Banking Panic Risk and Macroeconomic Uncertainty

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Abstract

We show that systemic risk in the banking sector breeds macroeconomic uncertainty. In a production economy with a banking sector, financial constraints of banks can lead to disastrous banking panics. We find that a higher probability of a banking panic increases uncertainty in the aggregate economy. We explore the implications of this banking panic-driven uncertainty for business cycles, asset prices and macroprudential regulation. Banking panic-driven uncertainty amplifies business cycle volatility, increases risk premia on asset prices and yields a new benefit from countercyclical bank capital buffers.

Keywords: Banking Panics, Systemic Risk, Endogenous Uncertainty, Macroprudential Policy

JEL Classification: E44, G12, G21, G28

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1 Introduction

In this paper, we study how systemic risk in the banking sector affects the real economy through a novel feedback loop between systemic risk and macroeconomic uncertainty and explore how macroprudential policy can help to dampen this negative feedback loop.

The financial crisis of 2007-2009 was associated with a significant rise in both systemic risk in the banking sector and macroeconomic uncertainty more broadly: Fears of a systemic banking panic resulting in a disastrous breakdown of the financial sector were widespread. Measures of systemic risk in the banking sector increased substantially. In the top left panel of Figure 1, we show the TED spread, which proxies default risk premia in the US banking sector and is thus a good indicator of systemic risk. The TED spread is usually close to zero, but increased almost tenfold from 0.38 in January 2007 to 3.35 in October 2008. This corresponds to an increase of roughly 7 standard deviations over the mean relative to the data from 1986-2007, which represents a substantial increase in systemic risk.

[Figure 1 about here.]

This risk spilled over into the aggregate economy: Measures of more broad financial and macroeconomic risk spiked, too. Consider for example the real uncertainty index constructed by Jurado, Ludvigson, and Ng (2015). We show it as the blue line in the top right panel of Figure 1. This index measures the conditional volatility in an exhaustive set of macroeconomic time series. The red line is a broader macro-financial uncertainty index, which additionally measures uncertainty in financial markets. During the financial crisis, it increased by about a third. This is an increase of 8 standard deviations over the mean relative to the data from 1986-2007. As we show in the bottom two panels of Figure 1, credit risk premia increased substantially, and investment and output plummeted. This negatively affected bank balance sheets and increased the likelihood of a systemic banking panic.

As a consequence of this disastrous event, the US and many other countries introduced a countercylical capital buffer (CCyB) for banks as a new policy instrument.[1] The stated purpose of such a policy is not to only to structurally rebalance the capital structure of banks, but also to reduce systemic risk in the economy by curbing excessive credit booms which can lead to severe downturns when they end.[2] However, the exact macroeconomic effects of this policy, in particular in a regime with elevated systemic risk, remain the subject of an ongoing debate.

These observations lead us to our research questions: How does an increase in systemic risk in the banking sector relate to an increase in macroeconomic uncertainty more broadly? What are the implications of endogenous systemic risk for business cycle dynamics and asset prices? And how does the spillover of systemic risk into the real economy affect the desirability of macroprudential policy?

To tackle these questions, we develop a simple model of a production economy with a financial sector, based on Gertler, Kiyotaki, and Prestipino (2019): Households lend to banks, which in turn lend to firms. Firms use these loans to make investments. Banks are subject to a moral hazard problem in the spirit of Gertler and Karadi (2011). This is a way to introduce a financial constraint for the banking sector. As a consequence of the moral hazard problem, banks face an incentive constraint that limits their borrowing to a time-varying multiple of their equity. We interpret this incentive constraint as a market-imposed capital requirement. Crucially, the incentive constraint implies that a bank with zero or negative net worth cannot operate and must default. Due to this constraint, banks face systemic banking panics in the spirit of Cole and Kehoe (2000) and Gertler and Kiyotaki (2015). A banking panic of that kind occurs, when expectations about a banking panic drive

[1] See e.g. `https://www.federalreserve.gov/newsevents/pressreleases/bcreg20160908b.htm` for the US.

[2] See e.g. Basel Committee on Banking Supervision (2010), page 7, paragraph 29: *As witnessed during the financial crisis, losses incurred in the banking sector during a downturn preceded by a period of excess credit growth can be extremely large. Such losses can destabilise the banking sector, which can bring about or exacerbate a downturn in the real economy. This in turn can further destabilise the banking sector. These interlinkages highlight the particular importance of the banking sector building up its capital defences in periods when credit has grown to excessive levels. The building up of these defences should have the additional benefit of helping to moderate excess credit growth.*

down the prices of banks' assets so much that the net worth of banks becomes negative. Banking panics are disastrous events, resulting in a large increase in risk premia as well as a contraction of output, consumption and investment. They arise with an endogenous, time-varying probability. We define the probability of such a banking panic as systemic risk, using the terms banking panic risk and systemic risk interchangeably.

Our first main result is that an increase in systemic risk leads to an increase in macroeconomic uncertainty, i.e. in the conditional volatility of output. The model therefore provides a tight link between systemic risk in the financial sector and more broadly defined macroeconomic uncertainty. To our knowledge, making this link explicit and studying its implications in a dynamic stochastic general equilibrium model is a novel contribution to the literature. Systemic risk increases the conditional volatility of the economy, because the probability of a banking panic is endogenous and highly state-dependent. Since the probability of a banking panic in a state with a good realization of the exogenous shock is unchanged, output in those states is unaffected. In states of the world with a bad realization of the exogenous shock, the possibility of a banking panic increases the range of bad outcomes. Therefore, the presence of banking panic risk widens the conditional distribution of output by creating downside risk. Our results are consistent with the results reported in Adrian, Boyarchenko, and Giannone (2019), who report that during times of financial stress, the conditional distribution of GDP in the US has higher downside risk. Moreover, the evidence in Giglio, Kelly, and Pruitt (2016) also provides strong support for the channel we emphasize by showing that an increase in systemic risk predicts a higher likelihood of a low realization of output.

For our second main result, we investigate the importance of this banking panic-driven uncertainty for macroeconomic dynamics. We find that banking panic-driven uncertainty is a novel channel that increases the unconditional volatility of macroeconomic aggregates and asset prices. We arrive at this result by comparing an economy with endogenous banking panic risk to an economy without banking panics. Crucially, in the model without banking panics, banks otherwise face the same financial constraints as in our baseline model with banking panics. The transmission mechanism through which banking panic-driven uncertainty amplifies shocks works through a precautionary savings channel and a financial constraints channel. A negative macroeconomic shock increases the likelihood of a banking panic. Macroeconomic uncertainty about future consumption increases. As a consequence, the returns on risk-free assets fall as savers seek to insure themselves against future uncertainty. The returns on risky assets increase, as risk-averse investors demand higher risk premia. Higher risk premia in turn lead to a higher required return on investment for the non-financial sector and hence lower investment and output. This is the precautionary savings channel. The moral hazard problem ties the borrowing capacity of banks to the market value of their net worth. As bank net worth is a risky asset, the return on banks' net worth increases which implies that the market price of banks' net worth falls. Banks are forced to contract lending, which increases the required return on investment for the non-financial sector. Output and investment fall. This is the financial constraints channel.

As our third main result, we investigate the importance of this novel banking panic uncertainty channel for the benefits from macroprudential policy. We focus on a dynamic capital requirement policy that the regulator sets to dampen credit booms, which lead to an excess build-up of systemic risk. In particular, we investigate the contributions of banking panics and systemic risk to the welfare gain of a policy that seeks to offset the feedback loop between asset prices, bank balance sheets and investment, i.e. the so called financial accelerator effect (Bernanke, Gertler, and Gilchrist (1999)). It is desirable, because the regulator can in that way correct for the fact that banks fail to internalize that their lending decisions, through asset prices, affect the likelihood of a banking panic. There is therefore a pecuniary externality in the model. Banking panics are inefficient, because they arise as a coordination of the agents on a dominated equilibrium. The panic equilibrium is dominated, because relative to the good equilibrium, lending to the non-financial sector is not undertaken by the most efficient lenders, i.e. the banks. When we again compare the two models with and without banking panic uncertainty, we find that there is a new benefit from this policy in the model with banking panic-driven uncertainty, since dampening the financial accelerator also reduces the likelihood of a banking panic, which lowers uncertainty. Put bluntly, we show that macroprudential policy is more beneficial in a regime with elevated systemic risk in the banking sector.

Literature Our model builds on recent work by Gertler, Kiyotaki, and Prestipino (2019). There are two key differences between our model and theirs: First, banking crises in our model are persistent, and second, households have recursive Epstein and Zin (1989) (EZ)-preferences, which allows us to calibrate the model using asset pricing data.[3] Relative to Gertler, Kiyotaki, and Prestipino (2019), we focus on the effects of banking panic risk on macroeconomic uncertainty and highlight the importance of this uncertainty channel.

More generally, our paper is at the intersection of the literature on financial crises in macroeconomic models and the literature on the effects of uncertainty on business cycles. We contribute to this literature by highlighting the effect of uncertainty that results from the possibility of banking panics as a new channel through which financial crises can affect macroeconomic dynamics. We argue that the macroeconomic uncertainty caused by the spike in systemic risk is an important feedback channel that amplifies the severity of financial crises. There are now many macroeconomics models of financial crises: Our paper belongs to a strand of the literature that models financial crises as rollover crises in the spirit of Calvo (1988) and Cole and Kehoe (2000), e.g. Gertler and Kiyotaki (2015), Gertler, Kiyotaki, and Prestipino (2016), Paul (2018), and Gertler, Kiyotaki, and Prestipino (2019). Other papers model financial crises as a financial constraint of a leveraged agent becoming binding, e.g. Mendoza (2010), Bianchi (2011), He and Krishnamurthy (2012) or Brunnermeier and Sannikov (2014).

Due to this focus on macroeconomic uncertainty, our paper also naturally connects to the macroeconomic literature on the effects of macroeconomic uncertainty shocks on macroeco-

[3] The use of EZ-preferences to match asset prices is common in the macro-finance literature, see e.g. Van Binsbergen, Fernández-Villaverde, Koijen, and Rubio-Ramírez (2012) or Rudebusch and Swanson (2012).

nomic dynamics. Relative to this literature, we first present banking panic risk as a novel channel through which macroeconomic uncertainty can arise endogenously. We second study how uncertainty feeds back into amplifying systemic risk. Third, we show that an increase in uncertainty due to banking panic risk is not symmetric, but concentrated in the left tail of the output distribution. In general, this literature focuses on exogenous, symmetric uncertainty shocks, e.g. Born and Pfeifer (2014), Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015), Leduc and Liu (2016) and Basu and Bundick (2017). Others, e.g. Fajgelbaum, Schaal, and Taschereau-Dumouchel (2017) or Cacciatore and Ravenna (2018) present mechanisms in which uncertainty arises endogenously or in which exogenous uncertainty shocks get endogenously amplified. The idea that small probabilities of large disasters can have big consequences for asset prices and macroeconomic dynamics has been explored, in a model with exogenous disasters, in Barro (2009) and Gourio (2012). Banking panics in our model can be interpreted as a particular kind of disasters that arise with an endogenous probability. Adrian, Boyarchenko, and Giannone (2019) and Alessandri and Mumtaz (2019) present empirical evidence that financial stress and macroeconomic uncertainty are connected.

The paper is lastly related to the literature on the macroeconomic effects of bank regulation, in particular dynamic capital requirements. We study endogenous banking panic-driven uncertainty as a novel channel which increases welfare gains from dynamic capital requirements. The macroeconomic effects of simple, static capital requirements have been studied for example in Angeloni and Faia (2013), Begenau and Landvoigt (2018) or Begenau (2019). Gertler, Kiyotaki, and Queralto (2012) discusses dynamic capital requirements in a model with exogenous disasters. Faria-e Castro (2019) investigates the macroeconomic effects of countercyclical capital buffers on banking panics, but not focus on the uncertainty channel. Akinci and Queralto (2017) consider the effects of macroprudential regulation in an economy in which banking crises arise when financial constraints in the banking sector become binding. Gersbach and Rochet (2017) study countercyclical capital buffers in an economy in which pecuniary externalities lead banks to excessively lend, which causes misallocation.

Outline We proceed as follows: In section 2, we introduce the model. We characterize the equilibrium and formalize banking panic risk in section 3. We explain how banking panic risk affects macroeconomic uncertainty, and how macroeconomic uncertainty in turn feeds back into the economy in section 4. We calibrate the model in section 5. In section 6, we show what a typical banking panic in the model looks like. We explore the connection between systemic risk and macroeconomic uncertainty in the model, as well their implications for macroeconomic dynamics in section 7. In section 8, we discuss macroprudential regulation. Finally, section 9 concludes.

2 Model

The model is a simple, stylized production economy with a financial sector, based on Gertler, Kiyotaki, and Prestipino (2019). The key feature of the model is that financial frictions in the banking sector can lead to self-fulfilling rollover crises on banks in the spirit of Calvo (1988), Cole and Kehoe (2000) and Gertler and Kiyotaki (2015).

There are many households which each consist of a measure f of workers and a measure $1 - f$ of bankers. Within each household, there is perfect consumption risk sharing. The households own and operate firms which produce consumption goods, firms which produce investment goods, and mutual funds. Workers supply a unit of labor in fixed supply, make loans to consumption goods producers and deposits to banks. Bankers own and operate banks. They use debt and their net worth to make loans to consumption goods producers. Banks accumulate retained earnings until they exit the economy with exogenous probability. In that case, they transfer the retained earnings as dividend income to their household. A moral hazard problem limits the ability of banks to issue debt to a time-varying multiple of their net worth, i.e. their leverage. Consumption goods producers own the capital stock, and use capital and labor to produce consumption goods. Investment goods producers transform consumption goods into investment goods using a technology which has decreasing returns to scale in the short run due to investment adjustment costs. Finally, mutual funds manage the portfolio of loans to consumption goods producers made directly by households against a fee. We begin by describing the non-standard part of the model, which are the household and the banking sector. We follow the convention that lower case letters for variables denote individual variables, while upper case letters denote aggregate variables.

2.1 Households

Preferences Households maximize utility from consumption. Their utility function V_t^H is given by Epstein and Zin (1989)-preferences, which are defined recursively as:

$$V_t^H = \left((1-\beta) \left(c_t^H \right)^{1-\sigma} + \beta \mathbb{E}_t \left[\left(V_{t+1}^H \right)^{1-\gamma} \right]^{\frac{1-\sigma}{1-\gamma}} \right)^{\frac{1}{1-\sigma}}, \tag{2.1}$$

where $\mathbb{E}_t$ denotes the expectation conditional on time t information and β is the discount factor of the household. c_t^H denotes household consumption in period t. γ is the coefficient of relative risk aversion, σ the inverse of the intertemporal elasticity of substitution of the household. These preferences imply that the stochastic discount factor of the household is given by

$$\Lambda_{t,t+1} = \beta \left(\frac{c_{t+1}^H}{c_t^H} \right)^{-\sigma} \left(\frac{V_{t+1}^H}{\mathbb{E}_t \left[\left(V_{t+1}^H \right)^{1-\gamma} \right]^{\frac{1}{1-\gamma}}} \right)^{\sigma-\gamma}. \tag{2.2}$$

With $\sigma = \gamma$, this preference specification collapses to constant relative risk aversion preferences. $\gamma > \sigma$ implies that households have a preference for early resolution of uncertainty.

Budget constraint Workers consume, make state-contingent long-term loans to consumption goods producers a_{t+1}^H through mutual funds and hold non-state-contingent one period debt d_{t+1}^H issued by banks. They also have access to a risk-free one period bond b_{t+1}, which is in zero net supply. We introduce this bond to ensure that the concept of a risk-free interest rate is well-defined. Since loans to consumption goods producers are effectively claims to the capital stock of those firms, they are valued at the market price of capital Q_t. The investments of workers into firms are managed by mutual funds, which charge a capital management fee f_t. Workers supply one unit of labor inelastically and receive a wage W_t as labor income.[4] They receive profits Π_t of firms and banks. Loans to banks yield a return $\tilde{R}^D_{t+1}$ in the subsequent period. Loans to firms pay a return R^A_{t+1}. The budget constraint of the household is given by

$$c^H_t + (Q_t + f_t)a^H_{t+1} + b^H_{t+1} + d^H_{t+1} = R^A_t a^H_t + \tilde{R}^D_t d^H_t + R^B_t b^H_t + W_t + \Pi_t. \tag{2.3}$$

2.2 Banks

Objective function Banks are operated by bankers. They maximize

$$V^B_t = \mathbb{E}_t \Lambda_{t,t+1}(1 - p_{t+1}) \left[\eta n^B_{t+1} + (1-\eta)V^B_{t+1}\right], \tag{2.4}$$

where $\Lambda_{t,t+1}$ is the stochastic discount factor of households from period t to $t+1$, η is a probability that the bank exits the economy, p_t is the probability that the bank defaults in period t and n^B_t is the net worth of the bank at the beginning of period t.

Entry and exit As in Gertler and Karadi (2011), we assume that with probability η, a banker will be forced to give up his bank, sell its assets, repay its liabilities and pay the net worth to households. We introduce this assumption to ensure that banks will not outsave their borrowing constraints. To keep the mass of bankers constant, an equal mass of workers will start operating a bank with start-up funding $n^{B,new}_t$. This start-up funding is given by a fraction υ of the total assets traded in the economy: $n^{B,new}_t = \upsilon A_t$.

[4] To keep the model as simple as possible, we model labor supply as constant. Endogenizing the labor supply choice is straightforward and would not substantially affect the results.

Net worth Banks issue debt d_{t+1}^B. They make loans to consumption good producers a_{t+1}^B, who use these loans to purchase capital. Since there are no financial frictions between the firms and banks, these loans can be understood as direct claims on the capital stock of firms.[5] In period t, incumbent banks obtain a gross return on loans, $R_t^A a_t^B$. They pay a return $R_t^D d_t^B$ to households on their debt. An incumbent bank's net worth at the beginning of period t is given by

$$n_t^B = R_t^A a_t^B - R_t^D d_t^B. \tag{2.5}$$

Banks will optimally accumulate net worth until they exit the economy. Since we focus on the macroeconomic dynamics in the short run, we assume that banks cannot issue additional equity. It is a common assumption in the literature that equity issuance carries at least some cost for banks, see e.g. Akinci and Queralto (2017), Begenau (2019) or Corbae and D'Erasmo (2018). Hence, the equity of banks corresponds to their net worth.

Balance sheet The balance sheet constraint of banks states that assets $Q_t a_{t+1}^B$ equal liabilities d_{t+1}^B plus equity n_t^B:

$$Q_t a_{t+1}^B = d_{t+1}^B + n_t^B. \tag{2.6}$$

We define the leverage of a bank ϕ_t^B as the value of its assets divided by the value of its equity:

$$\phi_t^B \equiv \frac{Q_t a_{t+1}^B}{n_t^B}. \tag{2.7}$$

Moral hazard problem To motivate the existence of a market-imposed capital requirement, we introduce the following moral hazard problem: banks can divert a fraction of their assets after they have made their borrowing and lending decisions. In particular, a fraction ψ, $0 < \psi < 1$ of their loans to firms can be diverted by the banker for personal consumption.

[5] This is obviously a modelling shortcut to make bank balance sheets responsive to current market prices. Another way to introduce state-contingency into bank balance sheets is through defaultable long-term debt, e.g. as in Ferrante (2018).

If bankers divert assets, they will not repay their liabilities. Their creditors, i.e. the workers of other households, will force the banks to exit the economy if they observe diversion. The owner of the bank will return to being a worker. Because diversion occurs at the end of the period before next period uncertainty realizes, an incentive constraint on the banks can ensure that diversion will never occur in equilibrium. This incentive constraint states that the benefit of diversion must be smaller or equal to the continuation value of the bank:

$$\psi Q_t a^B_{t+1} \leq V^B_t \tag{2.8}$$

Default The franchise value of operating a bank which does not receive an exit shock in period t, V^B_t, can be shown to be linear in the net worth of the bank:

Proposition 2.1. *The value function of the bank is linear in its net worth: $V^B_t = \Omega^B_t n^B_t$, where $\Omega^B_t > 0$ only depends on the aggregate state of the economy, but not on bank-specific variables.*

With this, we can show that the incentive constraint 2.8 of the bank implies a borrowing limit is linear in its net worth:

$$\begin{aligned} d^B_{t+1} &\leq \frac{\Phi_t}{1-\Phi_t} n^B_t, \\ \Phi_t &= \frac{\mathbb{E}_t \Lambda_{t,t+1}(\eta + (1-\eta)\Omega_{t+1})\frac{R^A_{t+1}}{Q_t} - \psi}{\mathbb{E}_t \Lambda_{t,t+1}(\eta + (1-\eta)\Omega_{t+1}) R^D_{t+1}}. \end{aligned} \tag{2.9}$$

This implies that creditors are not willing to lend to the bank, when the net worth of the bank is negative. Moreover, a negative net worth means by definition that the bank cannot repay its liabilities and is insolvent. Therefore, when

$$R^A_t a^B_t \leq R^D_t d^B_t, \tag{2.10}$$

the bank will default. The creditors of the bank, which are the workers of other households than the household the bank belongs to, will liquidate the assets of the bank.[6] The recovery rate on their debt is given by

$$x_t^D = \frac{R_t^A a_t^B}{R_t^D d_t^B}. \tag{2.11}$$

The return on deposits that households receive is hence

$$\tilde{R}_t^D = \begin{cases} R_t^D & \text{if the bank is solvent} \\ x_t^D R_t^D & \text{if the bank is insolvent} \end{cases}. \tag{2.12}$$

Regulation The regulator follows a dynamic policy, which corresponds to a countercyclical capital buffer. We model this policy as an upper bound on leverage:

$$\phi_t^B \leq \bar{\phi}_t^B, \tag{2.13}$$

$$\ln \bar{\phi}_t^B = \ln \bar{\phi}^B - \tau(\ln N_t^B - \ln N^B). \tag{2.14}$$

For $\tau > 0$, this formulation implies that the regulator tightens the leverage constraint whenever net worth of the aggregate banking sector N_t^B is higher than its net worth in the stochastic steady state N^B, with elasticity τ. ln denotes the natural logarithm.

2.3 Consumption goods producers

Consumption goods producers choose labor l_t^F, capital s_{t+1}^F and loans a_{t+1}^F to maximize

$$\mathbb{E}_t \sum_{s=t}^{\infty} \Lambda_{t,s} \Pi_s^F. \tag{2.15}$$

[6] This assumption ensures that bankers do not internalize the effect of their decisions on the recovery value of banks' creditors in default.

Profits Π_t^F are given by

$$\Pi_t^F = (k_t^F)^\alpha (l_t^F)^{1-\alpha} - W_t l_t^F + Q_t \underbrace{\left[a_{t+1}^F - \frac{R_t^A}{Q_t} a_t^F\right]}_{\text{Borrowing}} - Q_t \underbrace{\left[s_{t+1}^F - (1-\delta) k_t^F\right]}_{\text{Investment}}.$$

We make a distinction between beginning-of-period capital k_t^F and end-of-period capital s_t^F. Beginning-of-period capital is given by $k_t^F = Z_t s_t^F$. Following Merton (1973) and Gertler and Karadi (2011), Z_t is a capital quality shock which generates exogenous variation in the price of capital. We interpret it as fraction of the capital stock becoming obsolete and losing its economic value. The difference to depreciation δ is that the capital quality shock arises before production, whereas depreciation occurs after production. It follows an AR(1) process:

$$\ln(Z_t) = (1-\rho^Z)\mu^Z + \rho^Z \ln(Z_{t-1}) + \epsilon_t, \tag{2.16}$$

where $|\rho^Z| < 1$ and $\epsilon_t \sim N(0, \sigma^Z)$. Since firms refinance themselves exclusively with loans, their balance sheet constraint is $s_{t+1}^F = a_{t+1}^F$. Their optimality condition for bank loans implies that

$$R_t^A = Z_t \left(\alpha (k_t^F)^{\alpha-1} (l_t^F)^{1-\alpha} + (1-\delta) Q_t\right). \tag{2.17}$$

2.4 Capital goods producers

Capital goods producers transform consumption goods into capital goods with a technology that has decreasing returns to scale in the short run due to investment adjustment costs. They maximize profits Π_t^Q with respect to their output, i_t. Profits are given by

$$\Pi_t^Q = Q_t i_t - i_t - \frac{\theta}{2}\left(\frac{i_t}{I_{t-1}} - 1\right)^2 I_{t-1}. \tag{2.18}$$

Note that capital producers take aggregate investment in the last period, I_{t-1}, as given.[7] Hence, the problem of the capital producer is static.

2.5 Mutual funds

Competitive mutual funds manage the portfolio of loans that households directly invest into the consumption goods producers. Following Gertler, Kiyotaki, and Prestipino (2019), they face a cost function of providing this service, which is quadratic in the amount of loans $\tilde{a}_t^M$ they manage. There is a cutoff ζ below which the funds can manage capital as efficiently as banks. They maximize profits, which are given by

$$\Pi_t^M = f_t \tilde{a}_{t+1}^M - \frac{\chi}{2} \max\left(\frac{\tilde{a}_{t+1}^M}{A_t} - \zeta, 0\right)^2 A_t \tag{2.19}$$

We model this cost as a function of the share of capital managed by the funds and not as a function of the level to ensure that the mutual fund sector can scale with the economy in the long run. The cutoff ζ represents the share of investment projects above which the banking sector can better evaluate and monitor. If the mutual fund sector is forced to undertake a larger share of investment, e.g. due to the banking sector being insolvent, an efficiency loss arises.

2.6 Aggregation

Since the policy functions of an individual bank are linear in net worth, we will characterize the equilibrium in terms of the aggregate banking sector. The aggregate net worth of the

[7] Usually in the business cycle literature, firms internalize the effect of their investment decisions on future investment adjustment costs. Moreover, the investment adjustment cost is usually normalized with respect to I_t instead of I_{t-1}. Since the cost function under these two assumptions is very badly behaved for levels of investments far away from the lagged level of investment, and since we solve for the global equilibrium dynamics of the model, we have adopted this simpler, better behaved formulation.

banking sector is given by the sum of the net worth of incumbent and newly entering banks:

$$N_t^B = (1-\eta)n_t^B + \eta n_t^{B,new}.$$

Aggregate output is given by production net of the capital holding costs:

$$Y_t = K_t^\alpha - \frac{\chi}{2}\max\left(\frac{\tilde{a}_{t+1}^M}{A_t} - \zeta, 0\right)^2 A_t. \tag{2.20}$$

We define as aggregate investment $\tilde{I}_t$ as the total expenditure necessary to change the capital stock from K_t to S_{t+1}. Therefore, our measure of aggregate investment includes the investment adjustment costs: Define I_t as net investment excluding capital adjustment costs, that is

$$I_t = S_{t+1} - (1-\delta)K_t.$$

Then, investment is given by

$$\tilde{I}_t = I_t + \frac{\theta}{2}\left(\frac{I_t}{I_{t-1}} - \delta\right)^2 I_{t-1}. \tag{2.21}$$

There is a representative household. Hence, the individual consumption and aggregate consumption are equal, $c_t^H = C_t^H$. Household consumption can be inferred from the aggregate resource constraint:

$$C_t^H = Y_t - \tilde{I}_t \tag{2.22}$$

3 Equilibrium

In this section, we formalize the concept of systemic risk in the model. The model has an equilibrium with solvent banks and an equilibrium with insolvent banks. We characterize those equilibria in Appendix D. We discuss here equilibrium multiplicity in the model as well as equilibrium selection.

3.1 Equilibrium multiplicity and banking panics

Since the net worth of incumbent banks is among the state variables which determine the capital price, and the capital price vice versa determines the net worth of banks, there is the possibility for both equilibra to coexist given the same fundamental state of the economy in the model:[8] If bank creditors believe that the capital price is high, they will continue to lend to the banks, which thus remain solvent and allows them to lend, which will justify the high capital price. If bank creditors instead believe that the capital price is low, they will not lend to the banks, which as a consequence become insolvent and stop lending to the economy, justifying the low capital price. Note that in contrast to Diamond and Dybvig (1983), the decision of the bank creditors is not about whether to withdraw outstanding debt from the banks or not, but about whether they should keep lending to the banks or not. Strategic complementarity arises between the decisions of the bank creditors arises, because due to 2.8, it is not optimal to lend to a bank with a negative net worth.

Define two recovery values for an *individual* bank: The recovery value x^D denotes the recovery value of an insolvent, individual bank if no systemic bank default arises. The recovery value $x^{D,*}$ denotes the recovery value of an individual bank if a systemic bank default arises. We can divide the state space of the model into three zones. In the first zone, the safe zone, both the recovery value without a systemic bank default, x^D, as well as the recovery value of bank creditors with a systemic bank default, $x^{D,*}$, are bigger than one. This implies that independent of the beliefs of bank creditors about the solvency of the banking sector, the banking sector is solvent. In that case, the no-panic-equilibrium is the unique equilibrium of the economy.

In the second zone, the multiplicity zone, recovery values are bigger than one if the

[8] As noted by Thaler (2018) and Christiano (2018), there is the possibility of a third, partial default equilibrium in the model, which turns out not to be quantitatively relevant for our calibration.

banking sector as a whole is solvent, but smaller than one if there is a systemic bank default. In this zone, both the equilibrium with solvent banks and the equilibrium with insolvent banks exist, because the solvency of banks depends on the beliefs of bank creditors about the solvency of banks. We assume that agents coordinate on the equilibrium with insolvent banks if they observe the sunspot realization Ξ^R. If agents coordinate on the equilibrium with insolvent banks, we follow Gertler, Kiyotaki, and Prestipino (2019) in calling this a banking panic.

In the third zone, the crisis zone, recovery values are less than one both if banks there is no systemic bank default and if there is a systemic bank default. In that case, the panic-equilibrium is the unique equilibrium of the economy, because, independently of the beliefs of the bank creditors, the banking sector is insolvent. The expected probability that the economy will end up in the banking panic-equilibrium in the next period is then given by

$$\mathbb{E}_t p_{t+1} = \mathbb{E}_t \left[\underbrace{\mathbb{1}(x^D_{t+1} \leq 1 \text{ and } x^{D,*}_{t+1} \leq 1)}_{\text{Default due to insolvency}} + p^H \underbrace{\mathbb{1}(x^D_{t+1} > 1 \text{ and } x^{D,*}_{t+1} \leq 1)}_{\text{Default due to panic}} \right] \tag{3.1}$$

Note that the state-dependency of the banking panic probability arises only as a result of the state-dependency of the existence condition of the multiplicity zone and the crisis zone. There is no exogenous state-dependency built into the sunspot probability.

3.2 Decomposing the banking panic condition

It will be useful to decompose the recovery value of bank creditors into four components:

$$x^{D,*}_t = \underbrace{\frac{R^{A,*}_t}{R^A_t}}_{1-\text{Liquidation discount}} \underbrace{\frac{R^A_t/Q_{t-1}}{R^B_t}}_{\text{Firm credit spread}} \underbrace{\frac{R^B_t}{R^D_t}}_{\text{Bank credit spread}} \underbrace{\frac{\phi_{t-1}}{\phi_{t-1}-1}}_{\text{Bank leverage}}, \tag{3.2}$$

where R_t^B is the risk-free interest rate. The first term is inversely related to the liquidation discount, which reflects how much asset returns fall in a banking panic. The second and third term measure the spread between the return on bank assets and the return on bank liabilities, which can be interpreted as bank profitability. The last term is inversely related to bank leverage. The model predicts that a banking panic is more likely if the expected liquidation discount is higher, the realized firm credit spread is lower, the bank credit spread is higher and bank leverage is higher.

4 Banking panic risk and macroeconomic uncertainty

In this section, we illustrate how an increase in banking panic risk can increase macroeconomic uncertainty. We show that both banking panic risk and macroeconomic uncertainty are highly state-dependent. Finally, we discuss how macroeconomic uncertainty affects the economy and feeds back into banking panic risk through a precautionary savings channel and a financial frictions channel.

4.1 Measuring uncertainty

We measure macroeconomic uncertainty by the conditional volatility of output $StDev_t(Y_{t+1})$, which is given by

$$StDev_t(Y_{t+1}) = \left[\int_{\varepsilon_{t+1}} \left[p_{t+1}\left(Y_{t+1}^* - \mathbb{E}_t Y_{t+1}\right)^2 + (1-p_{t+1})\left(Y_{t+1} - \mathbb{E}_t Y_{t+1}\right)^2\right] dF(\varepsilon_{t+1})\right]^{\frac{1}{2}}, \tag{4.1}$$

with the conditional expectation of future output given by

$$\mathbb{E}_t Y_{t+1} = \int_{\varepsilon_{t+1}} \left[p_{t+1} Y_{t+1}^* + (1-p_{t+1}) Y_{t+1}\right] dF(\varepsilon_{t+1}). \tag{4.2}$$

Intuitively, this conditional volatility tells us how much uncertainty there is around the forecast for output in the next period.

We also split uncertainty into uncertainty about the lower tail of the output distribution, $StDev_t^-(Y_{t+1})$, and uncertainty about the upper tail of the output distribution, $StDev_t^+(Y_{t+1})$. We compute those statistics as

$$StDev_t^-(Y_{t+1}) = \left[\int_{\varepsilon_{t+1}} \left[p_{t+1}\left(Y_{t+1}^* - \mathbb{E}_t Y_{t+1}\right)^2 \mathbb{1}_{(Y_{t+1}^* \leq Q_t^{0.5}(Y_{t+1}))} \right.\right.$$
$$\left.\left. +(1-p_{t+1})\left(Y_{t+1} - \mathbb{E}_t Y_{t+1}\right)^2\right] \mathbb{1}_{(Y_{t+1} \leq Q_t^{0.5}(Y_{t+1}))} dF(\varepsilon_{t+1})\right]^{\frac{1}{2}}, \qquad (4.3)$$

and

$$StDev_t^+(Y_{t+1}) = \left[\int_{\varepsilon_{t+1}} \left[p_{t+1}\left(Y_{t+1}^* - \mathbb{E}_t Y_{t+1}\right)^2 \mathbb{1}_{(Y_{t+1}^* > Q_t^{0.5}(Y_{t+1}))} \right.\right.$$
$$\left.\left. +(1-p_{t+1})\left(Y_{t+1} - \mathbb{E}_t Y_{t+1}\right)^2\right] \mathbb{1}_{(Y_{t+1} > Q_t^{0.5}(Y_{t+1}))} dF(\varepsilon_{t+1})\right]^{\frac{1}{2}}, \qquad (4.4)$$

where $\mathbb{1}_{(.)}$ is an indicator function that takes the value one when the condition in brackets is fulfilled and is zero otherwise and $Q_t^{0.5}(Y_{t+1})$ is the conditional median of future output. Intuitively, these statistics measure the respective volatility in the left tail and in the right tail of the output distribution.

4.2 The effect of banking panic risk on macroeconomic uncertainty

To illustrate the effects of banking panic risk on conditional output volatility, we consider the following thought experiment: Suppose we compare two economies which are identical, economy A and economy B. The only difference is that in economy A, sunspot shocks can lead agents to coordinate on the panic equilibrium if multiple equilibria are possible, whereas in economy B, agents never coordinate on the panic equilibrium if multiple equilibria are possible. By how much is the conditional volatility of output in economy A in the region with equilibrium multiplicity higher than in economy B?

[Figure 2 about here.]

The top panel of Figure 2 shows the conditional distribution of output relative to the expected output conditional on no panic in a state of the world with high future banking panic risk. Economy A is the solid blue line and economy B the dashed red line. We compare the economies for the same state of the economy at time t. We can see that for economy B, the range of possible realizations of output is distributed symmetrically around expected output. In contrast to that in economy B, a second, albeit small peak of the distribution exists at around 7 percent below expected output in the no-run state. As a consequence of this second peak, the conditional volatility of output is roughly twice as high in the economy with panics compared to the economy without panics.

This increase in the conditional volatility of output will only arise in states of the world tomorrow where the banking panic equilibrium exists, which depends on the state of the world today. As a consequence, the conditional volatility of output is endogenously highly state-dependent. To illustrate this, consider the bottom panel of Figure 2. This compares the economy with panics to the economy without panics in a state in which there is no banking panic risk. In this state, the conditional volatility of future output is essentially identical in both economies. Banking panic risk thus only increases the left tail of the output distribution, and only during times of heightened financial stress, in line with the evidence in Giglio, Kelly, and Pruitt (2016) and Adrian, Boyarchenko, and Giannone (2019).

4.3 The feedback loop between banking panic risk and macroeconomic uncertainty

The increase in macroeconomic uncertainty due to the higher banking panic risk affects the macroeconomy through two channels:

First, a precautionary savings channel leads households to reduce their demand for bank debt and their demand for loans issued by the non-financial sector: This can be seen from the first-order conditions of the household. Consider first the first-order condition for the risk-free bond:

$$1 = \mathbb{E}_t \Lambda_{t,t+1} R^B_{t+1}. \tag{4.5}$$

An increase in uncertainty increases the stochastic discount factor by making future consumption more volatile. As a consequence, the risk-free return R^B_{t+1} must fall. Consider next the first-order condition for the direct lending of the household to the non-financial sector:

$$Q_t + f_t = \mathbb{E}_t \Lambda_{t,t+1} R^A_{t+1}. \tag{4.6}$$

As the stochastic discount factor increases, the expected return on firm loans will fall. Moreover, the covariance between the return on capital and the stochastic discount factor will become more negative, such that the household will demand a higher risk premium on firm loans. If the effect on the risk premium dominates the effect on the risk-free return, the price of capital will fall. This negatively impacts bank balance sheets, reduces bank lending and investment and increases bank leverage, which increases the future probability of a banking crisis.

Second, an increase in uncertainty operates through a financial constraints channel, which tightens the leverage constraint of banks 2.8. This leverage constraint can be rewritten as

$$\begin{aligned}\psi \phi^B_t &= \Omega^B_t \\ &= \mathbb{E}_t \Lambda_{t,t+1} (1 - p_{t+1}) \left[\eta + (1-\eta) \Omega^B_{t+1} \right] \frac{n^B_{t+1}}{n^B_t}\end{aligned} \tag{4.7}$$

There is a negative level effect, since the stochastic discount factor is lower. Moreover, the covariance of the stochastic discount factor, bank net worth growth n^B_{t+1}/n^B_t and the value of an additional unit of net worth in the next period Ω^B_{t+1} becomes more negative. Hence, the continuation value of operating a bank becomes more negative, such that bank creditors will tighten the bank leverage constraint, reducing bank lending, and hence investment and asset prices.

5 Calibration

We now turn to a quantitative evaluation of the macroeconomic effects of the banking panic-driven uncertainty channel. In this section, we outline the calibration strategy for the model and evaluate the model fit. The calibration is quarterly. We report the parameters in Table 1. We describe the data in Appendix A.

[Table 1 about here.]

Technology We calibrate the parameter of the production function, α, to match a capital income share of 36 percent. We set the depreciation rate δ to match an annual depreciation rate of 10 percent. To calibrate the autocorrelation ρ^Z and the standard deviation σ^Z of the capital quality process, we target the autocorrelation and standard deviation of output. We calibrate the investment adjustment cost parameter θ to target the volatility of investment.

Preferences We choose the preference parameters β, σ and γ to match asset prices. We set the discount factor of the household, β, to match the real risk-free interest rate in the stochastic steady state. We assume for this that the average interest rate between the first quarter of 1986 to the last quarter of 2006 corresponds to the stochastic steady state. We choose the inverse of the intertemporal elasticity of substitution, σ, to match the volatility of the real risk-free interest rate and the risk aversion, γ, to match the volatility of the credit spread.

Financial sector There are five parameters for the financial sector: The loan management fee parameters χ and ζ, the share of divertable assets ψ, the exit rate of bankers η and the initial endowment of new bankers υ. We set these parameters jointly to target the following moments: A share of intermediation through the banking sector of 50 percent in the stochastic steady state, in line with Gertler and Kiyotaki (2015), a leverage of of 10 in the stochastic steady state, in line with Gertler and Kiyotaki (2015), Begenau and Landvoigt (2018) and the evidence in Di Tella (2019), a credit spread of about 3.7 percent in the stochastic steady state, consistent with the average spread between the Moody's BAA yield and the Federal Funds Rate between the first quarter of 1986 and the last quarter of 2006, a planning horizon of banks of 2.5 years and an increase in the credit spread in a panic of 7.29 percent. This corresponds to the peak to trough change in the Moody's BAA spread over the federal funds rate from the first quarter of 2007 to the fourth quarter of 2008.

Sunspot We set the sunspot probability p^R to match a frequency of banking crises of about 2.5 percent per year, consistent with the frequency of financial crises in developed economies in Laeven and Valencia (2012). Finally, we set the persistence of the panic equilibrium π to target an average duration of a banking crisis of 3.25 years, which we also take from Laeven and Valencia (2012).

[Table 2 about here.]

Table 2 reports how well the model fits the targeted moments. The standard deviation of output is matched well, the standard deviation of investment is somewhat too low. The model can match the autocorrelation of output. It also does a good job at matching asset prices with reasonable parameters for household preferences: the deposit rate and the credit spread in the stochastic steady state are matched well. The standard deviation of the deposit rate and the standard deviation of the credit spread are matched well. The model can match the ratio of bank lending to total lending. Bank leverage in the stochastic steady state is slightly too low. This is difficult to remedy, since a decrease in the diversion parameter, which increases leverage in the deterministic steady state, increases instead the bank run probability without changing leverage substantially in the stochastic steady state. The frequency of banking panics, is also matched well. Interestingly, we found in numerical exercises that *increasing* the sunspot probability *reduces* the frequency of banking panics. This is, because an increase in the expected probability of a banking crisis forces banks to delever. This result is reminiscent of the volatility paradox discussed in Brunnermeier and Sannikov (2014). The banking panic duration and the increase in the credit spread during a banking panic are matched well. Overall, the model can match all moments quite well, which is remarkable, given that it is a highly nonlinear model with complex dynamics.

6 A typical banking panic

After having calibrated the model, we first use it to study what a typical realized banking panic looks like. The purpose of this exercise is to ensure that banking panics in the model capture some stylized facts about financial crises in the data: Namely that they are disastrous events which cause a long-lived fall in macroeconomic aggregates and asset prices.

6.1 Peak-to-trough changes during the financial crisis of 2007-2009 in the model and in the data

In Table 3, we report the ability of the model to fit data from the financial crisis in the US during the period of 2007-2009. For this exercise, we compare the effect of a typical banking panic in the model on macroeconomic aggregates and asset prices to the peak-to-trough changes in those variables in the data.[9] In line with Gertler, Kiyotaki, and Prestipino (2019), we assume that a banking panic happened in the data in the last quarter of 2008. Consistent with the NBER recession dates for the financial crisis, we compute the change

[9]To construct the tables and figures in this section, we follow Paul (2018): first, we simulate 10000 economies for 1000 periods. We then find all banking panics and compute the average path around a typical panic event. We discard all panics where another panic happens within 100 quarters before to 20 quarters after the panic to ensure that we capture only the effect of a single panic.

in output, consumption, and investment from the last quarter of 2007 to the second quarter of 2009. We compute the change in asset prices from the first quarter of 2007 to the last quarter of 2008, since the stress in the financial markets started earlier and peaked in the last quarter of 2008, simultaneously to the banking panic.

[Table 3 about here.]

The model does a good job at matching a fall in output of a similar magnitude as in the data. The model produces a somewhat too low fall in consumption around a typical banking panic compared to the financial crisis in the US. The fall in investment in the model is similar to the data. The fall in bank credit spreads is too small. This is natural, the model lumps together all bank liabilities, which includes not only market lending, which is our data counterpart, but also bank deposits. The model also matches the increase in the cost of financing to the real economy. Note that all of these dynamics besides the peak-to-trough change in the firm credit spread are untargeted and that we do not select the exogenous shocks in order to match any of these dynamics.

6.2 Model dynamics around a typical banking panic

After comparing the model to the data, we now focus on the mechanism of how a banking panic unfolds in the model. Figure 3 shows the dynamics of key macroeconomic and financial variables around a typical banking panic in a simulation of the model. The blue, solid line reports the average path of the respective variable around a typical panic. Since there is substantial heterogeneity in the paths, we also report the range in which 90 percent of all banking panics fall as the shaded area. The red, dashed line is the counterfactual average path, if there is no panic in period zero. The difference between the blue line and the red line gives us the additional impact of an average banking panic, given the same initial conditions and the same sequence of capital quality shocks.[10] The thin, black line reports the value of

[10] Alternatively, it gives us the additional change in the variable from moving from the equilibrium with solvent banks to the equilibrium with a systemic bank default.

the respective variable in the stochastic steady state.

[Figure 3 about here.]

In the first panel, we show the sequence of exogenous capital quality shocks around a typical banking panic. These shocks are of course identical for the panic and the no panic economies. We observe that banking panics typically arise after a sequence of negative capital quality shocks. In the second panel, we see that due to the negative capital quality shocks, the realized firm credit spread decreases. The bank credit spread increases slightly due to a higher default premium on bank debt. As a consequence, bank profitability, which is the difference between the firm credit spread and the bank credit spread, decreases. The bank equity-to-assets ratio decreases as well, which implies that bank leverage increases. Leverage is countercyclical, since the incentive constraint 2.8 ties leverage to the expected future value of net worth, which is high in bad times when the expected firm credit spread is high. Taken together, the lower realized firm credit spread, the higher bank credit spread and the higher bank leverage drive down the recovery value in a systemic bank default, which we can see in panel 6. This is despite a slight increase in the liquidation discount which is evident from panel 5.

In panel 7, we see that due to the lower recovery value, the ex ante probability of a banking panic is higher. If a panic is triggered, a big fall in the realized firm credit spread occurs in the period of the panic, bank equity and bank assets fall to zero and financial intermediation will only occur through the mutual fund sector. This leads to a spike in the expected firm credit spread, as mutual funds require a higher expected return than banks. As a consequence, we see in panel 9 investment decreases dramatically, and so does output due to both the lower capital stock and the efficiency losses due to the lack of intermediation.

After the banking panic, the net worth of the banking sector slowly rebuilds as new banks start to enter the economy. Expected returns on firm loans are high, due to the high required return of mutual funds. Newly entering banks are therefore highly profitable, which also means that they have a high leverage capacity. High bank leverage in turn lowers expected recovery values, which increases the likelihood of a second banking panic in the aftermath of the first one. Hence, credit spreads and conditional volatility remain elevated and investment and output subdued until the net worth of the banking sector has fully rebuild.

Overall, we can see that banking panics are dramatic events which substantially influence the dynamics of both macroeconomic aggregates and asset prices. Moreover, we can see that banking panic risk is reflected in asset prices even before the panic occurs. A particular strength of the model is that it produces the empirically observed co-movement in asset prices and quantities before and after banking panics.

7 Quantitative effects of banking panic risk

In the last section, we have studied the conditional response of the economy to a realized banking crisis. We have shown that both the build-up and the aftermath of a banking crisis are episodes of high systemic risk and high conditional output volatility. While banking crises are dramatic events, they are however also rare events, such that it is unclear whether systemic risk in the financial sector should have an effect on aggregate uncertainty and macroeconomic dynamics outside a banking panic. Therefore, we study next the unconditional effects of banking panic risk on macroeconomic uncertainty and business cycle dynamics. We first show that elevated banking panic risk increases macroeconomic uncertainty unconditionally. Second, we show that this time-varying uncertainty which amplifies the volatility of macroeconomic aggregates and asset prices.

[Table 4 about here.]

Table 4 shows that banking panic driven uncertainty amplifies macroeconomic volatility. We compare and simulate three different models: In the first model, panics are anticipated and materialize. To isolate the effect of banking-panic driven uncertainty, we report a second model, in which panics are anticipated, but never materialize. Finally, in the last model, crises are unanticipated and never materialize.

From column 1 of Table 4, we see that banking panic risk varies substantially over time: The unconditional probability of a banking panic is about 2 percent per year, the standard deviation of the probability of a banking panic is 0.8 percent per year. The probability of a panic is moreover countercyclical, since bank leverage is high and realized bank asset returns are low during recessions, leading to low recovery values for bank creditors and hence elevated banking panic risk.

From rows 4 to 6, we can see that banking panic risk increases aggregate uncertainty substantially. First, in the first and second column, we see that output volatility in the model with banking panics is about 0.55 percent, with a volatility of 0.15 percent. It is also strongly countercyclical. Comparing the second and the third column, we observe that banking panic risk roughly doubles the conditional expected output volatility, and increases the volatility of the expected volatility by a factor of about 3.

Decomposing expected volatility in the expected volatility about the left tail and the right tail, we can see that banking-panic risk increases expected volatility exclusively in the left tail of the output distribution: Expected volatility in the left tail increases from about 0.14 percent in the model without panics to 0.5 percent in the model with panic expectations, whereas expected volatility in the right tail in the model with expected panics is basically identical compared to the model without panics.

Comparing the unconditional realized volatilities of output, consumption and investment of the models with and without banking panics in Table 4, we see that realized banking panics increase the unconditional realized volatility of output, consumption and investment. Moreover, the realized volatility of the bank credit spread as well as the firm credit spread are higher. When we compare the model where we isolate the effect of banking panic uncertainty to the model without banking panics, we see that most of the increase in volatility comes from realized banking panics, and not banking panic anticipations: The volatility of output, investment and consumption in the economy without banking panics is nearly exactly as high as volatility in the economy with anticipated, but without materialized bank panics. This does, however, not mean, that banking panic risk does not amplify volatility: In the economy without banking panics, equilibrium leverage is higher, which makes balance sheets of banks more sensitive to asset price fluctuations. Compared to the model without banking crises, there are therefore two offsetting effects in the model with banking panics: On the one hand, banking panics introduce time-varying volatility, which increases volatility. On the other hand, as bankers and bank creditors internalize the default probability of an individual bank, equilibrium leverage is lower, which reduces volatility.

8 Macroprudential regulation

In this section, we discuss how the banking panic-driven uncertainty channel affects the desirability of a typical macroprudential policy, namely a countercyclical capital buffer (CCyB).

In the economy considered here, agents do not internalize how their decisions affect equilibrium prices. Since equilibrium prices feed back into the incentive constraint 2.8 of banks, there exists a pecuniary externality:[11] Banks lend and borrow too much during times of high net worth when the leverage constraint is loose, which forces them to contract borrowing and lending excessively during times of low net worth. A regulator could increase welfare by limiting bank lending in times of loose market leverage constraints. This relaxes leverage constraints in times of otherwise relatively tight leverage constraints, which stabilizes asset prices and reduces the frequency of banking panics. We show that in the presence of panic-driven uncertainty, the benefits from the CCyB are larger. Banking-panic driven uncertainty is therefore an important channel which macroprudential regulators should take into account.

[11] For discussions of optimal regulation in the presence of pecuniary externalities, see Dávila and Korinek (2017) and Bianchi and Mendoza (2018).

8.1 A capital requirement with a countercyclical buffer

Consider again the capital requirement we introduced in equation 2.14. We set $\bar{\phi} = \phi^B$, which is the value of leverage in the stochastic steady state. We do this, because the focus of our analysis is on the effects of the countercylical capital buffer on macroeconomic dynamics, and not on the optimal level of capital requirements. Due to our assumption that banks can only obtain additional equity by accumulating internal funds, an increase in the capital requirement forces banks to reduce lending to the nonfinancial sector. According to equation 2.7, total bank lending as a deviation from the stochastic steady state can be written as

$$\ln Q_t A_{t+1}^B - \ln QA^B = \ln \phi_t^B - \ln \phi^B + \ln N_t^B - \ln N^B. \tag{8.1}$$

If the capital requirement binds, this becomes

$$\begin{aligned} \ln Q_t A_{t+1}^B - \ln QA^B &= -\tau(\ln N_t^B - \ln N^B) + \ln N_t^B - \ln N^B \\ &= (1-\tau)(\ln N_t^B - \ln N^B). \end{aligned} \tag{8.2}$$

As a stylized example to illustrate the importance of banking panic-driven uncertainty for macroprudential regulation, we set $\tau = 1$. For that value, the regulator can reduce the comovement between net worth and bank lending, and hence the feedback loop between bank balance sheets and asset prices, completely. For τ less than 1, there is still positive comovement between net worth and bank lending, while for τ more than one, bank lending will start to comove negatively with bank lending. $\tau = 0$ corresponds to the case of a constant capital requirement.

[Figure 4 about here.]

Figure 4 illustrates how the combination of a capital requirement and the CCYB works. In the left panel, we plot the market leverage constraint as the red dashed line, the regulatory leverage constraint as the black dotted line, and the binding leverage constraint, which is the minimum of the two, as the blue solid line. In the right panel, we plot the policy functions for bank lending, $Q_t A^B_{t+1}$, implied by the respective constraints, as a function of bank net worth. The countercyclical capital requirement binds during times of high bank net worth. As net worth increases, the increase in net worth is exactly offset by a decrease in the leverage constraint, such that the overall policy for bank lending becomes insensitive to net worth fluctuations. Therefore, bank balance sheets and hence asset price fluctuations are decoupled. Hence, this policy can dampen the feedback loop between bank balance sheets and asset prices, i.e. the financial accelerator. There is therefore also a weaker pecuniary externality which creates excessive lending of banks during times of high net worth. Since the policy binds during times of high net worth, it will not bind during a banking panic, such that conditional banking panic dynamics are unchanged relative to the baseline model without regulation.

8.2 Benefits from macroprudential regulation

In this section, we evaluate the benefits of the macroprudential policy. First, we consider the benefit due to the policy in the baseline model. This welfare gain combines the effect from a reduction in the frequency of realized banking panics and the effect due to less uncertainty because of lower banking panic risk. To disentangle how much of that benefit is due to banking panic risk, we second compare the effect in the baseline model without realized banking panics to the effect in an economy without banking panic risk.

[Table 5 about here.]

Table 5 reports various measures that are commonly considered by policymakers: the level of output and consumption in the stochastic steady state, the volatility of output and consumption, the frequency of banking panics, and macroeconomic uncertainty as measured by the conditional consumption volatility described in equation 4.1.

The first two columns show the results for the economy with anticipated and realized banking panics. We can see that introducing the CCyB increases welfare, lowers the probability of a financial panic and lowers conditional expected output volatility. The CCyB affects the economy through two channels: First, with a CCyB, fewer banking panics will materialize. Hence, the realized volatility in the economy will be lower. Second, the CCyB also reduces the expected volatility in the economy by lowering expected banking panic risk. While the level of output and consumption are lower with the CCyB, the reduction in volatility nevertheless leads to a small welfare gain. A formal welfare analysis incorporating all the costs and benefits of dynamic capital requirements is however beyond the scope of this paper.

To isolate the effect of the CCyB on the banking panic-driven uncertainty channel, columns 3 and 4 report the effects of the macroprudential policy in the model with banking panic risk, but without realized banking panics. Such a capital requirement can undo the feedback loop between asset prices, bank lending and the net worth of banks, and therefore stabilize output and consumption. It does so by dampening the link between bank net worth and bank lending. Moreover, it reduces the likelihood of banking panics, and macroeconomic uncertainty in the form of the conditional volatility of output. Note that the reduction in unconditional output volatility is as large as in the model with realized panics, and the reduction in unconditional output volatility is even slightly larger. This is, because conditional output volatility is small when the banking sector rebuilds after a realized financial panic.

In contrast, we can see from the last two columns that in the model without banking panics, the capital requirement decreases conditional volatility much less than in the other two models. This is, since it does not have the additional benefit of reducing the frequency of banking panics. It can, however, still reduce the volatility of output and consumption. Taken together, our results imply that banking panic-driven uncertainty is an important novel channel that increases the welfare gains from macroprudential regulation.

9 Conclusion

In this paper, we show that systemic risk in the banking sector breeds macroeconomic uncertainty. We start with the observation that during the financial crisis of 2007-2008, both measures of systemic risk in the banking sector and measures of macroeconomic uncertainty spiked. Investment and asset prices fell, consistent with empirical evidence and theories on the effects of an increase in uncertainty on macroeconomic outcomes.[12] Motivated by these stylized facts, we adapt a model of a production economy with a financially constrained banking sector developed by Gertler, Kiyotaki, and Prestipino (2019) to study the link between systemic risk in the banking sector and macroeconomic uncertainty more broadly. We augment the model along two dimensions: Banks in the model are subject to occasional and disastrous banking panics. The probability of a banking panic, which we refer to as systemic risk, depends on the state of the economy. Systemic risk in the model is hence endogenous. First, households have Epstein and Zin (1989)-preferences and second, banking crises are persistent.

We have three main findings: First, we show that an increase in systemic risk leads to an increase in macroeconomic uncertainty. This is, because banking panics are more likely in future states of the world with bad realizations of the exogenous shock, such that an increase in the likelihood of a banking panic widens the left tail of the conditional distribution of future output. To our knowledge, establishing this link between banking panic risk and aggregate uncertainty and exploring its implications are novel contributions to the literature.

Second, we show that this endogenous uncertainty due to elevated banking panic risk feeds back into the economy by tightening the financial constraint in the banking sector. It does so through a financial constraints channel, which operates through the value of the banks' cash flows and a precautionary savings channel which operates through the risk premium charged by the households. This increases the unconditional volatility of macroeconomic aggregates and asset prices.

[12] E.g. Gourio (2012), Jurado, Ludvigson, and Ng (2015), Basu and Bundick (2017).

Third, we show that macroprudential policies that reduce the financial accelerator effect, like for example a countercyclical capital buffer, lead to higher welfare gains if there is endogenous banking panic risk. Therefore, we present a novel channel through which macroprudential policy can lead to welfare gains.

The role of endogenous uncertainty due to systemic risk is a fruitful topic for future research in both the literature on financial crises and the literature on the role of uncertainty for business cycles. First, it leads to a new channel through which disruptions in the banking sector can affect the aggregate economy. Second, it allows us a better understanding of where uncertainty in the economy comes from. Third, the banking panic uncertainty presented here is likely to be amplified through other channels that have been shown to amplify exogenous uncertainty shocks, like nominal frictions (Basu and Bundick (2017), Born and Pfeifer (2019)) or search frictions in the labor market (Leduc and Liu (2016), Cacciatore and Ravenna (2018)).

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A Data

The sample period is the first quarter of 1986 to the last quarter of 2018. In terms of macroeconomic aggregates, we use real gross domestic product, real gross private domestic investment and real personal consumption expenditures from the BEA. All aggregate series are detrended with a series-specific log-linear trend. The real interest rate is the federal funds rate minus the year-on-year change over the previous year in the price index for all urban consumers for all products. The bank credit spread is the TED spread. The firm credit spread is the Moody's BAA bond yield minus the federal funds rate. For asset prices, we use a pre-crisis sample to avoid the zero-lower bound period. We define the pre-crisis sample as the first quarter of 1986 to the last quarter of 2006.

B Full statement of the model

Households' problem

$$V_t^H = \max_{a_{t+1}^H, b_{t+1}^H, d_{t+1}^H, c_t^H} \left((1-\beta) \left(c_t^H\right)^{1-\sigma} + \beta \mathbb{E}_t \left[\left(V_{t+1}^H\right)^{1-\gamma} \right]^{\frac{1-\sigma}{1-\gamma}} \right)^{\frac{1}{1-\sigma}} \tag{B.1}$$

s.t., if no bank default:

$$\begin{aligned} c_t^H + (Q_t + f_t^H) a_{t+1}^H + d_{t+1}^H + b_{t+1}^H = \\ = W_t + R_t^A a_t^H + R_t^D d_t^H + R_t^B b_t^H + \Pi_t \end{aligned} \tag{B.2}$$

if bank default:

$$c_t^H + (Q_t + f_t^H) a_{t+1}^H + b_{t+1}^H = W_t + R_t^A a_t^H + x_t^D R_t^D d_t^H + R_t^B b_t^H + \Pi_t \tag{B.3}$$

x_t^D, defined below.

Banks' problem

$$V_t^B = \max_{a_{t+1}^B, d_{t+1}^B} \mathbb{E}_t \Lambda_{t,t+1} \left(\eta n_{t+1}^B + (1-\eta) V_{t+1}^B \right) \tag{B.4}$$

s.t.

$$n_t^B = \begin{cases} R_t^A a_t^B - R_t^D d_t^B & \text{if old} \\ \upsilon A_t & \text{if new} \end{cases} \tag{B.5}$$

$$Q_t a_{t+1}^B = \underbrace{d_{t+1}^B}_{\text{Debt}} + \underbrace{n_t^B}_{\text{Equity}} \tag{B.6}$$

$$\psi Q_t a_{t+1}^B \leq V_t^B \tag{B.7}$$

Consumption good producers' problem

$$V_t^F = \max_{a_{t+1}^F, k_{t+1}, l_t} \left(\Pi_t^F + \mathbb{E}_t \Lambda_{t,t+1} V_{t+1}^F \right) \tag{B.8}$$

s.t.

$$\Pi_t^F = e^{\mu^A} s_t^\alpha l_t^{1-\alpha} + (1-\delta) Q_t s_t - Q_t k_{t+1} - W_t l_t - R_t^A a_t^F + a_{t+1}^F \tag{B.9}$$

$$k_{t+1} = a_{t+1}^F \tag{B.10}$$

$$k_t = Z_t s_t \tag{B.11}$$

$$\ln Z_t = (1-\rho^Z)\mu^Z + \rho^Z \ln Z_{t-1} + \varepsilon_t^Z \tag{B.12}$$

Capital good producers' problem

$$V_t^Q = \max_{i_t} \left(\Pi_t^Q + \mathbb{E}_t \Lambda_{t,t+1} V_{t+1}^Q \right) \tag{B.13}$$

s.t.

$$\Pi_t^Q = Q_t i_t - i_t - \frac{\theta}{2} \left(\frac{i_t}{I_{t-1}} - 1 \right)^2 I_{t-1} \tag{B.14}$$

Mutual funds' problem

$$\max_{\tilde{a}_t^H} \Pi_t^L \tag{B.15}$$

s.t.

$$\Pi_t^L = f_t^H \tilde{a}_t^H - \frac{\chi}{2} \max\left(\frac{\tilde{a}_t^H}{A_t} - \zeta, 0\right)^2 A_t \tag{B.16}$$

Aggregation Profits of households

$$\Pi_t = \Pi_t^Q + \Pi_t^F + \Pi_t^L + \eta(R_t^A A_t^B - R_t^D D_t^B - \nu A_t) \tag{B.17}$$

Bank net worth

$$N_t^B = (1-\eta)(R_t^A A_t^B - R_t^D D_t^B) + \eta\nu A_t \tag{B.18}$$

Market clearing Deposits

$$D_{t+1}^H = D_{t+1}^B \tag{B.19}$$

Loans

$$A_{t+1}^H + A_{t+1}^B = A_{t+1}^F \tag{B.20}$$

Capital

$$I_t = S_{t+1} - (1-\delta)K_t \tag{B.21}$$

Labor

$$L_t = 1 \tag{B.22}$$

Loan services

$$\tilde{A}_{t+1}^H = \tilde{A}_{t+1}^M \tag{B.23}$$

Risk-free bond

$$B_{t+1}^H = 0 \tag{B.24}$$

Aggregate resource constraint

$$e^{\mu^A} S_t^{\alpha} L_t^{1-\alpha} = C_t^H + I_t \left(1 + \theta \left(\frac{I_t}{I_{t-1}} - 1\right)^2\right) \tag{B.25}$$

C Proofs

Proof of Proposition 2.1. We proceed as follows: We guess that the value function is linear in the net worth of an individual bank and then verify this guess. We guess that the value function can be written as

$$V_t^B = \Omega_t^B n_t^B. \tag{C.1}$$

The problem of a bank B.4 can be restated as follows:

$$\begin{aligned}
\Omega_t^B n_t^B &= \max_{a_{t+1}^B} \mathbb{E}_t (1 - p_{t+1}) \Lambda_{t,t+1} \left[\eta + (1-\eta)\Omega_{t+1}^B\right] n_{t+1}^B \\
&= \max_{a_{t+1}^B} \mathbb{E}_t (1 - p_{t+1}) \Lambda_{t,t+1} \left[\eta + (1-\eta)\Omega_{t+1}^B\right] \left[(R_{t+1}^A - R_{t+1}^D Q_t) a_{t+1}^B + R_{t+1}^D n_t^B\right] \\
&\text{s.t.} \\
Q_t a_{t+1}^B &\leq \Omega_t^B n_t^B.
\end{aligned}$$

The Lagrange is given by

$$\mathcal{L} = \mathbb{E}_t (1 - p_{t+1}) \Lambda_{t,t+1} \bar{\Omega}_{t+1}^B \left[(R_{t+1}^A - R_{t+1}^D Q_t) a_{t+1}^B + R_{t+1}^D n_t^B\right] (1 + \lambda_t) - \lambda_t Q_t a_{t+1}^B$$

where we substitute $\bar{\Omega}^B_{t+1} = \eta + (1-\eta)\Omega^B_{t+1}$. The first-order conditions are

$$
\begin{aligned}
\frac{\partial \mathcal{L}}{\partial a^B_{t+1}} = \mathbb{E}_t(1-p_{t+1})\Lambda_{t,t+1}\bar{\Omega}^B_{t+1}\left[(R^A_{t+1} - R^D_{t+1}Q_t)\right](1+\lambda_t) - \lambda_t Q_t - \\
-\mathbb{E}_t\frac{\partial p_{t+1}}{\partial a^B_{t+1}}\Lambda_{t,t+1}\bar{\Omega}^B_{t+1}n^B_{t+1}(1+\lambda_t) \geq 0 \\
\frac{\partial \mathcal{L}}{\partial \lambda_t} = \Omega^B_t n^B_t - Q_t a^B_{t+1} \geq 0 \\
\lambda_t \geq 0 \\
(\Omega^B_t n^B_t - Q_t a^B_{t+1})\lambda_t = 0.
\end{aligned}
$$

We can define a bank run cutoff for the exogenous shock as

$$
Z^*(a^B_{t+1}) = Z : n^B_{t+1} = 0.
$$

Taking the derivative with respect to the bank run probability amounts to computing the change in this bank run cutoff:

$$
\begin{aligned}
&\mathbb{E}_t\frac{\partial p_{t+1}}{\partial a^B_{t+1}}\Lambda_{t,t+1}\bar{\Omega}^B_{t+1}n^B_{t+1} \\
&= \frac{\partial}{\partial a^B_{t+1}}\left(\int_{Z^*(a^B_{t+1})}^{\infty}\Lambda_{t,t+1}\bar{\Omega}^B_{t+1}n^B_{t+1}dF(Z)\right) - \int_{Z^*(a^B_{t+1})}^{\infty}\Lambda_{t,t+1}\bar{\Omega}^B_{t+1}\frac{\partial n^B_{t+1}}{\partial a^B_{t+1}}dF(Z),
\end{aligned}
$$

which, by Leibniz' rule, collapses to

$$
-\frac{\partial Z^*(a^B_{t+1})}{\partial a^B_{t+1}}\Lambda_{t,t+1}\bar{\Omega}^B_{t+1}n^B_{t+1}|_{Z=Z^*(a^B_{t+1})},
$$

which is 0 since $n^B_{t+1}|_{Z=Z^*(a^B_{t+1})} = 0$. Thus, the first-order conditions simplify to

$$\frac{\partial \mathcal{L}}{\partial a^B_{t+1}} = \mathbb{E}_t(1-p_{t+1})\Lambda_{t,t+1}\bar{\Omega}^B_{t+1}\left[(R^A_{t+1} - R^D_{t+1}Q_t)\right](1+\lambda_t) - \lambda_t Q_t \geq 0 \tag{C.2}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_t} = \Omega^B_t n^B_t - Q_t a^B_{t+1} \geq 0 \tag{C.3}$$

$$\lambda_t \geq 0 \tag{C.4}$$

$$(\Omega^B_t n^B_t - Q_t a^B_{t+1})\lambda_t = 0. \tag{C.5}$$

Consider first the case where the borrowing constraint C.4 is binding. Then, the optimal policy of the bank is given by

$$\hat{a}^B_{t+1} \equiv \frac{a^B_{t+1}}{n^B_t} = \frac{\Omega^B_t}{\psi Q_t}.$$

With this, we can rewrite the value function as

$$\Omega^B_t = \frac{\mathbb{E}_t(1-p_{t+1})\Lambda_{t,t+1}\bar{\Omega}^B_{t+1}R^D_{t+1}}{1 - \psi\mathbb{E}_t(1-p_{t+1})\Lambda_{t,t+1}\bar{\Omega}^B_{t+1}\left[\frac{R^A_{t+1}}{Q_t} - R^D_{t+1}\right]}. \tag{C.6}$$

This expression only depends on aggregate variables, as we initially guessed. Consider next the case of the non-binding constraint. In that case, only A^B_{t+1}, i.e. the optimal policy of the entire banking sector, is pinned down by the first order condition C.2, with $\lambda_t = 0$. We assume that individual banks follow a rule

$$\hat{a}^B_{t+1} = \frac{A^B_{t+1}}{N^B_t}, \tag{C.7}$$

$$a^B_{t+1} = \hat{a}^B_{t+1} n^B_t. \tag{C.8}$$

This implies that the solution is again linear in the net worth of an individual bank, and we again can compute the value function of the bank as in C.6, showing that it only depends on aggregate values. Hence, we can indeed write the value function of the bank as $V^B_t =$

$\Omega_t^B n_t^B$. $\square$

D Full statement of the equilibrium

First, we characterize the equilibrium if the banking sector is solvent. We then highlight how the equilibrium changes if the banking sector is insolvent. Since we use the concept of a recursive competitive equilibrium, we switch to a recursive notation, i.e. $X_t = X$, $X_{t+1} = X'$, and $X_{t-1} = X_{-1}$ for any variable X. Bold symbols denote functions.

D.1 The equilibrium with solvent banks

The state of the economy is given by $\mathcal{Y} = (N^B, K, I_{-1}, Z, \Xi)$. $\Xi \in \left\{\Xi^R, \Xi^N\right\}$ is a sunspot shock that selects in which equilibrium the economy is if there are multiple equilibria. It evolves according to a Markov chain, with

$$Pr(\Xi = \Xi^R) = p^R \tag{D.1}$$

A recursive competitive equilibrium is a set of price functions $\mathbf{Q}(\mathcal{Y}), \mathbf{W}(\mathcal{Y}), \mathbf{R^A}(\mathcal{Y})$, $\mathbf{R^D}'(\mathcal{Y})$, $\tilde{\mathbf{R}}^{\mathbf{D}}(\mathcal{Y})$ and $\mathbf{f}(\mathcal{Y})$, perceived laws of motion of the states $\mathbf{K}'(\mathcal{Y}, \epsilon', \Xi')$ and $\mathbf{N^B}'(\mathcal{Y}, \epsilon', \Xi')$ and a perceived banking panic probability $\mathbf{p}(\mathcal{Y}, \epsilon', \Xi')$, a value function $\mathbf{V^H}(\mathcal{Y})$ and policy functions $\mathbf{C^H}(\mathcal{Y}), \mathbf{A^H}'(\mathcal{Y}), \mathbf{D^H}'(\mathcal{Y})$ and $\tilde{\mathbf{A}}^{\mathbf{H}'}(\mathcal{Y})$ for households, a value function $\mathbf{V^B}(\mathcal{Y})$ and policy functions $\mathbf{A^B}'(\mathcal{Y})$ and $\mathbf{D^B}'(\mathcal{Y})$ for banks, policy functions for consumption goods producers, $\mathbf{S}'(\mathcal{Y}), \mathbf{A^F}'(\mathcal{Y}), \mathbf{L}(\mathcal{Y})$, a policy function for capital producers, $\mathbf{I}(\mathcal{Y})$, and a policy function for mutual funds $\tilde{\mathbf{A}}^{\mathbf{M}'}(\mathcal{Y})$ that solve the respective optimization problems of all agents as defined in appendix B, clear the markets for retail loans,

$$\mathbf{A^F}'(\mathcal{Y}) = \mathbf{A^H}'(\mathcal{Y}) + \mathbf{A^B}'(\mathcal{Y}), \tag{D.2}$$

labor,

$$\mathbf{L^F}(\mathcal{Y}) = 1, \tag{D.3}$$

investment goods,

$$\mathbf{I}(\mathcal{Y}) = \mathbf{S^{F}}'(\mathcal{Y}) - (1-\delta)K, \tag{D.4}$$

bank liabilities,

$$\mathbf{D^B}(\mathcal{Y}) = \mathbf{D^H}(\mathcal{Y}), \tag{D.5}$$

and loan services,

$$\tilde{\mathbf{A}}^{\mathbf{H}'}(\mathcal{Y}) = \tilde{\mathbf{A}}^{\mathbf{M}'}(\mathcal{Y}), \tag{D.6}$$

ensure that the perceived laws of motion correspond to the actual laws of motion for capital,

$$\mathbf{K}'(\mathcal{Y}, \epsilon', \Xi') = Z \exp(\mu^Z + \sigma^Z \epsilon')\mathbf{S}'(\mathcal{Y}), \tag{D.7}$$

bank net worth,

$$\mathbf{N^{B}}'(\mathcal{Y}, \epsilon', \Xi') = \begin{cases} \mathbf{N}^{\mathbf{B}'}_{\text{No Run}}(\mathcal{Y}, \epsilon', \Xi') & \text{with probability } 1 - \mathbf{p}(\mathcal{Y}, \epsilon', \Xi') \\ 0 & \text{with probability } \mathbf{p}(\mathcal{Y}, \epsilon', \Xi') \end{cases} \tag{D.8}$$

$$\mathbf{N}^{\mathbf{B}'}_{\text{No Run}}(\mathcal{Y}, \epsilon', \Xi') = \left[\mathbf{R^A}(\mathbf{Y}'(\mathcal{Y}, \epsilon', \Xi'))\mathbf{A^{B}}'(\mathcal{Y}) - \mathbf{R^{D}}'(\mathcal{Y})\mathbf{D^{B}}'(\mathcal{Y})\right](1-\eta) + n^{B,new,\prime}\eta, \tag{D.9}$$

and satisfy the aggregate resource constraint 2.22. Asset returns are given by

$$\tilde{\mathbf{R}}^{\mathbf{D}}(\mathcal{Y}) = \mathbf{R}^D(\mathcal{Y}_{-1}) \tag{D.10}$$

and

$$\mathbf{R}^A(\mathcal{Y}) = Z\left(\alpha K^{\alpha-1} + (1-\delta)\mathbf{Q}(\mathcal{Y})\right). \tag{D.11}$$

We summarize the laws of motion of the state as $\mathbf{Y}'(\mathcal{Y}, \epsilon', \Xi')$. We specify the probability of a banking panic $\mathbf{p}(\mathcal{Y}, \epsilon', \Xi')$ below.

D.2 The equilibrium with a systemic bank default

We denote functions relating to the equilibrium with a systemic bank default with a star $(^*)$. If incumbent banks are insolvent, their net worth is 0. We assume that, conditional on the incumbent banks being insolvent, new bankers do not enter the economy and return their resources to the representative household. Hence, the aggregate net worth of the banking sector is 0 and the state of the economy collapses to $\mathcal{Y}^* = (K, I_{-1}, Z, \Xi)$. The asset demand of banks is zero, as is the amount of debt issued by banks:

$$\mathbf{A}^{\mathbf{B}'*}(\mathcal{Y}^*) = 0, \tag{D.12}$$

$$\mathbf{D}^{\mathbf{B}'*}(\mathcal{Y}^*) = 0. \tag{D.13}$$

The capital price is given by $\mathbf{Q}^*(\mathcal{Y}^*)$, the return to firm loans by

$$\mathbf{R}^{A*}(\mathcal{Y}^*) = Z\left(\alpha K^{\alpha-1} + (1-\delta)\mathbf{Q}^*(\mathcal{Y}^*)\right). \tag{D.14}$$

In the quantitative solution to the model, the demand for assets by banks, and hence the demand for assets overall, is increasing in the net worth of banks. Hence, the capital price with insolvent banks is lower than the capital price with solvent banks.

In the equilibrium with insolvent banks, the households recover the assets of the banks instead of their lending. Hence, the return on loans to banks is given by

$$\tilde{\mathbf{R}}^{\mathbf{D}*}(\mathcal{Y}^*) = \mathbf{x}^{\mathbf{D}*}(\mathcal{Y}_{-1}, \varepsilon, \Xi)\mathbf{R}^{D}(\mathcal{Y}_{-1}) \tag{D.15}$$

and

$$\mathbf{x}^{\mathbf{D}*}(\mathcal{Y}_{-1}, \varepsilon, \Xi) = \frac{\mathbf{R}^{\mathbf{A}*}(\mathcal{Y}^*)\mathbf{A}^{\mathbf{B}'}(\mathcal{Y}_{-1})}{\mathbf{R}^{\mathbf{D}'}(\mathcal{Y}_{-1})\mathbf{D}^{\mathbf{B}'}(\mathcal{Y}_{-1})}. \tag{D.16}$$

Incumbent banks exit once they are liquidated. Panics are persistent and continue into the next period with probability $1-\pi$. New banks start re-entering the economy at rate η only once the panic has ended. Formally, this assumption implies that the net worth of the banking sector evolves as

$$\mathbf{N^{B'*}}(\mathcal{Y}^*, \epsilon', \Xi') = \begin{cases} \eta n^{B,new'} & \text{with probability } \pi \\ 0 & \text{with probability } 1-\pi \end{cases} . \tag{D.17}$$

E Robustness

In this section, we explore how the results in section 7 depend on key model assumptions, namely EZ preferences and persistent banking panics. We investigate how the results change if we assume that banking panics only last one period, as in Gertler, Kiyotaki, and Prestipino (2019). We also investigate the importance of assuming EZ-preferences.

[Table 6 about here.]

First, we see that in the case of the model with EZ-preferences and one period panics, the banking panic probability is much lower. It also has a lower standard deviation. As a consequence, the conditional consumption volatility is much lower. Unconditional macroeconomic volatility is consequently also much lower.

Comparing the first and the fourth column, we see the effects of moving from EZ-preferences to log-utility, which corresponds to a decrease in the risk aversion and the intertemporal elasticity of substitution. As a consequence, the probability of banking panics increases slightly. Firm credit spreads are lower, as risk aversion is lower. Overall, the results are however very similar to the baseline model.[13]

Finally, comparing the first and the fifth column shows us how important the assumptions of EZ-preferences and persistent panics jointly are for the results. The model with log-utility

[13] In unreported results, we found that the main channel through which preferences matter is the IES, not the risk aversion. The IES in our baseline model is already quite close to 1. Thus, changing to log utility does not affect the economy very much.

and one-period panics produces lower banking panic risk and macroeconomic uncertainty as the baseline model. These risks are reflected in lower credit spreads, lower conditional volatility and lower unconditional volatility.

Overall, Table 6 tells us that our results are qualitatively robust to changes in the key assumptions, in particular preferences. Persistent panics and EZ-preferences are however important for the quantitative results of the model, especially for its asset pricing implications.

Figures

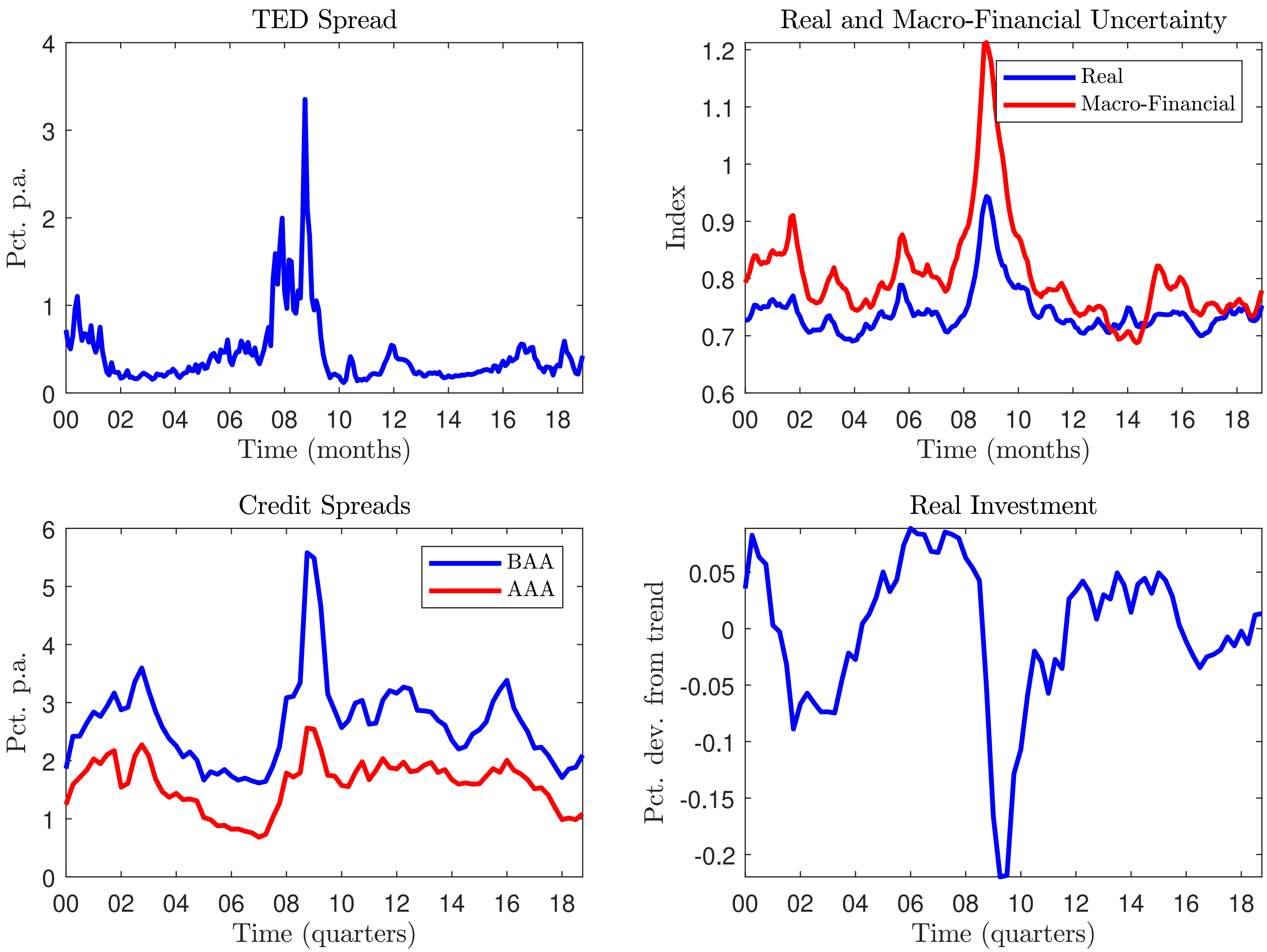

Figure 1: Measures of systemic risk (top left), aggregate uncertainty (top right), credit spreads (bottom left) and investment (bottom right).

Note: Sample period: 2000Q1 to 2018Q4. The data for the TED spread and uncertainty are monthly, the data for credit spreads and investment quarterly. The TED spread is the 3-month LIBOR minus the 3-month US treasury rate. The macroeconomic uncertainty indices, which measure real and macro-financial uncertainty, are taken from Jurado, Ludvigson, and Ng (2015), available at `https://www.sydneyludvigson.com/data-and-appendixes`. We use uncertainty at the 3-month-horizon. Credit spreads are relative to 10-year US treasuries. Real investment is the year-on-year change in real gross private domestic investment.

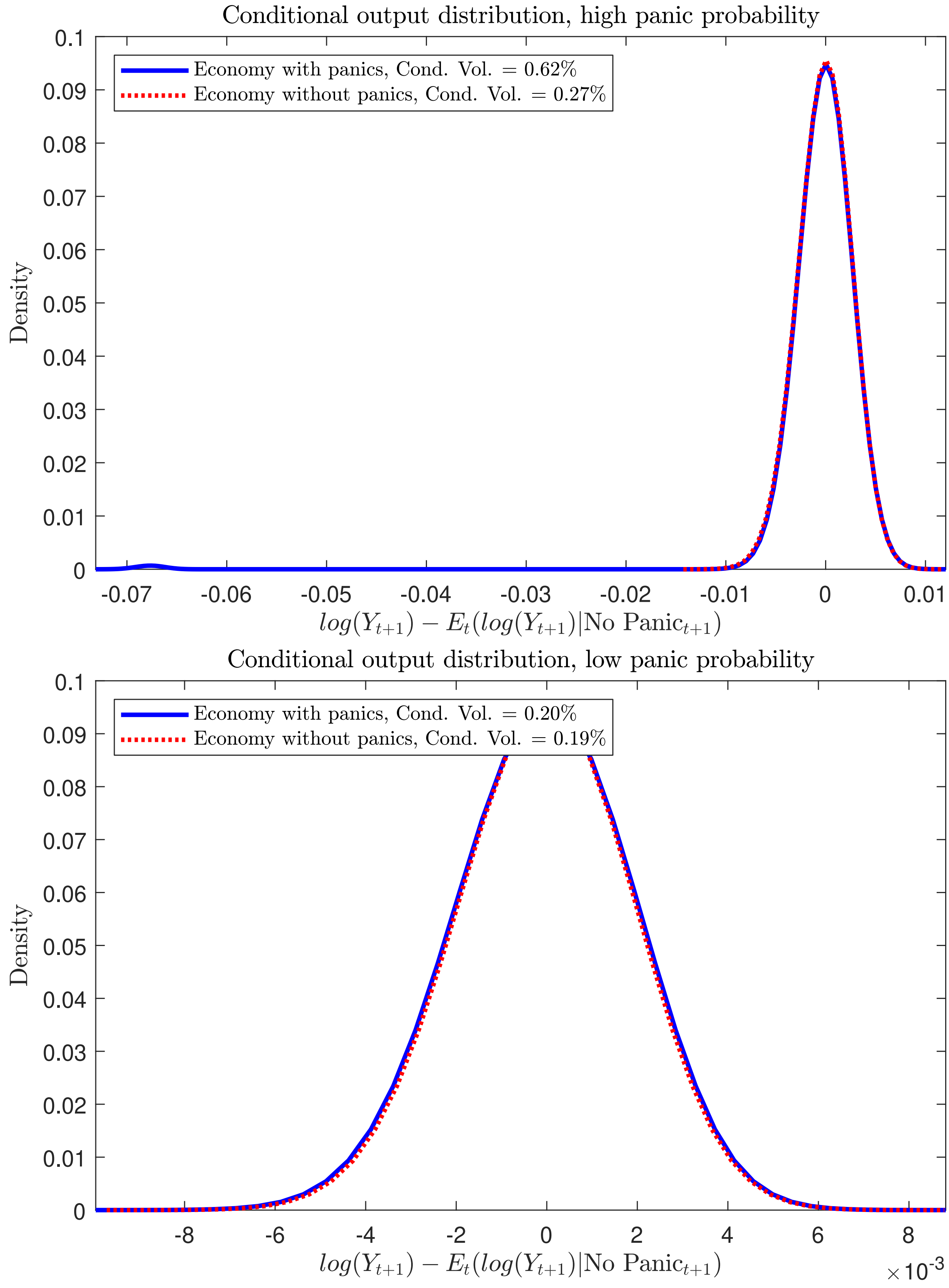

Figure 2: The conditional volatility of output in economies with and without sunspots.

Note: We hold the state of the economy at time t fixed. The policy functions come from the numerical solution of the model under the baseline calibration, where for the economy with sunspots, $p^R = 0.0075$ while for the economy without sunspots, $p^R = 0$.

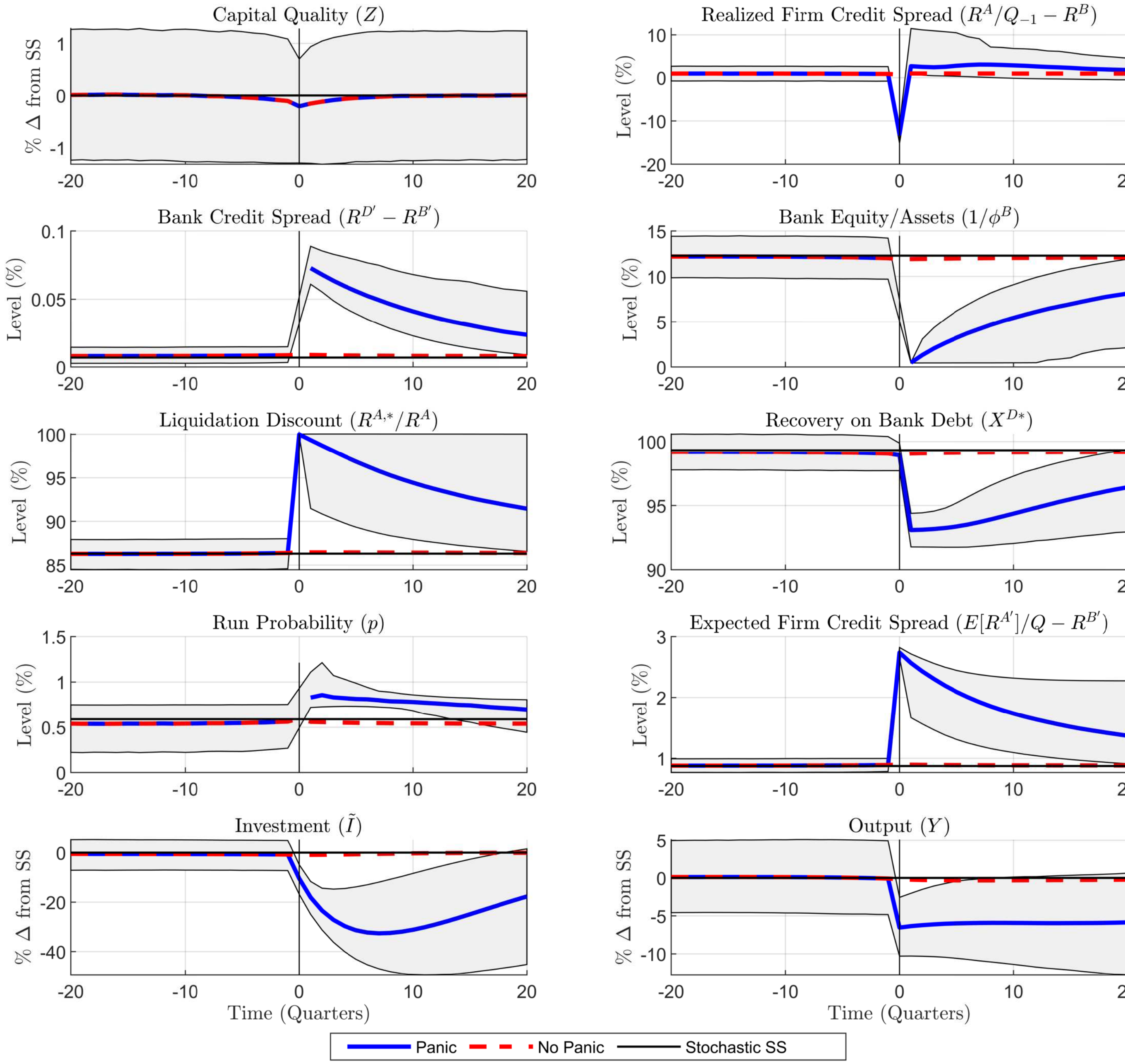

Figure 3: Dynamics around a typical banking panic.

Note: The blue line denotes the response of an average economy around a banking panic. Since there is substantial heterogeneity in the simulation, the shaded area reports the range within which 90 percent of the typical banking crises fall. The red line shows the average response across economies if no banking panic occurs, given the same initial conditions and the same sequence of shocks. Moments of a simulation of 10000 economies for 1000 periods. We drop all crises where a previous crisis occurred in the last 100 quarters before the panic until 20 periods after the panic.

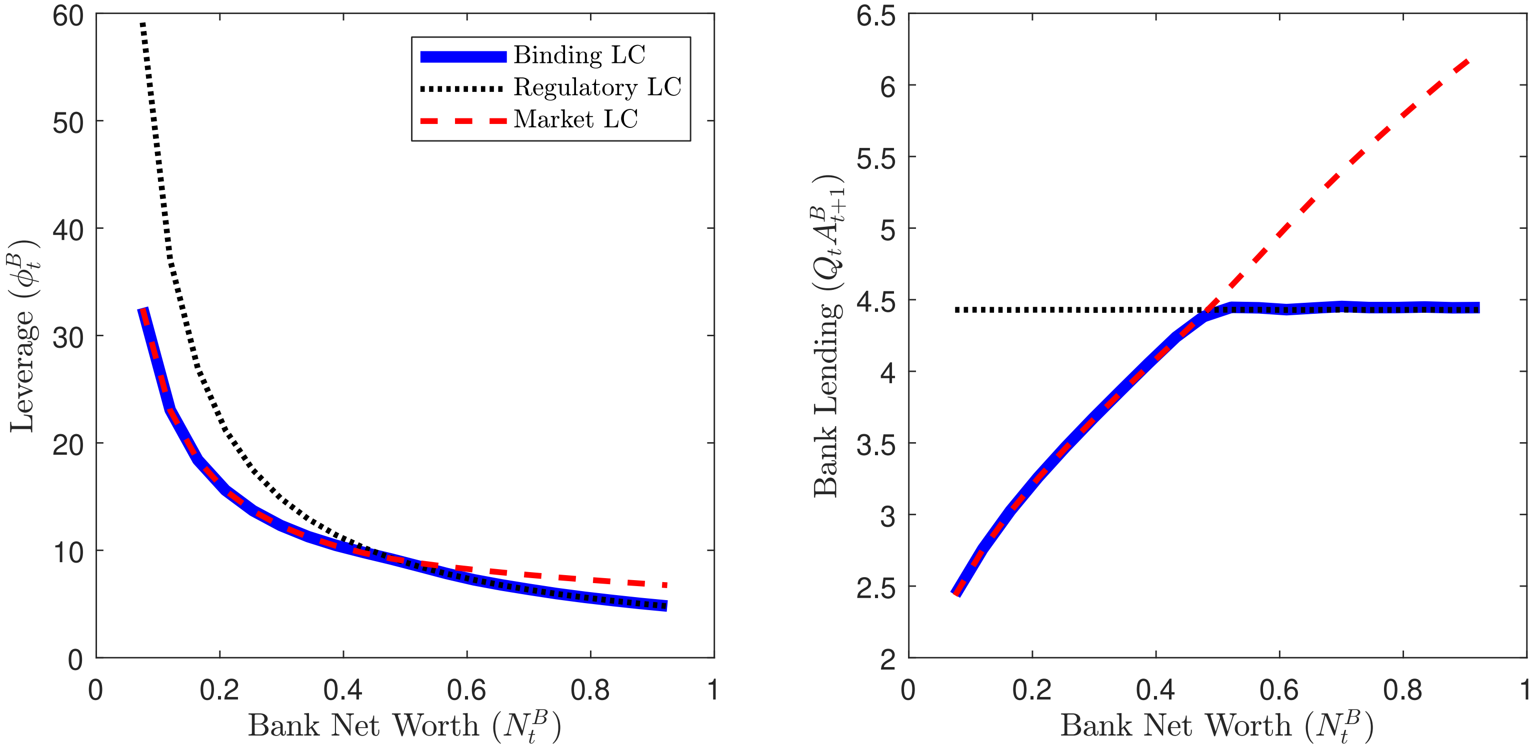

Figure 4: Policy functions with a countercyclical capital requirement.

Note: The policy functions for the binding bank leverage constraint and the regulatory leverage constraint (left panel) and bank lending (right panel) as a function of the net worth of the banking sector in the case of a countercyclical capital requirement. We set $\bar{\phi} = \phi^B$, i.e. to the value of leverage in the stochastic steady state, and $\tau = 1$.

Tables

Technology			
α	0.36	Production function	36 % Capital income share (standard value)
δ	0.025	Depreciation rate	10 % Annual depreciation rate (standard value)
θ	1.35	Investment adjustment cost	Volatility, investment (data)
ρ^Z	0.75	Autocorrelation, shock	Autocorrelation, output (data)
$\sigma^{\varepsilon,Z}$	0.005	Bolatility, shock	Volatility, output (data)
Preferences			
β	0.995	HH discount factor	Real risk-free rate: 1.87 % p.a. in SSS (data)
σ	0.8511	Inverse of IES	Real risk-free rate volatility (data)
γ	35	Rel. risk aversion	Credit spread volatility (data)
Finance			
χ	0.028	Intermediation cost	Bank intermed.: 50 % in SSS (Gertler and Kiyotaki (2015))
ζ	0.2409	Intermediation cost	Δ credit spread in panic: 7.29 % p.a. (data)
ψ	0.385	Diversion	Leverage: 10 in SSS (Gertler and Kiyotaki (2015))
η	0.0908	Exit Rate	Avg. credit spread: 3 % p.a. (data)
υ	1e-3	New banks' endowment	Small value
Sunspot			
p^R	0.0075	Sunspot prob.	Banking panic probability: 2.5 % p.a. (Laeven and Valencia (2012))
π	12/13	Reentry prob.	Banking panics last 13 quarters (Laeven and Valencia (2012))

Table 1: Calibration

	Data	Model
St. Dev., Output (%)	4.073	4.113
St. Dev., Investment (%)	12.311	11.081
Autocorrelation, Output	99.008	98.860
Deposit Rate in SSS (% p.a.)	1.870	1.834
Credit Spread in SSS (% p.a.)	3.886	3.492
St. Dev., Deposit Rate (%)	2.107	2.114
St. Dev., Credit Spread (%)	1.614	1.649
Bank Lending/Total Lending in SSS (%)	50.000	47.824
Bank Leverage in SSS	10.000	8.135
Bank Run Frequency (% p.a.)	2.500	2.369
Bank Run Duration (yrs)	3.250	3.271
Mean, Δ Credit Spread in Crisis (% p.a.)	7.290	7.426

Table 2: Targeted moments

Note: The simulated moments come from a simulation of 10000 economies for 2000 periods, discarding the first 1000 periods as burn-in. The stochastic steady state is computed as the state of the economy after a simulation of 1000 periods without any shocks.

	Data	Model
Output (%)	-3.983	-6.238
Consumption (%)	-2.394	-1.233
Investment (%)	-29.429	-22.715
Bank Credit Spread (% p.a.)	1.356	0.258
Firm Credit Spread (% p.a.)	7.293	7.426

Table 3: Peak-to-trough changes during the financial crisis of 2007-2009 in macroeconomic aggregates and asset prices in the model and the data.

Note: For output, consumption and investment, we define the peak of the great recession as the last quarter of 2007 and the trough as the second quarter of 2009, consistent with the NBER recession dates. For the bank credit spread and the firm credit spread, we define the peak as January 2007 and the trough as October 2008. The model moments come from a simulation of 10000 economies for 2000 periods, discarding the first 1000 periods as burn-in.

	With Panics	Only Uncertainty	No Panics
Systemic Risk			
Mean, Panic Probability (% p.a.)	2.239	2.161	-
St. Dev., Panic Probability (% p.a.)	0.775	0.652	-
Corr. with Output, Panic Probability (% p.a.)	-0.693	-0.869	-
Aggregate Uncertainty			
Mean, $StDev_t(Y_{t+1})$ (%)	0.591	0.552	0.267
St. Dev., $StDev_t(Y_{t+1})$ (%)	0.156	0.028	0.010
Corr. with Output, $StDev_t(Y_{t+1})$ (%)	-0.075	-0.450	-0.881
Aggregate Uncertainty, Left Tail			
Mean, $StDev_t^-(Y_{t+1})$ (%)	0.481	0.502	0.137
St. Dev., $StDev_t^-(Y_{t+1})$ (%)	0.058	0.030	0.006
Corr. with Output, $StDev_t^-(Y_{t+1})$ (%)	-0.140	-0.426	-0.811
Aggregate Uncertainty, Right Tail			
Mean, $StDev_t^+(Y_{t+1})$ (%)	0.298	0.230	0.229
St. Dev., $StDev_t^+(Y_{t+1})$ (%)	0.225	0.006	0.009
Corr. with Output, $StDev_t^+(Y_{t+1})$ (%)	-0.034	-0.771	-0.891
Macroeconomic Dynamics			
St. Dev., Output (%)	4.115	2.899	2.965
St. Dev., Consumption (%)	5.017	4.488	4.544
St. Dev., Investment (%)	11.060	3.780	3.596
Asset Prices			
Mean, Bank Credit Spread (% p.a.)	0.043	0.032	-0.001
Mean, Firm Credit Spread (% p.a.)	4.117	3.523	3.135
St. Dev., Bank Credit Spread (% p.a.)	0.039	0.015	0.005
St. Dev., Firm Credit Spread (% p.a.)	1.650	0.269	0.310

Table 4: The importance of banking-panic driven uncertainty for macroeconomic dynamics and asset prices.

Note: With Panics is the model with expected and realized banking panics. *Only Uncertainty* is the model with expected, but without realized banking panics. *No Panics* is the recalibrated model with neither expected nor realized banking panics. The moments come from a simulation of 10000 economies for 2000 periods, discarding the first 1000 periods as burn-in.

	With Panics		Only Uncertainty		No Panics	
	Baseline	CCyB	Baseline	CCyB	Baseline	CCyB
Macroeconomic Aggregates						
Output, Mean (Baseline = 100)	100.000	100.119	100.000	99.759	100.000	99.734
Consumption, Mean (Baseline = 100)	100.000	100.291	100.000	99.389	100.000	99.022
Output, St. Dev. (%)	4.113	3.756	2.900	2.493	2.966	2.558
Consumption, St. Dev. (%)	5.017	4.846	4.490	4.343	4.546	4.454
Systemic Risk and Aggregate Uncertainty						
Mean, Panic Probability (% p.a.)	2.239	1.799	2.161	1.675	-	-
Mean, $StDev_t(Y_{t+1})$ (%)	0.591	0.494	0.552	0.444	0.267	0.212
Mean, $StDev_t^-(Y_{t+1})$ (%)	0.481	0.406	0.502	0.405	0.137	0.114
Mean, $StDev_t^+(Y_{t+1})$ (%)	0.298	0.238	0.230	0.175	0.229	0.179
Welfare						
Welfare, Mean (Baseline = 100)	100.000	100.076	100.000	99.996	100.000	99.930

Table 5: The effects of a countercyclical capital requirement.

Note: With panics is the model with anticipated and realized banking panics. *Only Uncertainty* is the model with anticipated, but without realized banking panics. *No panics* is the model without banking panics. *Baseline* refers to the model without regulation, *CCyB* to the model with a countercyclical capital buffer. The moments come from a simulation of 10000 economies for 2000 periods, discarding the first 1000 periods as burn-in.

	EZ			Log Utility		
	Multi-period panics	One-period panics	No panics	Multi-period panics	One-period panics	No panics
Systemic Risk						
Mean, Panic Probability (% p.a.)	2.238	0.208	-	2.607	0.609	-
St. Dev., Panic Probability (% p.a.)	0.772	0.389	-	0.684	0.669	-
Corr. with Output, Panic Probability (% p.a.)	-0.696	-0.702	-	-0.574	-0.789	-
Aggregate Uncertainty						
Mean, $StDev_t(Y_{t+1})$ (%)	0.591	0.310	0.267	0.635	0.374	0.268
St. Dev., $StDev_t(Y_{t+1})$ (%)	0.156	0.042	0.010	0.163	0.054	0.010
Corr. with Output, $StDev_t(Y_{t+1})$ (%)	-0.075	-0.910	-0.881	-0.001	-0.918	-0.872
Aggregate Uncertainty, Left Tail						
Mean, $StDev_t^-(Y_{t+1})$ (%)	0.480	0.202	0.137	0.518	0.287	0.137
St. Dev., $StDev_t^-(Y_{t+1})$ (%)	0.058	0.050	0.006	0.070	0.060	0.006
Corr. with Output, $StDev_t^-(Y_{t+1})$ (%)	-0.140	-0.914	-0.811	0.033	-0.934	-0.812
Aggregate Uncertainty, Right Tail						
Mean, $StDev_t^+(Y_{t+1})$ (%)	0.298	0.233	0.229	0.311	0.235	0.230
St. Dev., $StDev_t^+(Y_{t+1})$ (%)	0.226	0.011	0.009	0.246	0.013	0.010
Corr. with Output, $StDev_t^+(Y_{t+1})$ (%)	-0.034	-0.878	-0.891	-0.019	-0.757	-0.879
Macroeconomic Dynamics						
St. Dev., Output (%)	4.112	2.981	2.966	4.146	3.051	3.023
St. Dev., Consumption (%)	5.008	4.543	4.546	4.918	4.483	4.476
St. Dev., Investment (%)	11.067	3.633	3.598	10.704	3.120	2.950
Asset Prices						
Mean, Bank Credit Spread (% p.a.)	0.043	0	0	0.051	0	0
Mean, Firm Credit Spread (% p.a.)	4.117	3.176	3.135	3.882	3.061	2.973
St. Dev., Bank Credit Spread (% p.a.)	0.039	0	0	0.034	0	0
St. Dev., Firm Credit Spread (% p.a.)	1.652	0.338	0.310	1.636	0.397	0.307

Table 6: The importance of preferences for the propagation of banking panic shocks.

Note: All models are with anticipated, but without realized banking crises to focus on the effect of panic-driven uncertainty. The moments come from a simulation of 10000 economies for 2000 periods, discarding the first 1000 periods as burn-in.