Imperfect Banking Competition and the Propagation of Uncertainty Shocks*

Tommaso Gasparini†
Banque de France

June 3, 2025

Abstract

Uncertainty shocks, by propagating through the banking sector, play a crucial role in driving business cycle fluctuations. To examine how the recent decline in U.S. banking competition has affected the transmission of these shocks, I develop a dynamic stochastic general equilibrium model featuring heterogeneous banks, imperfect banking competition and financial frictions. The model shows that reduced competition in the banking sector leads to higher borrowing rates and increased risk-taking by borrowers. As a result, uncertainty shocks generate more pronounced increases in defaults and sharper contractions in investment and output in less competitive banking environments. Quantitatively, the model implies that the recent decline in U.S. banking competition results in a 0.1 percentage points larger drop in GDP one year after an uncertainty shock. This finding is supported by panel local projection evidence indicating that lower banking competition amplifies the negative impact of uncertainty on GDP.

Keywords: Financial frictions, financial intermediaries, heterogeneous agents, market power, uncertainty. (JEL E32, E44, G21, L13)

* I thank Klaus Adam, Jean Barthélemy, Thorsten Beck, Katarzyna Budnik, Andrea Calef, Antoine Camous, Alex Clyde, Husnu Dalgic, Aurélien Espic, Isabel Gödl-Hanisch, Basile Grassi, Stéphane Guibaud, Hendrik Hakenes, Rustam Jamilov, Aicha Kharazi, Vivien Lewis, Jochen Mankart, Matthias Meier, Stéphane Moyen, Simone Nobili, Michela Rancan, Javier Suarez, Ernst-Ludwig von Thadden, Christian Wolf and participants at various conferences and seminars for helpful comments. Support by the German Research Foundation (DFG) through CRC TR 224 (Project C05) is gratefully acknowledged. The views expressed in this paper are solely mine and do not necessarily reflect the views of the Banque de France or the Eurosystem.

† Banque de France, tommaso.gasparini@banque-france.fr, `https://tommaso-gasparini-econ.github.io/`

1 Introduction

The recent conflict in Ukraine and the Covid-19 pandemic have led to a sharp increase in uncertainty.[1] In the presence of financial frictions, uncertainty shocks increase borrower defaults and lead to a contraction in both credit supply and GDP.[2] Credit markets play a crucial role in the transmission of uncertainty shocks and structural changes in these markets can affect how such shocks are propagated. In this paper I investigate how the recent decline in competition in the US banking sector has affected the transmission of uncertainty shocks.

Over the past decades, the US banking sector has become increasingly concentrated. Since 2000, the number of commercial banks has declined sharply, accompanied by a notable rise in bank asset concentration. By 2020, the number of commercial banks had halved compared to 2000, while the asset share held by the five largest banks increased from 23% to 36%.[3]

To analyze the implications of this decline in banking competition for the transmission of uncertainty shocks, I develop a New Keynesian business cycle model featuring financial frictions and a heterogeneous, imperfectly competitive banking sector. In the model, N heterogeneous banks compete à la Cournot to provide loans to entrepreneurs. Banks allocate their equity and deposits to finance loans to entrepreneurs. Entrepreneurs, who own and maintain physical capital, have insufficient net worth and therefore rely on bank loans to purchase capital goods. Banks optimize their loan supply decisions, taking into account loan demand and the probability of borrower default.

Entrepreneurs are subject to both idiosyncratic and aggregate shocks. Idiosyncratic shocks generate heterogeneous returns on entrepreneurs' capital stock, with some en-

[1] Caldara et al. (2022), Ferrara et al. (2022) and Anayi et al. (2022) document increased uncertainty following the Russian invasion of Ukraine. Similarly, Altig et al. (2020) and Baker et al. (2020) document higher uncertainty due to the Covid-19 pandemic.

[2] See for example Christiano et al. (2014), Caldara et al. (2016) and Alessandri and Mumtaz (2019).

[3] See Figure A.1 in Appendix A.

trepreneurs experiencing returns insufficient to repay their loans, leading to default. The level of uncertainty in the economy is given by the cross-sectional dispersion of idiosyncratic shocks. As uncertainty rises, the probability of experiencing low returns increases leading to a rise in defaults. Financial frictions amplify the effects of higher uncertainty, pushing banks to reduce their credit supply. This reduction in credit constrains entrepreneurs' ability to acquire capital, leading to lower investment and a contraction of output.

Lower banking competition can have two effects on the transmission of uncertainty shocks: a *risk-shifting* effect and a *pass-through* effect. The first effect, identified by Boyd and de Nicolò' (2005) and Martinez-Miera and Repullo (2010) implies that reduced competition leads banks to assume higher portfolio risk.[4] When borrowers take on more risk, uncertainty shocks trigger sharper increases in defaults and more pronounced contractions in bank lending. At the same time, the *pass-through* effect indicates that low competition results in an incomplete pass-through of shocks, as in Drechsler et al. (2017) and Corbae and D'Erasmo (2021).

The model incorporate both the *risk-shifting* effect and the *pass-through* effect. Within a partial equilibrium framework, I show that as borrowing rates rise, entrepreneurs take on more risk, which raises their probability of default. Furthermore, higher entrepreneurial risk-taking amplifies the impact of uncertainty shocks as it leads to a more pronounced rise in default rates after an increase in uncertainty. In less competitive banking sectors, banks leverage their greater market power to impose higher borrowing rates on borrowers. This implies that a less competitive banking sector can amplify the adverse effects of uncertainty shocks.

At the same time, as banks' market power increases, banks become less likely to pass shocks onto their borrowers. Specifically, an uncertainty shock raises the number of

[4] Empirical support for this effect is provided by Schaeck and Cihák (2014), Akins et al. (2016) and Berger et al. (2017).

non-performing loans and the associated monitoring costs for banks. In response, banks reduce their loan supply. However, this reduction is smaller for banks with greater market power, as their higher profit margins act as a buffer against the impact of the shock.

I calibrate the general equilibrium model to match several US credit market statistics. The model reveals that lower banking competition amplifies the effect of uncertainty shocks through the *risk-shifting* effect. Specifically, the *risk-shifting* effect leads to a sharper increase in borrower defaults following uncertainty shocks. In turn, banks respond by substantially reducing their loan supply, which further constrains entrepreneurs' financial resources. This deepens the credit crunch and results in larger declines in investment and output.

These findings suggest that, in the presence of uncertainty shocks, the *risk-shifting* effect dominates the *pass-through* effect, leading to greater business cycle fluctuations in less competitive banking environments. When calibrated to reflect the recent decline in U.S. banking competition, the model predicts a 0.1 percentage point larger reduction in GDP one year after an uncertainty shock.

The findings of the quantitative model are consistent with empirical evidence I provide in the paper. I combine the country-level dataset of Baker et al. (2023) with data on GDP and bank concentration. In a local projection framework, where uncertainty is instrumented using the disaster shocks of Baker et al. (2023), I find that the decline in GDP following a rise in uncertainty is significantly more pronounced when banking concentration is higher.

Related literature. This paper is related to the literature on imperfect competition in the banking industry. Boyd and de Nicolò' (2005), Martinez-Miera and Repullo (2010) and Hakenes and Schnabel (2011) develop models in which less competitive banking sectors charge higher borrowing rates and hold riskier portfolios. This occurs because borrowers optimally respond to higher borrowing costs by taking on more risk – a mechanism known as the *risk-shifting* effect. This channel is empirically supported by Schaeck and Cihák (2014), Akins et al. (2016) and Berger et al. (2017). In this paper, I incorporate this mechanism into a DSGE model to examine how it affects the transmission of uncertainty shocks.

I focus on uncertainty shocks since a growing body of research has shown that these shocks play a key role in business cycle fluctuations (Bloom 2009; Christiano et al. 2014; Caldara et al. 2016; Basu and Bundick 2017; Alessandri and Mumtaz 2019; Baker et al. 2023; Gasparini et al. 2024). This paper provides both model-based and empirical evidence that the negative effects of uncertainty on economic activity are amplified in environments with lower banking competition.

Scharfstein and Sunderam (2013), Drechsler et al. (2017), Cuciniello and Signoretti (2018), and Gödl-Hanisch (2022) explore the role of imperfect competition in the banking sector for the transmission of monetary policy. While Scharfstein and Sunderam (2013) find – both empirically and in a Cournot competition model – that high concentration in the US banking sector weakens monetary policy transmission, the monopolistic competition models of Gödl-Hanisch (2022) and Cuciniello and Signoretti (2018) suggest that monetary policy shocks have stronger effects when competition is lower. Drechsler et al. (2017), show that when policy rates rise, banks that raise deposits in concentrated markets increase their deposit rate by less and contract their lending by more than other banks. Unlike this strand of literature, I focus on shocks that affect the asset side of banks rather than their deposit funding.

Jamilov and Monacelli (forthcoming) develop a quantitative macroeconomic model with heterogeneous monopolistic financial intermediaries and find that imperfect competition for deposits reduces the impact of TFP shocks. Villa (2024) builds a model in which banks compete à la Cournout for loans and deposits and argues that a sudden rise in firms' default probability has stronger negative effects in less competitive banking sectors because banks extract higher markups. Unlike these studies, I introduce the *risk-shifting* effect, allowing bank competition to influence the riskiness of bank assets. Following Corbae and D'Erasmo (2021), and given the focus on shocks to bank assets, I assume that banks compete à la Cournot in the loan market.

Outline. The paper is structured as follows. In Section 2 I outiline the general equilibrium model. First, I describe the borrower side and I introduce the *risk-shifting* effect. Then, I describe the banking sector and the rest of the model. Section 3 displays the calibration and the results of the model. Section 4 provides empirical evidence that support the model's results. Finally, Section 5 concludes.

2 Quantitative model

In this section, I develop a general equilibrium model to investigate the impact of the recent fall in competition in the US banking sector on the propagation of uncertainty shocks. The analysis begins with the introduction of the entrepreneurial sector, where I show the presence of a *risk-shifting effect*, meaning that entrepreneurs tend to increase risk-taking when faced with higher interest rates. I then incorporate a heterogeneous banking sector into the framework and provide a comprehensive description of the remaining model components.

2.1 Entrepreneurial sector and *risk-shifting* effect

The entrepreneurial sector is modeled following Clerc et al. (2018). There exists a continuum of risk-neutral entrepreneurs, indexed by $j \in (0, 1)$, each of whom lives for two consecutive periods. Entrepreneurs born at time t have financial resources given by inherited wealth from the previous generation, $n_t^{E,j}$ and loans b_t^j provided by the banking sector. These resources are used to purchase capital goods from capital producers, which are subsequently rented out to final goods producers.

Entrepreneurs derive utility from donating part of their final wealth as dividends to households, $c_{t+1}^{E,j}$, and retaining the remainder as earnings for the next generation, $n_t^{E,j}$. Their utility function is given by: $(c_{t+1}^{E,j})^{\chi^E}(n_{t+1}^{E,j})^{1-\chi^E}$. The entrepreneur's maximization problem at time $t+1$ is:

$$\max_{c_{t+1}^{E,j},n_{t+1}^{E,j}} (c_{t+1}^{E,j})^{\chi^E}(n_{t+1}^{E,j})^{1-\chi^E},$$

subject to the budget constraint:

$$c_{t+1}^{E,j} + n_{t+1}^{E,j} \leq W_{t+1}^{E,j},$$

where $W_{t+1}^{E,j}$ denotes the entrepreneur's final wealth. The first-order conditions lead to the dividend rule $c_{t+1}^{E,j} = \chi^E W_{t+1}^{E,j}$ and the retained earnings rule $n_{t+1}^{E,j} = (1-\chi^E)W_{t+1}^{E,j}$.

Entrepreneurs' wealth at time $t+1$ is determined as:

$$W_{t+1}^{E,j} = \frac{\max[\omega_{t+1}^j R_{t+1}^E q_t K_t^j - R_t^F b_t^j, 0]}{\Pi_{t+1}}, \tag{1}$$

where ω_{t+1}^j represents an idiosyncratic productivity shock, R_{t+1}^E is the return per efficiency unit of capital, q_t is the price of capital, R_t^F is the borrowing rate, and $\Pi_{t+1} = P_{t+1}/P_t$ is the gross inflation rate. The idiosyncratic shock ω_{t+1}^j is independently and identically distributed across entrepreneurs and follows a log-normal distribution with mean one and standard deviation $\sigma_t = \sigma\varsigma_t$. The cdf and the pdf of the idiosyncratic shock are denoted by $F(\cdot)$ and $f(\cdot)$, respectively. The level of uncertainty is given by σ_t, while ς_t is an uncertainty shock that follows an AR(1) process:

$$\ln\varsigma_t = \rho\ln\varsigma_{t-1} + \varepsilon_t, \tag{2}$$

where $0 < \rho < 1$ and σ^{ε} is the standard deviation of the *iid* shock ε_t.

Entrepreneurs and banks enter into a financial contract where the loan repayment depends on the realization of a random productivity shock ω^j_{t+1}. If the shock exceeds a default cutoff $\bar{\omega}^j_{t+1}$, the entrepreneur pays the banks $R^F_t b^j_t$, otherwise the entrepreneur defaults. The default cutoff is given by:

$$\overline{\omega}^j_{t+1} = \frac{R^F_t b^j_t}{R^E_{t+1} q_t K^j_t}. \tag{3}$$

Unlike Bernanke et al. (1999), the default cutoff $\overline{\omega}^j_{t+1}$ varies with the realization of the aggregate state R^E_{t+1}. The probability of default of an entrepreneur is:

$$F^j_{t+1} = F(\overline{\omega}_{t+1}) = \int_0^{\overline{\omega}_{t+1}} f(\omega^j_{t+1}) \mathrm{d}\omega^j_{t+1} = \Phi\left(\frac{\log(\overline{\omega}^j_{t+1}) + 0.5\sigma^2_{t+1}}{\sigma_{t+1}}\right). \tag{4}$$

In case of default, the entrepreneur obtains nothing and banks must pay a monitoring cost ξ.

Similar to Gertler and Kiyotaki (2010), Gertler and Karadi (2011) and Kühl (2017), entrepreneurs face a moral hazard problem: at time t they can divert a fraction λ of their funds. To prevent this, the following incentive constraint must hold:[5]

$$\mathbb{E}_t\left(\lambda \frac{q_t K^j_t}{\Pi_{t+1}}\right) \leq \mathbb{E}_t(W^{E,j}_{t+1}) \tag{5}$$

Entrepreneurs maximize expected future wealth by choosing how much capital K^j_t to

[5] Note that since banks make positive profits because of imperfect competition in the banking sector, the financial contract cannot be derived using a banks' zero profit condition as in Bernanke et al. (1999). For this reason, I assume that entrepreneurs face both a costly state verification problem and an incentive constraint.

buy and how much to borrow b_t from banks:

$$\max_{K_t^j, b_t^j} \mathbb{E}_t(W_{t+1}^{E,j}),$$

subject to the resource constraint:

$$q_t K_t^j - b_t^j = n_t^{E,j}. \tag{6}$$

and to the incentive constraint (5).[6]

In the equilibrium described below, the constrain is always binding around the steady state under reasonable parameter values. Therefore, the loan demand and the demand for capital are implicitly determined by the incentive participation constraint:

$$\mathbb{E}_t \left\{ \frac{(1 - \Gamma(\overline{\omega}_{t+1}^j)) R_{t+1}^E}{\Pi_{t+1}} \right\} = \mathbb{E}_t \left\{ \frac{\lambda}{\Pi_{t+1}} \right\}, \tag{7}$$

where $\Gamma(\overline{\omega}_{t+1}^j) = \Gamma_{t+1}^j$ is the expected share of return that entrepreneurs retain after paying borrowing costs. Since all entrepreneurs face the same borrowing rate and expected return, the model can be aggregated by dropping the indices j from now on.

Propositions 1 and 2 demonstrate that higher borrowing rates reduce loan demand and entrepreneurial leverage while increasing default risk due to limited liability. Entrepreneurs do not lower their leverage sufficiently to offset higher borrowing costs, leading to a positive relationship between borrowing rates and both the default cutoff and default rate.

Proposition 1. *If R_{t+1}^E is a decreasing function of K_t, for a given q_t, loan demand is a decreasing function of the loan rate R_t^F.*

Proposition 2. *If R_{t+1}^E is a decreasing function of K_t, for a given q_t, the default rate*

[6] Note that entrepreneurs choose their probability of default by choosing K_t^j and b_t^j.

F_{t+1} and the default cutoff of entrepreneurs $\bar{\omega}_{t+1}$ increase with the borrowing rate R_t^F.

The proofs of Propositions 1 and 2 are provided in Appendix B.1.

Proposition 3 further shows that an increase in uncertainty has a greater impact on entrepreneurial defaults when the default cutoff is higher. Since entrepreneurs take more risk when they have a higher default cutoff, an increase in uncertainty has a larger impact on default rates.

Proposition 3. *If $\overline{\omega}_{t+1} \leq e^{-\sigma_{t+1}-0.5\sigma_{t+1}^2}$, if $\sigma_{t+1} \leq 1$ and if R_{t+1}^E is a decreasing function of K_t, for a given q_t, an increase in uncertainty results in a larger rise in the default rate of entrepreneurs when the default cutoff is higher.*

The proof of Proposition 3 is provided in Appendix B.1.[7]

In less competitive banking sectors, since banks charge higher borrowing rates, the default rate of entrepreneurs is higher. This mechanism, termed the *risk-shifting* effect by Martinez-Miera and Repullo (2010), implies that an uncertainty shock can rise the default rate of entrepreneurs more strongly in less competitive banking sectors, leading banks to reduce loans further. The stronger reduction in loans results in a more severe lack of resources for entrepreneurs, leading to a stronger decline in investment and output.

2.2 Banks

In this section, I present the banking sector. A fixed number of banks, N, compete à la Cournot for loans. Each bank is indexed by i and operates across two consecutive periods. Banks established at time t have equity in the form of inherited wealth from the previous generation of banks, $n_t^{F,i}$, and borrow deposits d_t^i from households. These financial resources are used to extend loans to entrepreneurs.

[7] The condition $\overline{\omega}_{t+1} \leq e^{-\sigma_{t+1}-0.5\sigma_{t+1}^2}$ implies that $F(\bar{\omega}_{t+1}) \leq \Phi(-1) \approx 15.87\%$ per quarter. The conditions of Proposition 3 are satisfied in equilibrium.

At time $t+1$, banks derive utility from distributing a portion of their final wealth as dividends to households, $c_{t+1}^{F,i}$ and by leaving the rest as retained earnings to the next generation of banks. They choose how much to distribute as dividends and how much to retain as earnings according to the utility function $(c_{t+1}^{F,i})^{\chi^{F,i}}(n_{t+1}^{F,i})^{1-\chi^{F,i}}$. Thus, the maximization problem of each bank at time $t+1$ is:

$$\max_{c_{t+1}^{F,i}, n_{t+1}^{F,i}} (c_{t+1}^{F,i})^{\chi^{F,i}}(n_{t+1}^{F,i})^{1-\chi^{F,i}},$$

subject to the resource constraint:

$$c_{t+1}^{F,i} + n_{t+1}^{F,i} \leq W_{t+1}^{F,i},$$

where $W_{t+1}^{F,i}$ is the final wealth of bank i established at time t. The first order conditions lead to the dividend payment rule:

$$c_{t+1}^{F,i} = \chi^{F,i} W_{t+1}^{F,i}, \tag{8}$$

and the earning retention rule:

$$n_{t+1}^{F,i} = (1-\chi^{F,i}) W_{t+1}^{F,i}. \tag{9}$$

The future wealth of each bank is given by:

$$W_{t+1}^{F,i} = \frac{\tilde{R}_{t+1}(b_t)b_t^i - R_t^D d_t^i - \gamma^i b_t^i}{\Pi_{t+1}}.$$

A bank's future wealth depends on the net return from lending to entrepreneurs, accounting for deposit costs and intermediation expenses. The return from lending is determined by the amount of loans extended, multiplied by the return per unit of loans,

$\tilde{R}_{t+1}$. Deposit costs are given by the deposit rate R_t^D times the amount of deposits. Additionally, each bank incurs a per-loan intermediation cost, γ^i, which varies across banks. All of these factors are discounted by the gross inflation rate Π_{t+1}.

In this model, banks are heterogeneous due to differences in their intermediation costs and dividends. The intermediation cost γ^i is a reduced-form tool which allows to capture heterogeneity in bank loan supply. It stands for real-world costs or subsidies associated with providing loans. The dividend parameter $\chi^{F,i}$ is a reduced-form parameter which allows to capture heterogeneity in leverage across banks.[8]

The return per unit of loans is:

$$\tilde{R}_{t+1} = (1 - F_{t+1})R_{t+1}^F + (1 - \xi) \int_0^{\overline{\omega}_{t+1}} \omega_{t+1} f(\omega_{t+1}) \mathrm{d}\omega_{t+1} \frac{R_{t+1}^E q_t K_t}{b_t}. \qquad (10)$$

The first term of Equation 10 represents the return from performing loans, while the second term represents the return from non-performing loans. When a loan defaults, banks incur a monitoring cost ξ to observe the entrepreneur's realized return on capital. This cost is proportional to the entrepreneur's gross payoff. Notably, all banks receive the same return from non-performing loans since they hold equal seniority.

At time t, each bank decides how much to lend to entrepreneurs and how much to borrow from households, taking the decisions of other banks as given. The objective is to maximize expected future wealth:

$$\max_{\{b_t^i, d_t^i\}} \mathbb{E}_t \frac{\tilde{R}_{t+1}(b_t) b_t^i - R_t^D d_t^i - \gamma^i b_t^i}{\Pi_{t+1}},$$

[8] The literature has introduced heterogeneity through various channels. Boissay et al. (2016) assume that financial intermediaries differ in their intermediation costs, Corbae and D'Erasmo (2021) introduce heterogeneity via deposit capacity shocks, Coimbra and Rey (2023) model banks with different value-at-risk constraints and Jamilov and Monacelli (forthcoming) incorporate ex-ante heterogeneity in banks' rates of return.

subject to the balance sheet constraint:

$$n_t^{F,i} + d_t^i \geq b_t^i, \tag{11}$$

and the loan demand (7) due to imperfect competition. The first order condition of the maximization problem, after substituting the balance sheet constraint, is:

$$\mathbb{E}_t \left\{ \frac{\frac{\partial \tilde{R}_{t+1}}{\partial b_t} b_t^i + \tilde{R}_{t+1} - R_t^D - \gamma^i}{\Pi_{t+1}} \right\} = 0.$$

Due to imperfect competition, the optimal decisions of each bank depend on how their lending affects the return they receive from entrepreneurs. The extent of this impact is determined by the slope of the loan demand curve and the level of competition in the banking sector.

Competition in the banking sector not only influences bank profitability but also determines how banks pass economic shocks onto borrowers. Larger banks have higher markups and earn higher profits, but pass shocks through to borrowers by a lesser extent, as profits partially absorb shocks. In contrast, smaller banks, adjust their loan supply more aggressively in response to shocks. An uncertainty shock raises the share of non-performing loans and monitoring costs, prompting banks to reduce lending. Since smaller banks have lower market power, they cut loan supply more sharply than larger banks. I define this relationship as the *pass-through* effect, the extent to which banking competition influences the transmission of shocks to borrowers.

If all banks have the same intermediation cost and the same dividend policy, the equilibrium is symmetric, and the first-order conditions can be aggregated as:

$$\mathbb{E}_t \left\{ \frac{\frac{\partial \tilde{R}_{t+1}}{\partial b_t} \frac{b_t}{N} + \tilde{R}_{t+1} - R_t^D - \gamma}{\Pi_{t+1}} \right\} = 0.$$

As the number of banks grows, the influence of any single bank's decision on loan returns diminishes, reducing banks' market power.

2.3 Rest of the model

The rest of the model follows a standard New Keynesian framework. Households maximize their utility choosing consumption, labor supply and deposits supply. The production sector comprises final, intermediate, and capital goods producers. Final goods producers are perfectly competitive and use intermediate goods to produce consumption bundles using a constant-elasticity-of-substitution technology. Final goods are sold to households and to capital producers. Intermediate goods producers use capital rented from entrepreneurs and labor to produce intermediate goods with a Cobb-Douglas technology, setting prices subject to quadratic adjustment costs. This leads to a standard New Keynesian Phillips curve. Capital goods producers buy the final good, convert it into capital, and sell it to entrepreneurs. The model is closed by a central bank that sets the policy rate following a monetary policy rule.

2.3.1 Gross return on capital

The price of capital q_t is time-varying and determined by the equilibrium of demand and supply of capital.

The gross return on capital is

$$R_t^E = \frac{r_t^K + (1-\delta)\, q_t}{q_{t-1}} \Pi_t.$$

The gross return on capital is given by the sum of the real rental rate on capital r_t^K and the real capital gains net of depreciation $(1-\delta)\, q_t$, divided by the real price per unit of capital in period $t-1$. Finally, the return is expressed in nominal terms and multiplied by the inflation rate.

2.3.2 Households

Households are infinitely lived and maximize their expected lifetime utility,

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left(\ln c_t - \varphi \frac{l_t^{1+\eta}}{1+\eta} \right), \tag{12}$$

where $\beta \in (0,1)$ is the discount factor, c_t is consumption, l_t is labor supply, $\varphi > 0$ is the relative weight on labor disutility and $\eta \geq 0$ is the inverse Frisch elasticity of labor supply. Households choose consumption, labor supply and deposit supply to maximize (12) subject to the budget constraint,

$$c_t + d_t \leq w_t l_t + \frac{R_t^D d_{t-1}}{\Pi_t} + \Xi_t^K + \sum_{i=1}^{N} \chi^{F,i} W_t^{F,i} + \chi^E W_t^E + \Xi_t^P + \sum_{i=1}^{N} \gamma^i b_t^i, \tag{13}$$

where w_t is the real wage, R_t^D is the gross interest rate on deposits paid in period t, Ξ_t^K and Ξ_t^P are profits earned by capital goods producers and intermediate goods producers, respectively, and $\sum_{i=1}^{N} \chi^{F,i} W_t^{F,i}$ and $\chi^E W_t^E$ are the dividends received by households from banks and entrepreneurs respectively. The first order conditions of the optimization problem lead to a labor supply equation, $w_t = \varphi l_t^{\eta} / \Lambda_t$, and an Euler equation, $1 = \mathbb{E}_t\{\beta_{t,t+1} R_{t+1}^D / \Pi_{t+1}\}$, where $\beta_{t,t+s} = \beta^s \Lambda_{t+s} / \Lambda_t$ is the household's stochastic discount factor and $\Lambda_t = 1/c_t$ is the Lagrange multiplier on the budget constraint.

2.3.3 Final goods producers

Final goods producers bundle the intermediate goods Y_{it}, with $i \in (0,1)$, taking as given their price P_{it}, and sell the output Y_t at the competitive price P_t. Final goods producers choose the amount of inputs Y_{it} that maximizes profits $P_t Y_t - \int_0^1 Y_{it} P_{it} \mathrm{d}i$, subject to the production function $Y_t = (\int_0^1 Y_{it}^{(\varepsilon-1)/\varepsilon} \mathrm{d}i)^{\varepsilon/(\varepsilon-1)}$, where $\varepsilon > 1$ is the elasticity of substitution between intermediate goods. The resulting demand for intermediate good i is $Y_{it}^d = (P_{it}/P_t)^{-\varepsilon} Y_t$. The price of final output, which is interpreted as the price index, is given by $P_t = (\int_0^1 P_{it}^{1-\varepsilon} \mathrm{d}i)^{1/(1-\varepsilon)}$. In a symmetric equilibrium, the price of a variety and the price index coincide, $P_t = P_{it}$.

2.3.4 Intermediate goods producers

Intermediate goods producers use capital and labor to produce intermediate goods according to a Cobb-Douglas production function. Because of the assumption of constant returns to scale the production function can be aggregated. Each producer produces a differentiated good using $Y_{it} = A_t K_{it-1}^{\alpha} l_{it}^{1-\alpha}$, where $\alpha \in (0,1)$ is the capital share in production, A_t is aggregate technology, K_{it-1} is capital and l_{it} is labor. Intermediate goods producers choose the amount of inputs to maximize profits given by $P_{it}Y_{it}/P_t - r_t^K K_{it-1} - w_t l_{it}$, where the real rental rate on capital r_t^K and the real wage w_t are taken as given, subject to the technological constraint and the demand constraint. The optimization problem results in a labor demand and a capital demand that are $w_t l_{it} = (1-\alpha) s_{it} Y_{it}$ and $r_t^K K_{it-1} = \alpha s_{it} Y_{it}$, respectively, where the Lagrange multiplier on the demand constraint, s_{it}, represents real marginal costs. By combining the two demands, it is possible to obtain an expression for real marginal costs that is symmetric across producers,

$$s_t = \frac{w_t^{1-\alpha} (r_t^K)^{\alpha}}{\alpha^{\alpha} (1-\alpha)^{1-\alpha}} \frac{1}{A_t}. \tag{14}$$

Firm i sets an optimal path for its product price P_{it} to maximize the present discounted value of future profits, subject to the demand constraint and to price adjustment costs,

$$\mathbb{E}_t \sum_{s=0}^{\infty} \beta_{t,t+s} \left[\frac{P_{it+s} Y_{it+s}^d}{P_{t+s}} - \frac{\kappa_p}{2} \left(\frac{P_{it+s}}{P_{it+s-1}} - 1 \right)^2 Y_{it+s} + s_{t+s} \left(Y_{it+s} - Y_{it+s}^d \right) \right]. \tag{15}$$

Price adjustment costs are given by the second term in square brackets in (15); they depend on firm revenues and on last period's aggregate inflation rate. The parameter $\kappa_p > 0$ scales the price adjustment costs. Under symmetry, all firms produce the same amount of output, and the firm's price P_{it} equals the aggregate price level P_t, such that the price setting condition is

$$\kappa_p \Pi_t(\Pi_t - 1) = \varepsilon s_t - (\varepsilon - 1) + \kappa_p \mathbb{E}_t \left\{ \beta_{t,t+1} \Pi_{t+1}(\Pi_{t+1} - 1) \frac{Y_{t+1}}{Y_t} \right\}. \tag{16}$$

Under symmetry across intermediate goods producers, profits (in real terms) are $\Xi_t^P = Y_t - r_t^K K_{t-1} - w_t l_t - 0.5 \cdot \kappa_p (\Pi_t - 1)^2 Y_t$.

2.3.5 Capital goods producers

Capital goods producers choose paths for investment I_t to maximize the expected present value of future profits given by $\mathbb{E}_t \sum_{s=0}^{\infty} \beta_{t,t+s} \left[q_{t+s} I_{t+s} - (1 + g_{t+s}) I_{t+s} \right]$. The term $g_t = 0.5 \cdot \kappa_I (I_t / I_{t-1} - 1)^2$ captures investment adjustment costs as in Christiano et al. (2014). Capital accumulation is defined as

$$I_t = K_t - (1 - \delta) K_{t-1}, \tag{17}$$

where $\delta \in (0, 1)$ is the capital depreciation rate. The maximization problem leads to the optimality condition for investment

$$1 = q_t - \frac{\kappa_I}{2} \left(\frac{I_t}{I_{t-1}} - 1 \right)^2 - \kappa_I \left(\frac{I_t}{I_{t-1}} - 1 \right) \frac{I_t}{I_{t-1}} + \mathbb{E}_t \left\{ \beta_{t,t+1} \kappa_I \left(\frac{I_{t+1}}{I_t} - 1 \right) \left(\frac{I_{t+1}}{I_t} \right)^2 \right\}. \tag{18}$$

In period t the profits of capital producers in real terms are $\Xi_t^K = q_t I_t - (1 + g_t) I_t$.

2.3.6 Central Bank

I assume the central bank sets the policy rate according to a standard Taylor rule. The monetary policy rule depends on its own lag, inflation and GDP growth. The respective feedback coefficients are τ_R, τ_Π and τ_y such that:

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\tau_R} \left[\left(\frac{\Pi_t}{\Pi}\right)^{\tau_\Pi} \left(\frac{GDP_t}{GDP_{t-1}}\right)^{\tau_y}\right]^{1-\tau_R}, \tag{19}$$

where GDP is defined as output net of default costs.

Since the deposit rate is risk-free, the policy rate and the deposit rate are identical, $R_t = R_t^D$.

2.3.7 Market clearing

The production of consumption goods must be equal to the sum of goods demanded by households, goods used for investment, resources lost when adjusting prices and investment, as well as resources lost in the recovery of funds associated with defaults,

$$Y_t = c_t + (1+g_t)I_t + \frac{\kappa_p}{2}\left(\Pi_t - 1\right)^2 Y_t + \mu^E G_t^E \frac{R_t^E q_{t-1} K_{t-1}}{\Pi_t}.$$

Labor demand must equal labor supply

$$(1-\alpha)s_t Y_t / l_t = \varphi_t l_t^\eta / \Lambda_t.$$

2.4 Equilibrium

An equilibrium is a set of allocations $\{l_t, K_t, I_t, c_t, Y_t, n_t^E, \{b_t^i, n_t^{F,i}, d_t^i\}_{i=1}^N\}_{t=0}^\infty$, prices $\{q_t, w_t, r_t^K, \Pi_t, s_t\}_{t=0}^\infty$ and rates of return $\{R_t^F, R_t^E, R_t^D, \tilde{R}_t\}_{t=0}^\infty$ for which given the monetary policy $\{R_t\}_{t=0}^\infty$ and shocks to uncertainty $\{\varsigma_t\}_{t=0}^\infty$

- Entrepreneurs and banks maximize expected future wealth,
- Producers maximize profits,
- Households maximize utility,
- All markets clear.

3 Results

This section presents the calibration of the model and examines the implications of the recent change in the level of competition for the transmission of uncertainty shocks.

3.1 Calibration

Table 1 lists the parameter values used to calibrate the model to the US economy for the period 2000Q1–2019Q4. This period was characterized by relatively high bank concentration. The discount factor β is chosen to match the average annual Federal Funds Effective Rate of 1.8%. The capital share in production α and the depreciation rate of capital are taken from Christiano et al. (2014). The fraction of resources lost due to entrepreneur defaults ξ is calibrated to match the charge-off rate on loans. The dividend payout ratio for entrepreneurs χ^E is chosen to match the return on equity of NFCs. The proportion of assets that entrepreneurs can divert λ is calibrated to match the investment-to-GDP ratio.

The number of banks N is set to the number of banks that cover 50% of total bank assets in the data. The dividend payout ratios $\chi^{F,i}$ are chosen to match the ratio of bank equity to assets of each bank. Intermediation costs γ^i are chosen to match the share of total assets held by each bank in the selected sample and the Lerner index for the banking sector from Wheelock and Wilson (2019).[9]

The inverse Frish labor elasticity η is taken from Christiano et al. (2014), while the elasticity of substitution between intermediate goods ϵ is taken from Christensen and Dib (2008) to match a markup of 1.2. The weight on labor disutility is chosen to normalize labor supply to 1.

The autocorrelation of the uncertainty shock ρ, the magnitude of the uncertainty shock σ^{ε}, price adjustment cost, investment adjustment cost, the smoothing parameter in the Taylor rule, and the Taylor rule coefficients for inflation and GDP growth are all calibrated to match the empirical impulse responses to an uncertainty shock derived from a VAR model similar to the one of Basu and Bundick (2017). The VAR model is described in Appendix C.1. A period corresponds to a quarter.

Table 1: Calibration of the baseline model

Variable	Meaning	Value	Target
β	Discount factor	0.9956	FED Funds Rate
α	Capital share in production	0.4	Christiano et al. (2014)
δ	Depreciation rate capital	0.025	Christiano et al. (2014)
ξ	Entrepreneur bankruptcy cost	0.3363	Charge-off rate loans
σ	Steady-state uncertainty	0.3788	Delinquency rate loans
χ^E	Dividend payout entrepreneurs	0.0252	ROE NFCs
N	Number of banks	17	Number of banks that cover 50% of total assets
$\chi^{F,i}$	Dividend payout banks	$0.0782 \leq \chi^{F,i} \leq 0.5940$	Bank equity ratios
λ	Proportion divertible assets entrepreneurs	0.6435	Investment/GDP
γ^i	Bank intermediation cost	$-0.1141 \leq \gamma^i \leq 0.0018$	Bank asset shares & Lerner index
η	Inverse Frisch labor elasticity	1	Christiano et al. (2014)
ε	Substitutability between goods	6	Christensen and Dib (2008)
φ	Weight on labor disutility	0.6090	Labor supply $= l = 1$
σ^{ε}	Size uncertainty shock	0.0452	VAR
ρ	Autocorrelation uncertainty shock	0.8383	VAR
κ_p	Price adjustment cost	332	VAR
κ_I	Investment adjustment cost	0.4366	VAR
τ_R	Coeff. TR for lag policy rate	0.6335	VAR
τ_{Π}	Coeff. TR for inflation	1.3717	VAR
τ_y	Coeff. TR for *GDP* growth	0.1392	VAR

Notes. The table describes the calibration of the baseline model.

[9] Negative values of γ^i can be due to the subsidies that banks receive for providing loans. One example is the too-big-to-fail subsidy.

3.2 Impact of uncertainty shocks

This section examines the effects of an uncertainty shock in the baseline model. Figure 1 compares the impulse responses of the baseline model with the responses of the VAR model to an uncertainty shock. The solid blue lines represent the VAR impulse responses, with 95% confidence intervals in light blue, while the dashed red lines show the impulse responses generated by the baseline model.

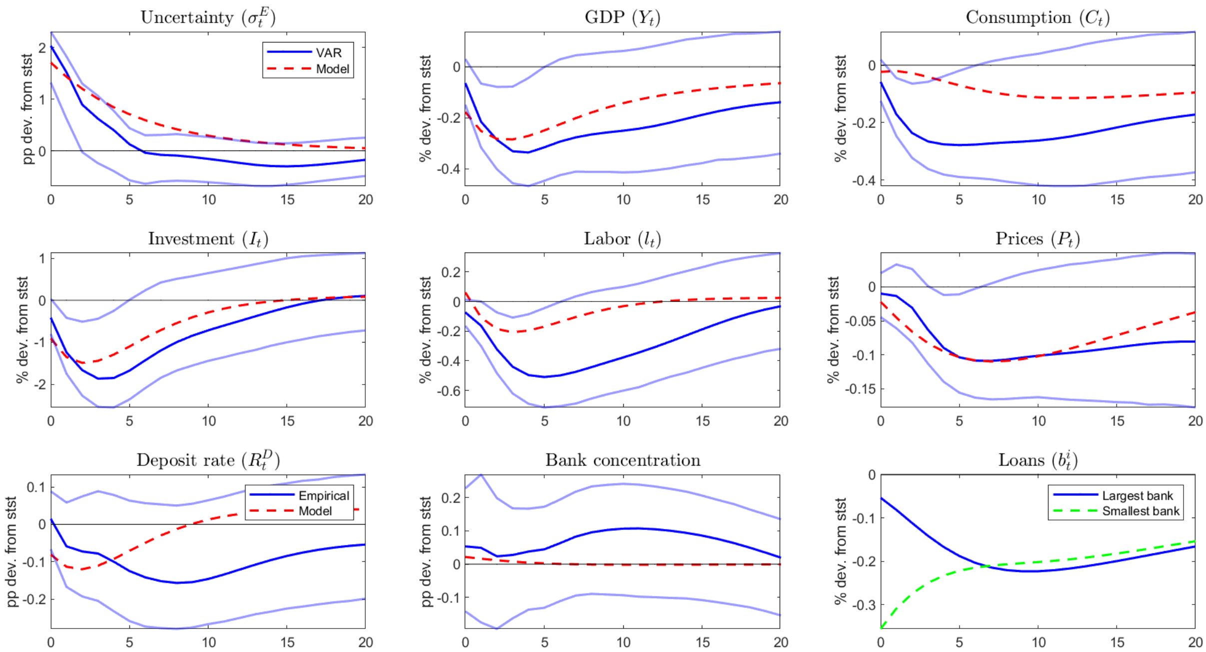
The baseline model can well match the empirical impulse responses. A rise in uncertainty leads to a contraction in economic activity, consumption, investment and GDP after the shock hits the economy. There is a demand-driven downturn as in Christiano et al. (2014). The shock causes a drop in inflation, prompting the central bank to lower the policy rate in response to falling prices and GDP. Additionally, bank concentration, measured by the share of assets held by the five largest banks, increases following the shock.

The last panel of Figure 1 compares the impulse responses of loans for the largest and smallest banks in the baseline model. The solid blue line represents the response of the largest bank, while the green dashed line represents the one of the smallest bank. Because of a lower intermediation cost, the largest bank has a higher market power compared to the smallest bank. As a consequence, due to the *pass-through* effect, the largest bank reduces its loan supply less aggressively, as its margins absorb part of the shock.

3.3 Implication of the recent fall in banking competition

Over the past two decades, banking competition in the US has declined. Reduced competition, through the *risk-shifting* effect, increases borrowers' default risk and can amplify the impact of uncertainty shocks. At the same time, the *pass-through* effect implies that lower banking competition may dampen the transmission of shocks by absorbing them in bank's profit margins. How has the recent decline in banking competition affected the

Figure 1: Comparison of VAR and model impulse responses to an uncertainty shock.



Notes. The graph compares the impulse responses of the baseline model with the empirical impulse responses from the VAR model described in Appendix C.1. The blue solid lines represent the VAR impulse responses with the 95% confidence intervals in light blue. The red dashed lines show the impulse responses of the baseline model. The last panel compares the impulse responses of loans for the largest and smallest banks in the baseline model.

impact of uncertainty shocks?

To address this question, I recalibrate the baseline model to reflect recent changes in the banking sector. Specifically, I construct a version of the model with high competition, calibrated to match the characteristics of the banking sector from 1980 to 1999.

In this high-competition model, the number of banks N is set to match the number of banks covering 50% of total bank assets during this period. The dividend payout ratios $\chi^{F,i}$ are calibrated to match the ratio of bank equity to assets of each bank. Intermediation costs γ^i are chosen to match the asset distribution among selected banks while maintaining the same average intermediation cost as the baseline model for comparability.

Table 2 presents the calibrated parameters for the high-competition model. The number of banks is higher in this model, reflecting the lower concentration in the banking sector. At the same time, the range of intermediation costs is narrower as larger banks capture a smaller share of total assets. Lastly, in the high-competition model, banks exhibit lower dividend payouts, consistent with reduced profitability in a more competitive environment.[10]

Table 2: Calibration of the model with high competition

Variable	Meaning	Value	Target
$\chi^{F,i}$	Dividend payout banks	$0.0259 \leq \chi^{F,i} \leq 0.4852$	Bank equity ratios
γ^i	Bank intermediation cost	$-0.0896 \leq \gamma^i \leq -0.0372$	Bank asset shares & average intermediation cost
N	Number of banks	103	Number of banks that cover 50% of total assets

Notes. The table describes the calibration of the model with high competition.

Table 3 compares the steady-state of the baseline model with the one of the high-competition model. In the high-competition model, banks extend more loans to entrepreneurs and do so with a lower markup, as reflected in the lower Lerner index. Greater competition leads to lower borrowing rates, which, in turn, reduce the probability of entrepreneur defaults, as indicated by Proposition 2, due to the *risk-shiting* effect. As a result of increased lending, GDP, investment, and consumption are all higher in the high-competition model.

Table 3: Steady-state comparison baseline and high-competition model

	2000-2019	1980-1999
GDP	3.6089	5.2487
Investment	0.6280	1.4530
Consumption	2.9810	3.7957
Loans	9.3629	21.6646
Lerner index	0.9000	0.6489
Firm default prob.	0.0306	0.0244
Interm. costs	-0.5710	-1.1379

Notes. The table compares the steady-state of the baseline model with the one of the model with high competition.

According to Proposition 3, the lower interest rate in the high-competition model should lead to a smaller increase in the default rate of entrepreneurs following an uncer-

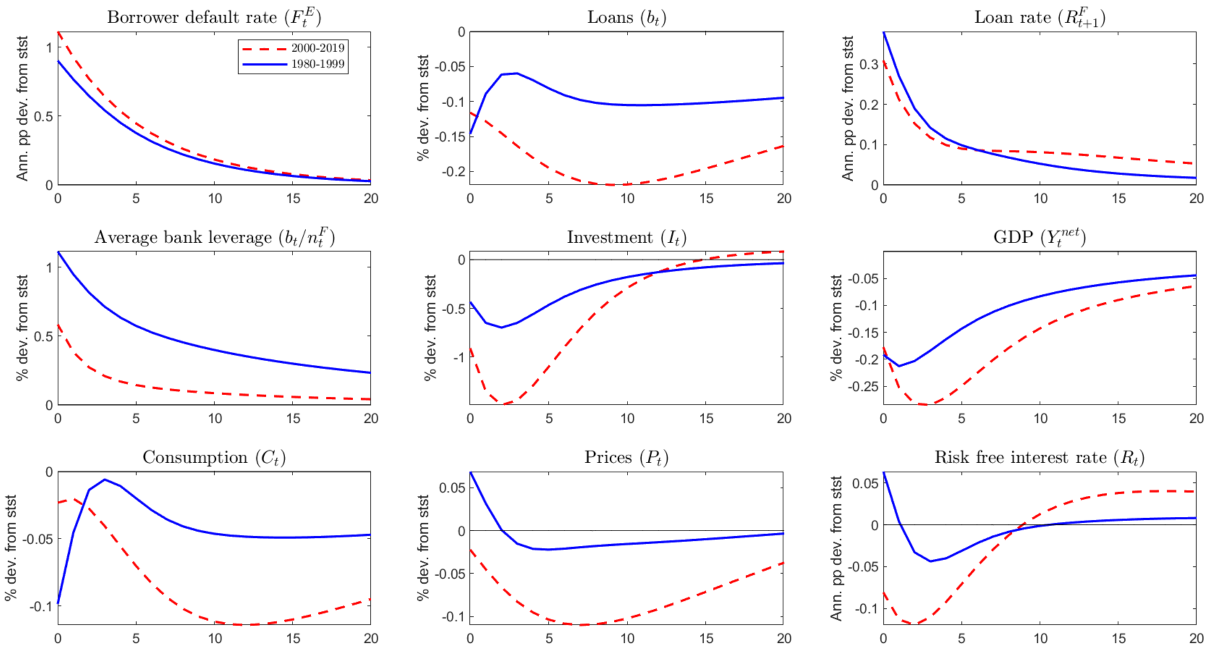
[10] Figure C.2.1 compares bank asset shares and the intermediation costs across the two models. Figure C.2.2 compares bank leverage and the dividend parameter across the two models.

tainty shock. Figure 2 compares the impulse responses of the baseline model (red dashed lines) with those of the high-competition model (blue solid lines). The figure shows that after an uncertainty shock, the default rate of entrepreneurs rises more in the baseline model due to the *risk-shifting* effect.

The stronger rise in defaults in the baseline model causes banks to cut credit more aggressively, despite the *pass-through* effect.[11] As a result of the more pronounced contraction in credit, bank leverage increases less in the baseline model. The stronger reduction in loan supply leads to larger declines in investment, consumption, GDP, and inflation, prompting the central bank to cut the policy rate more aggressively. After one year, the decline in GDP is 0.1 percentage points larger in the less competitive environment compared to the more competitive economy. As shown by Figure D.1 in the appendix, after 5 years, the cumulative loss in GDP is 1.1 percentage points larger in the less competitive environment.

[11] Figure D.2 in the appendix shows that the pass-through of a rise in the default probability of borrowers to borrowing costs is higher in the model with higher competition.

Figure 2: Effects of recent fall in banking competition.



Notes. The graph compares the impulse responses of the baseline model with the model calibrated to the period 1980-1999.

4 Empirical evidence

In this section, I provide empirical evidence indicating that the level of banking competition is negatively correlated with a the impact of uncertainty on economic activity.

I employ the quarterly country panel dataset created by Baker et al. (2023) and I merge it with information on GDP from IMF and bank concentration from the World Bank. The resulting dataset covers 34 countries over the period 2000Q1 to 2020Q1. Since data on banking concentration is available at an annual frequency, I linearly interpolate it to construct a quarterly measure of concentration. GDP is expressed in logs.

I estimate the following quarterly local projection model:

$$GDP_{i,t+h} - GDP_{i,t-1} = \alpha_{i,h} + \tau_{t,h} + \beta_h^R \tilde{R}_{i,t} + \beta_h^V \tilde{V}_{i,t} + \beta_h^C \tilde{C}_{i,t-1} + \beta_h^{RC} \tilde{R}_{i,t}\tilde{C}_{i,t-1} + \beta_h^{VC} \tilde{V}_{i,t}\tilde{C}_{i,t-1} + \epsilon_{i,t+h},$$

where $\alpha_{i,h}$ denotes country fixed effects for country i at horizon h, $\tau_{t,h}$ captures time fixed effects, $\tilde{R}_{i,t}$ is the country-demeaned measure of the first moment of national business conditions, $\tilde{V}_{i,t}$ is the country-demeaned measure of uncertainty, and $\tilde{C}_{i,t}$ is the country-demeaned share of total assets held by the 5 largest banks.

This model extends the framework of Baker et al. (2023) by incorporating banking concentration and interactions terms between concentration and the first and second moments. These interaction terms are included to isolate the effect of banking concentration on the impact of changes in first and second moments. Additionally, the country-demeaning of variables accounts for potential nonlinearities in country characteristics.

The coefficients of interest are β_h^V and β_h^{VC}, which measure the impact of an increase in uncertainty on real GDP. Specifically, β_h^V captures the impact of an increase in uncertainty on output when banking concentration is at the country average, while β_h^{VC} quantifies how the impact of an increase in uncertainty changes with variations in banking concentration. A negative β_h^{VC} implies that higher banking concentration amplifies the adverse effects of increases in uncertainty on output.

Similarly to Baker et al. (2023), I instrument the first and second moment variables, as well as their interactions with concentration, using disaster shocks.[12] The disaster shocks are weighted by the change in media coverage during the 15-day period following the shock compared to the preceding 15 days. This media-weighted approach gives a larger weight to more important shocks. Details on the dataset and descriptive statistics can be found in Appendix E.1.

As in Baker et al. (2023) there is a potential issue with this identification strategy. The first and second moment variables proxy for different channels through which disaster shocks have economic impact. The underlying exclusion restriction is that these effects impact economic activity only through shifts in the first and second moments of stock

[12] The instruments include disaster shocks and their interaction with country-demeaned concentration.

returns.

Figure 3a presents the estimated impulse responses of real output to a one-standard-deviation increase in uncertainty at different levels of banking concentration. The blue line represents the impulse response of output when concentration is at the country average, with the shaded blue area indicating the 90% confidence interval. The red line shows the impulse response when concentration is one standard deviation above the country average, with the corresponding red shaded area depicting the 90% confidence interval. The results indicate that an increase in uncertainty has a negative impact on output in both scenarios, but the fall in output is stronger and significant when banking concentration is higher.

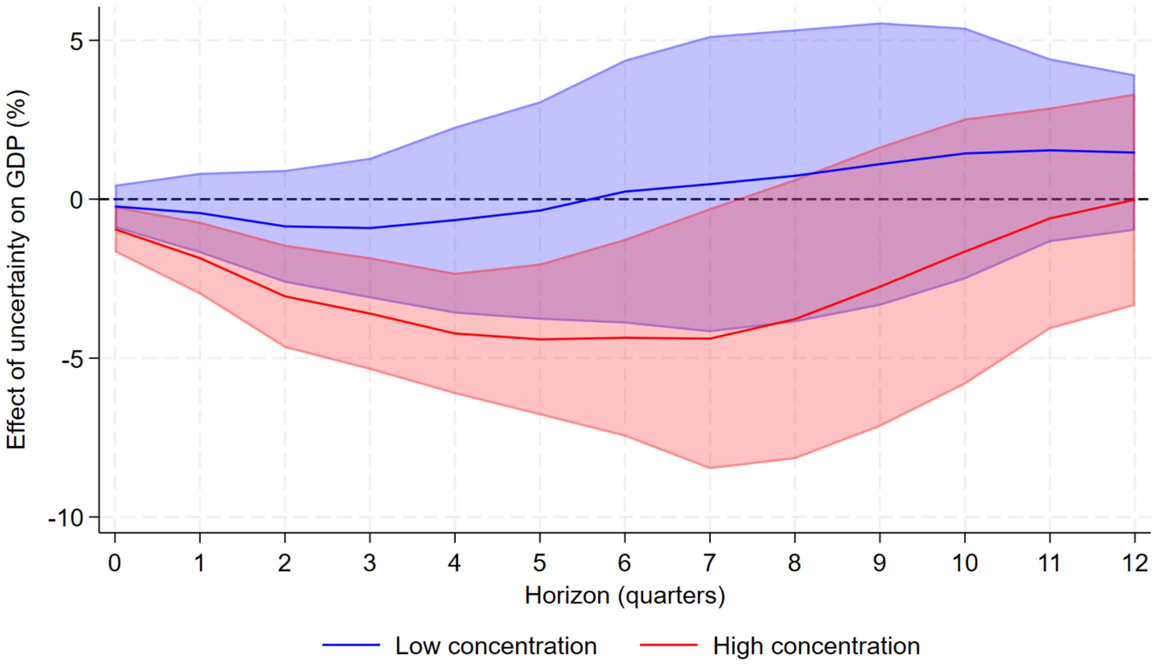
Figure 3b plots the difference between the two impulse responses. The difference is negative and significant at the 90% confidence level. The graph shows that the decline in output after an increase in uncertainty is significantly more pronounced when banking competition is lower.

The findings are robust to alternative specifications of the concentration measure. Specifically, the results hold when concentration is kept constant within a year and when the 3-bank asset concentration is used instead of the 5-bank asset concentration. These results are displayed in Appendix E.2.

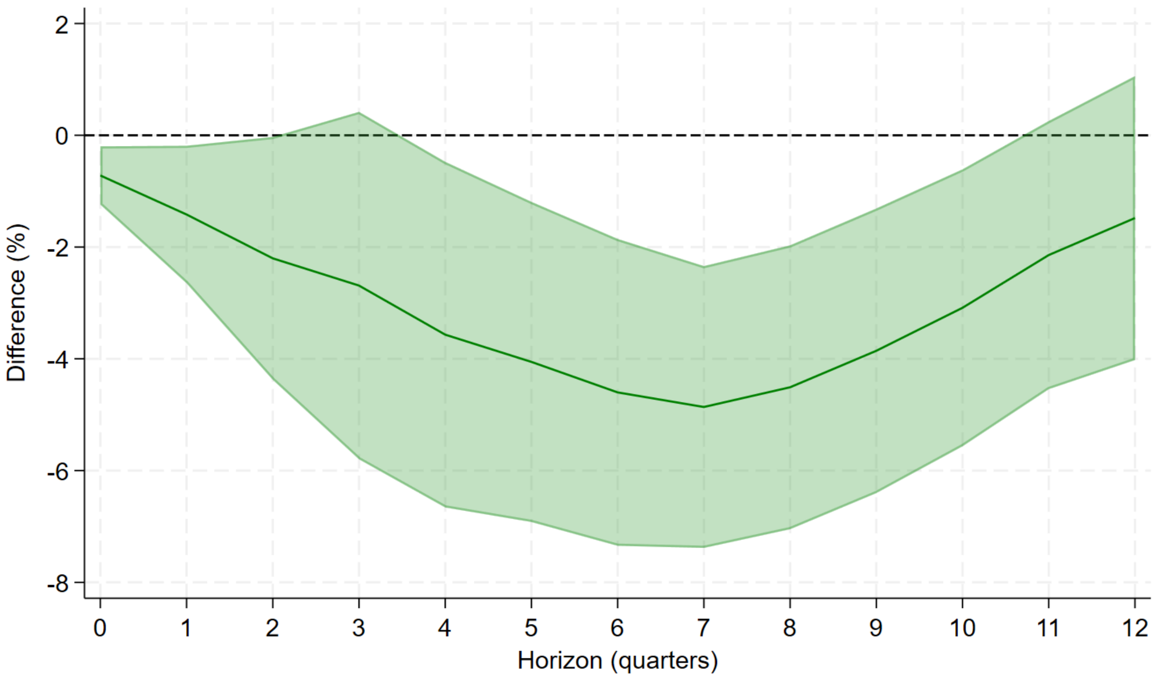
The empirical evidence presented in this section highlights the crucial role of banking sector competition in shaping the transmission of uncertainty shocks. The empirical evidence, as the quantitative model, show that reduced banking competition can exacerbate the effects of uncertainty shocks. The model shows that lower competition incentivizes borrowers to take on more risk, which, in turn, amplifies the economic consequences of uncertainty. Specifically, an increase in uncertainty results in a sharper rise in non-performing loans and a more pronounced contraction in investment, consumption, and GDP in less competitive banking environments.

Figure 3: Estimated IRFs to a one-standard-deviation uncertainty shock

(a) Impact of uncertainty shocks at different levels of banking concentration



(b) Difference between IRFs



Notes: Sample period: 2000Q1 to 2020Q1. Banking concentration is measured as the share of total assets held by the five largest banks.

5 Conclusion

The literature on uncertainty argues that uncertainty shocks play a crucial role in driving business cycles. In light of the recent decline in banking competition, I study how lower competition in the banking sector affects the propagation of uncertainty shocks.

I develop a calibrated New Keynesian dynamic stochastic general equilibrium model with heterogeneous banks, incorporating financial frictions and imperfect competition in the banking sector. A decline in banking competition leads banks to charge higher borrowing rates to entrepreneurs. This increases borrowers' risk-taking due to limited liability – a channel known as the *risk-shifting* effect.

An uncertainty shock increases entrepreneurial defaults to a greater extent in less competitive banking sectors due to increased risk-taking by entrepreneurs. This leads to a stronger increase in non-performing loans and a stronger reduction in banks' loan supply. As a result, investment and output fall more after an uncertainty shock when competition in the banking sector is lower.

The results of the quantitative model are consistent with empirical evidence. Empirically, I find a negative correlation between banking competition and the impact of uncertainty on real output.

References

Akins Brian, Li Lynn, Ng Jeffrey, and Rusticus Tjomme O. (2016), "Bank Competition and Financial Stability: Evidence from the Financial Crisis", *Journal of Financial and Quantitative Analysis* 51 (1), pp. 1–28.

Alessandri Piergiorgio and Mumtaz Haroon (2019), "Financial regimes and uncertainty shocks", *Journal of Monetary Economics* 101, pp. 31–46.

Altig Dave, Baker Scott, Barrero Jose Maria, Bloom Nicholas, Bunn Philip, Chen Scarlet, Davis Steven J., Leather Julia, Meyer Brent, Mihaylov Emil, Mizen Paul, Parker Nicholas, Renault Thomas, Smietanka Pawel, and Thwaites Gregory (2020), "Economic uncertainty before and during the COVID-19 pandemic", *Journal of Public Economics* 191, p. 104274.

Anayi Lena, Bloom Nicholas, Bunn Philip, Mizen Paul, Thwaites Gregory, and Yotzov Ivan (2022), "The impact of the war in Ukraine on economic uncertainty", VoxEU.org.

Andreasen Martin M., Caggiano Giovanni, Castelnuovo Efrem, and Pellegrino Giovanni (2023), "Does risk matter more in recessions than in expansions? Implications for monetary policy", *Journal of Monetary Economics*, p. 103533.

Baker Scott, Bloom Nicholas, Davis Steven, and Terry Stephen (2020), "COVID-Induced Economic Uncertainty", tech. rep. w26983, Cambridge, MA: National Bureau of Economic Research, w26983.

Baker Scott, Bloom Nicholas, and Terry Stephen (2023), "Using Disasters to Estimate the Impact of Uncertainty", *Review of Economic Studies*.

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

Berger Allen N., Klapper Leora F., and Turk-Ariss Rima (2017), "Bank competition and financial stability", *Handbook of Competition in Banking and Finance*, Edward Elgar Publishing, pp. 1–23.

Bernanke Ben S., Gertler Mark, and Gilchrist Simon (1999), "Chapter 21 The financial accelerator in a quantitative business cycle framework", *Handbook of Macroeconomics*, vol. 1, Elsevier, pp. 1341–1393.

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

Boissay Frédéric, Collard Fabrice, and Smets Frank (2016), "Booms and Banking Crises", *Journal of Political Economy* 124 (2), pp. 489–538.

Boyd John H. and de Nicolò' Gianni (2005), "The Theory of Bank Risk Taking and Competition Revisited", *The Journal of Finance* 60 (3), pp. 1329–1343.

Buch Claudia M., Koch Cathérine T., and Koetter Michael (2014), "Should I stay or should I go? Bank productivity and internationalization decisions", *Journal of Banking & Finance* 42, pp. 266–282.

Caldara Dario, Fuentes-Albero Cristina, Gilchrist Simon, and Zakrajšek Egon (2016), "The macroeconomic impact of financial and uncertainty shocks", *European Economic Review*, SI: The Post-Crisis Slump 88, pp. 185–207.

Caldara Dario, Conlisk Sarah, Iacoviello Matteo, and Penn Maddie (2022), "The Effect of the War in Ukraine on Global Activity and Inflation", FEDS Notes. Washington: Board of Governors of the Federal Reserve System.

Christensen Ian and Dib Ali (2008), "The Financial Accelerator in an Estimated New Keynesian Model", *Review of Economic Dynamics* 11 (1), pp. 155–178.

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

Clerc Laurent, Derviz Alexis, Mendicino Caterina, Moyen Stephane, Nikolov Kalin, Stracca Livio, Suarez Javier, and Vardoulakis Alexandros P. (2018), "Capital regulation in a macroeconomic model with three layers of default", *40th issue (June 2015) of the International Journal of Central Banking*.

Coimbra Nuno and Rey Hélène (2023), "Financial Cycles with Heterogeneous Intermediaries", *The Review of Economic Studies* 91 (2), pp. 817–857.

Corbae Dean and D'Erasmo Pablo (2021), "Capital Buffers in a Quantitative Model of Banking Industry Dynamics", *Econometrica* 89 (6), pp. 2975–3023.

Cuciniello Vincenzo and Signoretti Federico M. (2018), "Large banks, loan rate markup, and monetary policy", *40th issue (June 2015) of the International Journal of Central Banking*.

Dew-Becker Ian and Giglio Stefano (2023), "Cross-Sectional Uncertainty and the Business Cycle: Evidence from 40 Years of Options Data", *American Economic Journal: Macroeconomics* 15 (2), 65–96.

Drechsler Itamar, Savov Alexi, and Schnabl Philipp (2017), "The Deposits Channel of Monetary Policy", *The Quarterly Journal of Economics* 132 (4), pp. 1819–1876.

Ferrara Laurent, Mogliani Matteo, and Sahuc Jean-Guillaume (2022), "High-frequency macroeconomic risk measures in the wake of the war in Ukraine", VoxEU.org.

Gasparini Tommaso, Lewis Vivien, Moyen Stéphane, and Villa Stefania (2024), "Risky Firms and Fragile Banks: Implications for Macroprudential Policy", Working Paper 944, Banque de France.

Gödl-Hanisch Isabel (2022), "Bank Concentration and Monetary Policy Pass-Through".

Gertler Mark and Karadi Peter (2011), "A model of unconventional monetary policy", *Journal of Monetary Economics*, Carnegie-Rochester Conference Series on Public Policy: The Future of Central Banking April 16-17, 2010 58 (1), pp. 17–34.

Gertler Mark and Kiyotaki Nobuhiro (2010), "Chapter 11 - Financial Intermediation and Credit Policy in Business Cycle Analysis", *Handbook of Monetary Economics*, vol. 3, Elsevier, pp. 547–599.

Hakenes Hendrik and Schnabel Isabel (2011), "Capital regulation, bank competition, and financial stability", *Economics Letters* 113 (3), pp. 256–258.

Jamilov Rustam and Monacelli Tommaso (forthcoming), “Bewley Banks”, *Review of Economic Studies*.

Kühl Michael (2017), “Bank capital, the state contingency of banks’ assets and its role for the transmission of shocks”, *Journal of Macroeconomics*, Banking in Macroeconomic Theory and Policy 54, pp. 260–284.

Martinez-Miera David and Repullo Rafael (2010), “Does Competition Reduce the Risk of Bank Failure?”, *The Review of Financial Studies* 23 (10), pp. 3638–3664.

Martín-Oliver Alfredo, Ruano Sonia, and Salas-Fumás Vicente (2013), “Why high productivity growth of banks preceded the financial crisis”, *Journal of Financial Intermediation* 22 (4), pp. 688–712.

Mukherjee Kankana, Ray Subhash C., and Miller Stephen M. (2001), “Productivity growth in large US commercial banks: The initial post-deregulation experience”, *Journal of Banking & Finance* 25 (5), pp. 913–939.

Schaeck Klaus and Cihák Martin (2014), “Competition, Efficiency, and Stability in Banking”, *Financial Management* 43 (1), pp. 215–241.

Scharfstein David S and Sunderam Adi (2013), “Concentration in Mortgage Lending, Refinancing Activity and Mortgage Rates”, Working Paper 19156, National Bureau of Economic Research.

Villa Alessandro T (2024), “Macro Shocks and Firm Dynamics with Oligopolistic Financial Intermediaries”.

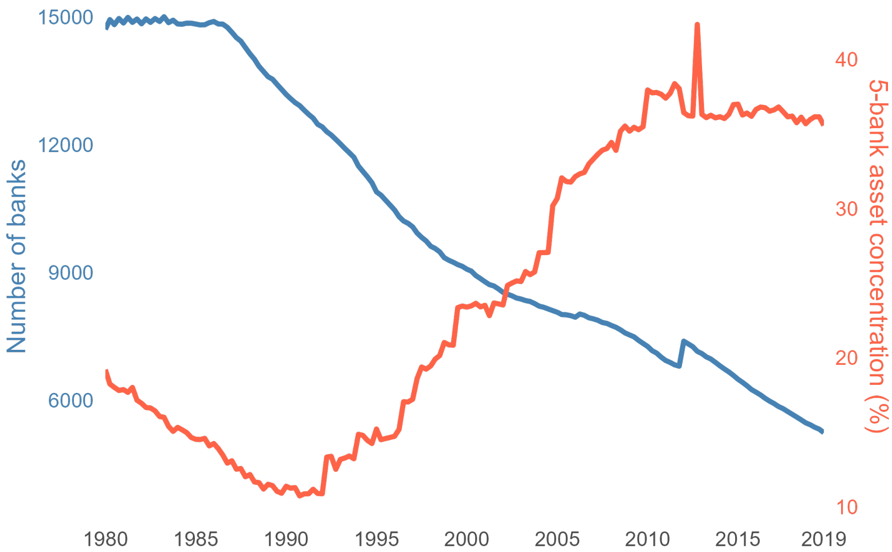
Wheelock David C. and Wilson Paul W. (2019), “New Estimates of the Lerner Index of Market Power for U.S. Banks”, Working Papers 2019-012, Federal Reserve Bank of St. Louis.

Wu Jing Cynthia and Xia Fan Dora (2016), “Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound”, *Journal of Money, Credit and Banking* 48 (2-3), pp. 253–291.

A Evolution of banking competition

Figure A.1 shows the evolution of the number of banks and the 5-bank asset concentration for the United States. The number of banks is the number of banks that filed a call report, while the 5-bank asset concentration is measured as the share of total assets held by the five largest banks. The data is taken from call reports. The number of banks has been decreasing since the late 1980s, while the 5-bank asset concentration has been increasing. This suggests that competition in the banking sector has decreased in recent years.

Figure A.1: Number of banks and asset concentration



Notes. Sample period: 1980 to 2019. The number of banks is measured as the number of banks that filed a call report. Bank concentration is measured as the share of total assets held by the five largest banks.

B Entrepreneurial optimization problem

B.1 Properties of loan demand

Expected share of return entrepreneurs obtain after borrowing costs

It is possible to rewrite the expected future wealth as:

$$\begin{aligned}\mathbb{E}_t(W^{E,j})_{t+1} &= \mathbb{E}_t\left\{\left(\int_{\overline{\omega}^j_{t+1}}^{\infty} \omega^j_{t+1} R^E_{t+1} q_t K^j_t f(\omega^j_{t+1}) \mathrm{d}\omega^j_{t+1} - (1 - F(\overline{\omega}_{t+1})) R^F_t b^j_t\right) \frac{1}{\Pi_{t+1}}\right\} \\ &= \mathbb{E}_t\left\{\left(\int_{\overline{\omega}^j_{t+1}}^{\infty} \omega^j_{t+1} R^E_{t+1} q_t K^j_t f(\omega^j_{t+1}) \mathrm{d}\omega^j_{t+1} - \int_{\overline{\omega}^j_{t+1}}^{\infty} R^F_t b^j_t f(\omega^j_{t+1}) \mathrm{d}\omega^j_{t+1}\right) \frac{1}{\Pi_{t+1}}\right\},\end{aligned} \tag{20}$$

where $f(\cdot)$ and $F(\cdot)$ are the pdf and cdf, respectively, of the distribution of ω_{t+1}.

Using the definition of the default cutoff (3), (20) can be simplified to:

$$\int_{\overline{\omega}^j_{t+1}}^{\infty} (\omega^j_{t+1} - \overline{\omega}^j_{t+1}) R^E_{t+1} q_t K^j_t f(\omega^j_{t+1}) \mathrm{d}\omega^j_{t+1}. \tag{21}$$

I can rewrite the term $\int_{\overline{\omega}^j_{t+1}}^{\infty} (\omega^j_{t+1} - \overline{\omega}^j_{t+1}) f(\omega^j_{t+1}) d\omega^j_{t+1}$ as:

$$\begin{aligned}\int_{\overline{\omega}^j_{t+1}}^{\infty} (\omega^j_{t+1} - \overline{\omega}^j_{t+1}) f(\omega^j_{t+1}) \mathrm{d}\omega^j_{t+1} &= \int_{\overline{\omega}^j_{t+1}}^{\infty} \omega^j_{t+1} f(\omega^j_{t+1}) \mathrm{d}\omega^j_{t+1} - \overline{\omega}^j_{t+1} \int_{\overline{\omega}^j_{t+1}}^{\infty} f(\omega^j_{t+1}) \mathrm{d}\omega^j_{t+1} \\ &= 1 - \left(\underbrace{\int_0^{\overline{\omega}^j_{t+1}} \omega^j_{t+1} f(\omega^j_{t+1}) \mathrm{d}\omega^j_{t+1}}_{\equiv G(\overline{\omega}^j_{t+1})} + \overline{\omega}^j_{t+1} \int_{\overline{\omega}^j_{t+1}}^{\infty} f(\omega^j_{t+1}) \mathrm{d}\omega^j_{t+1}\right) \\ &= 1 - \underbrace{\left(G(\overline{\omega}^j_{t+1}) + (1 - F(\overline{\omega}^j_{t+1}))\overline{\omega}^j_{t+1}\right)}_{\equiv \Gamma(\overline{\omega}^j_{t+1}) \geq 0}.\end{aligned} \tag{22}$$

We can express $\Gamma(\overline{\omega}^j_{t+1})$, the expected share of return that entrepreneurs obtain after paying borrowing costs, as:

$$\begin{aligned}\Gamma(\overline{\omega}^j_{t+1}) =& \int_0^{\overline{\omega}^j_{t+1}} \omega^j_{t+1} f(\omega^j_{t+1}) \mathrm{d}\omega^j_{t+1} + \overline{\omega}^j_{t+1} \int_{\overline{\omega}^j_{t+1}}^{\infty} f(\omega^j_{t+1}) \mathrm{d}\omega^j_{t+1} \\ =& \overline{\omega}^j_{t+1} F(\overline{\omega}^j_{t+1}) - \int_0^{\overline{\omega}^j_{t+1}} F(\omega^j_{t+1}) \mathrm{d}\omega^j_{t+1} + \overline{\omega}^j_{t+1}(1 - F(\overline{\omega}^j_{t+1})) \\ =& \overline{\omega}^j_{t+1} - \int_0^{\overline{\omega}^j_{t+1}} F(\omega^j_{t+1}) \mathrm{d}\omega^j_{t+1}. \end{aligned} \tag{23}$$

We can obtain an expression for $\Gamma'(\overline{\omega}^j_{t+1})$ by differentiating (22). This yields:

$$\Gamma'(\overline{\omega}^j_{t+1}) = G'(\overline{\omega}^j_{t+1}) - f(\overline{\omega}^j_{t+1})\overline{\omega}^j_{t+1} + (1 - F(\overline{\omega}^j_{t+1})), \tag{24}$$

where $G'(\overline{\omega}^j_{t+1})$ is obtained by differentiating the definition of $G(\overline{\omega}^j_{t+1})$ included in (22):

$$G'(\overline{\omega}^j_{t+1}) = \frac{\partial \int_0^{\overline{\omega}^j_{t+1}} \omega^j_{t+1} f(\omega^j_{t+1}) \mathrm{d}\omega^j_{t+1}}{\partial \overline{\omega}^j_{t+1}} = \overline{\omega}^j_{t+1} f(\overline{\omega}^j_{t+1}). \tag{25}$$

Combining (25) and (24), $\Gamma'(\overline{\omega}^j_{t+1})$ can be simplified to:

$$\Gamma'(\overline{\omega}^j_{t+1}) = 1 - F(\overline{\omega}^j_{t+1}) \geq 0. \tag{26}$$

Proof of Proposition 1

Proposition 1 states that loan demand decreases when the borrowing rate increases. In order to demonstrate it, let $\mathcal{I}$ be defined as:

$$\mathcal{I}_t \equiv \mathbb{E}_t \left\{ \frac{(1 - \Gamma(\overline{\omega}^j_{t+1}))R^E_{t+1}}{\Pi_{t+1}} \right\} - \mathbb{E}_t \left\{ \frac{\lambda}{\Pi_{t+1}} \right\}.$$

The derivative of the loan demand with respect to the borrowing rate is given by:

$$\frac{\mathrm{d}b_t}{\mathrm{d}R_t^F} = -\frac{\frac{\partial \mathcal{I}_t}{\partial R_t^F}}{\frac{\partial \mathcal{I}_t}{\partial b_t}}. \tag{27}$$

The numerator of (27) can be expressed as:

$$\frac{\partial \mathcal{I}_t}{\partial R_t^F} = \mathbb{E}_t \left\{ -R_{t+1}^E \Gamma'(\overline{\omega}_{t+1}) \frac{\partial \overline{\omega}_{t+1}}{\partial R_t^F} \frac{1}{\Pi_{t+1}} \right\}. \tag{28}$$

From the definition of the default cutoff (3), the term $\frac{\partial \overline{\omega}_{t+1}}{\partial R_t^F}$ is equal to:

$$\frac{\partial \overline{\omega}_{t+1}}{\partial R_t^F} = \frac{b_t}{R_{t+1}^E q_t K_t}. \tag{29}$$

Substituting the expressions for $\Gamma'(\overline{\omega}_{t+1})$ and $\frac{\partial \overline{\omega}_{t+1}}{\partial R_t^F}$ derived in (26) and (29) respectively, into (28):

$$\begin{aligned} \frac{\partial \mathcal{I}_t}{\partial R_t^F} &= \mathbb{E}_t \left\{ -R_{t+1}^E (1 - F(\overline{\omega}_{t+1})) \frac{b_t}{R_{t+1}^E q_t K_t} \frac{1}{\Pi_{t+1}} \right\} \\ &= \mathbb{E}_t \left\{ -(1 - F(\overline{\omega}_{t+1})) \frac{b_t}{q_t K_t} \frac{1}{\Pi_{t+1}} \right\} \leq 0. \end{aligned} \tag{30}$$

The denominator of (27) can be expressed as:

$$\frac{\partial \mathcal{I}_t}{\partial b_t} = \mathbb{E}_t \left\{ \left(-R_{t+1}^E \Gamma'(\overline{\omega}_{t+1}) \frac{\partial \overline{\omega}_{t+1}}{\partial b_t} + (1 - \Gamma(\overline{\omega}_{t+1})) R_{t+1}^{E\prime} \right) \frac{1}{\Pi_{t+1}} \right\}. \tag{31}$$

The term $\frac{\partial \overline{\omega}_{t+1}}{\partial b_t}$ is equal to:

$$\frac{\partial \overline{\omega}_{t+1}}{\partial b_t} = R^F \frac{R_{t+1}^E q_t K_t - (R_{t+1}^{E\prime} K_t + R_{t+1}^E) b_t}{(R_{t+1}^E q_t K_t)^2} = R_t^F \frac{R_{t+1}^E n_t^E - R_{t+1}^{E\prime} b_t K_t}{(R_{t+1}^E q_t K_t)^2} \geq 0. \tag{32}$$

Substituting the expressions for $\Gamma'(\overline{\omega}_{t+1})$ and $\frac{\partial \overline{\omega}_{t+1}}{\partial b_t}$ derived in (26) and (32) respectively, into (31):

$$\frac{\partial \mathcal{I}_t}{\partial b_t} = \mathbb{E}_t \left\{ \left(-R^E_{t+1}(1 - F(\overline{\omega}_{t+1}))R^F_t \frac{R^E_{t+1}n^E_t - R^{E\prime}_{t+1}b_t K_t}{(R^E_{t+1}q_t K_t)^2} + (1 - \Gamma(\overline{\omega}_{t+1}))R^{E\prime}_{t+1} \right) \frac{1}{\Pi_{t+1}} \right\} \leq 0. \tag{33}$$

Substituting (30) and (33) in (27):

$$\frac{\mathrm{d}b_t}{\mathrm{d}R^F_t} = -\frac{\mathbb{E}_t \left\{ (1 - F(\overline{\omega}_{t+1})) \frac{b_t}{q_t K_t} \frac{1}{\Pi_{t+1}} \right\}}{\mathbb{E}_t \left\{ \left(R^E_{t+1}(1 - F(\overline{\omega}_{t+1}))R^F_t \frac{R^E_{t+1}n^E_t - R^{E\prime}_{t+1}b_t K_t}{(R^E_{t+1}q_t K_t)^2} - (1 - \Gamma(\overline{\omega}_{t+1}))R^{E\prime}_{t+1} \right) \frac{1}{\Pi t+1} \right\}} \leq 0.$$

Since $\frac{\mathrm{d}b_t}{\mathrm{d}R^F_t} \leq 0$, loan demand is a decreasing function of the borrowing rate.

Proof of Proposition 2

Proposition 2 states that the default rate of entrepreneurs rises with the borrowing rate. This is because the default rate $F(\overline{\omega}_{t+1})$, is an increasing function of $\overline{\omega}_{t+1}$. This can be seen by taking the derivative of the default rate (4) with respect to the default threshold:

$$F'(\overline{\omega}_{t+1}) = f(\overline{\omega}_{t+1}) = \frac{1}{\overline{\omega}_{t+1}\sigma_t} \phi \left(\frac{\log(\overline{\omega}_{t+1}) + 0.5\sigma^2_t}{\sigma_t} \right) \geq 0, \tag{34}$$

where $\phi(\cdot)$ is the p.d.f. of the standard normal distribution.

In order to show that the entrepreneurial default rate increases with the borrowing rate, it is necessary to show that the default threshold $\overline{\omega}_{t+1}$ increases with the borrowing rate. The default threshold $\overline{\omega}_{t+1}$ increases with the borrowing rate if the following expression is positive:

$$\frac{\mathrm{d}\overline{\omega}_{t+1}}{\mathrm{d}R^F_t} = -\frac{\frac{\partial \mathcal{I}_t}{\partial R^F_t}}{\frac{\partial \mathcal{I}_t}{\partial \overline{\omega}_{t+1}}}. \tag{35}$$

The numerator of (35) is:

$$\frac{\partial \mathcal{I}_t}{\partial R_t^F} = \mathbb{E}_t \left\{ \frac{(1-\Gamma(\overline{\omega}_{t+1}))R_{t+1}^{E\prime}\frac{1}{q_t}\frac{\mathrm{d}b_t}{\mathrm{d}R_t^F}}{\Pi_{t+1}} \right\} \geq 0. \tag{36}$$

The denominator of (35) is:

$$\frac{\partial \mathcal{I}_t}{\partial \overline{\omega}_{t+1}} = \mathbb{E}_t \left\{ \frac{-(1-F(\overline{\omega}_{t+1}))R_{t+1}^{E}}{\Pi_{t+1}} \right\} \leq 0. \tag{37}$$

Substituting (36) and (37) in (35):

$$\frac{\mathrm{d}\overline{\omega}_{t+1}}{\mathrm{d}R_t^F} = -\frac{\mathbb{E}_t \left\{ \frac{(1-\Gamma(\overline{\omega}_{t+1}))R_{t+1}^{E\prime}\frac{1}{q_t}\frac{\mathrm{d}b_t}{\mathrm{d}R_t^F}}{\Pi_{t+1}} \right\}}{\mathbb{E}_t \left\{ \frac{-(1-F(\overline{\omega}_{t+1}))R_{t+1}^{E}}{\Pi_{t+1}} \right\}} \geq 0$$

Since the default rate increases with the default threshold that is increasing in the loan rate, the default rate increases with the loan rate.

Proof of Proposition 3

Proposition 3 states that if $\overline{\omega}_{t+1} \leq e^{-\sigma_{t+1}-0.5\sigma_{t+1}^2}$ and $\sigma_{t+1} \leq 1$, a rise in uncertainty leads to a stronger rise in the default rate of the entrepreneurs when the default cutoff is higher.

The effect of an increase of the default cutoff on the default rate is given by the derivative of (4) with respect to $\overline{\omega}_{t+1}$:

$$F'(\overline{\omega}_{t+1}) = \frac{1}{\overline{\omega}_{t+1}\sigma_{t+1}}\phi\left(\frac{\log(\overline{\omega}_{t+1}) + 0.5\sigma_{t+1}^2}{\sigma_{t+1}}\right). \tag{38}$$

In order to show that an increase in uncertainty has a stronger effect on the default rate when the default cutoff is higher, $\frac{\mathrm{d}F'_{t+1}}{\mathrm{d}\sigma_{t+1}}$ must to be positive:

$$\frac{\mathrm{d}F'_{t+1}}{\mathrm{d}\sigma_{t+1}} = -\frac{\frac{\mathrm{d}\overline{\omega}_{t+1}}{\mathrm{d}\sigma_{t+1}}\sigma_{t+1} + \overline{\omega}_{t+1}}{\overline{\omega}^2_{t+1}\sigma^2_{t+1}}\phi\left(\frac{\log(\overline{\omega}_{t+1}) + 0.5\sigma^2_{t+1}}{\sigma_{t+1}}\right) + \phi'\left(\frac{\log(\overline{\omega}_{t+1}) + 0.5\sigma^2_{t+1}}{\sigma_{t+1}}\right)\frac{1}{\overline{\omega}_{t+1}\sigma_{t+1}}\frac{\frac{1}{\overline{\omega}_{t+1}}\frac{\mathrm{d}\overline{\omega}_{t+1}}{\mathrm{d}\sigma_{t+1}}\sigma_{t+1} + 0.5\sigma^2_{t+1} - \log(\overline{\omega}_{t+1})}{\sigma^2_{t+1}}. \quad (39)$$

The term $\phi'(x)$ can be written as:

$$\phi'(x) = -\frac{1}{\sqrt{2\pi}}xe^{-0.5x^2}. \quad (40)$$

The term $\phi(x)$ can be written as:

$$\phi(x) = \frac{1}{\sqrt{2\pi}}e^{-0.5x^2}. \quad (41)$$

Substituting (40) and (41) into (39):

$$\frac{\mathrm{d}F'_{t+1}}{\mathrm{d}\sigma_{t+1}} = \frac{1}{\sqrt{2\pi}}e^{-0.5x^2}\frac{1}{\overline{\omega}_{t+1}\sigma^2_{t+1}}\Bigg(-\frac{\frac{\mathrm{d}\overline{\omega}_{t+1}}{\mathrm{d}\sigma_{t+1}}\sigma_{t+1} + \overline{\omega}_{t+1}}{\overline{\omega}_{t+1}} + \frac{\log(\overline{\omega}_{t+1}) + 0.5\sigma^2_{t+1}}{\sigma_{t+1}}\frac{\log(\overline{\omega}_{t+1}) - 0.5\sigma^2_{t+1} - \frac{1}{\overline{\omega}_{t+1}}\frac{\mathrm{d}\overline{\omega}_{t+1}}{\mathrm{d}\sigma_{t+1}}\sigma_{t+1}}{\sigma_{t+1}}\Bigg). \quad (42)$$

Equation 42 can be written as:

$$\frac{\mathrm{d}F'_{t+1}}{\mathrm{d}\sigma_{t+1}} = \frac{1}{\sqrt{2\pi}}e^{-0.5x^2}\frac{1}{\overline{\omega}_{t+1}\sigma^2_{t+1}}\Bigg(-\frac{\frac{\mathrm{d}\overline{\omega}_{t+1}}{\mathrm{d}\sigma_{t+1}}\sigma_{t+1}}{\overline{\omega}_{t+1}} - \frac{\log(\overline{\omega}_{t+1}) + 0.5\sigma^2_{t+1}}{\sigma_{t+1}}\frac{1}{\overline{\omega}_{t+1}}\frac{\mathrm{d}\overline{\omega}_{t+1}}{\mathrm{d}\sigma_{t+1}} - 1 + \frac{\log(\overline{\omega}_{t+1}) + 0.5\sigma^2_{t+1}}{\sigma_{t+1}}\frac{\log(\overline{\omega}_{t+1}) - 0.5\sigma^2_{t+1}}{\sigma_{t+1}}\Bigg). \quad (43)$$

Equation 43 is positive when $R^E_{t+1} \leq \frac{\lambda}{1-\Gamma\left(e^{-\sigma_{t+1}-0.5\sigma^2_{t+1}}\right)}$. In order to see that this assumption is sufficient, note that:

$$-\frac{\frac{\mathrm{d}\overline{\omega}_{t+1}}{\mathrm{d}\sigma_{t+1}}\sigma_{t+1}}{\overline{\omega}_{t+1}}+\frac{1}{\overline{\omega}_{t+1}}\frac{\mathrm{d}\overline{\omega}_{t+1}}{\mathrm{d}\sigma_{t+1}}, \tag{44}$$

is positive if $\frac{\mathrm{d}\overline{\omega}_{t+1}}{\mathrm{d}\sigma_{t+1}} \geq 0$. The effect of uncertainty on the default cutoff is:

$$\frac{\mathrm{d}\overline{\omega}_{t+1}}{\mathrm{d}\sigma_{t+1}} = R_t^F \frac{\mathrm{d}b_t}{\mathrm{d}\sigma_{t+1}} \frac{R^E_{t+1} q K_t - R^E b - R^{E\prime}_{t+1} K_t b_t}{(R^E_{t+1} q_t K_t)^2} = R_t^F \frac{\mathrm{d}b_t}{\mathrm{d}\sigma_{t+1}} \frac{R^E_{t+1} n^E - R^{E\prime}_{t+1} K_t b_t}{(R^E_{t+1} q_t K_t)^2}.$$

The effect of uncertainty on the default cutoff is positive if $\frac{\mathrm{d}b_t}{\mathrm{d}\sigma_{t+1}} \geq 0$. The effect of uncertainty on loan demand is:

$$\frac{\mathrm{d}b_t}{\mathrm{d}\sigma_{t+1}} = -\frac{\frac{\partial \mathcal{I}_t}{\partial \sigma_{t+1}}}{\frac{\partial \mathcal{I}_t}{\partial b_t}}. \tag{45}$$

The numerator of (45) can be expressed as:

$$\frac{\partial \mathcal{I}_t}{\partial \sigma_{t+1}} = \mathbb{E}_t \left\{ -\frac{\partial \Gamma(\overline{\omega}_{t+1})}{\partial \sigma_{t+1}} R^E_{t+1} \frac{1}{\Pi_{t+1}} \right\}. \tag{46}$$

Substituting the definition of $\Gamma(\overline{\omega}_{t+1})$, the term $\frac{\partial \Gamma(\overline{\omega}_{t+1})}{\partial \sigma_{t+1}}$ in (46) can be expressed as:

$$\begin{aligned}
\frac{\partial \Gamma(\overline{\omega}_{t+1})}{\partial \sigma_{t+1}} &= - \frac{\partial F(\overline{\omega}_{t+1})}{\partial \sigma_{t+1}} \overline{\omega}_{t+1} + \frac{\partial G(\overline{\omega}_{t+1})}{\partial \sigma_{t+1}} \\
&= - F'(\overline{\omega}_{t+1}) \overline{\omega}^2_{t+1} \frac{0.5\sigma^2_{t+1} - \log(\overline{\omega}_{t+1})}{\sigma_{t+1}} + F'(\overline{\omega}_{t+1}) \overline{\omega}^2_{t+1} \frac{-0.5\sigma^2_{t+1} - \log(\overline{\omega}_{t+1})}{\sigma_{t+1}} \\
&= - F'(\overline{\omega}_{t+1}) \overline{\omega}^2_{t+1} \sigma_{t+1} \leq 0.
\end{aligned}$$

Substituting the last expression into (46):

$$\frac{\partial \mathcal{I}_t}{\partial \sigma_{t+1}} = \mathbb{E}_t \left\{ F'(\overline{\omega}_{t+1}) \overline{\omega}^2_{t+1} \sigma_{t+1} R^E_{t+1} \frac{1}{\Pi_{t+1}} \right\}. \tag{47}$$

Substituting (47) and (33) into (45):

$$\frac{\mathrm{d}b_t}{\mathrm{d}\sigma_{t+1}} = \frac{\mathbb{E}_t\left\{F'(\overline{\omega}_{t+1})\overline{\omega}_{t+1}^2\sigma_{t+1}R_{t+1}^E\frac{1}{\Pi_{t+1}}\right\}}{R_{t+1}^E(1-F(\overline{\omega}_{t+1}))R_t^F\frac{R_{t+1}^E n_t^E - R_{t+1}^{E\prime}b_tK_t}{(R_{t+1}^E q_tK_t)^2} - (1-\Gamma(\overline{\omega}_{t+1}))R_{t+1}^{E\prime}} \geq 0.$$

Therefore, $\left(-\frac{\frac{\mathrm{d}\overline{\omega}_{t+1}}{\mathrm{d}\sigma_{t+1}}\sigma_{t+1}}{\overline{\omega}_{t+1}} + \frac{1}{\overline{\omega}_{t+1}}\frac{\mathrm{d}\overline{\omega}_{t+1}}{\mathrm{d}\sigma_{t+1}}\right) \geq 0$.

The assumption $\overline{\omega}_{t+1} \leq e^{-\sigma_{t+1}-0.5\sigma_{t+1}^2}$ implies that:

$$\begin{aligned}\overline{\omega}_{t+1} &\leq e^{-\sigma_{t+1}-0.5\sigma_{t+1}^2}\\ \log(\overline{\omega}_{t+1}) &\leq -\sigma_{t+1} - 0.5\sigma_{t+1}^2\\ \frac{\log(\overline{\omega}_{t+1}) + 0.5\sigma_{t+1}^2}{\sigma_{t+1}} &\leq -1. \end{aligned} \tag{48}$$

Because of (48) and since $-\frac{\frac{\mathrm{d}\overline{\omega}_{t+1}}{\mathrm{d}\sigma_{t+1}}\sigma_{t+1}}{\overline{\omega}_{t+1}} + \frac{1}{\overline{\omega}_{t+1}}\frac{\mathrm{d}\overline{\omega}_{t+1}}{\mathrm{d}\sigma_{t+1}} \geq 0$:

$$-\frac{\frac{\mathrm{d}\overline{\omega}_{t+1}}{\mathrm{d}\sigma_{t+1}}\sigma_{t+1}}{\overline{\omega}_{t+1}} - \frac{\log(\overline{\omega}_{t+1}) + 0.5\sigma_{t+1}^2}{\sigma_{t+1}}\frac{1}{\overline{\omega}_{t+1}}\frac{\mathrm{d}\overline{\omega}_{t+1}}{\mathrm{d}\sigma_{t+1}} \geq 0. \tag{49}$$

Moreover, because of (48):

$$-1 + \frac{\log(\overline{\omega}_{t+1}) + 0.5\sigma_{t+1}^2}{\sigma_t}\frac{\log(\overline{\omega}_{t+1}) - 0.5\sigma_{t+1}^2}{\sigma_t} \geq 0. \tag{50}$$

Finally, because of (49) and (50), (39) is positive and a rise in uncertainty leads to a stronger rise in the default rate of the entrepreneurs when the default cutoff is higher.

C Calibration

C.1 VAR model

Building on Basu and Bundick (2017) and Andreasen et al. (2023), I employ a VAR model to investigate the effects of uncertainty shocks on the US economy. The resulting impulse responses are used to calibrate the model described in Section 2.

C.1.1 Data sources and descriptive statistics

Table C.1.1 provides an overview of the data series used in the VAR analysis.

Table C.1.1: Data sources VAR analysis

Series	Source	Identifier
Cross-sectional uncertainty	Dew-Becker and Giglio (2023)	idio_iv
Real GDP	FRED	GDPC1
Real Personal Consumption Expenditures	FRED	PCECC96
Real Gross Private Domestic Investment	FRED	GPDIC1
Nonfarm Business Sector: Hours Worked for All Workers	FRED	HOANBS
Gross Domestic Product: Implicit Price Deflator	FRED	GDPDEF
Shadow rate	Wu and Xia (2016)	
5-bank asset concentration	Call reports	

Notes. List of data sources used in the VAR analysis.

Table C.1.2 presents the descriptive statistics of the dataset. All variables, except idiosyncratic uncertainty, the shadow rate and bank concentration are transformed into logarithms.

C.1.2 Model and empirical impulse responses

Following Basu and Bundick (2017) and Andreasen et al. (2023), the vector of endogenous variables in the model includes a measure of uncertainty, GDP, consumption, investment, hours worked, the GDP deflator, and the shadow rate of Wu and Xia (2016). Additionally, a measure of banking competition is included as the final variable in the vector.

Table C.1.2: Descriptive statistics

	Obs.	Mean	Median	St. dev	Min	Max
Idiosyncratic uncertainty (%)	80	23.135	19.640	8.809	15.681	51.670
GDP	80	9.738	9.733	0.112	9.538	9.950
Consumption	80	9.338	9.335	0.119	9.109	9.553
Investment	80	7.926	7.922	0.173	7.574	8.248
Hours worked	80	4.542	4.541	0.047	4.451	4.634
GDP deflator	80	4.480	4.488	0.109	4.278	4.650
Shadow rate (%)	80	1.244	1.092	2.397	-2.922	6.439
5-bank asset concentration (%)	80	33.019	35.553	5.052	22.816	42.345

Notes: Descriptive statistics of the dataset used in the VAR analysis. The sample period is 2000-2019.

Uncertainty is measured by the cross-sectional uncertainty of Dew-Becker and Giglio (2023), while banking competition is proxied by the share of total bank assets held by the five largest banks. An increase in concentration is interpreted as a fall in competition in the banking sector. All variables, except uncertainty, the shadow rate, and bank concentration, are transformed into logarithms. The model is estimated with two lags and the sample is restricted to the period between 2000 to 2019, a period characterized by high bank concentration.

Uncertainty shocks are identified using a Cholesky decomposition, with the uncertainty measure ordered first. This ordering implies that uncertainty shocks can have contemporaneous effects on other variables, while shocks to other variables do not contemporaneously affect uncertainty. This identification strategy is consistent with Basu and Bundick (2017) and the theoretical model developed in Section 2.

Figure 1 presents the estimated impulse responses to a one-standard-deviation uncertainty shock from the VAR model. The figure shows that uncertainty shocks have statistically significant contractionary effects on economic activity.

C.2 Calibration γ^i and $\chi^{F,i}$

Figure C.2.1 compares the share of assets held by each bank and their intermediation cost γ^i in the baseline model and in the model calibrated to the 1980-1999 period.

In the baseline model, the intermediation costs are calibrated to match the empirical asset share of each bank and the average bank Lerner index of Wheelock and Wilson (2019). In the model calibrated to the 1980-1999 period, the intermediation costs are calibrated to match the empirical asset share of each bank and the same average intermediation cost of the baseline model.[13]

The intermediation cost γ^i is a reduced-form tool which allows to capture heterogeneity in bank loan supply. It stands for real-world costs or subsidies associated with providing loans.

On the cost side, banks incur expenses such as operating branches, advertising, administrative overhead, and costs related to credit risk assessment and monitoring. Conversely, banks may benefit from subsidies that effectively lower their intermediation costs. An example is the implicit too-big-to-fail subsidy. Evidence from Mukherjee et al. (2001), Martín-Oliver et al. (2013) and Buch et al. (2014) suggests that there is a positive relationship between bank productivity and size.

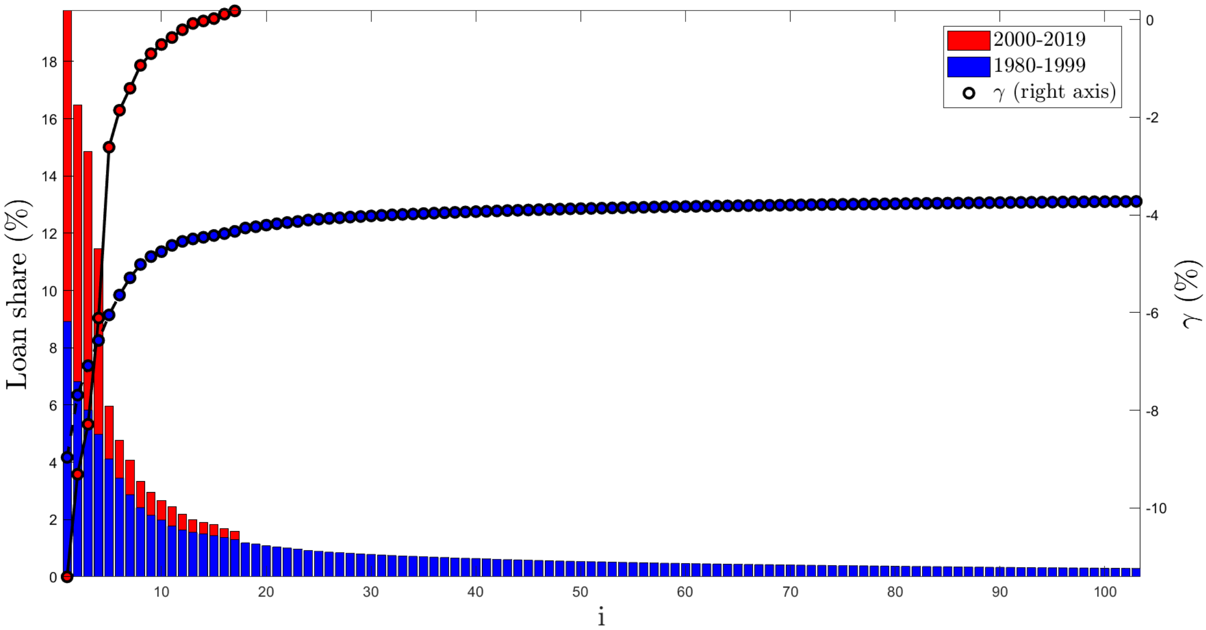
Figure C.2.2 compares the leverage of each bank and their dividend parameter $\chi^{F,i}$ in the baseline model and in the model calibrated to the 1980-1999 period.

In both models, the dividend parameters are calibrated to match the empirical leverage of each bank.

The dividend parameter $\chi^{F,i}$ is a reduced-form parameter which allows to capture heterogeneity in leverage across banks. In the model, because of their higher market power, large banks obtain larger profits than smaller banks. A larger dividend parameter for larger banks allows to reduce their equity accumulation and align bank leverages in

[13] Note also that the Lerner index of Wheelock and Wilson (2019) is available only from 2001 to 2018.

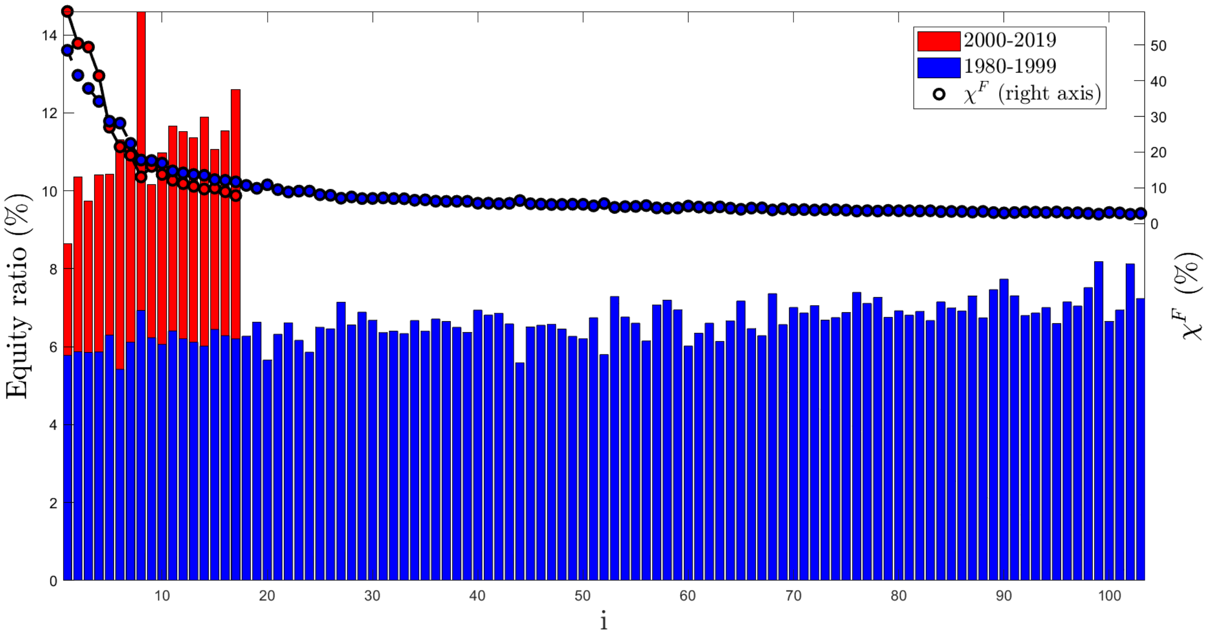
Figure C.2.1: Distribution of asset shares and intermediation costs.



Notes. The graph compares the share of assets held by banks (indexed by i) and their intermediation costs in the baseline model and in the model calibrated to the period 1980-1999. The shares are the same in the data.

the model with their empirical counterpart.

Figure C.2.2: Leverage and dividend parameter across banks.



Notes. The graph compares the share of assets held by banks (indexed by i) and their intermediation costs in the baseline model and in the model calibrated to the period 1980-1999. The leverages are the same in the data.

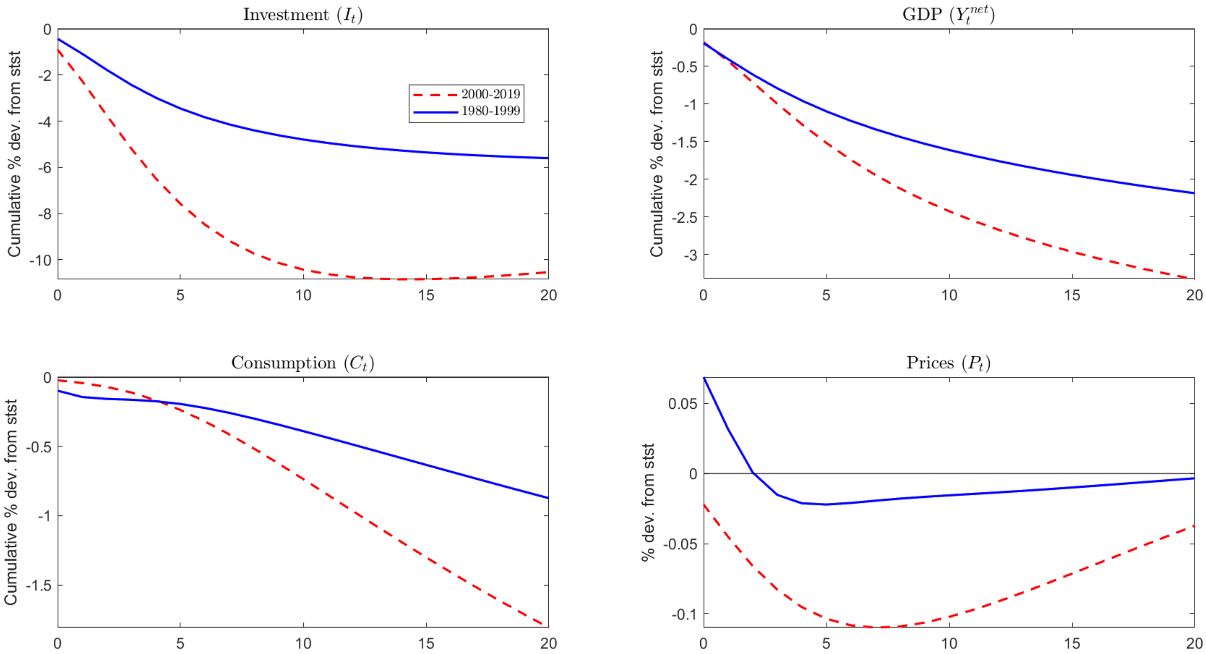
D Additional results

Figure D.1 shows the cumulated effects of an uncertainty shock in the baseline model and in the model calibrated to the 1980-1999 period. After 5 years, the cumulated fall in GDP is 1.1 percentage points larger in the baseline model.

Figure D.2 illustrates the pass-through to borrowing rates resulting from a one percentage point increase in the default rate triggered by an uncertainty shock. The pass-through is calculated by dividing the response of the borrowing rate by the rise in the default rate at the time the shock occurs.

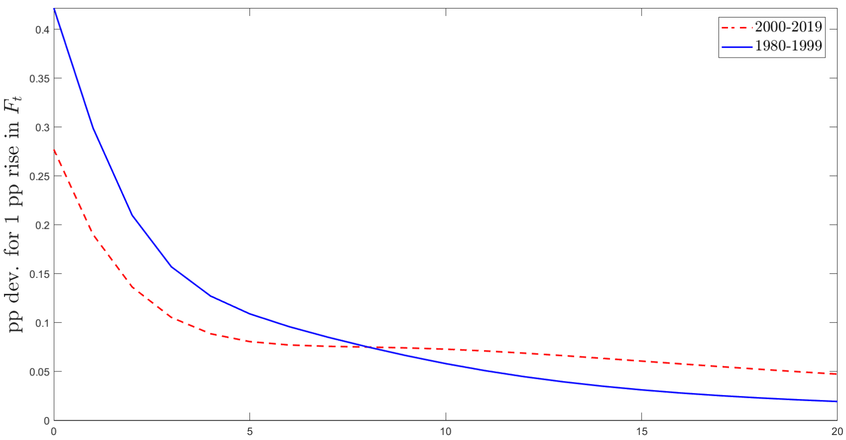
The figure reveals that the pass-through is higher in the model with greater banking competition. This result reflects both the increase in the deposit rate in the more competitive economy following the uncertainty shock and the greater responsiveness of competitive banks – consistent with the *pass-through* effect.

Figure D.1: Cumulative effects of recent fall in banking competition.



Notes. The graph compares the cumulated impulse responses of investment, GDP, consumption and inflation in the baseline model and in the model calibrated to the period 1980-1999.

Figure D.2: Pass-through in the two models.



Notes. The graph compares the pass-through of the baseline model with the one of the model calibrated to the period 1980-1999.

E Additional information empirical evidence

E.1 Data description and descriptive statistics

The local projection analysis is based on data from the IMF, the World Bank and Baker et al. (2023). Banking competition is proxied by the share of assets held by the five largest banks, which is available only at an annual frequency. To align this measure with the quarterly frequency of the local projections, I linearly interpolate the concentration data.

The first and second moments of national business conditions are derived from national stock market movements, combining both aggregate and cross-sectional information. At the aggregate level, the first moment of business conditions is proxied by the daily stock market return of the broadest national index, while uncertainty is represented by the standard deviation of daily stock market returns for the same index. At the cross-sectional level, these moments are calculated using individual firm-level returns. Specifically, the first moment is the average return across firms, while uncertainty is defined as the cross-sectional standard deviation of quarterly returns. The aggregate and cross-sectional measures are then combined by demeaning each, standardizing to a unit variance, and taking their average.

The disaster shocks considered in this analysis include four types of events: natural disasters, terrorist attacks, coups and revolutions. For each category, a value of one is assigned if a disaster shock occurred. To construct the final indexes, events are weighted by the increase in media coverage during the 15 days following the event compared to the 15 days preceding it. Media coverage is defined as the number of articles published in US-based, English-language newspapers mentioning the affected country.

Disaster shocks are defined as follows:

Natural disasters: Extreme weather events such as, droughts, earthquakes, insect infestations, pandemics, floods, extreme temperatures, avalanches, landslides, storms, volcanoes, fires and hurricanes.

Terrorist attacks: Bombings and other non-state sponsored attacks.

Coups: Military action resulting in the seizure of executive power by an opposition group.

Revolutions: A violent uprising or revolution that seeks to overthrow a government or substantially change the governance of a given region.

For each disaster shock category, country, and quarter, the shock variable is set to one if at least one such event occurred during that quarter. The weights for these shocks are determined by the percentage increase in media coverage 15 days after the event compared to the 15 days prior. The increase in media coverage is defined as the percentage increase in the number of articles, comparing the 15-day period after the event to the 15-day period before the event.

The disaster shock data span 59 countries from 1970Q1 to 2020Q1. However, due to the availability of bank concentration data only from 2000 onward, the combined dataset is limited to 34 countries between 2000Q1 and 2020Q1. A list of the countries included in the analysis is provided in Table E.1.1.

Table E.1.2 displays the descriptive statistics of the dataset.

E.2 Robustness of empirical evidence

This section presents the robustness of the local projection analysis. Figure E.2.1 shows that the results are robust when the level of concentration is held constant within a year. Additionally, Figure E.2.2 shows that the findings are robust when the 3-bank asset concentration measure is used instead of the 5-bank concentration measure.

Table E.1.1: Countries used in the empirical analysis.

Asia & Pacific	Europe & North America	LatAm & Caribbean	MENA	SSAF
Australia	Austria	Brazil	Israel	South Africa
China	Belgium	Chile	Turkey	
India	Canada	Colombia		
Indonesia	Denmark	Mexico		
Japan	Finland			
New Zealand	France			
Philippines	Germany			
Singapore	Ireland			
South Korea	Italy			
	Luxembourg			
	Netherlands			
	Norway			
	Portugal			
	Spain			
	Sweden			
	Switzerland			
	United Kingdom			
	United States			

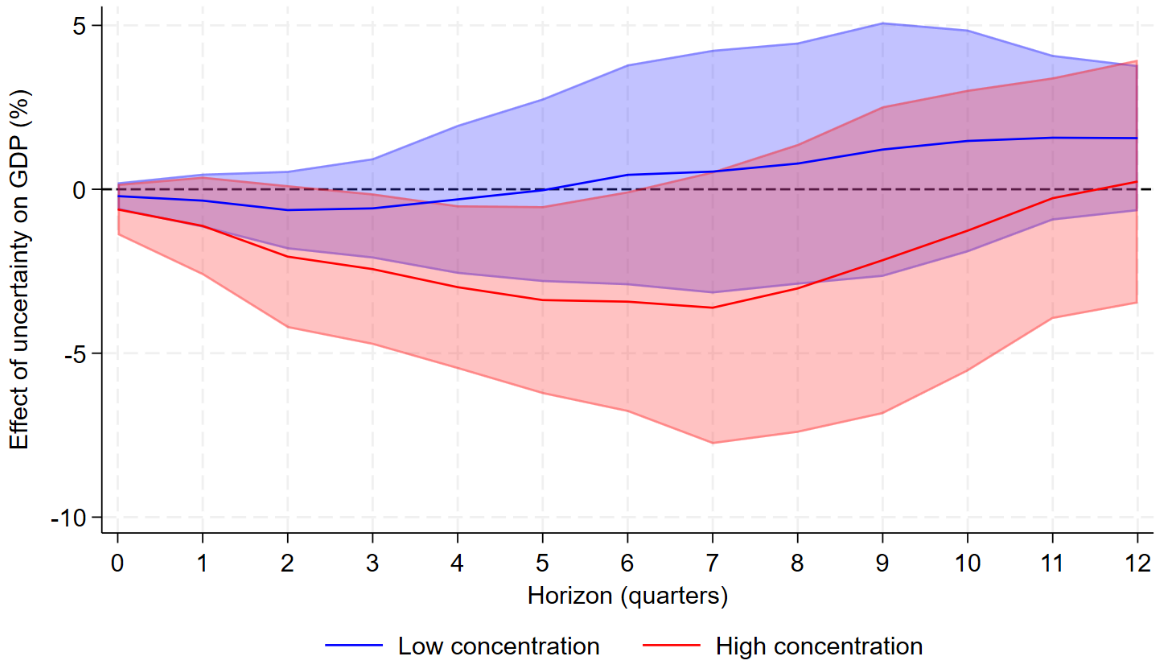
Table E.1.2: Descriptive statistics

	Obs.	Mean	Median	St. dev	Min	Max
GDP (log)	2548	13.55	13.03	2.67	8.96	21.75
First moment	4318	-0.02	0.05	1.36	-6.85	7.06
Uncertainty	4307	0.04	0.06	1.58	-4.78	4.91
Natural disasters	7065	0.13	0.00	0.49	0.00	7.98
Coups	7065	0.01	0.00	0.20	0.00	6.75
Revolutions	7065	0.00	0.00	0.03	0.00	1.11
Terrorist attacks	7065	0.01	0.00	0.10	0.00	3.59
5-bank asset concentration (interpol.)	2472	78.49	83.59	18.05	28.12	100.00
5-bank asset concentration	2472	78.38	83.51	18.26	28.12	100.00
3-bank asset concentration (interpol.)	2456	66.63	69.02	20.29	21.45	99.94

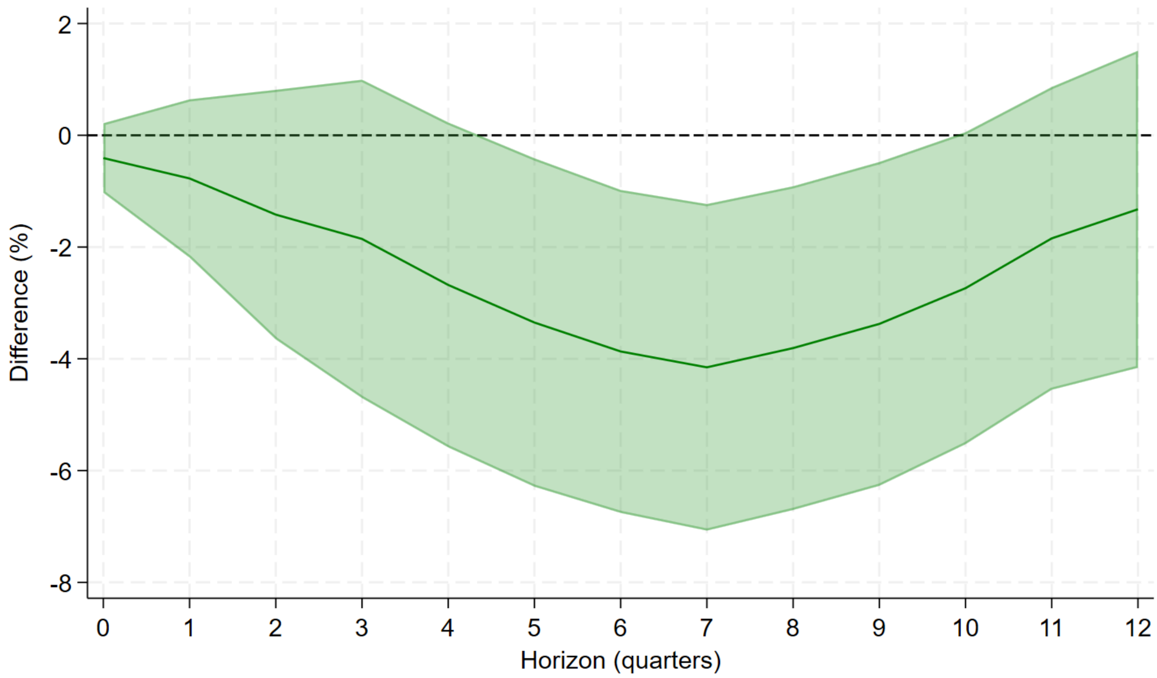
Notes: Descriptive statistics of the dataset used in the local projection analysis. The sample period is 2000Q1-2020Q1.

Figure E.2.1: Estimated IRFs to a one-standard-deviation uncertainty shock

(a) Impact of uncertainty shocks at different levels of banking concentration



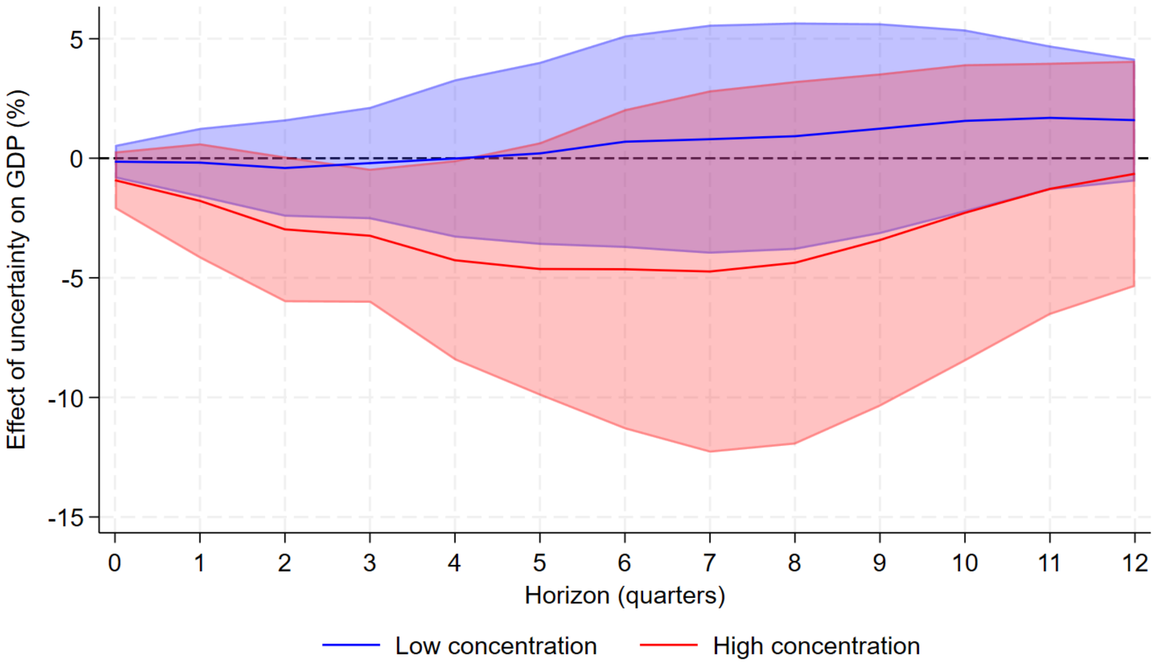
(b) Difference between IRFs



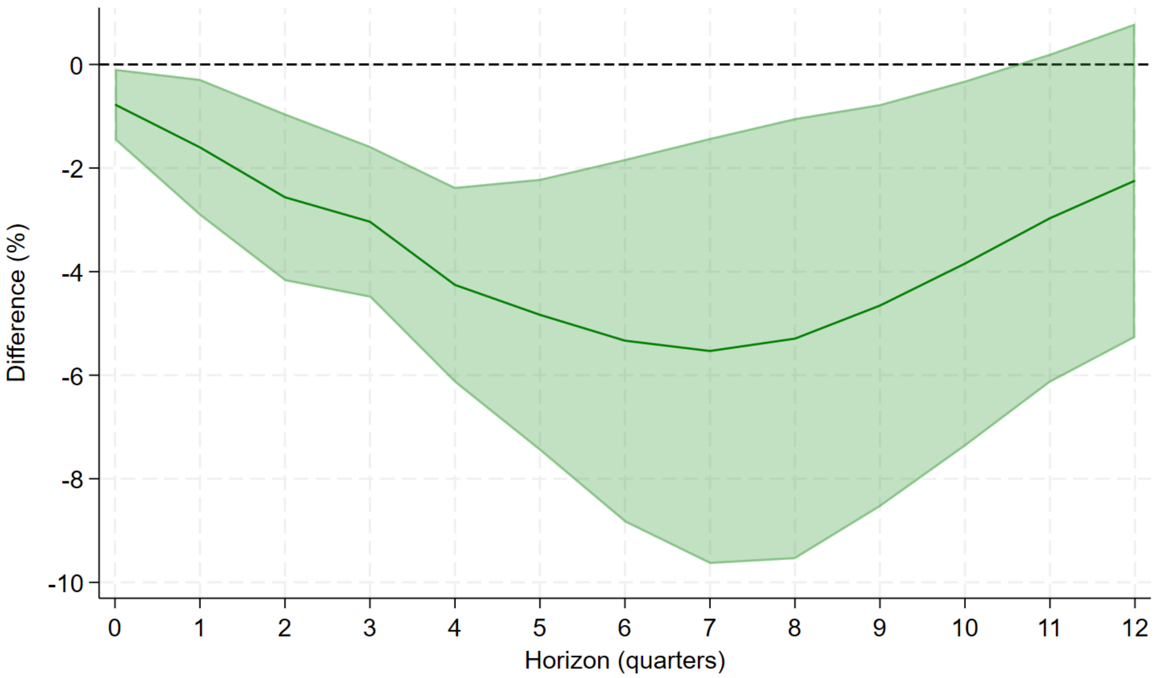
Notes: Sample period: 2000Q1 to 2020Q1. Banking concentration is measured as the share of total assets held by the five largest banks. The level of concentration is kept constant within a year.

Figure E.2.2: Estimated IRFs to a one-standard-deviation uncertainty shock

(a) Impact of uncertainty shocks at different levels of banking concentration



(b) Difference between IRFs



Notes: Sample period: 2000Q1 to 2020Q1. Banking concentration is measured as the share of total assets held by the three largest banks.