentiment on the subsequent industry relative investments is larger for competitive industries with higher product market competition, consistent with my prediction. Specifically, column (2) of panel A shows that the association term between *CREDIT_SENTIMENT* and *FLUIDITY* is significantly positive.

Panel B of Table 1.4 turns to results based on product markets similarity. Consistent with the finding in column (2) of panel A, column (2) of panel B reports that the association term between *CREDIT_SENTIMENT* and *SIMILARITY* is also significantly positive. The results in panels A and B of Table 1.4 together indicate that, for competitive industries, firms facing higher competition pressure conduct higher relative investments following high credit market sentiment. The findings confirm the channel of competition pressure.

Costly external financing

Valta (2012) find that the effect of product competition on loan spread is larger in industries with higher asset illiquidity. Similarly, Ortiz-Molina and Phillips (2011) find that, for competitive industries, asset liquidity is an important determinant for cost of capital. The findings of Valta and Ortiz-Molina and Phillips indicate that, in competitive industries with higher illiquidity, firms tend to face more difficulty in raising external capital. Thus, I conjecture that the positive effects of credit market sentiment on relative investments should be stronger for competitive industries with higher illiquidity. To examine my prediction, I use three proxies for industry illiquidity conditions, similar as Valta (2012). The first one is the proportion of firms without credit rating, *NON_RATE_RATIO*. The second proxy is industry average of book leverage net of cash, *NET_LEV*. Finally, I use the industry average of the inverse of the quick ratio, *ILLIQ*.

Panel C of Table 1.4 shows that the positive effects of credit market sentiment on industry relative investments are indeed larger for competitive industries with higher industry illiquidity. Specifically, column (2) of panel C shows that the association term between *CREDIT_SENTIMENT* and *NON_RATE_RATIO* is significantly positive for the subsequent relative investments of competitive industries. The findings indicate that credit market sentiment affects competitive industries' relative investment through difficulty of raising external capital. In panels D and E of Table 1.4, I observe similar results by using net leverage and inverse of quick ratio as proxies for industry illiquidity condition.

1.4.3 Credit market sentiment and financing activities

Since the finding in Table 1.3 indicates that competitive industries' investments increase with credit market sentiment, I next investigate who may provide financing to competitive industries during high credit market sentiment periods. Table 1.2 shows that credit market sentiment and economic conditions are highly correlated, while equity market sentiment and economic conditions are not. The high correlation suggests that, during high credit market sentiment periods, investment opportunities also appear to be abundant. When credit market sentiment is high, credit investors provide easy money, allowing firms that have difficulty in obtaining external capital to borrow and invest on rich opportunities. Since firms in competitive industries face difficulty in raising capital from the debt market, I predict that, during high credit market sentiment periods, firms in competitive industries are more likely to raise capital from the debt market rather than the equity market. In contrast, since firms in consolidated industries face a lower cost of debt, their debt financing activities should be less affected by credit market sentiment. In this subsection, I investigate how credit market sentiment affects financing activities of competitive industries vis-à-vis consolidated industries.

Table 1.5 reports the effects of credit market sentiment in year t on industry-level debt financing in years t to t+4. Panel A introduces the results for competitive industries. Columns (1) - (3) of Panel A show that, for competitive industries, high credit market sentiment in year t significantly elevates the debt financing from year t to year t+2. Specifically, the coefficients of *CREDIT_SENTIMENT* in year t on *DEBT_FINANCE* over years t to t+2 are respectively 0.010 (t-value=2.67), 0.014 (t-value=5.34) and 0.010 (t-value=2.42). Columns (4) and (5) of Panel A show that the effects of credit market sentiment on debt financing in years t+3 and t+4 are insignificant. Pane B of Table 1.5 turns to the results for consolidated industries. I find that credit market sentiment is insignificant for consolidated industries' debt financing activities.

Table 1.5 illustrates that, compared with their counterparts in consolidated industries, firms in competitive industries indeed suffer a difficulty in raising capital from the credit market when credit market sentiment is low, and raise more capital from the credit market when credit market sentiment is high. To further illustrate the financing effects of credit market sentiment, Figure 1.3 plots the effects of low and high credit market sentiment in year t on debt financing in year t+1 in which year *CREDIT_SENTIMENT* has the largest effect on competitive industries' *DEBT_FINANCE*. Similar to the investment pattern shown in Figure 1.2, when credit market sentiment is above its median level, firms in competitive industries obtain much more debt financing than their counterparts in consolidated industries. Conversely, when credit market sentiment is below the median level, the effect of credit market sentiment in year t on one-year-ahead debt financing is more negative for competitive industries than for consolidated industries.

In sum, Tables 1.3 and 1.5 collectively show that high credit market sentiment in year t significantly raises investments and debt financing of competitive industries over years t to t+2. This finding suggests that when credit market sentiment is high, easy money provided by credit investors helps finance investments of competitive industries, and that when credit market sentiment is low, competitive industries' investments and debt financing decrease substantially.

For comparison, I next investigate the effects of credit market sentiment in year t on equity financing in years t through t+4 of competitive and consolidated industries, and report the results in Table 1.6. I find that credit market sentiment is insignificant in explaining the equity financing of competitive and consolidated industries. The insignificant role of credit market sentiment in equity financing further affirms that during high sentiment periods, credit investors rather than equity investors provide easy money to firms in competitive industries.

Similar to Figures 1.2 and 1.3, Figure 1.4 plots the effects of low and high credit market sentiment in year t on equity financing in year t+1. First, I find that the effect of extremely high credit market sentiment (i.e., higher than its 90 percentile) on equity financing is negative for both competitive and consolidated industries. This finding complements the finding in Figure 1.3 that, at the time of high credit market sentiment, firms raise capital from the credit market, instead of the equity market. However, the effect of extremely low credit market sentiment (i.e., lower than its 10 percentile) on equity financing is also negative for both competitive and consolidated industries, since the extremely low credit market sentiment periods tend to coincide with the recession periods. Interestingly, Figure 1.4 shows that equity financing for both competitive and consolidated industries tend to occur when credit market sentiment is just below its media level.

1.5 Easy money and overcapacity

In Section 1.4, my findings illustrate that investments and debt financing of competitive industries in years t to t+2 are positively associated with credit market sentiment in year t, but not for consolidate industries. In this section, I further investigate the second prediction of the competitive myopia hypothesis that easy money leads to overcapacity as manifested by declines in sales growth and gross margin in competitive industries.

1.5.1 Credit market sentiment and sales growth

To examine the effect of credit market sentiment on industry–level sales growth, I use the following regression model:

$$SALES\_GROWTH_{j,\tau} = \alpha + \beta CREDIT\_SENTIMENT_t + CONTROLS_{j,t} + \varepsilon_{j,\tau},$$

$$\tau = t, .., t + 4. \quad (1.6)$$

CONTROLS in Equation (1.6) follow those in Equation (1.3), except for sales growth.

Panel A of Table 1.7 reports how credit market sentiment in year t affects industry-level sales growth in competitive industries from year t to year t+4. Column (2) of Panel A shows that high credit market sentiment significantly raises sales growth in the subsequent year. Specifically, *SALES_GROWTH* at the industry level in year t+1 is significantly and positively associated with *CREDIT_SENTIMENT* in year t at 0.135 (t-value=2.17). This finding illustrates that high credit market sentiment leads to an increase in one-year-ahead sales growth for competitive industries.

However, column (4) of Panel A shows that the longer-term effect of credit market sentiment on sales growth turns to be negative. Specifically, columns (4) reports that *SALES_GROWTH* in year t+3 shows a significantly negative association with *CREDIT_SENTIMENT* in year t at -0.170 (t-value=-2.12). In other words, easy money in year t predicts a decrease in sales growth in year t+3.

Panel B of Table 1.7 reports the effects of credit market sentiment on industry-level sales growth for consolidated industries. I find that credit market sentiment in year t is insignificant in explaining consolidated industries' sales growth in years t to t+4.

1.5.2 Credit market sentiment and gross margin

Next, I examine the effects of credit market sentiment in year t on the industry-level gross margin in years t to t+4, and report the results in Table 1.8. Panel A of Table 1.8 shows that the long-term effect of high credit market sentiment on the industry-level gross margin is indeed negative for competitive industries. Specifically, column (4) of Panel A shows that the gross margin in year t+3 is negatively associated with the credit market sentiment in year t, with a coefficient of -0.112 (t-value= -2.12). In contrast, Panel B of Table 1.7 shows that, for consolidated industries, credit market sentiment in year t does not predict declines in the industry-level gross margin in the near future.

Taken together, Tables 1.7 and 1.8 illustrate that, for competitive industries, easy money in year t indeed leads to overcapacity as manifested by the declines in sales growth and gross margin in year t+3. In contrast, firms in consolidated industries do not face similar overcapacity following high credit market periods. Therefore, my findings imply that, induced by high credit market sentiment in year t, competitive industries' cumulative investments over years t to t+2 lead to overcapacity in the industries. This evidence lends supports to my hypothesis that easy money triggers competitive myopia, and results in overcapacity. In the next section, I investigate the implications of overcapacity at the industry level on individual firms' operating and stock performance.

1.6 Easy money and declines in firms' operating and stock performance

In Section 1.4, I show that easy money raises competitive industries' investments and debt financing. In Section 1.5, I further find that easy money leads to overcapacity in competitive industries. In this section, I first test the third prediction of the competitive myopia hypothesis that high credit market sentiment can predict declines in competing firms' future cash flow and stock performance. Then, to shed further light on the long-term effect of investments undertaken during high credit market sentiment periods, I investigate whether the predictable declines are more severe for firms that invest more when credit market sentiment is high. Finally, I am interested in knowing whether credit market sentiment can explain competitive industries' booms and busts.

1.6.1 Credit market sentiment and declines in firms' performance

In this subsection, I investigate whether credit market sentiment in year t can predict firms' operating cash flow changes in years t to t+4. Similar to HP (2010), my regression models are as follows:

$$\Delta CASH\_FLOW_{i,\tau} = \alpha + \beta_1 CREDIT\_SENTIMENT_t$$
$$+\beta_2 FIRM\_RELATIVE\_INVEST_{i,t} + \Delta EBITDA_{i,t} + \Delta CAPEX_{i,t} + \varepsilon_{i,\tau}$$
$$\tau = t, .., t+4. \qquad (1.7)$$

where $\Delta CASH\_FLOW_{i,\tau}$ is the firm *i*'s change in operating cash flow in year τ. *FIRM_RELATIVE_INVEST*, Δ*EBITDA* and Δ*CAPX* are defined in Section 1.3.2. Following HP, I cluster standard errors by industry and time.

Table 1.9 reports the regression results based on Equation (1.7). Panel A of Table 1.9 presents the results for competitive industries. Column (1) of Panel A shows that, for competitive industries, Δ*CASH_FLOW* in year t is significantly and positively associated with *CREDIT_SENTIMENT* in year t at 0.015 (t-value=4.24). The high operating performance during high credit market sentiment periods may further strengthen credit investors' optimistic beliefs about future default probabilities.

However, with respect to the longer-term effects of credit market sentiment, columns (4) and (5) of Panel A show that Δ*CASH_FLOW* over years t+3 to t+4 are significantly and negatively associated with *CREDIT_SENTIMENT* in year t at -0.028 (t-value=-4.51) and -0.025 (t-value=-3.34). Thus, easy money indeed predicts the declines in future operating performance of firms in competitive industries. Moreover, following high credit market sentiment in year t, the decline in operating cash flow in year t+3 is in line with the existence of industry-level overcapacity in year t+3 for competitive industries.

Panel B of Table 1.9 reports the results for consolidated industries. For consolidated industries, Δ*CASH_FLOW* in year t is also significantly and positively associated with *CREDIT_SENTIMENT* in year t at 0.006 (t-value=3.15). However, in consolidated industries, firms do not suffer significant declines in operating cash flow over years t+3 to t+4 following high credit market sentiment in year t.

Next, I turn to the effect of credit market sentiment on stock performance. Similar to HP (2010), I specify my regression model as follows:

$$ABNORMAL\_RET_{i,\tau,s} = \alpha + \beta_1 CREDIT\_SENTIMENT_t$$
$$+\beta_2 FIRM\_RELATIVE\_INVEST_{i,t} + \varepsilon_{i,\tau,s,}$$
$$\tau = t, .., t+4. \tag{1.8}$$

$ABNORMAL\_RET_{i,\tau,,s}$ is the firm *i*'s monthly abnormal return in month s between July of year τ-1 and June of year τ. I also cluster standard errors by industry and time.

Table 1.10 reports the regression results based on Equation (1.8). Panel A of Table 1.10 presents the results for competitive industries. Column (1) of Panel A shows that, for competitive industries, firms' monthly abnormal stock returns in year t increase with high credit market sentiment in year t, similar to the positive effect on cash flow changes in year t. However, column (4) of Panel A shows that the effect of high credit market sentiment turns to be significantly negative on three-years-ahead stock performance. Specifically, the monthly stock returns in year t+3 are significantly and negatively associated with the credit market sentiment in year t, with a coefficient of -0.001 (t-value=-2.56).

Panel B of Table 1.10 shows the results for consolidated industries. Unlike the results for competitive industries, column (3) of Panel B reports that credit market sentiment in year t is insignificant in explaining three-years-ahead abnormal stock returns of firms in consolidated industries.

Taken together, Tables 1.9 and 1.10 show that easy money predicts declines in operating and stock performances of firms in competitive industries, but not for firms in concentrated industries. By providing firm-level evidence, the results in these two tables further confirm that easy money contributes to competitive industries' investment inefficiency problem. More importantly, my results demonstrate that, due to competitive myopia, credit market sentiment is an important predictor for competitive industries' future cash flow, but not for consolidated industries'.

1.6.2 Future operating and stock performance of firms that invest more when easy money is available

In this subsection, I further investigate whether firms that invest more when credit market sentiment is high experience more severe declines in future operating and stock performance.

Similar to the analysis in Section 1.6.1, I first focus on changes in operating cash flow. My regression model is specified as follow:

$$\Delta CASH\_FLOW_{i,\tau} = \alpha + \beta_1 HIGH\_SENTIMENT_t + \beta_2 FIRM\_RELATIVE\_INVEST_{i,t} + \beta_3 HIGH\_SENTIMENT_t * FIRM\_RELATIVE\_INVEST_{i,t} + CONTROLS_{i,t} + \varepsilon_{i,\tau},$$

$$\tau = t, .., t+4. \quad (1.9)$$

where $HIGH\_SENTIMENT_t$ is an indicator set to one if credit market sentiment in year t is higher than its 90 percentile and zero otherwise. Other specifications in Equation (1.9) follow Equation (1.7).

Table 1.11 reports the results based on Equation (1.9). In Panel A of Table 1.11, I present the results for competitive industries. Columns (4) and (5) show that, for competitive industries, while the coefficients of

HIGH_SENTIMENT$_t$ are marginally significant or insignificant, the coefficients of interactions between *HIGH_SENTIMENT*$_t$ and *FIRM_RELATIVE_INVEST*$_t$ are significantly negative at -0.0049 (t-value= -4.26) and -0.0045 (t-value=-2.02), respectively. These findings illustrate that, for competitive industries, declines in operating cash flow in years t+3 and t+4 largely concentrate in firms that invest more in year t when credit market sentiment is high.

Panel B of Table 1.11 turns to the results for consolidated industries. Columns (4) and (5) show that the interactions between *HIGH_SENTIMENT*$_t$ and *FIRM_RELATIVE_INVEST*$_t$ are insignificant for consolidated industries.

Next, I examine stock performance and use the following regression model:

$$ABNORMAL\_RET_{i,\tau,s} = \alpha + \beta_1 HIGH\_SENTIMENT_t + \beta_2 FIRM\_RELATIVE\_INVEST_{i,t} + \beta_3 HIGH\_SENTIMENT_t * FIRM\_RELATIVE\_INVEST_{i,t} + \varepsilon_{i,\tau,s}$$

$$\tau = t, .., t+4 \tag{1.10}$$

Table 1.12 reports the regression results based on Equation (1.10). Panel A of Table 1.12 presents the results for competitive industries. Similar to the cash flow results, Columns (3) and (4) of Panel A also show that firms in competitive industries that invest more in year t when credit market sentiment is high suffer larger stock performance declines in years t+3 and t+4. Again, in Panel B, I find that such declines do not occur for consolidated industries.

Taken together, Tables 1.11 and 1.12 illustrate that, for competitive industries, firms' intensive investments undertaken during high credit market sentiment periods lead to declines in future operating and stock performances, which sheds further light on the long-term consequences of these investments. Moreover, my findings further affirm that easy money contributes to the investment inefficiency problem of competitive industries.

1.6.3 Credit market sentiment and competitive industries' booms and busts

While I have presented evidence to show that easy money contributes to the investment inefficiency problem of competitive industries, a question remains. That is, can easy money explain competitive industries' booms and busts, as HP (2010) demonstrate? To address this question, I first replicate the findings of HP (2010) with the following regression models:

$$\Delta CASH\_FLOW_{i,t+3} = \alpha + \beta INDUSTRY_{j,t+1} + \gamma FIRM_{i,t+1} + CONTROLS_{i,t+1} + \varepsilon_{i,t+3}, \quad (1.11)$$

$$ABNORMAL\_RET_{i,t+3,s} = \alpha + \beta INDUSTRY_{j,t+1} + \gamma FIRM_{i,t+1} + \varepsilon_{i,t+3,s,} \quad (1.12)$$

where $\Delta CASH\_FLOW_{i,t+3}$ is the firm i's change in operating cash flow from year $t+1$ to year $t+3$, while $ABNORMAL\_RET_{i,t+3,s}$ is the firm i's abnormal return in month s between July of year t+2 and June of year t+3. $INDUSTRY_{j,t+1}$ includes $RELATIVE\_VALUATION_{j,t+1}$, $RELATIVE\_INVEST_{j,,t+1}$, and $NEW\_FINANCE_{j,t+1}$ of industry j at year *t+1*.[10] $FIRM_{i,t+1}$ includes $RELATIVE\_VALUATION\_RESI_{i,t+1}$, $RELATIVE\_INVEST\_RESI_{i,t+1}$, and $NEW\_FINANCE\_RESI_{i,t+1}$ of firm *i* in year *t+1*.[11]

Panel A of Table 1.13 presents the results. Columns (1) and (2) of Panel A report my replication results based on Equation (1.11). Column (1) shows that, for competitive industries, $\Delta CASH\_LOW_{t+3}$ are significantly and negatively associated with $RELATIVE\_VALUATION_{t+1}$ and $RELATIVE\_INVEST_{t+1}$. Column (2) shows that, for consolidated industries, these associations are insignificant. These results are consistent with HP's findings that industry booms predict the declines in firms' future operating performance.

After confirming HP's findings, I add $CREDIT\_SENTIMENT_t$ into the regression model and report the results in columns (3) and (4) of Panel A in Table 1.13. Column (3) shows that, for competitive industries, the coefficient of $CREDIT\_SENTIMENT_t$ is significantly negative at -0.023 (t-value=-3.98). Moreover, in the presence of $CREDIT\_SENTIMENT_t$, the coefficients of $RELATIVE\_VALUATION_{t+1}$ and $RELATIVE\_INVEST_{t+1}$ become insignificant at -0.008 (t-value=-1.41) and -0.009 (t-value=-1.64). The results suggest that adding $CREDIT\_SENTIMENT_t$ to the regression model weakens the explanatory power of $RELATIVE\_VALUATION_{t+1}$ and $RELATIVE\_INVEST_{t+1}$ on $\Delta CASH\_FLOW_{i,t+3}$, in terms of both economic

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[10] *RELATIVE_VALUATION*, *RELATIVE_INVEST*, and *NEW_FINANCE* are defined in APPENDIX 1.A.

[11] *RELATIVE_VALUATION_RESI*, *RELATIVE_INVEST_RESI*, and *NEW_FINANCE_RESI* are defined in APPENDIX 1.A.

impact and statistical significance. In column (4), I observe insignificant effect of *CREDIT_SENTIMENT*$_t$ for consolidated industries.

Panel B of Table 1.13 reports the results for firm-level monthly abnormal stock returns. Consistent with HP, Column (1) shows that, for competitive industries, firm-level monthly abnormal returns in year t+3 are significantly and negatively associated *RELATIVE_VALUATION* and *RELATIVE_INVEST* in year t+1. However, in column (3), I add *CREDIT_SENTIMENT*$_t$ as an additional explanatory variable, which shows a significant coefficient of -0.001 with a t-statistics of -2.52. Similar to the cash flow results, the presence of *CREDIT_SENTIMENT*$_t$ makes the roles of *RELATIVE_VALUATION*$_{t+1}$ and *RELATIVE_INVEST*$_{t+1}$ in predicting firms' future stock performance insignificant or marginally significant. In column (4), I observe that *CREDIT_SENTIMENT*$_t$ is insignificant for consolidated industries. As a robustness check, I follow HP (2010) and use *FITTED_HHI* to define competitive and consolidated industries. I obtain similar results, as shown in APPENDIX 1.G.

Overall, Table 1.13 shows that credit market sentiment weakens the power of industry booms in predicting competitive industries' busts. My findings suggest that the effects of competitive industries' booms on their busts are largely driven by credit market sentiment. In other words, easy money, when available, triggers competitive myopia and leads to competitive industries' booms and the subsequent busts.

1.7 Conclusion

Studies have demonstrated that firms in competitive industries tend to make inefficient investments, and suffer booms and busts. Who would finance inefficient investments? Is financing part of the problem? To address these questions, I synthesize the studies on competitive industries' inefficient investment problem and difficulty of obtaining external financing, and develop a new hypothesis to show that financing is an integral part of competitive industries' investment inefficiency problem.

Specifically, I hypothesize that when easy money becomes available, competitive pressure prompts firms in competitive industries to take advantage of easy money to invest and strengthen their current competitive positions. As competing firms would behave similarly, their managers (and investors) overlook the developing risk of overcapacity at the industry level, until overcapacity materializes and firms' profitability declines. My hypothesis predicts that easy money elevates competitive industries' investments and debt financing, leads to overcapacity at the industry level, and predicts declines in future cash flow and stock performance. In contrast, due to barriers to entry, consolidated industries do not have similar problems associated with competitive industries, making them less affected in the presence of easy money.

Consistent with my hypothesis, I find that, for competitive industries, high credit market sentiment in year t raises industry-level relative investments and debt financing in years t to t+2, but not for consolidated industries. I also find that, for competitive industries, high credit market sentiment in year t predicts declines in industry-level sales and gross margin in year t+3, suggesting that overcapacity at the industry level exists in year t+3. In contrast, I do not observe similar effects of credit market sentiment for consolidated industries.

Furthermore, I find that, for competitive industries, firms' cash flow and stock performance in year t+3 are significantly and negatively related to credit market sentiment in year t, whereas there is little such relations for consolidated industries. Moreover, such predictable declines in performance are especially severe for firms that invest more during periods with high credit market sentiment. My results illustrate that, due to competitive myopia, credit market sentiment is an important predictor for competitive industries' future cash flow, but not for consolidated industries'.

In addition, I investigate whether credit market sentiment can explain competitive industries' booms and busts. I first confirm the finding of HP (2010) that industry booms predict industry busts in competitive industries. However, the predictive power of industry booms becomes insignificant in the presence of credit market sentiment. My findings illustrate that industry booms in competitive industries are largely driven by high credit market sentiment, and that excessive investments induced by easy money lead to industry busts.

Overall, my study suggests that financing is an integral part of competitive industries' investment inefficient problem, and that competitive myopia triggered by easy money can explain why competitive industries tend to suffer booms and busts.

CHAPTER 2 ECONOMIC POLICY UNCERTAINTY AND LOBBYING INITIATION DECISION

2.1 Introduction

According to the Center for Responsive Politics (CRP), firms have spent billions of dollars in recent years to lobby policymakers in the U.S. Studies find that lobbying firms benefit from political access (Alexander et al., 2009; Richter et al., 2009; Yu and Yu, 2011; Chen et al., 2015; Croci et al., 2016; Gounopoulos et al., 2017). The findings reflect that corporate lobbying is an important investment for businesses. Research also finds that once a firm starts lobbying, it is highly likely to continue lobbying (Kerr et al., 2014). This high persistence of lobbying raises important questions: what determines corporate lobbying in the first place? When is a good time for a non-lobbying firm to initiate lobbying? Despite the importance of corporate lobbying, there is limited evidence on the determinants of lobbying initiation decisions (Lambert, 2018).[12] My interest in this paper is understanding how economic policy uncertainty affects the lobbying initiation decisions of non-lobbying firms.

Theories and studies on economic policy uncertainty and corporate lobbying offer competing views on the relation between policy uncertainty and the decision to initiate lobbying. On the one hand, benefits of lobbying initiation increase with policy uncertainty from three perspectives. First, high policy uncertainty adversely affects corporate investment (Gulen and Ion, 2016), initial public offering activity (Colak, Durnev, and Qian, 2017), innovation (Xu, 2017), and merger and acquisition activity (Bonaime et al.,

[12] For instance, Hill et al. (2013) investigate firm-level characteristics as determinants of corporate lobbying.

2018). However, lobbying can mitigate these adverse effects by allowing firms to access policy information and understand the timing, content, and potential impact of policy decisions. Second, as high policy uncertainty indicates that proposed policies are not yet settled (Pástor and Veronesi, 2012), firms can lobby in an attempt to influence policy outcomes in their favor (Duchin and Sosyura, 2012; Blau et al., 2013; Adelino and Dinc, 2014). Third, to the extent that high policy uncertainty increases firms' political risk, firms have a strong incentive to initiate lobbying to manage such political risk (Hassan et al., 2019).

On the other hand, the costs of lobbying initiation increase with policy uncertainty due to two channels. Kerr et al. (2014) argue that when non-lobbying firms initiate lobbying, they face significant barriers which consist of lobbying entry expenses and returns to experience.[13] First, lobbying entry expenses are elevated during periods of high policy uncertainty, because (existing) lobbying firms demand more political access at such times, and political access is a scarce resource (Brown and Huang, 2017). Specifically, when policy uncertainty is high, lobbying firms engage good lobbyists to capture high lobbying benefits. Thus, it is difficult for non-lobbying firms to find good lobbyists to represent them unless they are willing to pay high expenses to attract good lobbyists and initiate lobbying. Second, new lobbying firms' lack of experience leads them to expend great effort in communicating with lobbyists, due to the channel of returns to

[13] Lobbying entry expenses include the costs of searching for and hiring the right lobbyists, educating these new hires about the firm's interests, developing a lobbying agenda, researching the potential allies and opponents of the firm's lobbying efforts, and investigating how best to affect the political process (e.g., which policymakers to invest in). Returns to experience capture the fact that firms become more effective at lobbying over time, as they learn more about the lobbying process, establish deeper relationships with policymakers, and identify effective strategies to pursue their interests.

experience. When policy uncertainty is high, however, lobbyists spend limited effort on communicating with new lobbying firms, as they are busy with existing lobbying firms.[14] Thus, returns to experience make the lobbying activities of new lobbying firms less effective during times of high policy uncertainty.

In sum, when policy uncertainty is high, lobbying initiation offers substantial benefits including access to policy information, the chance to affect policy outcomes, and risk management. At the same time, lobbying initiation involves high costs and barriers at such times, as the channels of lobbying entry expenses and returns to experience lead to high entry expenses and low lobbying effectiveness. Given the tension between these benefits and costs, I investigate how policy uncertainty affects the lobbying initiation decisions of non-lobbying firms.

To examine my research questions, I collect data on a large sample of U.S. firms from 1999 to 2015 and analyze their lobbying behavior. The data on corporate lobbying are obtained from the Senate Office of Public Records (SOPR) and the CRP. I use firms' lobbying registration files to identify their first lobbying activities. I use the economic policy uncertainty (EPU) index constructed by Baker, Bloom, and Davis (BBD; 2016) as my main measure of policy uncertainty.[15] Nagar et al. (2019) stress that this index has found widespread acceptance in the economics and finance literatures.

[14] In contrast, when policy uncertainty is low, lobbyists have more time to work with new lobbying firms.

[15] The BBD index is a monthly weighted average of three components: (i) the volume of articles covering economic policy-related uncertainty in 10 leading U.S. newspapers, (ii) federal tax code uncertainty, and (iii) disagreement among economic forecasters, such as monetary policy forecast disagreement and fiscal policy forecast disagreement.

First, I verify that corporate lobbying creates economic value by providing access to policy information. That is, I find that corporate lobbying mitigates the adverse effects of policy uncertainty on business activities in terms of corporate investment, hiring, and sales growth. Next, I find that the probability of non-lobbying firms initiating the lobbying process is inversely related to EPU. Specifically, my empirical results suggest that a one-standard-deviation increase in policy uncertainty is associated with an 18.9% decline in the probability of non-lobbying firms' lobbying initiation. This finding is interesting, as it runs counter to the view that firms have stronger incentives to lobby when EPU is high. Nevertheless, it provides baseline evidence consistent with my hypothesis that the costs of initiating lobbying vary with EPU.

I further test the cost hypothesis through the channels of lobbying entry expenses and returns to experience. For the lobbying entry expenses channel, I first find that non-lobbying firms pay significantly higher entry expenses if they choose to start the lobbying process when EPU is high, and they are less likely to start lobbying when entry expenses are higher. I then conduct a sharper analysis to understand the mechanisms regulating this channel from the supply and demand sides. Regarding the supply side, I first find that the number of lobbyists is stable over time and does not change significantly with EPU, suggesting that the supply of lobbying services is inelastic. I then use a negative supply shock.[16] Holding the demand constant,

[16] The negative shock is the guilty plea of Mr. Jack Abramoff, a high-powered lobbyist, to charges of bribery and corruption in January 2006.The guilty plea made it more difficult for lobbyists to provide lobbying services and created a negative supply shock to lobbying services. Borisov et al. (2016) describe the aftermath: "The guilty plea generated intense public and media scrutiny of the lobbying process, making it damaging for politicians to be

a negative supply shock should increase the price of lobbying services and raise lobbying entry expenses. Indeed, I find that existing lobbying firms' lobbying expenses increase more with EPU after the shock than before, and that non-lobbying firms' likelihood of lobbying initiation is more negatively related to EPU after the shock than before. Regarding the demand side, I find that existing lobbying firms spend more on lobbying during high-EPU periods, implying that lobbying firms' demand for lobbying services increases when there are more benefits of lobbying. Furthermore, I find that when lobbying firms spend more on lobbying, non-lobbying firms are less likely to initiate lobbying. Thus, my findings support two mechanisms—the inelastic supply of lobbying services and existing lobbying firms' time-varying demand for lobbying services—that work together to regulate the lobbying entry expenses faced by non-lobbying firms.

To verify the returns to experience channel, I examine whether lobbying experience matters for lobbying firms capturing economic value of lobbying. Notably, firms become more effective at lobbying over time as they learn and deepen their relationships with lobbyists and policymakers (Kerr et al., 2014). I find that the adverse effects of policy uncertainty on business activities are weaker for lobbying firms with more years of lobbying experience. This finding indicates that lobbying experience influences how effective lobbying is in capturing policy information benefits. It also supports the returns to experience hypothesis that experience matters for lobbying effectiveness.

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associated with lobbyists, thereby limiting the latter group's political access and influence." Indeed, I find that the number of lobbyists declines gradually after the guilty plea.

As a robustness check, I conduct four tests. First, to mitigate concerns about measurement error in the EPU index, I regress the U.S. EPU index on the Canadian EPU index and use the regression residuals to measure policy uncertainty, similar to the approach of Gulen and Ion (2016) and Kaviani et al. (2019). Second, I follow Julio and Yook (2012) and Bhattacharya et al. (2017), and use presidential elections to proxy for policy uncertainty, as the election setting mitigates concerns that policy uncertainty may be endogenous to economic conditions (Julio and Yook, 2012) and concerns about time-varying omitted variables and reverse causality (Bhattacharya et al., 2017). Third, to address the concern that the BBD EPU index captures first-moment economic policy information rather than second-moment information, I use a proxy based on firm-level political uncertainty developed by Hassan et al. (2019). Finally, I verify my main finding by using a specific industry, the healthcare industry, and relevant policy uncertainty. I find consistent results for all four robustness analyses.

Finally, I conduct three cross-sectional analyses to show that the costs of initiating lobbying affect certain types of non-lobbying firms more than others through the channels of lobbying entry expenses and returns to experience. First, the channel of lobbying entry expenses indicates that the negative effect of policy uncertainty should be more pronounced for constrained firms than for unconstrained firms, as financially constrained firms have fewer resources than their unconstrained counterparts. Indeed, I find that when EPU is high, constrained firms are less likely to initiate lobbying.

Next, the channel of returns to experience suggests that the negative effect of policy uncertainty on lobbying initiation should be stronger for firms farther away from Washington, D.C. and for government suppliers. First, the distance matters because more distant firms have a harder time communicating with lobbyists who spend most of their time in D.C. This difficulty lowers lobbying effectiveness, as new lobbying firms have to talk often with lobbyists to become effective at lobbying. Moreover, such difficulties in communication are more severe when economic policy uncertainty is high, because lobbyists at such times are busy with existing lobbying firms and have limited time to talk with new lobbying firms, including those that are far away. Second, when policy uncertainty is high, government suppliers that initiate lobbying also have lower lobbying effectiveness than their counterparts. Government suppliers mainly lobby for the purpose of winning government contracts, but when policy uncertainty is high, policymakers and lobbyists are typically too busy with important policy issues to handle specific government contracts. Indeed, I find that when EPU is high, more distant firms and government suppliers are less likely to initiate lobbying compared to other non-lobbying firms. These results further support returns to experience being a channel through which policy uncertainty negatively affects lobbying initiation decisions.

I contribute to the literature in three ways. First, I add to the literature on the adverse effects of EPU on corporate activity (Durnev, 2013; Baker et al., 2016; Gulen and Ion, 2016; Colak, Durnev, and Qian, 2017; Xu, 2017; Bonaime et al., 2018). Previous studies argue that the adverse effects of EPU on business activities arise largely from the real options channel.

Extending the literature, I show that policy uncertainty negatively affects lobbying initiation activities and propose two underlying channels. The returns to experience channel is unique in a way that it affects the effectiveness of corporate lobbying, which is little discussed in the literature. Moreover, the mechanisms regulating the lobbying entry expenses channel illustrate a novel point: when policy uncertainty is high, the business activities of some firms can interact with those of other firms. That is, the lobbying activities of lobbying firms drive out the lobbying activities of non-lobbying firms.

Second, I also contribute to the lobbying literature (Hill et al., 2013; Kerr et al., 2014). I show that a period of low policy uncertainty is a good time to initiate lobbying, as non-lobbying firm face lower entry expenses and have higher effectiveness at such times. Thus, my finding helps explain why many firms stay on the sidelines when lobbying would appear to be particularly beneficial. Moreover, I provide empirical evidence to verify the returns to experience hypothesis of Kerr et al (2014). Finally, I identify existing lobbying firms' time-varying demand for lobbying services and the inelastic supply of lobbying services as two mechanisms that regulate the channel of lobbying entry expenses. Combined, these two mechanisms make political access a scarce resource, especially when policy uncertainty is high.

Finally, I offer an interesting implication for policy stability. Kerr et al. (2014) note that "barriers to entry induce persistence in firms' efforts to affect the political process, in essence fixing the 'players in the game,' which in turn contributes to greater stability in policy." My finding that lobbying entry barriers increase with policy uncertainty implies that it is more difficult for non-lobbying firms to get "in the game" precisely when it is more critical (in terms of accessing information or influencing policy outcomes) to be in the game.

The rest of the paper is organized as follows. Section 2.2 describes the data, variables, and summary statistics for lobbying firms and non-lobbying firms. Section 2.3 investigates how policy uncertainty affects non-lobbying firms' lobbying initiation decisions. Section 2.4 tests the channels of lobbying entry expenses and returns to experience. Section 2.5 conducts robustness analyses. Section 2.6 uses cross-sectional analyses on the effects of lobbying entry barriers on financially constrained firms, firms that are far away from D.C., and firms with government customers. Section 2.7 concludes the paper.

2.2 Data

In this section, I first describe the EPU index developed by Baker et al. (2016). I then present my lobbying data and discuss the methods used to capture non-lobbying firms' lobbying initiation decisions.

2.2.1 Measuring economic policy uncertainty

Following Brogaard and Detzel (2015), Gulen and Ion (2016), and Bonaime et al. (2018), I measure policy uncertainty using the BBD EPU index (*EPU INDEX*), which consists of three components. The first component is based on article counts quantifying the newspaper coverage of policy-related economic uncertainty in 10 large newspapers.[17] The second

[17] Specifically, for each newspaper, the number of articles containing the terms "uncertainty" or "uncertain," "economic" or "economy," "congress," "legislation," "White House," "regulation," "Federal Reserve," or "deficit" is counted in each month. Then, for each

component is the number of federal tax code provisions set to expire in the next 10 years.[18] The third component uses the extent of disagreement among professional forecasters on the Consumer Price Index (CPI) and government spending as proxies for uncertainty about monetary and fiscal policies, respectively.[19] The overall BBD policy uncertainty index is a weighted average of the three components.[20] The overall index and its components start from 1985 and run through the present. The data are publicly available on the BBD index website.[21] I examine how both the overall BBD policy uncertainty index and its separate components affect lobbying initiation decisions.

2.2.2 Corporate lobbying data

The Lobbying Disclosure Act of 1995 requires lobbyists to disclose their clients' lobbying activity to the Secretary of the SOPR. These records were filed semiannually before 2008 and quarterly thereafter. Lobbying activity records include registration, regular lobbying activity, and termination records. More specifically, a lobbyist files a registration report

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month, the raw count is scaled by the total count of articles in the newspaper. The 10 resulting time-series counts are normalized to unit standard deviations and then summed within each month. The 10 large newspapers are USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the New York Times, and the Wall Street Journal.

[18] The second component of the BBD index is based on reports by the Congressional Budget Office, which compiles lists of temporary federal tax code provisions. I calculate the annual dollar-weighted number of tax code provisions scheduled to expire over the next 10 years, which gives a measure of the level of uncertainty regarding the future path of the federal tax code.

[19] More specifically, the monetary policy part is given as the interquartile range of CPI forecasts, whereas the fiscal policy part is the interquartile range of forecasts of purchases of goods and services by federal, state, and local governments.

[20] The weights are 1/2 for the news-based component, 1/6 for the tax component, and 1/3 for the dispersion in economic forecasts component (1/6 for the CPI forecast disagreement subcomponent and 1/6 for the government spending forecast disagreement subcomponent).

[21] The data are available on the BBD index website: http://www.policyuncertainty.com/methodology.html.

when he or she starts to lobby on behalf of a client. Subsequently, the lobbyist files a lobbying activity report (or, in the case of no lobbying activity, a no-activity report) on behalf of the client every quarter (every half-year before 2008). The lobbying activity report includes detailed information on lobbying activity, such as lobbying issues and expenses. If the lobbying expenses are under $5,000 in a quarter ($10,000 in a half-year), the lobbyist can report these expenses as zero. There is no upper limit on the amount of lobbying expenses. Finally, the lobbyist files a termination record if his or her client decides to terminate lobbying.

Similar to Kerr et al. (2014), my lobbying data come from two sources: the SOPR and the CRP. The CRP data are available from 1998 and mainly include lobbying expense information,[22] whereas the SOPR data start in 1999.[23] My sample thus covers the period from 1999 to 2015. I rely on the registration records of the SOPR to identify firms' lobbying initiation. Furthermore, using the subsidiary structure identified by the CRP, I aggregate subsidiary data to the parent firm. I also follow the name-matching procedure of Gao and Huang (2016) to match client firms in the lobbying data with firms from Compustat. Finally, for each firm, I aggregate semiannual records (before 2008) and quarterly records (2008 and after) to obtain the annual data.

My sample focuses on U.S. domestic firms and excludes firms in the financial (SIC 6000-6999) and utility (SIC 4900-4999) industries. I also exclude firms with non-positive sales. My final sample consists of 55,769

[22] https://www.opensecrets.org/lobby/.
[23] https://www.senate.gov/legislative/Public_Disclosure/database_download.htm.

firm-year observations, of which 1,208 (or 2.17%) correspond to new lobbying firm-years.

2.2.3 Descriptive statistics

Table 2.1 reports the descriptive statistics for my sample. In Panel A, I report the descriptive statistics separately for lobbying and non-lobbying firms. I find that lobbying firms have larger total assets, lower leverage, and higher cash flows than non-lobbying firms. This suggests that larger and more profitable firms are more likely to lobby. The mean of the annual lobbying expenses for lobbying firms is $913,080, with a median of $140,000 and a much larger standard deviation of $2,459,833. In Panel B, I compare new lobbying firms (i.e., those that have recently initiated lobbying) to firms that continue not to lobby. Compared to firms that continue not to lobby, new lobbying firms have larger total assets and lower leverage. The average start-up lobbying costs for new lobbying firms is $90,902, with a median of approximately $40,000 and a standard deviation of $266,423.

In general, after initiating lobbying, lobbying firms tend to increase their lobbying expenditures over time. To illustrate, Figure 2.1 plots Google's spending path, showing that it initiated lobbying in 2003 with $80,000 in lobbying expenses. It then gradually increased its lobbying expenditures to over $18 million in 2012. It has since remained at approximately $15 million to $16 million annually.

Table 2.2 presents the distribution of my sample firms over time and their average annual lobbying expenses during my sample period. Column (1) shows that the total number of firms, both lobbying and non-lobbying, in my sample decreased from 5,772 at the beginning of my sample period in 1999 to 3,310 in 2015.[24] The total number of sample firms varies over time mainly because of mergers and acquisitions, initial public offerings, delistings, and firm exits. Columns (2) and (3) show that across all firms, the lobbying participation rate increased steadily from 11.66% in 1999 to 21.89% in 2009, remaining stable at approximately 20% thereafter. The lobbying participation rate of approximately 20% in more recent years is similar to that documented by Gao and Huang (2016).

Column (4) shows that the average annual lobbying expenses per lobbying firm increased from approximately $607,332 in 1999 to over $1 million in 2009, and the average has since stayed above this level. In aggregate, the total annual lobbying expenses across all lobbying firms in my sample has amounted to over $1 billion each year since 2009, implying large-scale corporate lobbying in the U.S. in recent years.

Table 2.2 shows that, on average, 71 (or 2.17% of) non-lobbying firms choose to initiate the lobbying process each year during my sample period, ranging from 34 in 2011 and 2013 to 133 in 1999. Start-up lobbying costs vary widely, from a low of $46,136 in 2006 to a high of $360,277 in 2013, with an average of approximately $90,000 during my sample period.

Table 2.3 lists the top 10 industries[25] in terms of total lobbying expenses. The top three industries are communications, pharmaceutical products, and business services. This suggests that firms in these industries

[24] A similar pattern is observed by Doidge et al. (2017), who note, "Since the listing peak in 1996, the propensity to be listed is lower for all firm size categories and industries, the new list rate is low, and the delist rate is high."
[25] The industry classification is based on the 48 Fama–French (1992) industries, with the remaining firms categorized as a 49th industry.

are highly sensitive to government regulations and economic policies and hence strongly incentivized to lobby policymakers.

2.3 Regression analysis

In this section, I first verify that corporate lobbying creates economic value by providing access to policy information, particularly when policy uncertainty is high. Then, I address how policy uncertainty affects the lobbying initiation decisions of non-lobbying firms.

2.3.1 Preliminary findings: Economic value of lobbying

Prior studies show that high policy uncertainty adversely affects corporate activities, since businesses face significant uncertainty regarding the timing, content, and potential impact of policy decisions, due to a lack of access to policy information (Baker et al., 2016; Gulen and Ion, 2016). However, Drutman (2015) notes that lobbyists can identify members of Congress who have influence over certain issues, and their connections allow them to reach out to these key policymakers. Lobbyists also have expertise in gathering relevant policy information. For these reasons, corporate lobbying improves firms' access to information about the policy process, and lobbying firms have a better understanding of the timing, content, and potential impact of policy decisions than do non-lobbying firms. Thus, I analyze whether lobbying allows firms to mitigate the adverse effects of policy uncertainty on business activities by using the following regression model:

$$Business\ activity_{i,t} = \alpha_0 + \beta_1 EPU\_INDEX_t + \beta_2 LOBBY_{i,t} + \beta_3 EPU\_INDEX_t * LOBBY_{i,t} + CONTROLS_{i,t} + \varepsilon_{i,t}. \quad (2.1)$$

For the dependent variable, I consider three business activities: capital expenditures (*CAPEX*), employment (Δ*EMPLOYEES*), and sales growth (*SALES_GROWTH*). $LOBBY_{i,t}$ is a dummy variable that equals one if firm *i* lobbies in year *t* and zero otherwise. Following Gulen and Ion (2016), I include *TOBIN's Q*, *CASH_FLOW*, and *SALES_GROWTH* to control for firm characteristics. I also include GDP growth and firm-fixed effects and use clustered standard errors by firm and year for significance tests. I conduct regression analysis based on a sample in which lobbying firms and non-lobbying firms are matched with propensity scores.[26]

Table 2.4 presents the estimation results for the regression model in Equation (2.1). Consistent with my prediction that corporate lobbying mitigates the adverse effects of policy uncertainty, β_3 is significantly positive in all three regressions.[27] More specifically, column (1) shows that although the coefficient on *EPU_INDEX*, β_1, is negative, -0.025 (*t*=-9.50), the coefficient on the interaction variable *EPU_INDEX*LOBBY*, β_3, is 0.011 (*t*=2.78). These results suggest that corporate lobbying mitigates almost half of the adverse impact of policy uncertainty. Corporate lobbying allows lobbying firms to take advantage of policy information and move ahead of non-lobbying rivals. Thus, corporate lobbying has economic value.

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[26] My matching procedure follows Wellman (2017). The model that I use to match lobbying firms with non-lobbying firms is expressed as Equation (2) below. APPENDIX 2.B shows that the sample of lobbying firms and the propensity score-matched sample of non-lobbying firms are highly comparable.

[27] Consistent with the findings of Baker et al. (2016) and Gulen and Ion (2016) that EPU adversely affects corporate investment, hiring, and sales growth, β_1 is significantly negative using all three measures of business activities.

2.3.2 Main findings: EPU and the lobbying initiation decision

My previous findings indicate that corporate lobbying provides policy information benefits when policy uncertainty is high. Because non-lobbying firms suffer the depressing effect of policy uncertainty, they should have strong incentives to initiate lobbying for the purpose of accessing policy information during periods of high policy uncertainty. However, as discussed in Section 2.1, I also posit that lobbying entry barriers increase with EPU. In this subsection, I test how economic policy uncertainty affects the lobbying initiation decisions of non-lobbying firms.

I model the probability of non-lobbying firms' lobbying initiation in a given calendar year as a function of the average level of EPU in that year, controlling for firm-, industry-, and macro-level variables.[28] Specifically, my empirical analysis is based on the following probit model:

$$Prob(INITIATION_{i,t}) = \alpha_0 + \beta_1 EPU\_INDEX_t + CONTROLS_{i,t} + \varepsilon_{i,t}, \qquad (2.2)$$

where *INITIATION* is an indicator that equals one if non-lobbying firm *i* initiates lobbying in calendar year *t* and zero otherwise;[29] EPU_INDEX_t is the mean of the monthly logged BBD policy uncertainty index in year *t*; and $CONTROLS_{i,t}$ includes three sets of control variables. Following Hill et al. (2013) and Gao and Huang (2016), I first control for six firm-level

[28] Adelino and Dinc (2014) also analyze a concurrent association.

[29] As a firm's lobbyist is required to file a registration record when starting to lobby on behalf of the firm, I identify a non-lobbying firm's first entry into the lobbying process based on the filing year of its earliest registration record. In practice, a firm could hire different lobbyists and thus have different registration filings. As my aim is to identify the year of lobbying initiation, I focus on the earliest registration filing. On and after the filing year, a non-lobbying firm becomes a lobbying firm, which is then excluded from the lobbying initiation decision analysis in subsequent years.

characteristics: *SIZE*, *MTB*, *R&D*, *LEVERAGE*, *CASH_FLOW*, and *HERFINDAHL*. *SIZE* is the natural logarithm of the book value of total assets. *MTB* is the sum of the market value of equity and the book value of debt scaled by total assets. *R&D* is research and development expenses scaled by total assets. *LEVERAGE* is the book value of total debt scaled by total assets. *CASH_FLOW* is earnings before interest, taxes, depreciation, and amortization scaled by total assets. *HERFINDAHL*, a measure of competition among firms within an industry, is the annual sum of squared market shares in firm *i*'s industry, according to the Fama–French (1992) 48-industry classification. I also control for industry-fixed effects.[30]

Next, I include a control to address the concern that high EPU may coincide with poor economic conditions, in which case poor economic conditions may confound the effects of EPU on firms' lobbying decisions. To control for economic conditions, I follow Bonaime et al. (2018) and use investment opportunities (*INVEST_OPPORTUNITY*), which is the first principal component of three variables: (i) the University of Michigan index of consumer confidence, (ii) the National Activity Index from the Chicago Federal Reserve Board, and (iii) the average one-year-ahead GDP growth forecast from the Livingston Survey of Professional Forecasters.

Finally, I include a control to address the concern that the BBD EPU index may correlate with other macro uncertainties. To do so, I again follow Bonaime et al. (2018) and include in the regression *MACRO_UNCERTAINTY*, which is given as the first principal component of four macro uncertainty variables: (i) the monthly index of

[30] Following the literature, I use industry-fixed effects in the probit model.

macroeconomic uncertainty proposed by Jurado, Ludvigson, and Ng (2015), (ii) the VXO implied volatility index, (iii) the cross-sectional standard deviation of monthly returns from the Center for Research in Security Prices (CRSP), and (iv) the cross-sectional standard deviation of year-on-year sales growth from Compustat. All macro-level variables are measured as the averages over the same calendar year.

Table 2.5 reports the regression results based on various specifications of the probit model in Equation (2.2). Consistent with my hypothesis, in column (1), I find that the likelihood of non-lobbying firms' lobbying initiation is negatively related to *EPU_INDEX*. More specifically, the coefficient on *EPU_INDEX* is -0.320 (*t*=-3.48). Although the unconditional mean probability of non-lobbying firms' lobbying initiation is 2.17% (as shown in Table 2.2), the results here suggest that the marginal effect of a one-standard-deviation increase in *EPU_INDEX* is associated with a 0.41% decrease in lobbying initiation probability, an 18.9% decline relative to the unconditional mean probability. This finding implies that fewer non-lobbying firms initiate lobbying when EPU is high. This finding contradicts the view that firms have stronger incentives to lobby when EPU is high. However, it is consistent with my hypothesis that lobbying entry barriers increase with EPU.

To shed further light on these results, in Figure 2.2, I summarize the frequency of lobbying initiation for firms separated into three (tercile) groups according to their *EPU_INDEX* in the year they initiate the lobbying process. The figure shows an approximate average of 82 initiating firms per year during low-EPU periods but only 57 per year during high-EPU periods.

The results in column (1) of Table 2.5 also show that the probability of lobbying initiation is positively related to *SIZE* but negatively related to *CASH_FLOW*. This evidence is consistent with Hill et al. (2013) and Gao and Huang (2016). It suggests that holding all else constant, larger firms and firms with lower cash flow are more likely to start lobbying in a given year. The probability of lobbying initiation is also positively related to R&D expenses, which is consistent with the strong lobbying incentives of high R&D firms as documented by Kerr et al. (2014).

In columns (2) to (5) of Table 2.5, I replace the overall *EPU_INDEX* in column (1) with its news-, tax-, government spending, and CPI-based components, respectively. I find a significantly negative coefficient on each of the components of *EPU_INDEX*, except for the tax-based component. These results suggest that the effect of high *EPU_INDEX* on the likelihood of a firm initiating the lobbying process is not driven by any particular component of the index. Overall, the findings in Table 2.5 suggest that high EPU reduces the likelihood of non-lobbying firms choosing to initiate the lobbying process through high lobbying entry barriers.

2.4 Channel tests

The findings in Section 2.3 suggest that policy uncertainty depresses lobbying initiation decisions through lobbying entry barriers. Because lobbying entry barriers consist of lobbying entry expenses and returns to experience (Kerr et al., 2014), I conduct tests to verify lobbying entry expenses channel and returns to experience channel.

2.4.1 Lobbying entry expenses channel

In this subsection, I first test the channel of lobbying entry expenses. I then conduct a sharper analysis to understand the mechanisms regulating this channel from the supply and demand sides.

2.4.1.1 Testing the channel

To capture lobbying entry expenses, I use the costs a non-lobbying firm spends in the first year of lobbying.[31] These costs include the costs of searching for and hiring a lobbyist and of educating the lobbyist about the company's interests. If high policy uncertainty depresses the lobbying initiation decisions through the channel of high lobbying entry expenses, lobbying entry expenses should increase with EPU. I test this conjecture and report the results in Figure 2.3 and Table 2.6.

In Figure 2.3, I separate the sample years into three groups—low-, medium-, and high-EPU years—and graph the average lobbying entry expenses across the initiating firms in each group. Lobbying entry expenses average approximately $91,000 during low-EPU years but increase by 127% to approximately $207,000 during high-EPU years. These figures clearly demonstrate that firms' lobbying initiating costs are higher during high-EPU periods.

Table 2.6 further shows that lobbying entry expenses are positively and significantly related to policy uncertainty, and that non-lobbying firms are less likely to initiate lobbying in years during which the average

[31] The dollars spent in the first year of lobbying are one part of the lobbying entry expenses. The efforts CEOs spend to initiate lobbying (not reflected in dollars) are another part. When a non-lobbying firm starts lobbying, the CEO expends great effort in communicating with the lobbyist (Kerr et al., 2014) because the CEO needs to learn the complicated lobbying process, and the hired lobbyist needs to understand the firm's policy or lobbying interests.

lobbying entry expenses are higher. Thus, the findings shown in Figure 2.3 and Table 2.6 confirm that policy uncertainty depresses lobbying initiation through the channel of lobbying entry expenses.

2.4.1.2 Mechanisms regulating the channel

Inelastic supply of lobbying services

I use the number of registered lobbyists as a proxy for the supply of lobbying services. At the federal level, the number of policymakers is limited, and each policymaker has limited time for lobbyists. This implies that the number of lobbyists is also limited. Furthermore, good lobbyists have political access and maintain close social relations with policymakers. This suggests that the number of lobbyists that can provide lobbying services to firms is stable.

Figure 2.4 shows the number of registered lobbyists every year during my sample period, alongside the BBD EPU index. In 1999, there were 12,924 registered lobbyists. This number slightly decreased to 11,853 in 2001 and then gradually increased to 14,826 in 2006. After 2006, it began to gradually decline, reaching 11,543 by 2015. Thus, as expected, the number of registered lobbyists does not change much. Nor does it change with EPU, as their correlation is insignificantly different from zero. The figure illustrates an inelastic supply of lobbying services.

With an inelastic supply of lobbying services, more demand for lobbying services by existing lobbying firms would reduce the capacity of lobbyists to recruit new clients. In other words, new clients are less likely to enter the lobbying market when lobbyists are busy meeting the demand of existing clients and cannot provide adequate or effective lobbying services to new clients. Thus, I hypothesize that lobbying entry expenses are regulated by the inelastic supply of lobbying services.

To test the supply-side mechanism, I use one supply shock to lobbying services and determine how this exogenous shock affects non-lobbying firms' lobbying initiation decisions. For the supply shock, I use the guilty plea of Mr. Jack Abramoff, a prominent lobbyist, to charges of bribing government officials in January 2006. Borisov et al. (2016) describe the aftermath as follows: "The guilty plea generated intense public and media scrutiny of the lobbying process, making it damaging for politicians to be associated with lobbyists, thereby limiting the latter group's political access and influence." By making it more difficult for lobbyists to provide lobbying services, the guilty plea created a negative supply shock to lobbying services. Figure 2.4 shows that the number of registered lobbyists gradually declined after the guilty plea. The negative supply shock is likely to have increased the price of lobbying services and the lobbying entry expenses faced by non-lobbying firms.

Panel A of Table 2.7 shows that with respect to the supply shock, existing lobbying firms' lobbying expenses increase more with EPU in the post-plea period than in the pre-plea period. The results confirm that a lower supply of lobbying services increases the price of lobbying services. Panel A of Table 2.7 also shows that the negative supply shock to lobbying services makes the inverse relation between the likelihood of non-lobbying firms' lobbying initiation and EPU stronger in the post-plea period than in the pre-plea period. The results are consistent with my hypothesis that the inelastic supply of lobbying services regulates the lobbying entry expenses faced by non-lobbying firms.

Time-varying demand for lobbying services of existing lobbying firms

The findings in Table 2.4 show that lobbying firms benefit from access to policy information, particularly when policy uncertainty is high. Given the large benefits of lobbying when policy uncertainty is high, lobbying firms would be expected to demand more lobbying services at such times. If the supply of lobbying services is inelastic, then greater demand for lobbying services should increase the price of these services. Thus, I expect existing lobbying firms to spend more on lobbying when policy uncertainty is high.[32] More importantly, the high average lobbying expenses of existing lobbying firms price non-lobbying firms out of the lobbying market, increasing lobbying entry expenses. Thus, I posit that the second mechanism regulating lobbying entry expenses is existing lobbying firms' demand for lobbying services.

To examine the demand-side mechanism, I study how the average lobbying expenses of existing lobbying firms affect the lobbying initiation of non-lobbying firms. Panel B of Table 2.7 shows that EPU is positively associated with the lobbying expenses of existing lobbying firms. My estimation implies that a one-standard-deviation increase in EPU_INDEX_t is associated with a \$165,020 increase in lobbying expenses for the average lobbying firm. In my sample, annual lobbying expenses average approximately \$913,080. Thus, a one-standard-deviation increase in

[32] Ludema et al. (2017) suggest that a firm's lobbying expenditures can signal its lobbying incentives and, in turn, the potential gain or harm it faces from policymaking.

EPU_INDEX increases annual lobbying expenses by approximately 18% relative to the average. These findings are consistent with the notion that existing lobbying firms' demand for lobbying services varies with time and increases with policy uncertainty. Panel B of Table 2.7 also shows that *AVG_LOBBY_EXP*, the annual average lobbying expenses across all lobbying firms in a given year, is negatively associated with the likelihood of non-lobbying firms' lobbying initiation. This result supports my hypothesis that time-varying demand for lobbying services also regulates the lobbying entry expenses faced by non-lobbying firms.

2.4.2 Returns to experience channel

If only the lobbying entry expenses channel works, non-lobbying firms can simply overcome the lobbying entry barrier by paying more. In this case, non-lobbying firms may not necessarily be less likely to initiate lobbying when policy uncertainty is high. However, the returns to experience channel also matters, given that experience influences how effective firms are at capturing lobbying benefits. Thus, even when firms invest a large amount of capital to initiate lobbying, their lack of experience limits their lobbying efficiency. In this subsection, I verify the returns to experience channel.

Kerr et al. (2014) argue that firms become more effective at lobbying over time as they learn and deepen their relationships with lobbyists and policymakers. I test the returns to experience channel by examining whether lobbying experience matters for lobbying firms capturing economic value of lobbying. As the previous analysis shows that the economic value of lobbying comes from mitigating the adverse effects of policy uncertainty, my regression model is as follows:

$$Business\ activity_{i,t} = \alpha_0 + \beta_1 EPU\_INDEX_t + \beta_2 LOBBY\_YEAR_{i,t} + \beta_3 EPU\_INDEX_t * LOBBY\_YEAR_{i,t} + CONTROLS_{i,t} + \varepsilon_{i,t}. \quad (2.3)$$

$LOBBY\_YEAR_{i,t}$ is the number of years a firm has engaged in the lobbying process.[33] Kerr et al. (2014) suggest that a firm's lobbying experience increases with the number of years it has engaged in the lobbying process. Other specifications follow Equation (2.1), except that I run the regression in Equation (2.3) only on the sample of lobbying firms.

Table 2.8 reports the regression results based on Equation (2.3). Consistent with the returns to experience hypothesis of Kerr et al. (2014), I find that for firms with a longer lobbying history, the mitigating effect of lobbying on the negative relation between EPU and a firm's business activity is stronger. My findings suggest that even if non-lobbying firms initiate lobbying when EPU is high, they cannot capture much of the lobbying benefits right away. More importantly, my results illustrate that although a non-lobbying firm may spend a substantial amount of money to initiate lobbying, their lack of experience limits the investment efficiency of lobbying. This finding supports the low returns to initial experience as an important component of the lobbying entry barriers. More importantly, the findings indicate that returns to experience make investment in lobbying different from other types of investment.

The channel of returns to experience could be particularly important when policy uncertainty is high. Panel B of Table 2.7 shows that during

[33] If a firm terminates lobbying and then restarts lobbying several years later, the missing years are not counted in calculating the number of lobbying years.

periods of high policy uncertainty, lobbying firms have great demand for lobbying services. Lobbyists are engaged by existing lobbying firms and spend limited time and effort on new lobbying firms at such times. Because lobbying firms, in the initial stage, have to expend great effort to communicate with lobbyists, lobbyists' limited efforts could further constrain the lobbying effectiveness of firms with limited experience. In contrast, when policy uncertainty is low, lobbyists and lobbying firms have sufficient time to work together, mitigating the negative effect of limited experience on lobbying effectiveness.

In sum, I verify the channels of lobbying entry expenses and returns to experience in this section. Combined, the two channels indicate that when policy uncertainty is high, non-lobbying firms face high lobbying entry expenses, and low lobbying effectiveness due to a lack of experience.

2.5 Robustness tests

The findings in Section 2.3 document a strong negative association between policy uncertainty and the lobbying initiation decisions of non-lobbying firms. In this section, I conduct robustness tests to support my main finding. To mitigate concerns about measurement error in the EPU index, I regress the U.S. EPU index on the Canadian EPU index and use the regression residuals to measure policy uncertainty. I then use presidential elections, which are exogenous to economic conditions, to proxy for policy uncertainty. To address concerns that the EPU index captures first-moment economic policy information rather than second-moment information, I use a proxy based on firm-level political uncertainty proposed by Hassan et al. (2019). Finally, I verify my main finding using the healthcare industry.

2.5.1 Residual of policy uncertainty

One concern regarding the EPU index is measurement error (Gulen and Ion, 2016). That is, the EPU index may reflect economic uncertainty other than policy uncertainty. Although I control for macro-level investment opportunity and uncertainty in my analysis, the measurement error concern may still remain. To address this issue, I follow Gulen and Ion (2016) and Kaviani et al. (2019) by using the residual of the regression of *EPU_INDEX* on Canadian policy uncertainty as the proxy for U.S. policy uncertainty.

I first regress U.S. policy uncertainty on Canadian policy uncertainty while controlling for macro-level investment opportunity and uncertainty. Then, I take the regression residuals as a proxy for economic policy uncertainty and replace *EPU_INDEX* in Equation (2.2) with the U.S. policy uncertainty residual, *RESID_EPU*. As Gulen and Ion (2016) note, *RESID_EPU* presents a cleaner measure of economic policy uncertainty in the U.S. The basic idea behind this procedure is leveraging similarities between the U.S. and Canadian economies. Due to extensive international trade, the two economies are highly integrated. Economic uncertainty shocks that affect the U.S. are very likely to affect Canada, as well. Thus, the part of the U.S. policy uncertainty index orthogonal to the Canadian policy uncertainty index excludes the effects of any general uncertainty affecting both the U.S. and Canada.

Column (1) of Table 2.9 presents the results based on the residual of the U.S. policy uncertainty index. I find that the residual part of *EPU_INDEX* is significantly and negatively associated with the likelihood of non-lobbying firms' lobbying initiation. Specifically, the coefficient of

RESID_EPU is negative, at -0.230 (t-value=-2.37). The magnitude of this coefficient is close to 3/4 of the level documented in Table 2.5. Thus, I conclude that measurement error does not seem to fully explain the negative effect of policy uncertainty on non-lobbying firms' lobbying initiation.

2.5.2 Presidential elections

Following Julio and Yook (2012) and Bhattacharya et al. (2017), I use presidential elections as a traditional measure of policy uncertainty. Baker et al. (2016) show that EPU is higher during U.S. presidential election years than in other years. Moreover, Julio and Yook (2012) argue that, since the timing of U.S. presidential elections is prescheduled, the elections are exogenous to economic conditions, business cycles, and general economic uncertainty. Finally, Bhattacharya et al. (2017) point out that the presidential election setting also mitigates concerns about time-varying omitted variables and reverse causality. Thus, presidential elections provide an exogenous setting for me to infer causal effects of EPU on non-lobbying firms' lobbying initiation and to establish causality.

Column (2) of Table 2.9 reports the effects of presidential elections on the lobbying initiation decisions of non-lobbying firms. I find that the coefficient on *ELECTION* is significantly negative, at -0.154, with t=-2.53. This result shows that non-lobbying firms are less likely to initiate lobbying during U.S. presidential election years. My findings lend support to the view that the probability of lobbying initiation is lower when EPU is higher.

2.5.3 Alternative measure of policy uncertainty

One concern regarding the BBD EPU index as a measure of policy uncertainty is that the EPU index captures first-moment economic policy information rather than second-moment information. To deal with this concern, I consider an alternative measure of policy uncertainty. Hassan et al. (2019) propose a firm-level political uncertainty measure by using a training library of political text and counting synonyms for "risk" or "uncertainty" in conference calls. Critically, they verify that this measure captures information about the second moment, but not the first moment. Because they show that the average firm-level political uncertainty in a year shows a high correlation with the BBD EPU index and rises substantially during elections, I use the mean of firm-level political uncertainty in a year, *PRISK*, as the alternative measure of policy uncertainty. The data for *PRISK* are available from 2001.

Column (3) of Table 2.9 reports the effect of policy uncertainty on non-lobbying firms' lobbying initiation based on the alternative measure of policy uncertainty. I find that *PRISK* also has a negative effect on non-lobbying firms' lobbying initiation. That is, the coefficient of *PRISK* is significant at -0.004 (t-value=-2.46). Thus, the finding in column (3) of Table 2.9 lends me confidence that the negative effect of policy uncertainty on non-lobbying firms' lobbying initiation is not driven by the EPU index capturing first-moment economic policy information.

2.5.4 The healthcare industry case

In this subsection, to further illustrate the negative effect of policy uncertainty on the lobbying initiation decisions of non-lobbying firms, I focus on a particular industry. I choose the healthcare industry for two reasons. First, lobbying plays a significant role in the healthcare industry. Based on CRP records for the period 1998 to 2017, healthcare is the second most common lobbying issue, after the federal budget, and the pharmaceutical industry ranks highest in terms of industry-level lobbying expenses. The large scale of lobbying in this industry makes my focus meaningful. Second, because the Affordable Care Act represents a large shock to the entire healthcare system, healthcare policy uncertainty exhibits substantial variation during my sample period. It is therefore interesting to examine how healthcare policy uncertainty, an industry-level uncertainty, affects the lobbying initiation decisions of non-lobbying firms in this industry.

I follow Koijen et al. (2016) in identifying the healthcare industry, which includes medical equipment, pharmaceutical products, and health services. Similarly, the probit results reported in column (4) of Table 2.9 show that the coefficient on *HEALTHCAREPU* is negative and statistically significant at the 5% level, suggesting that non-lobbying firms in the healthcare industry are indeed less likely to initiate lobbying when healthcare policy uncertainty is high. This result further supports my principal finding that policy uncertainty depresses the lobbying initiation of non-lobbying firms.

2.6 Cross-sectional analysis

Based on the channels of lobbying entry expenses and returns to experience, I conduct three cross-sectional analyses to show that time-varying entry barriers affect certain types of non-lobbying firms more than others. My analyses focus on how lobbying entry barriers affect financially constrained non-lobbying firms, how non-lobbying firms' distance from D.C. affects their lobbying initiation decisions, and how non-lobbying firms with government customers approach the lobbying initiation decision.

2.6.1 Financial constraints and lobbying initiation decisions

The channel of lobbying entry expenses indicates that non-lobbying firms face high entry expenses when policy uncertainty is high. As financially constrained firms have fewer resources than their unconstrained counterparts to handle high entry expenses, the deterrent effect of entry barriers should be larger for constrained non-lobbying firms than for unconstrained ones. The channel of lobbying entry expenses thus predicts that the inverse relation between the likelihood of non-lobbying firms' lobbying initiation and EPU is stronger for constrained non-lobbying firms than for unconstrained non-lobbying firms.

To test this prediction, I use three proxies for financial constraints: firm size, the *WW* index constraint measure of Whited and Wu (2006), and the *HP* index constraint measure of Hadlock and Pierce (2010). Firm size is a good measure of financial constraints because smaller firms tend to have less capacity to access capital markets and are more likely to be in financial distress (Fama and French, 1992). Farre-Mensa and Ljungqvist (2016) suggest that the *HP* and *WW* constraint measures can better capture firms' financial constraints than Kaplan and Zingales' (1997) *KZ* index.

Panel A of Table 2.10 presents the cross-sectional probit results. My focus in this table is on the interactions between *EPU_INDEX* and the three financial constraint measures. Whereas *EPU_INDEX* remains significantly negative, the interaction between *EPU_INDEX* and *SIZE* is significantly positive. This suggests that non-lobbying firms, especially smaller ones, are indeed less likely to initiate the lobbying process when EPU is high. Moreover, the interactions *EPU_INDEX*HP* and *EPU_INDEX*WW* are significantly negative. This suggests that when EPU is high, non-lobbying firms, especially more financially constrained ones, are again less likely to start lobbying. These findings further support the view that EPU affects the lobbying initiation decisions of non-lobbying firms through the channel of lobbying entry expenses. Consequently, financially constrained non-lobbying firms are more likely to delay their lobbying entry until policy uncertainty decreases.[34]

2.6.2 Distance from D.C. and lobbying initiation decisions

In the second cross-sectional analysis, I rely on the channel of returns to experience and consider how a non-lobbying firm's distance from D.C. affects its lobbying initiation decision. The returns to experience channel notes that firms become more effective at lobbying as they communicate more with lobbyists. Greater distances increase the difficulty of communicating, socializing, and maintaining close relations with lobbyists and policymakers, who are in D.C. most of the time. Thus, if a distant firm hires lobbyists, the lobbying effectiveness is likely reduced by the difficulty of maintaining close relations with lobbyists and policymakers. Such communication difficulties are more severe when policy uncertainty is

[34] Adelino and Dinc (2014) find that during the financial crisis, financially constrained firms lobbied more to obtain stimulus funds. As I explain below, their findings are not inconsistent with my results. First, they focus on the lobbying decisions of lobbying firms, whereas I focus on the lobbying decisions of non-lobbying firms. Second, they find that while the Stimulus Act was still unsettled, firms lobbied for stimulus funds. This finding is consistent with my finding that when EPU is high, lobbying firms lobby more to influence policy outcomes.

high, given that lobbyists are busy with existing lobbying firms at such times. Consequently, when policy uncertainty is high, non-lobbying firms farther away from D.C. face higher lobbying entry barriers than do those located near D.C.

To test my hypothesis, I follow Alam et al. (2014) and use zip codes to measure the geographic distance between a firm's headquarters and D.C.[35] Panel B of Table 2.10 reports the cross-sectional probit results. In column (1), I find that *DISTANCE* is significantly negative, at -0.0419 (*t*=-2.53). This indicates that non-lobbying firms farther away from D.C. are less likely to initiate lobbying. In column (2), I add the interaction term between *EPU_INDEX* and *DISTANCE*. The results show that although *DISTANCE* becomes insignificant, the coefficient of the interaction term is significantly negative, at -0.0164 (*t*=-2.29). The results indicate that non-lobbying firms farther away from D.C. are less likely to initiate lobbying during high-EPU periods. The evidence is consistent with my hypothesis that lobbying entry barriers increase with policy uncertainty, especially for non-lobbying firms that are distant from D.C. Moreover, my findings support the channel of returns to experience.

2.6.3 Government customers

My third cross-sectional analysis is also based on the channel of returns to experience and focuses on government suppliers. The returns to experience channel indicates that lobbying effectiveness is low for new lobbying firms, including government suppliers. Furthermore, the lobbying efforts of government suppliers may be more ineffective if the lobbying is

[35] I set the zip code for Washington D.C. to 20001.

initiated when policy uncertainty is high. It is because policymakers and lobbyists at such times mainly work on large policy issues and have little time for the issues of interest to government suppliers (i.e., winning specific government contracts).[36] Consequently, the negative effect of lobbying entry barriers should be stronger for government suppliers than for non-government suppliers.

Panel C of Table 2.10 shows the cross-sectional probit results for government suppliers. Column (1) of Panel C reports that *GOVERN_CUSTOMER* shows a significant coefficient of 0.367 (t-value=6.94). The results illustrate that non-lobbying firms with government customers are more likely to initiate lobbying. The results also suggest that, on average, high lobbying interests overcome barriers to entry. However, in column (2), I find that the interaction term between *GOVERN_CUSTOMER* and *EPU_INDEX* is negative, at -0.356 (t-value=-2.47). When policy uncertainty is high, government suppliers are less likely to initiate lobbying than are non-government suppliers. My results suggest that lobbying entry barriers increase with policy uncertainty more for government suppliers than for non-government suppliers. Moreover, the third cross-sectional analysis further confirms that policy uncertainty depresses the lobbying initiation decisions of non-lobbying firms through the channel of returns to experience.

[36] The insight that government suppliers mainly lobby for the purpose of winning government contracts comes from Drutman (2015).

2.7 Conclusion

Despite the importance of corporate lobbying, the evidence on the determinants of corporate lobbying is limited. In this paper, I examine how EPU affects the lobbying initiation decisions of non-lobbying firms. Insights from previous studies offer competing views on this relationship. On the one hand, when EPU is high, lobbying initiation offers substantial benefits including access to policy information, the chance to affect policy outcomes, and risk management. On the other hand, non-lobbying firms face higher lobbying entry barriers when EPU is high, given the lobbying entry expenses and returns to experience channels.

Consistent with my lobbying entry barrier hypothesis, I find that when EPU is higher, non-lobbying firms are less likely to initiate lobbying. The depressing effect of EPU is robust and economically meaningful. Using alternative measures of policy uncertainty, I mitigate concerns related to BBD EPU index measurement error, the index capturing first-moment economic policy information rather than second-moment information, policy uncertainty being endogenous to economic conditions, and time-varying omitted variable bias.

I verify that EPU affects lobbying initiation decisions through the channels of lobbying entry expenses and returns to experience. I further find that the negative effect of EPU on lobbying initiation is stronger for financially constrained non-lobbying firms, non-lobbying firms that are more distant from D.C., and government suppliers. Additionally, cross-sectional analyses confirm that policy uncertainty affects the lobbying initiation decisions of non-lobbying firms through the channels of lobbying entry expenses and returns to experience.

In sum, my results indicate that periods of low policy uncertainty are a good time to initiate lobbying, and they shed new light on the channels through which policy uncertainty affects business activities. My findings also help explain why many firms stay on the sidelines even when it would appear particularly beneficial for them to enter the lobbying market.

APPENDIX 1.A VARIABLE DEFINITIONS

Variable	Definition
Industry-level variables	
RELATIVE_INVEST	Industry relative investment measured using a three-step procedure (details in Section 1.3.2.2)
FIRM_ RELATIVE_INVEST	Firms' total relative investment.
DEBT_FINANCE	Industry average net debt financing (long-term debt/issuance minus long-term debt/reduction).
EQUITY_FINANCE	Industry average net equity financing (sale of common and preferred stock minus purchase of common and preferred stock).
SIZE	The natural logarithm of total assets.
TOBIN'S Q	Tobin's Q measured as market value of equity plus the book value of assets minus book value of equity plus deferred taxes, all divided by book value of assets.
LEVERAGE	Total long-term debt divided by total assets.
ROE	Earnings divided by last year's book equity.
SALES_GROWTH	Sales growth measured as percentage change in sales.
CASH_FLOW	Operating income before depreciation net of interest expenses, income taxes, and common dividends scaled by lagged total assets.
CASH	(Cash and short-term investment)/total assets
HHI	Herfindahl index is sales concentration at the industry level based on segment data.
FITTED_HHI	Fitted Herfindahl index developed by Hoberg and Phillips (2010).
GROSS_MARGIN	(Sales-cost of goods sold)/sales
∆*CASH_FLOW*	Firm's change in operating cash flow (operating income/ total assets).
RELATIVE_VALUATION	Industry relative valuation measured using a three-step procedure. First, I follow HP and Pastor and Veronesi (2003) and use *AGE*, *DD*, *LEV*, *SIZE*, *ROE*, and *VOLP* to predict firm's valuation. Then, firm's total relative valuation is the difference between firm's raw valuation and predicted component. Finally, industry relative valuation is the average of firms' total relative valuation in the industry.
RELATIVE_VALUATION_RESI	Firms' total relative valuation minus *RELATIVE_VALUATION*.
RELATIVE_INVEST_RESI	Firms' total relative investment minus *RELATIVE_INVEST*.
NEW_FINANCE	Summed total amount of new financing over firms in the industry divided by total assets of the industry.
NEW_FINANCE_RESI	Firms' total new financing minus *NEW_FINANCE*. Firms' total new financing is sum of a firm's net equity issuance and net debt issuance divided by assets.
∆*EBITDA*	Past-year's changes in earnings before interest and taxes plus depreciation.
∆*CAPEX*	Past-year's changes in capital expenditures.
ABNORMAL_RET	Monthly abnormal returns between July of year t and June of year t+1.
Macro-level variables	
CREDIT_SENTIMENT	Credit market sentiment is excess bond premium developed by Gilchrist and Zakrajšek (2012)

	multiplied by (-1).
HIGH_SENTIMENT	High credit market sentiment indicator set to one if credit market sentiment is higher than its 10 percentile and zero otherwise.
EQUITY_SENTIMENT	Sentiment index developed by Baker and Wurgler(2006).
ECONOMIC_CONDITION	Economic conditions measured as the first principle component of the following three variables. 1.Consumer confidence, survey-based index of consumer confidence developed by University of Michigan 2. CFNAI, the Chicago Fed National Activity Index 3. Expected GDP growth, the average one-year-ahead GDP forecast from the bi-annual Livingstone Survey of Professional Forecasters
MACRO_UNCERTAINTY	Macro uncertainty measured the first principle component of the following four variables. 1. JLN uncertainty, macroeconomic uncertainty index developed by Jurado, Ludvigson and Ng (2015) 2. CS σ past returns, cross-sectional standard deviation of cumulative returns from the past three months, using the entire CRSP universe 3. CS σ past sales growth, cross-sectional standard deviation of year-on-year sales growth, using the entire Compustat quarterly universe

APPENDIX 1.B CREDIT MARKET SENTIMENT AND RELATIVE INVESTMENT: FIRM LEVEL EVIDENCE

This table reports how credit market sentiment in year t affects firms' relative investment in years t to t+4. Dependent variable is firm-level total relative investment. The explanatory variable is credit market sentiment. Panel A (panel B) reports results based on competitive (consolidated) industries. All control variables are winsorized at the 1% and 99% levels. In all models, I include firm fixed effects and cluster standard errors by firm and year. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively. Statistical significance for the difference in the coefficient of *CREDIT_SENTIMENT* between competitive versus consolidated industries is indicated by a, b, and c, for significance at the 1%, 5% and 10%, respectively.

Panel A: Competitive industries

Dependent variable	*FIRM_RELATIVE_INVEST*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	0.1483**	0.2365***b	0.2073***	0.1035*	-0.0382
	(2.39)	(5.16)	(6.34)	(1.76)	(-0.73)
EQUITY_SENTIMENT(t)	0.0230	-0.0469	-0.1277***	-0.1164***	-0.0592**
	(0.42)	(-1.13)	(-5.64)	(-4.09)	(-2.50)
SIZE(t)	0.0904***	0.0114	-0.0628***	-0.1419***	-0.1229***
	(3.32)	(0.58)	(-4.09)	(-7.12)	(-5.57)
TOBIN'S Q(t)	-0.0049	-0.0112	0.0191***	0.0004	-0.0095
	(-0.90)	(-1.63)	(3.29)	(0.07)	(-1.42)
LEVERAGE(t)	-0.0513	-0.5704***	-0.5161***	-0.2687***	-0.2175***
	(-0.61)	(-6.61)	(-6.04)	(-3.99)	(-3.04)
ROE(t)	-0.1307***	0.1743***	0.1124***	0.0782***	0.0406*
	(-4.11)	(6.96)	(5.43)	(3.83)	(1.93)
SALES_GROWTH(t)	0.2715***	0.1370***	0.0464***	0.0196	0.0355*
	(17.74)	(9.16)	(3.75)	(1.37)	(1.86)
CASH_FLOW(t)	0.3453***	1.0752***	0.6841***	0.3559***	0.1817**
	(4.33)	(12.90)	(8.11)	(4.14)	(2.38)
CASH(t)	-0.3395***	0.6456***	0.4383***	0.3154***	0.2494***
	(-5.25)	(8.30)	(6.69)	(4.51)	(3.27)
ECONOMIC_CONDITION(t)	-0.0127	-0.0032	-0.0253*	-0.0797***	-0.0531**
	(-0.47)	(-0.13)	(-1.86)	(-3.68)	(-2.53)
MACRO_UNCERTAINTY(t)	-0.0479	-0.0264	0.0014	0.0664***	0.0680***
	(-1.45)	(-1.01)	(0.07)	(3.04)	(2.91)
N	78941	69184	62535	56112	50589
R^2	0.2626	0.2839	0.2758	0.2588	0.2509

Panel B: Consolidated industries

Dependent variable	*FIRM_RELATIVE_INVEST*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	0.0560	0.0710b	0.1199*	-0.0142	0.0098
	(0.52)	(1.00)	(1.69)	(-0.16)	(0.12)
EQUITY_SENTIMENT(t)	-0.0979	0.0651	-0.1007**	-0.0873**	-0.0043
	(-1.50)	(0.85)	(-2.67)	(-2.41)	(-0.09)
SIZE(t)	0.0863**	-0.0362	-0.1035**	-0.1265***	-0.1281***
	(2.11)	(-0.93)	(-2.31)	(-2.72)	(-3.04)
TOBIN'S Q(t)	-0.0139	-0.0293	0.0564	0.0622**	-0.0118
	(-0.41)	(-1.21)	(0.96)	(2.19)	(-0.34)
LEVERAGE(t)	-0.2186	-0.8007***	-0.4994**	-0.1926	0.2407
	(-0.96)	(-3.76)	(-2.53)	(-0.95)	(1.02)
ROE(t)	-0.0746	0.4500***	0.3035***	0.1163	-0.1113
	(-0.72)	(4.71)	(3.47)	(1.11)	(-1.12)
SALES_GROWTH(t)	0.3675***	0.2590***	-0.0127	-0.0911	0.0004
	(5.29)	(3.87)	(-0.24)	(-1.27)	(0.01)
CASH_FLOW(t)	-0.3935	0.6821**	0.1858	-0.1129	0.5061
	(-1.18)	(2.52)	(0.64)	(-0.36)	(1.29)
CASH(t)	-0.6664***	0.9117***	0.5268***	0.3829	0.0374
	(-3.19)	(5.96)	(2.81)	(1.33)	(0.12)
ECONOMIC_CONDITION(t)	0.0190	0.0558*	0.0327	-0.0514**	-0.0960***
	(0.49)	(1.93)	(0.65)	(-2.14)	(-3.37)
MACRO_UNCERTAINTY(t)	0.0398	-0.0445*	-0.0090	-0.0484*	-0.0072
	(1.13)	(-1.71)	(-0.18)	(-1.71)	(-0.38)
N	18031	15743	14324	12943	11405
R^2	0.2637	0.2910	0.2589	0.2655	0.2723

APPENDIX 1.C CREDIT MARKET SENTIMENT AND RELATIVE INVESTMENT: EVIDENCE BASED ON FITTED HHI

This table reports how credit market sentiment affects industry relative investment based on alternative measure of Compustat HHI. I use *FITTED_HHI* developed by HP to redefine competitive and consolidated industries. Panel A (panel B) reports results based on competitive (consolidated) industries. All control variables are winsorized at the 1% and 99% levels. In all models, I include three-digit SIC industry fixed effects and cluster standard errors by industry and year. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively. Statistical significance for the difference in the coefficients of *CREDIT_SENTIMENT* between competitive versus consolidated industries is indicated by a, b, and c, for significance at the 1%, 5% and 10%, respectively.

Panel A: Competitive industries

Dependent variable	*RELATIVE_INVEST*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	0.2788***b	0.2446***b	0.2949***	0.1358*c	-0.0322
	(4.30)	(3.64)	(4.03)	(1.73)	(-0.49)
EQUITY_SENTIMENT(t)	0.1039***	0.0457	-0.0188	-0.0438	-0.0184
	(3.54)	(1.31)	(-0.72)	(-1.06)	(-0.67)
SIZE(t)	-0.0090	-0.0434	-0.0599	-0.1000**	-0.1515**
	(-0.15)	(-1.55)	(-1.16)	(-2.24)	(-2.69)
TOBIN'S Q(t)	-0.0539	0.2683*	-0.0245	-0.0064	0.0484
	(-0.93)	(1.71)	(-0.42)	(-0.14)	(0.41)
LEVERAGE(t)	-2.3887***	-1.1711*	-0.6434	-0.6718	0.0202
	(-3.32)	(-1.90)	(-0.84)	(-0.82)	(0.04)
ROE(t)	-0.9736***	0.2163	0.4502**	0.1918	0.2238
	(-3.33)	(1.35)	(2.14)	(0.70)	(0.55)
SALES_GROWTH(t)	0.0995**	-0.0401	-0.0485	-0.0302	-0.0024
	(2.11)	(-0.86)	(-1.51)	(-0.80)	(-0.07)
CASH_FLOW(t)	1.3729*	-0.4728	-0.9587*	-0.2843	0.4973
	(1.93)	(-0.55)	(-1.83)	(-0.40)	(0.58)
CASH(t)	-1.5805***	-0.3516	-0.1525	0.5943	0.1102
	(-2.81)	(-0.38)	(-0.21)	(0.81)	(0.17)
ECONOMIC_CONDITION(t)	0.0355	0.0258	-0.0304	-0.0953***	-0.0954***
	(1.21)	(1.68)	(-1.02)	(-3.89)	(-3.49)
MACRO_UNCERTAINTY(t)	0.0701***	0.0170	-0.0352	-0.0898**	-0.0935**
	(3.03)	(0.69)	(-1.41)	(-2.55)	(-2.58)
N	1725	1714	1713	1712	1708
R^2	0.1463	0.1407	0.1349	0.1298	0.1053

Panel B: Consolidated industries

Dependent variable	*RELATIVE_INVEST*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	0.0253b	0.0610b	0.1947**	-0.0177c	-0.0148
	(0.24)	(0.97)	(2.64)	(-0.20)	(-0.18)
EQUITY_SENTIMENT(t)	-0.0383	0.0133	-0.0108	-0.0820**	-0.0854
	(-1.27)	(0.50)	(-0.42)	(-2.18)	(-1.64)
SIZE(t)	-0.0291	-0.1113**	-0.0642	-0.0109	-0.0329
	(-0.68)	(-2.17)	(-1.34)	(-0.29)	(-0.87)
TOBIN'S Q(t)	-0.0208	0.0211	0.0377	0.0773	0.0482
	(-0.22)	(0.27)	(0.44)	(0.79)	(0.69)
LEVERAGE(t)	-0.5946	0.3034	1.4959**	0.6700	0.7643
	(-0.77)	(0.53)	(2.17)	(0.99)	(1.26)
ROE(t)	0.3834	0.4779	0.3119	0.4080	0.2627
	(1.06)	(1.35)	(1.32)	(1.51)	(1.27)
SALES_GROWTH(t)	0.3488**	-0.0656	-0.1224	0.0044	-0.0918
	(2.14)	(-1.32)	(-1.13)	(0.07)	(-1.29)
CASH_FLOW(t)	-0.9329	-0.1437	0.8797	0.9355	-0.0348
	(-0.83)	(-0.14)	(1.10)	(1.20)	(-0.06)
CASH(t)	-3.0266***	-0.1655	0.6764	0.1082	0.2349
	(-2.94)	(-0.30)	(0.77)	(0.15)	(0.33)
ECONOMIC_CONDITION(t)	-0.0309	0.0364	0.0112	0.0004	-0.0319
	(-1.00)	(1.50)	(0.50)	(0.01)	(-1.31)
MACRO_UNCERTAINTY(t)	-0.0296	-0.0548**	-0.0086	-0.0364*	0.0060
	(-1.11)	(-2.54)	(-0.53)	(-1.95)	(0.28)
N	1696	1656	1634	1621	1614
R^2	0.1865	0.2036	0.1666	0.1769	0.1435

APPENDIX 1.D ALTERNATIVE MEASURE OF CREDIT MARKET SENTIMENT AND RELATIVE IVNESTMENT: HYS

This table reports how the alternative measure of credit market sentiment affects industry relative investments. The alternative measure of credit market sentiment is high-yield bond issuance, *HYS*, proposed by Greenwood and Hanson (2013). The sample is for *HYS* is from 1977 to 2008. Panel A (panel B) reports results based on competitive (consolidated) industries. All control variables are winsorized at the 1% and 99% levels. In all models, I include three-digit SIC industry fixed effects and cluster standard errors by industry and year. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively. Statistical significance for the difference in the coefficients of *LOG_HYS* between competitive versus consolidated industries is indicated by a, b, and c, for significance at the 1%, 5% and 10%, respectively.

Panel A: Competitive industries

Dependent variable	*RELATIVE_INVEST*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
LOG_HYS(t)	0.0523	0.0965***b	0.0726*	0.0252	-0.0376
	(1.69)	(3.75)	(1.71)	(0.51)	(-1.12)
EQUITY_SENTIMENT(t)	-0.0310	-0.0216	-0.0564**	-0.0407	-0.0140
	(-1.09)	(-0.89)	(-2.10)	(-1.31)	(-0.50)
SIZE(t)	-0.0089	0.0174	0.0133	-0.0112	-0.0319*
	(-0.55)	(1.17)	(0.77)	(-0.47)	(-1.70)
TOBIN'S Q(t)	-0.0193	-0.0031	0.0256	0.0230	0.0329
	(-0.78)	(-0.14)	(1.30)	(0.90)	(1.39)
LEVERAGE(t)	-0.0109	-0.0244	-0.0581	-0.0366	0.0051
	(-0.41)	(-0.80)	(-1.54)	(-0.86)	(0.15)
ROE(t)	-0.0027	0.0291	-0.0141	-0.0923**	-0.1029***
	(-0.06)	(0.49)	(-0.34)	(-2.56)	(-2.95)
SALES_GROWTH(t)	-0.7784	-0.6382	-0.6814*	-0.8220*	-0.8917
	(-1.60)	(-1.35)	(-1.80)	(-1.79)	(-1.58)
CASH_FLOW(t)	0.0574	0.4486**	0.3539**	0.2491*	0.4025***
	(0.24)	(2.22)	(2.31)	(1.89)	(2.79)
CASH(t)	0.0001	0.0001	-0.0209	0.0002*	-0.0001
	(0.16)	(0.48)	(-0.61)	(1.70)	(-0.74)
ECONOMIC_CONDITION(t)	0.9784	0.9587*	0.3728	-0.5207	-1.2239***
	(1.42)	(1.89)	(0.71)	(-1.41)	(-2.90)
MACRO_UNCERTAINTY(t)	-0.5669	0.0518	0.4276	0.1291	0.1759
	(-1.00)	(0.10)	(0.78)	(0.29)	(0.38)
N	2270	2270	2270	2269	2268
R^2	0.2101	0.2777	0.1563	0.1608	0.1461

Panel B: Consolidated industries

Dependent variable	*RELATIVE_INVEST*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
LOG_HYS(t)	0.0338	-0.0014b	0.0685	0.0008	-0.0199
	(0.53)	(-0.03)	(1.40)	(0.01)	(-0.47)
EQUITY_SENTIMENT(t)	-0.0168	-0.0230	-0.1200***	-0.1098**	-0.0192
	(-0.44)	(-0.58)	(-2.77)	(-2.40)	(-0.42)
SIZE(t)	-0.0053	0.0453	0.0450**	-0.0007	-0.0528***
	(-0.20)	(1.65)	(2.21)	(-0.03)	(-2.94)
TOBIN'S Q(t)	0.0564**	0.0702***	0.0157	0.0113	0.0090
	(2.26)	(3.10)	(0.73)	(0.75)	(0.48)
LEVERAGE(t)	-0.0218	-0.0287	-0.0479	-0.0109	-0.0485
	(-0.44)	(-0.66)	(-1.09)	(-0.20)	(-1.21)
ROE(t)	-0.1261	0.0084	0.0477	0.0560	0.0054
	(-1.56)	(0.12)	(0.42)	(0.85)	(0.10)
SALES_GROWTH(t)	-1.1395*	-0.1381	0.0670	-0.5705	-0.1874
	(-1.70)	(-0.25)	(0.10)	(-0.92)	(-0.32)
CASH_FLOW(t)	-0.1966	0.1648	-0.0039	-0.1343	0.0893
	(-1.16)	(0.81)	(-0.04)	(-1.56)	(0.69)
CASH(t)	0.0473*	-0.0537	-0.0367*	-0.0408*	-0.0039
	(1.75)	(-1.10)	(-1.88)	(-2.00)	(-0.19)
ECONOMIC_CONDITION (t)	-0.6551	-0.8546	0.9876*	0.4831	0.4031
	(-1.00)	(-1.64)	(1.91)	(1.34)	(1.09)
MACRO_UNCERTAINTY(t)	-1.1751	-0.4350	-0.4221	-0.4639	-0.2825
	(-1.57)	(-0.81)	(-0.52)	(-0.73)	(-0.47)
N	2239	2135	2079	2046	2028
R^2	0.1079	0.1248	0.1214	0.1179	0.1245

APPENDIX 1.E ALTERNATIVE MEASURE OF CREDIT MARKET SENTIMENT AND RELATIVE INVESTMENT: LOOSE OF LOAN STANDARDS

This table reports how the alternative measure of credit market sentiment affects industry relative investments. The alternative measure of credit market sentiment is the yearly average of quarterly percentage of loan officers reporting a loosening of underwriting standards, *LOOSE*. The sample is for *LOOSE* is from 1990 to 2015. Panel A (panel B) reports results based on competitive (consolidated) industries. All control variables are winsorized at the 1% and 99% levels. In all models, I include three-digit SIC industry fixed effects and cluster standard errors by industry and year. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively. Statistical significance for the difference in the coefficients of *LOOSE* between competitive versus consolidated industries is indicated by a, b, and c, for significance at the 1%, 5% and 10%, respectively.

Panel A: Competitive industries

Dependent variable	*RELATIVE_INVEST*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
LOOSE(t)	0.0027*c	0.0057***b	0.0073***	0.0053***	0.0014
	(1.73)	(5.58)	(7.28)	(3.38)	(0.94)
EQUITY_SENTIMENT(t)	0.0852*	0.0428**	-0.0389	-0.0671**	-0.0598
	(1.88)	(2.27)	(-1.59)	(-2.07)	(-1.52)
SIZE(t)	0.0053	-0.0270	-0.1291***	-0.1531***	-0.1089***
	(0.16)	(-0.88)	(-5.54)	(-5.05)	(-3.84)
TOBIN'S Q(t)	-0.0246	-0.0019	-0.0150	-0.0563	-0.0857**
	(-0.44)	(-0.03)	(-0.29)	(-1.36)	(-2.71)
LEVERAGE(t)	-0.7562	-0.9965*	-0.1678	-0.3803	-0.8125
	(-1.24)	(-1.87)	(-0.33)	(-0.74)	(-1.18)
ROE(t)	0.0158	0.1662	0.1666	0.1992**	0.3069**
	(0.08)	(1.02)	(1.52)	(2.32)	(2.12)
SALES_GROWTH(t)	-0.0001	0.0002	0.0075	0.0001	-0.0003**
	(-0.44)	(0.89)	(0.27)	(0.60)	(-2.15)
CASH_FLOW(t)	1.2214**	0.8249**	0.5952	-0.1109	-0.9215**
	(2.15)	(2.14)	(1.18)	(-0.35)	(-2.73)
CASH(t)	-0.5086	-0.0296	0.4893	0.2980	0.0436
	(-0.80)	(-0.05)	(0.77)	(0.59)	(0.09)
ECONOMIC_CONDITION(t)	-0.0452	-0.0412***	-0.0015	0.0242	0.0625**
	(-1.60)	(-2.89)	(-0.09)	(0.98)	(2.51)
MACRO_UNCERTAINTY(t)	-0.0043	-0.0079	-0.0783***	-0.1083***	-0.1010***
	(-0.15)	(-0.37)	(-4.46)	(-3.67)	(-3.42)
N	1825	1824	1762	1697	1631
R^2	0.2558	0.3443	0.2164	0.2406	0.2043

Panel B: Consolidated industries

Dependent variable	*RELATIVE_INVEST*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
LOOSE(t)	-0.0017c	0.0001b	0.0050***	0.0031	0.0042
	(-0.65)	(0.06)	(2.98)	(1.17)	(1.67)
EQUITY_SENTIMENT(t)	-0.0342	-0.0286	-0.0008	-0.0291	0.0216
	(-0.63)	(-0.72)	(-0.02)	(-0.68)	(0.50)
SIZE(t)	0.0229	-0.0088	-0.0198	0.0240	-0.0216
	(0.45)	(-0.17)	(-0.58)	(0.30)	(-0.39)
TOBIN'S Q(t)	-0.0951	0.0045	-0.0065	0.0342	0.0129
	(-1.25)	(0.07)	(-0.13)	(0.42)	(0.16)
LEVERAGE(t)	-0.5553	0.3415	0.3404	-0.1402	0.4757
	(-0.87)	(0.75)	(0.64)	(-0.18)	(0.72)
ROE(t)	-0.2741	0.0730	0.0450	-0.1217	0.0698
	(-1.57)	(0.42)	(0.46)	(-1.56)	(0.50)
SALES_GROWTH(t)	0.0694**	-0.0983	-0.0683**	-0.0916***	0.0192
	(2.37)	(-1.14)	(-2.73)	(-3.34)	(0.48)
CASH_FLOW(t)	-0.5837	-0.5506	0.8557**	0.7662**	0.5142
	(-0.84)	(-0.90)	(2.20)	(2.40)	(1.50)
CASH(t)	-0.7565	0.4691	0.0676	0.0310	-0.3792
	(-0.88)	(0.67)	(0.10)	(0.04)	(-0.63)
ECONOMIC_CONDITION(t)	-0.0238	-0.0629***	-0.0023	0.0202	0.0260
	(-1.26)	(-3.11)	(-0.14)	(0.95)	(1.24)
MACRO_UNCERTAINTY(t)	0.0588	0.0505	-0.0030	-0.0092	-0.0946**
	(1.46)	(1.45)	(-0.10)	(-0.24)	(-2.40)
N	1805	1725	1617	1521	1433
R^2	0.1191	0.1345	0.1571	0.1580	0.1874

APPENDIX 1.F CREDIT MARKET SENTIMENT RESIDUAL AND RELATIVE INVESTMENT

This table reports how the residual of credit market sentiment affects industry relative investments. The residual of credit market sentiment is orthogonal to macro-level economic condition. Panel A (panel B) reports results based on competitive (consolidated) industries. All control variables are winsorized at the 1% and 99% levels. In all models, I include three-digit SIC industry fixed effects and cluster standard errors by industry and year. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively. Statistical significance for the difference in the coefficients of *CREDIT_SENTIMENT_RESI* between competitive versus consolidated industries is indicated by a, b, and c, for significance at the 1%, 5% and 10%, respectively.

Panel A: Competitive industries

Dependent variable	*RELATIVE_INVEST*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT_RESI(t)	0.1440***	0.2353***b	0.1434**	0.0680	-0.0444
	(2.78)	(5.95)	(2.60)	(1.11)	(-1.08)
EQUITY_SENTIMENT(t)	0.0162	0.0184	-0.0386*	-0.0445*	-0.0374
	(0.60)	(0.96)	(-1.72)	(-1.74)	(-1.57)
SIZE(t)	-0.0031	-0.0135	-0.0284	-0.0477	-0.0375
	(-0.15)	(-0.73)	(-1.16)	(-1.65)	(-1.46)
TOBIN'S Q(t)	-0.0217	0.0023	-0.0262	-0.0771**	-0.0947***
	(-0.56)	(0.04)	(-0.61)	(-2.03)	(-2.92)
LEVERAGE(t)	-0.7838*	-0.6493	-0.4964	-0.5939	-0.8805*
	(-1.93)	(-1.60)	(-1.41)	(-1.60)	(-1.86)
ROE(t)	0.1677	0.3211*	0.2480*	0.2488**	0.3399**
	(0.78)	(1.84)	(1.99)	(2.17)	(2.49)
SALES_GROWTH(t)	0.0000	0.0001	0.0005*	0.0001	-0.0001
	(0.12)	(0.63)	(2.00)	(1.40)	(-1.37)
CASH_FLOW(t)	0.7895	0.7555*	0.2220	-0.4848	-0.9369***
	(1.51)	(1.75)	(0.51)	(-1.46)	(-2.73)
CASH(t)	-0.4653	0.3782	0.8313*	0.3888	0.0743
	(-1.02)	(0.97)	(1.76)	(1.04)	(0.19)
ECONOMIC_CONDITION(t)	0.0136	0.0408***	0.0187	-0.0321*	-0.0594***
	(0.78)	(3.64)	(1.26)	(-1.88)	(-4.00)
MACRO_UNCERTAINTY(t)	0.0219	0.0204	-0.0031	-0.0237	-0.0427**
	(1.06)	(1.65)	(-0.16)	(-1.07)	(-2.24)
N	2724	2723	2661	2596	2530
R^2	0.1917	0.2632	0.1404	0.1478	0.1391

Panel B: Consolidated industries

Dependent variable	*RELATIVE_INVEST*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT_RESI(t)	0.1245	0.0572b	0.1245	-0.0246	0.0659
	(1.00)	(0.78)	(1.55)	(-0.25)	(0.64)
EQUITY_SENTIMENT(t)	-0.0021	-0.0189	-0.0918**	-0.1133**	-0.0201
	(-0.05)	(-0.68)	(-2.63)	(-2.63)	(-0.50)
SIZE(t)	-0.0277	-0.0593*	-0.0553*	-0.0111	-0.0454
	(-0.73)	(-1.74)	(-1.77)	(-0.27)	(-1.55)
TOBIN'S Q(t)	-0.1355	0.0113	0.0324	0.0404	-0.0213
	(-1.65)	(0.17)	(0.45)	(0.56)	(-0.32)
LEVERAGE(t)	-1.0427*	-0.1585	0.1065	-0.5622	0.0643
	(-1.83)	(-0.43)	(0.20)	(-1.01)	(0.12)
ROE(t)	0.3463	0.2100	0.3227**	-0.1754	0.3022
	(1.06)	(0.86)	(2.39)	(-0.97)	(1.23)
SALES_GROWTH(t)	0.2500***	-0.0530	-0.1716**	-0.1673***	-0.0472
	(2.84)	(-1.13)	(-2.67)	(-2.96)	(-0.75)
CASH_FLOW(t)	-1.3309	-0.8958	0.0891	0.4880	1.1080
	(-1.34)	(-1.42)	(0.13)	(0.78)	(1.68)
CASH(t)	-1.3609*	-0.4963	-0.3698	-0.7626	-0.3897
	(-1.95)	(-1.10)	(-0.63)	(-1.06)	(-0.85)
ECONOMIC_CONDITION(t)	-0.0098	0.0395*	0.0563**	0.0091	-0.0511***
	(-0.43)	(1.79)	(2.67)	(0.46)	(-3.81)
MACRO_UNCERTAINTY(t)	-0.0090	-0.0659***	-0.0136	-0.0192	0.0052
	(-0.29)	(-2.88)	(-0.65)	(-0.99)	(0.27)
N	2694	2573	2447	2344	2258
R^2	0.0949	0.1132	0.1183	0.1126	0.1224

APPENDIX 1.G CREDIT MARKE SENTIMENT AND BOOM-BUST CYCLES: EVIDENCE BASED ON FITTED HHI

This table reports that credit market sentiment explains boom-bust cycles. I follow HP (2010) and use *FITTED_HHI* to define competitive and consolidated industries. The availability of *FITTED_HHI* makes the sample from 1977 to 2004. Panel A reports results based on Equation (1.11). In panel A, dependent variable is changes of operating cash flow. Panel B reports results based on Equation (1.12). Dependent variable in panel B is monthly abnormal returns between July of year t+2 and June of year t+3. Columns (1) and (3) (Columns (2) and (4)) are results based on competitive (consolidated) industries. All control variables are winsorized at the 1% and 99% levels. I cluster standard errors by industry and year. Numbers in parentheses are t-statistics and time. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Differences significant from the opposing tercile (competitive versus consolidated industries) are indicated at the 1% (a), 5% (b) and 10% (c).

Panel A: Firm-level cash flow changes

Dependent variable	Δ*CASH_FLOW(t+3)*			
Industry	Competitive	Consolidated	Competitive	Consolidated
	(1)	(2)	(3)	(4)
CREDIT_SENTIMENT(t)			-0.0311***b	-0.0124*b
			(-3.10)	(-1.78)
RELATIVE_VALUATION(t+1)	-0.0207***a	0.0049a	-0.0088*c	0.0010c
	(-2.65)	(1.34)	(-1.70)	(0.23)
RELATIVE_VALUATION_RESI(t+1)	-0.0014	0.0000	0.0014	0.0025
	(-0.34)	(0.01)	(0.27)	(0.85)
RELATIVE_INVEST(t+1)	-0.0062**	-0.0050*	-0.0026	-0.0033
	(-2.03)	(-1.65)	(-0.97)	(-0.92)
RELATIVE_INVEST_RESI(t+1)	-0.0029**	-0.0009	-0.0041**	-0.0011
	(-2.11)	(-0.44)	(-2.43)	(-0.39)
NEW_FINANCE(t+1)	0.0185	-0.0244	-0.0594	-0.0313
	(1.21)	(-0.63)	(-0.98)	(-0.52)
NEW_FINANCE_RESI(t+1)	0.0617***	0.0464***	0.0614***	0.0408*
	(3.91)	(3.17)	(2.91)	(1.75)
Δ*EBITDA(t+1)*	-0.0001	-0.0016***	0.0004	-0.0017***
	(-0.68)	(-4.26)	(0.57)	(-3.26)
Δ*CAPX(t+1)*	-0.0006**	-0.0011***	-0.0010***	-0.0016***
	(-2.21)	(-3.09)	(-2.59)	(-3.90)
N	29911	10772	29911	10772
R^2	0.0143	0.0121	0.0199	0.0146

Panel B: Firm-level stock returns

Dependent variable	*ABNOMAL_RET(t+3)*			
Industry	Competitive	Consolidated	Competitive	Consolidated
	(1)	(2)	(3)	(4)
CREDIT_SENTIMENT(t)			-0.0043**	-0.0009
			(-2.31)	(-0.83)
RELATIVE_VALUATION(t+1)	-0.0008*	-0.0004	-0.0005	-0.0005
	(-1.71)	(-0.84)	(-0.80)	(-0.86)
RELATIVE_VALUATION_RESI(t+1)	-0.0017***	-0.0006*	-0.0017***	-0.0006*
	(-4.34)	(-1.71)	(-4.30)	(-1.72)
RELATIVE_INVEST(t+1)	-0.0003*	-0.0004	0.0001	-0.0003
	(-1.75)	(-1.24)	(0.47)	(-1.16)
RELATIVE_INVEST_RESI(t+1)	-0.0001	-0.0001	-0.0000	-0.0001
	(-0.61)	(-0.46)	(-0.06)	(-0.44)
NEW_FINANCE(t+1)	-0.0052**	-0.0052	-0.0013	-0.0052
	(-2.33)	(-1.48)	(-0.37)	(-1.49)
NEW_FINANCE_RESI(t+1)	-0.0001	0.0009	-0.0004	0.0009
	(-0.19)	(0.56)	(-1.23)	(0.56)
N	322885	114141	322885	114141
R^2	0.0001	0.0000	0.0002	0.0000

APPENDIX 2.A VARIABLE DEFINITIONS

Variable	Definition
Lobbying variables	
INITIATION	An indicator set to one if a non-lobbying firm imitates lobbying, zero otherwise.
NON_LOBBY	An indicator set to one if a firm does not lobby.
ENTRY_EXPENSES	Entry barriers defined as lobbying expenses that firms spent in the year of lobbying initiation.
AVG_LOBBY_EXP	Average lobbying expenses in a year.
AVG_ENTRY_EXP	Average lobbying expenses in the year of lobbying initiation.
LOBBY	An indicator set to one if a firm lobbies in a given year, zero otherwise.
LOBBY_EXPENSES	The natural logarithm of lobbying expenses.
LOBBY_YEAR	The number of years that a lobbying firm has lobbied.
LOBBYIST_PRICE	Total annual lobbying expenses divided by total number of lobbyists. Total annual lobbying expenses and total number of lobbyists are available from the CRP.
Firm/industry-level variables	
SIZE	The natural logarithm of total assets.
MTB	The market value of equity divided by book value of equity.
R&D	The ratio of research and development expenditures to lagged total assets.
LEVERAGE	The ratio of the book value of total debt to the book value of total assets.
CASH_FLOW	Operating income before depreciation net of interest expenses, income taxes, and common dividends scaled by lagged total assets.
HERFINDAHL	Herfindahl index is sales concentration at the industry level.
WW	WW index is constructed following Whited and Wu (2006) and Hennessy and Whited (2007), as -0.091[(ib+dp)/at]-0.062[indicator set to one if dvc+dvp is positive, and zero otherwise]+0.021[dltt/at]-0.044[ln(at)]+0.102[average industry sales growth]-0.035[sales growth]. Firms are sorted into terciles based on index values in the previous year. Firms in the top tercile are coded as constrained, and those in the bottom tercile are coded as unconstrained.
HP	Hadlock and Pierce (2010) index, constructed as -0.737Size+0.043Size^2-0.04Age. Size is capped at (the log of)

	\$4.5 million, and age is capped at 37 years. Firms are sorted into terciles based on index values in the previous year. Firms in the top tercile are coded as constrained, and those in the bottom tercile are coded as unconstrained.
TOBIN's Q	Tobin's Q measured as market value of equity plus the book value of assets minus book value of equity plus deferred taxes, all divided by book value of assets.
CAPEX	Capital expenditure scaled by lagged total assets.
SALES_GROWTH	Sales growth measured as percentage change in sales.
Δ*EMPLOYEES*	Employee change measured as the percentage change in the number of employees.
DISTANCE	Natural logarithm of the distance between a firm's headquarter and Washington, D.C. (zip code 20001).
GOVERN_CUSTOMER	Government customer dummy variable that is equal to one if a firm has at least one government customer and zero otherwise.
Macro-level variables	
EPU_INDEX	Economic policy uncertainty measured as natural logarithm of Baker, Bloom, and Davis (BBD) index.
RESI_EPU	The residual of the regression of *EPU_INDEX* on Canadian policy uncertainty and macro-level controls.
HEALTHCAREPU	Healthcare policy uncertainty measured as natural logarithm of healthcare component of Baker, Bloom, and Davis (BBD) index.
PRISK	The average of firm-level political uncertainty proposed by Hassan et al. (2019) in a year.
INVEST_OPPORTUNITY	Investment opportunity measured as the first principal component of the following three variables. 1. Consumer confidence, survey-based index of consumer confidence developed by the University of Michigan 2. CFNAI, the Chicago Fed National Activity Index 3. Expected GDP growth, the average one-year-ahead GDP forecast from the biannual Livingstone Survey of Professional Forecasters
MACRO_UNCERTAINTY	Macro uncertainty measured as the first principal component of the following four variables. 1. JLN uncertainty, macroeconomic uncertainty index developed by Jurado, Ludvigson, and Ng (2015) 2. VXO index, implied volatility based on trading of S&P 100 options 3. CS σ past returns, cross-sectional standard deviation of cumulative returns from the past three months, using the entire

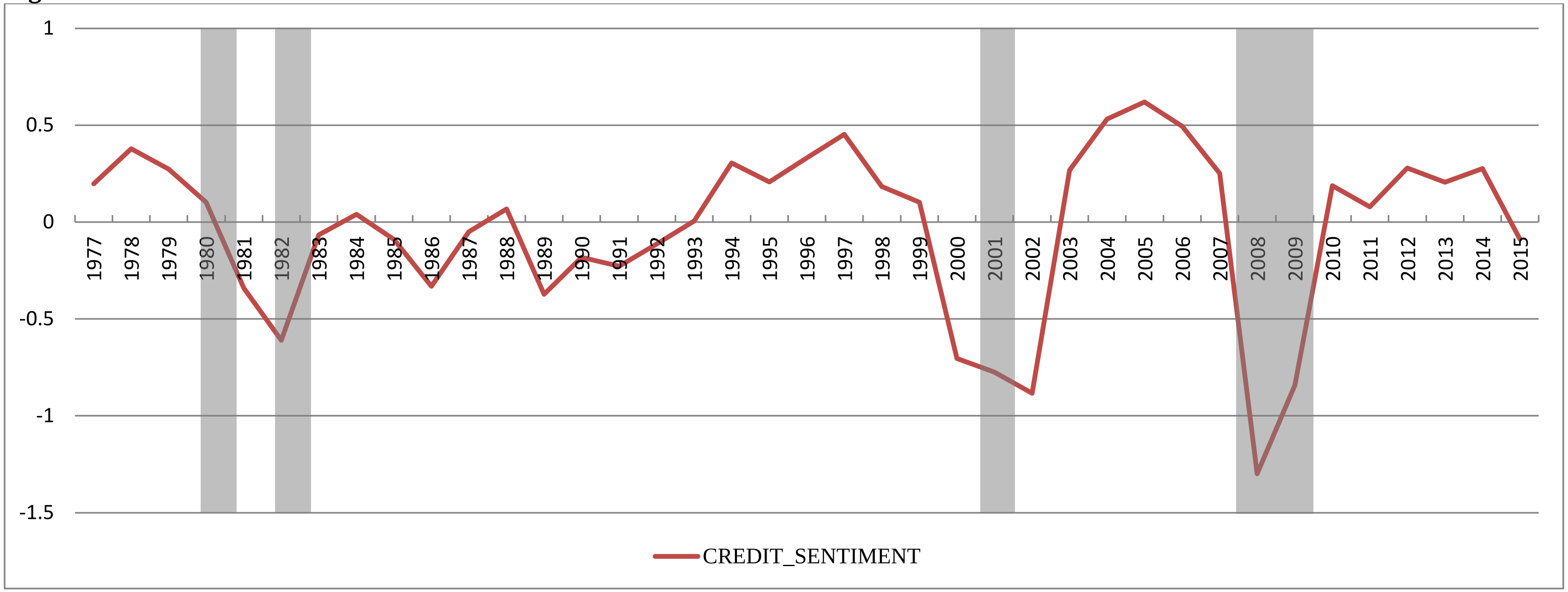
	CRSP universe 4. CS σ past sales growth, cross-sectional standard deviation of year-on-year sales growth, using the entire Compustat quarterly universe
ELECTION	A dummy variable equal to one if it is a presidential election year and zero otherwise.
POST_PLEA	Post-guilty plea period, defined as a dummy variable equal to one if the year is after 2006 (inclusive) and zero otherwise.
GDP_GROWTH	Expected GDP growth measured as the average one-year-ahead GDP forecast from the biannual Livingstone Survey of Professional Forecasters.

APPENDIX 2.B COVARIATE BALANCE BETWEEN LOBBYING FIRMS AND MATCHED NON-LOBBYING FIRMS

This table reports the univariate comparisons between lobbying firms and matched non-lobbying firms' characteristics. Lobbying firms and non-lobbying firms are matched based on propensity scores.

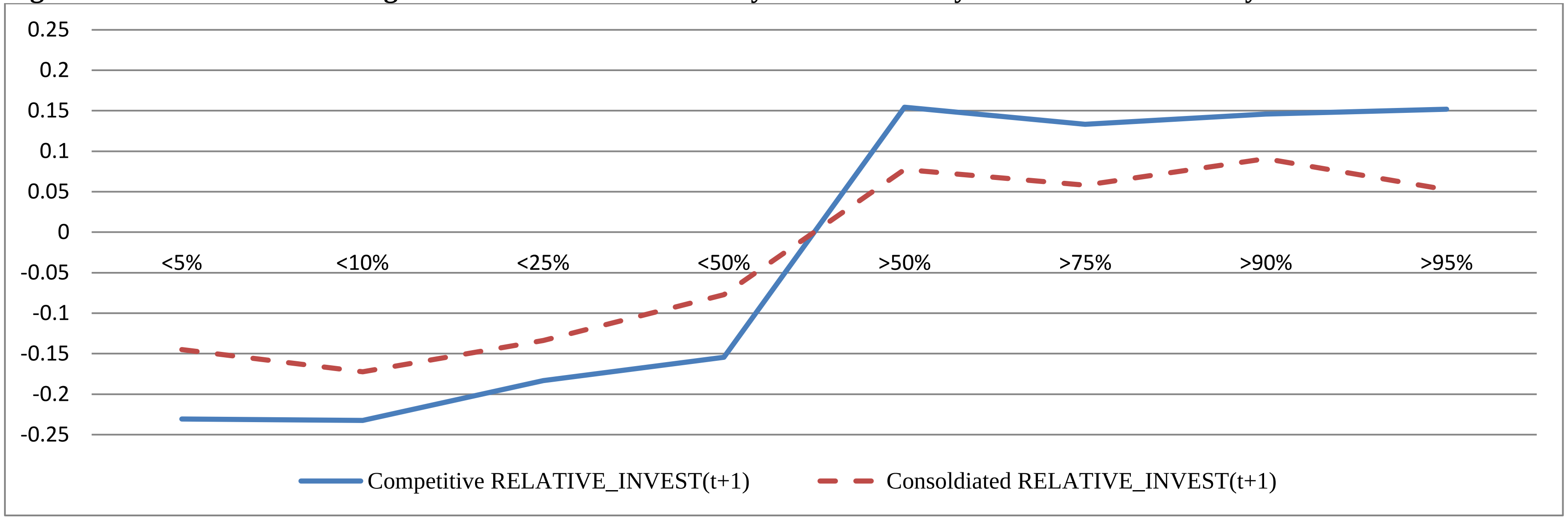
Variable	*LOBBY*=0	*LOBBY* =1	Difference in mean	T-statistic
SIZE	6.3318	6.3463	-0.0290	-0.9251
MTB	3.3521	3.2827	0.0694	0.5883
R&D	0.1065	0.0982	0.0083	0.3414
LEVERAGE	0.2765	0.2754	0.0011	0.1128
CASH_FLOW	0.0012	0.0121	-0.0109	-1.1288

Figure 1.1 Credit market sentiment over time



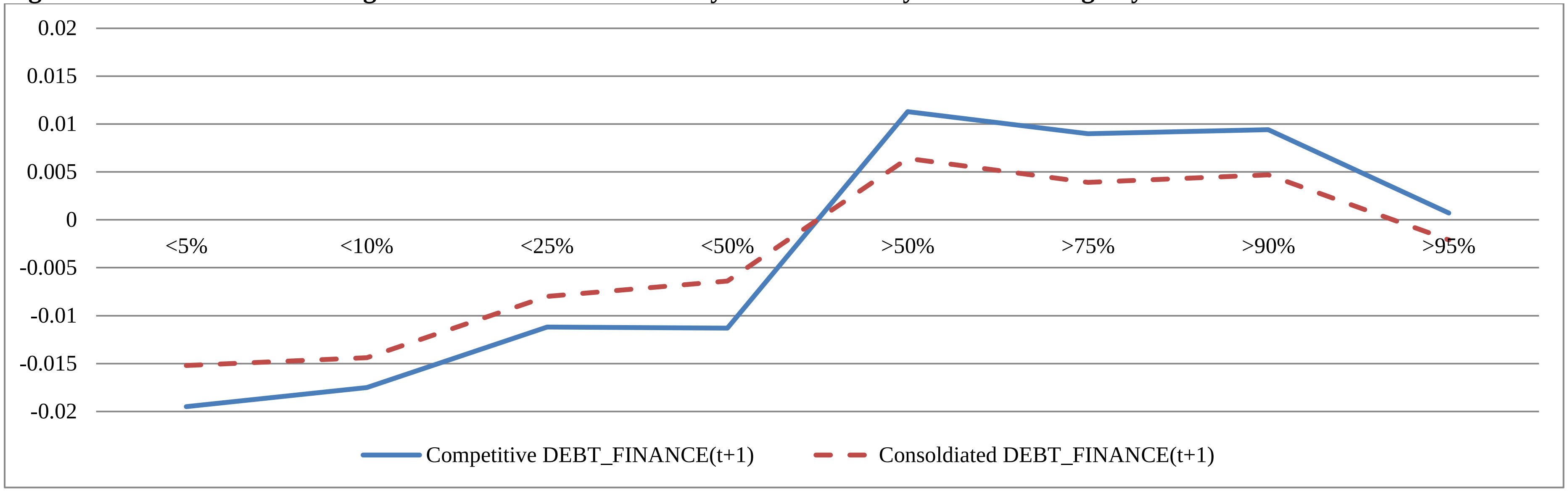
This figure plots the dynamic of credit market sentiment over years. The shaded vertical bars present yearly NBER recession indicator. Following Mclean and Zhao (2014), the yearly NBER recession indicator is set to one if at least 6 out of 12 months are during an economic recession defined by NBER, and zero otherwise.

Figure 1.2 Effects of low and high credit market sentiment in year t on industry relative investment in year t+1



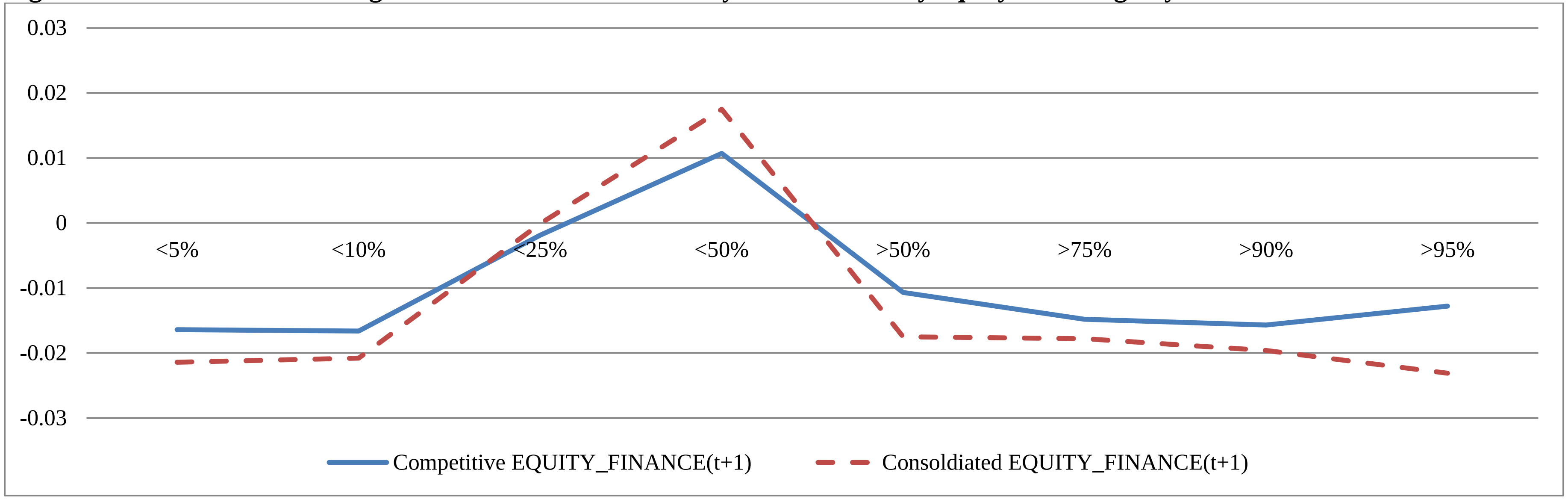
This figure plots the effects of low and high credit market sentiment in year t on relative investment in year t+1. The solid (dash) line is for competitive (consolidated) industries. High (low) credit market sentiment is defined as when credit market sentiment exceeds (falls) a given percentile threshold.

Figure 1.3 Effects of low and high credit market sentiment in year t on industry debt financing in year t+1



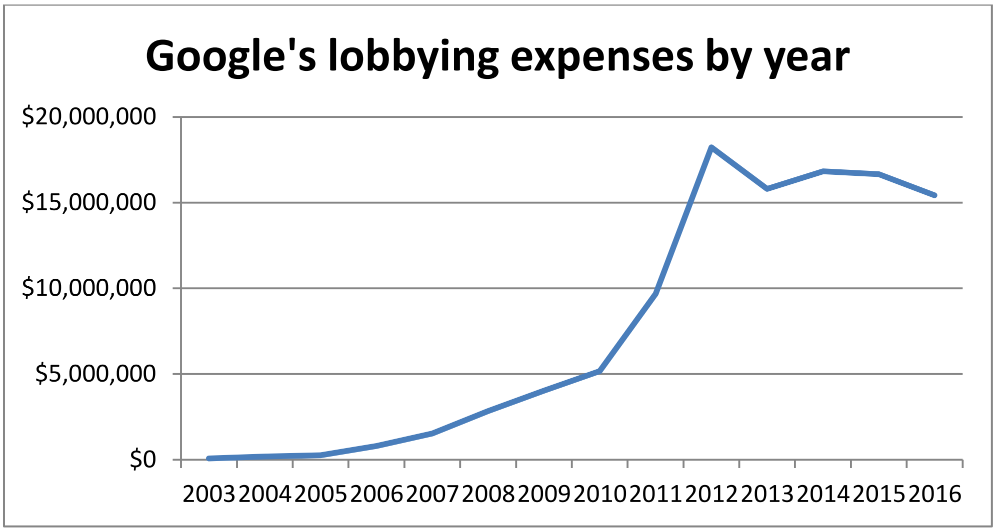
This figure plots the effects of low and high credit market sentiment in year t on industry debt financing in year t+1. The solid (dash) line is for competitive (consolidated) industries. High (low) credit market sentiment is defined as when credit market sentiment exceeds (falls) a given percentile threshold.

Figure 1.4 Effects of low and high credit market sentiment in year t on industry equity financing in year t+1



This figure plots the effects of low and high credit market sentiment in year t on industry equity financing in year t+1. The solid (dash) line is for competitive (consolidated) industries. High (low) credit market sentiment is defined as when credit market sentiment exceeds (falls) a given percentile threshold.

Figure 2.1 Google's lobbying expenses by year

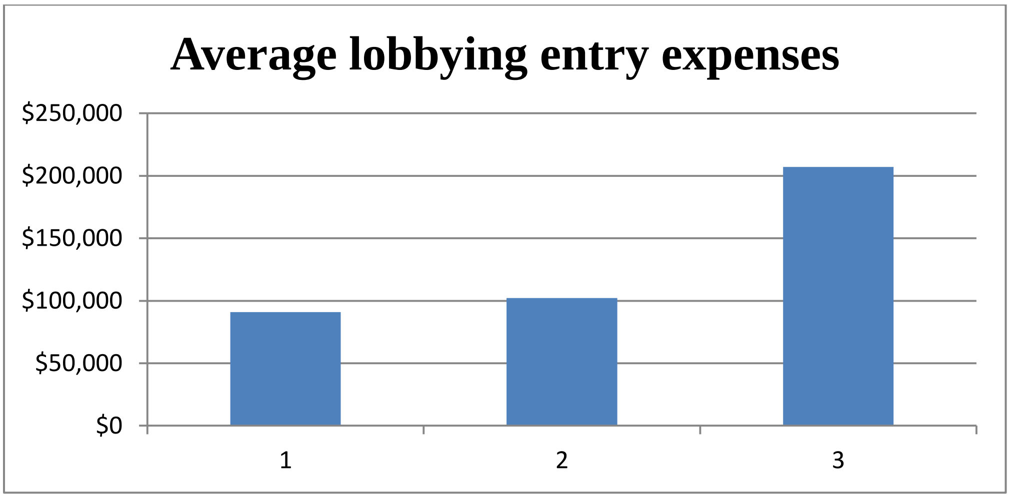


This figure shows the lobbying expenses of Google over the years.

Figure 2.2 Average number of lobbying initiation firms in low-, medium-, and high-EPU years

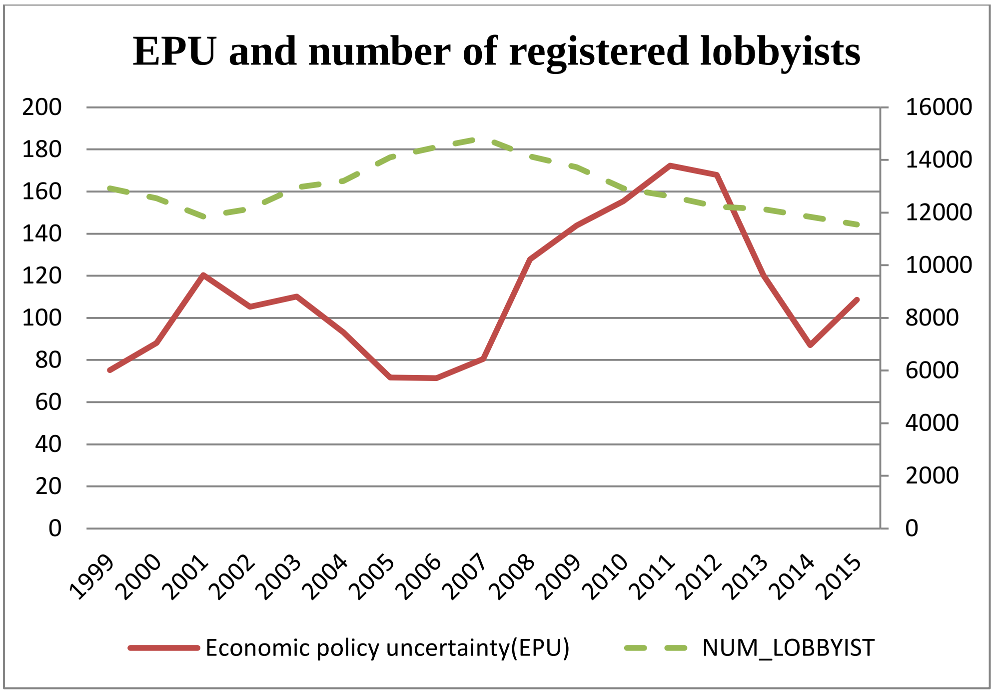
This figure shows the average number of lobbying initiation firms by *EPU_INDEX* tercile. Group 1 shows the low EPU years (tercile 1), while group 3 shows the high EPU years (tercile 3).

Figure 2.3 Average lobbying entry costs per firm in low-, medium-, and high-EPU years



This figure shows the average lobbying entry expenses (dollars amount) by *EPU_INDEX* tercile. Group 1 shows the low EPU years (tercile 1), while group 3 shows the high EPU years (tercile 3).

Figure 2.4 Number of registered lobbyists and policy uncertainty over time



This figure plots economic policy uncertainty (solid line) and the number of registered lobbyists (dashed line) over time. The level of economic policy uncertainty is shown in the left scale, while the number of lobbyists is shown in the right scale.

Table 1.1 Summary statistics

This table reports summary statistics for the main variables used in this study. Panel A reports summary statistics of firm-level variables in competitive and consolidated industries. Firm-level variables are used for firm-level analysis in the Section 1.6. Panel B reports summary statistics of industry-level variables in competitive and consolidated industries. Panel C reports summary statistics of market-level variables. Industry-level variables are used for industry-level analysis in Sections 1.4 and 1.5. The sample periods of panels B and C are 1977-2015. All variables are defined in Appendix A. Except for *ABNORMAL_RET*, all variables in panel A and B are winsorized at the 1% and 99% levels.

Panel A: Firm level variables			
Competitive industries			
Variable	MEAN	STD	N
FIRM_RELATIVE_INVEST	-0.090	1.139	75,407
Δ*CASH_FLOW*	-0.008	0.112	75,407
ABNORMAL_RET	0.000	0.181	884,705
Δ*EBITDA*	0.044	0.829	75,407
Δ*CAPX*	0.320	0.912	75,407
Consolidated industries			
Variable	MEAN	STD	N
FIRM_RELATIVE_INVEST	-0.071	1.311	17,681
Δ*CASH_FLOW*	-0.006	0.082	17,681
ABNORMAL_RET	0.000	0.158	208,868
Δ*EBITDA*	0.047	0.755	17,681
Δ*CAPX*	0.310	0.870	17,681

Panel B: Industry level variables

Competitive industries			
Variable	MEAN	STD	N
RELATIVE_INVEST	-0.051	0.512	2724
DEBT_FINANCE	0.011	0.036	2724
EQUITY_FINANCE	0.033	0.060	2724
SIZE	5.722	1.403	2724
TOBIN'SQ	1.575	0.588	2724
LEV	0.196	0.083	2724
ROE	0.052	0.135	2724
GROSS_MARGIN	0.197	0.519	2724
SALES_GROWTH	0.258	0.632	2724
CASH_FLOW	0.104	0.066	2724
CASH	0.123	0.076	2724
Consolidated industries			
Variable	MEAN	STD	N
RELATIVE_INVEST	-0.039	0.923	2694
DEBT_FINANCE	0.008	0.060	2694
EQUITY_FINANCE	0.025	0.102	2694
SIZE	5.367	1.461	2694
TOBIN'SQ	1.545	0.643	2694
LEV	0.184	0.102	2694
ROE	0.078	0.170	2694
GROSS_MARGIN	0.246	0.441	2694
SALES_GROWTH	0.164	0.438	2694
CASH_FLOW	0.122	0.076	2694
CASH	0.114	0.081	2694

Panel C: Market level variables

Variable	MEAN	STD	N
CREDIT_SENTIMENT	-0.029	0.434	39
EQUITY_SENTIMENT	0.182	0.694	39
INVESTMENT_OPPORTUNITY	-0.051	1.441	39
MACRO_UNCERTAINTY	0.017	1.081	39

Table 1.2 Correlation coefficients between credit market sentiment and other macro variables

This table reports correlation coefficients between credit market sentiment (*CREDIT_SENTIMENT*) and other macro variables. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

		(1)	(2)	(3)	(4)
(1)	*CREDIT_SENTIMENT*	1			
(2)	*EQUITY_SENTIMENT*	-0.18	1		
(3)	*ECONOMIC_CONDITION*	0.51***	-0.06	1	
(4)	*MACRO_UNCERTAINTY*	-0.08	0.15	-0.08	1

Table 1.3 Credit market sentiment and industry relative investments

This table reports how credit market sentiment in year t affects industry relative investments in years t to t+4. The dependent variable is industry-level *RELATIVE_INVEST*. For the explanatory variable *CREDIT_SENTIMENT*, I multiply excess bond premium developed by Gilchrist and Zakrajsek (2012) by -1. Panel A (panel B) reports results based on competitive (consolidated) industries. All control variables are winsorized at the 1% and 99% levels. In all models, I include three-digit SIC industry fixed effects and cluster standard errors by industry and year. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively. Statistical significance for the difference in the coefficients of *CREDIT_SENTIMENT* between competitive versus consolidated industries is indicated by a, b, and c, for significance at the 1%, 5% and 10%, respectively.

Panel A: Competitive industries

Dependent variable	*RELATIVE_INVEST*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	0.1567***	0.2171***b	0.1495**	0.0620	-0.0478
	(3.18)	(5.63)	(2.71)	(1.04)	(-1.17)
EQUITY_SENTIMENT(t)	0.0148	0.0183	-0.0416*	-0.0469*	-0.0372
	(0.57)	(0.89)	(-1.90)	(-1.92)	(-1.57)
SIZE(t)	0.0046	0.0007	-0.0322	-0.0486*	-0.0397
	(0.21)	(0.04)	(-1.34)	(-1.70)	(-1.57)
TOBIN'S Q(t)	-0.0389	0.0031	-0.0176	-0.0705*	-0.0925***
	(-1.08)	(0.06)	(-0.42)	(-1.87)	(-2.87)
LEVERAGE(t)	-0.7781**	-0.6307*	-0.4788	-0.6734*	-0.7887*
	(-2.07)	(-1.73)	(-1.38)	(-1.87)	(-1.82)
ROE(t)	0.1663	0.2876*	0.2610**	0.2265**	0.3135**
	(0.80)	(1.78)	(2.14)	(2.06)	(2.46)
SALES_GROWTH(t)	0.0986***	0.0339*	-0.0108	-0.0317*	-0.0206
	(2.88)	(1.76)	(-0.34)	(-1.79)	(-0.98)
CASH_FLOW(t)	0.7528	0.8197*	0.2013	-0.4541	-0.8646**
	(1.59)	(1.98)	(0.47)	(-1.38)	(-2.69)
CASH(t)	-0.5402	0.4820	0.8240*	0.4225	0.1241
	(-1.28)	(1.32)	(1.81)	(1.21)	(0.33)
INVESTMENT_OPPORTUNITY(t)	-0.0152	0.0033	-0.0109	-0.0435**	-0.0515**
	(-0.82)	(0.23)	(-0.55)	(-2.07)	(-2.64)
MACRO_UNCERTAINTY(t)	0.0246	0.0202	-0.0059	-0.0247	-0.0435**
	(1.21)	(1.41)	(-0.29)	(-1.12)	(-2.30)
N	2724	2723	2661	2596	2530
R^2	0.1796	0.2295	0.1376	0.1484	0.1390

Panel B: Consolidated industries

Dependent variable	*RELATIVE_INVEST*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	0.0865	0.0620b	0.1175	0.0273	0.0618
	(0.76)	(0.89)	(1.54)	(0.33)	(0.66)
EQUITY_SENTIMENT(t)	-0.0277	-0.0431	-0.0929***	-0.0819**	-0.0081
	(-0.83)	(-1.59)	(-2.83)	(-2.13)	(-0.24)
SIZE(t)	-0.0252	0.0328	-0.0697***	0.0130	-0.0520**
	(-0.75)	(1.53)	(-3.10)	(0.46)	(-2.39)
TOBIN'S Q(t)	0.0382	0.0699***	0.0401	0.0080	-0.0079
	(1.28)	(2.75)	(0.44)	(0.46)	(-0.39)
LEVERAGE(t)	-0.0575**	-0.0735**	-0.1295	-0.0283	-0.0571**
	(-2.05)	(-2.65)	(-0.34)	(-0.92)	(-2.54)
ROE(t)	-0.1107**	-0.0182	0.1108	0.0024	-0.0410
	(-2.49)	(-0.40)	(1.31)	(0.05)	(-1.06)
SALES_GROWTH(t)	-0.7977**	-0.3723	-0.0991*	-0.5185	0.0950
	(-2.15)	(-1.58)	(-1.90)	(-1.37)	(0.30)
CASH_FLOW(t)	-0.2238	0.1387	0.3755	-0.0678	0.0173
	(-1.37)	(0.72)	(0.77)	(-1.30)	(0.22)
CASH(t)	0.1549**	0.0609	-0.1753	-0.1173**	-0.0489
	(2.39)	(0.97)	(-0.40)	(-2.34)	(-0.86)
INVESTMENT_OPPORTUNITY(t)	-0.5573	-0.2309	0.0321	0.5781	1.0530**
	(-1.00)	(-0.50)	(1.37)	(1.30)	(2.29)
MACRO_UNCERTAINTY(t)	-0.9627*	-0.1876	0.0180	-0.7774*	-0.0519
	(-1.96)	(-0.52)	(0.81)	(-1.72)	(-0.15)
N	2694	2573	2447	2344	2258
R^2	0.1223	0.1328	0.1414	0.1232	0.1345

Table 1.4 Cross-sectional analyses for competitive industries

This table reports cross-sectional analyses for effects of credit market sentiment on relative investments of competitive industries. Panels A and B present results for competitive industries with various levels of product competition. To proxy for competition, I use product similarity in panel A and product similarity in panel B. Panels C-E document results for competitive industries with different illiquidity conditions. The proxies for industry illiquidity are proportion of firms without credit rating (NON_RATE_RATIO) in panel C, net leverage (NET_LEV) in panel D, and inverse of quick ratio (ILLIQ) in panel E. Due to a high correlation between net leverage and book leverage, I do not control book leverage in panel D. All control variables are winsorized at the 1% and 99% levels. In all models, I include three-digit SIC industry fixed effects and cluster standard errors by industry and year. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Product Market Fluidity

Dependent variable	*RELATIVE_INVEST*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	0.2072***	0.1378**	0.1002*	0.0979	-0.0243
	(2.90)	(2.12)	(1.79)	(1.23)	(-0.27)
FLUIDITY(t)	-0.0322	-0.0376*	-0.0285	-0.0714***	-0.0889***
	(-1.63)	(-2.10)	(-1.30)	(-3.39)	(-5.46)
*CREDIT_SENTIMENT(t) *FLUIDITY(t)*	0.0098	0.0184**	0.0135	0.0030	0.0015
	(1.23)	(2.28)	(1.53)	(0.25)	(0.12)
EQUITY_SENTIMENT(t)	0.1082*	0.0372	-0.0640**	-0.0685**	-0.0478
	(1.81)	(1.21)	(-2.35)	(-2.25)	(-1.36)
SIZE(t)	-0.0028	-0.0072	-0.0525	-0.0510	0.0494
	(-0.07)	(-0.21)	(-1.36)	(-1.13)	(0.86)
TOBIN'S Q(t)	-0.0321	-0.0332	-0.0501	-0.0941*	-0.0758
	(-0.69)	(-0.60)	(-1.01)	(-1.94)	(-1.63)
LEVERAGE(t)	-0.0901	-0.9608*	-0.6435	-0.5968	-0.3602
	(-0.15)	(-1.90)	(-1.26)	(-1.44)	(-0.68)
ROE(t)	0.0978	-0.0032	0.1403	0.1457*	0.0045
	(0.72)	(-0.02)	(1.19)	(1.92)	(0.03)
SALES_GROWTH(t)	0.0608**	0.0377**	0.0426*	0.0190	-0.0011
	(2.22)	(2.11)	(1.75)	(0.76)	(-0.03)
CASH_FLOW(t)	0.5544	1.2301***	0.8777**	-0.4173	-1.2019**
	(1.61)	(2.96)	(2.27)	(-0.85)	(-2.76)
CASH(t)	-0.4673	0.9394*	1.3192**	1.2493**	0.7975**
	(-0.89)	(2.00)	(2.32)	(2.66)	(2.67)
ECONOMIC_CONDITION(t)	-0.0467	-0.0053	-0.0374	-0.0650**	-0.0584**
	(-1.69)	(-0.33)	(-1.55)	(-2.62)	(-2.31)
MACRO_UNCERTAINTY(t)	-0.0509*	-0.0519***	-0.0096	0.0220	0.0638**
	(-1.82)	(-3.05)	(-0.45)	(0.92)	(2.30)
N	1305	1304	1242	1177	1111
R^2	0.2742	0.3013	0.2449	0.2525	0.3008

Panel B: Product similarity

Dependent variable	*RELATIVE_INVEST*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	0.2373***	0.2314***	0.2040***	0.1167*	-0.0249
	(4.96)	(4.44)	(2.96)	(1.76)	(-0.45)
SIMILARITY(t)	0.0094	-0.0051	-0.0187	-0.0331	-0.0152
	(1.71)	(-0.42)	(-1.43)	(-1.69)	(-0.65)
*CREDIT_SENTIMENT(t) *SIMILARITY(t)*	0.0015	0.0131**	0.0104	0.0020	-0.0001
	(0.22)	(2.11)	(1.34)	(0.21)	(-0.01)
EQUITY_SENTIMENT(t)	0.0902	0.0207	-0.0733***	-0.0861**	-0.0658*
	(1.48)	(0.61)	(-2.88)	(-2.73)	(-1.82)
SIZE(t)	-0.0071	-0.0210	-0.0795**	-0.0808*	-0.0033
	(-0.20)	(-0.64)	(-2.21)	(-1.86)	(-0.06)
TOBIN'S Q(t)	-0.0287	-0.0335	-0.0429	-0.0841	-0.0672
	(-0.62)	(-0.60)	(-0.85)	(-1.61)	(-1.39)
LEVERAGE(t)	-0.0870	-0.7956	-0.5519	-0.6755	-0.5843
	(-0.15)	(-1.43)	(-1.07)	(-1.53)	(-1.11)
ROE(t)	0.1121	0.1432	0.2393**	0.1875**	0.1157
	(0.84)	(0.95)	(2.15)	(2.49)	(0.86)
SALES_GROWTH(t)	0.0625**	0.0361*	0.0372	0.0100	0.0015
	(2.22)	(1.86)	(1.54)	(0.37)	(0.04)
CASH_FLOW(t)	1.0084*	1.1193**	0.4216	-0.3864	-1.2029**
	(2.07)	(2.19)	(1.03)	(-0.75)	(-2.61)
CASH(t)	-0.6424	0.8401	0.9004	0.7156	0.2711
	(-1.11)	(1.57)	(1.51)	(1.21)	(0.49)
ECONOMIC_CONDITION(t)	-0.0509*	-0.0185	-0.0586**	-0.0767**	-0.0638**
	(-1.80)	(-1.18)	(-2.43)	(-2.41)	(-2.37)
MACRO_UNCERTAINTY(t)	-0.0530*	-0.0532***	-0.0129	0.0127	0.0563**
	(-1.95)	(-3.17)	(-0.61)	(0.52)	(2.14)
N	1382	1381	1319	1254	1188
R^2	0.2626	0.2858	0.2433	0.2190	0.2423

Panel C: Proportion of firms without credit rating

Dependent variable	*RELATIVE_INVEST*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	-0.0608	0.0568	0.0160	0.0008	-0.0648
	(-0.68)	(0.71)	(0.17)	(0.01)	(-0.69)
NON_RATE_RATIO(t)	-0.0400	-0.0078	-0.0835	-0.1987*	0.0034
	(-0.27)	(-0.08)	(-0.87)	(-1.82)	(0.03)
*CREDIT_SENTIMENT*NON_RATE_RATIO(t)*	0.3096***	0.2441**	0.1985*	0.1123	0.0438
	(3.18)	(2.52)	(1.79)	(0.76)	(0.33)
EQUITY_SENTIMENT(t)	0.0228	0.0312	-0.0336	-0.0418	-0.0458**
	(0.89)	(1.58)	(-1.54)	(-1.55)	(-2.10)
SIZE(t)	-0.0033	-0.0002	-0.0410	-0.0755**	-0.0317
	(-0.12)	(-0.01)	(-1.49)	(-2.50)	(-1.23)
TOBIN'S Q(t)	-0.0392	0.0083	-0.0290	-0.0820**	-0.0976***
	(-1.01)	(0.15)	(-0.71)	(-2.20)	(-2.98)
LEVERAGE(t)	-0.8477*	-0.7075	-0.5705	-0.7272*	-1.0139**
	(-1.96)	(-1.68)	(-1.58)	(-1.88)	(-2.12)
ROE(t)	0.1903	0.3126*	0.3188**	0.3069**	0.3679**
	(0.86)	(1.86)	(2.52)	(2.61)	(2.63)
SALES_GROWTH(t)	0.0972***	0.0001	-0.0190	-0.0397**	-0.0176
	(2.85)	(0.58)	(-0.59)	(-2.22)	(-0.75)
CASH_FLOW(t)	0.8782	0.6402	0.0527	-0.6680*	-1.2422***
	(1.47)	(1.48)	(0.11)	(-1.95)	(-3.98)
CASH(t)	-0.4664	0.3908	0.8230*	0.4138	-0.1184
	(-1.06)	(1.02)	(1.75)	(1.08)	(-0.33)
ECONOMIC_CONDITION(t)	-0.0168	0.0011	-0.0080	-0.0422*	-0.0488**
	(-0.93)	(0.08)	(-0.39)	(-1.89)	(-2.63)
MACRO_UNCERTAINTY(t)	0.0240	0.0235	0.0016	-0.0138	-0.0421**
	(1.19)	(1.67)	(0.08)	(-0.61)	(-2.12)
N	2724	2723	2661	2596	2642
R^2	0.2009	0.2643	0.1429	0.1525	0.1343

Panel D: Net leverage

Dependent variable	*RELATIVE_INVEST*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	0.1448***	0.2038***	0.1290**	0.0555	-0.0469
	(2.96)	(5.71)	(2.48)	(0.86)	(-1.13)
NET_LEV(t)	-0.0205	-0.0257*	-0.0124	0.0137	0.0324
	(-1.04)	(-1.98)	(-0.74)	(0.67)	(1.02)
*CREDIT_SENTIMENT(t)*NET_LEV(t)*	0.0132	0.0395**	0.0367	0.0368	0.0199
	(0.40)	(2.28)	(1.31)	(1.34)	(0.65)
EQUITY_SENTIMENT(t)	0.0154	0.0258	-0.0373*	-0.0383	-0.0303
	(0.63)	(1.40)	(-1.69)	(-1.49)	(-1.20)
SIZE(t)	-0.0026	0.0028	-0.0276	-0.0520*	-0.0437*
	(-0.14)	(0.16)	(-1.20)	(-1.87)	(-1.80)
TOBIN'S Q(t)	-0.0264	0.0045	-0.0279	-0.0737**	-0.0894***
	(-0.85)	(0.10)	(-0.84)	(-2.35)	(-3.43)
ROE(t)	0.1610	0.3072**	0.2468**	0.2549**	0.3554***
	(0.83)	(2.04)	(2.62)	(2.50)	(3.10)
SALES_GROWTH(t)	0.0001	0.0001	0.0005**	0.0002*	-0.0001
	(0.29)	(0.73)	(2.06)	(1.82)	(-0.93)
CASH_FLOW(t)	0.8050*	0.7120**	0.2926	-0.3841	-0.8018***
	(1.78)	(2.19)	(0.87)	(-1.36)	(-3.21)
CASH(t)	-0.1601	0.6321**	0.9884***	0.6466**	0.5159*
	(-0.46)	(2.55)	(3.18)	(2.55)	(1.98)
ECONOMIC_CONDITION(t)	-0.0142	0.0032	-0.0062	-0.0440**	-0.0517***
	(-0.83)	(0.26)	(-0.33)	(-2.10)	(-2.74)
MACRO_UNCERTAINTY(t)	0.0197	0.0172	-0.0053	-0.0237	-0.0406**
	(1.02)	(1.21)	(-0.27)	(-1.07)	(-2.24)
N	2724	2723	2661	2596	2642
R^2	0.1871	0.2595	0.1373	0.1459	0.1351

Panel E: Asset illiquidity

Dependent variable	*RELATIVE_INVEST*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	0.1385***	0.1815***	0.1416***	0.0419	-0.0114
	(2.76)	(6.15)	(3.00)	(0.73)	(-0.25)
ILLIQ(t)	-0.0536***	-0.0345***	-0.0153	0.0201	0.0227
	(-4.70)	(-3.19)	(-1.25)	(1.26)	(0.63)
*CREDIT_SENTIMENT(t)*ILLIQ(t)*	-0.0010	0.0306*	0.0175	0.0399	-0.0437
	(-0.05)	(1.76)	(0.71)	(1.48)	(-1.27)
EQUITY_SENTIMENT(t)	-0.0156	-0.0096	-0.0484**	-0.0606***	-0.0465**
	(-0.58)	(-0.50)	(-2.37)	(-3.01)	(-2.29)
SIZE(t)	-0.0117	0.0063	-0.0244	-0.0433	-0.0250
	(-0.61)	(0.40)	(-1.05)	(-1.68)	(-1.18)
TOBIN'S Q(t)	0.0178	0.0257	-0.0112	-0.0657**	-0.0963***
	(0.54)	(0.90)	(-0.35)	(-2.38)	(-3.10)
LEVERAGE(t)	-0.3474	-0.7087***	-0.4996**	-0.7409***	-0.9700***
	(-1.19)	(-2.88)	(-2.23)	(-2.80)	(-2.90)
ROE(t)	0.2120	0.3549**	0.2512***	0.1939**	0.2256**
	(1.33)	(2.47)	(3.25)	(2.06)	(2.44)
SALES_GROWTH(t)	0.0931***	0.0456**	-0.0156	-0.0298	-0.0115
	(2.77)	(2.14)	(-0.47)	(-1.58)	(-0.52)
CASH_FLOW(t)	0.7050*	0.6916**	0.2285	-0.5665*	-0.9510***
	(1.69)	(2.29)	(0.77)	(-1.78)	(-3.79)
CASH(t)	-0.2780	0.3055	0.5961**	0.0890	-0.2655
	(-1.02)	(1.46)	(2.20)	(0.35)	(-1.05)
ECONOMIC_CONDITION(t)	-0.0278*	-0.0018	-0.0151	-0.0466**	-0.0497***
	(-1.80)	(-0.15)	(-0.78)	(-2.22)	(-2.84)
MACRO_UNCERTAINTY(t)	0.0011	0.0019	-0.0134	-0.0344	-0.0410**
	(0.06)	(0.18)	(-0.60)	(-1.47)	(-2.22)
N	2724	2723	2661	2596	2642
R^2	0.1864	0.2707	0.1528	0.1306	0.1351

Table 1.5 Credit market sentiment and industry debt financing

This table reports how credit market sentiment affects industry debt financing. The dependent variable is industry-level *DEBT_FINANCE*. Panel A (panel B) reports results based on competitive (consolidated) industries. All control variables are winsorized at the 1% and 99% levels. In all models, I include three-digit SIC industry fixed effects and cluster standard errors by industry and year. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively. Statistical significance for the difference in the coefficients of *CREDIT_SENTIMENT* between competitive versus consolidated industries is indicated by a, b, and c, for significance at the 1%, 5% and 10%, respectively.

Panel A: Competitive industries

Dependent variable	*DEBT_FINANCE*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	0.0102**c	0.0139***b	0.0099**	0.0031	0.0010
	(2.67)	(5.34)	(2.42)	(0.64)	(0.24)
EQUITY_SENTIMENT(t)	0.0031	0.0010	-0.0006	-0.0008	-0.0008
	(1.58)	(0.68)	(-0.31)	(-0.48)	(-0.53)
SIZE(t)	-0.0013	-0.0015	-0.0023	-0.0035	-0.0027
	(-0.99)	(-1.12)	(-1.25)	(-1.55)	(-1.25)
TOBIN'S Q(t)	0.0060***	0.0103***	0.0071***	0.0043**	-0.0019
	(3.06)	(4.47)	(3.24)	(2.08)	(-1.03)
LEVERAGE(t)	0.2136***	-0.0221	-0.0734***	-0.0484**	-0.0647**
	(8.52)	(-1.10)	(-3.52)	(-2.29)	(-2.20)
ROE(t)	0.0025	0.0212**	0.0212***	0.0149	0.0187*
	(0.34)	(2.20)	(3.16)	(1.68)	(1.91)
SALES_GROWTH(t)	0.0076***	0.0041***	0.0006	-0.0014	-0.0026
	(4.61)	(2.80)	(0.50)	(-0.78)	(-1.67)
CASH_FLOW(t)	0.0406**	0.0318	0.0310	0.0399*	-0.0268
	(2.25)	(1.59)	(1.63)	(1.75)	(-1.40)
CASH(t)	0.0170	-0.0133	-0.0185	0.0286	-0.0020
	(0.90)	(-0.65)	(-0.87)	(1.16)	(-0.08)
INVESTMENT_OPPORTUNITY(t)	-0.0005	0.0008	-0.0003	-0.0014	-0.0014
	(-0.53)	(0.91)	(-0.18)	(-0.93)	(-1.26)
MACRO_UNCERTAINTY(t)	0.0020	0.0013	0.0007	-0.0011	-0.0002
	(1.40)	(1.21)	(0.40)	(-0.51)	(-0.11)
N	2724	2723	2661	2596	2530
R^2	0.2474	0.2171	0.1807	0.1472	0.1309

Panel B: Consolidated industries

Dependent variable	*DEBT_FINANCE*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	0.0003c	0.0038b	0.0033	0.0070	0.0061
	(0.06)	(0.95)	(0.98)	(1.18)	(1.08)
EQUITY_SENTIMENT(t)	-0.0001	0.0034*	0.0029	0.0015	0.0018
	(-0.04)	(1.96)	(1.68)	(0.66)	(0.87)
SIZE(t)	0.0014	-0.0007	-0.0006	-0.0035**	-0.0051***
	(0.86)	(-0.54)	(-0.42)	(-2.31)	(-2.97)
TOBIN'S Q(t)	0.0002	0.0064**	0.0068***	0.0034	0.0035
	(0.08)	(2.67)	(2.91)	(1.66)	(1.37)
LEVERAGE(t)	0.1582***	-0.0665***	-0.0688***	-0.0467***	-0.0676***
	(9.74)	(-4.63)	(-4.39)	(-4.54)	(-4.40)
ROE(t)	0.0074	0.0076*	0.0086	0.0119	-0.0036
	(1.03)	(1.69)	(1.15)	(1.66)	(-0.35)
SALES_GROWTH(t)	0.0120***	0.0010	-0.0004	0.0042	-0.0015
	(4.08)	(0.39)	(-0.17)	(1.05)	(-0.59)
CASH_FLOW(t)	-0.0026	0.0282***	0.0468***	-0.0050	0.0040
	(-0.14)	(3.73)	(2.73)	(-0.27)	(0.17)
CASH(t)	0.0343*	-0.0090	-0.0251*	0.0043	-0.0381*
	(1.89)	(-0.64)	(-1.90)	(0.23)	(-1.73)
INVESTMENT_OPPORTUNITY(t)	0.0029**	0.0038***	0.0043***	-0.0022	-0.0042**
	(2.10)	(3.25)	(4.50)	(-1.22)	(-2.55)
MACRO_UNCERTAINTY(t)	0.0024	-0.0017	-0.0017	-0.0013	-0.0031**
	(1.27)	(-0.98)	(-0.92)	(-0.95)	(-2.32)
N	2694	2573	2447	2344	2258
R^2	0.1934	0.1672	0.1758	0.1323	0.1442

Table 1.6 Credit market sentiment and industry equity financing

This table reports how credit market sentiment affects industry equity financing. The dependent variable is industry-level *EQUITY_FINANCE*. Panel A (panel B) reports results based on competitive (consolidated) industries. All control variables are winsorized at the 1% and 99% levels. In all models, I include three-digit SIC industry fixed effects and cluster standard errors by industry and year. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively. Statistical significance for the difference in the coefficients of *CREDIT_SENTIMENT* between competitive versus consolidated industries is indicated by a, b, and c, for significance at the 1%, 5% and 10%, respectively.

Panel A: Competitive industries

Dependent variable	*EQUITY_FINANCE*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	-0.0006	-0.0029	0.0038	0.0036	-0.0056
	(-0.17)	(-0.55)	(0.69)	(0.60)	(-1.06)
EQUITY_SENTIMENT(t)	0.0054**	-0.0007	0.0038	0.0055**	-0.0023
	(2.39)	(-0.22)	(1.03)	(2.45)	(-0.77)
SIZE(t)	-0.0203***	-0.0203***	-0.0194***	-0.0183***	-0.0187***
	(-10.45)	(-8.88)	(-7.70)	(-6.41)	(-6.80)
TOBIN'S Q(t)	0.0374***	0.0315***	0.0136***	0.0044	0.0056
	(7.82)	(6.23)	(3.20)	(1.29)	(1.47)
LEVERAGE(t)	-0.0092	0.0513	0.0506	0.1016**	0.0663
	(-0.34)	(1.59)	(1.42)	(2.25)	(1.38)
ROE(t)	-0.0043**	-0.0031	0.0021	0.0016	0.0004
	(-2.53)	(-1.28)	(1.04)	(0.68)	(0.20)
SALES_GROWTH(t)	0.0072***	0.0018	0.0012	0.0010	0.0036***
	(4.15)	(0.94)	(0.83)	(0.64)	(3.43)
CASH_FLOW(t)	-0.1579***	-0.1147***	-0.0883**	0.0018	0.0181
	(-5.55)	(-3.27)	(-2.71)	(0.05)	(0.53)
CASH(t)	0.1030***	-0.0601	-0.0837*	-0.0239	-0.0636
	(2.74)	(-1.38)	(-1.90)	(-0.52)	(-1.30)
ECONOMIC_CONDITION (t)	0.0005	-0.0032*	-0.0040*	-0.0025	-0.0014
	(0.47)	(-1.77)	(-1.97)	(-1.22)	(-0.87)
MACRO_UNCERTAINTY(t)	-0.0030**	0.0009	0.0014	-0.0005	0.0006
	(-2.11)	(0.49)	(0.68)	(-0.28)	(0.35)
N	2724	2723	2661	2596	2530
R^2	0.6458	0.5363	0.5006	0.4807	0.4863

Panel B: Consolidated industries

Dependent variable	*EQUITY_FINANCE*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	-0.0013	0.0009	-0.0040	-0.0039	-0.0037
	(-0.26)	(0.13)	(-0.54)	(-0.45)	(-0.36)
EQUITY_SENTIMENT(t)	0.0047	0.0092**	0.0075	0.0069	0.0001
	(1.19)	(2.21)	(1.50)	(1.59)	(0.01)
SIZE(t)	-0.0164***	-0.0172***	-0.0177***	-0.0160***	-0.0187***
	(-7.18)	(-6.53)	(-8.00)	(-5.27)	(-5.81)
TOBIN'S Q(t)	0.0296***	0.0103*	-0.0023	-0.0030	-0.0040
	(5.34)	(2.01)	(-0.49)	(-0.61)	(-0.66)
LEVERAGE(t)	-0.0204	0.0327	0.0495*	0.0996***	0.1469***
	(-0.86)	(1.25)	(1.70)	(2.94)	(5.77)
ROE(t)	-0.0049	-0.0019	0.0000	0.0041*	0.0042**
	(-1.32)	(-0.66)	(0.01)	(1.88)	(2.09)
SALES_GROWTH(t)	0.0267***	0.0138***	-0.0044	0.0028	-0.0036
	(4.14)	(2.81)	(-0.94)	(0.66)	(-1.10)
CASH_FLOW(t)	-0.3467***	-0.0398	-0.0497	-0.0466	-0.0491
	(-6.78)	(-0.82)	(-1.36)	(-1.07)	(-0.96)
CASH(t)	0.1524*	-0.0747*	-0.0322	-0.0034	0.0075
	(1.98)	(-1.70)	(-0.63)	(-0.08)	(0.28)
ECONOMIC_CONDITION(t)	0.0030	-0.0056**	-0.0023	-0.0010	-0.0018
	(1.18)	(-2.14)	(-1.08)	(-0.29)	(-0.39)
MACRO_UNCERTAINTY(t)	0.0010	-0.0051**	-0.0058*	-0.0058*	-0.0010
	(0.44)	(-2.09)	(-2.00)	(-1.93)	(-0.31)
N	2694	2573	2447	2344	2258
R^2	0.3125	0.2045	0.2193	0.2172	0.2255

Table 1.7 Credit market sentiment and industry sales growth

This table reports how credit market sentiment affects industry-level sales growth. As dependent variable is sales growth, I do not additionally control sales growth in this analysis. Panel A (panel B) reports results based on competitive (consolidated) industries. All control variables are winsorized at the 1% and 99% levels. In all models, I include three-digit SIC industry fixed effects and cluster standard errors by industry and year. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively. Statistical significance for the difference in the coefficients of *CREDIT_SENTIMENT* between competitive versus consolidated industries is indicated by a, b, and c, for significance at the 1%, 5% and 10%, respectively.

Panel A: Competitive industries

Dependent variable	*SALES_GROWTH*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	0.0936	0.1352**b	-0.0956	-0.1698**b	-0.0299
	(1.13)	(2.17)	(-0.75)	(-2.12)	(-1.16)
EQUITY_SENTIMENT(t)	0.0353	-0.0102	-0.0530	0.0113	0.0227**
	(1.18)	(-0.31)	(-1.66)	(0.21)	(2.04)
SIZE(t)	-0.0867*	-0.1485***	-0.1640***	-0.1588***	-0.0816***
	(-1.79)	(-4.01)	(-4.64)	(-5.20)	(-5.59)
TOBIN'S Q(t)	0.1826*	0.2128***	0.1053	0.1080	0.0479**
	(1.91)	(2.94)	(1.59)	(1.56)	(2.28)
LEVERAGE(t)	-0.7608	-0.2965	0.4981	-0.5184	0.2975
	(-1.28)	(-0.36)	(0.74)	(-0.72)	(1.56)
ROE(t)	0.0126	0.0299	0.0482	-0.0094	-0.0036
	(0.12)	(0.62)	(0.98)	(-0.29)	(-0.31)
CASH_FLOW(t)	-1.5555**	-1.4943**	-0.6978	-1.0747	-0.2510*
	(-2.44)	(-2.32)	(-1.10)	(-1.68)	(-1.73)
CASH(t)	0.4915	1.5408**	2.0488**	0.5939	-0.1200
	(0.61)	(2.03)	(2.49)	(0.68)	(-0.52)
ECONOMIC_CONDITION(t)	0.0171	-0.0143	-0.0078	-0.0062	0.0011
	(0.66)	(-0.87)	(-0.34)	(-0.29)	(0.13)
MACRO_UNCERTAINTY(t)	0.0144	-0.0100	-0.0798	-0.0701**	-0.0083
	(0.41)	(-0.37)	(-1.47)	(-2.47)	(-0.71)
N	2724	2723	2661	2596	2530
R^2	0.1265	0.1537	0.1462	0.1453	0.3534

Panel B: Consolidated industries

Dependent variable	SALES_GROWTH				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	-0.0230	-0.0042b	-0.0551	-0.0237b	-0.0181
	(-0.39)	(-0.07)	(-1.31)	(-0.90)	(-0.76)
EQUITY_SENTIMENT(t)	0.0743***	0.0740***	0.0279	0.0267***	0.0349***
	(2.86)	(3.72)	(1.49)	(2.73)	(4.45)
SIZE(t)	-0.0619***	-0.0434***	-0.0447***	-0.0406***	-0.0407***
	(-4.12)	(-2.98)	(-3.12)	(-4.75)	(-4.49)
TOBIN'S Q(t)	0.2204***	0.0767	0.0532	0.0015	0.0084
	(3.07)	(1.54)	(1.60)	(0.19)	(0.99)
LEVERAGE(t)	0.3701	0.3611*	0.4579*	0.1094	0.0394
	(1.43)	(1.74)	(1.98)	(1.17)	(0.39)
ROE(t)	0.1456	-0.0492	-0.0008	-0.0052	0.0054
	(1.02)	(-1.17)	(-0.03)	(-0.45)	(0.52)
CASH_FLOW(t)	-0.0469	-0.4111	0.2585	-0.0728	0.0329
	(-0.22)	(-1.32)	(1.35)	(-0.84)	(0.42)
CASH(t)	-0.2311	0.1041	0.7785**	0.0370	-0.1441
	(-0.81)	(0.30)	(2.54)	(0.29)	(-1.19)
ECONOMIC_CONDITION (t)	0.0256*	0.0329**	0.0305**	0.0034	-0.0016
	(1.89)	(2.20)	(2.32)	(0.47)	(-0.25)
MACRO_UNCERTAINTY(t)	0.0070	0.0047	0.0207	-0.0024	-0.0099
	(0.29)	(0.22)	(1.12)	(-0.24)	(-1.34)
N	2694	2573	2447	2344	2258
R^2	0.1285	0.1174	0.1223	0.2121	0.2259

Table 1.8 Credit market sentiment and industry gross margin

This table reports how credit market sentiment affects industry-level gross margin. Panel A (panel B) reports results based on competitive (consolidated) industries. All control variables are winsorized at the 1% and 99% levels. In all models, I include three-digit SIC industry fixed effects and cluster standard errors by industry and year. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively. Statistical significance for the difference in the coefficients of *CREDIT_SENTIMENT* between competitive versus consolidated industries is indicated by a, b, and c, for significance at the 1%, 5% and 10%, respectively.

Panel A: Competitive industries

Dependent variable	*GROSS_MARGIN*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	-0.0137	-0.0602	-0.0955**b	-0.1115**b	-0.0776b
	(-0.48)	(-1.55)	(-2.31)	(-2.12)	(-1.63)
EQUITY_SENTIMENT(t)	0.0351	0.0380*	0.0389	0.0309	0.0352
	(1.66)	(1.85)	(1.36)	(1.40)	(1.37)
SIZE(t)	0.0263	0.0247	0.0257	0.0268	0.0261
	(1.03)	(0.83)	(0.75)	(0.67)	(0.63)
TOBIN'S Q(t)	0.0043	-0.0052	-0.0097	-0.0104	0.0064
	(0.17)	(-0.20)	(-0.25)	(-0.28)	(0.26)
LEVERAGE(t)	0.9315**	0.9320**	0.8740*	0.7855*	1.0601**
	(2.50)	(2.03)	(1.80)	(1.80)	(2.18)
ROE(t)	-0.0370*	-0.0312	-0.0366	0.0131	-0.0179
	(-1.73)	(-1.01)	(-0.73)	(0.44)	(-0.50)
SALES_GROWTH(t)	-0.1571*	-0.0501	-0.0141	-0.0187	-0.0471
	(-1.84)	(-0.64)	(-0.12)	(-0.29)	(-0.73)
CASH_FLOW(t)	3.3836***	2.9342**	3.0845**	2.6027*	2.4065*
	(2.92)	(2.46)	(2.09)	(1.97)	(1.75)
CASH(t)	0.0646	-0.0735	-0.0173	-0.0812	-0.1533
	(0.19)	(-0.21)	(-0.04)	(-0.18)	(-0.43)
ECONOMIC_CONDITION(t)	0.0047	0.0118	0.0190	0.0253	0.0238
	(0.53)	(0.83)	(1.14)	(1.51)	(1.56)
MACRO_UNCERTAINTY(t)	-0.0221	0.0184	0.0159	0.0038	0.0128
	(-1.37)	(1.31)	(1.14)	(0.31)	(1.22)
N	2724	2723	2661	2596	2530
R^2	0.5506	0.5292	0.5134	0.4976	0.5036

Panel B: Consolidated industries

Dependent variable	*GROSS_MARGIN*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	-0.0415	-0.0240	0.0218b	0.0510b	0.0904**b
	(-1.33)	(-0.59)	(0.61)	(1.57)	(2.57)
EQUITY_SENTIMENT(t)	0.0155	0.0107	0.0140	-0.0046	0.0075
	(1.38)	(1.29)	(1.20)	(-0.38)	(0.76)
SIZE(t)	0.0059	-0.0004	0.0001	-0.0087	0.0025
	(0.52)	(-0.04)	(0.01)	(-0.75)	(0.22)
TOBIN'S Q(t)	-0.0314	-0.0049	-0.0199	0.0209	0.0025
	(-1.04)	(-0.29)	(-0.72)	(1.08)	(0.10)
LEVERAGE(t)	0.0918	-0.1280	-0.2124*	-0.1683	-0.2743
	(1.23)	(-1.45)	(-1.86)	(-0.94)	(-1.20)
ROE(t)	0.0133**	0.0042	0.0368*	0.0285	0.0310**
	(2.29)	(0.53)	(1.69)	(1.64)	(2.33)
SALES_GROWTH(t)	0.0134	-0.0044	0.0126	0.0101	0.0297
	(0.27)	(-0.07)	(0.23)	(0.19)	(0.46)
CASH_FLOW(t)	1.2219***	0.3171**	0.0186	0.0182	0.3163
	(5.46)	(2.31)	(0.11)	(0.15)	(1.25)
CASH(t)	-0.0034	-0.3467*	-0.4529	-0.0422	0.0213
	(-0.02)	(-1.97)	(-1.34)	(-0.15)	(0.06)
ECONOMIC_CONDITION(t)	0.0106	0.0065	0.0093	-0.0023	-0.0064
	(1.26)	(0.95)	(1.02)	(-0.23)	(-0.70)
MACRO_UNCERTAINTY(t)	0.0033	0.0010	0.0085	0.0098	0.0127
	(0.30)	(0.08)	(0.75)	(0.62)	(0.77)
N	2694	2573	2447	2344	2258
R^2	0.3834	0.3423	0.3349	0.3029	0.3444

Table 1.9 Credit market sentiment and firm-level cash flow

This table reports that credit market sentiment predicts firms' cash flow declines. Dependent variable is changes of operating cash flow. I report results for competitive (consolidated) industries in panel A (B). All control variables are winsorized at the 1% and 99% levels. Following HP, I cluster standard errors by industry and year. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively. Statistical significance for the difference in the coefficients of *CREDIT_SENTIMENT* between competitive versus consolidated industries is indicated by a, b, and c, for significance at the 1%, 5% and 10%, respectively.

Panel A: Competitive industries					
Dependent variable	Δ*CASH_FLOW*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	0.0153***a	-0.0028	-0.0073*	-0.0276***a	-0.0253***b
	(4.24)	(-0.41)	(-1.78)	(-4.51)	(-3.34)
FIRM_RELATIVE_INVEST(t)	-0.0103***	-0.0045***	-0.0024***	-0.0018	-0.0009
	(-6.27)	(-4.43)	(-4.59)	(-1.34)	(-0.59)
Δ*EBITDA(t)*	-0.0002	0.0002	-0.0001**	-0.0001	0.0001
	(-0.85)	(0.50)	(-2.57)	(-0.32)	(0.16)
Δ*CAPEX(t)*	0.0003**	-0.0002**	-0.0001**	-0.0003***	-0.0003**
	(2.02)	(-2.43)	(-2.05)	(-2.80)	(-2.37)
N	75407	74301	67361	60305	54247
R^2	0.0056	0.0014	0.0046	0.0055	0.0044

Panel B: Consolidated industries

Dependent variable	ΔCASH_FLOW				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	0.0058***a	-0.0012	-0.0022	-0.0062a	-0.0065b
	(3.15)	(-0.40)	(-0.82)	(-1.59)	(-1.64)
FIRM_RELATIVE_INVEST(t)	-0.0044***	-0.0022***	-0.0007	0.0000	0.0013
	(-5.14)	(-3.67)	(-1.43)	(0.02)	(1.34)
Δ*EBITDA(t)*	0.0004	-0.0003	-0.0003***	-0.0007**	-0.0008***
	(1.14)	(-0.94)	(-3.13)	(-2.55)	(-3.16)
Δ*CAPEX(t)*	0.0004	-0.0002	-0.0002	-0.0005	-0.0006
	(1.23)	(-1.52)	(-1.28)	(-1.27)	(-1.12)
N	17681	17630	16005	14468	13068
R^2	0.0043	0.0015	0.0017	0.0023	0.0028

Table 1.10 Credit market sentiment and firm-level stock performance

This table reports that credit market sentiment predicts firms' stock performance declines. Dependent variable is monthly abnormal returns between July of year t-1 and June of year t. Following HP, abnormal return is a firm's raw return less that of a portfolio matched on the basis of NYSE/Amex breakpoints of size, industry-adjusted book-to-market, and past-year returns as in Daniel et al. (1997).I report results for competitive (consolidated) industries in panel A (B). All control variables are winsorized at the 1% and 99% levels. Following HP, I cluster standard errors by industry and year. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively. Statistical significance for the difference in the coefficients of *CREDIT_SENTIMENT* between competitive versus consolidated industries is indicated by a, b, and c, for significance at the 1%, 5% and 10%, respectively.

Panel A: Competitive industries

Dependent variable	*ABNORMAL_RET*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	0.0023*	-0.0001	-0.0003	-0.0012**	-0.0008**
	(1.72)	(-0.19)	(-0.63)	(-2.56)	(-2.15)
FIRM_RELATIVE_INVEST(t)	-0.0004*	-0.0004***	-0.0001	-0.0003**	-0.0002
	(-1.95)	(-2.76)	(-1.24)	(-2.27)	(-1.30)
N	884705	787352	704067	633651	572601
R^2	0.0001	0.0000	0.0000	0.0000	0.0000

Panel B: Consolidated industries

Dependent variable	*ABNORMAL_RET*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
CREDIT_SENTIMENT(t)	0.0008	-0.0010	0.0004	-0.0005	-0.0005
	(0.92)	(-0.97)	(0.43)	(-0.81)	(-0.58)
FIRM_RELATIVE_INVEST(t)	-0.0003**	-0.0001	-0.0004	0.0001	-0.0001
	(-2.44)	(-0.62)	(-1.43)	(0.60)	(-0.90)
N	208868	188443	169808	152571	136403
R^2	0.0000	0.0000	0.0000	0.0000	0.0000

Table 1.11 Cash flow of firms that invest more during high credit market sentiment periods

This table reports that cash flow declines are severe for firms that invest more during high credit market sentiment period. Dependent variable is changes of operating cash flow. I present results for competitive (consolidated) industries in panel A (B). All control variables are winsorized at the 1% and 99% levels. I cluster standard errors by industry and year. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively. Statistical significance for the difference in the coefficients of *FIRM_INVEST_RESI*HIGH_SENTIMENT* between competitive versus consolidated industries is indicated by a, b, and c, for significance at the 1%, 5% and 10%, respectively.

Panel A: Competitive industries

Dependent variable	Δ*CASH_FLOW*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
HIGH_SENTIMENT(t)	0.0111***	-0.0002	-0.0074	-0.0172*	-0.0043
	(4.47)	(-0.03)	(-1.16)	(-1.75)	(-0.43)
FIRM_RELATIVE_INVEST(t)	-0.0096***	-0.0044***	-0.0039**	-0.0024*	-0.0026*
	(-5.60)	(-3.57)	(-2.44)	(-1.65)	(-1.77)
*FIRM_RELATIVE_INVEST(t)*HIGH_SENTIMENT(t)*	-0.0051	-0.0017	0.0010	-0.0049***a	-0.0045**a
	(-1.55)	(-0.89)	(0.48)	(-4.26)	(-2.02)
Δ*EBITDA(t)*	-0.0002	0.0002	0.0002	-0.0003***	-0.0014***
	(-0.87)	(0.51)	(0.42)	(-3.11)	(-3.89)
Δ*CAPEX(t)*	0.0003**	-0.0002**	-0.0004**	-0.0003***	-0.0001
	(2.00)	(-2.43)	(-2.33)	(-2.60)	(-0.39)
N	75407	74301	67361	60305	54247
R^2	0.0043	0.0014	0.0013	0.0020	0.0014

Panel B: Consolidated industries

Dependent variable	∆*CASH_FLOW*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
HIGH_SENTIMENT(t)	0.0002	0.0109***	0.0093***	0.0040*	-0.0064*
	(0.07)	(2.61)	(3.82)	(1.87)	(-1.87)
FIRM_RELATIVE_INVEST(t)	-0.0042***	-0.0023***	-0.0008	0.0004	0.0014
	(-4.77)	(-3.71)	(-0.91)	(0.41)	(1.22)
*FIRM_RELATIVE_INVEST(t)*HIGH_SENTIMENT(t)*	-0.0036	0.0035	0.0032	-0.0004a	0.0070a
	(-0.88)	(0.66)	(1.22)	(-0.13)	(1.54)
∆*EBITDA(t)*	0.0004	-0.0003	-0.0005	-0.0007***	-0.0008**
	(1.16)	(-0.95)	(-1.48)	(-3.05)	(-2.34)
∆*CAPEX(t)*	0.0004	-0.0002	-0.0005	-0.0006*	-0.0005
	(1.27)	(-1.53)	(-1.63)	(-1.74)	(-1.01)
N	17681	17630	16005	14468	13068
R^2	0.0039	0.0021	0.0014	0.0015	0.0018

Table 1.12 Stock performance of firms that invest more during high credit market sentiment periods

This table reports that stock performance declines are severe for firms that invest more during high credit market sentiment period. Dependent variable is monthly abnormal returns between July of year t-1 and June of year t. I report results for competitive (consolidated) industries in panel A (B). All control variables are winsorized at the 1% and 99% levels. I cluster standard errors by industry and year. Numbers in parentheses are t-statistics, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% level, respectively. Statistical significance for the difference in the coefficients of *FIRM_INVEST_RESI*HIGH_SENTIMENT* between competitive versus consolidated industries is indicated by a, b, and c, for significance at the 1%, 5% and 10%, respectively.

Panel A: Competitive industries

Dependent variable	*ABNORMAL_RET*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
HIGH_SENTIMENT(t)	0.0002	-0.0003	-0.0004	-0.0023*	-0.0012*
	(0.21)	(-0.53)	(-0.55)	(-1.72)	(-1.92)
FIRM_RELATIVE_INVEST(t)	-0.0003	-0.0005***	-0.0002*	-0.0003**	-0.0004***
	(-1.58)	(-3.36)	(-1.68)	(-2.34)	(-3.02)
*FIRM_RELATIVE_INVEST(t)*HIGH_SENTIMENT(t)*	-0.0006	0.0004	0.0000	-0.0013**	-0.0005**a
	(-1.57)	(0.58)	(0.10)	(-2.45)	(-2.39)
N	884705	787352	704067	633651	572601
R^2	0.0000	0.0000	0.0000	0.0001	0.0000

Panel B: Consolidated industries

Dependent variable	*ABNORMAL_RET*				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
HIGH_SENTIMENT(t)	-0.0006	-0.0022**	-0.0018*	-0.0011	0.0009
	(-0.71)	(-2.11)	(-1.74)	(-0.96)	(0.87)
FIRM_RELATIVE_INVEST(t)	-0.0007***	-0.0001	-0.0001	0.0001	-0.0004
	(-3.27)	(-0.35)	(-0.54)	(0.52)	(-1.51)
*FIRM_RELATIVE_INVEST(t)*HIGH_SENTIMENT(t)*	0.0002	-0.0004	-0.0006	-0.0003	0.0010a
	(0.41)	(-0.97)	(-0.67)	(-0.67)	(1.09)
N	208868	188443	169808	152571	136403
R^2	0.0000	0.0000	0.0000	0.0000	0.0000

Table 1.13 Credit market sentiment and boom-bust cycles

This table reports that credit market sentiment explains boom-bust cycles. Panel A reports results based on Equation (1.11). In panel A, dependent variable is changes of operating cash flow. Panel B reports results based on Equation (1.12). Dependent variable in panel B is monthly abnormal returns between July of year t+2 and June of year t+3. Columns (1) and (3) (columns (2) and (4)) are results based on competitive (consolidated) industries. All control variables are winsorized at the 1% and 99% levels. I cluster standard errors by industry and year. Numbers in parentheses are t-statistics and time. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Differences significant from the opposing tercile (competitive versus consolidated industries) are indicated at the 1% (a), 5% (b) and 10% (c).

Panel A: Firm-level operating cash flow changes

Dependent variable	ΔCASH_FLOW(t+3)			
Industry	Competitive	Consolidated	Competitive	Concentrated
	(1)	(2)	(3)	(4)
CREDIT_SENTIMENT(t)			-0.0226***a	-0.0057a
			(-3.98)	(-1.31)
RELATIVE_VALUATION(t+1)	-0.0119**b	-0.0015b	-0.0083	-0.0010
	(-2.01)	(-0.64)	(-1.41)	(-0.34)
RELATIVE_VALUATION_RESI(t+1)	0.0014	-0.0016	0.0041*	-0.0014
	(0.33)	(-0.91)	(1.87)	(-0.64)
RELATIVE_INVEST(t+1)	-0.0126***b	-0.0019b	-0.0086	-0.0021
	(-2.88)	(-1.48)	(-1.64)	(-1.44)
RELATIVE_INVEST_RESI(t+1)	-0.0038***	-0.0012	-0.0036**	-0.0012
	(-4.85)	(-1.28)	(-2.32)	(-0.91)
NEW_FINANCE(t+1)	-0.0368	0.0339	-0.0602	0.0157
	(-0.94)	(1.48)	(-1.40)	(0.52)
NEW_FINANCE_RESI(t+1)	0.0574***	0.0315*	0.0678***	0.0268
	(6.78)	(1.84)	(4.28)	(1.09)
Δ*EBITDA(t+1)*	-0.0001	-0.0006***	0.0002	-0.0005*
	(-1.30)	(-2.84)	(0.44)	(-1.95)
Δ*CAPX(t+1)*	-0.0002**	-0.0003	-0.0004**	-0.0006
	(-2.03)	(-1.18)	(-2.32)	(-1.40)
N	60305	14468	60305	14468
R^2	0.0142	0.0040	0.0114	0.0025

Panel B: Firm-level stock returns

Dependent variable	*ABNOMAL_RET (t+3)*			
Industry	Competitive	Concentrated	Competitive	Concentrated
	(1)	(2)	(3)	(4)
CREDIT_SENTIMENT(t)			-0.0012**	-0.0005
			(-2.52)	(-0.69)
RELATIVE_VALUATION(t+1)	-0.0008**	-0.0005	-0.0005	-0.0004
	(-2.23)	(-1.11)	(-1.20)	(-1.00)
RELATIVE_VALUATION_RESI(t+1)	-0.0014***	-0.0011***	-0.0014***	-0.0011***
	(-5.67)	(-4.14)	(-5.66)	(-4.15)
RELATIVE_INVEST(t+1)	-0.0006***	-0.0003	-0.0003*	-0.0003
	(-4.48)	(-1.40)	(-1.84)	(-1.27)
RELATIVE_INVEST_RESI(t+1)	0.0000	-0.0005*	0.0001	-0.0005*
	(0.12)	(-1.94)	(0.33)	(-1.91)
NEW_FINANCE(t+1)	-0.0088*b	0.0037b	-0.0091*	0.0039
	(-1.81)	(0.91)	(-1.85)	(0.96)
NEW_FINANCE_RESI(t+1)	0.0002	0.0022	0.0000	0.0022
	(0.28)	(1.10)	(0.08)	(1.11)
N	633651	152571	633651	152571
R^2	0.0001	0.0000	0.0001	0.0000

Table 2.1 Summary statistics

This table reports the summary statistics of the sample. All variables are winsorized at the 1% and 99% levels. Panel A reports summary statistics of lobbying firms and non-lobbying firms. Panel B reports the summary statistics of the sample used for the lobbying initiation decisions of non-lobbying firms. The sample consists of initiation (new lobbying) firms and remaining non-lobbying firms.

Panel A: Lobbying firms versus non-lobbying firms

	Lobbying firms				Non-lobbying firms				Difference in Means	
Variable	N	Mean	Median	Std	N	Mean	Median	Std	Difference	p-value
SIZE	12,614	7.327	7.596	2.173	59,349	4.514	4.685	2.339	2.813	0.000
MTB	12,614	2.594	1.752	2.480	59,349	3.065	1.671	3.420	-0.471	0.000
R&D	12,614	0.060	0.008	0.137	59,349	0.092	0.000	0.210	-0.033	0.000
LEVERAGE	12,614	0.274	0.226	0.352	59,349	0.346	0.163	0.736	-0.073	0.000
CASH_FLOW	12,614	0.052	0.125	0.464	59,349	-0.227	0.079	1.266	0.279	0.000
LOBBY_EXPENSES(dollar amount)	12,614	913,080	140,000	2,459,833	59,349	N/A	N/A	N/A	N/A	N/A

Panel B: Initiation firms versus remaining non-lobbying firms

	Initiation (new lobbying) firms				Remaining non-lobbying firms				Difference in Means	
Variable	N	Mean	Median	Std	N	Mean	Median	Std	Difference	p-value
SIZE	1,208	5.855	6.165	2.074	54,561	4.378	4.576	2.303	1.476	0.000
MTB	1,208	3.847	2.005	4.541	54,561	3.435	1.669	4.546	0.412	0.428
R&D	1,208	0.118	0.017	0.243	54,561	0.094	0.000	0.222	0.023	0.000
LEVERAGE	1,208	0.251	0.167	0.348	54,561	0.364	0.162	0.841	-0.113	0.000
CASH_FLOW	1,208	-0.177	0.087	1.248	54,561	-0.273	0.077	1.537	0.096	0.031
LOBBY_EXPENSES (dollar amount)	1,208	90,902	40,000	266,423	54,561	N/A	N/A	N/A	N/A	N/A

Table 2.2 Sample firms and their lobbying expenses across years

This table reports how the sample firms vary across years. *LOBBY* is the number of lobbying firms, and *LOBBY %* is the percentage of lobbying firms in that calendar year. Column (4) reports the average annual lobbying expenses of lobbying firms. *INITIATION* reports the number of non-lobbying firms that initiate lobbying, and *INITIATION %* is the percentage of non-lobbying firms initiating lobbying in a given calendar year. Column (8) reports the average lobbying expenses of firms in the first year when they start lobbying.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year	Total	*LOBBY*	*LOBBY %*	*LOBBY_EXPENSES*(mean)	Total	*INITIATION*	*INITIATION%*	*LOBBY_EXPENSES* (mean)
1999	5,772	673	11.66	$607,332	5,232	133	2.54	$47,753
2000	5,764	649	11.26	$664,249	5,125	62	1.21	$91,467
2001	5,377	679	12.63	$638,255	4,717	117	2.48	$52,829
2002	4,994	699	14.00	$666,051	4,252	97	2.28	$46,324
2003	4,664	753	16.14	$669,587	3,849	109	2.83	$98,367
2004	4,570	773	16.91	$705,095	3,659	71	1.94	$91,512
2005	4,395	835	19.00	$681,916	3,430	105	3.06	$77,095
2006	4,275	863	20.19	$775,475	3,231	82	2.54	$46,136
2007	4,096	835	20.39	$774,696	3,035	72	2.37	$78,412
2008	3,876	805	20.77	$992,438	2,798	64	2.29	$62,237
2009	3,705	811	21.89	$1,071,922	2,626	73	2.78	$129,062
2010	3,558	769	21.61	$1,161,660	2,455	42	1.71	$119,057
2011	3,408	719	21.10	$1,203,636	2,306	34	1.47	$260,100
2012	3,355	698	20.80	$1,210,909	2,255	39	1.73	$181,432
2013	3,393	699	20.60	$1,239,191	2,278	34	1.49	$360,277

2014	3,451	684	19.82	$1,243,035	2,332	38	1.63	$67,763
2015	3,310	670	20.24	$1,276,797	2,189	36	1.64	$89,486
Average	4,233	742	17.53	$916,603	3,281	71	2.17	$90,902

Table 2.3 Top 10 industries with the highest lobbying expenses during the sample period, 1999-2015

This table reports the top 10 industries with the highest lobbying expenses during the sample period, 1999-2015. *LOBBY* is the number of lobbying-year observations, and *LOBBY %* is the percentage of lobbying-year observations. *INITIATION* reports the number of firm-year observations in which firms initiate lobbying after 1999, and *INITIATION %* is the percentage of firms-year observations in which firms initiate lobbying in a given calendar year.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Industry	Total	*LOBBY*	*LOBBY %*	*LOBBY_EXPENSES* (sum)	Total	*INITIATION*	*INITIATION* %	*LOBBY_EXPENSES* (sum)
Communication	2,640	824	31.212	$1,448,086,979	1,688	67	3.97	$11,757,500
Pharmaceutical Products	5,938	1,112	18.727	$1,378,931,352	4,403	162	3.68	$20,728,486
Business Services	11,858	1,636	13.797	$1,116,112,002	9,773	190	1.94	$14,228,519
Aircraft	403	193	47.891	$766,455,635	208	7	3.37	$1,120,000
Transportation	1,860	571	30.699	$750,393,160	1,256	33	2.63	$2,712,166
Petroleum and Natural Gas	3,626	529	14.589	$728,533,320	2,959	57	1.93	$8,263,250
Electronic Equipment	5,075	634	12.493	$720,097,777	4,175	83	1.99	$6,596,000
Retail	4,046	538	13.297	$496,605,145	3,288	52	1.58	$3,988,795
Chemicals	1,693	547	32.310	$445,228,079	1,060	27	2.55	$1,783,718
Automobiles and Trucks	1,163	265	22.786	$387,935,103	838	21	2.51	$1,095,000

Table 2.4 Economic value of corporate lobbying

This table reports the economic value of corporate lobbying. Using the propensity score-matched sample of lobbying and non-lobbying firms, columns (1)-(3) document how corporate lobbying mitigates the adverse effects of EPU on business activities. The business activities considered incorporate capital expenditure scaled by lagged total assets in column (1), the change in the number of employees scaled by the lagged number of employees in column (2), and sales growth in column (3). Control variables are similar to those in Gulen and Ion (2016). All firm control variables are winsorized at the 1% and 99% levels. In all of the models, I include firm-fixed effects and cluster standard errors by firm and by year. Numbers in parentheses are t-statistics. Significance at the 10% (*), 5% (**), or 1% level (***) is indicated.

Dependent variable	*CAPEX*	Δ*EMPLOYEES*	*SALES_GROWTH*
	(1)	(2)	(3)
EPU_INDEX	-0.0248***	-0.0953***	-0.1049***
	(-9.50)	(-7.39)	(-9.25)
LOBBY	-0.0538***	-0.2548***	-0.1683**
	(-2.92)	(-2.85)	(-2.32)
*EPU_INDEX*LOBBY*	0.0109***	0.0489***	0.0340**
	(2.78)	(2.59)	(2.21)
TOBIN's Q	0.0019***	0.0140***	0.0374***
	(3.66)	(4.98)	(11.38)
CASH_FLOW	-0.0235***	-0.0357	-0.0001***
	(-3.04)	(-1.17)	(-3.36)
SALES_GROWTH	0.0118***	0.0968***	
	(7.92)	(11.46)	
GDP_GROWTH	-0.0709***	0.4426***	-0.0222
	(-2.64)	(3.26)	(-0.18)
Constant	0.1382***	0.1987*	0.5381**
	(4.53)	(1.69)	(2.30)
N	15206	15206	15206
R^2	0.6069	0.3733	0.2322

Table 2.5 EPU and lobbying initiation decisions of non-lobbying firms

Using the probit model, this table reports how EPU affects the lobbying initiation decisions of non-lobbying firms. The dependent variable is a dummy variable equal to one if a non-lobbying firm starts lobbying in the year and zero otherwise. For the explanatory variable *EPU_INDEX*, I use the BBD policy uncertainty index in column (1) and its subcomponents in columns (2)-(5). I drop the 129 observations from the shipping containers industry, which has no new lobbying firms during my sample period. Note that the number of observations is 55,640, which is 129 fewer than 55,769 observations shown in Table 2.2. All firm control variables are winsorized at the 1% and 99% levels. In all of the models, I include Fama–French 48 industry fixed effects and cluster standard errors by firm and by year. Numbers in parentheses are t-statistics. Significance at the 10% (*), 5% (**), or 1% level (***) is indicated.

	Probit model				
Dependent variable	*INITIATION*	*INITIATION*	*INITIATION*	*INITIATION*	*INITIATION*
	Overall index	News component	Tax component	Gov. spending component	CPI component
	(1)	(2)	(3)	(4)	(5)
EPU_INDEX	-0.3200***	-0.2218**	-0.0214	-0.2197**	-0.3628**
	(-3.48)	(-2.05)	(-0.86)	(-2.55)	(-2.13)
SIZE	0.1779***	0.1771***	0.1768***	0.1785***	0.1773***
	(23.06)	(23.34)	(22.34)	(22.88)	(21.37)
MTB	-0.0009	-0.0008	-0.0008	-0.0008	-0.0007
	(-0.79)	(-0.77)	(-0.71)	(-0.74)	(-0.66)
R&D	0.2526***	0.2502***	0.2528***	0.2551***	0.2571***
	(3.29)	(3.27)	(3.34)	(3.38)	(3.45)
LEVERAGE	-0.0504**	-0.0499**	-0.0510**	-0.0503**	-0.0522**
	(-2.10)	(-2.09)	(-2.15)	(-2.15)	(-2.17)
CASH_FLOW	-0.0616***	-0.0614***	-0.0604***	-0.0616***	-0.0600***
	(-3.30)	(-3.27)	(-3.25)	(-3.36)	(-3.21)
HERFINDAHL	-0.4195	-0.5099	-0.5679	-0.3840	-0.5966
	(-0.60)	(-0.74)	(-0.80)	(-0.52)	(-0.86)
INVEST_OPPORTUNITY	-0.0285	-0.0163	-0.0114	-0.0151	-0.0230
	(-1.05)	(-0.64)	(-0.39)	(-0.55)	(-0.78)
MACRO_UNCERTAINTY	0.0169	0.0212	0.0040	0.0160	0.0210
	(0.62)	(0.75)	(0.11)	(0.60)	(0.79)
Constant	-1.1686*	-1.5866**	-2.4859***	-1.7160***	-0.9652
	(-1.92)	(-2.37)	(-6.90)	(-3.27)	(-1.17)
N	55640	55640	55640	55640	55640
Pseudo R^2	0.0771	0.0762	0.0752	0.0770	0.0761

Table 2.6 Channel test: Time-varying lobbying entry expenses

This table reports how EPU affects the lobbying initiation decisions of non-lobbying firms through the lobbying entry expenses channel. Column (1) reports the effect of EPU on the lobbying entry expenses in the year when a non-lobbying firm starts lobbying. The dependent variable is the natural logarithm of lobbying entry expenses. Column (2) reports the effect of the average lobbying entry expenses on the lobbying initiation decisions of non-lobbying firms. The regression is based on the probit model, with the dependent variable equal to one if the observation is from the year the non-lobbying firm initiates lobbying. Control variables follow the ones used in Table 6. All firm control variables are winsorized at the 1% and 99% level. In all of the models, I include Fama–French 48 industry fixed effects and cluster standard errors by firm and by year. Numbers in parentheses are t-statistics. Significance at the 10% (*), 5% (**), or 1% level (***) is indicated.

	OLS	Probit
Dependent variable	*ENTRY_EXPENSES*	*INITIATION*
	(1)	(2)
EPU_INDEX	0.4477***	
	(3.02)	
AVG_ENTRY_EXP		-0.1566***
		(-2.59)
SIZE	0.1465***	0.1793***
	(7.40)	(21.83)
MTB	0.0035**	-0.0009
	(2.12)	(-0.81)
R&D	0.1802	0.2584***
	(1.21)	(3.49)
LEVERAGE	-0.0600	-0.0515**
	(-0.46)	(-2.08)
CASH_FLOW	0.0366	-0.0627***
	(1.30)	(-3.34)
HERFINDAHL	-0.0086	-0.2908
	(-0.01)	(-0.41)
INVEST_OPPORTUNITY	0.0420	0.0024
	(1.26)	(0.14)
MACRO_UNCERTAINTY	-0.0460	0.0101
	(-1.41)	(0.36)
Constant	8.0867***	-0.9122
	(13.05)	(-1.13)
N	915	55640
R^2/Pseudo R^2	0.0987	0.0773

Table 2.7 Mechanisms regulating the channel of lobbying entry expenses

This table reports mechanisms regulating lobbying entry expenses. In Panel A, I introduce the mechanism of supply of lobbying services. I use the guilty plea of Jack Abramoff to illustrate the supply of lobbying services. *POST_PLEA* is a dummy variable equal to one if year t is after 2006 (inclusive) and zero otherwise. In Panel B, I turn to the mechanism of demand for lobbying services. I use the average lobbying expenses of existing lobbying firms as the demand of lobbying services. In Panel C, motivated by the two mechanisms, I propose an additional proxy for lobbying entry expenses. The proxy is the total lobbying expenses divided by the number of lobbyists, *LOBBYIST_PRICE*. All firm control variables are winsorized at the 1% and 99% levels. In all of the models, I include Fama–French 48 industry fixed effects and cluster standard errors by firm and by year. Numbers in parentheses are t-statistics. Significance at the 10% (*), 5% (**), or 1% level (***) is indicated.

Panel A: Supply of lobbying services

Dependent variable	*LOBBY_EXPNESES*	*INITIATION*
	(1)	(2)
EPU_INDEX	-0.2304	-0.1074
	(-1.08)	(-1.38)
POST_PLEA	-1.8891*	0.6786
	(-1.99)	(1.53)
*EPU_INDEX*POST_PLEA*	0.4684**	-0.1987**
	(2.18)	(-2.09)
SIZE	0.3645***	0.1823***
	(10.41)	(22.33)
MTB	0.0001	-0.0008
	(0.66)	(-0.99)
R&D	-0.1011	0.2653***
	(-1.21)	(4.16)
LEVERAGE	0.0008	-0.0466
	(1.47)	(-1.48)
CASH_FLOW	-0.0107	-0.0628***
	(-0.39)	(-4.63)
HERFINDAHL	0.5402	-0.0420
	(1.40)	(-0.07)
INVEST_OPPORTUNITY	-0.0211	-0.0603***
	(-1.12)	(-4.42)
MACRO_UNCERTAINTY	-0.0356	-0.0115
	(-1.68)	(-1.03)
Constant	10.4820***	-2.1570***
	(9.27)	(-4.91)
N	10596	55640
R^2/Pseudo R^2	0.8016	0.0797

Panel B: Demand for lobbying services

Dependent variable	*LOBBY_EXPNESES*	*INITIATION*
	(1)	(2)
EPU_INDEX	0.3011***	
	(3.88)	
AVG_LOBBY_EXP		-0.8906***
		(-6.76)
SIZE	0.3085***	0.1843***
	(7.77)	(24.75)
MTB	0.0001	-0.0009
	(0.53)	(-0.77)
R&D	-0.1034	0.2861***
	(-1.25)	(3.78)
LEVERAGE	-0.0009	-0.0471**
	(-1.48)	(-2.02)
CASH_FLOW	-0.0138	-0.0637***
	(-0.49)	(-3.46)
HERFINDAHL	0.8960*	0.0286
	(2.03)	(0.03)
INVEST_OPPORTUNITY	-0.0878***	-0.0492***
	(-6.53)	(-2.80)
MACROUN_CERTAINTY	-0.1045***	-0.0471**
	(-4.08)	(-2.51)
Constant	8.6902***	8.2455***
	(18.75)	(4.81)
N	10596	55640
R^2/Pseudo R^2	0.7946	0.0829

Table 2.8 Channel test: Returns to experience in lobbying

This table reports how lobbying experience affects the effectiveness in capturing information benefits. In this table, I only use lobbying firms in the analysis. In column (1), the dependent variable is capital expenditure scaled by lagged total assets. In column (2), the dependent variable is the change in the number of employees, Δ*EMPLOYEES*, scaled by the lagged number of employees. In column (3), the dependent variable is sales growth. The *LOBBY_YEAR* is the years in which a firm spent in lobbying. Control variables are similar to those in Gulen and Ion (2016). All firm control variables are winsorized at the 1% and 99% levels. In all of the models, I include firm-fixed effects and cluster standard errors by firm and by year. Numbers in parentheses are t-statistics. Significance at the 10% (*), 5% (**), or 1% level (***) is indicated.

Dependent variable	*CAPEX*	Δ*EMPLOYEES*	*SALES_GROWTH*
	(1)	(2)	(3)
EPU_INDEX	-0.0286***	-0.1096**	-0.1492*
	(-3.39)	(-2.89)	(-1.90)
LOBBY_YEAR	-0.0156**	-0.0583***	-0.1064**
	(-2.65)	(-2.99)	(-2.56)
*EPU_INDEX*LOBBY_YEAR*	0.0030**	0.0120**	0.0195**
	(2.46)	(2.89)	(2.24)
TOBIN's Q	0.0021***	0.0114***	0.0115
	(3.21)	(3.69)	(1.67)
CASH_FLOW	-0.0333***	-0.0335	-0.1095*
	(-4.70)	(-0.95)	(-1.79)
SALES_GROWTH	0.0180***	0.1987***	
	(4.87)	(10.59)	
GDP_GROWTH	-0.1713***	0.2468	0.2746
	(-3.64)	(1.24)	(0.44)
Constant	0.1945***	0.5214***	0.9027**
	(4.56)	(2.77)	(2.26)
N	12283	11975	12283
R^2	0.5570	0.2325	0.2249

Table 2.9 Robustness analyses

This table reports robustness analyses for the effect of policy uncertainty on lobbying initiation decisions. In column (1), the explanatory variable is the residual of the regression of *EPU_INDEX* on Canadian policy uncertainty. I use presidential elections as a proxy for policy uncertainty in column (2). In column (3), the proxy for policy uncertainty is measured as the average firm-level political uncertainty in a year, which is available from 2001. Finally, in column (4), I conduct an analysis in the healthcare industry by using healthcare policy uncertainty. In all of the models, I include Fama–French 48 industry fixed effects and cluster standard errors by firm and year. Numbers in parentheses are t-statistics. Significance at the 10% (*), 5% (**), or 1% level (***) is indicated.

Dependent variable	*INITIATION*	*INITIATION*	*INITIATION*	*INITIATION*
	(1)	(2)	(3)	(4)
RESI_EPU	-0.2300**			
	(-2.37)			
ELECTION		-0.1536**		
		(-2.53)		
PRISK_AVG			-0.0036**	
			(-2.46)	
HEALTHCAREPU				-0.1645**
				(-2.44)
SIZE	0.1783***	0.1777***	0.1752***	0.1536***
	(22.76)	(19.36)	(20.92)	(8.32)
MTB	-0.0010	-0.0008	0.0000	-0.0005
	(-0.87)	(-0.64)	(0.01)	(-0.21)
R&D	0.2521***	0.2595***	0.3053***	0.1385
	(3.30)	(3.38)	(3.35)	(1.37)
LEVERAGE	-0.0523**	-0.0512**	-0.0439*	-0.0155
	(-2.13)	(-2.08)	(-1.84)	(-0.35)
CASH_FLOW	-0.0635***	-0.0616***	-0.0494**	-0.0299
	(-3.36)	(-2.97)	(-2.39)	(-0.95)
HERFINDAHL	-0.3709	-0.5589	0.6338	1.1743
	(-0.54)	(-0.98)	(1.04)	(0.24)
INVEST_OPPORTUNITY	0.0146	0.0094	0.0386	-0.0098
	(0.65)	(0.61)	(1.51)	(-0.51)
MACRO_UNCERTAINTY	0.0464*	0.0283	0.0737***	-0.0014
	(1.78)	(1.44)	(3.13)	(-0.08)
Constant	-2.6755***	-2.5690***	-2.7174***	-1.7979***
	(-8.44)	(-8.81)	(-6.32)	(-4.06)
N	55640	55640	45310	7905
Pseudo R^2	0.0766	0.0771	0.0756	0.0458

Table 2.10 Cross-sectional analysis

This table reports the effect of EPU on the lobbying initiation decisions of non-lobbying firms with different degrees of firm characteristics. In Panel A, I show results for non-lobbying firms with different degrees of financial constraints. In column (1), firm size is a proxy of financial constraints. In column (2), the WW index proposed by Whited and Wu (2006) is used to measure financial constraints. In column (3), the HP index proposed by Hadlock and Pierce (2010) is used to measure financial constraints. The methods used to measure the WW and HP indexes follow Farre-Mensa and Ljungqvist (2016). Because firm size is a proxy of financial constraints, I do not include size as a firm control in all three columns. Except for size, other control variables follow the ones used in Table 5. Panel B shows results for non-lobbying firms with various degrees of distance from Washington D.C. The variable *DISTANCE* is the natural logarithm of distance between a firm's headquarter and Washington D.C. To calculate the distance, I use the zip code of a firm's headquarter and set 20001 as the zip code for Washington D.C. In Ppanel C, I report how the lobbying initiation decision differs between firms with and without government customers. *GOVERN_CUSTOMER* is an indicator set to one if a non-lobbying firm has at least one government customer and zero otherwise. All firm control variables are winsorized at the 1% and 99% levels. In all of the models I include Fama–French 48 industry fixed effects and cluster standard errors by firm and by year. Numbers in parentheses are t-statistics. Significance at the 10% (*), 5% (**), or 1% level (***) is indicated.

Panel A: Financial constraints

Dependent variable	*INITIATION*	*INITIATION*	*INITIATION*
	(1)	(2)	(3)
EPU_INDEX	-0.5717***	-0.2106**	-0.3301***
	(-3.35)	(-2.50)	(-3.13)
SIZE	-0.0205		
	(-0.21)		
*EPU_INDEX*SIZE*	0.0441**		
	(2.04)		
WW		0.6690	
		(1.10)	
*EPU_INDEX*WW*		-0.2466**	
		(-2.05)	
HP			0.8383
			(1.41)
*EPU_INDEX*HP*			-0.2967**
			(-2.25)
MTB	-0.0001	-0.0001	-0.0001
	(-1.63)	(-0.86)	(-1.56)
R&D	0.1382*	0.1952**	0.2915***
	(1.88)	(2.00)	(4.82)
LEVERAGE	-0.0609*	-0.1078***	-0.1245***
	(-1.84)	(-4.79)	(-4.77)
CASH_FLOW	-0.1416***	0.0258	-0.0110
	(-6.88)	(1.43)	(-0.86)
HERFINDAHL	-0.4341	0.0975	-0.0088
	(-0.63)	(0.11)	(-0.01)
INVEST_OPPORTUNITY	-0.0298	-0.0412***	-0.0312
	(-1.10)	(-2.68)	(-1.25)
MACRO_UNCERTAINTY	0.0170	0.0005	0.0163
	(0.63)	(0.03)	(0.63)
Constant	-0.0363	-0.6530	0.0801
	(-0.04)	(-1.21)	(0.12)
N	55640	34129	36544
Pseudo R^2	0.0789	0.0404	0.0495

Panel B: Distance to Washington, D.C.

Dependent variable	*INITIATION*	*INITIATION*
	(1)	(2)
EPU_INDEX	-0.2972***	-0.1933*
	(-3.25)	(-1.81)
DISTANCE	-0.0419**	0.0462
	(-2.53)	(1.20)
*EPU_INDEX*DISTANCE*		-0.0164**
		(-2.29)
SIZE	0.1745***	0.1746***
	(22.99)	(22.77)
MTB	-0.0004	-0.0004
	(-0.36)	(-0.37)
R&D	0.2398***	0.2365***
	(3.11)	(3.03)
LEVERAGE	-0.0577**	-0.0576**
	(-2.15)	(-2.15)
CASH_FLOW	-0.0577***	-0.0578***
	(-2.93)	(-2.92)
HERFINDAHL	-0.2584	-0.2643
	(-0.42)	(-0.43)
INVEST_OPPORTUNITY	-0.0314	-0.0313
	(-1.17)	(-1.17)
MACRO_UNCERTAINTY	0.0148	0.0150
	(0.55)	(0.55)
Constant	-1.0171*	-1.5812**
	(-1.81)	(-2.54)
N	51212	51212
Pseudo R^2	0.0759	0.0765

Panel C: Government customer

	Probit model	
Dependent variable	*INITIATION*	
	(1)	(2)
EPU_INDEX	-0.3185***	-0.2884***
	(-3.47)	(-3.11)
GOVERN_CUSTOMER	0.3671***	2.0012***
	(6.94)	(3.07)
*GOVERN_CUSTOMER*EPU_INDEX*		-0.3558**
		(-2.47)
SIZE	0.1803***	0.1805***
	(22.90)	(22.79)
MTB	-0.0008	-0.0008
	(-0.75)	(-0.75)
R&D	0.2580***	0.2589***
	(3.36)	(3.37)
LEVERAGE	-0.0490**	-0.0488**
	(-2.02)	(-2.00)
CASH_FLOW	-0.0635***	-0.0636***
	(-3.39)	(-3.40)
HERFINDAHL	-0.4157	-0.4199
	(-0.59)	(-0.59)
INVEST_OPPORTUNITY	-0.0278	-0.0275
	(-1.03)	(-1.01)
MACRO_UNCERTAINTY	0.0182	0.0184
	(0.67)	(0.68)
Constant	-1.2007**	-1.3410**
	(-1.98)	(-2.18)
N	55640	55640
Pseudo R^2	0.0813	0.0816

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