Uncertainty, Firm Investment, and Financial Heterogeneity

By Zhenning Zhao*

Draft: March 28, 2023

This paper compares the performance of firms facing asset-based financial constraints (ABC) versus earning-based financial constraints (EBC) when faced with uncertainty shocks. The results show that firms with earning-based financial constraints perform better than those with asset-based financial constraints when uncertainty increases, cutting investment by a smaller amount. The improvement is attributed to the division of uncertainty between the entrepreneurs and the banking sector and the restriction on borrowing in high-default-probability situations. The study finds that the latter is the main channel and the financial heterogeneity model predicts investment growth with a 10% higher correlation to actual data compared to the original financial accelerator model.

Economic fluctuations are heavily influenced by uncertainty, which can stem from a range of factors including government policies, geopolitical tensions, and natural disasters. When uncertainty reaches excessive levels, it can have a detrimental impact on investment, consumer spending, and economic growth. The COVID-19 pandemic has led to unprecedented levels of uncertainty in the global economy, with both policymakers and markets closely monitoring the situation. The World Bank has identified year 2022 as a year of significant uncertainty[1], and the IMF has observed a surge in global uncertainty in response to the ongoing conflict in Ukraine[2]. As a result, managing uncertainty has become a crucial concern for policymakers, who must balance the need for stability and predictability with the need to respond to rapidly evolving circumstances.

Economic uncertainty often leads to a deterioration of financial conditions, which can amplify the negative effects of uncertainty. In this context, it is impor-

* University of Texas at Austin, Economics Department.

[1]The link to the website: https://www.worldbank.org/en/news/podcast/2022/12/01/2022-review-year-uncertainty-forecasts-conflict-inflation-food-pandemic-development-podcast

[2]The link to the website: https://www.imf.org/en/Blogs/Articles/2022/04/15/global-economic-uncertainty-surging-amid-war-may-slow-growth

tant to understand the nuance differences of firm-level responses to uncertainty, as this can provide insight into the mechanisms through which uncertainty affects aggregate economic outcomes. By analyzing the varying responses of different firms to uncertainty, policymakers and researchers can gain a more comprehensive understanding of how uncertainty affects economic activity and develop more effective strategies to manage and mitigate its impact. This paper explores this issue, specifically examining the impact of uncertainty on firms' investment decisions in light of their financial type heterogeneity.

Historically, academic researchers have devoted significant attention to asset-based financial constraints, which permit creditors to claim the liquidation value of specific physical assets (i.e., collateral) in the event of default under Chapter 7 bankruptcy. Kiyotaki and Moore (1997) work represents a prominent example of research in this area. However, recent studies, including Lian and Ma (2021), suggest that only a small percentage (20%) of US non-financial corporate debt is collateral-based. Instead, most debts are subject to earnings-based financial constraints, which are governed by Chapter 11 bankruptcy and allow creditors to claim a portion of the future cash flow values of the restructured firm during a default. While the Kiyotaki and Moore Borrowing Capacity Framework is frequently used to compare these two types of financial constraints, it may not be ideal for answering this question. In the case of earnings-based debt, firms generally do not encounter an explicit borrowing limit. The major components of these debts consist of cooperative loans that operate within the credit market, and the primary constraint is the borrowing cost. As a result, the Financial Accelerator Framework, which emphasizes the impact of borrowing costs, developed by Bernanke, Gertler and Gilchrist (1998), may be more relevant for investigating issues linked to earnings-based financial constraints.

This paper provides compelling empirical evidence that firms with a higher earning-based debt ratio are less impacted by uncertainty shocks. Specifically, when idiosyncratic volatility at the firm-level increases, firms typically scale back their investments. However, those with a higher earning-based debt ratio display a smaller reduction in investment. To identify the uncertainty shocks, I employ the same method as Alfaro, Bloom and Lin (2019) and use the exposure to aggregate economy shocks as an instrument. Next, I utilize the Capital IQ dataset in combination with the Compustat-CRSP dataset to differentiate between earning-based and asset-based loans, following the methodology of Lian and Ma (2021).

Finally, I run regressions on the panel data using interaction terms between the instrumented uncertainty shocks and the earning-based debt ratios to explore the different responses of firm-level investment. The results reveal that firms with earning-based financial constraints tend to decrease their investments less when uncertainty increases, as compared to firms with asset-based financial constraints. These results remain robust even after controlling for the size of the financial constraint.

To better understand the primary mechanism that underlies this observation, I develop an earning-based financial accelerator model. This model is built upon the financial accelerator model with risk shocks proposed by Christiano, Motto and Rostagno (2014), with the addition of earning-based financial constraints. Unlike traditional asset-based financial accelerator models where entrepreneurs lose all net worth to the bank under default, the earning-based financial accelerator model punishes entrepreneurs by requiring them to transfer a fraction of earnings to the bank for a specified period. This mechanism creates two channels to mitigate the impact of risk shocks.

The first channel is that dividing risky earnings between entrepreneurs and banks allows banks to bear a portion of the idiosyncratic uncertainty shocks, which can be offset with each other by investing in multiple firms. The second channel, which is more significant, is that the bank punishes entrepreneurs more severely when they have a higher likelihood of default, leading to a negative feedback loop where fewer entrepreneurs have incentives to default when uncertainty increases. The earning-based financial accelerator model demonstrates that this second channel is the primary driver, accounting for about 70% of the difference in investment impacts between earning-based and asset-based financially constrained firms when risk increases.

Finally, I integrate both the asset-based and earning-based financial accelerator models into a financial heterogeneity model to examine the general equilibrium effect. The model categorizes entrepreneurs into two groups based on the types of financial constraints they face. These fractions are predetermined and calibrated to reflect the proportion of financial constraints in the data. The primary objective of this exercise is to determine how financial heterogeneity can enhance our understanding of business cycle fluctuations. Using US data from 2001 to 2019, the results demonstrate that the financial heterogeneity model improves the correlation of predicted investment fluctuations with actual data by about

10%, surpassing the traditional financial accelerator model. This underscores the significance of factoring in firm heterogeneity beyond just size to better comprehend business cycle fluctuations.

In summary, this paper emphasizes the significant difference of firm-level responses to increases in uncertainty, particularly in relation to investment. This finding has critical policy implications, such as highlighting the greater resilience of earning-based financial constraints to uncertainty shocks. As a result, policymakers should consider promoting earning-based debts over asset-based debts. Additionally, during periods of heightened uncertainty, the paper's results suggest that market supervisors should pay closer attention to asset-based financially constrained firms to prevent the emergence of large-scale financial crises.

The rest of the paper is structured as follows: the next section places this study in the existing literature. Section 2 outlines the primary dataset and methodology used in the empirical analysis. Section 3 presents the empirical evidence. Sections 4 and 5 provide a detailed explanation of the earning-based financial accelerator model and financial heterogeneity model, respectively. Finally, section 6 concludes.

I. Literature Review

Since the publication of Bloom (2009), there has been growing attention among economic researchers to the significance of uncertainty shocks as a driving factor of the business cycle. Various studies have demonstrated that uncertainties have an impact through the channel of inflation expectations in Istrefi and Piloiu (2014), effective demand in Basu and Bundick (2017), monetary policy decisions in Creal and Wu (2017), general equilibrium in Bloom et al. (2018), and the second moment news (Berger, Dew-Becker and Giglio (2020)). To measure aggregate-level uncertainties, researchers have employed different approaches, such as those used in Jurado, Ludvigson and Ng (2015), Ludvigson, Ma and Ng (2015), Baker, Bloom and Davis (2016), Carriero, Clark and Marcellino (2017), Carriero, Clark and Marcellino (2018), and Husted, Rogers and Sun (2019). Prior literature has addressed the endogeneity problem of aggregate uncertainties or focused on the identification of various types of uncertainties, such as those arising from productivity versus those related to policy. More recent studies utilizing micro-level data, such as Coibion et al. (2021) and Kumar, Gorodnichenko and Coibion (2022), have found robust causal evidence that uncertainty shocks have a direct effect on household and firm decisions.

Similarly, financial frictions is another hot topic in economic research. There are two primary approaches to modeling financial frictions in the literature. The first category builds upon the borrowing capacity framework developed in Hart and Moore (1994) and Kiyotaki and Moore (1997). Several subsequent works, such as Shleifer and Vishny (1992), Kocherlakota (2000), Cordoba and Ripoll (2004), Iacoviello (2005), Bianchi and Mendoza (2010), and Jermann and Quadrini (2012), have significantly advanced the model in the traditional DSGE models. Some more recent studies have combined this model with heterogenous firm models to explore the effects of firm size distributions. Examples include Khan and Thomas (2013), Guerrieri et al. (2015), Cao and Nie (2017), and Jensen et al. (2020). This type of model assumes that firm's borrowing capacity is limited by the amount of fixed capital they can provide as collateral, making it particularly suitable for examining asset-based financial constraints. As a result, most recent studies examining the impact of financial constraint types uses this borrowing capacity framework. For instance, all of the literature on financial type heterogeneity that I am aware of, including Greenwald (2018), Lian and Ma (2021), Drechsel (n.d.), Caglio, Darst and Kalemli-Özcan (2021) amd Zhao (2022), utilized this framework.

The financial accelerator framework, which was first developed by Bernanke, Gertler and Gilchrist (1998) and based on costly state verification methods from Townsend (1979) and Gertler and Bernanke (1989), represents the second approach to modeling financial frictions. One of the major advantages of this model is its ability to study the credit spread endogenously within the framework. Researchers such as Carlstrom and Fuerst (1997), Gilchrist and Zakrajšek (2012),Christiano, Motto and Rostagno (2014), and Carlstrom, Fuerst and Paustian (2015) have further developed the financial accelerator model in the DSGE setup to examine the amplification effect of various types of shocks. However, no paper has yet explored the earning-based financial constraint within the financial accelerator model, despite its better alignment with the nature of this type of constraint. This paper aims to fill in this gap in the literature.

In the literature studying uncertainty shocks and financial constraints, some researchers investigate the interplay between the two. Arellano, Bai and Kehoe (2018), and Fernández-Villaverde and Guerrón-Quintana (2020) are notable examples. Of these, the studies most closely related to this paper are those by

Christiano, Motto and Rostagno (2014) and Alfaro, Bloom and Lin (2019). The former presents a financial accelerator framework for examining risk shocks in a straightforward manner, which serves as the foundation for the model proposed in this paper. The latter proposes an empirical analysis framework and suggests the use of exposures to aggregate-level uncertainties as an instrument to address the endogeneity problem arising from the entanglement of first and second moment shocks.

II. Data and Methodology

The data used in this paper consists of two main parts: the classification of debt types and the data on idiosyncratic uncertainty shocks.

The primary dataset used in this paper to identify the debt types is the Capital IQ Capital Structure dataset, which offers a comprehensive view of the debt capital structures of over 60,000 public and private firms worldwide. The dataset includes various attributes of each debt component, such as security type, secured level, interest rate, maturity date, interest type, benchmark, convertible type, issued currency, benchmark spread, and more. The data covers the period from 2001 to 2019, and it provides in-depth information on a firm's debt capital structure based on its 10-K filings for publicly listed companies. The Capital IQ dataset was selected as the main source due to its comprehensive description of a firm's debts. In the previous study, Lian and Ma (2021), the Capital IQ dataset was combined with data from FISD, DealScan, and SDC Platinum for firm-level analysis, and the composition procedure in this paper follows a similar approach, with details outlined in the appendix. Given that Lian and Ma (2021) provides a detailed description of asset-based and earnings-based debts, here we will only provide a brief overview of the main components of the two categories.

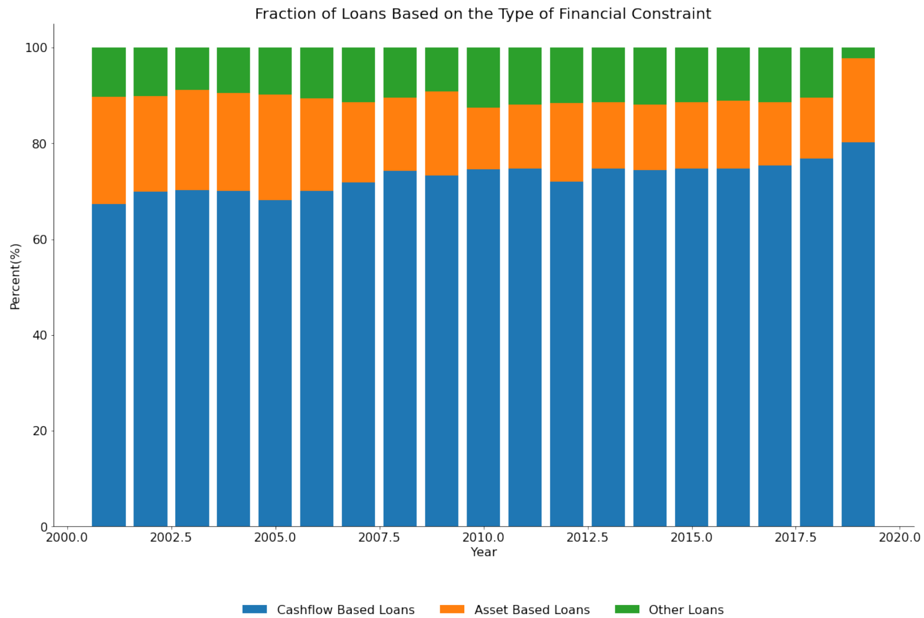
The asset-based debts primarily consist of commercial mortgages, asset-based loans, capitalized leases, and secured debt. Commercial mortgages are typically debt backed by real estate for corporate purposes. Asset-based loans are non-mortgage business loans that are secured by physical assets, such as inventory, receivables, machinery, equipment, and specialized assets like oil and gas reserves. A capital lease is a debt where the leased asset appears on the balance sheet. Secured debt is a loan secured by collateral, such as property or assets, that the lender can seize if the borrower defaults on the loan. In summary, all of these debts use physical assets as collateral and can be classified as asset-based debts.

In contrast, earning-based debts primarily consist of corporate bonds and cash-flow based loans. Unlike debts secured by physical collateral, corporate bonds are typically unsecured, and if they are secured, it is through a lien on the corporate entity. Similarly, cashflow based loans are backed by the borrower's current cash-flow, with creditors paying close attention to the borrower's cashflow and often imposing earning-based covenants to enforce the earning-based constraints.

In addition to asset-based and earning-based debts, firms can also borrow from the government or from private individuals, which are categorized as "other debts." The asset-based, earning based, and other debts will be the three types of debts that will be examined in this study. For each firm in each year, we will calculate the earning-based debt ratio, defined as the amount of earning-based borrowings divided by the total debt a firm borrows, and the asset-based debt ratio in a similar manner. Figure 1 displays the fraction of each type of debt by year on an aggregate level. It demonstrates that earning-based debt is the dominant type of debt among US public firms, and there has been a trend of increasing earning-based debts over the past two decades, rising from around 65% in the early 2000s to about 80% at the end of 2019. These results align with those found in Lian and Ma (2021).

Another crucial piece of information that is required is the firm-level uncertainty shocks. I follow the methodology outlined in Alfaro, Bloom and Lin (2019), utilizing both realized and implied uncertainty shocks to reinforce the empirical results. The realized uncertainty shocks are calculated as the changes in the standard error of the firm's realized stock returns for the previous year, and the implied uncertainty shocks are determined through the changes of the implied volatility derived from the firm-level option data. However, due to the high endogeneity of stock prices and option prices, an OLS regression faces endogeneity problems. To address this, Alfaro, Bloom and Lin (2019) proposed using the firm's exposure to 9 aggregate factors[3] as instruments. The underlying idea is that while fluctuations in the aggregate factors will impact the firm's uncertainties, the firm-level variables will hardly have effects on the aggregate factors since the impact of one firm is negligible. When the aggregate level factors experience fluctuations, firms that have a higher level of exposure to these factors will experience larger

[3]The aggregate factors employed in this paper includes: the oil price, the growth in the exchange rates of seven major currencies (Euro, Canadian Dollar, Japanese Yen, British Pound, Swiss Franc, Australian Dollar, and Swedish Krona), as designated by the Federal Reserve, and the growth in economic policy uncertainty, as defined by Baker, Bloom and Davis (2016).



Note: This figure depicts the aggregate fraction of the three types of debt over the years from 2001 to 2019, as identified from the Capital IQ dataset.

Figure 1. Aggregate Decompositions of Debts

Table 1—Data Description

Variable	Observation	Mean	Standard Error	Min	25 Percentile	Median	75 Percentile	Max
Investment Rate	37122	0.22	0.14	-0.24	0.11	0.19	0.31	0.50
Asset Based Loan Ratio	37122	0.27	0.37	0.00	0.00	0.04	0.49	1.00
Cashflow Based Loan Ratio	37122	0.68	0.39	0.00	0.36	0.89	1.00	1.00
Realized Uncertainty Shock	37122	-0.03	0.33	-0.85	-0.26	-0.05	0.17	1.01
Implied Uncertainty Shock	23621	-0.03	0.20	-0.52	-0.16	-0.04	0.07	0.65
Realized Return	37122	0.15	0.61	-0.88	-0.19	0.07	0.35	3.82
Employment Growth	37122	0.03	0.21	-1.00	-0.04	0.02	0.10	1.00
Intangible Asset Growth	37122	0.05	0.37	-1.00	-0.04	0.00	0.08	1.00
Dividend Payout Growth	37122	0.03	0.32	-1.00	0.00	0.00	0.05	1.00
Debt Growth	37122	0.05	0.46	-1.00	-0.15	0.00	0.22	1.00
Cost of Goods Growth	37122	0.06	0.26	-1.00	-0.03	0.06	0.16	1.00
Sales Growth	37122	0.06	0.25	-1.00	-0.03	0.06	0.16	1.00
Cash Holding Growth	37122	0.04	0.55	-1.00	-0.30	0.05	0.40	1.00
Profit Growth	37122	0.06	0.40	-1.00	-0.05	0.03	0.20	1.00
Tangibility	37122	0.57	0.46	0.00	0.21	0.45	0.84	3.76
Leverage	37122	0.57	0.26	0.04	0.40	0.55	0.70	2.31
ROA	37122	0.04	0.19	-1.97	0.02	0.07	0.12	0.59
Log Employment Size	37122	6.44	2.15	-1.91	5.03	6.57	7.90	11.89
Tobin's Q	37122	0.81	2.02	-5.12	-0.61	0.91	2.22	5.75

Note: This table presents the descriptive statistics of the key variables in the Capital IQ-Compustat-CRSP linked dataset. The dataset encompasses 5,865 companies from 2001 to 2019. The definitions of the variables can be found in the appendix.

fluctuations as a result. With this in mind, I adopt the same instrument variables[4], obtaining the annual firm-level shock and instrument variable data until 2019 from the authors, and merge it with the Capital IQ dataset. Additionally, I supplemented the dataset with information from the Compustat and CRSP datasets to account for firm-level controls.For each variable, I trim the data at the 0.5 and 99.5 percentiles by year to reduce the impact of outliers. The data is summarized in Table 1. The combined dataset used in the analysis includes data from 5,865 firms and covers the period from 2001 to 2019. The main dependent variable is the investment rate, which is defined as the ratio of the investment expenditure divided by the average capital stock between the current year and the previous year. The definition of other independent variables can be found in the appendix. Only records with positive values for total assets, total debts, sales, cost of goods, cash, employment, dividends, and fixed capital will be included in the final dataset.

III. Firm Level Empirical Evidence

A. *Effect of Debt Heterogeneity*

What is the impact of a firm's debt type on its investment behavior during times of increased uncertainty? To answer this question, I start with the regression model that includes an interaction term between the uncertainty shocks and the fraction of earnings-based debt. The regression is formulated as follows:

$$\begin{aligned} InvRate_{i,t} = {} & \beta_0 + \beta_1 VolShock_{i,t-1} + \gamma X_{i,t-1} + \delta_i + \eta_t + \epsilon_{i,t} \\ & + \beta_2 VolShock_{i,t-1} \times EBRatio_{i,t-1} + \beta_3 EBRatio_{i,t-1} \end{aligned} \tag{1}$$

where $InvRate_{i,t}$ represents the investment rate for firm i in year t, $VolShock_{i,t-1}$ represents either the realized or implied volatility shocks, instrumented with the firm's exposure to aggregate factors, and $EBRatio_{i,t-1}$ represents the earnings-based debt ratio. $X_{i,t-1}$ includes control variables, separated into two categories: aggregate factor controls and firm-level controls. The aggregate factor controls include changes in the first moment, as uncertainty increases are typically accompanied by a recession of the first moment shocks. The firm-level controls

[4]The calculation of the instruments and shocks is not covered in this paper, but a brief introduction of the construction of the instruments is provided in the appendix.

Table 2—Regression with Earning based Debt Ratio × Uncertainty Shock

Panel A: First Stage				
VARIABLES	(1) Realized First Stage			(2) Implied First Stage
F Stat	78.42			42.81
P Value	0.00			0.00
Observations	34,704			22,236
R-squared	0.093			0.114

Panel B: Second Stage				
VARIABLES	(3) Realized OLS	(4) Realized IV	(5) Implied OLS	(6) Implied IV
Realized Shock × Earning Based Debt Ratio	0.011**	0.020***		
	(0.005)	(0.006)		
Implied Shock × Earning Based Debt Ratio			0.018**	0.083***
			(0.008)	(0.022)
Realized Shock	-0.016***	-0.065***		
	(0.005)	(0.018)		
Implied Shock			-0.044***	-0.172***
			(0.010)	(0.057)
Earning Based Debt Ratio	0.007*	0.007*	0.008**	0.009**
	(0.004)	(0.004)	(0.003)	(0.004)
Observations	34,704	34,704	22,236	22,236
R-squared	0.176	0.161	0.214	0.194

Note: This table displays the results of the first regression. Panel A presents the results of the first-stage regression. Panel B presents the results of both the OLS and IV regressions with the realized and implied volatility shocks. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: p<0.01, **: p<0.05, *: p<0.1

include Tobin's Q, tangibility, leverage, return on assets, log of firm size, realized stock return, investment rate, employment growth, intangible asset growth, debt growth, cost of goods sold growth, sales growth, cash growth, profit growth, and dividend growth.

Note that in the regression, the independent variables and controls are lagged by one year to address the simultaneity of the firm's investment, debt structure changes, and uncertainty shocks. The firm fixed effects are represented by δ_i, and the yearly fixed effects are represented by η_t. The regression is run on panel data with standard errors clustered at the 2-digit SIC industrial level.

The regression results are displayed in Table 2. The first stage regression results are shown in Panel A of the table. The results indicate that both realized and implied uncertainty shocks can be effectively instrumented using aggregate shock exposure. The two F statistics for the instrument variables are 74.92 and 41.53, both with p-values close to zero, indicating a strong correlation between

Table 3—Financial Constraint: Whited and Wu (2006)

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Cashflow Based Loan Ratio	0.010**	0.009		
	(0.004)	(0.008)		
Realized Shock × WW Index	-0.008	-0.119		
	(0.021)	(0.076)		
Implied Shock × Cashflow Based Loan Ratio			0.015*	0.062***
			(0.009)	(0.017)
Implied Shock × WW Index			-0.083	-0.363
			(0.063)	(0.264)
Realized Shock	-0.018**	-0.087***		
	(0.008)	(0.032)		
Implied Shock			-0.067***	-0.263**
			(0.021)	(0.126)
WW Index	0.267***	0.268***	0.275***	0.275***
	(0.035)	(0.035)	(0.054)	(0.052)
Cashflow Based Loan Ratio	0.008**	0.007*	0.008**	0.008**
	(0.004)	(0.004)	(0.003)	(0.004)
Observations	34,704	34,704	22,236	22,236
R-squared	0.180	0.164	0.218	0.198

Note: The table presents the regression results controlling for financial constraint size, represented by the WW index from Whited and Wu (2006). A higher value of the WW index indicates a better financial situation for the firm. Both firm-fixed effects and time-fixed effects have been included in each regression. The standard errors are displayed in parentheses. ***: p<0.01, **: p<0.05, *: p<0.1

the instruments and the target shocks. Panel B of the table shows that the main effect of uncertainty on a firm's investment is negative, aligning with the main conclusions of Alfaro, Bloom and Lin (2019)[5]. Indeed, when idiosyncratic uncertainty increases, firms tend to become more cautious about the future, resulting in postponed investment decisions. Additionally, heightened uncertainty may also raise the risk of default, leading to further reduction in investment.

A key insight from Panel B is the positive coefficient for the interaction term between the earnings-based debt ratio and the uncertainty shocks. This indicates that if a firm has a higher proportion of earnings-based debt, it will be more resilient to the negative effects of increased uncertainty on investment, as the decline in investment will be less severe. This result is statistically significant for both the regression with the realized and implied uncertainty shocks.

The initial regression results provide a general understanding of the impact

[5]It is not surprising that the same main effect is found, as the data used in the regression is the same as in Alfaro, Bloom and Lin (2019). The appendix demonstrates that replicating the baseline regression from Alfaro, Bloom and Lin (2019) with a different time period yields results that are very similar to those in the original study.

Table 4—Financial Constraint: Hadlock and Pierce (2010)

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Earnings-Based Debt Ratio	0.009**	0.012*		
	(0.005)	(0.007)		
Realized Shock × HP Index	-0.002	-0.014*		
	(0.003)	(0.008)		
Implied Shock × Earnings-Based Debt Ratio			0.014*	0.073***
			(0.008)	(0.019)
Implied Shock × HP Index			-0.009	-0.020
			(0.007)	(0.016)
Realized Shock	-0.022*	-0.111***		
	(0.013)	(0.039)		
Implied Shock			-0.078***	-0.232**
			(0.029)	(0.101)
HP Index	0.032*	0.033*	0.028*	0.027*
	(0.018)	(0.018)	(0.016)	(0.016)
Earnings-Based Debt Ratio	0.007**	0.007**	0.008**	0.009***
	(0.004)	(0.004)	(0.003)	(0.003)
Observations	34,704	34,704	22,236	22,236
R-squared	0.177	0.161	0.214	0.199

Note: The table presents the regression results controlling for financial constraint size, represented by the HP index from Hadlock and Pierce (2010). A higher value of the HP index indicates a better financial situation for the firm. Both firm-fixed effects and time-fixed effects have been included in each regression. The standard errors are displayed in parentheses. ***: p<0.01, **: p<0.05, *: p<0.1

of various types of financial constraints on a firm's investment response to uncertainty shocks. However, as demonstrated by Alfaro, Bloom and Lin (2019), financial frictions can interact with uncertainty shocks in a way that intensifies the effect of the shocks on the firm's response. This phenomenon is referred to as the "financial uncertainty accelerator", whereby a tighter financial constraint results in a stronger response of the firm to uncertainty shocks. particularly since larger and publicly traded firms are generally found to have looser financial constraints and also tend to rely more heavily on earning-based debt financing.

To alleviate these worries, I conducted the following regression:

$$\begin{aligned} InvRate_{i,t} = \beta_0 &+ \beta_1 VolShock_{i,t-1} + \gamma X_{i,t-1} + \delta_i + \eta_t + \epsilon_{i,t} \\ &+ \beta_2 VolShock_{i,t-1} \times EBRatio_{i,t-1} + \beta_3 EBRatio_{i,t-1} \\ &+ \beta_4 VolShock_{i,t-1} \times FC_{i,t-1} + \beta_5 FC_{i,t-1} \end{aligned} \tag{2}$$

where $FC_{i,t-1}$ represents proxies for the strength of the financial constraints. In this study, two proxies were selected for this variable, both of which were drawn from past empirical regressions in the literature. The first is the index proposed in Whited and Wu (2006), denoted as WW index, and the second is the index proposed in Hadlock and Pierce (2010), denoted as HP index[6]. I also show in the appendix that the regression is robust to using the size of the firm or the leverage ratio of the firm as proxies for the financial constraints. Both the index developed by Whited and Wu (2006) and the one by Hadlock and Pierce (2010) take into account not only a firm's size and leverage, but also other factors such as profitability, age, and industry. A higher value on either index suggests that a firm has less stringent financial constraints and is more likely to secure debt financing.

The primary regression results are presented in table 3 and table 4. The results show that uncertainty shocks are amplified by financial frictions, as demonstrated in the study by Alfaro, Bloom and Lin (2019). The addition of controls for the financial uncertainty accelerator does not alter the impact of financial constraint heterogeneity. The coefficient for the interaction between the earnings-based debt ratio and the uncertainty shocks remains significantly positive, reducing the overall effect of uncertainty shocks on investment. This result is significant for both measures of uncertainty shocks and for both measures of financial constraints. Additionally, considering the type of financial constraint can result in a less effective financial uncertainty accelerator for implied volatility shocks, highlighting the stronger explanatory power of the type of financial constraint over its size.

B. *Robustness Check and Further Discussions*

In addition to the baseline regressions, I conducted several variations of the regression to ensure the robustness of the results. This section provides a brief overview of the main regression results performed in the paper. Due to the limit of space only the first robustness regression result is shown in the text. The rest of the regression results can be found in the appendix.

The most important regression to enhance the robustness of the analysis is to use dummy variables to categorize the firms based on their earnings-based debt ratio. The result of this regression is shown in 5. The dummy variables were set to 1 if the earnings-based debt ratio was above the yearly median, and 0 if not, thereby controlling for any influence from abnormal firms. This also allowed

[6]The definitions of WW index and HP index are shown in the appendix.

Table 5—Robustness Check: Regression with Dummy for Earning Based Debt Ratio

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × High Cashflow Based Loan Ratio	0.005	0.008*		
	(0.003)	(0.004)		
Implied Shock × High Cashflow Based Loan Ratio			0.009	0.034***
			(0.006)	(0.011)
Realized Shock	-0.012***	-0.056***		
	(0.004)	(0.018)		
Implied Shock			-0.036***	-0.128***
			(0.008)	(0.048)
High Cashflow Based Loan Ratio	0.006***	0.005**	0.005**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	34,704	34,704	22,236	22,236
R-squared	0.176	0.161	0.214	0.196

Note: The table presents the result of the robustness check with the dummy variable indicating whether the earnings-based debt ratio was above the yearly median or not. The standard errors are displayed in parentheses. ***: p<0.01, **: p<0.05, *: p<0.1

for the separation of the quantitative results for firms with higher earnings-based debt ratios and those with lower earnings-based debt ratios. The regression results showed that a 1 percent increase in uncertainty led to a decrease in investment rate by approximately 5.6% to 12.8% for firms with a low earnings-based debt ratio and 0.8% to 3.4% less for firms with a high earnings-based debt ratio. The decrease in investment was approximately 14% to 26% less for firms with a high earnings-based debt ratio. This empirical result will be compared with the results from the model simulation.

Other than using dummy variables, I also performed other robustness tests. First, the regressions were tested using the asset-based debt ratio, which is nearly equal to 1 minus the earnings-based debt ratio, ignoring other forms of debt that only account for a small fraction of the total debt borrowed by firms. The results of this test showed that the coefficient of interest had an opposite sign compared to the baseline regression, as predicted. This exercise helped confirm that the results were not significantly impacted by other forms of debt that firms borrow.

The second robustness check adopted the method of Alfaro, Bloom and Lin (2019), who utilized lags of three indicators of financial constraints to develop their constraint size measurement. The use of lags aimed to eliminate the contemporaneous relationship between a firm's borrowing behavior and uncertainty shocks, facilitating the identification of causality. In a similar vein, I conducted a regression by taking a one-year lag of both the type and size measurements of financial constraints, and the results were consistent with the baseline regressions.

The third robustness test I conducted was to control for the interplay between the idiosyncratic uncertainty shock and aggregate factors. This is important because the fraction of the earnings-based debt ratio may increase during certain periods, such as when financial constraints become tighter, the dominance of earnings-based loans increases, or aggregate uncertainty levels rise. The goal of this test was to eliminate these concerns. I used the credit spread between Moody BAA and AAA bonds as a proxy for overall financial conditions, the aggregate earnings-based debt ratio to indicate the type of financial constraint, and the VIX Index to represent the level of aggregate uncertainty. The results showed that even after controlling for the interplay between the idiosyncratic uncertainty shock and these factors, the main conclusion remained unchanged.

In addition to investment rates, I also examined the impact of financial constraint heterogeneity on firm-level variables. For example, when uncertainty increases, firms tend to hold more cash, and this effect is even stronger for firms with earnings-based financial constraints. This suggests that in general, firms facing earnings-based financial constraints perform better than those facing asset-based constraints when faced with uncertainty shocks. I also investigated the effects of uncertainty shocks on the firm's profits, stock returns, sales, cost of goods, intangible capital growth, employment growth, the payoff to equity holders, and the amount of debt borrowed, but the response of these variables was not significantly impacted by the type of financial constraint.

Lastly, I tested whether the impact of the financial constraint type remains unchanged when the size of the financial constraint changes, by including the triple interaction of idiosyncratic uncertainty shocks, size, and type of financial constraints. However, there is no significant difference between groups of firms with tighter or looser financial constraints. Additionally, the regression analysis of forward investment rates did not reveal any significant dynamic effects.

In conclusion, the results of the empirical analysis indicate that firms with a higher proportion of earnings-based debt tend to be less sensitive to changes in investment due to uncertainty shocks. The impact of the type of financial constraint is substantial, even after taking into account the size of the financial constraint.

IV. Asset-Based and Earning-Based Financial Constraint in Model

The results of the empirical study indicate that during periods of heightened uncertainty, firms with earnings-based constraints have better performance compared to those with asset-based financial constraints. However, what is the underlying reason for this outcome? To address this question, in this section, I will integrate the concept of earnings-based financial constraints into the financial accelerator model, based on the works of Bernanke, Gertler and Gilchrist (1998) and Christiano, Motto and Rostagno (2014). I will start by summarizing the traditional financial accelerator model and explaining why it can be considered as the framework for asset-based financial constraints. Next, I will incorporate the earnings-based financial accelerator by modifying the formal contracting problem to fit this framework. Finally, I will compare the impulse response functions of both models and demonstrate that the earnings-based constraint model predicts a lower response to risk shocks. A more comprehensive model that accounts for heterogeneous firms will be presented in the following section.

A. Asset-Based Financial Accelerator

We begin with the traditional financial accelerator framework, as illustrated in Figure 2. In this model, the fixed capital is produced by a fixed capital producer and held by entrepreneurs. There is one parent entrepreneur and a continuum of child entrepreneurs. The parent entrepreneur uses a combination of internal funds, represented by the net worth N_t, and external funds B_t, obtained through borrowing from the bank, to purchase the fixed capital on the market. The interest rate Z_t for the borrowed funds is negotiated with the bank. After acquiring K_{t+1} units of fixed capital at a price of Q_t in period t, the parent entrepreneur divides the fixed capital evenly among a continuum of child entrepreneurs.

Each child entrepreneur experiences an idiosyncratic effectiveness shock ω, drawn from a log-normal distribution with a mean of 1 and standard deviation σ_t. As explained by Christiano, Motto and Rostagno (2014), the effectiveness shock represents the different levels of effectiveness that different entrepreneurs may exhibit in utilizing the same unit of fixed capital. For instance, a capable entrepreneur such as Elon Musk or Steve Jobs may produce higher returns from the same unit of fixed capital compared to less skilled entrepreneurs. The shock to the standard error σ_t of the effectiveness shock represents uncertainty

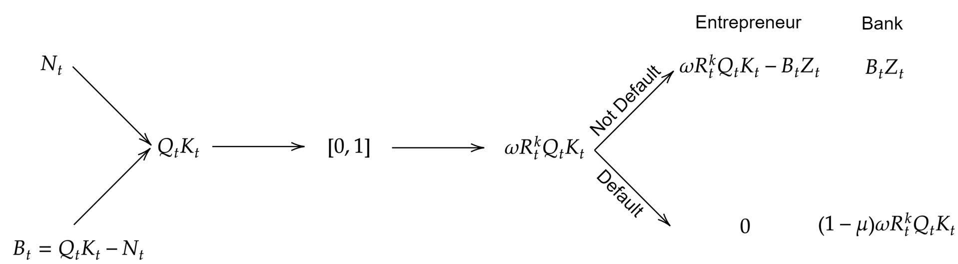


FIGURE 2. ASSET-BASED FINANCIAL ACCELERATOR

shocks. Suppose the aggregate capital return is represented by R^k_{t+1}, then a child entrepreneur with an effectiveness shock of ω will have an idiosyncratic capital return of ωR^k_{t+1}.

The decision of whether to default or repay the borrowed funds is based on the realized ω. If the child entrepreneur decides to repay, they return B_tZ_t to the bank and keep the remaining returns $\omega R^k_{t+1}Q_tK_{t+1} - B_tZ_t$. If the entrepreneur defaults, they declare bankruptcy and receive nothing, while the bank can claim $(1-\mu)\omega Q_tK_{t+1}$, after accounting for monitoring costs μ. Since ω is independent for each entrepreneur, their decisions are also independent. At the end of each period, the parent entrepreneur collects the funds from each child entrepreneur and uses them as the net worth for the next period. Since wealth is redistributed among the entrepreneurs in each period independently, this is a static problem and the formal contracting problem can be solved easily.

We can observe that when the entrepreneur's effectiveness is strong enough, they will be able to generate sufficient returns to pay back the debt to the bank. However, if the effectiveness is too weak, causing repayment of the debt to result in negative revenue, the entrepreneur will opt for default. There is a threshold value $\bar{\omega}_{t+1}$, such that when $\omega_{t+1} > \bar{\omega}_{t+1}$, the entrepreneur will not default, but if $\omega_{t+1} \leq \bar{\omega}_{t+1}$, the entrepreneur will default. The threshold $\bar{\omega}_t$ satisfies the following equation:

$$Z_t(Q_tK_{t+1} - N_t) = \bar{\omega}_{t+1}R^k_{t+1}Q_tK_{t+1}$$

The left-hand side of the equation represents the cost of external funds, while the right-hand side represents the returns on fixed capital. The expected payoff for entrepreneurs can be expressed using the relationship between $\bar{\omega}_t$ and Z_t as follows:

$$\begin{aligned}
&\int_{\bar{\omega}_{t+1}}^{+\infty} [\omega_{t+1} R^k_{t+1} Q_t K_{t+1} - Z_t(Q_t K_{t+1} - N_t)] d\Phi(\omega_{t+1}) \\
=&\int_{\bar{\omega}_{t+1}}^{+\infty} (\omega_{t+1} - \bar{\omega}_{t+1}) d\Phi(\omega_{t+1}) R^k_{t+1} Q_t K_{t+1}
\end{aligned}$$

Similarly, the expected payoff for the banks can be expressed as:

$$\begin{aligned}
&\int_0^{\bar{\omega}_{t+1}} \omega_{t+1}(1-\mu) R^k_{t+1} Q_t K_{t+1} d\Phi(\omega_{t+1}) + \int_{\bar{\omega}_{t+1}}^{+\infty} Z_{t+1}(Q_t K_{t+1} - N_t) d\Phi(\omega_{t+1}) \\
=&[\int_0^{\bar{\omega}_{t+1}} \omega_{t+1}(1-\mu) d\Phi(\omega_{t+1}) + \int_{\bar{\omega}_{t+1}}^{+\infty} \bar{\omega}_{t+1} d\Phi(\omega_{t+1})] R^k_{t+1} Q_t K_{t+1}
\end{aligned}$$

where the second line is a result of the relationship between $\bar{\omega}_{t+1}$ and Z_{t+1}. We can define $f(\bar{\omega}_{t+1}) = \int_{\bar{\omega}_{t+1}}^{+\infty} (\omega_{t+1} - \bar{\omega}_{t+1}) d\Phi(\omega_{t+1})$ and $g(\bar{\omega}_{t+1}) = \int_0^{\bar{\omega}_{t+1}} \omega_{t+1}(1-\mu) d\Phi(\omega_{t+1}) + \int_{\bar{\omega}_{t+1}}^{+\infty} \bar{\omega}_{t+1} d\Phi(\omega_{t+1})$, where $\Phi(\omega_{t+1})$ is the cumulative probability function of a log-normal distribution. Under the log-normal distribution, both functions $f(.)$ and $g(.)$ have closed-form solutions[7].

The entrepreneurs aim to maximize their expected returns, which are defined as the ratio of payoffs to net worth. Let $L_t = Q_t K_{t+1}/N_t$ represent the leverage ratio and R_t denote the risk-free interest rate. The formal contracting problem that the entrepreneurs solve can then be expressed as follows:

$$\begin{aligned}
&max_{\bar{\omega}_{t+1}, L_t} E_t[f(\bar{\omega}_{t+1}, \sigma_t) R^k_{t+1} L_t] \\
&\qquad s.t.\ E_t[\frac{g(\bar{\omega}_{t+1}, \sigma_t) R^k_{t+1} L_t}{L_t - 1}] = R_t
\end{aligned}$$

The constraint ensures that the expected return received by the bank is equal to the risk-free interest rate, as free entry conditions dictate that the expected

[7]Under the assumption of log-normal distribution, we have that

$$\begin{aligned}
f(\omega, \sigma) &= 1 - \Psi(\frac{ln\omega}{\sigma} - \frac{1}{2}\sigma) - \omega(1 - \Psi(\frac{ln\omega}{\sigma} + \frac{1}{2}\sigma)) \\
g(\omega, \sigma) &= (1-\mu)\Psi(\frac{ln\omega}{\sigma} - \frac{1}{2}\sigma) + \omega(1 - \Psi(\frac{ln\omega}{\sigma} + \frac{1}{2}\sigma))
\end{aligned}$$

return must be sufficient to pay the households. The entrepreneurs take this into account when solving for the optimal contracts that maximize their own returns. The solution to the problem results in the first-order conditions, which can be combined into a single equation through log-linearization:

$$r^k_{t+1} - r_t = \nu l_t + \chi \hat{\sigma}_t \tag{3}$$

The equation presented captures the key features of financial accelerator models. Bernanke, Gertler and Gilchrist (1998) found that ν is positive, indicating that an increase in a firm's leverage leads to an increase in credit spread. Higher borrowing costs reduce entrepreneurs' demand for capital and hence, investment. An increase in uncertainty, as demonstrated by Christiano, Motto and Rostagno (2014), increases the likelihood of default, which in turn leads to lower repayments for banks. This prompts banks to increase the credit spread ($\chi > 0$), causing a rise in the financial cost of the firm and a decrease in investment.

While the traditional financial accelerator model has straightforward logic, it only applies to firms that are financially constrained based on their assets. In this model, if entrepreneurs choose to default, they are forced to declare bankruptcy and earn no income. The entire value of the firm is transferred to the bank after liquidation. The bank has no memory of this event and does not punish the entrepreneurs in the future. These features align closely with asset-based financial constraints, where entrepreneurs use all of the firm's value as collateral in the current period. To compare the earning-based financial accelerator with the asset-based financial accelerator, it is crucial to develop a model that better fits earning-based financial constraints in reality.

B. Earnings-Based Financial Accelerator

Earnings-based debts have the following features: Firstly, in case of default, the company typically does not liquidate its assets. Secondly, the company undergoes restructuring, with debt holders having claims on a portion of its future earnings. Lastly, this type of debt is mostly obtained from credit markets, where financing costs, such as credit spreads, are used to control borrowing behavior, instead of limiting it through maximum borrowing capacity. The Earnings-Based financial accelerator framework, depicted in Figure 3, effectively captures these characteristics.

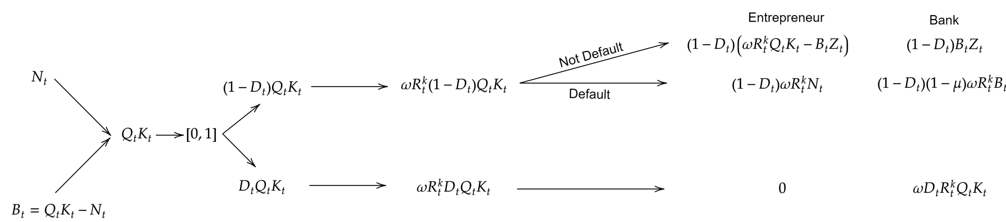


FIGURE 3. EARNINGS-BASED FINANCIAL ACCELERATOR

In the Earnings-Based financial accelerator framework, the parent entrepreneur has access to the same funding sources as in a traditional financial accelerator. The negotiated interest rate is again represented by Z_t. The parent entrepreneur still divides the fixed capital evenly among child entrepreneurs each period, maintaining the static nature of the formal contracting problem.

Child entrepreneurs, who draw idiosyncratic shocks ω from the same log-normal distribution, however, are unable to obtain all the earnings from holding K_{t+1} amount of fixed capital as in the previous case. The total return that the entrepreneur receives, $\omega R^k_{t+1} Q_t K_{t+1}$, is now divided into two parts: risky fund returns and punishment fund returns. The fraction of the punishment fund is represented by D_t and is exogenous to the entrepreneur's decision. The bank holds claims on the returns of the punishment fund, while the entrepreneur receives no returns from it. The entrepreneur has claims on the returns of the risky funds, but must pay the interest $B_t Z_t$ to the bank. If the entrepreneur experiences a shock such that the return from fixed capital is insufficient, they may choose to default. In this scenario, instead of being forced to liquidate all assets, the company undergoes a restructuring process. The entrepreneur and the bank receive returns based on the fraction of funds they provide, with the future fraction of the punishment fund also changing.

We will address the determination of the fraction of the punishment fund later. For now, let's concentrate on the formal contracting problem given D_t. We observe that the default decision only depends on the returns from the risky funds. The cutoff value of ω, represented by $\bar{\omega}$, now satisfies the following equation:

$$\bar{\omega}_{t+1} R^k_{t+1}(1-D_t)N_t = \bar{\omega}_{t+1} R^k_{t+1}(1-D_t)Q_t K_{t+1} - Z_{t+1}(1-D_t)(Q_t K_{t+1} - N_t)$$

The left-hand side of the equation represents the return in the event of default, while the right-hand side represents the return when the entrepreneur chooses not to default. It is worth noting that in the case of default, the entrepreneur receives returns as if leverage had not been employed. The equation can be re-written in a form that is comparable to a similar equation in the traditional financial accelerator model, as $Z_{t+1} = \bar{\omega}_{t+1} R^k_{t+1}$.

Next, we analyze the entrepreneurs' payoffs. By definition, it can be expressed as follows:

$$(1 - D_t)R^k_{t+1}[\int_0^{\bar{\omega}_{t+1}} N_t \omega_{t+1} d\Phi(\omega_{t+1}) + \int_{\bar{\omega}_{t+1}}^{+\infty} (\omega_{t+1} Q_t K_{t+1} - Z_{t+1} B_t) d\Phi(\omega_{t+1})]$$

The first part of this expression represents the return from the risky fund in the event of default, while the second part represents the return in the case where the entrepreneur does not default. By using the relationship between $\bar{\omega}_{t+1}$ and Z_t that was established previously, we can eliminate the variable Z_t, similarly to the traditional financial accelerator model. By dividing the expression by the net worth, the return for the entrepreneurs can be expressed as follows:

$$\begin{aligned} &R^k_{t+1}(1 - D_t)[\int_0^{\bar{\omega}_{t+1}} \omega_{t+1} d\Phi(\omega_{t+1})] + \int_{\bar{\omega}_{t+1}}^{\infty} \bar{\omega}_{t+1} d\Phi(\omega_{t+1}) \\ &+R^k_{t+1}(1 - D_t) \int_{\bar{\omega}_{t+1}}^{+\infty} (\omega_{t+1} - \bar{\omega}_{t+1}) d\Phi(\omega_{t+1}) L_t \end{aligned}$$

Notice that the second line features the function $f(.)$. To simplify the expression of the return[8], we can define $h(\bar{\omega}_{t+1}, \sigma_t) = \int_0^{\bar{\omega}_{t+1}} \omega_{t+1} d\Phi(\omega_{t+1})$.

Similarly the expected return for the bank can then be represented as follows:

$$\begin{aligned} D_t R^k_{t+1} Q_t K_{t+1} + &(1 - D_t) B_t \int_0^{\bar{\omega}_{t+1}} \omega_{t+1} d\Phi(\omega_{t+1})(1 - \mu) R^k_{t+1} \\ &+(1 - D_t) B_t \int_{\bar{\omega}_{t+1}}^{+\infty} Z_t d\Phi(\omega_{t+1}) \end{aligned}$$

The first term in the above equation represents the payoff from the punishment

[8]Notice that when the monitoring cost is sufficiently small, the function $h(.)$ will be very similar to the function $g(.)$. Under log-normal distribution, we have

$$h(\omega, \sigma) = \Psi(\frac{ln\omega}{\sigma} - \frac{1}{2}\sigma) + \omega(1 - \Psi(\frac{ln\omega}{\sigma} + \frac{1}{2}\sigma))$$

fund, the second term indicates the payoff from the risky fund in the case of default, and the third term represents the payoff from the risky fund in the case of no default. By eliminating the variable Z_t and calculating the returns by dividing B_t, we obtain:

$$\frac{R^k_{t+1} D_t L_t}{L_t - 1} + (1 - D_t)[\int_0^{\bar{\omega}_{t+1}} \omega_{t+1} d\Phi(\omega_{t+1})(1-\mu) + \int_{\bar{\omega}_{t+1}}^{+\infty} \bar{\omega}_{t+1} d\Phi(\omega_{t+1})] R^k_{t+1}$$

Here, the function $g(.)$ appears again. By combining the returns for entrepreneurs and banks, we can formulate the formal contracting problem for entrepreneurs in the earnings-based financial accelerator model:

$$max_{\bar{\omega}_{t+1}, L_t} (1 - D_t) R^k_{t+1} h(\bar{\omega}_{t+1}, \sigma) + (1 - D_t) R^k_{t+1} f(\bar{\omega}_{t+1}, \sigma) L_t$$
$$s.t.\ R^k_{t+1} D_t \frac{L_t}{L_t - 1} + (1 - D_t) g(\bar{\omega}_{t+1}, \sigma) R^k_{t+1} = R_t$$

In comparison to the traditional financial accelerator model, both the objective function and the constraint are different, leading to completely different First-Order Conditions (FOCs)[9]. By combining and log-linearizing the FOCs, a distinct relationship is established between the credit spread, leverage, and risk:

$$r^k_{t+1} - r_t = \tilde{\nu} l_t + \tilde{\chi} \hat{\sigma}_t + \tilde{\varphi} d_t \tag{4}$$

From the FOCs, we can also determine the expression for the cutoff as:

$$\hat{\omega}_{t+1} = o(l_t, \sigma_t, d_t, r^k_{t+1} - r_t) \tag{5}$$

In comparison to the traditional financial accelerator, not only are $\tilde{\nu}$ and $\tilde{\chi}$ different from ν and χ, but also an additional term, d_t, which represents the log-linearized fraction of punishment funds, appears in the equation. We will now examine the determination of d_t.

We can observe that the entrepreneurs prefer to have more of the risky funds as they always receive a positive return from these funds. On the other hand, the bank would like to have a higher proportion of punishment funds as this

[9]By taking the FOCs with respect to $\bar{\omega}_{t+1}$ and L_t, two FOCs are obtained, while the third FOC serves as a constraint. To solve the model, I used the three FOCs directly rather than combining them into one, as is done in the traditional financial accelerator model.

would increase their return. This relationship can be explained with the following proposition:

PROPOSITION 1: *When $L_t > 1$, the return of the bank increases in D_t.*

The proof can be found in the appendix, but the concept is easy to understand. The penalties allows the banks to impose a burden on entrepreneurs by requiring them to work for free. As a result, the bank would become a free-rider, taking advantage of a large portion of the penalty funds. With entrepreneurs wanting a lower D_t and banks wanting a higher D_t, the fraction of D_t cannot be unilaterally decided by either party. Instead, the two parties negotiate at the start of each period to determine D_t.

More specifically, we assume that the banks and the entrepreneurs negotiated with each other through Nash Bargaining:

If a larger proportion of entrepreneurs defaulted in the previous period, they will have less bargaining power during negotiations, resulting in a higher D_t. This relationship is captured by the following transitional equation for D_t:

$$D_{t+1} = (1-\psi)D_t + (1-D_t)\Phi(\bar{\omega}_{t+1}, \sigma_t)$$

where ψ is a forgiveness rate and $\Phi(\bar{\omega}_{t+1}, \sigma_t)$ represents the current probability of default. If there is a prolonged period without any defaults, the bank will not punish the entrepreneurs, and D_t will be 0. However, if a large proportion of entrepreneurs decide to default, the bank will respond by setting a high fraction of punishment funds in the following periods. The existence of the ψ parameter ensures that not all funds are punished and serves a similar role as the parameter N in Zhao (2022) N-period enforcement model. This ad-hoc law of motion for D_t captures the essence of earnings-based financial constraints in reality and is analogous to the situation in Chapter 11 where the restructuring process determines the value of a firm and the payouts of cash flow-based debt. By taking the log-linearization, we obtain:

$$(6) \quad d_{t+1} = [1-\psi-\Phi(\omega)]d_t + \frac{(1-D)\Phi_\omega(\bar{\omega},\sigma)\bar{\omega}}{D}\hat{\omega}_{t+1} + \frac{(1-D)\Phi_\sigma(\bar{\omega},\sigma)\sigma}{D}\hat{\sigma}_t$$

C. General Equilibrium

The model operates similarly to traditional financial accelerator models, as explained below and depicted in Figure 4.

The model consists of three main blocks. The first block represents the standard household, whose utility function is given by $U = \sum_t \beta^t E_t[\log(C_t) + \xi \log(1 - H_t)]$, where C_t represents consumption and H_t represents labor. The household has access to a risk-free bond provided by the central bank and a savings account at a bank. By the law of one price, the banks must offer the risk-free interest rate to households. The household earns income through wages received for providing labor to wholesale goods producers and through savings in the bank and government bond. Finally, the household consumes the final goods produced by final goods producers.

The second block represents the standard New Keynesian producer. This block follows the traditional New Keynesian model, where wholesale goods producers rent capital and labor to produce intermediate goods. The producers face the typical Calvo-type price stickiness. The intermediate goods they produce are then transformed into final goods by the final goods producers using a constant elasticity of substitution technology. The final goods are sold to households for consumption or to fixed capital producers to produce fixed capital.

The third and final block represents the fixed capital producers. The economy assumes the presence of fixed capital producers who operate in a perfectly competitive market with free entry. They borrow existing capital, K_t, from entrepreneurs and purchase final goods at a price of 1. They use the technology $\Phi(\frac{I_t}{K_t})K_t$ to produce the investment goods. After production, they return all the borrowed capital goods to the entrepreneurs without cost and sell the newly produced investment goods at the market price, Q_t.

Every period, the entrepreneurs will allocate a fraction of their net worth, specifically $1 - \gamma$, for personal consumption. Additionally, they will work as managers for the wholesale firms, providing labor. Therefore, their net wealth in the next period will be a combination of their remaining net worth from the previous period and the income they earned from providing labor as managers for the wholesale good producers.

The model reaches an equilibrium when market clearing conditions are satisfied in the final goods market, labor market, and fixed capital market. To complete

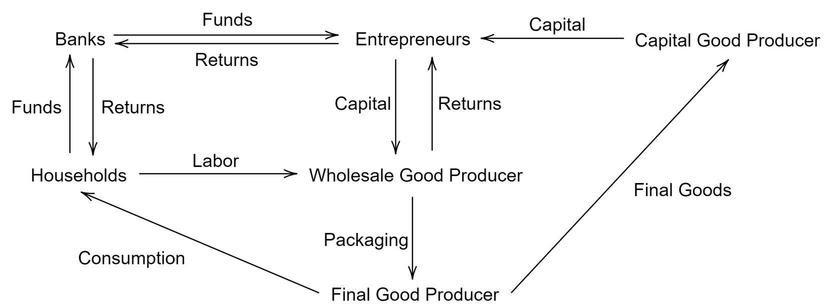


Figure 4. General Equilibrium Model

the model, we assume that the central bank sets monetary policy based on a Taylor rule with interest rate persistence, as described by the following equation:

$$r_t = \rho r_{t-1} + \zeta \pi_{t-1} + e_t^r \tag{7}$$

To solve the two general equilibria separately, we need to combine all the partial equilibrium optimal conditions and the market clearing conditions. The complete system of equations can be found in the appendix.

D. Simulation Result

To demonstrate the impact of different types of financial accelerators, I start with comparing the earning-based financial accelerator model to the asset-based financial accelerator model separately, while including only one type of financial constraint in the model each time.

The models are calibrated quarterly, with the parameter values listed in Table 6. The discounting factor β is set to 0.99 to achieve a target annual interest rate of 4 percent. The depreciation rate δ is set to 0.025 to achieve a target annual depreciation rate of 10 percent for fixed capital. The technology parameters α and Ω are set to 0.35 and 0.9846, respectively, to achieve a target labor share of 35 percent and entrepreneur share of 64 percent in the US. The elasticity of substitution between goods η is set to 11 to achieve a steady-state markup of 10 percent. The entrepreneur survival rate γ is set to 0.9728 to match a quarterly natural net worth shrinking rate of 2.72 percent. The price stickiness parameter

Table 6—Parameter Calibration

Variable	Name	Value	Target
β	Utility Discounting Factor	0.99	4% Annual Interest Rate
δ	Quarterly Depreciation Rate	0.025	10% Annual Depreciation Rate
α	Labor Share	0.35	35% Labor Share in the US
Ω	Entrepreneur Labor Share	0.9846	64% of Entrepreneur Labor Share
η	Elasticity of Substitution Between Goods	11	10% Steady State Markup
γ	Entrepreneur Survival Rate	0.9728	2.72% Quarterly Natual Net Worth Shrinking Rate
θ	Price Stickiness	0.75	25% of Price Changing
ξ	Labor Preference Parameter	3.3122	25% of Working Hours of a Day
φ	Fixed Capital Producer Technology	0.25	Common Value
ρ	Taylor Rule Persistence	0.90	Common Value
ζ	Taylor Rule Inflation Reaction	1.1	Common Value
μ	State Verification Cost	0.20	Common Value
$\bar{G}/\bar{Y}$	Steady State G/Y ratio	0.20	Common Value
σ	Steady State ω Standard Error	0.1533	2% Credit Spread
ρ_s	Risk Shock Persistence	0.88	30% Difference from Robust Empirical Analysis

Note: The table displays the parameter values used to solve the impulse response functions (IRFs) of two financial accelerator models in response to risk shocks. To ensure comparable steady states and mitigate the impact of differences in financial friction magnitudes, the same parameter values are employed for both models. The calibration of the models is mostly based on Eric Sims' notes.

θ is set to 0.75 to match a 25 percent price changing rate. The labor preference parameter ξ is set to 3.3122 to match a 25 percent share of working hours in a day. The steady-state government expenditure ratio $\bar{G}/\bar{Y}$ is 20 percent. Most of the other parameters are set according to common calibrations provided in the notes of Eric Sims, with two exceptions: the steady-state standard error of the effectiveness shock, σ, and the persistence of the risk shock ρ_s, which are to be determined.

To set the first parameter σ, I target a credit spread of 2 percent in the steady state for the traditional asset-based financial accelerator model. Using the same set of deep parameters, I then determined the steady state for the earnings-based financial accelerator model to achieve the same credit spread. Table 7 shows that most of the targeted and untargeted steady-state variables are identical between the two scenarios. Notably, the credit spread in the earnings-based financial accelerator model coincides with that of the asset-based model, eliminating the effect of different financial friction sizes.

The second parameter to be determined is the persistence of the risk shock, denoted by ρ_s. Since this parameter is related to the dynamic effects of the model, simulation methods are used to calibrate it. Given all other parameters, I simulate the asset-based and earnings-based financial accelerator models separately for 126 periods (quarters), which corresponds to the 19 years of available data. Each

Table 7—Comparison between Empirical Result and Simulation Result

	VARIABLES	(1) Emperical Result	(2) Simulation Result
β_2	Implied Shock × High Cashflow Based Loan Ratio	0.034	0.186
β_1	Implied Shock	-0.128	-0.512
β_3	High Cashflow Based Loan Ratio	0.005	-1.481
$\lvert\beta_2/\beta_1\rvert$	Effect of the Types of the Financial Constraint	26.56%	36.33%

Note: The table compares the simulation result to the empirical result. The empirical result is the same as in column 4 in table 5. The simulation is obtained by pooling the simulation data of the asset based and earnings based financial accelerators and run OLS regressions following equation (8).

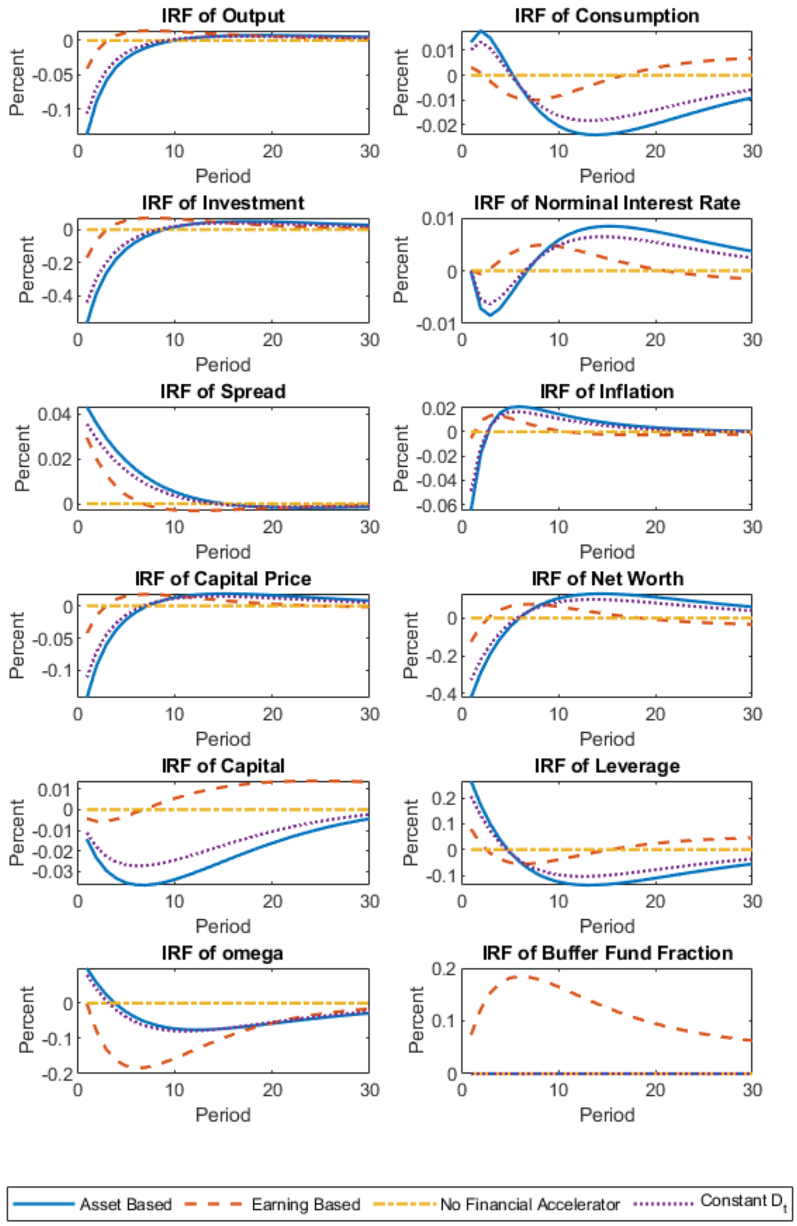
simulation represents a firm, and I simulate 2933 firms for each model to match the number of firms in the data. After the simulation, I pool the simulated investment rates[10] and the growth in the standard error of the effectiveness shocks, denoted as $\Delta\sigma_{i,t}$, to run a regression similar to the empirical analysis:

$$InvRate_{i,t} = \beta_0 + \beta_1 \Delta\sigma_{i,t} + \beta_2 \Delta\sigma_{i,t} \times 1(EBC)_{i,t} + \beta_3 1(EBC)_{i,t} + \epsilon_{i,t} \tag{8}$$

I focus on the ratio of β_2/β_1 because the definition of uncertainty is not the same in the data and in the model. The ratio measures the effect of financial constraint type relative to the main effect, allowing for comparison between the data and the model. After calibrating the model, I find that $\rho_s = 0.88$ yields a ratio of β_2/β_1 of 36.3%. This means that, compared to asset-based financially constrained firms, earnings-based financially constrained firms are about 36% less affected by risk shocks in the model. This parameter choice replicates the empirical result well, as the scale of the effect in the data is about 30% with the implied volatility shocks.

After carefully calibrating the models, I present the impulse response functions (IRFs) of the two models to risk shocks in Figure 5, which clearly illustrates the results and mechanisms. We observe that as uncertainty levels increase (i.e., σ increases), investment decreases in both models, but the earnings-based financial accelerator model experiences a smaller drop. To provide a comparison, I also include the results of the no-financial-accelerator model as a baseline, in which the credit spread is irrelevant to the leverage ratio and risk shocks. As the risk shocks only affect the model through the credit spread channel, it is natural to see that the risk shock has no effect in the absence of a financial accelerator. By

[10] Since the model's variables are in log forms, I take the exponential of the simulated investment rates to match the empirical results.



Note: This figure displays the impulse response function of the endogenous variables in response to a 1 percent increase in the standard deviation of the idiosyncratic effectiveness shocks, which is indicative of an increase in risk shocks.

Figure 5. Impulse Response Function of Risk Shock

examining the IRFs of most of the endogenous variables, we can see that the earnings-based financial accelerator model lies between the asset-based financial accelerator and the baseline New Keynesian model, indicating that earnings-based financial constraints have a weaker effect than asset-based financial constraints.

When we delve deeper into the mechanisms, we can identify two reasons why earning-based financial accelerator models lead to a smoother impulse response function (IRF) of investment in response to positive risk shocks. Firstly, to simplify the model under the earning-based financial accelerator, we assume that the formal contracting problem remains static. This means that the fraction of punishment funds is the same for entrepreneurs with different current effectiveness shocks. Under earning-based financial constraints, the existence of punishment funds allows for the sharing of idiosyncratic risk between entrepreneurs and banks. Since the bank signs contracts with a continuum of entrepreneurs, and there are no aggregate-level effectiveness shocks, idiosyncratic shocks borne by the bank will cancel each other out, thus reducing the overall effect of the risk shock on the economy.

The second, and more critical, channel relates to the punishment fund itself. According to the earning-based financial constraints, the transition equation of D_t requires banks to impose stricter penalties on entrepreneurs when there are more defaulting entrepreneurs. Figure 5 shows that when a positive risk shock hits the economy, entrepreneurs have a higher likelihood of defaulting due to the existence of a financial accelerator. Under the asset-based financial accelerator, banks can only raise the interest rate as a form of punishment. However, with the earnings-based financial accelerator, banks can also increase the fraction of the punishment funds to punish entrepreneurs. Since risk shocks have some persistence, banks punish entrepreneurs more severely in the earnings-based financial accelerator than in the asset-based financial accelerator when the level of uncertainty increases in subsequent periods. This, in turn, reduces the entrepreneurs' incentive to default in the following periods, resulting in a smaller impact on investment. To measure the impact of the two channels, I examined the impulse response functions (IRFs) of a counterfactual scenario in which D_t is held constant at the steady state, i.e., $d_t = 0$. By fixing D_t, we can isolate the effect of the two channels. The difference between fixing D_t and the asset-based financial accelerator represents the effect of the first mechanism, while the remaining difference between fixing D_t and the earnings-based financial accelerator is the effect of the second mechanism. Figure 5 shows that the second channel is the primary channel. In terms of quantity, the effect of canceled idiosyncratic shocks, i.e. the first channel, accounts for only about 30% of the difference between the IRFs of the two types of firms on the impact.

In summary, the earnings-based financial accelerator model exhibits a weaker response to risk shocks compared to the traditional asset-based financial accelerator model. This finding aligns perfectly with the empirical results.

V. Heterogeneous Financial Accelerator Model

In the previous session, we examined the asset-based and earnings-based financial accelerator models independently without accounting for general equilibrium effects. This raises the question of how financial heterogeneity can help us better explain fluctuations in the business cycle. To explore this question, I developed a heterogeneous financial accelerator model and calibrated it using Bayesian estimation to target US aggregate data. I will first explain the setup of the heterogeneous firm model, followed by a discussion of the calibration strategy and how we measure the model's goodness-of-fit. Finally, I will present the results, which show that the heterogeneous firm model increases the correlation between the model-predicted investment and actual data by approximately 10%.

In the heterogeneous firm model, the key difference from the traditional financial accelerator model lies in the entrepreneur sector. Rather than treating all child entrepreneurs as a single type, the parent entrepreneur divides them into two categories, one following asset-based financial constraints and the other following earnings-based financial constraints. The fraction of net worth invested in the asset-based financial-constrained firms is denoted as J. Using the definition of leverage ratio, we obtain:

$$L = \frac{Q_t K_t}{N_t} = \frac{Q_t K_t^A}{N_t} + \frac{Q_t K_t^E}{N_t} = J L_t^A + (1-J) L_t^E$$

Here, K_t^i and L_t^i with $i \in A, E$ represent the amount of capital and leverage ratio of the two types of firms, respectively. After log-linearization, we have an affine function of the leverage ratios. At the steady state we assume that L^A and L^E

Table 8—Bayesian Estimation

Variables	Prior Distribution	prior mean	Traditional Financial Accelerator Postior Mean	90% CI		Heterogenous Financial Accelerator Postior Mean	Postior 90% CI LB	
TFP Shock Standard Error	Inverse Gamma	0.0010	0.0095	0.0098	0.0111	0.0112	0.0126	0.0127
Government Expenditure Shock Standard Error	Inverse Gamma	0.0010	0.0403	0.0400	0.0467	0.0457	0.0530	0.0518
Montary Policy Shock Standard Error	Inverse Gamma	0.0010	0.0036	0.0037	0.0041	0.0042	0.0047	0.0048
Risk Shock Standard Error	Inverse Gamma	0.0010	0.0003	0.0003	0.0007	0.0015	0.0011	0.0030
Net Worth Shock Standard Error	Inverse Gamma	0.0010	0.0179	0.0194	0.0207	0.0227	0.0236	0.0253
Labor Supply Shock Standard Error	Inverse Gamma	0.0010	0.0407	0.0416	0.0478	0.0501	0.0547	0.0564
Markup Shock Standard Error	Inverse Gamma	0.0010	0.0109	0.0114	0.0127	0.0136	0.0148	0.0152
Observation Shock Standard Error	Inverse Gamma	0.0010	0.0003	0.0002	0.0006	0.0007	0.0009	0.0013
Montary Policy Persistence	Beta	0.9000	0.1734	0.2192	0.2317	0.2767	0.3044	0.3443
Taylor Rule Parameter	Normal	1.2000	1.1865	1.1853	1.1973	1.1978	1.2067	1.2089

Note: The table shows the Bayesian estimation result of the two models. The parameters are chosen to match the targeted aggregate variables from 2001 to 2019. the iteration number in the MCMC method is set to 2000, The scale parameter of the jumping distribution's covariance matrix is set to 0.8.

are calibrated to have the same value, which means

$$l = Jl_t^A + (1-J)l_t^E$$

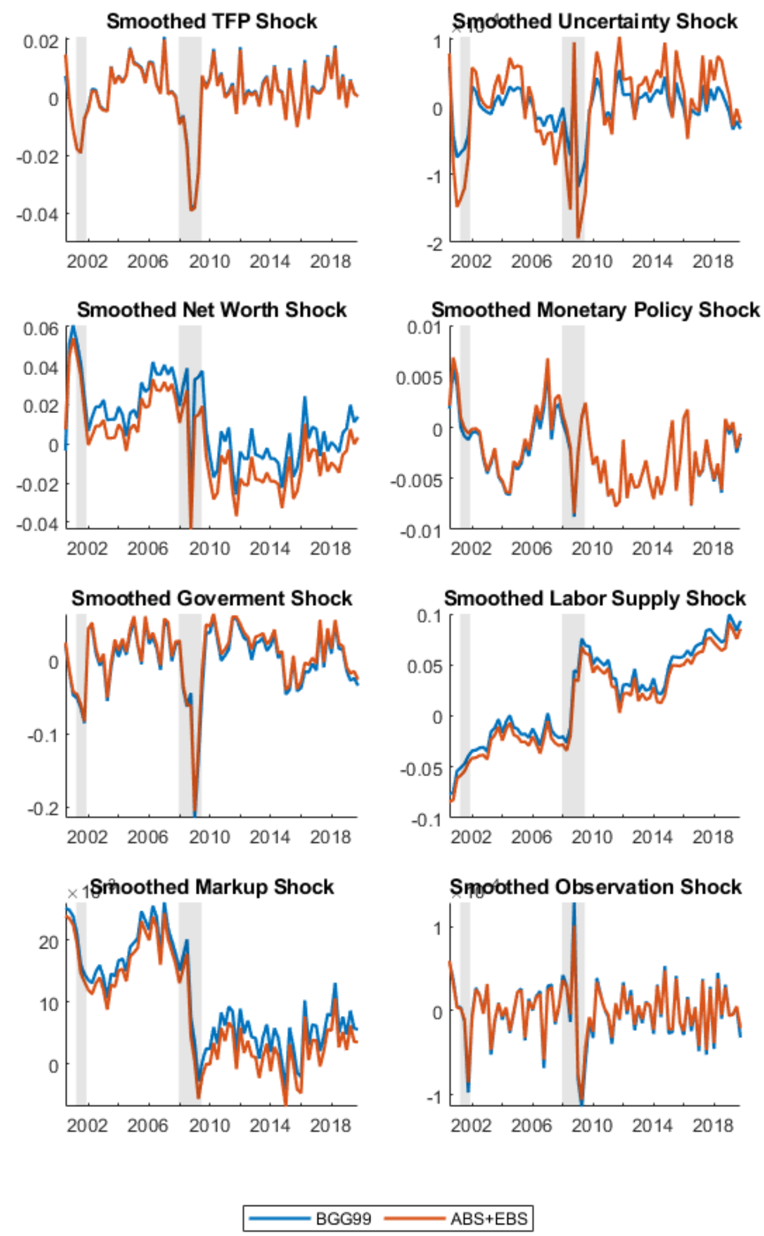
In the model, J is treated as a parameter as set to be 30% to match the empirical fraction of the asset based debt ratio from the Capital IQ dataset. Although the assumption of a constant and exogenously given fraction of asset-based financial accelerator firms is unrealistic, abstracting from the endogenous choice of firm type allows for a simple and computationally tractable model.

The entrepreneurs in the asset-based financial accelerator sector follow equation 3, while those in the earnings-based sector follow equations 4 and 5. Note that the leverage ratio l_t in these equations is adjusted to l_t^A and l_t^E to match the two sectors. The log-linearized definitions of the two sectors can be expressed as follows:

$$k_t^i = n_t + l_t^i - q_t, \quad \delta i_t^A = k_{t+1}^A - (1-\delta)k_t^A$$

for $i \in \{A, E\}$. Here, k_t^i denotes the amount of capital in sector i at time t.

Our objective is to verify whether incorporating financial heterogeneity can provide a more comprehensive explanation for the fluctuations in aggregate-level investment. To achieve this, I calibrated both the financial heterogeneity model and the traditional financial accelerator model to reach the same steady state, using the identical parameters as in the previous section. The model incorporates 8 shocks, including TFP shocks, government expenditure shocks, risk shocks, net worth shocks, markup shocks, observation shocks, labor supply shocks, and monetary policy shocks. The government expenditure shocks and TFP shocks are



Note: This figure displays the shocks identified with two models. The BGG99 model corresponds to the traditional financial accelerator model developed in Bernanke et. al. (1999). "ABS+EBS" denotes the financial heterogeneity model that I developed in this paper. The shocks are obtained using the Kalman smoother.

Figure 6. Smoothed Shocks

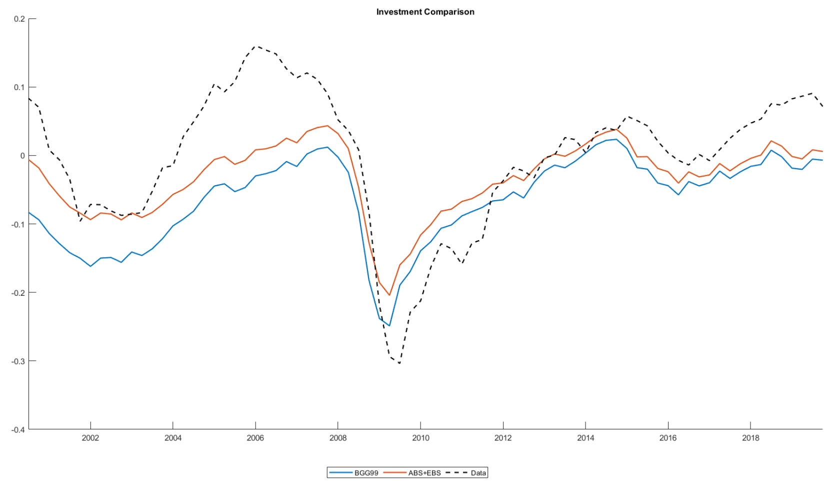
assumed to follow an AR(1) process with a persistence of 0.95. The persistance of the risk shock is again 0.88 from previous calibrations. The standard errors of the shocks and the parameters in the Taylor rule for monetary policy are the only remaining variables to be determined through Bayesian estimation.

To calibrate the model, I targeted six time series data from the St. Louis Federal Reserve Bank. Specifically, I used the deviation of real personal consumption expenditure for consumption, the deviation of industrial production for output, the PCE deflator for inflation, and the Moody BAA-AAA bond spread for credit spread. The real wage is calculated as the nominal compensation per hour in the non-farm business sector divided by the consumption deflator. For the real variables, the percentage deviations from the long-term trend were considered, where the long-term trend is defined as the 10-year moving average of each variable centered at each period. The targeted data covers the period from 2001 to 2019 in quarterly frequency.

After calibrating both models using Bayesian estimation and obtaining the posterior distribution through MCMC methods, I used a state space Kalman filter model and smoother to extract shocks from both models. The results of the estimation are presented in Table 8, while the shocks are compared directly in Figure 6.

Figure 6 suggests that while most of the smoothed shocks are similar for the two models, the uncertainty shocks identified in the heterogeneous firm model have a slightly larger standard deviation than the traditional asset-based financial accelerator model. This indicates that the traditional financial accelerator model tends to underestimate risk shocks compared to the heterogeneous firm model.

To evaluate the performance of the two models, I analyzed the correlation between the variations in investment generated by each model and the actual data. Figure 7 displays the time series data alongside the model-predicted percentage deviation of aggregate investment for both models. The investment deviation in the data is derived from private investment divided by the investment deflator. Notably, investment was not specifically targeted during calibration, thus the correlation between the models and the data represents an out-of-sample accuracy. As shown in the figure, the heterogeneous firm model implies a time series that is closer to the data, indicating that considering financial heterogeneity can enhance the explanatory power of the model. Specifically, the correlation between the traditional financial accelerator model in Bernanke, Gertler and Gilchrist (1998)



Note: This figure displays the investment implied by the two models and the true investment time series data. The BGG99 model corresponds to the traditional financial accelerator model developed in Bernanke, Gertler and Gilchrist (1998). "ABS+EBS" denotes the financial heterogeneity model that I developed in this paper.

FIGURE 7. INVESTMENT FROM THE MODELS AND THE DATA

and the data is 77.91%, while the financial heterogeneity model has a correlation of 88.46%, which represents an improvement of approximately 10 percentage points, indicating a better model performance.

VI. Conclusion

This paper presents compelling evidence that firms with a higher earning-based debt ratio experience smaller impacts in response to uncertainty shocks. Specifically, when firm-level idiosyncratic volatility increases, firms tend to reduce their investment scale, but those with a higher earning-based debt ratio exhibit a smaller reduction in investment. This finding highlights the importance of financial constraints, even when controlling for their size, and underscores the significant role played by the type of financial constraint a firm faces. In this study, I propose an earning-based financial accelerator, by introducing an additional method of punishment for entrepreneurs who are more likely to default. I show that such constraints exhibit a negative feedback mechanism that plays a self-constraining role when the risk in the economy increases. This finding sheds light on the reason behind the empirical observations. Furthermore, the financial heterogeneity model outperforms traditional financial accelerator models in explaining investment fluctuations in the aggregate data, with the model-implied investment showing a 10% higher correlation with actual data.

Scholars are paying more and more attention to the interactions among uncertainty, financial heterogeneity, and firm investment. This paper contributes to this growing body of research, but there are still opportunities for further improvement in this field. One possible extension is to incorporate a dynamic formal contracting problem for the earning-based financial accelerator model. Currently, each firm in the model is assumed to be the same and without a history. However, due to the nature of earning-based debts, there is a naturally occurring dynamic effect that this paper ignores for simplicity. A promising direction for future research is to combine the earning-based financial accelerator model with firms of heterogeneous capital size, and investigate the relationship between firm size distribution and uncertainties.

REFERENCES

Alfaro, Iván, Nicholas Bloom, and Xiaoji Lin. 2019. "The Finance Uncertainty Multiplier." Social Science Research Network SSRN Scholarly Paper ID 3093871, Rochester, NY. (document), I, II, III.A, 5, III.A, III.A, III.B, A.A2, A.A3, A.A4, A1, A2, A3

Arellano, Cristina, Yan Bai, and Patrick J. Kehoe. 2018. "Financial Frictions and Fluctuations in Volatility." *Journal of Political Economy*, 127(5): 2049–2103. I

Baker, Scott R., Nicholas Bloom, and Steven J. Davis. 2016. "Measuring Economic Policy Uncertainty." *The Quarterly Journal of Economics*, 131(4): 1593–1636. I, 3

Basu, Susanto, and Brent Bundick. 2017. "Uncertainty Shocks in a Model of Effective Demand." *Econometrica*, 85(3): 937–958. I

Berger, David, Ian Dew-Becker, and Stefano Giglio. 2020. "Uncertainty Shocks as Second-Moment News Shocks." *The Review of Economic Studies*, 87(1): 40–76. I

Bernanke, Ben, Mark Gertler, and Simon Gilchrist. 1998. "The Financial Accelerator in a Quantitative Business Cycle Framework." National Bureau of Economic Research Working Paper 6455. (document), I, IV, IV.A, V, V

Bianchi, Javier, and Enrique G. Mendoza. 2010. "Overborrowing, Financial Crises and 'Macro-prudential' Taxes." I

Bloom, Nicholas. 2009. "The Impact of Uncertainty Shocks." *Econometrica*, 77(3): 623–685. I

Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J. Terry. 2018. "Really Uncertain Business Cycles." *Econometrica*, 86(3): 1031–1065. I

Caglio, Cecilia R., R. Matthew Darst, and Ṣebnem Kalemli-Özcan. 2021. "Collateral Heterogeneity and Monetary Policy Transmission: Evidence from Loans to SMEs and Large Firms." I

Cao, Dan, and Guangyu Nie. 2017. "Amplification and Asymmetric Effects without Collateral Constraints." *American Economic Journal: Macroeconomics*, 9(3): 222–266. I

Carlstrom, Charles T., and Timothy S. Fuerst. 1997. "Agency Costs, Net Worth, and Business Fluctuations: A Computable General Equilibrium Analysis." *The American Economic Review*, 87(5): 893–910. I

Carlstrom, Charles T., Timothy S. Fuerst, and Matthias Paustian. 2015. "Inflation and Output in New Keynesian Models with a Transient Interest Rate Peg." *Journal of Monetary Economics*, 76: 230–243. I

Carriero, Andrea, Todd E. Clark, and Massimiliano Giuseppe Marcellino. 2018. "Endogenous Uncertainty." Social Science Research Network SSRN Scholarly Paper ID 3152579, Rochester, NY. I

Carriero, Andrea, Todd E. Clark, and Massimiliano Marcellino. 2017. "Measuring Uncertainty and Its Impact on the Economy." *The Review of Economics and Statistics*, 100(5): 799–815. I

Christiano, Lawrence J., Roberto Motto, and Massimo Rostagno. 2014. "Risk Shocks." *American Economic Review*, 104(1): 27–65. (document), I, IV, IV.A, IV.A

Coibion, Olivier, Dimitris Georgarakos, Yuriy Gorodnichenko, Geoff Kenny, and Michael Weber. 2021. "The Effect of Macroeconomic Uncertainty on Household Spending." I

Cordoba, Juan-Carlos, and Marla Ripoll. 2004. "Credit Cycles Redux*." *International Economic Review*, 45(4): 1011–1046. I

Creal, Drew D., and Jing Cynthia Wu. 2017. "Monetary Policy Uncertainty and Economic Fluctuations." *International Economic Review*, 58(4): 1317–1354. I

Drechsel, Thomas. n.d.. "Earnings-Based Borrowing Constraints and Macroeconomic Fluctuations." *American Economic Journal: Macroeconomics.* I

Fernández-Villaverde, Jesús, and Pablo A. Guerrón-Quintana. 2020. "Uncertainty Shocks and Business Cycle Research." *Review of Economic Dynamics*, 37: S118–S146. I

Gertler, Mark, and Ben Bernanke. 1989. "Agency Costs, Net Worth and Business Fluctuations." In *Business Cycle Theory.* , ed. Finn Kydland. Edward Elgar Publishing Ltd. I

Gilchrist, Simon, and Egon Zakrajšek. 2012. "Credit Spreads and Business Cycle Fluctuations." *American Economic Review*, 102(4): 1692–1720. I

Greenwald, Daniel. 2018. "The Mortgage Credit Channel of Macroeconomic Transmission." I

Guerrieri, Luca, Matteo Iacoviello, Francisco Covas, John C. Driscoll, Mohammad R. Jahan-Parvar, Michael T. Kiley, Albert Queralto, and Jae Sim. 2015. "Macroeconomic Effects of Banking Sector Losses Across Structural Models." I

Hadlock, Charles J., and Joshua R. Pierce. 2010. "New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index." *The Review of Financial Studies*, 23(5): 1909–1940. III.A, A3

Hart, Oliver, and John Moore. 1994. "A Theory of Debt Based on the Inalienability of Human Capital*." *The Quarterly Journal of Economics*, 109(4): 841–879. I

Husted, Lucas, John Rogers, and Bo Sun. 2019. "Monetary Policy Uncertainty." *Journal of Monetary Economics.* I

Iacoviello, Matteo. 2005. "House Prices, Borrowing Constraints, and Monetary Policy in the Business Cycle." *American Economic Review*, 95(3): 739–764. I

Istrefi, Klodiana, and Anamaria Piloiu. 2014. "Economic Policy Uncertainty and Inflation Expectations." Social Science Research Network SSRN Scholarly Paper ID 2510829, Rochester, NY. I

Jensen, Henrik, Ivan Petrella, Søren Hove Ravn, and Emiliano Santoro. 2020. "Leverage and Deepening Business-Cycle Skewness." *American Economic Journal: Macroeconomics*, 12(1): 245–281. I

Jermann, Urban, and Vincenzo Quadrini. 2012. "Macroeconomic Effects of Financial Shocks." *American Economic Review*, 102(1): 238–271. I

Jurado, Kyle, Sydney C. Ludvigson, and Serena Ng. 2015. "Measuring Uncertainty." *American Economic Review*, 105(3): 1177–1216. I

Khan, Aubhik, and Julia K. Thomas. 2013. "Credit Shocks and Aggregate Fluctuations in an Economy with Production Heterogeneity." *Journal of Political Economy*, 121(6): 1055–1107. I

Kiyotaki, Nobuhiro, and John Moore. 1997. "Credit Cycles." *Journal of Political Economy*, 105(2): 211–248. (document), I

Kocherlakota, Narayana R. 2000. "Creating Business Cycles Through Credit Constraints." *Federal Reserve Bank of Minneapolis Quarterly Review*, 24(3): 2–2. I

Kumar, Saten, Yuriy Gorodnichenko, and Olivier Coibion. 2022. "The Effect of Macroeconomic Uncertainty on Firm Decisions." I

Lian, Chen, and Yueran Ma. 2021. "Anatomy of Corporate Borrowing Constraints*." *The Quarterly Journal of Economics*, 136(1): 229–291. (document), I, II, II, A.A1

Ludvigson, Sydney C, Sai Ma, and Serena Ng. 2015. "Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response?" National Bureau of Economic Research Working Paper 21803. I

Shleifer, Andrei, and Robert W. Vishny. 1992. "Liquidation Values and Debt Capacity: A Market Equilibrium Approach." *The Journal of Finance*, 47(4): 1343–1366. I

Townsend, Robert M. 1979. "Optimal Contracts and Competitive Markets with Costly State Verification." *Journal of Economic Theory*, 21(2): 265–293. I

Whited, Toni M., and Guojun Wu. 2006. "Financial Constraints Risk." *The Review of Financial Studies*, 19(2): 531–559. III.A, A2

Zhao, Dongchen. 2022. "Low Interest Rates, Debt Heterogeneity, and Firm Dynamics." I, IV.B

Appendix A: Appendix to the Empirical Analysis

A1. Identification of the Debt Types

While Lian and Ma (2021) relies on different data sources, this paper primarily uses the Capital IQ dataset. However, the process for identifying the types of financial debt is similar. For this study, debt structure data was collected from the 10-K filings of firms between the years 2001 to 2019. The identification of the types of debts followed the steps outlined below:

Step 1: Identify asset-based loans using the following criteria:

- Debt descriptions that contain certain words related to asset-based loans such as asset-based, ABL, borrowing base, mortgage, real estate, building, equipment, machine, aircraft, fixed asset, inventory, receivable, working capital, automobile, vehicle, capital lease, SBA, small business, oil, drill, rig, reserve-based, factoring, industrial revenue bond, finance company, capital lease, construction, and project finance.
- Secured resolvers
- Mortgage loans or mortgage notes
- Commercial lease structures

Step 2: Identify other types of loans using the following criteria:

- Loans that do not meet the criteria for asset-based loans in step 1
- Debt descriptions that contain certain words related to other loan types, such as MR, MRS, MS, director, executive, chairman, founder, shareholder, related parties, government, pollution control bond, insurance-related, vendor, seller, supplier, landlord, and affiliated.

Step 3: Identify earning-based loans using the following criteria:

- Debt descriptions that contain certain words related to earning-based loans, such as cash flow-based, cash flow, cash flow loan, debenture, first lien, second lien, third lien, term facility, term loan facility, term loan, syndicated, tranche, acquisition line, bridge loan, bonds, senior subordinated, senior notes, notes due, private placement, and medium-term notes.

- Debt types including debenture, note payable, corporate bond, or term loan.
- Debt that is not first lien or secured debt.

Step 4: All other secured debts are classified as asset-based loans, and all other debts are classified as the other type of loans.

A2. *Instrument Variable Construction*

The instrument variable used in this paper is based on the approach described in Alfaro, Bloom and Lin (2019). For a more detailed explanation, readers are referred to that paper. Here, I provide a brief overview of how the instrument variable is constructed.

To obtain firm-level exposure to aggregate factors, the following two steps are followed:

Step 1: Using firm-year level data, a regression is run as follows:

$$r^a dj_{i,t} = \alpha_j + \sum_c \beta_j^c r_t^c + \epsilon_{i,t}$$

This regresses the daily risk-adjusted stock return of firm i on changes in the prices of aggregate factors c for each industry j. The regression is clustered at the industrial level to improve the robustness of the estimation. The coefficients β_j^c represent the industrial-level exposure to the aggregate factor c.

Step 2: Using the estimated exposures β, the instrument variables are constructed as follows:

$$z_{i,t-1}^c = |\beta_{j,t-3}^c| \Delta\sigma_{t-1}^c$$

For each factor c, a corresponding instrument is constructed, where $\Delta\sigma_{t-1}^c$ represents the variation of factor c. When the aggregate factor has higher uncertainty, industries with higher exposure to that factor will have greater idiosyncratic volatility.

A3. *Definition of the Firm Level Variables*

The definitions of the firm level variables are listed as follows:

- Investment Rate:

$$InvRate_{i,t} = \frac{2capx_{i,t}}{ppent_{i,t} + ppent_{i,t-1}}$$

To eliminate the effect of outliers, the investment rate has been winsorized at -0.5 and 0.5. However, even if we do not winsorize the data at these values, the main result remains unchanged. Winsorization has brought the replication of the Alfaro, Bloom and Lin (2019) closer to their original results.

- Employment Growth Rate:

$$Emp_{i,t} = \frac{2(Emp_{i,t} - Emp_{i,t-1})}{Emp_{i,t} + Emp_{i,t-1}}$$

- Intangible Capital Growth Rate:

$$Intan_{i,t} = \frac{2(Intan_{i,t} - Intan_{i,t-1})}{Intan_{i,t} + Intan_{i,t-1}}$$

- Payout Growth Rate:

$$Payout_{i,t} = \frac{2(Payout_{i,t} - Payout_{i,t-1})}{Payout_{i,t} + Payout_{i,t-1}}$$

where $Payout = dvc + dvp$.

- Debt Growth Rate:

$$Debt_{i,t} = \frac{2(Debt_{i,t} - Debt_{i,t-1})}{Debt_{i,t} + Debt_{i,t-1}}$$

where $Debt = dlc + dltt$.

- Cost of Goods Growth Rate:

$$COGS_{i,t} = \frac{2(COGS_{i,t} - COGS_{i,t-1})}{COGS_{i,t} + COGS_{i,t-1}}$$

- Sales Growth Rate:

$$Sales_{i,t} = \frac{2(Sales_{i,t} - Sales_{i,t-1})}{Sales_{i,t} + Sales_{i,t-1}}$$

- Cash Holdings Growth Rate:

$$che_{i,t} = \frac{2(che_{i,t} - che_{i,t-1})}{che_{i,t} + che_{i,t-1}}$$

- Profit Growth Rate:

$$ebitda_{i,t} = \frac{2(ebitda_{i,t} - ebitda_{i,t-1})}{ebitda_{i,t} + ebitda_{i,t-1}}$$

- Tangibility:

$$ebitda_{i,t} = \frac{ppegt_{i,t}}{at_{i,t-1}}$$

- Leverage:

$$leverage_{i,t} = \frac{ppegt_{i,t}}{at_{i,t}}$$

- Return on Asset:

$$ROA_{i,t} = \frac{ebit_{i,t}}{at_{i,t-1}}$$

- Firm Size:

$$Size_{i,t} = log(Emp_{i,t})$$

- WW index:

$$\begin{aligned} WWIndex_{i,t} &= -0.091(oibdp_t)/at_{t-1} - 0.062 \times 1(payout_t > 0) \\ &+ 0.021(dltt_t/at_{t-1}) - 0.044log(at_{t-1}) \\ &+ 0.102 * \Delta(IndSALE_t) - 0.035\Delta(sales_t) \end{aligned}$$

- HP index:

$$HPIndex_{i,t} = -0.737log(at_t)^2 + 0.043log(at_t)^2 - 0.040age_t$$

A4. Baseline Regression Result

The baseline regression analysis replicates the regression in Alfaro, Bloom and Lin (2019). Table A1 shows the result of the regression in equation (1), where no financial constraint size effect is considered, while table A2 and A3 shows the result of the regression in equation (2), where the size effect is considered. The estimation effect is close to the result in the original paper. In the baseline regression the estimated coefficient is -0.041 and -0.058 for the realized and implied volatility shocks in the original paper. Here the replication result with a subset of time periods of data gives an estimation of -0.046 and -0.094, which are all close to the original regression result.

A5. Robust Regression Result

In addition to vanilla regressions, I conducted robust regressions to strengthen the credibility of the empirical analysis. Table A4 and A5 show the regression results using firm size and firm leverage ratio as proxies for the size of financial constraint. Table A6 shows the regression results using asset-based debt ratio instead of earning-based debt ratio. To address the endogeneity problem caused by the simultaneity of uncertainty shocks and borrowing behaviors, I used lagged financial constraint-related variables, and the results are presented in table A7, A8, and A9. Moreover, I controlled for interaction terms between firm-level uncertainty shocks and aggregate factors, and the regression results are shown in table A10, A11, and A12.

Apart from robust regressions, I also examined the effect of different types of financial constraints on firm-level variables other than investment. Table A13 shows the results for profit growth, table A14 for cash holdings growth, table A15 for the firm's stock return, table A16 for sales growth, table A17 for the growth of the cost of goods, table A18 for intangible capital growth, table A20 for the payout growth to stockholders, and table A21 for the debt growth.

Table A1—Baseline Regression

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Uncertainty Shock	-0.009***	-0.051***		
	(0.003)	(0.017)		
Implied Uncertainty Shock			-0.031***	-0.109**
			(0.007)	(0.043)
Observations	34,704	34,704	22,236	22,236
R-squared	0.176	0.161	0.213	0.197

Note: This table presents the results of both the OLS and IV regressions with the realized and implied volatility shocks replicating the result in Alfaro, Bloom and Lin (2019). The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: p<0.01, **: p<0.05, *: p<0.1

Table A2—Baseline Regression Controlling for WW Index

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × WW Index	-0.025	-0.134**		
	(0.019)	(0.062)		
Implied Shock × WW Index			-0.124*	-0.447*
			(0.067)	(0.232)
Realized Shock	-0.017**	-0.080**		
	(0.007)	(0.032)		
Implied Shock			-0.071***	-0.228*
			(0.024)	(0.116)
WW Index	0.240***	0.241***	0.212***	0.212***
	(0.036)	(0.035)	(0.042)	(0.041)
Observations	36,074	36,074	23,224	23,224
R-squared	0.175	0.163	0.212	0.199

Note: This table presents the results of both the OLS and IV regressions with the realized and implied volatility shocks replicating the result in Alfaro, Bloom and Lin (2019), controlling for financial constraint size, represented by the WW index from Whited and Wu (2006). The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: p<0.01, **: p<0.05, *: p<0.1

Table A3—Baseline Regression Controlling for HP Index

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × HP Index	-0.003	-0.017**		
	(0.003)	(0.007)		
Implied Shock × HP Index			-0.011*	-0.030*
			(0.007)	(0.016)
Realized Shock	-0.021*	-0.111***		
	(0.012)	(0.040)		
Implied Shock			-0.075**	-0.218**
			(0.028)	(0.095)
HP Index	0.032*	0.033*	0.026	0.026
	(0.018)	(0.018)	(0.017)	(0.017)
Observations	34,704	34,704	22,236	22,236
R-squared	0.177	0.161	0.214	0.200

Note: This table presents the results of both the OLS and IV regressions with the realized and implied volatility shocks replicating the result in Alfaro, Bloom and Lin (2019), controlling for financial constraint size, represented by the HP index from Hadlock and Pierce (2010). The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: p<0.01, **: p<0.05, *: p<0.1

Table A4—Robustness Check: Financial Constraint with Firm Size

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Cashflow Based Loan Ratio	0.009*	0.010		
	(0.004)	(0.011)		
Realized Shock × Firm Size	0.001	0.005		
	(0.002)	(0.005)		
Realized Shock	-0.016***	-0.058***		
	(0.004)	(0.013)		
Implied Shock × Cashflow Based Loan Ratio			0.013	0.067***
			(0.009)	(0.017)
Implied Shock × Firm Size			0.005	0.010
			(0.004)	(0.010)
Implied Shock			-0.048***	-0.162***
			(0.011)	(0.049)
Firm Size	-0.016***	-0.015***	-0.015***	-0.014***
	(0.003)	(0.003)	(0.004)	(0.004)
Cashflow Based Loan Ratio	0.007*	0.006*	0.007**	0.008**
	(0.004)	(0.004)	(0.003)	(0.004)
Observations	34,704	34,704	22,236	22,236
R-squared	0.176	0.163	0.214	0.199

Note: This table presents the robust regression results, controlling for financial constraint size, represented by log of the firm size measured with employment. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: p<0.01, **: p<0.05, *: p<0.1

Table A5—Robust Check: Firm Leverage

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Cashflow Based Loan Ratio	0.012**	0.021***		
	(0.005)	(0.006)		
Realized Shock × Firm Leverage	-0.007	-0.003		
	(0.009)	(0.018)		
Realized Shock	-0.013**	-0.063***		
	(0.006)	(0.014)		
Implied Shock × Cashflow Based Loan Ratio			0.018**	0.079***
			(0.008)	(0.023)
Implied Shock × Firm Leverage			-0.000	0.025
			(0.015)	(0.028)
Implied Shock			-0.044***	-0.184***
			(0.010)	(0.049)
Firm Leverage	-0.041***	-0.036***	-0.039***	-0.031***
	(0.005)	(0.006)	(0.007)	(0.011)
Cashflow Based Loan Ratio	0.007*	0.007*	0.008**	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	34,704	34,704	22,236	22,236
R-squared	0.176	0.161	0.214	0.194

Note: This table presents the robust regression results, controlling for financial constraint size, represented by the firm's leverage ratio. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: p<0.01, **: p<0.05, *: p<0.1

Table A6—Robustness Check: Regression with Asset Based Loan Ratio

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Asset Based Loan Ratio	-0.012**	-0.025***		
	(0.005)	(0.006)		
Implied Shock × Asset Based Loan Ratio			-0.017*	-0.082***
			(0.009)	(0.024)
Realized Shock	-0.006**	-0.044**		
	(0.003)	(0.017)		
Implied Shock			-0.028***	-0.092**
			(0.007)	(0.042)
Asset Based Loan Ratio	-0.007	-0.007*	-0.008**	-0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	34,704	34,704	22,236	22,236
R-squared	0.176	0.160	0.214	0.195

Note: This table presents the robust regression results with asset based debt ratio. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: p<0.01, **: p<0.05, *: p<0.1

Table A7—Robustness Check: Break Simultaneity

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Lagged Cashflow Based Loan Ratio	0.007*	0.025***		
	(0.004)	(0.007)		
Implied Shock × Lagged Cashflow Based Loan Ratio			0.011	0.072***
			(0.008)	(0.024)
Realized Shock	-0.016***	-0.070***		
	(0.004)	(0.014)		
Implied Shock			-0.039***	-0.163***
			(0.010)	(0.054)
Lagged Cashflow Based Loan Ratio	0.008**	0.008**	0.010**	0.010**
	(0.003)	(0.003)	(0.004)	(0.004)
Observations	29,119	29,119	19,450	19,450
R-squared	0.176	0.158	0.216	0.196

Note: This table presents the robust regression results with cashflow based debt ratio lagged for one year. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: p<0.01, **: p<0.05, *: p<0.1

Table A8—Robust Check: Break Simultaneity Controlling for WW index

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Lagged Cashflow Based Loan Ratio	0.006	0.015*		
	(0.004)	(0.008)		
Realized Shock × Lagged WW Index	-0.024	-0.094**		
	(0.019)	(0.046)		
Implied Shock × Lagged Cashflow Based Loan Ratio			0.006	0.055***
			(0.008)	(0.020)
Implied Shock × Lagged WW Index			-0.104***	-0.294
			(0.036)	(0.219)
Realized Shock	-0.021***	-0.085***		
	(0.006)	(0.023)		
Implied Shock			-0.067***	-0.242**
			(0.015)	(0.111)
Lagged WW Index	0.192***	0.185***	0.185***	0.184***
	(0.029)	(0.029)	(0.041)	(0.039)
Lagged Cashflow Based Loan Ratio	0.008**	0.007**	0.010**	0.009**
	(0.003)	(0.004)	(0.004)	(0.004)
Observations	29,119	29,119	19,450	19,450
R-squared	0.178	0.163	0.219	0.197

Note: This table presents the robust regression results with cashflow based debt ratio lagged for one year, controlling for the WW index lagged by one year. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: p<0.01, **: p<0.05, *: p<0.1

Table A9—Robustness Check: Break Simultaneity Controlling for HP index

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Lagged Cashflow Based Loan Ratio	0.003	0.013*		
	(0.004)	(0.008)		
Realized Shock × Lagged HP Index	-0.005*	-0.018***		
	(0.003)	(0.006)		
Implied Shock × Lagged Cashflow Based Loan Ratio			0.005	0.059***
			(0.008)	(0.022)
Implied Shock × Lagged HP Index			-0.009*	-0.030**
			(0.005)	(0.013)
Realized Shock	-0.033***	-0.131***		
	(0.011)	(0.024)		
Implied Shock			-0.068***	-0.275***
			(0.020)	(0.093)
Lagged HP Index	0.069***	0.069***	0.070***	0.061***
	(0.011)	(0.011)	(0.017)	(0.019)
Lagged Cashflow Based Loan Ratio	0.008**	0.008**	0.011**	0.011**
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	29,119	29,119	19,450	19,450
R-squared	0.180	0.160	0.219	0.196

Note: This table presents the robust regression results with cashflow based debt ratio lagged for one year, controlling for the HP index lagged by one year. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: p<0.01, **: p<0.05, *: p<0.1

Table A10—Robustness Check: Interacted with Credit Spread

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Cashflow Based Loan Ratio	0.011**	0.018***		
	(0.005)	(0.006)		
Realized Shock × Credit Spread	-0.031***	-0.106***		
	(0.008)	(0.028)		
Realized Shock	0.017*	0.077***		
	(0.010)	(0.028)		
Implied Shock × Cashflow Based Loan Ratio			0.018**	0.080***
			(0.008)	(0.022)
Implied Shock × Credit Spread			-0.032**	-0.128***
			(0.013)	(0.036)
Implied Shock			-0.010	0.014
			(0.015)	(0.056)
Credit Spread	-0.001	0.006	0.004	0.010
	(0.005)	(0.006)	(0.006)	(0.007)
Cashflow Based Loan Ratio	0.007*	0.007*	0.008**	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	34,704	34,704	22,236	22,236
R-squared	0.177	0.169	0.214	0.206

Note: This table presents the robust regression results controlling for the interactions between the uncertainty shocks and the credit spread. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: p<0.01, **: p<0.05, *: p<0.1

Table A11—Robustness Check: Interacted with Aggregate Cashflow Based Debt Ratio

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Cashflow Based Loan Ratio	0.011**	0.022***		
	(0.005)	(0.006)		
Realized Shock × Aggregate CFB Ratio	-0.119	-1.587		
	(0.085)	(1.513)		
Realized Shock	0.069	1.106		
	(0.062)	(1.101)		
Implied Shock × Cashflow Based Loan Ratio			0.018**	0.085***
			(0.008)	(0.025)
Implied Shock × Aggregate CFB Ratio			-0.147	-1.214
			(0.201)	(2.419)
Implied Shock			0.063	0.720
			(0.147)	(1.761)
Aggregate CFB Ratio	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Cashflow Based Loan Ratio	0.007*	0.007*	0.008**	0.009**
	(0.004)	(0.004)	(0.003)	(0.004)
Observations	34,704	34,704	22,236	22,236
R-squared	0.176	0.162	0.214	0.196

Note: This table presents the robust regression results controlling for the interactions between the uncertainty shocks and the aggregate cashflow based debt ratio. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: p<0.01, **: p<0.05, *: p<0.1

Table A12—Robustness Check: Interacted with VIX Index

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Cashflow Based Loan Ratio	0.011**	0.025***		
	(0.004)	(0.007)		
Realized Shock × VIX	-0.000	0.001		
	(0.000)	(0.001)		
Realized Shock	-0.007	-0.133***		
	(0.006)	(0.035)		
Implied Shock × Cashflow Based Loan Ratio			0.018**	0.089***
			(0.008)	(0.027)
Implied Shock × VIX			-0.000	-0.001
			(0.001)	(0.002)
Implied Shock			-0.041***	-0.193***
			(0.014)	(0.067)
VIX	0.000	0.003***	-0.000	0.002*
	(0.000)	(0.001)	(0.000)	(0.001)
Cashflow Based Loan Ratio	0.007*	0.007*	0.008**	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	34,704	34,704	22,236	22,236
R-squared	0.176	0.109	0.214	0.173

Note: This table presents the robust regression results controlling for the interactions between the uncertainty shocks and the VIX index. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: p<0.01, **: p<0.05, *: p<0.1

Table A13—Regression with EBITDA

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Cashflow Based Loan Ratio	0.007	0.052		
	(0.016)	(0.044)		
Implied Shock × Cashflow Based Loan Ratio			-0.008	0.168
			(0.045)	(0.133)
Realized Shock	-0.000	-0.257*		
	(0.013)	(0.142)		
Implied Shock			0.061	-0.519
			(0.041)	(0.399)
Cashflow Based Loan Ratio	-0.029***	-0.030***	-0.029	-0.030
	(0.008)	(0.008)	(0.019)	(0.019)
Observations	34,704	34,704	22,236	22,236
R-squared	0.081	0.055	0.100	0.066

Note: This table presents the robust regression for the growth rate of the firm's profit. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$

Table A14—Regression with Cash Holdings

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Cashflow Based Loan Ratio	0.078***	0.126***		
	(0.028)	(0.041)		
Implied Shock × Cashflow Based Loan Ratio			0.164***	0.270***
			(0.055)	(0.083)
Realized Shock	-0.009	0.007		
	(0.021)	(0.056)		
Implied Shock			0.023	0.078
			(0.042)	(0.171)
Cashflow Based Loan Ratio	-0.054***	-0.052***	-0.073***	-0.068***
	(0.017)	(0.016)	(0.019)	(0.019)
Observations	34,704	34,704	22,236	22,236
R-squared	0.084	0.083	0.085	0.084

Note: This table presents the robust regression for the growth rate of the firm's cash holdings. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$

Table A15—Regression with Stock Return

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Cashflow Based Loan Ratio	0.015	0.030		
	(0.012)	(0.036)		
Implied Shock × Cashflow Based Loan Ratio			-0.001	0.070
			(0.020)	(0.097)
Realized Shock	-0.037***	-0.248**		
	(0.012)	(0.117)		
Implied Shock			-0.056**	-0.581*
			(0.026)	(0.296)
Cashflow Based Loan Ratio	0.011**	0.009**	0.001	-0.004
	(0.005)	(0.004)	(0.007)	(0.007)
Observations	34,704	34,704	22,236	22,236
R-squared	0.131	0.069	0.150	0.041

Note: This table presents the robust regression for the stock return. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: p<0.01, **: p<0.05, *: p<0.1

Table A16—Regression with Sale Growth

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Cashflow Based Loan Ratio	0.011	0.031		
	(0.013)	(0.034)		
Implied Shock × Cashflow Based Loan Ratio			-0.001	0.066
			(0.023)	(0.096)
Realized Shock	-0.034***	-0.240**		
	(0.012)	(0.112)		
Implied Shock			-0.053*	-0.559*
			(0.031)	(0.296)
Cashflow Based Loan Ratio	0.008	0.008	-0.002	-0.002
	(0.007)	(0.006)	(0.007)	(0.008)
Observations	36,253	36,253	23,345	23,345
R-squared	0.129	0.080	0.147	0.059

Note: This table presents the robust regression for the growth rate of the firm's sales. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: p<0.01, **: p<0.05, *: p<0.1

Table A17—Regression with Cost of Goods

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Cashflow Based Loan Ratio	0.010	0.019		
	(0.012)	(0.028)		
Implied Shock × Cashflow Based Loan Ratio			-0.008	0.104
			(0.022)	(0.073)
Realized Shock	-0.024***	-0.156***		
	(0.007)	(0.055)		
Implied Shock			-0.061***	-0.562***
			(0.021)	(0.198)
Cashflow Based Loan Ratio	0.019***	0.018***	0.009	0.006
	(0.006)	(0.006)	(0.005)	(0.006)
Observations	34,704	34,704	22,236	22,236
R-squared	0.129	0.107	0.134	0.059

Note: This table presents the robust regression for the growth rate of the firm's cost of goods. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: p<0.01, **: p<0.05, *: p<0.1

Table A18—Regression with Intangible Capital Growth

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Cashflow Based Loan Ratio	0.008	0.026		
	(0.013)	(0.028)		
Implied Shock × Cashflow Based Loan Ratio			-0.022	0.050
			(0.051)	(0.066)
Realized Shock	-0.011	0.020		
	(0.013)	(0.036)		
Implied Shock			-0.015	0.159*
			(0.045)	(0.091)
Cashflow Based Loan Ratio	-0.008	-0.007	-0.015	-0.009
	(0.009)	(0.010)	(0.011)	(0.012)
Observations	34,704	34,704	22,236	22,236
R-squared	0.047	0.046	0.057	0.047

Note: This table presents the robust regression for the growth rate of the firm's intangible capital. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: p<0.01, **: p<0.05, *: p<0.1

TABLE A19—REGRESSION WITH EMPLOYMENT GROWTH

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Cashflow Based Loan Ratio	0.017**	0.011		
	(0.007)	(0.016)		
Implied Shock × Cashflow Based Loan Ratio			-0.002	0.064
			(0.017)	(0.039)
Realized Shock	-0.016***	-0.041**		
	(0.005)	(0.019)		
Implied Shock			-0.005	-0.125
			(0.013)	(0.082)
Cashflow Based Loan Ratio	0.008	0.008	0.008	0.009
	(0.005)	(0.005)	(0.006)	(0.007)
Observations	34,704	34,704	22,236	22,236
R-squared	0.129	0.127	0.138	0.133

Note: This table presents the robust regression for the growth rate of the firm's employment. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$

TABLE A20—REGRESSION WITH PAYOUT

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Cashflow Based Loan Ratio	0.048*	0.065		
	(0.025)	(0.048)		
Implied Shock × Cashflow Based Loan Ratio			0.011	0.142
			(0.071)	(0.123)
Realized Shock	-0.084***	-0.105*		
	(0.023)	(0.061)		
Implied Shock			-0.192***	-0.404**
			(0.064)	(0.171)
Cashflow Based Loan Ratio	0.011	0.012	-0.014	-0.010
	(0.016)	(0.016)	(0.017)	(0.016)
Observations	36,253	36,253	23,345	23,345
R-squared	0.016	0.016	0.021	0.020

Note: This table presents the robust regression for the growth rate of the firm's payout to the stockholders. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$

Table A21—Regression with Debt Capacity

VARIABLES	(1) Realized OLS	(2) Realized IV	(3) Implied OLS	(4) Implied IV
Realized Shock × Cashflow Based Loan Ratio	0.033	0.039		
	(0.023)	(0.036)		
Implied Shock × Cashflow Based Loan Ratio			0.112	0.225
			(0.087)	(0.136)
Realized Shock	-0.054**	-0.146***		
	(0.021)	(0.045)		
Implied Shock			-0.126	-0.486***
			(0.084)	(0.157)
Cashflow Based Loan Ratio	-0.067***	-0.068***	-0.096***	-0.096***
	(0.013)	(0.013)	(0.016)	(0.018)
Observations	34,704	34,704	22,236	22,236
R-squared	0.060	0.057	0.062	0.051

Note: This table presents the robust regression for the growth rate of the firm's debt. The coefficients of the control variables have been omitted. Firm-fixed effects and time-fixed effects have been incorporated into each regression. Standard errors are shown in parasynthesis. ***: p<0.01, **: p<0.05, *: p<0.1

Appendix B: Appendix to the Financial Accelerator Model

B1. Optimal Conditions for the Asset Based Financial Accelerator

Solving the contracting problem will give us the key relationship in the traditional financial accelerator model. Denote the Lagrange multiplier as Λ_{t+1}. Solving the first order condition will give us:

$$
\begin{aligned}
[\omega] :& E_t[f_\omega(\bar{\omega}_{t+1}, \sigma_t) + \Lambda_{t+1} g_\omega(\bar{\omega}_{t+1}, \sigma_t)] = 0 \\
[L] :& E_t[R^k_{t+1} f(\bar{\omega}_{t+1}, \sigma_t) + \Lambda_{t+1} R^k_{t+1} g(\bar{\omega}_{t+1}, \sigma_t) - \Lambda_{t+1} R_t] = 0 \\
[\Lambda] :& E_t[\frac{g(\bar{\omega}_{t+1}, \sigma_t) R^k_{t+1} L_t}{L_t - 1}] = R_t
\end{aligned}
$$

After log-linearization The first FOC becomes

$$
\begin{aligned}
\bar{\omega} f_{\omega\omega}(\bar{\omega}, \sigma)\hat{\omega}_{t+1} + \Lambda g_\omega(\bar{\omega}, \sigma)\lambda_{t+1} + \Lambda \bar{\omega} g_{\omega\omega}(\bar{\omega}, \sigma)\hat{\omega}_{t+1} \\
+ \sigma f_{\omega\sigma}(\bar{\omega}, \sigma^2)\hat{\sigma}_t + \Lambda \sigma g_{\omega\sigma}(\bar{\omega}, \sigma)\hat{\sigma}_t = 0
\end{aligned}
$$

Use the fact of $\Lambda = -f_\omega(\bar{\omega}, \sigma)/g_\omega(\bar{\omega}, \sigma)$, we have

$$
\lambda_{t+1} = [\frac{\bar{\omega} f_{\omega\omega}(\bar{\omega}, \sigma)}{f_\omega(\bar{\omega}, \sigma)} - \frac{\bar{\omega} g_{\omega\omega}(\bar{\omega}, \sigma)}{g_\omega(\bar{\omega}, \sigma)}]\hat{\omega}_{t+1} + [\frac{\sigma f_{\omega\sigma}(\bar{\omega}, \sigma)}{f_\omega(\bar{\omega}, \sigma)} - \frac{\sigma g_{\omega\sigma}(\bar{\omega}, \sigma)}{g_\omega(\bar{\omega}, \sigma)}]\hat{\sigma}_t
$$

Define the first term and the second term as Φ_ω and Φ_σ, then

$$
\lambda_{t+1} = \Phi_\omega \hat{\omega}_{t+1} + \Phi_\sigma \hat{\sigma}_t \tag{B1}
$$

The second and the third FOC becomes

$$
\begin{aligned}
r^k_{t+1} - r_t + \frac{\bar{\omega} f_\omega(\bar{\omega}, \sigma)}{f(\bar{\omega}, \sigma)}\hat{\omega}_{t+1} + \frac{\sigma f_\sigma(\bar{\omega}, \sigma)}{f(\bar{\omega}, \sigma)}\hat{\sigma}_t = \lambda_{t+1} - l_t \\
\frac{\bar{\omega} g_\omega(\bar{\omega}, \sigma)}{g(\bar{\omega}, \sigma)}\hat{\omega}_{t+1} + \frac{\sigma g_\sigma(\bar{\omega}, \sigma)}{g(\bar{\omega}, \sigma)}\hat{\sigma}_t + r^k_{t+1} = r_t + \frac{1}{L-1} l_t
\end{aligned}
$$

Define $\zeta_f = \frac{\sigma f_\sigma(\bar{\omega}, \sigma)}{f(\bar{\omega}, \sigma)}$ and $\zeta_g = \frac{\sigma g_\sigma(\bar{\omega}, \sigma)}{g(\bar{\omega}, \sigma)}$, the second and the third FOC becomes

$$
r^k_{t+1} - r_t + \theta_f \hat{\omega}_{t+1} + \zeta_f \hat{\sigma}_t = \lambda_{t+1} - l_t \tag{B2}
$$

$$
r^k_{t+1} - r_t + \theta_g \hat{\omega}_{t+1} + \zeta_g \hat{\sigma}_t = \frac{1}{L-1} l_t \tag{B3}
$$

Combine the three FOC equations, we have

$$(r^k_{t+1} - r_t) = \frac{\Phi_\omega - \theta_f - \theta_g(L-1)}{(L-1)(\Phi_\omega - (\theta_f - \theta_g))} l_t - \frac{\theta_g(\zeta_f - \Phi_\sigma) + (\Phi_\omega - \theta_f)\zeta_g}{\Phi_\omega - (\theta_f - \theta_g)} \hat{\sigma}_t$$

Lastly, use the relationship $\theta_g(L-1) = -\theta_f$, we have

$$r^k_{t+1} - r_t = \frac{\Phi_\omega}{(L-1)\Phi_\omega - \theta_f L} l_t - \frac{\theta_g(\zeta_f - \Phi_\sigma) + (\Phi_\omega - \theta_f)\zeta_g}{\Phi_\omega - (\theta_f - \theta_g)} \hat{\sigma}_t$$

B2. Optimal Conditions for the Earning Based Financial Accelerator

The first order conditions are

$$\begin{aligned} [\omega] :& h_\omega + f_\omega L_t = \Lambda_t g_\omega \\ [L] :& (1 - D_t) f(\bar{\omega}_{t+1}, \sigma)(L_t - 1)^2 + \Lambda_t D_t = 0 \\ [\lambda] :& (1 - D_t) g(\bar{\omega}_{t+1}, \sigma) R^k_{t+1} = R_t - R^k_{t+1} D_t \frac{L_t}{L_t - 1} \end{aligned}$$

log-linearize the first equation we have:

$$\begin{aligned} (\frac{\omega h_{\omega\omega}}{f_\omega L} - h_\omega \frac{\omega g_{\omega\omega}}{g_\omega f_\omega L})\hat{\omega}_t + (\frac{\sigma h_{\omega\sigma}}{f_\omega L} - h_\omega \frac{\sigma g_{\omega\sigma}}{g_\omega f_\omega L})\sigma_t & \\ + \Phi_\omega \hat{\omega}_t + \Phi_\sigma \hat{\sigma}_t + l_t = \frac{\Lambda}{\Lambda - h_\omega / g_\omega} \lambda_t & \end{aligned} \tag{B4}$$

Notice that with μ close to 0, we have that $\Phi_\omega \hat{\omega}_t + \Phi_\omega \sigma_t + l_t = \frac{\Lambda}{\Lambda - 1} \lambda_t$. The second FOC will give us

$$\frac{\omega f_\omega}{f} \hat{\omega}_t + \frac{\sigma f_\sigma}{f} \sigma_t + 2 \frac{L}{L-1} l_t = \lambda_t + \frac{1}{1-D} d_t$$

which can be written as

$$\theta_f \hat{\omega}_t + \zeta_f \sigma_t + 2 \frac{L}{L-1} l_t = \lambda_t + \frac{1}{1-D} d_t \tag{B5}$$

The third FOC will give us:

$$r^k_{t+1} - r_t = \frac{DL}{(L-1)^2} \frac{R^k}{R} l_t - (1 - g \frac{R^k}{R}) d_t - (1 - \frac{R^k}{R} \frac{LD}{L-1})(\theta_g \hat{\omega}_t + \zeta_g \sigma_t) \tag{B6}$$

B3. The Full Financial Accelerator Model

Resource Constraint Block:

The market clearing condition in the model is

$$Y_t = C_t + I_t + G_t + C_t^e$$

Notice that $T_t = G_t$. The equation after log-linearization is

$$y_t = \frac{C}{Y}c_t + \frac{I}{Y}i_t + \frac{G}{Y}g_t + \frac{C^e}{Y}c_t^e \tag{B7}$$

Household:

The household solves the following problem:

$$max \sum_t \beta^t E_t[log(C_t) + \xi log(1 - H_t)]$$
$$s.t.\ C_t + B_{t+1} - T_t = W_t H_t + R_{t-1}B_t$$

The constraint is the budget constraint. The household receives labor income and interest rate income from varies assets. Notice that the households do not have access to the fixed capital. They can only buy the government bond, or save using the bank, and they will only face the risk-free interest rate.

Solving the first order condition first gives us the Euler's equation:

$$\frac{1}{C_t} = \beta R_t E_t[\frac{1}{C_{t+1}}]$$

which after the log-linearization gives us:

$$c_t = -r_t + E_t c_{t+1} \tag{B8}$$

The second equation comes from the household FOC is the intratemporal tradeoff between consumption and labor. After the log-linearization we have:

$$\frac{H}{1-H}h_t = w_t - c_t \tag{B9}$$

Raw Capital Producer and Aggregate Capital Accumulation:

Notice that the fixed capital is produced by the raw capital good producer and hold by the entrepreneurs. The following equation is the first important piece for the financial accelerator model. With the existence of the financial friction, we should use the definition of the return of fixed capital:

$$E[R^k_{t+1}] = E_t[\frac{RR_{t+1} + (1-\delta)Q_{t+1}}{Q_t}]$$

Notice that this implies that $E[R^k_{t+1}] \neq R_t$ because fixed capital is not directly hold by the households. We now solve for the the log-linearized version of this equation.

$$E_t r^k_{t+1} = \frac{RR}{RR + (1-\delta)} E_t rr_{t+1} + \frac{1-\delta}{RR + (1-\delta)} E_t q_{t+1} - q_t$$

We can define $\epsilon = \frac{1-\delta}{RR+(1-\delta)}$ as a parameter. Then we have

$$E_t r^k_{t+1} = (1-\epsilon) E_t rr_{t+1} + \epsilon E_t q_{t+1} - q_t \tag{B10}$$

In the economy, we assume there are raw capital producers who produce in a perfect competition market with free entry. They borrow the existing capital K_t from the household and buy final goods at a price of 1. They produce using the technology of $\Phi(\frac{I_t}{K_t})K_t$. After the production they return all the existing capital goods back to the households and sell the newly produced investment good at the market price Q_t. The raw capital producers solve the following problem:

$$max\ Q_t \Phi(\frac{I_t}{K_t}) K_t - I_t$$

They also sell all the existing fixed raw capital and buy new capitals in each period at the price Q_t. We assume that $\Phi(0) = 0, \Phi(\delta) = 1, \Phi'(\delta) = 1$. Their choosing variable is I_t. The FOC of this problem will give us the definition of Tobin's Q:

$$Q_t = [\Phi'(\frac{I_t}{K_t})]^{-1}$$

We can take logs and solve for $q_t = -\Phi''(\delta)\delta(i_t - k_t)$. Notice that we define

$-\Phi''(\delta)\delta = \varphi > 0$ as a parameter. Hence the log-linearized equation is:

$$q_t = \varphi(i_t - k_t) \tag{B11}$$

Lastly, the capital accumulation equation evolves according to the following equation, which can be transferred by taking logs:

$$k_{t+1} = \delta k_t + \frac{I}{K} i_t - \delta k_t + (1-\delta)k_t$$

which means the log-linearized equation is:

$$k_{t+1} = (1-\delta)k_t + \delta i_t \tag{B12}$$

The FOC with respect to K_{t+1} will give us that $\lambda_t = \Phi'(\frac{I_t}{K_t})\mu_t$.

The New Keynesian Block:

The final good producer use the Dixit-Stiglitz packaging technology. The final good producer solves the following problem:

$$max\ P_t Y_t - (\int_0^1 P_{it} Y_{it} di)$$
$$s.t.\ Y_t = (\int_0^1 Y_{it}^{\frac{\eta-1}{\eta}} di)^{\frac{\eta}{\eta-1}}$$

The first order condition gives us that

$$Y_{it} = (\frac{P_{it}}{P_t})^{-\eta} Y_t,\ P_t = (\int_0^1 P_{it}^{1-\eta} di)^{\frac{1}{1-\eta}}$$

Notice that the demand function implies that $Y_{it} = \Upsilon_t Y_t$, where Υ_t denote the price dispersion:

$$\Upsilon_t = (1-\theta)(\frac{P_{it}^\star}{P_t})^{-\eta} + \theta(\frac{P_{it-1}}{P_t})^{-\eta}$$

with probability $1-\theta$, the intermediate firm will change the price to the optimal level $\Pi_t^\star = \frac{P_{it}^\star}{P_t}$. With probability θ, the price is fixed at the previous level. Hence:

$$\Upsilon_t = (1-\theta)(\Pi_t^\star)^{-\eta} + \theta \Pi_t^\eta D_{t-1}$$

By taking log-linearization we notice that $\upsilon_t = 0$, hence $y_{it} = y_t$ and that is why we can ignore y_{it}.

Next, the wholesale firms use effective capital and labor to produce. Notice that the wholesale firms borrow capital from the entrepreneurs, and will return the capital back to the entrepreneurs. Their outputs are the intermediate goods Y_t^M. Suppose they are monopolistic competitors, and the markup is defined as $X_t = P_t/MC_t$:

$$min\ RR_tK_t + W_tH_t + W_t^eH_t^e$$
$$Y_t^M \leq A_tK_t^\alpha(H_t^\Omega H_t^{e1-\Omega})^{1-\alpha}$$

The first order condition gives us that:

$$P_tRR_t = MC_t\alpha\frac{Y_t}{K_t},\ P_tW_t = MC_t(1-\alpha)\Omega\frac{Y_t}{H_t},\ P_tW_t^e = MC_t(1-\alpha)(1-\Omega)\frac{Y_t}{H_t^e}$$

Using the definition of the real markup, we Can change P/MC into X. We assume that the entrepreneurs have 1 unit of labor endowment and will not have any disutility from working. Hence we assume that $H_t^e = 1$, and it will simplify the equation. After log-linearization, we get:

$$rr_t = y_t - k_t - x_t \tag{B13}$$

$$w_t = y_t - h_t - x_t \tag{B14}$$

$$w_t^e = y_t - x_t \tag{B15}$$

The aggregate production function after log-linearization gives us that

$$y_t = a_t + \alpha k_t + (1-\alpha)\Omega h_t \tag{B16}$$

The retailer who are allowed to change price in period t solves the following problem:

$$maxE_t\sum_{k=0}^{\infty}\theta^k\beta^k\frac{C_t}{C_{t+k}}[(\frac{P_{it}}{P_{t+k}})^{1-\eta}Y_{t+k} - X_{t+k}^{-1}(\frac{P_{it}}{P_{t+k}})^{-\eta}Y_{t+k}]$$

where θ denotes the probability of not changing the price. θ denotes the price stickiness. When $\theta = 1$ it corresponds to the most sticky case. When $\theta = 0$, we are in the flexible price case.

The optimal relative reset price $\Pi_t^\star = \frac{P_{it}^\star}{P_t}$ satisfies

$$\begin{aligned}
\Pi_t^\star &= \frac{\eta}{\eta-1}\frac{X_{1,t}}{X_{2,t}} \\
X_{1,t} &= X_t^{-1}Y_t + \theta E_t \Lambda_{t,t+1}\Pi_{t+1}^{\eta} X_{1,t+1} \\
X_{2,t} &= Y_t + \theta E_t \Lambda_{t,t+1}\Pi_{t+1}^{\eta-1} X_{2,t+1} \\
1 &= (1-\theta)(\Pi_t^\star)^{1-\eta} + \theta(\Pi_t)^{\eta-1}
\end{aligned}$$

Following the standard procedure we can obtain the usual NKPC function:

$$\pi_t = -\kappa x_t + \beta E_t \pi_{t+1} \tag{B17}$$

where $\kappa = \frac{(1-\theta)(1-\theta\beta)}{\theta}$.

External Finance Premium and Entrepreneur's Problem:

Each period, $1-\gamma$ fraction of entrepreneurs die and consume their net worth. Hence the aggregate consumption of entrepreneurs is:

$$C_t^e = (1-\gamma)V_t$$

where V_t is entrepreneurial equity. After the fraction of entrepreneurs die, the left will form the new net worth by:

$$N_t = \gamma V_t + W_t^e$$

Since γ is close to 1 and W_t^e is almost 0, we have $V_t \approx N_t$, and:

$$c_t^e = n_t \tag{B18}$$

For the asset-based financial accelerator model, notice that the value of the entrepreneurial equity should be the following:

$$V_t = R_t^k Q_{t-1}K_t - R_{t-1}(Q_{t-1}K_t - N_{t-1}) - \mu \int_0^{\bar{\omega}_t} \omega_t \phi(\omega_t) R_t^k Q_{t-1} K_t d\omega_t$$

The first term is the entire return from sending capitals to the wholesale firm. The second term is the fraction obtained by the bank. The third term is the monitoring cost that vanished. Hence, the entire return is divided by three pieces, the expected bank profit, the expected entrepreneur profit, and the monitoring cost. We can transfer the monitoring cost back to household such that there is no waste in the economy. Hence, the aggregate evolution equation of N_t is

$$N_t = \gamma[R_t^k Q_{t-1}K_t - R_{t-1}(Q_{t-1}K_t - N_{t-1}) - \mu \int_0^{\bar{\omega}_t} \omega_t \phi(\omega_t) R_t^k Q_{t-1} K_t d\omega_t] + W_t^e$$

Notice that we can ignore the integral part of the model which is super small due to the fact that μ is close to 0. Take logs and linearize the equation will result in the following aggregate net worth transition equation:

$$\begin{aligned} n_t =& \frac{\gamma RK}{N}(r_t^k - r_{t-1}) + \gamma R(r_{t-1} + n_{t-1}) \\ &+ (R^k - R)\frac{\gamma K}{N}(q_{t-1} + k_t + r_t^k) + \frac{W^e}{N} w_t^e \end{aligned} \tag{B19}$$

For the earning-based financial accelerator model, notice that the aggregate evolution equation of N_t is:

$$\begin{aligned} N_t = \gamma[&R_t^k Q_{t-1}K_t - R_{t-1}(Q_{t-1}K_t - N_{t-1}) \\ &- \mu(1 - D_t) \int_0^{\bar{\omega}_t} \omega_t \phi(\omega_t) R_t^k (Q_{t-1}K_t - N_t) d\omega_t] + W_t^e \end{aligned}$$

where only the high order terms are affected, hence the aggregate transition equation of N_t after log-linearization is not affected.

Finally, to close the asset-based and earnings-based financial accelerator models, we will incorporate the corresponding external finance premium equation derived from formal contracting problems, and the monetary policy rule.

B4. Steady State

In order to determine the parameters put into the model, we will need to first solve for the steady state. At the steady state we have:

Equation (B7) becomes $Y = C + I + G + C^e$.

Equation (B8) becomes $R = \frac{1}{\beta}$.

Equation (B9) becomes $\frac{\xi}{1-H} = \frac{W}{C}$.

Equation (B10) becomes $R^k = RR + (1 - \delta)$.

Equation (B11) becomes $Q = 1$.

Equation (B12) becomes $I = \delta K$.

Equation (B13)-(B15) becomes:

$$XRR = \alpha \frac{Y}{K},\ XH = (1-\alpha)\Omega \frac{Y}{W},\ X = (1-\alpha)(1-\Omega)\frac{Y}{W^e}$$

Equation (B16) becomes $Y = AK^{\alpha}(H^{\Omega})^{1-\alpha}$.

Equation (B17) becomes $X = \frac{\eta}{\eta-1}$.

Equation (B18) becomes $C^e = (1-\gamma)N$.

Equation (B19) becomes:$N = \gamma[R^k K - R(K-N)] + W^e$.

For the asset-based financial accelerator models, equation (B1) - (B3) becomes

$$\begin{aligned} f_{\omega}(\bar{\omega},\sigma) + \Lambda g_{\omega}(\bar{\omega},\sigma) &= 0 \\ R^k f(\bar{\omega},\sigma) + \Lambda R^k g(\bar{\omega},\sigma) &= \Lambda R \\ \frac{g(\bar{\omega},\sigma)R^k L}{L-1} &= R \end{aligned}$$

Also by definition, $L = K/N$. From the equations above, solve for the endogenous variables at the steady state for the asset-based financial accelerator. For the earning-based financial accelerator models, equation (B4) - (B6) becomes

$$\begin{aligned} h_{\omega}(\bar{\omega},\sigma) + f_{\omega}(\bar{\omega},\sigma)L &= \Lambda g_{\omega}(\bar{\omega},\sigma) \\ (1-D)f(\bar{\omega},\sigma)(L-1)^2 + \Lambda D &= 0 \\ (1-D)g(\bar{\omega},\sigma)R^k &= R - R^k D\frac{L}{L-1} \end{aligned}$$

Lastly, equation equation (6) becomes $\psi D = (1-D)\Phi(\bar{\omega},\sigma)$.

From the 18 equations above, solve for the endogenous variables at the steady state for the earning-based financial accelerator.

B5. Proof of the Proposition

Proof of Proposition 1: Suppose the bank decides the allocation of the punishment funds. The bank will choose D_t to maximize the their return, which means:

$$max_{D_t}\ (1-D_t)g(\bar{\omega}_{t+1},\sigma)R^k_{t+1} + R^k_{t+1}D_t\frac{L_t}{L_t-1}$$

The FOC of the gives us $\frac{L_t}{L_t - 1} - g(.)$. By the definition of function g, when $L > 1$, we have:

$$\int_0^{\bar{\omega}_{t+1}} \omega_{t+1} d\Phi(\omega_{t+1})(1-\mu) + \int_{\bar{\omega}_{t+1}}^{+\infty} \bar{\omega}_{t+1} d\Phi(\omega_{t+1}) \leq$$
$$\int_0^{\bar{\omega}_{t+1}} \omega_{t+1} d\Phi(\omega_{t+1}) + \int_{\bar{\omega}_{t+1}}^{+\infty} \omega_{t+1} d\Phi(\omega_{t+1}) \leq$$
$$\int_{-\infty}^{+\infty} \omega_{t+1} d\Phi(\omega_{t+1}) = 1 \leq \frac{L_t}{L_t - 1}$$

Hence the return is increasing in D_t.

B6. Definition of the Shocks

- Monetary Policy Shock: $r_t^n = \rho r_{t-1}^n + \zeta \pi_{t-1} + e_t^{rn}$, where r_t^n denotes the nominal interest rate.
- TFP Shock: $a_t = \rho_a a_{t-1} + e_t^a$.
- Government Spending Shock: $g_t = \rho_g g_{t-1} + e_t^g$.
- Risk Shock: $\sigma_t = \rho^s \sigma_{t-1} + e_t^s$.
- Net Worth Shock: $n_t = \gamma \bar{R}\bar{K}/\bar{N}(r_t^k - r_{t-1}) + \gamma * \bar{R} * (r_{t-1} + n_{t-1} + e_t^n) + (\bar{R}^k - \bar{R})\gamma \bar{K}/\bar{N}(q_{t-1} + k_t + r_t^k) + \bar{W}^e \bar{N} * w_t^e$, where e_t^n denotes the shock.
- Labor Supply Shock: $w_t - c_t = (\bar{H}/(1-\bar{H}))h_t + e_t^h$.
- Markup Shock: $\pi = -\kappa x_t + \beta \pi_{t+1} + e_t^x$.
- Observation Shock: $y_t^{obs} = y_t + e_t^{obs}$.