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# Uncertainty, Endogenous Asset Portfolio, and Credit Distortion

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We analyze the heterogeneous impact of uncertainty on large and small firms. Initially, we empirically examine the data of listed companies in China using local projection method and find that uncertainty has a significantly greater impact on small firms. Subsequently, we build a DSGE model incorporating heterogeneous firms and introduce an endogenous asset portfolio (EAP) mechanism. The EAP mechanism generates heterogeneous effects on the two types of firms through debt default risk, leading to dynamic differences in credit price and quantity. Under this mechanism, decisions by firms and banks contribute to credit distortion from both the demand and supply sides respectively. We observe that the degree of credit distortion is related to the initial default risk of firms. Policy simulations indicate that fiscal subsidy policies should focus on reducing the level of information asymmetry and should be reasonably combined with macro-prudential policies.

*Key Words*: Uncertainty; Endogenous asset portfolio; Information asymmetry; Default risk; Credit distortion.
*JEL Classification Numbers*: E44, E51, G11.

## 1. INTRODUCTION

The impact of uncertainty on the macroeconomy and its effects have been hot topics in the economics literature for the past few decades. Following the Great Recession in 2008, the impact of uncertainty on the financial system has drawn significant attention in academic research (Bloom, 2009; Jurado et al., 2015; Bordo et al., 2016; Valencia, 2017; Alessandri and Bottero, 2020). Most relevant literature has focused on studying the impact of uncertainty on credit, banks, and firm investment. Recently, several studies have also highlighted that uncertainty has a differentiated impact on heterogeneous firms (Liu and Zhang, 2020; Berger et al., 2022; Alfaro et al., 2024; Correa et al., 2023; Kim et al., 2023). Firms experiencing more

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severe declines in credit and investment under uncertainty shocks tend to display higher risk, rely more on bank financing, face tighter financing constraints, and are typically privately owned. These characteristics are often associated with small firms. Compared to large firms, small firms encounter greater challenges in surviving in uncertain environments, and these heterogeneous impacts undoubtedly contribute to credit market contraction and distortion.

Our paper examines the heterogeneous impact of uncertainty on both large and small firms, employing both empirical analysis and theoretical modeling. Consistent with several related research (Chritiano et al., 2014; Jurado et al., 2015; Baek, 2020), we focus on macroeconomic uncertainty, which causes fluctuations in aggregate economic output. And our work focuses on the volatility of future capital investment returns due to uncertainty. Initially, we conduct an empirical analysis to assess the varied impact of uncertainty on firms, using data from listed companies in China. Subsequently, we develop a model that incorporates heterogeneous firms and calibrate it with China's data to scrutinize its response to uncertainty shocks. The findings from both empirical and theoretical approaches consistently highlight a more substantial negative impact of uncertainty on small firms, ultimately resulting in credit distortion.

To motivate the research question, we initially empirically analyze the heterogeneous impact of uncertainty on large and small firms. In order to visually depict the impulse response of uncertainty shocks and compare the heterogeneous impact on large and small firms, we employ the local projection (LP) method proposed by Jordà (2005) to examine the heterogenous impact of uncertainty on firms' default risk, financing cost, and bank credit. After controlling for firm-level and macroeconomic variables, uncertainty leads to an increase in firms' default risk, financing cost, and a decrease in bank credit. Comparing the results for large and small firms, we find that regardless of the dependent variable, uncertainty has a consistent impact on both types of firms, but the impact is greater for small firms.

Subsequently, we develop a medium-scale DSGE model incorporating heterogeneous firms and an Endogenous Asset Portfolio (EAP) mechanism between firms and banks. The EAP mechanism, grounded in the asymmetric information between banks and firms, operates based on firms' expected default risk. As uncertainty increases, firms make decisions regarding the structure of their investment projects, leading to EAP and endogenous levels of default risk. Banks also determine their supply of credit shares based on the expected default risk of borrowers, resulting in EAP for banks. Therefore, in our model, the EAP mechanism influences the credit shares of both large and small firms from both the supply and demand sides through firms' debt default risk. After calibrating the model with China's data, we examine its response to uncertainty shocks and find that, in line with empirical results, small firms exhibit greater fluctuations in default risk, financing premium, and credit. Furthermore, a challenge in related empirical research lies in separating the demand and supply effects of credit. An advantage of our model is that it allows us to study the contributions of firms' and banks' respective decisions based on the EAP mechanism to the dynamics of the model. This enables us to compare the supply and demand effects of the credit decline to some extent. We also analyze the impact of initial differences in default risk between the two types of firms. Finally, we consider fiscal subsidy policies and macroprudential policies based on the EAP mechanism and asymmetric information between banks and firms. We find that reducing the level of asymmetric information between banks and firms through fiscal subsidy policies effectively mitigates financial risk and distortions in the credit market. Through a comparison of welfare improvements and financial system stability, we find that fiscal subsidy policies and macroprudential policies have different policy focuses and should be reasonably combined to mitigate the negative impact of uncertainty on the economy.

**Related Literature.** Our paper is connected to the following areas of research. First, we explore the impact of uncertainty on credit. Existing research has established a negative correlation between uncertainty and credit. This correlation is partly attributed to the real-option channel, where increasing uncertainty leads households to postpone consumption and increase precautionary savings (Luo and Young, 2010), and leads firms and banks to postpone investment and adopt a wait-and-see approach, anticipating a decrease in uncertainty (Bernanke, 1983; McDonald and Siegel, 1986; Bloom, 2009; Nishimura and Ozaki, 2007; Correa et al., 2023). This results in a contraction of credit and a decline in investment during this period. On the other hand, the financial friction channel amplifies the negative impact of uncertainty on firm net worth, as the decline in "skin in the game" after a shock magnifies the negative impact of uncertainty (Alfaro et al., 2024). Uncertainty increases firms' default risk (Christiano et al., 2014; Gilchrist et al., 2014; Arellano et al., 2019), thereby raising loan spreads (Kaviani et al., 2020; Barraza and Civelli, 2020; Berger et al., 2022), leading to a decrease in credit supply and demand. Second, we examine the impact of uncertainty on both bank credit supply and firm credit demand. Increased uncertainty leads to reductions in both (Kim et al., 2023). The decrease in bank credit supply stems from banks' self-insurance motives in the face of increased borrower risk, resulting in a wait-and-see strategy (Valencia, 2017; Correa et al., 2023). The decrease in bank credit is also due to a reduction in risk-taking (Wu et al., 2022), and balance sheet constraints (Bordo et al., 2016; Correa et al., 2023). The decrease in firm credit demand arises from the real-option channel's delayed investment (Bernanke, 1983; Bloom, 2009) and increased financing cost (Barraza and Civelli, 2020; Berger et al., 2022). Third, we explore the impact of uncertainty on heterogeneous firms. Several studies have found heterogeneous effects of uncertainty on different types of firms. Liu and Zhang (2020) empirically study the impact of economic policy uncertainty (EPU) on firm credit with China's data and find that EPU significantly reduced the investment and net debt of privately-owned firms (POE) in China, but has no significant impact on state-owned firms (SOE). Berger et al. (2022) find that EPU increases firms' loan spreads, with higher-risk borrowers facing higher levels of spreads. Alfaro et al. (2024) empirically examine the greater impact of uncertainty on constrained firms, leading to a more severe decline in investment. They subsequently build a DSGE model containing heterogeneous firms and analyze the amplification of financial friction within it. Kim et al. (2023) empirically test the negative impact of uncertainty on credit, finding that it is greater for financially constrained firms, with similar results for firm investment.

Among these, our work is most closely related to Baek (2020), Gertler et al. (2012), and Ferrante (2018). Baek (2020) examines a risk-shifting channel for firms, where a severe moral hazard problem between firms and banks arises: when uncertainty increases, firms transfer more risk to banks, leading to a decline in the quality of firms' investment projects, thereby amplifying the impact of uncertainty on the real economy. In our model, the relationship between firms' investment project returns and risk is presented in a more general form. To some extent this weakens the amplification effect of uncertainty on the real economy, but allows for a clearer analysis of the credit risk issues behind the EAP mechanism of firms. Gertler et al. (2012) follow Gertler and Kiyotaki (2010) by considering the issue of banks engaging in external financing and endogenizing bank risk. Unlike Gertler et al. (2012) in their endogenization of the liability side of banks (household deposits), we consider the decision-making on the asset side of banks (firm credit). Similar to Jin and Xiong (2023), we incorporate the optimization decision of the asset portfolio (the shares of different credit borrowers) into the moral hazard problem of banks. However, we also assume that banks consider the default risk of borrowers when deciding on the asset portfolio. Like firms, banks generate an EAP mechanism when weighing their options. Ferrante (2018) introduces another endogenous asset portfolio mechanism: banks engage in a costly effort to screen good and bad loan projects. In his model, traditional banks that pay based on the worst-case-scenario and shadow banks that pay based on expected returns exhibit different decision-making behaviors, leading to the endogenization of bank asset quality and asset transfer effects during crises. Unlike Ferrante (2018) in their characterization of information asymmetry between banks and depositors as loan sources and the risk of bank runs, our model considers the information asymmetry between banks and borrowing firms, focusing primarily on banks' consideration of firm default risk.

The core contribution of our paper is that, based on empirical evidence of the differential impact of uncertainty on heterogeneous firms, we propose an EAP mechanism that operates on both borrowers and lenders. We find that incorporating this mechanism into a DSGE model containing banks and heterogeneous firms can explain the distortions in credit markets when uncertainty increases. To the best of our knowledge, no other study simultaneously considers the interaction of asset portfolio mechanisms between firms and banks and their macroeconomic impact. In the context of high uncertainty, our research provides policy implications for how fiscal subsidy policies and macroprudential policies can be coordinated to promote financial stability and improve welfare in economies with information frictions.

The remaining sections of the paper are as follows. Section 2 describes the heterogeneous impact of uncertainty on small and large firms tested through the LP method. Section 3 introduces our DSGE model and the relevant theoretical analysis. Section 4 presents the calibration of the model and the associated quantitative results. Finally, section 5 concludes.

## 2. THE EFFECTS OF UNCERTAINTY ON HETEROGENEOUS FIRMS: LP EVIDENCE

To motivate our research question, we first present empirical evidence of the heterogeneous impact of uncertainty on large and small firms. To this end, we employ the local projection (LP) method to separately examine changes in default risk, financing cost, and bank credit for large and small firms when uncertainty increases. The data used in our analysis consists of financial data from Chinese listed companies, sourced from the China Stock Market & Accounting Research Database (CSMAR).

We employ the LP method for empirical testing for two main reasons. First, we aim to capture the changing trends of uncertainty's medium-to-long-term impact on firms, rather than a general average causal relationship as seen in OLS regression results. By estimating the different lag coefficients of uncertainty using LP, we can generate impulse responses to uncertainty shocks, as in our model. On one hand, this approach allows for a more intuitive comparison of the heterogeneous impact of uncertainty on the two types of firms. On the other hand, such results are more amenable to comparison with model results. Second, while VAR methods can also generate impulse responses, they pose challenges in handling panel data. Moreover, the LP method, based on OLS logic for estimation, provides more robust statistical inferences, mitigating the issue of substantial estimation bias when shocks occur at distant observation periods (Jordà, 2005). In recent years, the LP method has emerged as a widely used alternative to VAR in research (Jordà and Taylor, 2016; Iacoviello and Navarro, 2019; Hom and Thürwächter, 2021).

### 2.1. Data and estimation methodology

The firm-level data used in our analysis consists of quarterly panel data from the CSMAR database covering the period from 2001Q1 to 2022Q4. Our primary focus is on three key indicators: corporate debt default risk, financing costs (credit prices), and bank credit (credit quantity). We adopt the simplified Expected Default Probability (EDP) proposed by Bharath and Shumway (2008) as a proxy for default risk, the ratio of corporate financial expenses to total liabilities as an indicator of financing cost, and the ratio of long-term and short-term borrowings to total operating income from the balance sheet as an indicator of bank credit. As for the measurement of uncertainty, there is currently no unified standard in the literature. Our analysis leans towards an aggregate measure of uncertainty at the macroeconomic level, and the characterization of uncertainty in the model follows this approach. Therefore, we employ a method proposed by Jurado et al. (2015) to measure uncertainty, estimating a GARCH(1,1) model for quarterly GDP growth rates in China to obtain the level of macroeconomic uncertainty.

In addition to these variables, we control for various firm-level factors. These include firm size, leverage ratio, profitability, growth potential, cash flow, current profitability, proportion of independent directors, and asset turnover. This allows us to capture the individual effects at the firm level. At the macroeconomic level, we control for quarterly effects. Since uncertainty is a quarterly time series data, we control for annual fixed effects in firm borrowing and investment. We exclude firms with ST records, those in the financial industry, and those with missing or outlier data. We also apply winsorization at the 1st and 99th percentiles to continuous variables.

Differing from the analysis of exposure measures by Iacoviello and Navarro (2019), our focus lies in the differential impact of uncertainty on large and small firms, rather than the marginal effect of firm size. Therefore, we estimate the model using a subsample approach. We classify firms with an average asset size below the median during the sample period as small firms, and those above as large firms. The model specification for the local projection method estimation is as follows:

$$\ln y_{i,t+h} - \ln y_{i,t} = \beta_0^h + \beta^h Uncertainty_t + \sum \alpha^h X_{i,t} + Quarter_t + Year_t + \gamma_i^h + \varepsilon_{i,t},$$

where $y_{i,t}$ represents the three variables of corporate default risk, financing cost, and bank credit. $Uncertainty_t$ represents the aggregate macroeconomic uncertainty. $X_{i,t}$ represents a series of firm-level control variables affecting y. $Quarter_t$ represents quarterly dummy variables used to control for seasonal effects, and $Year_t$ is used to control for annual fixed effects in firm borrowing and investment. $\gamma_t^h$ represents firm fixed effects. Regression coefficient standard errors are clustered at the firm level.

### 2.2. Empirical results

We plot the trend of the coefficient $\beta^h$ representing uncertainty's impact on firms according to the value of h, where h ranges from 1 to 12, signifying uncertainty's impact on firms over a period of 1 to 3 years. By varying $\beta^h$ , we can approximate the impulse response of uncertainty shocks on firms. Figure 1 illustrates the changing trend of uncertainty's impact on large and small firms, with three separate graphs representing the estimated results when the dependent variables are default risk, financing cost, and bank credit. [1]

**FIG. 1.** The heterogeneous impact of uncertainty on large and small firms. **Note.** The vertical axis represents the percentage change in the relevant variables, while the horizontal axis represents h in equation (1), i.e., the quarters following the shock. The solid blue line represents the impact on small firms and the solid red line represents large firms. The shaded area represents the 90% confidence interval.


From Figure 1, it is evident that uncertainty has a heterogeneous impact on large and small firms. Uncertainty leads to an increase in corporate default risk and financing cost, as well as a reduction in credit, with all three effects being more pronounced for small firms. Why are small firms more affected by uncertainty? What is the underlying relationship among default risk, financing cost, and credit quantity? In the following section, we attempt to provide theoretical explanations for these questions through our model.

## 3. THE MODEL

We develop a multi-sector DSGE model that incorporates heterogeneous firms (i.e., large and small firms), with the primary financial friction in

[1] The detailed results of local projection can be found in Appendix B.1.

the model arising from the interaction between firms and banks. Taking into account the asymmetric information between the borrowing and lending parties, we extend the firm sector from Bernanke et al. (1999) and the banking sector from Gertler and Karadi (2011). We introduce an endogenous asset portfolio (EAP) mechanism between banks and firms. As indicated by our empirical findings in Section 2, under the EAP mechanism, heightened uncertainty leads to significant heterogeneous responses from both types of firms. The anticipated increase in financing cost accelerates the default risk for small firms, not only raising the financing premium but also leading banks to reduce credit supply to small firms due to the heightened expected default risk. The EAP mechanism explains the heterogeneous fluctuations in credit quantities and prices for both types of firms from both the supply and demand sides, providing an endogenous theoretical mechanism to explain the heterogeneous responses of small and large firms and credit distortions under uncertainty shocks. The subsequent discussion primarily emphasizes the differences in the mechanisms for the two types of firms, with the superscript "b" representing large firms and "s" representing small firms for the relevant variables.

### 3.1. Households

Representative households derive income from deposit interest and wages, and maximize their expected discounted utility by choosing consumption $C_t$, savings $D_t$, and labor supplied to large and small firms $L_t^b, L_t^s$. The utility function is given by

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[ \ln\left(C_t - vC_{t-1}\right) - \phi_L^b \frac{1}{1+\sigma_L} \int_0^1 {L_{it}^b}^{1+\sigma_L} di - \phi_L^s \frac{1}{1+\sigma_L} \int_0^1 {L_{it}^s}^{1+\sigma_L} di \right],$$

where $\beta$ is the discount factor for the household sector, $v$ is the consumption habit of the household sector, $\phi_L^b$ and $\phi_L^s$ represent the heterogeneous labor supplied by the representative household, and $\sigma_L$ is the reciprocal of the Frisch labor supply elasticity. The household's budget constraint is given by

$$P_t C_t + D_t + T_t = D_{t-1} R_{t-1} + \int_0^1 W_{it}^b L_{it}^b + \int_0^1 W_{it}^s L_{it}^s + \Pi_t,$$

where $D_t$ and $R_t$ represent deposits and deposit interest rates, $W_{it}$ denotes the nominal wage of individual $i$. $\Pi_t$ represents the profits obtained by the production sector, which are subsequently transferred to the household sector, and $T_t$ denotes the taxes levied by the government to implement relevant policies. The wage setting follows the Calvo sticky form as referenced in Erceg et al. (2000), where the wage in each period is adjusted with probability $1 - \theta^p$.

### 3.2. Firms

The EAP mechanism in the firm sector arises from firms' capital investment decisions, where some firms face a trade-off between investment projects with differing risks and returns. We make certain adjustments to Baek (2020) framework, specifically regarding the positive correlation between the risk and return of investment projects. Firms must decide on investment portfolios, choosing between high-risk, high-return projects (referred to as H projects) and low-risk, low-return projects (referred to as L projects). Firms engage in costly effort to identify H projects, thereby increasing the proportion of H projects in the investment portfolio to enhance the expected return on capital. The trade-off between expected returns and effort cost leads to the endogenization of default risk and asset portfolio. Firms transfer additional default risk to banks, causing banks to raise the financing premium they demand.

Following Bernanke et al. (1999) and Christiano et al. (2014), we assume that firms purchase original capital $K_t^i$ using credit obtained from banks $B_t^i$ and their own net worth $N_t^E$. After making investment decisions, they undergo a post-investment idiosyncratic effective capital transformation shock $\omega$ that converts it into effective capital $\omega K_t^i$, which is then sold to intermediate goods producers for production and capital returns. The effective capital transformation rate $\omega$ is a random variable with an expected value $\mathbb{E}(\omega) = 1$ and follows a log-normal distribution: $\log(\omega) \sim N(\mu, \sigma)$, where $\sigma$ represents the level of uncertainty.

In each period, firms purchase original capital using a combination of their own net worth and credit obtained from banks:

$$Q_t^i K_t^i = N_{i,t}^E + B_t^i, \quad i = b, s.$$

When signing a debt contract with the bank, the bank and the firm agree on a contract interest rate. After the project is settled, the firm needs to repay the principal and interest according to the contract interest rate. The final return of the capital investment project is uncertain and depends on the realized value of the effective capital conversion rate $\omega$. Therefore, for the firm, there exists a threshold value for the effective capital conversion rate $\bar{\omega}$ that determines:

$$\bar{\omega}_{t+1}^i R_{i,t+1}^k Q_t^i K_t^i = B_t^i Z_{t+1}^i, \quad i = b, s, \tag{1}$$

where $Z_t^i$ is the contract interest rate, representing the firm's financing cost. The difference between the financing cost and the risk-free rate $Z_t^i - R_t$ is defined as the financing premium for the firm. When the final conversion rate $\omega < \bar{\omega}$ is such that the firm's capital project returns are insufficient to repay the debt, it leads to default. When $\omega \geq \bar{\omega}$ is achieved, the firm can repay the debt as usual and obtain the remaining returns as profit. Therefore, the firm's expected return is:

$$\int_{\bar{\omega}_{t+1}}^{\infty} \left(\omega R_{t+1}^{k} Q_t K_t - Z_{t+1} B_t\right) dF(\omega).$$

Actually, small firms usually face higher levels of information asymmetry and default risk. Their investment decisions are more flexible, and they tend to pursue high returns in the short term to accumulate capital quickly. We assume that their capital investment projects consist of both L and H projects, each with different distributions of their respective effective capital conversion rates: $\omega^L \sim F^L(\omega), \omega^H \sim F^H(\omega)$. The L projects are similar to the investment projects of large firms, with an expected conversion rate $\mathbb{E}(\omega) = 1$ and a standard deviation $\sigma$. The difference with H projects lies in their higher expected effective capital conversion rate (with an expected value $a, a > 1$), but with higher risk (with a higher cross-sectional standard deviation $b\sigma, b > 1$). Specifically, the distribution of the two is as follows:

$$\log\left(\omega^L\right) \sim N\left(-\frac{1}{2}\sigma^2, \sigma^2\right), \log\left(\omega^H\right) \sim N\left(-\frac{1}{2}(b\sigma)^2 + \log(a), (b\sigma)^2\right).$$

Small firms tend to favor H projects with higher expected returns and may underestimate the high default rates associated with high risk when making investment decisions. Motivated to maximize their own returns, small firms prefer to choose H projects with higher expected returns during investment decisions. They will exert more effort in identifying projects that align with their preferences in investment project selection, thereby increasing their probability of obtaining high-risk projects and enhancing overall expected returns. Through effort $e_t$, small firms increase the probability of obtaining H projects $p(e_t)$, ultimately achieving an effective capital conversion rate that is the weighted average of the two types of projects based on probability. The expected returns and risk of capital investment projects are endogenously determined by this effort.

$$F_t(\omega) = p\left(e_t\right) F_t^H(\omega) + \left(1 - p\left(e_t\right)\right) F_t^L(\omega). \tag{2}$$

However, such effort is costly. We assume that the cost exists in the form of a capital value. Therefore, firms need to balance the higher expected returns brought by H projects with the cost incurred by effort to maximize the expected returns of capital investment. The formula for their expected returns is as follows:

$$\int_{\bar{\omega}_{t+1}}^{\infty} \left(\omega R_{t+1}^{k} Q_t K_t - Z_{t+1} B_t\right) dF(\omega) - c(e_t) Q_t K_t. \tag{3}$$

The first part of the equation represents the expected profit of the capital project obtained by the firm, which is the expected return of the project when there is no default, minus the repayment of debt principal and interest. In the second part, the firm's effort cost $c(e_t)$ incurred to increase the probability of obtaining H projects is considered as a part of the firm's total assets, which will reduce the expected returns. Following Baek (2020), the probability function is set as a linear function of effort behavior, and the cost is set as a quadratic function: $p(e_t) = \zeta e_t, c(e_t) = {e_t}^2/2$. Solving the profit maximization problem for small firms yields the first-order condition for the level of effort: [2]

$$\zeta R^k_{t+1}(a-1) + \zeta R^k_{t+1}\left(o^H\left(\bar{\omega}_{t+1}\right) - o^L\left(\bar{\omega}_{t+1}\right)\right) \geq e_t, \tag{4}$$

where $o^H(\bar{\omega}_{t+1}), o^L(\bar{\omega}_{t+1})$ respectively represent the loss of bank income share when H and L projects default. Equation (4) represents the incentive compatibility constraint, where the left side denotes the benefit of one unit of effort, and the right side denotes the cost of one unit of effort. The first part on the left side represents the direct effect of one unit of effort, which is manifested as the excess expected return of H projects. The second part represents the indirect effect of one unit of effort, denoted as $(o^H(\bar{\omega}_{t+1}) - o^L(\bar{\omega}_{t+1}))$, arising from the excess return due to risk transfer from H projects.

In this context, the firm transfers more risk to the bank, enhancing the return frontier when the capital investment project succeeds. Therefore, the effort to increase the probability of H projects enhances the firm's expected return from two perspectives. Through equation (4), we can derive the relationship between the firm's asset portfolio and the level of uncertainty $\sigma$ in lemma 1 when $F^L < F^H < 0.5$.

LEMMA 1. $\partial e/\partial\sigma > 0$. *As the level of uncertainty $\sigma$ increases, small firms will elevate their effort level and choose more H projects when determining their asset portfolio.*

*Proof.* See appendix A.3. ∎

However, the increase in $\sigma$ will lead to a rise in the probability of project default $F_t(\bar{\omega}_{t+1})$ and an expected increase in financing costs. This will incentivize small firms to pursue H projects with high returns to compensate for the expected loss in their own returns due to the heightened uncertainty. Consequently, the small firm debt default rate will increase, accelerating risk accumulation in the economy.

[2] The derivation of the relevant optimization problem for small firms can be found in Appendix A.2.1.

The firm purchases raw capital from the capital producer, and their returns are generated by renting out effective capital to intermediate goods producers and subsequently reselling the effective capital without depreciation at the current period. The rate of return on one unit of effective capital is given by:

$$R^k_{i,t+1} = \pi_{t+1} \frac{r^k_{i,t+1} + Q^i_{t+1}(1-\delta)}{Q^i_t}, \quad i = b, s. \tag{5}$$

Consistent with Bernanke et al. (1999), after the firm sells effective capital to obtain capital project returns, a proportion $1-\gamma^i$ of firms exit each period, and an equal number of new firms enter. Additionally, the new entrants receive transfer payments $w^e$ from households as start-up funds each period. The net worth accumulation process for the new entrants is given by:

$$N^E_{i,t+1} = \frac{\gamma^i}{\pi^i_t} \left[ \int_{\bar{\omega}_{t+1}}^{\infty} \left( \omega R^k_{i,t+1} Q^i_t K^i_t - Z^i_{t+1} B^i_t \right) dF^i(\omega) - c(e_t) Q^i_t K^i_t \right] + w^e, \quad i = b, s. \tag{6}$$

### 3.3. Banks

The EAP mechanism of the banking sector stems from the bank's credit supply decisions to two types of firms, where the bank faces the tradeoff in credit allocation between large and small firms. Following Gertler et al. (2012), we introduce a moral hazard problem of banks, with the distinction that we consider the bank's decision-making behavior regarding the asset side (firm credit). Similar to Jin and Xiong (2023), we assume that higher level of information asymmetry leads to more severe agency problems in small firm credit, thereby increasing the fraction of asset that can be diverted. Additionally, since unrecoverable credit in the event of default will reduce the bank's expected present value of income, the bank is sensitive to the default risk of firms. Therefore, apart from adjusting credit rate, the bank balances the credit allocation between small and large firms based on the expected default risk, leading to the endogenization of the bank's asset portfolio. This process results in banks reducing the credit supply to small firms.

Banks absorb deposits from the household sector and, combined with its own capital $N^B_t$, provides credit to firms, accumulating bank capital through the interest rate spread on deposits and credit. Its balance sheet is given by

$$B^b_t + B^s_t = D_{t+1} + N^B_t. \tag{7}$$

Banks sign debt contracts with firms, and the income from credit is divided into two parts: the first part is the credit income obtained at the contracted interest rate when the firm repays the principal and interest normally. The second part pertains to income acquired in case of the firm's default, where the bank liquidates the capital project and receives all project income, denoted as $\Pi_t^i$. For the bank, the income from the second part is uncertain and uncontrollable, depending on the actual income from the firm's investment. Besides, this process will incur a certain income loss due to liquidation costs, denoted as $\mu^i$. Therefore, the bank's expected income loss mainly stems from the firm's default behavior. Banks need to determine the credit contract interest rate considering the expected default risk of the firm to ensure that the ultimate realized income from the credit is not lower than its minimum expected income:

$$\left(1-F_t^i\left(\bar{\omega}_{t+1}^i\right)\right) Z_{t+1}^i B_t^i+(1-\mu^i)\int_0^{\bar{\omega}_{t+1}^i} \omega R_{i,t+1}^k Q_t^i K_t^i dF^i(\omega)\geq R_{i,t}^L B_t^i, \quad i=b,s. \tag{8}$$

On the left-hand side of equation (8), the first part represents the expected return for the bank when the firm does not default —specifically, the credit principal and interest outlined in the debt contract. The second part signifies the portion of the capital project return, net of liquidation cost, that the bank obtains in place of the firm in the event of default (denoted as $\Pi_t^i$), where $\mu^i$ is the cost ratio for the bank to monitor and liquidate the capital project. On the right-hand side of equation (8) is the minimum expected return required for bank credit. Due to the existence of reserve requirements for commercial banks, the minimum expected loan rate is determined as $(1-RR_t)(R_{b,t}^L-1)=R_t-1$, where $R_t$ is the deposit interest rate, and $RR_t$ is the reserve requirement ratio.

Furthermore, since 2004, China has implemented differential reserve requirements, tying the reserve requirement ratio for financial institutions to factors such as their capital adequacy ratio and asset quality. Due to varying risk levels among credit recipients, financial intermediaries with lower asset quality and higher non-performing credit ratios face higher reserve requirement constraints. This, in turn, raises the minimum expected return rate. Therefore, in light of the different risk levels, we assume that banks impose a risk premium for credit to small firms. The level of this premium is related to the overall asset portfolio quality of the bank. In principal, there is an additional component to the minimum expected return rate for credit to small firms $R_{s,t}^L$, which positively correlates with the share of small firm credit: $R_{s,t}^L=(R_{b,t}^L)^{1+\xi x_t}$.

Bank managers need to maximize the expected present value of their own lifetime net assets under financing constraints

$$V_t=\max \mathbb{E}_t \sum_{k=0}^{\infty} \Lambda_{t,t+k+1}\theta^k\left(1-\theta\right) N_{t+k+1}^B,$$

where $\Lambda_{t,t+k+1} = \beta^{k+1}\lambda_{t+k+1}/\lambda_t$ is the household subjective discount factor, and $\theta$ is the bank's survival rate. As mentioned earlier, the accumulation of a bank's net assets comes from the interest rate spread on deposits and credit. However, a portion of the income from credit $\Pi_t^i$ is uncertain due to the risk of default by the borrowing firms. This portion depends on the realized return of the capital project at the end of the default and involves the period and cost of project liquidation and monitoring. At the beginning of the period, the bank cannot accurately anticipate the magnitude of $\Pi_t^i$. Following Ferrante (2018), we assume that due to the uncertainty and low value of this fraction of income, the bank makes decisions based on the worst-case-scenario. That is, the bank expects the realized value $\Pi_t^i$ to be 0, as its lowest possible value. [3] Therefore, its expected net asset accumulation is:

$$\mathbb{E}_t(N_{t+1}^B) = \left(1 - F_t^b(\bar{\omega}_{t+1}^b)\right) Z_{t+1}^b B_t^b + \left(1 - F_t^s(\bar{\omega}_{t+1}^s)\right) Z_{t+1}^s B_t^s - R_t D_{t+1}.$$

We consider the agency problem in banks as discussed in Gertler and Karadi (2011), while also incorporating the optimization problem of asset portfolio management by bank managers as introduced in Gertler et al. (2012) and Jin and Xiong (2023). We assume that bank managers can divert a fraction of total assets in each period. Due to the higher level of information asymmetry of small firms, the asset value of small firms is more challenging to accurately reflect on the balance sheet. Thus, the more severe agency problem allows banks to transfer more credit of small firms.

Specifically, the total assets that the bank can transfer in each period are denoted as $\lambda B_t^b + \lambda(1 + \iota/2x_t)B_t^s$, where $x_t = B_t^s/(B_t^s + B_t^b)$ represents the share of small firm credit. Therefore, the transfer ratio of total assets is $\Theta(x_t) = \lambda\left(1 + \iota/2x_t^2\right)$, which is related to the bank's asset portfolio. However, the assets diverted by the bank will be audited in the next period, leading to the cessation of net asset accumulation by the bank and entering into bankruptcy liquidation. Therefore, the condition for the normal operation of the bank is that the net present value of expected returns must not be lower than the value of the transferable assets, i.e., it needs to satisfy the incentive compatibility constraint:

$$V_t \geq \Theta(x_t)\left(B_t^b + B_t^s\right), \Theta(x_t) = \lambda\Big(1 + \frac{\iota}{2}x_t^2\Big). \tag{9}$$

The present value of expected returns can be expressed as $V_t = \mu_t B_t^b + m_t B_t^s + \eta_t N_t^B$, where $\mu_t, m_t$ respectively represent the present value of

[3]In Ferrante (2018), traditional banks make decisions based on worst-case-scenarios, while shadow banks employ different decision-making mechanisms. As this paper does not account for the presence of shadow banks, we refer to their characterization of traditional banks here.

expected returns or marginal value to the bank from a unit credit to large and small firms:

$$\mu_t = \beta(1-\theta)\Lambda_{t,t+1}\left[\left(1-F_t^b(\bar{\omega}_{t+1}^b)\right)Z_{t+1}^b - R_t\right] + \beta\theta\Lambda_{t,t+1}\frac{B_{t+1}^b}{B_t^b}\mu_{t+1}, \tag{10}$$

$$m_t = \beta(1-\theta)\Lambda_{t,t+1}\left[\left(1-F_t^s(\bar{\omega}_{t+1}^s)\right)Z_{t+1}^s - R_t\right] + \beta\theta\Lambda_{t,t+1}\frac{B_{t+1}^s}{B^s}m_{t+1}. \tag{11}$$

From equations (10) and (11), it can be observed that the firm's default risk $F_t^i(\bar{\omega}_{t+1}^i)$ decreases the present value of expected returns for the bank. On one hand, as in equation (9), the share of small firm credit $x_t$ can increase the bank's returns by raising the asset transfer ratio $\Theta(x_t)$. However, on the other hand, the higher default risk of small firms can reduce its returns. Therefore, bank managers need to make a take-off on the allocation of credit. The optimization problem is to choose the optimal leverage ratio $\phi_t = (B_t^b + B_t^s)/N_t^B$, and asset portfolio $x_t = B_t^s/(B_t^s + B_t^b)$ under the incentive compatibility constraint and balance sheet constraint to maximize the present value of expected returns. Solving the optimization problem yields the determination of the optimal leverage ratio and asset portfolio: [4]

$$\phi_t = \frac{\eta_t}{\Theta(x_t) - \mu_t(1-x_t) - m_t x_t}, \tag{12}$$

$$x_t = \frac{\mu_t}{m_t - \mu_t}\left[-1 + \sqrt{1 + \frac{2}{\iota}\left(\frac{m_t - \mu_t}{\mu_t}\right)^2}\right]. \tag{13}$$

From equation (13), it can be observed that the bank's asset portfolio depends on the present value of expected returns from the two types of firm unit credit $\mu_t, m_t$, which is related to the default risk of the two types of firms. We can derive the relationship between the bank's asset portfolio and the level of uncertainty $\sigma$ from equations (10), (11) and (13) as stated in lemma 2.

LEMMA 2. $\partial x/\partial\sigma < 0$. *When uncertainty levels increase, banks reduce their credit supply to small firms due to the heightened risk of default.*

*Proof.* See appendix A.4. ∎

Following Gertler and Karadi (2011), we assume that in each period, a certain proportion of bank managers exit while an equal number of new

[4]The derivation of the relevant optimization problem for banks can be found in Appendix A.2.2.

bank managers enter, receiving initial financing from representative households. This initial financing is measured as a certain proportion of total bank assets. The total net asset accumulation of the banking sector is represented as:

$$\begin{aligned} N_t^B &= \theta[\left(1 - F_{t-1}^b(\bar{\omega}_t^b)\right) Z_t^b B_{t-1}^b + \left(1 - F_{t-1}^s(\bar{\omega}_t^s)\right) Z_t^s B_{t-1}^s \\ &+ \Pi_{t-1}^b + \Pi_{t-1}^s - R_{t-1} D_t] + \chi \left(B_{t-1}^b + B_{t-1}^s\right), \end{aligned} \tag{14}$$

where $\theta$ represents the survival rate of the banking sector and $\chi$ represents the proportion of initial financing. Unlike the expected net asset accumulation $\mathbb{E}_t(N_{t+1}^B)$ when making optimal decisions, the realized value of capital project liquidation returns $\Pi_{t-1}^i$ from the previous period at time t is known and will enter the total revenue of the banking sector as a part of the net asset accumulation.

## 3.4. Production

### *3.4.1. Capital producers*

The capital goods producer repurchases the firm's effective capital goods from the previous period, which have not depreciated, and invests in producing new capital goods to sell to the firm sector. Following the framework of Christiano et al. (2010), there exists a quadratic adjustment cost in the investment goods formation process. The capital accumulation equation is as follows:

$$K_{t+1}^i = \left((\zeta e_t)a + (1 - \zeta e_t)\right)(1-\delta)K_t^i + \left[1 - \frac{\kappa}{2}\left(\frac{I_t^i}{I_{t-1}^i} - 1\right)^2\right] I_t^i, \quad i = b, s. \tag{15}$$

It is important to note that, as the capital goods producer repurchases effective capital, the corresponding repurchase share for small firms includes a premium for the H project's effective capital conversion rate. After solving the profit maximization problem, the capital goods producer obtains the first-order condition for investment goods:

$$\begin{aligned} 1 &= Q_t^i \left[1 - \frac{\kappa}{2}\left(\frac{I_t^i}{I_{t-1}^i} - 1\right)^2 - \kappa \frac{I_t^i}{I_{t-1}^i}\left(\frac{I_t^i}{I_{t-1}^i} - 1\right)\right] \\ &+ \beta \frac{\lambda_{t+1}}{\lambda_t} Q_{t+1}^i \kappa \left(\frac{I_{t+1}^i}{I_t^i}\right)^2 \left(\frac{I_{t+1}^i}{I_t^i} - 1\right), \quad i = b, s. \end{aligned} \tag{16}$$

### *3.4.2. Intermediate goods producers*

Assuming perfect competition among intermediate goods producers, they hire labor from the household sector at the real wage rate $w_t^i$ and rent effective capital from the firm sector at the capital rental rate $r_{i,t}^k$ for production, using a Cobb-Douglas production function:

$$Y_t^i(h) = A_t \left[ ((\zeta e_{t-1})a + (1-\zeta e_{t-1})) K_{t-1}^i(h) \right]^{\alpha_i} L_t^i(h)^{1-\alpha_i}, \quad i = b, s. \tag{17}$$

Similarly, as effective capital $\omega K_{t-1}^i$ is used in production, there is a premium for the effective capital conversion rate in the production process of small firms. Given the real wage rate $w_t^i$ and capital rental rate $r_{i,t}^k$, intermediate goods producers solve the cost minimization problem and obtain the relationship between the two types of production factors: $\alpha_i w_t^i L_t^i = (1-\alpha_i) r_{i,t}^k K_{t-1}^i$ , and the real marginal cost: $mc_t^i = 1/A_t \left( w_t^i/(1-\alpha_i) \right)^{1-\alpha_i} \left( r_{i,t}^k/\alpha_i \right)^{\alpha_i}$. Additionally, intermediate goods producers aggregate the intermediate goods produced by large and small firms $Y_t^b(h), Y_t^s(h)$ to form a bundle:

$$Y_t(h) = \left[ \omega^{\frac{1}{\varepsilon}} Y_t^b(h)^{\frac{\varepsilon-1}{\varepsilon}} + (1-\omega)^{\frac{1}{\varepsilon}} Y_t^s(h)^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}},$$

where $\omega$ represents the output share of large firms, and $\varepsilon$ represents the substitution elasticity between intermediate goods of large and small firms. Intermediate goods producers solve the profit maximization problem to obtain the demand for the two types of intermediate goods:

$$Y_t^b(h) = \omega \left( \frac{P_t^b(h)}{P_t(h)} \right)^{-\varepsilon} Y_t(h), \quad Y_t^s(h) = (1-\omega) \left( \frac{P_t^s(h)}{P_t(h)} \right)^{-\varepsilon} Y_t(h).$$

Simultaneously, the clearing of the intermediate goods market determines the overall price of intermediate goods:

$$P_t(h) = \left[ \omega \left( P_t^b(h) \right)^{1-\varepsilon} + (1-\omega) \left( P_t^s(h) \right)^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}}.$$

### *3.4.3. Final goods producers*

Assuming monopolistic competition, the final goods producer purchases distinct intermediate goods from intermediate goods producers $Y_t(h)$ for bundling and, using a constant elasticity of substitution (CES) production function, obtains the final goods

$$Y_t = \left( \int_0^1 Y_t(h)^{\frac{\sigma_p-1}{\sigma_p}} \right)^{\frac{\sigma_p}{\sigma_p-1}},$$

where $\sigma_p$ represents the substitution elasticity of different intermediate goods. By solving the profit maximization problem, the final goods producer can obtain the demand function for intermediate goods $Y_t(h)$ and by clearing the final goods market, the overall price index can be obtained, represented as

$$Y_t(h) = \left(\frac{P_t(h)}{P_t}\right)^{-\sigma_p} Y_t, P_t = \left(\int_0^1 P_t(h)^{1-\sigma_p}\right)^{\frac{1}{1-\sigma_p}}.$$

To account for the presence of nominal rigidities, we assume that the pricing strategy of the monopolistically competitive final goods producer follows the Calvo (1983) staggered pricing mechanism, where each period any producer has a probability of $\theta^p$ not being able to adjust prices and a probability $1 - \theta^p$ of setting prices to maximize profit: $P_t(h) = P^*$. Additionally, to eliminate monopoly distortions in the steady state, we assume that the government provides a subsidy $\tau = 1/\sigma$ to the producers' marginal costs, resulting in the profit function:

$$\mathbb{E}_t \sum_{k=0}^{\infty} (\beta\theta^p)^k \Lambda_{t,t+k} \left[Y_{t+k}(h)\left(P_t(h) - (1-\tau)MC_{t+k}(h)\right)\right],$$

where $\Lambda_{t,t+k} = u'(C_{t+k})/u'(C_t)$. Given the intermediate goods demand, solving the profit maximization problem yields the optimal pricing:

$$P_t^* = \frac{\sigma_p}{\sigma_p - 1} \frac{\mathbb{E}_t \sum_{k=0}^{\infty} (\beta\theta^p)^k \lambda_{t+k} (1-\tau)\, mc_{t+k} P_{t+k}^{\sigma_p} Y_{t+k}}{E_t \sum_{k=0}^{\infty} (\beta\theta^p)^k \lambda_{t+k} P_{t+k}^{\sigma_p - 1} Y_{t+k}}.$$

Since all intermediate goods producers that can adjust prices will set the same optimal price, we can obtain from the definition of prices:$P_t^{1-\sigma} = (1-\theta^p) P_t^{*1-\sigma_p} + \theta^p P_{t-1}^{1-\sigma_p}$.

### 3.5. Government and equilibrium

The government, through monetary policy, determines the deposit interest rate. They also formulate corresponding macro-prudential policies, implicit guarantees, debt subsidies, and other fiscal subsidy policies to maintain the balance of financial system stability. We assume that the central bank formulates standard monetary policy according to the Taylor rule, whereby the deposit interest rate is linked to inflation and the real output gap:

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_r} \left(\frac{\pi_t}{\pi}\right)^{(1-\rho_r)\phi_\pi} \left(\frac{GDP_t}{GDP}\right)^{(1-\rho_r)\phi_y}. \tag{18}$$

The budget constraint of the government is given by

$$G_t + G_t^{guarantee} + B_t^{subsidy} = \left(1 - F_{t-1}^s(\bar{\omega}_t^s)\right) R_{t-1} B_{t-1}^{subsidy} + T_t, \quad (19)$$

where $G_t^{guarantee}$ and $B_t^{subsidy}$ represent the implicit guarantee subsidy and debt subsidy provided by the government to firms, where the debt subsidy only needs to be repaid by the firm at the risk-free interest rate upon successful investment. Finally, the market clearing condition is:

$$GDP_t = C_t + I_t^b + I_t^s + G_t = Y_t - \mu^i G_{t-1}^i \left(\bar{\omega}_t^i\right) R_{i,t}^k Q_{t-1}^i K_{t-1}^i, \quad i = b, s. \quad (20)$$

Following Christiano et al. (2014), debt default increases resource losses in the economy, as the liquidation costs arising from debt default are considered as resource depletion within financial frictions and do not enter into the calculation of the real gross domestic product. The total debt in the end is simply the sum of the two types of firm credit:

$$B_t = B_t^b + B_t^s. \quad (21)$$

## 4. QUANTITATIVE ANALYSIS

### 4.1. Calibration

The model parameters in this paper can be divided into three main parts: the parameters of the standard sector, the firm sector, and the banking sector. We estimate all the steady-state structural parameters using a calibration approach based on previous research findings and actual data. All the data is adjusted to correspond to quarterly periods.

For the calibration of the parameters of the standard sector, certain structural parameters are set to standard values. Specifically, we set the inverse of the Frisch labor supply elasticity to $\sigma_L = 2$, the capital depreciation rate to $\delta = 0.025$, and $\sigma_p = \sigma_w = 6$ for the markup over wages and prices in the steady state at 20%. We also set the frequency of price and wage adjustments for intermediate goods producers to once per year $\theta^p = \theta^w = 0.75$, and the consumption inertia parameter to $v = 0.7$. Based on the annual interest rate for one-year RMB deposits from October 2015 to April 2021, which was 1.50%, we calibrate the household discount factor as $\beta = 0.996$. Following Chang et al. (2019), we set the elasticity of substitution between intermediate goods for two types of firms to $\varepsilon = 3$ and the output share of large firms to $\omega = 0.45$. Given that consumption and investment are close in proportion in China, and large firms are mostly capital-intensive, we set the capital-output elasticity to $\alpha_b = 0.55$ for large firms and $\alpha_s = 0.5$ for small firms.

For the calibration of the parameters of the firm sector, we first set $a = 1.01, b = 2$ to represent the quarterly expected return of H projects, which is 1% higher than that of L projects but entails twice the uncertainty. We also set the transfer payments received by new entrant firms from households to $w^e = 0.1$. For other parameters, we calibrate them by targeting certain objectives. Following Baek (2020), we set the annual capital return spread for large firms as $(R_b^k)^4 - R^4 = 1.2\%$ and for small firms as $(R_s^k)^4 - R^4 = 2.65\%$, resulting in a weighted average spread of 2% for both types of firms, consistent with Bernanke et al. (1999). We then control for some moment conditions and calibrate the steady-state leverage ratios $QK/N^E$ for large and small firms as 1.66 and 1.33, respectively, based on the mean asset-liability ratios of firms in the sample. According to China's economic data, we calibrate the steady-state share of consumption goods $C/Y$ to 0.45. Finally, we calibrate the overall default rate for firms in the steady state based on the weighted average of the maximum credit loss probabilities for different types of credit, as reported by the China Banking and Insurance Regulatory Commission from 2011Q1 to 2022Q4, resulting in a quarterly average credit default rate of 1.024%. We set the steady-state default rate $(1 - x)F^b(\bar{\omega}) + xF^s(\bar{\omega}) = 0.01$ for the two types of firms as a weighted average based on their credit shares. Under the baseline, we set the default rates for large and small firms at 0.84% and 1.26%, respectively, indicating that the default risk for small firms is 50% higher than that for large firms, reflecting the presence of H projects in their asset portfolios. Using this method, we calculate $\sigma^b, \sigma^s, \bar{\omega}^b, \bar{\omega}^s$, obtain the liquidation costs of capital projects for the two types of firms as $\mu^b = 0.0626$ and $\mu^s = 0.1497$, and the survival rates of firms as $\gamma^b = 0.9883$ and $\gamma^s = 0.9790$. Due to the higher level of information asymmetry and default risk, small firms have higher capital project verification and liquidation costs, as well as lower survival rates. After calibration, we obtain $\zeta e = 51.37\%$, indicating that around half of the assets in the portfolio of small firms are high-risk projects, with their return volatility being twice that of low-risk projects, corresponding to the difference in the steady-state default rates of the two types of firms. Finally, through $B = QK - N^E$, we obtain the total credit for the two types of firms. We calculate the credit share of small firms to be $x = 0.3844$, which is close to the 42.9% reported by Baek (2020). As our model incorporates the impact of the supply side of banks, it leads to more severe credit distortions.

We adopt a similar approach to calibrate the parameters of the banking sector. First, following Aoki et al. (2016), we calibrate the survival rate of

**TABLE 1.**

Parameter calibration

| **Parameter** | **Description** | **Value** | **Target** |
|---|---|---|---|
| Panel A | Fixed parameters | | |
| $\beta$ | discount rate | 0.996 | data |
| $\sigma_L$ | inverse of Frisch elasticity | 2 | |
| $\theta^p, \theta^w$ | nominal rigidity | 0.75 | |
| $\delta$ | depreciation rate of capital | 0.025 | standard |
| $v$ | consumption inertia | 0.7 | |
| $\omega$ | output share of big firm | 0.45 | Chang et al. (2019) |
| $\varepsilon$ | output elasticity of substitution | 3 | |
| $\alpha_b$ | capital share of big firm | 0.55 | large firms are |
| $\alpha_s$ | capital share of small firm | 0.5 | capital-intensive |
| $a$ | expected return of H projects | 1.01 | characteristics of |
| $b$ | volatility multiplier of H projects | 2 | H projects |
| $w^e$ | transfer to new firm | 0.1 | standard |
| $F(\bar{\omega})$ | average default rate | 0.01 | data |
| $RR$ | deposit-reserve ratio | 0.074 | |
| $\theta$ | survival probability of bank | 0.96 | Aoki et al. (2016) |
| $\phi$ | bank leverage | 4 | Gertler and Karadi (2011) |
| Panel B | Calibrated parameters | | |
| $\mu^b$ | monitor cost of big firm | 0.0626 | |
| $\mu^s$ | monitor cost of small firm | 0.1497 | |
| $\gamma^b$ | survival probability of big firm | 0.9883 | $R_i^k - R_i^L = 0.012, 0.0265;$ |
| $\gamma^s$ | survival probability of small firm | 0.9790 | $Q^i K^i / N_i^E = 1.66, 1.33;$ |
| $x$ | credit share of small firm | 0.3844 | $C/Y = 0.45;$ |
| $\zeta e$ | H projects share of small firm | 0.5137 | $F^i(\bar{\omega}) = 0.0084, 0.0126;$ |
| $\xi$ | risk premium | 0.5393 | $\phi = 4;$ |
| $\lambda$ | severity of agency cost | 0.2172 | $R_s^k - R_s^L = 2(R_b^k - R_b^L);$ |
| $\iota$ | bias of bank finance | 0.2828 | |
| $\chi$ | transfer fraction to new banks | 0.0084 | |

banks as $\theta = 0.96$. Based on Gertler and Karadi (2011), we calibrate their steady-state leverage ratio as $\phi = 4$. According to the adjustment of the reserve requirement ratio by the People's Bank of China in September 2023, we calibrate $RR = 0.074$ to be the weighted average reserve requirement ratio of 7.4%. We calibrate $R^k - R^L$ of small firms to be twice that of large firms in the steady state and get $\xi$. Finally, based on the calibrated values of $x$ obtained from the firm sector parameters and other targeted objectives, we calculate the values of $\lambda, \iota, \chi$ for the banking sector.

We calibrate the policy parameters of monetary policy based on China's data and set the persistence parameter for exogenous shocks to $\rho = 0.9$. Following the standard practice in most literature, we calibrated the steady-state government expenditure to $G = 0.2Y$. Under the baseline, the fiscal subsidy policy and macroprudential policy parameters are set to 0. Panel A of Table 1 provides the descriptions, values, and targets of the main parameters or steady-state variables in the model, while Panel B introduces the values of the parameters or moment conditions obtained through target calibration.

### 4.2. Quantitative Analysis of the baseline model

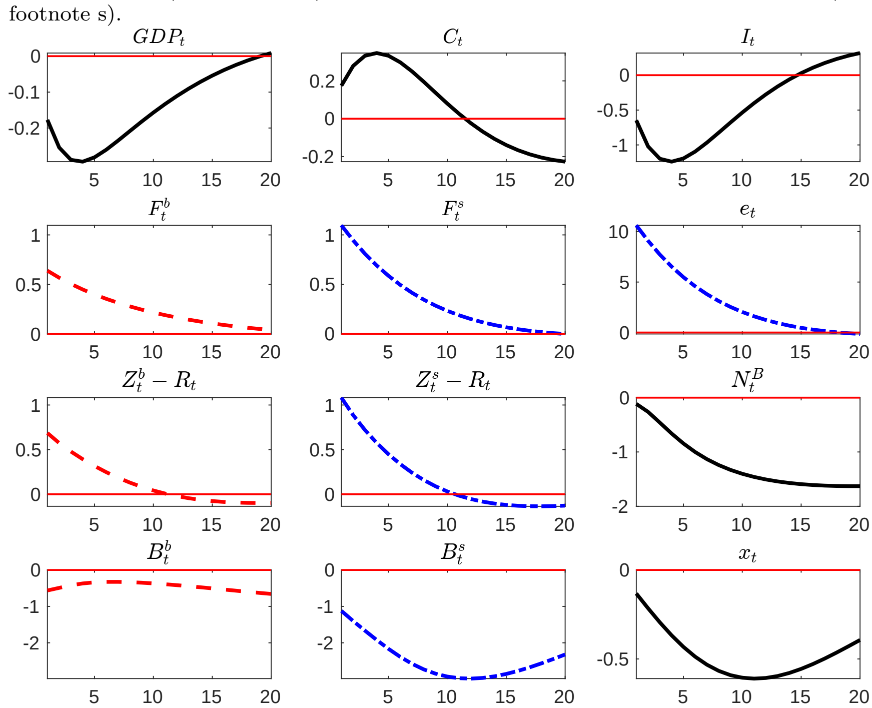
#### *4.2.1. Uncertainty shocks*

We first consider the dynamics of the baseline model driven by uncertainty shocks. When the level of uncertainty increases, the volatility of investment project returns increases, leading to an increase in the default risk of firms. Due to the presence of H investment projects in their asset portfolios and the results obtained from equation (4), uncertainty shocks increase the proportion of H projects in the asset portfolios of small firms, further increasing their default risk when facing shocks. The heterogeneity in default risk between the two types of firms leads to a further widening of the differences in their financing environments, driving the dynamic heterogeneity between large and small firms.

Although banks cannot observe the effort level of firms to identify H projects, the higher degree of information asymmetry leads to higher expected default risk $\mathbb{E}_t(F_t^s(\bar{\omega}_{t+1}^s))$ for small firms. As mentioned earlier, this has supply and demand effects: on one hand, according to the debt contract constraint in equation (8), higher expected default risk lead banks to increase the credit rate $Z_t^i$ they demand, which in turn reduces the credit demand of firms. On the other hand, an increase in default rates reduces the marginal yield of credit to large and small firms $\mu_t, m_t$, leading banks to actively reduce their lending to both types of firms. Moreover, the accelerated increase in the default rate of small firms leads to a faster decline in the marginal yield of their credit, suggesting a decline on $m_t - \mu_t$. According to equation (13), this reduces the credit share of small firms. Under the combined effects of supply and demand, the impact of uncertainty shocks on the two types of firms exhibits heterogeneity.

Figure 2 illustrates the heterogeneous responses of real economy variables and credit-related variables of the two types of firms to uncertainty shocks. The horizontal axis represents the observation period after the shock, with one period representing one quarter. The vertical axis represents the percent change relative to their own steady state, where the default risk $F_t^i$, financing premium $Z_t^i - R_t$, and small firm credit share $x_t$ are represented as percent change in absolute value.

**FIG. 2.** Impulse response under uncertainty shock. **Note.** The red dashed line represents big firm (top footnote b) and the blue dot-dashed line represents small firms(top footnote s).




Under uncertainty shocks, heightened default risk has triggered a contraction in both credit demand and supply, resulting in decreased asset prices and reduced capital requirements. Consequently, overall investment levels have declined, leading to a reduction in output. The decrease in deposit rates, coupled with the contraction in credit scale driven by lower output, has diminished households' demand for deposits, temporarily boosting consumption levels. In a higher uncertainty environment, small firms intensify their efforts $e_t$ to identify H projects to cover higher financing cost, resulting in a greater transfer of risk to banks. The EAP mechanism of firms has amplified the impact of uncertainty shocks on the risk levels of small firms, leading to a more pronounced increase in their default rates compared to large firms.

With higher levels of uncertainty, banks anticipate an increase in corporate default risk, particularly severe for small firms, resulting in varying degrees of increase in financing premiums for the two types of firms $Z_t^i - R_t$, thereby causing different levels of decline in credit demand. Furthermore, as higher default rates reduce the marginal returns on bank credit, the EAP mechanism of banks further reduces the credit supply to small firms. With the dual effect of demand and supply channels, the credit for small firms has declined more severely, with their credit share $x_t$ continuously decreasing during the observation period.

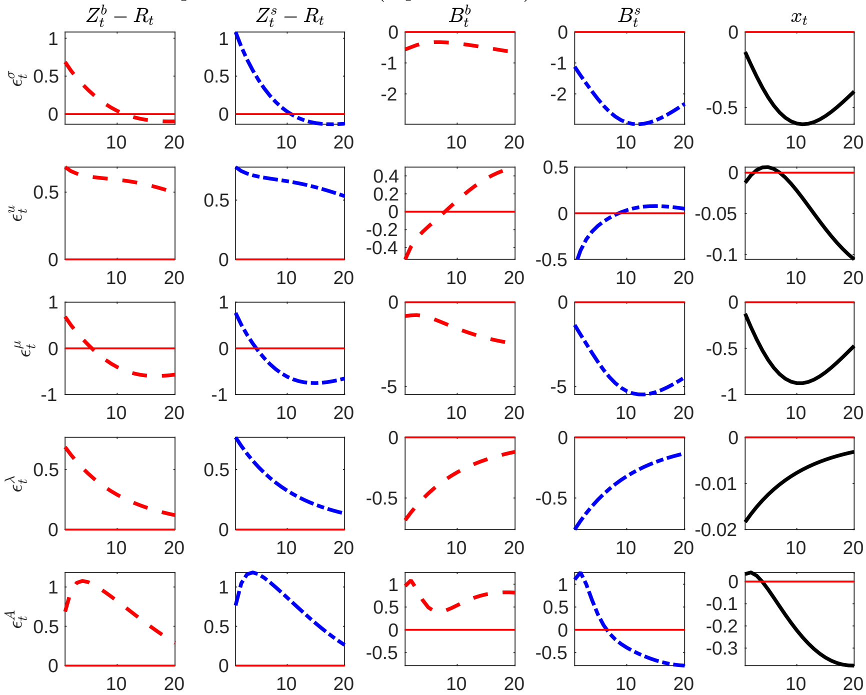
With higher levels of uncertainty, banks anticipate an increase in corporate default risk, particularly for small firms, resulting in varying degrees of increase in financing premiums for the two types of firms $Z_t^i - R_t$,. This causes different levels of decline in credit demand. Furthermore, higher default rates reduce the marginal returns on bank credit, leading the EAP mechanism of banks to further reduce credit supply to small firms. With the dual effect of demand and supply channels, credit for small firms has declined more severely, and their credit share $x_t$ continuously decreases during the observation period.

*4.2.2. Other shocks*

In addition to uncertainty shocks $\epsilon_t^\sigma$, we also simulated the heterogeneous impacts of other shocks on the borrowing behavior of the two types of firms, including demand shocks, firm financial frictions shocks, bank financial frictions shocks, and technological shocks. We standardize the size of the shocks so that the initial impact on the financing premium for large firms $Z_t^b - R_t$ remains consistent across all types of shocks. Figure 3 presents the dynamics of credit-related variables for small and large firms under various types of shocks.

The demand shock $\epsilon_t^u$ increased households' subjective discount factors, reducing their deposit demand, and the tightening of bank balance sheets led to credit contraction. The firm and bank financial frictions shocks $\epsilon_t^\mu, \epsilon_t^\lambda$ respectively raised the liquidation costs of bank investment projects $\mu^i$ and the leverage ratio constraints of banks, causing credit contraction by increasing the level of financial frictions. Unlike the previous types of shocks, the technological shock $\epsilon_t^A$ has a positive impact on the economic and financial system, promoting credit expansion by increasing the production sector's demand for capital. By comparing these shocks, it is evident that during credit contraction, small firms exhibit higher levels of fluctuation in financing premiums and credit volume. During credit expansion, the

**FIG. 3.** Heterogeneous impulse responses of two types of firms under different shocks. **Note.** The red dashed line represents big firm (top footnote b) and the blue dot-dashed line represents small firms(top footnote s).




increase in firm leverage raises banks' expectations of default risk for both types of firms, thereby elevating the level of financing premiums. Similar to the results of uncertainty shocks, regardless of whether the credit market is in a contraction or expansion state, the credit share of small firms has declined, owing to the dual impact of price and quantity, demand and supply under the EAP mechanism of firms and banks.

### 4.3. Comparative testing of mechanisms

In our previous analysis, the dynamic differences between the two types of firms under uncertainty shocks are the result of the combined effect of the EAP mechanisms of firms and banks, with the credit and credit share of small firms being simultaneously influenced by both supply and demand. In this section, through a series of counterfactual experiments, we isolate the EAP mechanisms of firms and banks from the baseline and compare the dynamics of the model under uncertainty shocks.

Our aim is to differentiate the impacts caused by the decision-making behaviors of firms and banks, compare the differences in the effects of the EAP mechanism of banks and firms on the credit price and volume. We want to, as much as possible, separate the demand and supply factors in the fluctuations of credit for small firms, thereby comparing the explanatory power of the supply and demand aspects. We present the fluctuations and correlations of relevant variables under several mechanisms, where "noBank" represents the closure of the EAP mechanism of banks, i.e., the closure of the GK framework, "noFirm" represents the closure of the EAP mechanism of firms, i.e., the absence of H projects, and "noEAP" represents the simultaneous closure of both EAP mechanisms. Consistent with the baseline, the steady-state default rates and credit of the two types of firms remain unchanged in several scenarios, with the main difference lying in the model dynamics driven by uncertainty shocks.

*4.3.1. Volatility under different mechanisms*

Table 2 presents the ratio of the volatility of relevant variables under several mechanisms to the baseline. The fluctuation in default risk for the two types of firms is mainly related to the EAP mechanism of firms. Due to the presence of H projects in their asset portfolio and their efforts to identify H projects, the default risk of small firms is more significantly affected by uncertainty, and its default risk fluctuation is more closely associated with the firm asset portfolio mechanism. Therefore, under the "noFirm" and "noEAP" scenarios, where the EAP mechanism of firms is closed, the fluctuation in default risk for small firms decreases. On the other hand, the decision-making of banks is based on the expectation of default risk, and their EAP mechanism has little impact on firm default rates. The fluctuation in default rates under "noBank" is basically consistent with the baseline.

**TABLE 2.**

Volatility of relevant variables under different mechanisms.

| | std($F_t^b$) | std($F_t^s$) | std($Z_t^b - R_t$) | std($Z_t^s - R_t$) | std($B_t^b$) | std($B_t^s$) | std($x_t$) |
|---|---|---|---|---|---|---|---|
| noBank | 1.0000 | 1.0000 | 0.1830 | 0.3435 | 0.9547 | 0.9932 | 1.0078 |
| noFirm | 1.0039 | 0.9367 | 0.8573 | 0.8332 | 0.9772 | 0.6413 | 0.4393 |
| noEAP | 1.0039 | 0.9367 | 0.1900 | 0.2766 | 0.9525 | 0.6280 | 0.4371 |

The decision-making behavior of firms involves adjusting the proportion of their own investment projects, leading to changes in the fluctuation of firm default risk. The decision-making behavior of banks involves adjusting credit rate (price) and credit supply (quantity) based on the expectation of firm default risk, with the adjustment to the price also affecting firm credit demand. By comparing the fluctuation in financing premiums for the two types of firms under different mechanisms, it is apparent that the decision-making behavior of banks has a greater impact on the price. Closing the EAP mechanisms of both banks and firms reduces the fluctuation in financing premiums for both types of firms, but the reduction in fluctuation is greater under the "noBank" and "noEAP" scenarios. Comparing the fluctuation in credit for the two types of firms, it becomes apparent that the decision-making behavior of firms has a greater impact on quantity, primarily affecting small firms. Under the "noFirm" and "noEAP" scenarios, the fluctuation in both credit and credit share for small firms significantly decreases.

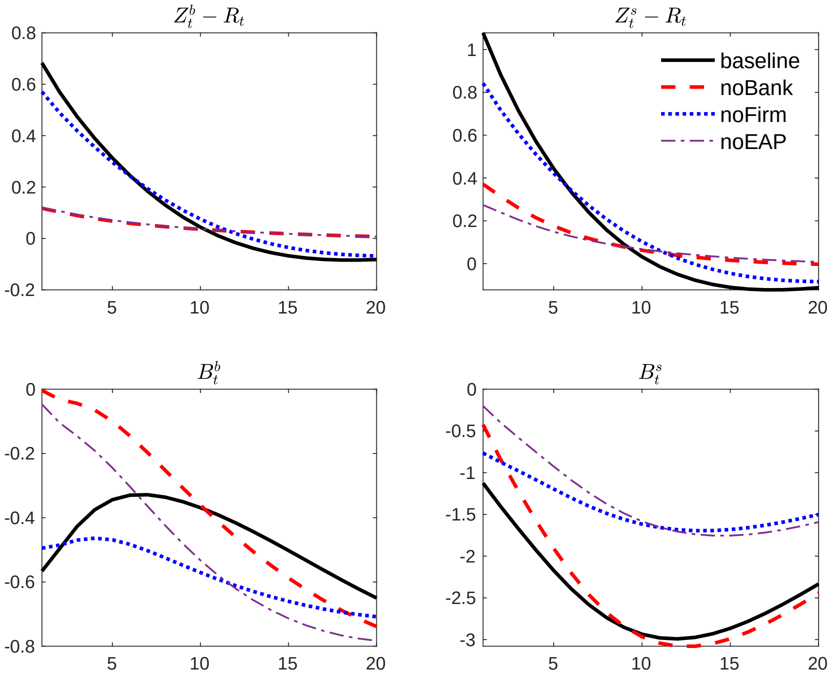
*4.3.2. Model dynamics under different mechanisms*

Table 2 compares the impact of the EAP mechanism of banks and firms on credit-related behavior, in terms of both price and quantity, considering overall volatility. Figure 4 presents specific fluctuation patterns of credit quantity and price for the two types of firms under various mechanisms.

Figure 4 provides a more intuitive illustration of the dynamic differences under different mechanisms. Consistent with the results in Table 2, the impact of banks' EAP mechanism on financing premiums is more significant. Under the scenarios of "noBank" and "noEAP", where the bank's EAP mechanism is closed, the increase in financing premiums for both types of firms is significantly constrained. In contrast, the impact of bank decisions on credit quantity is lower, indicating that bank decisions are more focused on adjusting credit rate (price) rather than adjusting the level of credit supply (quantity). Similarly corresponding to the results in Table 2, the EAP mechanism of firms has a greater impact on credit quantity, especially for small firms. Under the scenarios of "noFirm" and "noEAP", where the firm's EAP mechanism is closed, the reduction in credit quantity for small firms is significantly reduced, indicating that the decision-making behavior of firms has a greater impact on credit quantity.

It is important to note that, compared to the baseline level, there are still differences in the fluctuation levels of small firm credit under the "noBank" scenario, and in the fluctuation of firm financing premiums under the "noFirm" scenario. Although the impact of both bank and firm EAP mechanisms focus differently, they both tighten the financing constraints of firms in terms of price and quantity, leading to more severe credit tight-

**FIG. 4.** Dynamics of credit price and quantity under different mechanisms.




ening for small firms. Under the baseline of the joint impact of bank's and firm's EAP mechanisms, the increase in financing premiums for both small and large firms is the highest, and the reduction in credit quantity for small firms is the most severe. In contrast, under the scenario of "noEAP" where both EAP mechanisms are closed, the fluctuation amplitude of both financing premiums and credit quantity is the lowest among the various scenarios. The EAP mechanisms of banks and firms deepen the financing difficulties of small firms from both the supply and demand sides, leading to more severe distortions in the credit market.

### *4.3.3. Who drives who?*

Table 3 presents the correlation coefficients among the credit-related variables of interest under different mechanisms. We attempt to address some questions that we are interested through the correlation of certain variables, namely who drives who: to what extent does the expected default risk drive the level of financing premiums required by banks? To what extent do the changes in credit quantity for small and large firms explain their respective share changes? To what extent does the credit contraction of firms depend on both demand and supply factors?

In comparison with the baseline, we can address the aforementioned questions. For the first question, we find that the bank's EAP mechanism plays a significant role. Banks adjust credit rate and credit supply based on expected default risk. Reducing credit supply can partially offset the effect of increasing financing premiums. Therefore, bank decisions reduce the correlation between expected default risk and financing premiums. Under the scenarios of "noBank" and "noEAP", where the bank's EAP mechanism is closed, banks only adjust credit rate in response to changes in expected default risk, leading to expected default risk driving the dynamics of financing premiums almost entirely.

**TABLE 3.**

Correlations of relevant variables under different mechanisms.

| | corr$(F_t^b, Z_t^b - R_t)$ | corr$(F_t^s, Z_t^s - R_t)$ | corr$(B_t^b, x_t)$ | corr$(B_t^s, x_t)$ | corr$(Z_t^b - R_t, B_t^b)$ | corr$(Z_t^s - R_t, B_t^s)$ |
|---|---|---|---|---|---|---|
| baseline | 0.7637 | 0.8701 | 0.5531 | 0.9578 | $-0.3121$ | $-0.2303$ |
| noBank | 0.9992 | 0.9977 | 0.5509 | 0.9610 | $-0.1114$ | $-0.3506$ |
| noFirm | 0.8429 | 0.8872 | 0.8107 | 0.9515 | $-0.2687$ | $-0.3079$ |
| noEAP | 0.9997 | 0.9987 | 0.7898 | 0.9471 | $-0.2271$ | $-0.3543$ |

For the second question, we find that under any scenario, the change in credit share for small firms primarily depends on the change in their own credit quantity. This is partly due to the higher default risk of small firms, which makes them more affected by uncertainty shocks. This leads to a more severe decline in credit quantity due to the increase in financing premiums and the decrease in bank supply. Additionally, the acceleration of default risk under the EAP mechanism of small firms further contributes to the difference in credit quantity changes between the two types of firms. Under the scenarios of "noFirm" and "noEAP", where the firm's EAP mechanism is closed, the difference in default risk changes between the two types of firms is smaller, leading to a significant increase in the correlation between credit quantity and credit share for large firms.

The answer to the third question is not straightforward, but we can make a rough judgment based on the results from Figure 4 and Table 3: the contraction of credit is more dependent on demand factors. Under the baseline, the dynamic of firm credit quantity is influenced by both bank supply and firm demand, leading to a higher magnitude of decline in credit quantity for both types of firms. However, under the "noBank" scenario, the change in firm credit quantity is entirely determined by the fluctuation of financing premiums at the demand level, resulting in a reduced degree of credit contraction. By comparing the two scenarios, we can analyze $\mathrm{corr}(Z_t^s - R_t, B_t^s)$ and isolate the impact of demand factors.

For large firms, in addition to being influenced by bank supply and their own demand, their credit quantity is also affected by absorbing some of the credit losses from small firms. Banks reduce the credit supply to large firms based on expected default risk, but at the same time, a portion of the credit resources lost by small firms, which experience faster risk increases, flows to large firms, to some extent mitigating the credit fluctuation of large firms. In Figure 4, under the baseline scenario, the credit fluctuation of large firms lies between that of the "noBank" and "noFirm" scenarios, indicating that large firms are to some extent influenced by the credit quantity of small firms. Due to the multiple factors influencing their credit quantity and the relatively small differences in credit quantity fluctuation under various mechanisms (Table 2), we primarily address this from the perspective of small firms.

For large firms, in addition to being influenced by bank supply and their own demand, their credit quantity is also affected by absorbing some of the credit losses from small firms. Banks reduce the credit supply to large firms based on expected default risk, but at the same time, a portion of the credit resources lost by small firms, which experience faster risk increases, flows to large firms, to some extent mitigating the credit fluctuation of large firms. In Figure 4, under the baseline scenario, the credit fluctuation of large firms lies between that of the "noBank" and "noFirm" scenarios, suggesting that large firms are influenced to some extent by the credit quantity of small firms. Given the multiple factors affecting their credit quantity and the relatively minor differences in credit quantity fluctuation under various mechanisms (Table 2), we primarily address this from the perspective of small firms.

For small firms, the level of credit contraction influenced by financing premiums can be to some extent reflected by $\mathrm{corr}(Z_t^s - R_t, B_t^s)$. By comparing the baseline, which includes bank supply factors, with the "noBank" scenario, which represents purely demand factors, we find that the crowding-out effect of supply factors on demand factors does not lead to a significant change in the correlation coefficient ($-0.3606$ vs. $-0.2302$). Similarly, comparing the "noFirm" and "noEAP" scenarios, the introduction of supply factors does not lead to a significant change in the correlation coefficient $\mathrm{corr}(Z_t^s - R_t, B_t^s)$ ($-0.3079$ vs. $-0.3543$). Although it is difficult to quantify the extent to which large firms are influenced by the fluctuation of small firm credit quantity, our rough comparative analysis of the correlation of relevant variables suggests that demand factors have a greater explanatory power for the credit contraction of both types of firms.

### 4.4. Impact of differences in default rates

When calibrating the steady state, our focus is on the overall default rate. Based on the data calibration, the steady-state default rate for the two types of firms, weighted by credit share, is 1%. Given that the volatility of returns for H projects is twice that of L projects, we set the default rate for small firms to be 1.5 times that of large firms under the baseline assumption, corresponding to half of their asset portfolio being comprised of H projects. Actually, the proportion of H projects in the asset portfolio of small firms may be lower or higher, leading to varying differences in the steady-state default rates of the two types of firms. In order to explore the impact of the difference in steady-state default rates between the two types of firms on the dynamics of the model, we maintain the overall default rate at 1% and alter the scenario of the difference in default rates between the two types of firms. We consider scenarios where the steady-state default rates for the two types of firms are the same ($F^s = F^b$), and where the default rate for small firms is twice that of large firms ($F^s = 2F^b$). We compare the differences in the dynamics of the model under the two scenarios with the baseline and Table 4 presents the volatility of relevant variables under the three scenarios.

**TABLE 4.**

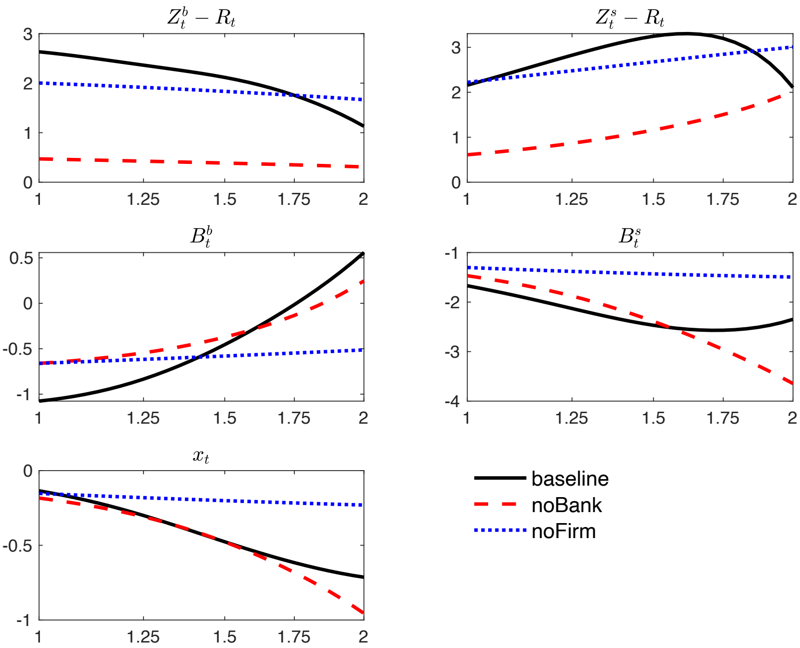
Volatility of correlated variables with different default rates.

| | std$(F_t^b)$ | std$(F_t^s)$ | std$(Z_t^b - R_t)$ | std$(Z_t^s - R_t)$ | std$(B_t^b)$ | std$(B_t^s)$ | std$(x_t)$ |
|---|---|---|---|---|---|---|---|
| $F^s = F^b$ | 0.0158 | 0.0130 | 0.0132 | 0.0112 | 0.0703 | 0.0889 | 0.0069 |
| $F^s = 1.5F^b$ | 0.0138 | 0.0208 | 0.0106 | 0.0171 | 0.0444 | 0.1289 | 0.0234 |
| $F^s = 2F^b$ | 0.0124 | 0.0277 | 0.0056 | 0.0127 | 0.0391 | 0.1155 | 0.0348 |

The most visually striking difference in the three scenarios of changes in default rate in Table 4 lies in the volatility of default rates for the two types of firms. As the steady-state difference in default rates between the two types of firms increases, the default risk for large firms decreases while that for small firms increases, amplifying the differential responses of the two types of firms to uncertainty shocks. In terms of volatility of $F_t^b, F_t^s$, the steady-state level of default risk is positively correlated with default rate volatility under uncertainty shocks. After enlarging the difference, the default rate volatility for large firms decreases, while for small firms, it increases.

The changes in credit and pricing for large firms align with the changes in default risk. As the steady-state default risk and default rate volatility decrease, the fluctuation in financing premium and credit for large firms gradually decreases. However, the situation is different for small firms: when the steady-state default rate for small firms increases from being the same as that for large firms to 1.5 times the baseline scenario, the fluctuation in financing premium and credit intensifies, consistent with the increase in their risk level. However, when the steady-state default rate for small firms further increases to $F^s = 2F^b$, the fluctuation in their financing premium and credit decreases. We believe this is related to the decision-making behavior of banks. According to equation (9), the decrease in the share of credit to small firms $x_t$ will damage the expected present value of bank profits. As shown in Table 4, as the difference in default rates between the two types of firms gradually increases, the fluctuation of $x_t$ continues to rise. Banks consider a trade-off between risk and reward, and will restrict the fluctuation in the price and quantity of credit for small firms when $x_t$ decreases too much.

**FIG. 5.** Model dynamics under different default rate differentials



To provide a more intuitive analysis of the dynamic relationship between default risk differentials and the model, Figure 5 illustrates the volatility of relevant variables under different default rate differentials. We simultaneously present the scenarios of “noBank” and “noFirm”. The horizontal axis represents the steady-state default rate ratio between small and large firms, while the vertical axis represents the average volatility of each variable during the observation period.

Consistent with the results in Table 4, as the differential in default rates between the two types of firms gradually increases, the rise of financing premium and the reduction in credit for large firms are restrained due to the decrease in default risk. Within a certain range, the increase in steady-state default risk for small firms also leads to a further increase in the financing premium and a reduction in credit. However, as mentioned earlier, when the default risk for small firms rises to a certain level, banks, in order to mitigate the loss caused by excessive decrease of $x_t$, will limit the extent to which financing constraints on small firms tighten, leading to a decrease in the fluctuation of the financing premium and credit for small firms.

By comparing different mechanisms, it can be observed that the EAP mechanism of firms is more sensitive to the differential in steady-state default risk, and the dynamics of relevant variables under the noFirm scenario are less affected by the differential in default risk. This is because the steady-state default risk determines the proportion of H projects in the asset portfolio of small firms, thereby affecting their response to uncertainty shocks. Furthermore, we can further validate our conjecture regarding bank decision-making through the “noBank” scenario. Under the “noBank” scenario, banks do not engage in decision-making behavior, their profits are no longer affected by the decrease of $x_t$. Therefore, they do not restrict the increase in credit rate for small firms. The financing premium for small firms increases with the rise in default risk, and their credit decreases accordingly. Compared to the “noBank” scenario, in the baseline scenario influenced by bank decision-making, the decrease of $x_t$ is restrained when the default risk for small firms is high.

### 4.5. Fiscal subsidies and macroprudential policies

The analysis above indicates that under negative shocks such as uncertainty shocks, the EAP mechanism exacerbates the credit contraction from both the supply and demand sides, with small firms experiencing more severe negative impacts. Due to their inherently higher default risk and the amplification of their response to uncertainty shocks by the EAP mechanism, banks correspondingly increase their financing premium requirements. Furthermore, as the expected default rate on credit would impair bank's expected profits, the endogenous asset portfolio mechanism of banks leads to a further decline in their credit supply to small firms. Under the combined effect of these two mechanisms, small firms face more severe financing difficulties, with their credit simultaneously affected in terms of pricing, quantity, supply, and demand. This leads to a continuous decline in their share of credit and exacerbating distortions in the credit market.

The increased risk of small firm bankruptcies, along with the rise in financing premium and the restriction of credit supply by banks, heightens the risk of business failures. With investment project failures, debt defaults, and other phenomena, this inevitably increases the fragility of the financial system, amplifies the negative impact of uncertainty shocks and raises the likelihood of systemic financial risks. In this section we consider relevant fiscal subsidy policies and macro-prudential policies of government departments to regulate the borrowing behavior of small firms, aiming to mitigate the impact of uncertainty shocks and the distortions in the credit market.

*4.5.1. Fiscal subsidy policies*

We examine two types of fiscal subsidy policies, one being implicit guarantee policies and the other being debt subsidy policies, targeting banks and firms respectively. Both policies aim to alleviate the financing difficulties of small firms from the perspectives of price and quantity, as well as supply and demand. Considering that the decision-making behavior of banks depends on the expected default risk of firms, in the implicit guarantee policy, the government provides implicit guarantees for the debt financing of small firms, promising to compensate banks for a portion of their default losses in the event of firm default. Therefore, the debt contract constraint (8) changes to

$$\left(1 - F_t^s\left(\bar{\omega}_{t+1}^s\right)\right) Z_{t+1}^s B_t^s + \Pi_t^s + G_t^{guarantee} = R_{s,t}^L B_t^s, \tag{22}$$

where $G_t^{guarantee} = \kappa^g(log(F_t^s/F^s))R_{s,t}^L B_t^s$ represents the subsidy for implicit guarantees. $\kappa^g$ represents the intensity of the subsidy, i.e., when the default rate of small firms increases, the government uses fiscal revenue to repay a portion $\kappa^g$ of the bank's minimum expected return on behalf of the small firms. The expected losses for banks in the event of debt default decrease, leading to a reduction in $Z_t^s$ and a decrease in the financing premium for small firms. Additionally, the subsidy for implicit guarantees will increase the expected returns on credit for small firms, thereby altering the optimization problem for banks, equation (11) becomes

$$\begin{aligned} m_t &= \beta(1-\theta)\Lambda_{t,t+1}\left[\left(1-F_t^s(\bar{\omega}_{t+1}^s)\right)Z_{t+1}^s + \kappa^{g}\left(\log\left(F_t^s/F^s\right)\right)R_{s,t}^L - R_t\right] \\ &+ \beta\theta\Lambda_{t,t+1}\frac{B_{t+1}^s}{B_t^s}m_{t+1}. \end{aligned} \tag{23}$$

The marginal expected return on credit for small firms increases, thus alleviating the bank's behavior of restraining its credit supply. From equations (22) and (23), it can be derived that, by reducing the bank's default losses, implicit guarantee policies alleviate the financing constraints of small firms from the perspectives of supply and demand.

Considering that small firms incur significant credit losses, in the debt subsidy policy, the government subsidizes a portion of the credit resources for small firms: $B_t^{subsidy} = \kappa_t^{subsidy}B_t^s$. This portion of government debt only needs to be repaid at the risk-free interest rate $R_t$. After the subsidy, a proportion $1-\kappa_t^{subsidy}$ of the total credit for small firms comes from banks, where $\kappa_t^{subsidy} = \kappa^s log(B_t^s/B_t)$ represents the intensity of the subsidy. When the level of credit for small firms decreases, the government uses fiscal revenue to provide a proportion $\kappa^s$ of credit losses. The credit interest rate for debt subsidies is lower than the bank credit interest rate $Z_t^s$, thus the default threshold is determined by

$$\bar{\omega}_{t+1}^s R_{s,t+1}^k Q_t^s K_t^s = \left(1-\kappa_t^{subsidy}\right)B_t^s Z_{t+1}^s + \kappa_t^{subsidy}R_t B_t^s.$$

Therefore, equation (8) changes to

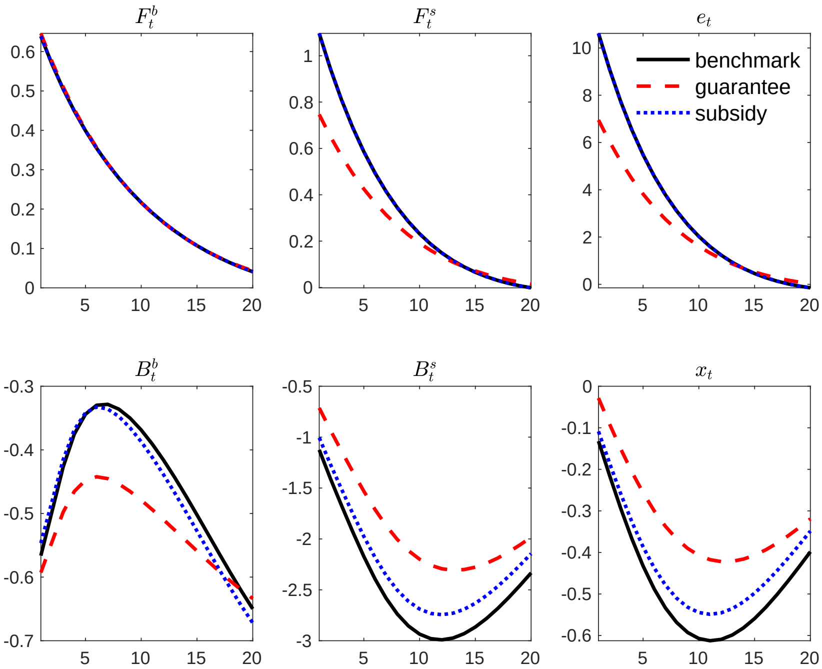
$$\begin{aligned} \left(1-F_t^s(\bar{\omega}_{t+1}^s)\right)Z_{t+1}^s B_t^s + \Pi_t^s &= \Big[\kappa_t^{subsidy}\left(1-F_t^s(\bar{\omega}_{t+1}^s)\right)R_t \\ &+ \left(1-\kappa_t^{subsidy}\right)R_{s,t}^L\Big]B_t^s. \end{aligned} \tag{24}$$

From equation (24), it can be seen that the debt subsidy policy also effectively reduces the financing costs for small firms. Additionally, as the bank's balance sheet becomes $B_t^b + \left(1-\kappa_t^{subsidy}\right)B_t^s = D_{t+1} + N_t^B$, its share of credit supply to small firms decreases, which also to some extent affects the supply level. Therefore, equation (11) becomes

$$\begin{aligned} m_t &= \beta(1-\theta)\Lambda_{t,t+1}\left[\left(1-\kappa_t^{subsidy}\right)\left(1-F_t^s(\bar{\omega}_{t+1}^s)\right)Z_{t+1}^s - R_t\right] \\ &+ \beta\theta\Lambda_{t,t+1}\frac{B_{t+1}^s}{B_t^s}m_{t+1}. \end{aligned} \tag{25}$$

From equations (24) and (25), it can be derived that, as $\kappa_t^{subsidy}$ proportion of credit are replaced by the lower-cost government debt subsidy, the debt subsidy policy also alleviates the financing constraints of small firms from the perspectives of supply and demand. Both types of fiscal subsidy policies, targeting banks and firms respectively, focus on default losses and credit losses, but both can alleviate the financing constraints of small firms. To assess the regulatory effects of the two types of fiscal subsidy policies, we set $\kappa^g = \kappa^s = 0.1$ representing the intensity of the subsidy for both to be 10%, and compare the dynamics of relevant variables under uncertainty shocks. Figure 6 illustrates the dynamic differences between the two policies and the baseline model, where "guarantee" represents the implicit guarantee policy, and "subsidy" represents the debt subsidy policy.

**FIG. 6.** The regulatory effects of different fiscal subsidy policies




From Figure 6, it can be observed that in terms of preventing default risk, the debt subsidy policy has almost no impact, while the implicit guarantee policy significantly reduces the default risk for small firms. This is because the implicit guarantee policy reduces the bank's default losses. As a result, it lowers the level of asymmetric information between banks and firms.

As in equation (8), banks will reduce the credit interest rate $Z_t^s$ due to the decrease in default losses, leading to a decrease in the financing cost for small firms. As shown in Figure 6, the implicit guarantee policy means that small firms do not need to exert additional effort to increase the proportion of H projects to recover financing costs, resulting in a significant decrease in their effort level and consequently a decrease in the default risk. Under the implicit guarantee policy, the increase in default risk levels for the two types of firms are closer, resulting in higher credit losses for large firms and vice versa for small firms. In comparison, due to the effective control of default risk, the contraction of credit supply and demand for small firms is fully restrained. The regulatory effect of the implicit guarantee policy is superior, as it effectively reduces default risk while more extensively alleviating distortions in the credit market.

*4.5.2. Macroprudential policies*

In addition to fiscal subsidy policies, we also consider some macroprudential policies to ensure the stability of the financial system. In macroprudential policies, the government regulates the policy interest rate and the reserve requirement ratio to target the total amount of credit:

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_r} \left(\frac{\pi_t}{\pi}\right)^{(1-\rho_r)\phi_\pi} \left(\frac{GDP_t}{GDP}\right)^{(1-\rho_r)\phi_y} \left(\frac{B_t}{B}\right)^{\kappa^{MP}}, \tag{26}$$

$$\frac{RR_t}{RR} = \left(\frac{B_t}{B}\right)^{\kappa^{MP}}. \tag{27}$$

Furthermore, assuming that the government implements macroprudential policies to restrict the leverage ratio of banks in order to prevent and control systemic financial risks:

$$\frac{\lambda_t}{\lambda} = \left(\frac{B_t}{B}\right)^{\kappa^{MP}} \tag{28}$$

In order to evaluate the effectiveness of combining fiscal subsidy policies (here we only consider the more effective implicit guarantee policy) with macroprudential policies, we quantify the welfare effects, financial stability effects, and credit market maintenance effects of policy combinations at levels of policy intensity $\kappa^g, \kappa^{MP}$ ranging from 0 to 1. We use equivalent consumption compensation to measure household welfare, and define the lifetime discounted utility of households under the baseline as

$V_0^a = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t U(C_t^a, L_t^a)$, where $C_t^a, L_t^a$ represents the consumption and labor levels of households under the scenario a. The lifetime discounted utility of households in scenario b under the regulation of fiscal subsidy policies and macroprudential policies is: $V_0^b = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t U\big(C_t^b, L_t^b\big)$. Under policy regulation, household welfare will be improved, and the level of welfare improvement can be measured by the proportion $\Delta$ of equivalent consumption compensation:

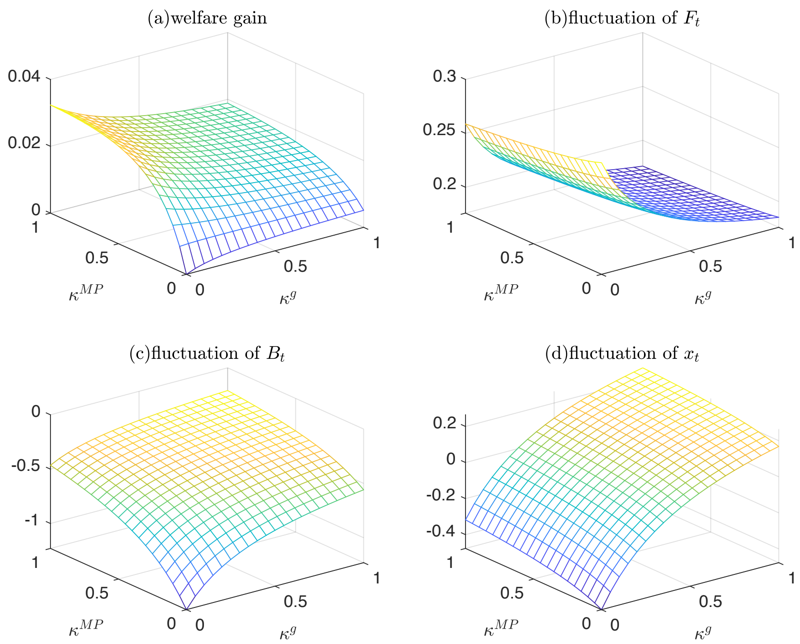
$$V_0^b = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t U\left((1+\Delta)\, C_t^a, L_t^a\right)$$

We use the level of consumption compensation to represent the level of welfare gain. Given the utility function form, we can obtain: $\Delta = \exp^{(1-\beta)\left(V_0^b - V_0^a\right)} - 1$. In addition to the improvement in households' welfare, we also want to evaluate the role of policy combinations in preventing financial risks, maintaining stability in the credit market, and reducing distortions. We measure the level of financial risk by calculating the average volatility of relevant variables during the observation period, using the volatility of two types of firm-weighted average default rates $F_t = (1-x_t)F_t^b + x_t F_t^s$. We use the overall credit and the volatility of the share of credit to small firms to respectively represent the degree of credit market tightening and distortion. Figure 7 illustrates the regulatory effects of fiscal subsidy policies and macro-prudential policies on households' welfare, financial stability, and the credit market under different policy intensities.

From panel (a) of Figure 7, it can be observed that both fiscal subsidy policies and macro-prudential policies, when used separately, can enhance households' welfare, and the level of welfare improvement increases with the intensity of the policies. In comparison, macro-prudential policies are more effective in enhancing the level of households' welfare, while fiscal subsidy policies mainly target debt contracts between banks and firms, with limited impact on improving households' welfare. In addition, when these two types of policies are used in combination, the fiscal subsidy policy, as the funds come from households' taxes $T_t$ may reduce households' welfare within a certain range. From the perspective of improving households' welfare, macro-prudential policies have greater policy space.

In panel (b) of Figure 7, it can be seen that in terms of preventing financial risks, the role of macro-prudential policies is relatively small, while the fiscal subsidy policy, which reduces information asymmetry between banks and firms, may sacrifice the level of households' welfare, but it significantly

**FIG. 7.** The regulatory effects of combining fiscal subsidy policies with macro-prudential policies.




restrains overall firm default risk. As shown in Figure 6, this is mainly due to the inhibition of the EAP mechanism for small firms by the fiscal subsidy policy. This reduces banks' expected losses from credit to small firms, thereby lowering their financing premium levels. Consequently, the proportion of H projects in the asset portfolio of small firms decreases, thereby preventing an increase in overall financial risk. With the increase in the intensity of fiscal subsidies, overall firm default risk continues to decrease.

Panels (c) and (d) of Figure 7 demonstrate the regulatory effects of policy combinations on the credit market. From panel (c), it can be observed that both fiscal subsidy policies and macro-prudential policies effectively reduce the overall volatility of credit. The fiscal subsidy policy increases the demand and supply of credit to small firms by reducing information asymmetry between small firms and banks, mainly by boosting the credit level of small firms to restrain credit contraction. The macro-prudential policy reduces the financing cost of both large and small firms by lowering policy interest rates and reserve requirements, and relaxing bank leverage ratio regulations, thus overall restraining credit contraction. Numerically, both policies similarly restrain credit market contraction, leading to a significant reduction in overall credit as policy intensity increases from 0 to 1. Furthermore, under the combined use of the two policies, the degree of credit market contraction is further restrained. However, for credit market distortion, the effect of the macro-prudential policy is limited. From panel (d), it can be seen that, in contrast, the fiscal subsidy policy which mainly targeting small firms, significantly reduces credit market distortion. When its intensity is sufficient, the share of credit to small firms even increases. Nevertheless, similar to the results in panel (c), the combined use of the two policies can further reduce the degree of credit market distortion.

From the results of Figure 7, it is evident that fiscal subsidy policies and macro-prudential policies possess different regulatory effects on the macroeconomy. While macro-prudential policies are more effective in enhancing households' welfare, fiscal subsidy policies, with limited policy space, may potentially compromise household welfare. In terms of preventing financial risks, macro-prudential policies play a relatively small role, whereas fiscal subsidy policies have a significant impact by reducing information asymmetry between banks and firms, thereby effectively restraining the influence of the EAP mechanism of banks and firms. In regulating the credit market, both types of policies can significantly curb credit market contraction. Moreover, fiscal subsidy policies targeting small firms prove effective in reducing credit market distortion and increasing the share of credit to small firms. While the emphasis of the two policies differs from the focus on improving households' welfare, their combined use yields superior regulatory effects on the credit market. The selection and implementation intensity of fiscal subsidy and macro-prudential policies, as indicated by the results in Figure 7, should be carefully determined based on actual economic conditions and objectives. A judicious combination is essential to mitigate the negative impact of uncertainty on the economy.

## 5. CONCLUSION

Not only the Great Recession of 2008, but also recent events such as the Covid-19 pandemic and geopolitical conflicts have led to heightened global economic uncertainty, attracting significant attention to the impact of uncertainty on the economy. This paper focuses on the impact of uncertainty on credit, particularly the heterogeneous effects on firms. We provide empirical evidence of the heterogeneous impact of uncertainty on large and small firms and build a DSGE model incorporating heterogeneous firms to analyze the underlying theoretical mechanisms of these effects. To motivate our research question, we use data from listed Chinese companies and employ the local projection method to study the impact of uncertainty on large and small firms. We find that uncertainty increases firms' default risk and financing costs, leading to reduced bank lending, with small firms experiencing a greater impact. Subsequently, we propose an endogenous asset portfolio (EAP) mechanism and incorporate it into the model, demonstrating how this mechanism can generate and explain heterogeneous firm responses and credit distortions under uncertainty shocks.

The EAP mechanism in our model arises from asymmetric information between banks and firms, affecting both the demand for credit by firms and the supply of credit by banks. Firms make a trade-off on the cost of effort in choosing between high-risk, high-return investment projects and low-risk, low-return investment projects, endogenizing their default risk in the process. Banks, in turn, make a trade-off on their lending supply based on the expected default risk of the borrowing firms, endogenizing the firms' share of credit. Consequently, debt default risk endogenizes the asset portfolio of firms and banks, with uncertainty being a significant driver as it directly leads to an increase in debt default risk. Specifically, uncertainty increases the volatility of investment project returns for firms, thereby raising default rates. The EAP mechanism for small firms leads to a greater increase in default rates, as these firms have a higher proportion of high-risk projects in their investment portfolio, with this proportion increasing over time. Due to the substantial losses incurred by banks from firm defaults, banks reduce their lending supply based on the expected default risk, and as the default risk of small firms increases more, banks cut their supply to these firms to a greater extent. We compare the EAP mechanisms of firms and banks and find that both contribute to differences in the price and quantity responses of firm credit under uncertainty shocks. Subsequently, we explore the dynamic correlations between the credit-related variables and attempt to separate the demand and supply effects of credit contraction, finding that the demand effect of firms has a greater explanatory power for credit contraction. We also analyze the impact of default risk on firms in the steady state, revealing that under unchanged overall conditions, the greater the difference in default risk between the two types of firms, the more severe the credit distortion. Finally, we analyze the role of fiscal subsidy policies and macroprudential policies under the EAP mechanism. Fiscal subsidy policies that reduce the level of asymmetric information between banks and firms effectively lower firm default risk, thereby restraining the EAP mechanism and more effectively mitigating macroeconomic fluctuations. Macroprudential policies and fiscal subsidy policies have different focus, with the former promoting a higher welfare level, while the latter more significantly reduces financial system volatility and credit distortions. Both policies should be reasonably combined depending on the circumstances.

Ultimately, our research could be extended further. We focus on the impact of uncertainty on firms. But when uncertainty increases, how risky projects or assets have a heterogeneous impact on household consumption is also an important question, as studied in Luo et al. (2020). Futhermore, our model does not encompass the effects of firms delaying investment through the real-option channel of uncertainty impact, as our considerations primarily revolving around the impact of increased financing costs. Additionally, we only consider the EAP mechanism for small firms. Large firms may also have such mechanisms, potentially facing additional constraints in their decision-making. Another important issue is the principal-agent problem between banks and depositors, as well as the risk of bank runs, which we have not taken into account. Furthermore, our model only involves banks determining the share of credit supply. If banks also have an effort mechanism for screening credit applicants, as in Ferrante (2018), the interaction between bank and firm efforts would be an interesting question. These issues represent potential directions for future research.

## APPENDIX: MODEL DETAILS

### A.1. DEFINITION OF AUXILIARY VARIABLES IN DEBT CONTRACT

1. Firm default risk $F(\bar{\omega})$:

$$F(\bar{\omega}) = \int_0^{\bar{\omega}} dF(\bar{\omega}) = \int_0^{\bar{\omega}} f(\bar{\omega}) d\omega,$$

where $f(\bar{\omega})$ is the probability density function of $\omega$.

2. Share of capital gains on default $G(\bar{\omega})$:

$$G(\bar{\omega}) = \int_0^{\bar{\omega}} \omega dF(\omega).$$

3. Bank's share of earnings $\Gamma(\bar{\omega})$

$$\Gamma(\bar{\omega}) = \int_{\bar{\omega}}^{\infty} \bar{\omega} dF(\omega) + \int_0^{\bar{\omega}} \omega dF(\omega) = (1 - F(\bar{\omega}))\,\bar{\omega} + G(\bar{\omega}).$$

4. Bank's share of losses on default $o(\bar{\omega})$

$$o(\bar{\omega}) = \int_0^{\bar{\omega}} (\bar{\omega} - \omega) dF(\omega) = \bar{\omega} F(\bar{\omega}) - G(\bar{\omega}).$$

## A.2. SOLUTION OF OPTIMIZATION PROBLEMS

### A.2.1. Optimization problem of small firms

(1) The decision of $e_t$:

The expected return of firms is:

$$\int_{\bar{\omega}_{t+1}}^{\infty} \left(\omega R_{t+1}^k Q_t K_t - Z_{t+1} B_t\right) dF(\omega) - c(e_t) Q_t K_t.$$

Based on the determination of $\bar{\omega}_{t+1}$, the expected returns can be rewritten as

$$R_{t+1}^k Q_t K_t \left( \int_{\bar{\omega}_{t+1}}^{\infty} (\omega - \bar{\omega}_{t+1}) dF(\omega) \right) - c(e_t) Q_t K_t, \tag{A.1}$$

where

$$\begin{aligned}
\int_{\bar{\omega}_{t+1}}^{\infty} \omega dF(\omega) &= p(e_t) \int_{\bar{\omega}_{t+1}}^{\infty} \omega dF^H(\omega) + (1 - p(e_t)) \int_{\bar{\omega}_{t+1}}^{\infty} \omega dF^L(\omega) \\
&= p(e_t) \Big( a - G_t^H(\bar{\omega}_{t+1}) \Big) + \Big( 1 - p(e_t) \Big) \Big( 1 - G_t^L(\bar{\omega}_{t+1}) \Big) \\
&= (\zeta e_t) a + (1 - \zeta e_t) - G_t(\bar{\omega}_{t+1}).
\end{aligned}$$

And

$$\int_{\bar{\omega}_{t+1}}^{\infty} \bar{\omega}_{t+1} dF(\omega) = \bar{\omega}_{t+1} \int_{\bar{\omega}_{t+1}}^{\infty} dF(\omega) = \bar{\omega}_{t+1} \left(1 - F(\bar{\omega}_{t+1})\right).$$

Therefore, the first part of equation (A.1) can be rewritten as

$$R_{t+1}^k Q_t K_t \left[ (\zeta e_t) a + (1 - \zeta e_t) - \bar{\omega}_{t+1} + \bar{\omega}_{t+1} F_t(\bar{\omega}_{t+1}) - G_t(\bar{\omega}_{t+1}) \right].$$

The expected returns of firms, (A.1), can be obtained from the settings of $o\left(\bar{\omega}_{t+1}\right) = \int_0^{\bar{\omega}_{t+1}} \left(\bar{\omega}_{t+1} - \omega\right) dF\left(\omega\right) = \bar{\omega}_{t+1} F_t(\bar{\omega}_{t+1}) - G_t(\bar{\omega}_{t+1})$ and $c(e_t)$ as:

$$Q_t K_t \left[ \left( (\zeta e_t) a + (1 - \zeta e_t) \right) R_{t+1}^k - \bar{\omega}_{t+1} R_{t+1}^k + o(\bar{\omega}_{t+1}) R_{t+1}^k - e_t^2/2 \right].$$

We solve the profit maximization problem for small firms, taking the derivative with respect to $e_t$ yields the F.O.C for the effort level:

$$\zeta R^k_{t+1}(a-1) + \zeta R^k_{t+1}\left(o^H(\bar{\omega}_{t+1}) - o^L(\bar{\omega}_{t+1})\right) = e_t.$$

(2) The decision of $\bar{\omega}_t$

The profit maximization problem for the firm involves selecting the optimal leverage ratio $L_t$, default threshold $\bar{\omega}_{t+1}$, and effort level $e_t$ to screen H projects, subject to the incentive compatibility constraint (4) the debt contract constraint (8). The profit function is given by:

$$\max_{L_t,\bar{\omega}_{t+1},e_t} \int_{\bar{\omega}_{t+1}}^{\infty} \left(\omega R^k_{t+1} Q_t K_t - Z_{t+1} B_t\right) dF(\omega) - c(e_t) Q_t K_t,$$

which can be rewritten as

$$\max_{L_t,\bar{\omega}_{t+1},e_t} L_t N^E_t \left[\left((\zeta e_t)a + (1-\zeta e_t)\right) R^k_{t+1} - \bar{\omega}_{t+1} R^k_{t+1} + o(\bar{\omega}_{t+1}) R^k_{t+1} - e^2_t/2\right].$$

And the debt contract constraint (8) can be transformed into

$$\bar{\omega}_{t+1} - o(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1}) = \frac{L_t - 1}{L_t}\frac{R^L_t}{R^k_{t+1}}.$$

Therefore, the Lagrangian function corresponding to the optimization problem is:

$$\begin{aligned}
\mathbb{L} =& L_t N^E_t \left[\left((\zeta e_t)a + (1-\zeta e_t)\right) R^k_{t+1} - \bar{\omega}_{t+1} R^k_{t+1} + o(\bar{\omega}_{t+1}) R^k_{t+1} - e^2_t/2\right] \\
&+ \lambda^1_t \left[\frac{L_t - 1}{L_t}\frac{R^L_t}{R^k_{t+1}} - \bar{\omega}_{t+1} + o(\bar{\omega}_{t+1}) + \mu G_t(\bar{\omega}_{t+1})\right] \\
&+ \lambda^2_t \left[e_t - \zeta R^k_{t+1}(a-1) - \zeta R^k_{t+1}\left(o^H(\bar{\omega}_{t+1}) - o^L(\bar{\omega}_{t+1})\right)\right],
\end{aligned}$$

where $\lambda^1_t, \lambda^2_t$ are the Lagrange multipliers for the debt contract constraint and the incentive compatibility constraint, respectively. By obtaining the F.O.Cs for $L_t, \bar{\omega}_t, e_t$ and combining them, we can derive the F.O.C for $\bar{\omega}_{t+1}$:

$$\begin{aligned}
& (1 - o'(\bar{\omega}_{t+1}))\left[R^k_{t+1}\left(\bar{\omega}_{t+1} - o(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1})\right) - R^L_t\right] \\
=\ & \left[X_{1t} - (1 - o'(\bar{\omega}_{t+1}) - \mu G'_t(\bar{\omega}_{t+1}))\right] X_{2t},
\end{aligned}$$

where

$$\begin{aligned}
X_{1t} &= \zeta^2 R^k_{t+1}[o^H(\bar{\omega}_{t+1}) - o^L(\bar{\omega}_{t+1}) \\
&+ \mu\big(G^H(\bar{\omega}_{t+1}) - G^L(\bar{\omega}_{t+1})\big)]\big(o^{H\prime}(\bar{\omega}_{t+1}) - o^{L\prime}(\bar{\omega}_{t+1})\big), \\
X_{2t} &= \left((\zeta e_t)a + (1-\zeta e_t)\right) R^k_{t+1} - \bar{\omega}_{t+1} R^k_{t+1} + o(\bar{\omega}_{t+1}) R^k_{t+1} - e^2_t/2.
\end{aligned}$$

### A.2.2. Optimization problem of banks

The bank's optimization problem involves selecting the optimal bank leverage ratio $\phi_t$ and asset portfolio $x_t$ to maximize the expected net present value of assets, subject to the incentive compatibility constraint (4):

$$\max_{\phi_t, x_t} V_t = \mu_t B_t^b + m_t B_t^s + \eta_t N_t^B, \text{ s.t. } V_t \geq \Theta(x_t)\big(B_t^b + B_t^s\big),$$

which can be rewritten as:

$$\max_{\phi_t, x_t} \mu_t \phi_t (1 - x_t) + m_t \phi_t x_t + \eta_t - \theta_t \Theta(x_t)\phi_t,$$

where $\theta_t$ is the Lagrange multipliers for incentive compatibility constraint. Then we can get F.O.C of $\phi_t$ and $x_t$:

$$\mu_t(1 - x_t) + m_t x_t = \theta_t \Theta(x_t) \;, \; m_t - \mu_t = \theta_t \lambda \iota x_t.$$

Combing them with equation (4), we can get the decision of $\phi_t$ and $x_t$:

$$\begin{aligned}\phi_t =& \frac{\eta_t}{\Theta(x_t) - \mu_t(1 - x_t) - m_t x_t},\\ x_t =& \frac{\mu_t}{m_t - \mu_t}\left[-1 + \sqrt{1 + \frac{2}{\iota}\left(\frac{m_t - \mu_t}{\mu_t}\right)^2}\,\right].\end{aligned}$$

## A.3. PROOF OF LEMMA 1

From $o\big(\bar{\omega}\big) = \int_0^{\bar{\omega}} \big(\bar{\omega} - \omega\big) dF\big(\omega\big) = \bar{\omega}F(\bar{\omega}) - G(\bar{\omega})$, it follows that for L projects:

$$o^L(\bar{\omega}) = normcdf\left(\frac{\log(\bar{\omega})}{\sigma} + \frac{\sigma}{2}\right)\bar{\omega} - normcdf\left(\frac{\log(\bar{\omega})}{\sigma} - \frac{\sigma}{2}\right).$$

Therefore,

$$\begin{aligned}\frac{\partial o^L(\bar\omega)}{\partial\sigma} =& normpdf\left(\frac{\log(\bar\omega)}{\sigma}+\frac{\sigma}{2}\right)\bar\omega\left(-\frac{\log(\bar\omega)}{\sigma^2}+\frac{1}{2}\right)\\ &- normpdf\left(\frac{\log(\bar\omega)}{\sigma}-\frac{\sigma}{2}\right)\left(-\frac{\log(\bar\omega)}{\sigma^2}-\frac{1}{2}\right)\\ =& normpdf\left(\frac{\log(\bar\omega)}{\sigma}+\frac{\sigma}{2}\right)\bar\omega\left(-\frac{\log(\bar\omega)}{\sigma^2}+\frac{1}{2}\right)\\ &- normpdf\left(\frac{\log(\bar\omega)}{\sigma}+\frac{\sigma}{2}\right)\bar\omega\left(-\frac{\log(\bar\omega)}{\sigma^2}-\frac{1}{2}\right)\\ =& normpdf\left(\frac{\log(\bar\omega)}{\sigma}+\frac{\sigma}{2}\right)\bar\omega.\end{aligned}$$

Similarly, for H projects:

$$\begin{aligned}o^H(\bar\omega) =& normcdf\left(\frac{\log(\bar\omega)-\log(a)}{b\sigma}+\frac{b\sigma}{2}\right)\bar\omega\\ &- normcdf\left(\frac{\log(\bar\omega)-\log(a)}{b\sigma}-\frac{b\sigma}{2}\right)a.\end{aligned}$$

Therefore,

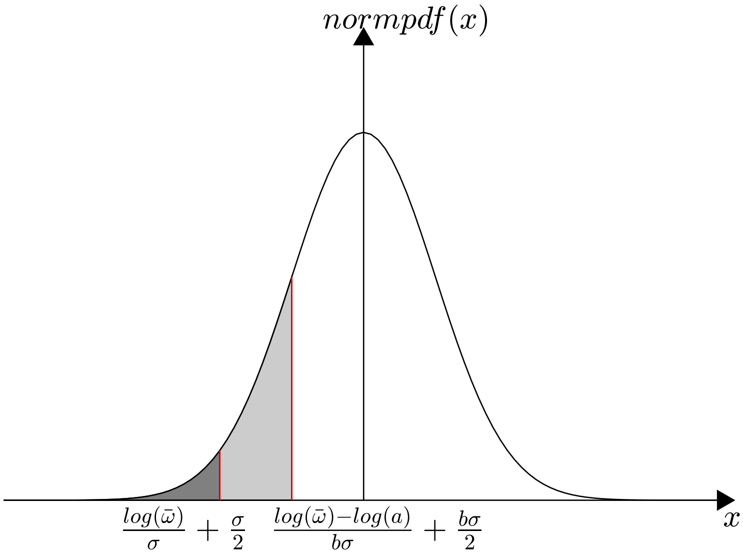
$$\begin{aligned}\frac{\partial o^H(\bar\omega)}{\partial\sigma} =& normpdf\left(\frac{\log(\bar\omega)-\log(a)}{b\sigma}+\frac{b\sigma}{2}\right)\bar\omega\left(-\frac{\log(\bar\omega)-\log(a)}{b\sigma^2}+\frac{b}{2}\right)\\ &- normpdf\left(\frac{\log(\bar\omega)-\log(a)}{b\sigma}-\frac{b\sigma}{2}\right)a\left(-\frac{\log(\bar\omega)-\log(a)}{b\sigma^2}-\frac{b}{2}\right)\\ =& normpdf\left(\frac{\log(\bar\omega)-\log(a)}{b\sigma}+\frac{b\sigma}{2}\right)\bar\omega\left(-\frac{\log(\bar\omega)-\log(a)}{b\sigma^2}+\frac{b}{2}\right)\\ &- normpdf\left(\frac{\log(\bar\omega)-\log(a)}{b\sigma}+\frac{b\sigma}{2}\right)a\frac{\bar\omega}{a}\left(-\frac{\log(\bar\omega)-\log(a)}{b\sigma^2}-\frac{b}{2}\right).\end{aligned}$$

Combining them we can get

$$\begin{aligned}&\frac{\partial(o^H(\bar\omega)-o^L(\bar\omega))}{\partial\sigma}\\ =&\bar\omega\left[normpdf\left(\frac{\log(\bar\omega)-\log(a)}{b\sigma}+\frac{b\sigma}{2}\right)b - normpdf\left(\frac{\log(\bar\omega)}{\sigma}+\frac{\sigma}{2}\right)\right].\end{aligned}$$

Due to the higher default rate of H projects, $F^L(\bar\omega) < F^H(\bar\omega) < 0.5$, and $F^L(\bar\omega) = normcdf\left(\frac{\log(\bar\omega)}{\sigma}+\frac{\sigma}{2}\right), F^H(\bar\omega) = normcdf\left(\frac{\log(\bar\omega)-\log(a)}{b\sigma}+\frac{b\sigma}{2}\right)$, we can get that $0 > \frac{\log(\bar\omega)-\log(a)}{b\sigma}+\frac{b\sigma}{2} > \frac{\log(\bar\omega)}{\sigma}+\frac{\sigma}{2}$, as shown in Figure 8.

**FIG. 8.** Probability density function of the standard normal distribution.




We can learn from Figure 8 that $normpdf\left(\frac{\log(\bar{\omega})-\log(a)}{b\sigma}+\frac{b\sigma}{2}\right) > normpdf\left(\frac{\log(\bar{\omega})}{\sigma}+\frac{\sigma}{2}\right)$. Besides, for $b>1, \bar{\omega}>0$, we can get that $\frac{\partial(o^H(\bar{\omega})-o^L(\bar{\omega}))}{\partial\sigma} > 0$. As the effort level of small firms is determined by

$$\zeta R^k_{t+1}(a-1)+\zeta R^k_{t+1}\left(o^H(\bar{\omega}_{t+1})-o^L(\bar{\omega}_{t+1})\right)=e_t,$$

which implies that when the level of uncertainty increases, small firms tend to increase their effort level $e_t$, thus proving:

$$\frac{\partial e}{\partial\sigma}=\frac{\partial(o^H(\bar{\omega})-o^L(\bar{\omega}))}{\partial\sigma}>0.$$

## A.4. PROOF OF LEMMA 2

1. Relationship among $\mu_t, m_t$ and $\sigma_t$

We can learn from equation (10) and (11) that $\mu_t, m_t \propto ((1-F_t(\bar{\omega}_{t+1}))\,Z_{t+1}-R_t)$. The debt contract condition suggests that

$$(1-F_t(\bar{\omega}_{t+1}))\,Z_{t+1}B_t+(1-\mu)\int_0^{\bar{\omega}_{t+1}}\omega R^k_{t+1}Q_tK_t dF(\omega)=R^L_tB_t.$$

Therefore,

$$(1-F_t(\bar{\omega}_{t+1}))\,Z_{t+1}-R_t=R_t^L-R_t-(1-\mu)R_{t+1}^kQ_tK\int_0^{\bar{\omega}_{t+1}}\omega_t dF(\omega),$$

where $G(\omega)=\int_0^{\bar{\omega}_{t+1}}\omega dF(\omega)=normcdf\left(\frac{\log(\bar{\omega})}{\sigma}-\frac{\sigma}{2}\right)$. And

$$\frac{\partial G(\omega)}{\partial\sigma}=normpdf\left(\frac{\log(\bar{\omega})}{\sigma}-\frac{\sigma}{2}\right)\left(-\frac{\log(\bar{\omega})}{\sigma^2}-\frac{1}{2}\right).$$

We know that $F(\bar{\omega})=normcdf(\frac{\log(\bar{\omega})}{\sigma}+\frac{\sigma}{2})<0.5$ so $\frac{\log(\bar{\omega})}{\sigma}+\frac{\sigma}{2}<0$, which means that $-\frac{\log(\bar{\omega})}{\sigma^2}>\frac{1}{2}$. So we can get that $\frac{\partial G(\omega)}{\partial\sigma}>0$ and $\frac{\partial[(1-F(\bar{\omega}))Z-R]}{\partial\sigma}<0$. Then: $\mu_t,m_t\propto(-G(\omega))$, which suggests that $\mu_t,m_t$ will decrease as the level of uncertainty increases:

$$\frac{\partial\mu}{\partial\sigma}<0,\frac{\partial m}{\partial\sigma}<0.$$

2. Relationship between $\frac{\partial\mu}{\partial\sigma}$ and $\frac{\partial m}{\partial\sigma}$

As for big firms, $\frac{\partial\mu}{\partial\sigma}\propto-\frac{\partial G^b(\omega)}{\partial\sigma}<0$, and for small firms: $\frac{\partial m}{\partial\sigma}\propto-\frac{\partial G^s(\omega)}{\partial\sigma}<0$, where

$$\begin{aligned}G^s(\bar{\omega})=&\zeta eG^H(\bar{\omega})+(1-\zeta e)G^L(\bar{\omega})\\=&(\zeta e)normcdf\left(\frac{\log(\bar{\omega})-\log(a)}{b\sigma}-\frac{b}{2}\sigma\right)\\&+(1-\zeta e)normcdf\left(\frac{\log(\bar{\omega})}{\sigma}-\frac{1}{2}\sigma\right),\end{aligned}$$

where

$$\begin{aligned}\frac{\partial G^H(\bar{\omega})}{\partial\sigma}=&normpdf\left(\frac{\log(\bar{\omega})-\log(a)}{b\sigma}-\frac{b}{2}\sigma\right)\left(-\frac{\log(\bar{\omega})-\log(a)}{b\sigma^2}-\frac{b}{2}\right)\\=&normpdf\left(\frac{\log(\bar{\omega})-\log(a)}{b\sigma}+\frac{b}{2}\sigma\right)a\frac{\bar{\omega}}{a}\left(-\frac{\log(\bar{\omega})-\log(a)}{b\sigma^2}-\frac{b}{2}\right),\end{aligned}$$

and

$$\begin{aligned}\frac{\partial G^L(\bar{\omega})}{\partial\sigma}=&normpdf\left(\frac{\log(\bar{\omega})}{\sigma}-\frac{1}{2}\sigma\right)\left(-\frac{\log(\bar{\omega})}{\sigma^2}-\frac{1}{2}\right)\\=&normpdf\left(\frac{\log(\bar{\omega})}{\sigma}+\frac{1}{2}\sigma\right)\bar{\omega}\left(-\frac{\log(\bar{\omega})}{\sigma^2}-\frac{1}{2}\right).\end{aligned}$$

We have proved that $normpdf\left(\frac{\log(\bar{\omega})-\log(a)}{b\sigma}+\frac{b}{2}\sigma\right) > normpdf\left(\frac{\log(\bar{\omega})}{\sigma}+\frac{1}{2}\sigma\right) > 0$, and we can learn from $0 > \frac{\log(\bar{\omega})-\log(a)}{b\sigma}+\frac{b}{2}\sigma > \frac{\log(\bar{\omega})}{\sigma}+\frac{1}{2}\sigma$ that $0 < -\frac{\log(\bar{\omega})-\log(a)}{b\sigma^2}-\frac{b}{2} < -\frac{\log(\bar{\omega})}{\sigma^2}-\frac{1}{2}$. Then we can simply prove that $\frac{\partial G^H(\bar{\omega})}{\partial\sigma}-\frac{\partial G^L(\bar{\omega})}{\partial\sigma} > 0$. Besides, we can learn from $\frac{\partial e}{\partial\sigma} > 0$ so that $\frac{\partial G^s(\bar{\omega})}{\partial\sigma} > \frac{\partial G^b(\bar{\omega})}{\partial\sigma} > 0$, and

$$\frac{\partial m}{\partial\sigma} < \frac{\partial\mu}{\partial\sigma} < 0.$$

3. Relationship between $x_t$ and $\sigma_t$

From $(1-F_t(\bar{\omega}_{t+1}))\,Z_{t+1}-R_t = R_t^L-R_t-(1-\mu)R_{t+1}^kQ_tK\int_0^{\bar{\omega}_{t+1}}\omega_t dF(\omega)$, it is known that $(1-F(\bar{\omega})Z)-R$ falls as $F(\bar{\omega})$ and $\bar{\omega}$ rise. Therefore, combining the previous proof, we can obtain:

$$m < \mu, m' < \mu'.$$

Therefore, we get that

$$\partial\left(\frac{m-\mu}{\mu}\right)/\partial\sigma = \frac{(m'-\mu')\,\mu-\mu'(m-\mu)}{\mu^2} < 0.$$

From the decision of bank's asset portfolio:

$$x_t = \frac{\mu_t}{m_t-\mu_t}\left[-1+\sqrt{1+\frac{2}{l}\left(\frac{m_t-\mu_t}{\mu_t}\right)^2}\right].$$

Let $\frac{m-\mu}{\mu} = t$, then $x = -\frac{1}{t}+\frac{1}{t}\sqrt{1+\frac{\iota}{2}t^2}$. It can be obtained by simple differentiation:

$$\frac{\partial x}{\partial t} = \frac{\sqrt{(2/\iota)t^2+1}-1}{t^2\sqrt{(2/\iota)t^2+1}} > 0.$$

Therefore, when the level of uncertainty increases, i.e., $\frac{m_t-\mu_t}{\mu_t}$ decreases, the bank will reduce $x_t$, thus reducing the share of credit supplied to small firms, thus proving:

$$\frac{\partial x}{\partial\sigma} < 0.$$

## A.5. MODEL EQUATIONS

### A.5.1. Auxiliary variables

1. Big firms

$$\begin{aligned}
F_t^b(\bar{\omega}_{t+1}) &= normcdf\left(\frac{\log(\bar{\omega}_{t+1}^b)+(\sigma_t^b)^2/2}{\sigma_t^b}\right),\\
f_t^b(\bar{\omega}_{t+1}) &= normcdf\left(\frac{\log(\bar{\omega}_{t+1}^b)+(\sigma_t^b)^2/2}{\sigma_t^b}\right)/\bar{\omega}_{t+1}^b\sigma_t^b\\
G_t^b(\bar{\omega}_{t+1}) &= normcdf\left(\frac{\log(\bar{\omega}_{t+1}^b)+(\sigma_t^b)^2/2}{\sigma_t^b}-\sigma_t^b\right), G_t^{b\prime}(\bar{\omega}_{t+1})=\bar{\omega}_{t+1}^b f_t^b(\bar{\omega}_{t+1})\\
\Gamma_t^b(\bar{\omega}_{t+1}) &= \bar{\omega}_{t+1}^b\left(1-F_t^b(\bar{\omega}_{t+1})\right)+G_t^b(\bar{\omega}_{t+1}),\ \Gamma_t^{b\prime}(\bar{\omega}_{t+1})=1-F_t^b(\bar{\omega}_{t+1})
\end{aligned}$$

2. Small firms

$$\begin{aligned}
F_t^L(\bar{\omega}_{t+1}) &= normcdf\left(\frac{\log(\bar{\omega}_{t+1}^s)+(\sigma_t^s)^2/2}{\sigma_t^s}\right),\\
F_t^H(\bar{\omega}_{t+1}) &= normcdf\left(\frac{\log(\bar{\omega}_{t+1}^s)-\log(a)}{b\sigma_t^s}+\frac{b}{2}\sigma_t^s\right)\\
G_t^L(\bar{\omega}_{t+1}) &= normcdf\left(\frac{\log(\bar{\omega}_{t+1}^s)+(\sigma_t^s)^2/2}{\sigma_t^s}-\sigma_t^s\right),\\
G_t^H(\bar{\omega}_{t+1}) &= normcdf\left(\frac{\log(\bar{\omega}_{t+1}^s)-\log(a)}{b\sigma_t^s}-\frac{b}{2}\sigma_t^s\right)\\
f_t^L(\bar{\omega}_{t+1}) &= normpdf\left(\frac{\log(\bar{\omega}_{t+1}^s)+(\sigma_t^s)^2/2}{\sigma_t^s}\right)/\bar{\omega}_{t+1}^s\sigma_t^s,\\
f_t^H(\bar{\omega}_{t+1}) &= normpdf\left(\frac{\log(\bar{\omega}_{t+1}^s)-\log(a)}{b\sigma_t^s}+\frac{b}{2}\sigma_t^s\right)/b\bar{\omega}_{t+1}^s\sigma_t^s\\
o^L(\bar{\omega}_{t+1}) &= \bar{\omega}_{t+1}F_t^L(\bar{\omega}_{t+1})-G_t^L(\bar{\omega}_{t+1}), o^H(\bar{\omega}_{t+1})=\bar{\omega}_{t+1}F_t^H(\bar{\omega}_{t+1})-G_t^H(\bar{\omega}_{t+1})\\
o^{L\prime}(\bar{\omega}_{t+1}) &= F_t^L(\bar{\omega}_{t+1}), o^{H\prime}(\bar{\omega}_{t+1})=F_t^H(\bar{\omega}_{t+1})\\
F_t^s(\bar{\omega}_{t+1}) &= \zeta e_t F_t^H(\bar{\omega}_{t+1})+(1-\zeta e_t)F_t^L(\bar{\omega}_{t+1}),\\
f_t^s(\bar{\omega}_{t+1}) &= \zeta e_t f_t^H(\bar{\omega}_{t+1})+(1-\zeta e_t)f_t^L(\bar{\omega}_{t+1})\\
G_t^s(\bar{\omega}_{t+1}) &= \zeta e_t G_t^H(\bar{\omega}_{t+1})+(1-\zeta e_t)G_t^L(\bar{\omega}_{t+1}),\quad G_t^{s\prime}(\bar{\omega}_{t+1})=\bar{\omega}_{t+1}^s f_t^s(\bar{\omega}_{t+1})\\
o(\bar{\omega}_{t+1}) &= \bar{\omega}_{t+1}^s F_t^s(\bar{\omega}_{t+1})-G_t^s(\bar{\omega}_{t+1}), o'(\bar{\omega}_{t+1})=F_t^s(\bar{\omega}_{t+1})\\
X_{1t} &= \zeta^2 R_{t+1}^k\Bigg[o^H(\bar{\omega}_{t+1})-o^L(\bar{\omega}_{t+1})+\mu\Bigg(G^H(\bar{\omega}_{t+1})\\
&\quad -G^L(\bar{\omega}_{t+1})\Bigg)\Bigg]\Bigg(o^{H\prime}(\bar{\omega}_{t+1})-o^{L\prime}(\bar{\omega}_{t+1})\Bigg)\\
X_{2t} &= \left((\zeta e_t)a+(1-\zeta e_t)\right)R_{t+1}^k-\bar{\omega}_{t+1}R_{t+1}^k+o(\bar{\omega}_{t+1})R_{t+1}^k-{e_t}^2/2
\end{aligned}$$

### A.5.2. All endogenous variables and model equations

There are 54 endogenous variables in the model: $\{\lambda_t, C_t, R_t, L_t^b, L_t^s, w_t^b, w_t^s, w_t^{b*}, w_t^{s*}, H_{1t}, H_{2t}, H_{3t}, H_{4t}, GDP_t, Y_t, Y_t^b, Y_t^s, A_t, K_t^b, K_t^s, \pi_t, x_{1t}, x_{2t}, mc, mc_t^b, mc_t^s, I_t^b, I_t^s, Q_t^b, Q_t^s, R_{b,t}^k, R_{s,t}^k, r_{b,t}^k, r_{s,t}^k, N_{b,t}^E, N_{s,t}^E, \sigma_t^b, \sigma_t^s, \bar{\omega}_{t+1}^b, \bar{\omega}_{t+1}^s, e_t, B_t^b, B_t^s, Z_t^b, Z_t^s, N_t^B, \mu_t, m_t, \eta_t, x_t, R_{b,t}^L, R_{s,t}^L\}$, and 54 equations:

$$\lambda_t = \beta \lambda_{t+1} R_t / \pi_{t+1} \tag{A.2}$$

$$\lambda_t = \frac{1}{C_t - vC_{t-1}} - \beta \frac{v}{C_{t+1} - vC_t} \tag{A.3}$$

$$w_t^{b^*} = \frac{\sigma_w}{\sigma_w - 1} \frac{H_{1t}}{H_{2t}} \tag{A.4}$$

$$\begin{aligned} H_{1t} &= \phi_L^b \left( w_t^b / w_t^{b^*} \right)^{\sigma_w(1+\sigma_L)} \left( L_t^b \right)^{1+\sigma_L} (1 - 1/\sigma_w) \\ &+ \beta \theta_p (\pi_{t+1})^{\sigma_w(1+\sigma_L)} \left( w_{t+1}^b / w_{t+1}^{b^*} \right)^{\sigma_v(1+\sigma_L)} H_{1t+1} \end{aligned} \tag{A.5}$$

$$H_{2t} = \lambda_t \left( w_t^b / w_t^{b*} \right)^{\sigma_w} L_t^b + \beta \theta_p (\pi_{t+1})^{\sigma_w - 1} \left( w_{t+1}^b / w_{t+1}^{b*} \right)^{\sigma_w} H_{2t+1} \tag{A.6}$$

$$\left( w_t^b \right)^{1-\sigma_w} = (1 - \theta_p) \left( w_t^{b^*} \right)^{1-\sigma_w} + \theta (\pi_t)^{\sigma_w - 1} \left( w_{t-1}^b \right)^{1-\sigma_w} \tag{A.7}$$

$$w_t^{s^*} = \frac{\sigma_w}{\sigma_w - 1} \frac{H_{3t}}{H_{4t}} \tag{A.8}$$

$$\begin{aligned} H_{3t} = \phi_L^s & \left( w_t^s / w_t^{s^*} \right)^{\sigma_w(1+\sigma_L)} (L_t^s)^{1+\sigma_L} (1 - 1/\sigma_w) \\ &+ \beta \theta_p (\pi_{t+1})^{\sigma_w(1+\sigma_L)} \left( w_{t+1}^s / w_{t+1}^{s^*} \right)^{\sigma_w(1+\sigma_L)} H_{3t+1} \end{aligned} \tag{A.9}$$

$$H_{4t} = \lambda_t (w_t^s / w_t^{s*})^{\sigma_w} L_t^s + \beta \theta_p (\pi_{t+1})^{\sigma_w - 1} \left( w_{t+1}^s / w_{t+1}^{s*} \right)^{\sigma_w} H_{4t+1} \tag{A.10}$$

$$(w_t^s)^{1-\sigma_w} = (1 - \theta_p) \left( w_t^{s^*} \right)^{1-\sigma_w} + \theta (\pi_t)^{\sigma_w - 1} \left( w_{t-1}^s \right)^{1-\sigma_w} \tag{A.11}$$

$$\pi_t^* = \frac{\sigma_p}{\sigma_p - 1} \pi_t \frac{x_{1t}}{x_{2t}} \tag{A.12}$$

$$x_{1t} = \lambda_t Y_t (mc_t - 1/\sigma_p) + \beta \theta_p (\pi_{t+1})^{\sigma_p} x_{1t+1} \tag{A.13}$$

$$x_{2t} = \lambda_t Y_t + \beta \theta_p (\pi_{t+1})^{\sigma_p - 1} x_{2t+1} \tag{A.14}$$

$$(\pi_t)^{1-\sigma_p} = (1-\theta_p)(\pi_t^*)^{1-\sigma_p} + \theta_p \tag{A.15}$$

$$Y_t^b = A_t \left(K_{t-1}^b\right)^{\alpha_b} \left(L_t^b\right)^{1-\alpha_b} \tag{A.16}$$

$$Y_t^s = A_t \left[((\zeta e_t)a + (1-\zeta e_t))\, K_{t-1}^s\right]^{\alpha_s} (L_t^s)^{1-\alpha_s} \tag{A.17}$$

$$mc_t^b = \frac{1}{A_t}\left(\frac{r_{b,t}^k}{\alpha_b}\right)^{\alpha_b}\left(\frac{w_t^b}{1-\alpha_b}\right)^{1-\alpha_b} \tag{A.18}$$

$$mc_t^s = \frac{1}{A_t}\left(\frac{r_{s,t}^k}{\alpha_s}\right)^{\alpha_s}\left(\frac{w_t^s}{1-\alpha_s}\right)^{1-\alpha_s} \tag{A.19}$$

$$mc_t = \left[\omega\left(mc_t^b\right)^{1-\varepsilon} + (1-\omega)\,(mc_t^s)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}} \tag{A.20}$$

$$Y_t^b = \omega\left(\frac{mc_t^b}{mc_t}\right)^{-\varepsilon} Y_t \tag{A.21}$$

$$Y_t^s = (1-\omega)\left(\frac{mc_t^s}{mc_t}\right)^{-\varepsilon} Y_t \tag{A.22}$$

$$(1-\alpha_b) r_{b,t}^k K_{t-1}^b = \alpha_b w_t^b L_t^b \tag{A.23}$$

$$(1-\alpha_s) r_{s,t}^k K_{t-1}^s = \alpha_s w_t^s L_t^s \tag{A.24}$$

$$R_{b,t+1}^k = \pi_{t+1}\frac{r_{b,t+1}^k + Q_{t+1}^b(1-\delta)}{Q_t^b} \tag{A.25}$$

$$R_{s,t+1}^k = \pi_{t+1}\frac{r_{s,t+1}^k + Q_{t+1}^s(1-\delta)}{Q_t^s} \tag{A.26}$$

$$K_{t+1}^b = (1-\delta)\,K_t^b + \left[1 - \frac{\kappa}{2}\left(\frac{I_t^b}{I_{t-1}^b} - 1\right)^2\right] I_t^b \tag{A.27}$$

$$K_{t+1}^s = ((\zeta e_t)a + (1-\zeta e_t))\,(1-\delta)\,K_t^s + \left[1 - \frac{\kappa}{2}\left(\frac{I_t^s}{I_{t-1}^s} - 1\right)^2\right] I_t^s \tag{A.28}$$

$$1 = Q_t^b \left[ 1 - \frac{\kappa}{2} \left( \frac{I_t^b}{I_{t-1}^b} - 1 \right)^2 - \kappa \frac{I_t^b}{I_{t-1}^b} \left( \frac{I_t^b}{I_{t-1}^b} - 1 \right) \right] + \beta Q_{t+1}^b \frac{\lambda_{t+1}}{\lambda_t} \kappa \left( \frac{I_{t+1}^b}{I_t^b} \right)^2 \left( \frac{I_{t+1}^b}{I_t^b} - 1 \right) \quad \text{(A.29)}$$

$$1 = Q_t^s \left[ 1 - \frac{\kappa}{2} \left( \frac{I_t^s}{I_{t-1}^s} - 1 \right)^2 - \kappa \frac{I_t^s}{I_{t-1}^s} \left( \frac{I_t^s}{I_{t-1}^s} - 1 \right) \right] + \beta Q_{t+1}^s \frac{\lambda_{t+1}}{\lambda_t} \kappa \left( \frac{I_{t+1}^s}{I_t^s} \right)^2 \left( \frac{I_{t+1}^s}{I_t^s} - 1 \right) \quad \text{(A.30)}$$

$$\frac{Q_{t-1}^b K_{t-1}^b}{N_{b,t-1}^E} \frac{R_{b,t}^k}{R_{b,t-1}^L} \Big( \Gamma_{t-1}^b(\bar{\omega}_t) - \mu^b G_{t-1}^b(\bar{\omega}_t) \Big) = \frac{Q_{t-1}^b K_{t-1}^b}{N_{b,t-1}^E} - 1 \quad \text{(A.31)}$$

$$\left(1 - \Gamma_t^b(\bar{\omega}_{t+1})\right) \frac{R_{b,t+1}^k}{R_{b,t}^L} + \frac{\Gamma_t^{b\prime}(\bar{\omega}_{t+1})}{\Gamma_t^{\prime}(\bar{\omega}_{t+1}) - \mu^b G_t^{b\prime}(\bar{\omega}_{t+1})} \left[ \frac{R_{b,t+1}^k}{R_{b,t}^L} \left( \Gamma_t^b(\bar{\omega}_{t+1}) - \mu^b G_t^b(\bar{\omega}_{t+1}) \right) - 1 \right] = 0 \quad \text{(A.32)}$$

$$N_{b,t}^E = \frac{\gamma^b}{\pi_t} \left[ \left( R_{b,t}^k - R_{b,t-1}^L - \mu^b G_{t-1}^b(\bar{\omega}_t) R_{b,t}^k \right) Q_{t-1}^b K_{t-1}^b + R_{b,t-1}^L N_{b,t-1}^E \right] + w^e \quad \text{(A.33)}$$

$$\frac{Q_{t-1}^s K_{t-1}^s}{N_{s,t-1}^E} \frac{R_{s,t}^k}{R_{s,t-1}^L} \Big( \Gamma_{t-1}^s(\bar{\omega}_t) - \mu^s G_{t-1}^s(\bar{\omega}_t) \Big) = \frac{Q_{t-1}^s K_{t-1}^s}{N_{s,t-1}^E} - 1 \quad \text{(A.34)}$$

$$\zeta R_{s,t+1}^k (a-1) + \zeta R_{s,t+1}^k \left( o^H(\bar{\omega}_{t+1}) - o^L(\bar{\omega}_{t+1}) \right) = e_t \quad \text{(A.35)}$$

$$(1 - o'(\bar{\omega}_{t+1})) \left[ R_{s,t+1}^k \left( \bar{\omega}_{t+1} - o(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1}) \right) - R_{s,t}^L \right] = \left[ X_{1t} - \left(1 - o'(\bar{\omega}_{t+1}) - \mu G_t'(\bar{\omega}_{t+1})\right) \right] X_{2t} \quad \text{(A.36)}$$

$$N_{s,t}^E = \frac{\gamma^s}{\pi_t} \left\{ \left[ \left( ((\zeta e_t) a + (1 - \zeta e_t) \right) R_{s,t}^k - R_{s,t-1}^L - \mu^s G_{t-1}^s(\bar{\omega}_t) R_{s,t}^k \right] Q_{t-1}^s K_{t-1}^s + R_{s,t-1}^L N_{s,t-1}^E \right\} + w^e \quad \text{(A.37)}$$

$$Z^b_{t+1} = \bar{\omega}^b_{t+1} R^k_{b,t+1} Q^b_t K^b_t / B^b_t \tag{A.38}$$

$$Z^s_{t+1} = \bar{\omega}^s_{t+1} R^k_{s,t+1} Q^s_t K^s_t / B^s_t \tag{A.39}$$

$$x_t = \frac{B^s_t}{B^b_t + B^s_t} \tag{A.40}$$

$$\mu_t = \beta(1-\theta)\Lambda_{t,t+1}\left[\left(1 - F^b_t(\bar{\omega}^b_{t+1})\right) Z^b_{t+1} - R_t\right] + \beta\theta\Lambda_{t,t+1}\frac{B^b_{t+1}}{B^b_t}\mu_{t+1} \tag{A.41}$$

$$m_t = \beta(1-\theta)\Lambda_{t,t+1}\left[\left(1 - F^s_t(\bar{\omega}^s_{t+1})\right) Z^s_{t+1} - R_t\right] + \beta\theta\Lambda_{t,t+1}\frac{B^s_{t+1}}{B^s} m_{t+1} \tag{A.42}$$

$$\eta_t = 1 - \theta + \beta\theta\frac{\lambda_{t+1}}{\lambda_t}\frac{N^B_{t+1}}{N^B_t}\eta_{t+1} \tag{A.43}$$

$$B^b_t = (1 - x_t)\phi_t N^B_t \tag{A.44}$$

$$\phi_t = \frac{\eta_t}{\Theta(x_t) - \mu_t(1 - x_t) - m_t x_t} \tag{A.45}$$

$$x_t = \frac{\mu_t}{m_t - \mu_t}\left[-1 + \sqrt{1 + \frac{2}{\iota}\left(\frac{m_t - \mu_t}{\mu_t}\right)^2}\right] \tag{A.46}$$

$$\begin{aligned} N^B_t = \theta\big[\left(R^L_{b,t} - R_{t-1}\right) B^b_t + \left(R^L_{s,t} - R_{t-1}\right) B^s_t + R_{t-1} N^B_{t-1}\big] \\ + \chi\big(B^b_{t-1} + B^s_{t-1}\big) \end{aligned} \tag{A.47}$$

$$R^L_{b,t} = \frac{R_t - RR_t}{1 - RR_t} \tag{A.48}$$

$$R^L_{s,t} = (R^L_{b,t})^{1+\xi x_t} \tag{A.49}$$

$$\begin{aligned} Y_t = C_t + I^b_t + I^s_t + G_t + \mu^b G^b_{t-1}(\bar{\omega}_t) R^k_{b,t} Q^b_{t-1} K^b_{t-1} \\ + \mu^s G^s_{t-1}(\bar{\omega}_t) R^k_{s,t} Q^s_{t-1} K^s_{t-1} \end{aligned} \tag{A.50}$$

$$GDP_t = C_t + I^b_t + I^s_t + G_t \tag{A.51}$$

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_r} \left(\frac{\pi_t}{\pi}\right)^{(1-\rho_r)\phi_\pi} \left(\frac{GDP_t}{GDP}\right)^{(1-\rho_r)\phi_y} \tag{A.52}$$

$$\frac{A_t}{A} = \left(\frac{A_{t-1}}{A}\right)^{\rho_A} \epsilon_t^A \tag{A.53}$$

$$\frac{\sigma_t^b}{\sigma^b} = \left(\frac{\sigma_{t-1}^b}{\sigma^b}\right)^{\rho_\sigma} \epsilon_t^\sigma \tag{A.54}$$

$$\frac{\sigma_t^s}{\sigma^s} = \left(\frac{\sigma_{t-1}^s}{\sigma^s}\right)^{\rho_\sigma} \frac{\sigma^b}{\sigma^s}\epsilon_t^\sigma \tag{A.55}$$

## APPENDIX B

**Results not shown**

### B.1. RESULTS OF LOCAL PROJECTION

Table 5-7 presents detailed results of the heterogeneous impact of uncertainty on firms estimated using the local projection method.

**TABLE 5.**

Heterogeneity in the effect of uncertainty on default risk.

| Panel A. Default risk of big firm | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| h | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Uncertainty | $-.0014^{***}$ | $-.0015^{***}$ | $-0.0009$ | $.0015^{**}$ | $.0036^{***}$ | $.0054^{***}$ | $.0073^{***}$ | $.0086^{***}$ | $.0074^{***}$ | $.0076^{***}$ | $.008^{***}$ | $.0068^{***}$ |
| | (−0.0002) | (−0.0004) | (−0.0006) | (−0.0007) | (−0.0009) | (−0.0011) | (−0.0013) | (−0.0015) | (−0.0017) | (−0.0019) | (−0.0023) | (−0.0026) |
| Observations | 76447 | 74526 | 72604 | 70684 | 68966 | 67248 | 65497 | 63812 | 62275 | 60738 | 59147 | 57664 |
| R-squared | 0.0112 | 0.0157 | 0.0207 | 0.0265 | 0.0356 | 0.0465 | 0.0594 | 0.0746 | 0.0782 | 0.0839 | 0.0907 | 0.1008 |
| Adj $R^2$ | −0.0247 | −0.021 | −0.0168 | −0.0118 | −0.0033 | 0.0071 | 0.0199 | 0.0348 | 0.0376 | 0.0426 | 0.0495 | 0.059 |
| F-stat | 45.2871 | 14.9052 | 2.2913 | 4.4641 | 16.2046 | 24.3192 | 30.8238 | 33.9274 | 19.907 | 16.3535 | 11.8618 | 6.8164 |
| Panel B. Default risk of small firm | | | | | | | | | | | | |
| h | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| uncertainty | $-0.0001$ | $.0006^{**}$ | $.0023^{***}$ | $.0043^{***}$ | $.0075^{***}$ | $.0102^{***}$ | $.0132^{***}$ | $.0152^{***}$ | $.0159^{***}$ | $.018^{***}$ | $.0233^{***}$ | $.0256^{***}$ |
| | (−0.0001) | (−0.0003) | (−0.0004) | (−0.0005) | (−0.0006) | (−0.0007) | (−0.0009) | (−0.001) | (−0.0011) | (−0.0012) | (−0.0015) | (−0.0016) |
| Observations | 64675 | 62437 | 60192 | 57961 | 56032 | 54103 | 52087 | 50245 | 48546 | 46850 | 45061 | 43454 |
| R-squared | 0.0177 | 0.0219 | 0.0273 | 0.0341 | 0.0503 | 0.0698 | 0.0938 | 0.1228 | 0.1225 | 0.1267 | 0.1349 | 0.1462 |
| Adj $R^2$ | −0.029 | −0.0263 | −0.0223 | −0.0169 | −0.0017 | 0.0171 | 0.0421 | 0.071 | 0.069 | 0.0716 | 0.0802 | 0.0906 |
| F-stat | 0.5791 | 5.2395 | 33.274 | 84.547 | 177.1926 | 217.3135 | 240.0099 | 245.641 | 225.1067 | 231.9992 | 250.2709 | 250.8416 |

Standard errors are in parentheses.
$^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$

**TABLE 6.**

Heterogeneity in the effect of uncertainty on financing cost.

| Panel A. Financing cost of big firm | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| h | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Uncertainty | .001*** | .001*** | .0011*** | .0008*** | .0008*** | .0006*** | .0007*** | .001*** | .0004*** | .0007*** | .0008*** | 0 |
| | (−0.0001) | (−0.0002) | (−0.0002) | (−0.0001) | (−0.0001) | (−0.0002) | (−0.0002) | (−0.0002) | (−0.0001) | (−0.0001) | (−0.0001) | (−0.0001) |
| Observations | 96303 | 96303 | 96255 | 94378 | 92438 | 90574 | 88715 | 86897 | 85091 | 83306 | 81528 | 79822 |
| R-squared | 0.0406 | 0.0377 | 0.0339 | 0.0173 | 0.0471 | 0.0596 | 0.0608 | 0.0407 | 0.0696 | 0.0799 | 0.0797 | 0.0726 |
| Adj $R^2$ | 0.0209 | 0.0179 | 0.0141 | −0.003 | 0.0271 | 0.0398 | 0.0409 | 0.0203 | 0.0495 | 0.06 | 0.0598 | 0.0523 |
| F-stat | 14.8278 | 7.835 | 10.5146 | 7.8255 | 7.6811 | 4.386 | 4.889 | 7.6054 | 5.5127 | 11.5437 | 11.8038 | 6.613 |
| Panel B. Financing cost of small firm | | | | | | | | | | | | |
| h | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Uncertainty | .0027*** | .0034*** | .0035*** | .0025*** | .0027*** | .0023*** | .0025*** | .0034*** | .0022*** | .0018*** | .0017*** | .001*** |
| | (−0.0002) | (−0.0003) | (−0.0002) | (−0.0002) | (−0.0002) | (−0.0002) | (−0.0002) | (−0.0002) | (−0.0002) | (−0.0002) | (−0.0002) | (−0.0002) |
| Observations | 92617 | 92594 | 92533 | 89599 | 86699 | 83717 | 81067 | 78416 | 75970 | 73372 | 71135 | 69023 |
| R-squared | 0.0071 | 0.012 | 0.0241 | 0.0628 | 0.0533 | 0.0545 | 0.0639 | 0.0741 | 0.0793 | 0.0852 | 0.1034 | 0.1183 |
| Adj $R^2$ | −0.0255 | −0.0204 | −0.0079 | 0.0319 | 0.0212 | 0.0237 | 0.0332 | 0.0445 | 0.0491 | 0.0571 | 0.0764 | 0.092 |
| F-stat | 35.7963 | 32.2267 | 35.3819 | 27.701 | 36.2009 | 31.235 | 30.7242 | 36.2029 | 39.7503 | 37.3209 | 33.5918 | 21.4392 |

Standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**TABLE 7.**

Heterogeneity in the effect of uncertainty on credit.

| Panel A. Credit of big firm | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| h | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Uncertainty | −.0061*** | −.009*** | −.0097*** | −.0105*** | −.0113*** | −.0124*** | −.0117*** | −.0115*** | −.011*** | −.0113*** | −.0102*** | −.0103*** |
| | (−0.0005) | (−0.0007) | (−0.0007) | (−0.0006) | (−0.0007) | (−0.0009) | (−0.001) | (−0.0009) | (−0.0009) | (−0.001) | (−0.001) | (−0.0009) |
| Observations | 82303 | 81288 | 80437 | 78421 | 76523 | 74739 | 73001 | 71392 | 69804 | 68286 | 66807 | 65406 |
| R-squared | 0.5925 | 0.5622 | 0.4959 | 0.045 | 0.4551 | 0.4684 | 0.4227 | 0.0895 | 0.4122 | 0.4382 | 0.4041 | 0.1293 |
| Adj $R^2$ | 0.5837 | 0.5527 | 0.4849 | 0.0238 | 0.4428 | 0.4564 | 0.4096 | 0.0688 | 0.3986 | 0.4251 | 0.39 | 0.1085 |
| F-stat | 43.0526 | 46.3312 | 48.9784 | 57.0746 | 60.399 | 60.7947 | 56.8427 | 60.3578 | 55.604 | 57.0793 | 53.0401 | 55.5243 |
| Panel B. Credit of small firm | | | | | | | | | | | | |
| h | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Uncertainty | −.0111*** | −.016*** | −.0147*** | −.0133*** | −.0184*** | −.021*** | −.0199*** | −.0158*** | −.0179*** | −.0204*** | −.0184*** | −.0148*** |
| | (−0.0007) | (−0.0011) | (−0.0011) | (−0.001) | (−0.0012) | (−0.0014) | (−0.0016) | (−0.0015) | (−0.0015) | (−0.0016) | (−0.0017) | (−0.0017) |
| Observations | 57478 | 55860 | 54429 | 52242 | 50241 | 48447 | 46763 | 45274 | 43801 | 42373 | 41061 | 39853 |
| R-squared | 0.4767 | 0.4299 | 0.3606 | 0.0501 | 0.3302 | 0.3455 | 0.3094 | 0.0953 | 0.3039 | 0.3201 | 0.2942 | 0.1211 |
| Adj $R^2$ | 0.4593 | 0.4107 | 0.3387 | 0.0177 | 0.3072 | 0.3232 | 0.2859 | 0.0644 | 0.2798 | 0.297 | 0.2698 | 0.0905 |
| F-stat | 1043.599 | 388.5716 | 39.8696 | 38.4824 | 326.7896 | 128.6352 | 449.3054 | 127.1219 | 1141.1029 | 375.5255 | 236.9281 | 389.5711 |

Standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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