Macroprudential Policy and Financial Crises*

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Abstract

We analyze the effectiveness of macroprudential policy with respect to reducing the frequency and severity of financial crises. To this end, we develop a New-Keynesian DSGE model in which the economy fluctuates between two regimes which are characterized by different degrees of financial frictions. In particular, the two regimes are calibrated to match empirical facts on financial crises in the US. The probability of a regime switch is determined endogenously, capturing the risk of bank leverage buildup. We find that regime-specific macroprudential policies are more effective in reducing the probability and length of financial crises than policies neglecting the current state of the economy, because they incentivize banks to strengthen their balance sheets during normal times, thereby reducing leverage buildup and transitions to the crisis regime. We also find that regime-specific monetary policies which are more accomodative during financially turbulent times, can moderate the economic downturn and reduce the time spent in financial crises.

Keywords: endogenous regime-switching, financial turmoil, financial frictions, macroprudential policy, monetary policy
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1 Introduction

The Great Financial Crisis of 2007-2009 and the subsequent Great Recession reminded us starkly of the great importance of financial factors for the real economy. It is commonly agreed that the preceding buildup of financial risk in the financial intermediation sector has been one of the main causes of the severeness of the financial and economic downturns. This has brought the potential role of macroprudential policy in addressing the buildup of financial imbalances to the forefront of policy discussions worldwide.

The European Systemic Risk Board (ESRB) specifies the objective of macroprudential policy as "preventing and mitigating systemic risks to financial stability", where the latter are defined as "risks of disruption to the financial system with the potential to have serious consequences for the real economy" (ESRB, 2014). Yet, in macroeconomic modelling, macroprudential policy has often been implemented as a business cycle policy in form of a feedback rule containing different macroeconomic or financial indicators (e.g., Rubio and Carrasco-Gallego, 2014; Angelini et al., 2014; Gelain and Ilbas, 2017; De Paoli and Paustian, 2017; Leduc and Natal, 2018). Furthermore, standard DSGE models are not suited to capture the time-varying risk of financial disruptions associated with time-varying financial imbalances.

In order to make the predictions of theoretical accounts of macroprudential policy more relevant for actual policy-making, it is necessary to adopt a view closer to the one by the ESRB. Therefore, we develop a New Keynesian DSGE model with a financial sector which allows for endogenous regime switches between "normal times" and "times of financial turmoil". The model does well in matching the development of certain real and financial variables around identified US financial crises. We use this model to analyze the design of macroprudential policies and show that regime-specific policies are better able to reduce the likelihood of entering into financially turbulent times and the severity of financial disruptions than policies disregarding the current state of the economy. The reason is that appropriately designed regime-specific macroprudential policies improve the resilience of the banking sector during tranquil times.[1] Our framework also allows us to analyze regime-specific monetary policies. We find that monetary policies which are more accomodative during financially turbulent times, can moderate the economic downturn and reduce the time spent in financial crises.

Our model features leverage-constrained financial intermediaries as in Gertler and Karadi (2011), however, compared to their framework, we allow certain parameters defining the financial friction to vary over time. In partic-

[1] We are currently working on a formal welfare analysis.

ular, we calibrate key parameters determining financial conditions to identify a low financial frictions regime and a high financial friction regime which resemble "normal times" and times of financial turbulence identified in US data. The probability of a regime switch is determined endogenously based on bank leverage which is supposed to capture systemic risk in the financial sector. As, e.g., in Akinci and Queralto (2020) we amend the model by allowing banks to issue equity. This feature provides financial intermediaries with an additional margin to affect the evolution of their net wealth and thereby the strength of their balance sheet. As equity issuance is costly, banks tend to issue too little equity in periods of financial tranquility, which, however, increases the risk of entering a financially turbulent period (with stronger financial frictions). Such a period is characterized by elevated credit spreads and rapid deleveraging in the banking sector which both have serious adverse consequences for the real economy. Into this model, we introduce macroprudential policy in the form of regulatory capital buffer.

As common solution methods are unsuitable to analyze regime-switching DSGE models (RS-DSGE), we solve the model using the RISE toolkit which relies on perturbation methods (Binning and Maih, 2017; Maih, 2015). Compared to other common perturbation methods used to solve regime-switching DSGE models (e.g., OccBin by Guerrieri and Iacoviello, 2015), the solution method underlying RISE allows for endogenous regime switches, i.e., agents take into account that their behavior affects the likelihood of switching to a different regime and appropriately designed policy can affect the likelihood of regime changes. It is therefore well suited to analyze the effects of macroprudential policy on the behavior of banks and the macroeconomy in general. Relying on perturbation methods facilitates the solution and estimation of a medium-scale DSGE model, which can be more informative about the interaction between monetary and macroprudential policy.

A similar analysis of macroprudential policy in the context of a DSGE model with occasionally binding financial constraints is conducted by Akinci and Queralto (2020). However, while in their model the two regimes are characterized by the presence and the absence of financial friction, respectively, we distinguish between a low friction and a high friction regime, which – from our point of view – more closely resembles reality, where financial frictions are always present. Furthermore, we consider a closed economy with a monetary policy transmission mechanism, whereas Akinci and Queralto (2020) consider a small open economy. Akinci and Queralto (2020) solve their model with projection methods, while we use perturbation methods which facilitates the analysis of a nominal version of the model. Karmakar (2016) analyzes capital requirements within a similar setup of the banking sector but uses the penalty function approach to deal with occasionally binding incentive constraints. The penalty function approach is generally associated with lower accuracy especially in more complex models (see, e.g., Bluwstein et al., 2020). Holden et al. (2020) and Bocola (2016) also employ banking models in the spirit of Gertler and Kiyotaki (2010) and Gertler and Karadi (2011) with the incentive constraint binding only occasionally. However, neither of the two analyzes macroprudential policy. Boissay et al. (2021) use a New Keynesian model with endogenous financial crises to study the effects of monetary policy on the probability and size of financial crises. We plan to extend our analysis into this direction.

In the next section we look at data to identify periods of financial turmoil. Section 3 gives an overview of the theoretical model. The calibration of standard and regime-specific parameters is outlined in Section 4. Section 5 discusses the solution method. Results are discussed in Section 6 and 7. Section 8 concludes.

2 Chronology of Financial Crises in the US

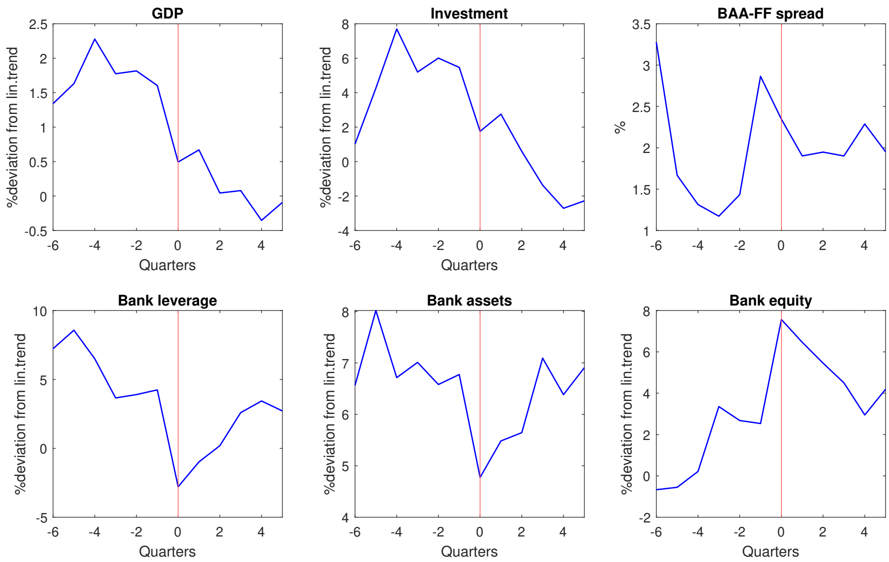
Standard dating of financial crises over the last 40 years, pioneered by Reinhart and Rogoff (2008), recognizes two big crises – the Great Recession and the Savings and Loans Crisis of the mid 1980s. By this classification, crises are rare events that result in failure of banks and assistance to financial institutions. Other authors have revisited the chronology of crises defined by Reinhart and Rogoff (2008), by exploring the crisis narrative in more detail (e.g., policy discussions about financial crisis), measuring the number of failed institutions or distress mergers and revising written records on financial crises (journal records, public speeches of leading policy makers). Table 1 gives some examples of alternative classifications of financial crisis periods. In particular, Lopez-Salido and Nelson (2010) identify 1973-1975, 1982-1984 as two additional crisis. By interpreting a financial crisis even more broadly, as any form of heightened stress to the US financial system, Brave and Butters (2012) also include the Asian Crisis.

Crisis	Period	LSN	RR	LV	BB
Commercial Bank Capital Squeeze	1973-1975	✓	-	-	✓
Less Developed Countries Debt Threat	1982-1984	✓	-	-	✓ (*)
Savings and Loan Crisis	1988-1991	✓	✓ (*)	✓ (*)	✓
Asian Crisis and NASDAQ Bubble	1997-2002	-	-	-	✓
Great Recession and aftermath	2007-2009	✓	✓	✓ (*)	✓ (*)

Notes: LSN: Lopez-Salido and Nelson (2010); RR: Reinhart and Rogoff (2008); LV: Laeven and Valencia Laeven and Valencia (2018); BB: Brave and Butters (2012). Time frame: 1971Q1-2019Q4. (*)Different timing

Table 1: Chronology of US Financial Crises

We set up a nonlinear model which endogenously generates financial crisis. Then, we compare how model-based financial and real variables match the empirical facts around financial crisis, as classified by Lopez-Salido and Nelson (2010). These authors define crisis periods as financially turbulent periods. Figure 1 plots the dynamics of US variables around such financially turbulent times. Prior to the beginning of financial turbulence, the economy is growing. In these boom times, financial vulnerabilities are being build up. Banks are enlarging their balance sheets and increasing their leverage. At the beginning of financial turbulence, the financial sector is still leveraging up (increasing already high leverage). Financial crisis is associated with the decline in GDP, investment, asset prices, bank equity and elevated spreads. The decline of real GDP from the peak-to-trough is 3%, whereas investment falls by 11%. The BAA-FF spread increases by roughly 200bp relative to its trough.



Notes: Sample: US data (1973Q3:2019Q4). The data is reported in logs and linearly detrended, with exception of the credit spread. Book leverage is calculated as the ratio of bank assets and bank equity. Definition of crises periods according to Lopez-Salido and Nelson (2010).

Figure 1: Dynamics Around Financial Turmoil Periods

3 Model

3.1 Overview

We set up a representative agent New Keynesian model of a closed economy with a financial intermediation sector along the lines of Gertler and Karadi (2011) and Gertler and Kiyotaki (2010). In this model, intermediate goods firms require funding from banks to finance capital purchases. Banks are subject to a financial friction, which requires them to have some "skin in the game", giving rise to a time-varying external finance premium and an acceleration of disturbances in the financial sector. In the original setup of the banking sector, the banking sectors' equity is determined exogenously by a set of parameter values. However, as in reality it is a choice variable of the bank and additionally considered to be a crucial variable for the stability of the financial system, we deviate from the original setup in this point. Instead, we allow bankers to adjust the amount of equity in the bank every period (see also Akinci and Queralto, 2020; Gertler et al., 2020a,b).

Furthermore, we assume that the economy endogenously shifts between two regimes, $r_t \in (l, h)$, which are characterized by different degrees of financial frictions – **l**ow and **h**igh frictions – and meant to represent "normal times" and "times of financial turmoil", respectively.

Besides financial intermediaries, there is a household sector, a consumption goods producing sector, an intermediate goods producing sector, a capital goods producing sector and a monetary authority. The model features capital adjustment costs and price rigidities.

In the following subsections we will describe the model in more detail and present the equilibrium equations. In section 6 we will also introduce macroprudential policy into the model.

3.2 Households

Within each household, there are two member types, workers and bankers. While the worker supplies work, L_t, to intermediate goods firms and deposits, D_t, to banks, the banker manages a financial intermediary and transfers retained earnings back to her household when the lifetime of the bank ends. Furthermore, the household can choose to adjust net wealth of the bank via equity issuance. Within the family, there is perfect consumption risk sharing, which allows to maintain the representative agent framework. As in Gertler and Karadi (2011), it is assumed that a fraction $1-f$ of household members are depositors, while a fraction f are bankers. Between periods there is a random turnover between the two groups: with probability $\theta(r_r)$ a banker will stay a banker and with probability $1-\theta(r_t)$ she will become a depositor. The relative proportions are kept fixed. New bankers are provided with some start-up funds from their respective households.

The lifetime utility of a representative worker, who draws utility from consumption C_t and disutility from labor L_t, is given by

$$E_t \sum_{k=0}^{\infty} \beta \left(\log C_{t+k} - \psi_L \frac{L_{t+k}^{1+\phi_L}}{1+\phi_L} \right).$$

Parameters $0 < \beta < 1$, ψ_L and $\phi_L > 0$ denote, respectively, the household's subjective discount factor, the weight of disutility of labor and the inverse of labor supply elasticity.

The household's budget constraint is given by

$$C_t + D_t = R_{t-1} D_{t-1} + w_t L_t + NP_t + T_t,$$

where NP_t denotes net profits from the ownership of firms (financial and non-financial), T_t are lump-sum taxes, w_t denotes the real wage rate and R_t the gross real riskfree rate of return from deposit holdings between $t-1$ and t.

Hence, the consumption Euler equation and the household labor supply condition take the following forms

$$\lambda_t = \beta E_t R_t \lambda_{t+1}, \tag{1}$$

$$w_t = \frac{\psi_L L_t^{\phi_L}}{\lambda_t}, \tag{2}$$

where $\lambda_t \equiv \frac{1}{C_t}$ denotes the marginal utility of consumption.

3.3 Banks

Each bank channels deposits from households, d_t, intra-period non-contingent debt, $d_{W,t}$, and internal funds, n_t, to non-financial firms. Intra-period non state-contingent debt can only be used to finance intra-period working capital loans, $d_{W,t} = s_{W,t}$, which firms use to finance their wage bill in advance.[2] The gross rate of return on working capital loans is given by $R_{L,t}$. Profits from the extension of intra-period loans, $(R_{L,t} - R_{t-1}) s_{W,t}$, can be used to finance risky inter-period capital loans provided in the same period. Therefore, a bank's balance sheet is given by

$$Q_t s_t = d_t + n_t + (R_{L,t} - R_{t-1}) s_{W,t},$$

[2] With respect to working capital loans, we follow Akinci and Queralto (2020) who, in turn, follow the timing assumptions proposed by (?). Hence, for a more detailed description of the modelling of intra-period working capital loans, the reader is therefore referred to Appendix C of Akinci and Queralto (2020) or the original work by (?).

where s_t denote state-contingent claims on a unit of capital used in intermediate goods production held by an individual bank and Q_t denotes the price of a unit of capital.

Net worth evolves according to

$$n_t = R_{k,t} Q_t s_t + e_{t-1} + R_{t-1} d_{t-1},$$

where $R_{k,t}$ is the state-contingent gross real rate of return on capital assets and e_t is new equity provided to the bank by its respective household at the end of period t.

As it is assumed that each period a fraction 1-$\theta(r_t)$ of bankers exits the business with i.i.d. probability and pays out accumulated earnings to their respective households.[3] Note that parameter -$\theta(r_t)$ is regime-specific, i.e., is calibrated to take on different values in the two different regimes.

To motivate the requirement to build up net worth, the following moral hazard problem is assumed: After having borrowed external funds, $d_{L,t} + d_t$, but before repaying its creditors back and before the exit shock realizes, the banker can choose to divert the fraction λ of available funds back to the household. The cost associated with this fraud is that the depositors recover the remaining fraction $1-\lambda$ and force the banker into bankruptcy. Therefore, for households to be willing to deposit funds with the bank, the following incentive constraint must hold

$$V_t \geq \lambda(Q_t s_t + (1-\Delta_{L,t}) s_{W,t}), \tag{3}$$

where V_t stands for the continuation value of the bank and $\Delta_{L,t} \equiv R_{L,t} - R_{t-1}$ denotes the working capital wedge.

To solve the banker's maximization problem, define the objective of the bank recursively as

$$\begin{aligned} V_t = \max \quad & E_t \Lambda_{t,t+1}[(1-\theta(r_t))(R_{k,t+1} Q_t s_t - R_t d_t) \\ & + \theta(r_t)[(V_{t+1}(n_{t+1}) - e_t) - C(e_t, n_t)]], \end{aligned}$$

If the banker exits, it pays out assets minus liabilities at the beginning of the next period, before further equity is issued. If it stays in business, it has the opportunity to issue more equity. In that case, it maximizes expected future payouts net of equity issuance and associated costs. Equity issuance costs are assumed to take a quadratic form, $C(e_t, N_t) = \frac{\kappa(r_t)}{2} x_t^2 N_t$, where $x_t \equiv \frac{e_t}{N_t}$. Parameter $\kappa(r_t)$ drives the cost of raising equity and is also assumed to be regime-specific.

Now, guess that the value function is linear in net worth, $V_t(n_t) = \gamma_t n_t$, where γ_{t+1} captures the value of an extra unit of net wealth in the next period.

[3] This arrangement precludes bankers from aggregating so much net worth that the incentive constraint becomes irrelevant for them.

Define

$$\mu_t \equiv E_t \Lambda_{t,t+1}(1-\theta(r_t)+\theta(r_t)\gamma_{t+1})(R_{k,t+1}-R_t), \tag{4}$$

$$\upsilon_t \equiv E_t \Lambda_{t,t+1}(1-\theta(r_t)+\theta(r_t)\gamma_{t+1})R_t, \tag{5}$$

$$\nu_{e,t} \equiv E_t \Lambda_{t,t+1}(\gamma_{t+1}-1), \tag{6}$$

where μ_t is the marginal gain from expanding bank assets, υ_t is the the marginal gain of an additional unit of net worth, and $\nu_{e,t}$ the marginal gain of an additional unit of equity.

Hence, the problem of the bank simplifies to

$$\gamma_t n_t = \max_{s_t, s_{W,t}, e_t} \mu_t Q_t s_t + \upsilon_t \Delta_{L,t} s_{W,t} + \theta(r_t)(\nu_{e,t} e_t - C(e_t, n_t))$$

subject to the incentive constraint

$$\begin{aligned}\mu_t Q_t s_t + \upsilon_t \Delta_{L,t} s_{W,t} + \upsilon_t n_t + \theta(r_t)(\upsilon_t e_t - C(e_t, n_t)) \\ \leq \lambda(Q_t s_t - (1-\Delta_{L,t}) s_{W,t}).\end{aligned}$$

Letting ζ_t denote the Lagrange multiplier on the incentive constraint, the solution to the maximization problem of the bank is given by

$$\nu_{e,t} = \kappa(r_t) x_t \tag{7}$$

and

$$\begin{gathered}(1+\zeta_t)\mu_t = \zeta_t \lambda \quad \text{and} \\ (1+\zeta_t)\upsilon_t \Delta_{L,t} = \xi_t \lambda (1-\Delta_{L,t}),\end{gathered}$$

which can be combined into

$$\Delta_{L,t} = \frac{\mu_t}{\mu_t + \upsilon_t}. \tag{8}$$

Note that the coefficients of the value functions exclusively depend on aggregate variables and, hence, the same first-order conditions apply to the entire banking sector, which makes aggregation trivial. Assuming that the incentive constraint binds,[4] it can be expressed in terms of the coefficients of the value function,

$$Q_t S_t + (1-(R_{L,t}-R_{t-1})S_{W,t}) = \frac{\upsilon_t + \theta(r_t)\frac{\kappa(r_t)}{2}x_t^2}{\lambda - \mu_t} N_t \equiv \phi_t N_t. \tag{9}$$

[4]Parameters and steady state values are chosen such that the incentive constraint binds in the steady state. Holding the variance of shocks small enough guarantees that the incentive constraint also binds in a stochastic environment.

The capital letters stand for the aggregated values of the respective variables, i.e., $Q_t S_t + (1 - \Delta_{L,t} S_{W,t})$ denote total assets of the banking system and N_t aggregate net wealth. ϕ_t is the ratio of intermediated assets to net wealth, which can be referred to as the leverage ratio. Note that it is determined endogenously in this model. Recognizing from equation (9) and the binding incentive constraint that $\gamma_t = \phi_t \lambda$, the guess could be verified.

Finally, the evolution of aggregate bank net wealth is given by

$$N_t = (N_{n,t} + N_{e,t}) \Xi_{N,t}, \text{ with} \tag{10}$$

$$\begin{aligned} N_{e,t} = \theta(r_t) \big[&(R_{k,t} - R_{t-1}) Q_{t-1} S_{t-1} + R_{t-1} N_{t-1} \\ &+ R_{t-1} \Delta_{L,t} S_{W,t-1} + e_{t-1} \big], \end{aligned} \tag{11}$$

$$N_{n,t} = \omega(r_t) Q_t S_{t-1}, \tag{12}$$

where $N_{e,t}$ denotes existing bankers' net worth, $N_{n,t}$ denotes new bankers' net worth and regime-specific $\omega(r_t)$ is the fraction of the assets given to new bankers by their respective households. Variable $\Xi_{N,t}$ denotes an exogenous disturbance to the net worth of bankers.

3.4 Intermediate Goods Firms

Competitive intermediate goods producing firms sell their products to final goods producers at price $P_{m,t}$.

The Cobb-Douglas production function of the representative intermediate goods firm is given by

$$Y_t^m = A_t (K_{t-1})^{\alpha} L_t^{1-\alpha}, \tag{13}$$

where $Y_{m,t}$ denotes intermediate output and A_t technology. Parameter α denotes the output elasticity of capital. Capital stock K_{t-1} was bought from capital goods producers in the previous period at price Q_{t-1}. To finance capital purchases, the firm issues state-contingent securities to financial intermediaries in the same amount as the capital stock and at the same price, i.e.,

$$Q_t K_t = Q_t S_t. \tag{14}$$

After being used in production, the depreciated capital stock $(1-\delta)\xi_t K_{t-1}$ is sold back to capital goods producers.

Hence, the firm chooses labor demand optimally as follows,

$$w_t = \frac{\alpha Y_t^m}{L_t}. \tag{15}$$

Optimal choice of the capital stock implies that the ex-post real return on capital is given by

$$R_{k,t} = \frac{\frac{\alpha P_{m,t} Y_{m,t}}{K_{t-1}} + (1-\delta) Q_t}{Q_{t-1}}. \tag{16}$$

3.5 Capital Goods Firms

Competitive capital goods firms produce new capital and refurbish depreciated capital using final output as input. The law of motion for capital is given by

$$K_t = \left\{ (1-\delta)\, K_{t-1} + \left(1 - f\left(\frac{I_t}{I_{t-1}} \right) \right) I_t \right\}, \tag{17}$$

where I_t denotes investment and $f(\cdot)$ investment adjustment costs (in consumption units). Their functional form is given by

$$f\left(\frac{I_t}{I_{t-1}} \right) = \frac{\eta_I}{2} \left(\frac{I_t}{I_{t-1}} - 1 \right)^2, \tag{18}$$

with $\eta_I > 0$, denoting the inverse elasticity of investment with respect to the price of capital. The capital goods producer chooses investment I_t to maximize lifetime profits given by

$$E_t \sum_{k=0}^{\infty} \Lambda_{t,t+k} \left\{ Q_{t+k} I_{t+k} - \left(1 + f\left(\frac{I_{t+k+1}}{I_{t+k}} \right) \right) I_{t+k} \right\},$$

with $\Lambda_{t,t+1} \equiv \beta \frac{\lambda_{t+1}}{\lambda_t}$ denoting the real stochastic discount factor.

From solving the optimization problem of the capital goods firm, the real price of one unit of capital is obtained,

$$Q_t = 1 + f\left(\frac{I_t}{I_{t-1}} \right) + \frac{I_t}{I_{t-1}} f'\left(\frac{I_t}{I_{t-1}} \right) - E_t \left\{ \Lambda_{t,t+1} f'\left(\frac{I_{t+1}}{I_t} \right) \frac{{I_{t+1}}^2}{{I_t}^2} \right\}. \tag{19}$$

3.6 Final Goods Firms

Final output, Y_t, is assumed to be a CES composite of mass unity of differentiated final products,

$$Y_t = \left(\int_0^1 Y_t(f)^{\frac{\epsilon-1}{\epsilon}} df \right)^{\frac{\epsilon}{\epsilon-1}},$$

with $0 < \epsilon$. $Y_t(f)$ denotes output by retailer f. The corresponding price index is given by

$$P_t = \left(\int_0^1 P_t(f)^{1-\epsilon} df. \right)^{\frac{1}{1-\epsilon}},$$

where $P_t(f)$ denotes the price of variety f.

Given that consumers allocate consumption expenditures optimally between varieties, final goods firm f faces the following demand by consumers

$$Y_t(f) = \left(\frac{P_t(f)}{P_t}\right)^{-\epsilon} Y_t,$$

i.e., its share in total home final goods production Y_t, depends on its relative price.

It is assumed that each unit of final output is assembled costlessly from one unit of intermediate output. Real marginal cost is therefore given by the real intermediate output price $P_{m,t}$. It is further assumed that each period a firm faces a positive probability σ that it is not able to reset its price (Calvo-style pricing). If not able to reset its price, a firm can partly index its price to the lagged rate of inflation.

Hence, the price chosen by an optimizing final goods firm is given by

$$\tilde{P}_t = \frac{\epsilon}{\epsilon - 1} \frac{E_t \sum_{k=0}^{\infty} \sigma^k \beta^k \lambda_{t+k} \Pi_{t,t+k}^{\epsilon} \Pi_{t-1,t+k-1}^{-\epsilon\sigma_\pi} Y_{t+k} P_{m,t+k}}{E_t \sum_{k=0}^{\infty} \sigma^k \beta^k \lambda_{t+k} \Pi_{t,t+k}^{\epsilon-1} \Pi_{t-1,t+k-1}^{(1-\epsilon)\sigma_\pi} Y_{t+k}} P_t, \tag{20}$$

where $\Pi_t \equiv \frac{P_t}{P_{t-1}}$ denotes inflation between $t-1$ and t and σ_π denotes the degree of price indexation. The dynamics of the price index are given by

$$P_t = \left(\sigma \Pi_{t-1}^{\sigma_\pi(1-\epsilon)} P_{t-1}^{1-\epsilon} + (1-\sigma)\tilde{P}_t^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}}. \tag{21}$$

3.7 Further Equilibrium Equations

The aggregate resource constraint holds, i.e.,

$$Y_t = C_t + \left(1 + f\left(\frac{I_t}{I_{t-1}}\right)\right) I_t + \theta(r_t) \frac{\kappa(r_t)}{2} x_t^2 N_t \tag{22}$$

In the benchmark version of the model, the central bank adjusts the nominal interest rate according to the following Taylor rule

$$\frac{R_t^n}{R^n} = \left(\frac{R_{t-1}^n}{R^n}\right)^{\rho_r} \left(\frac{\pi_t}{\pi}\right)^{\kappa_\pi(1-\rho_r)} \left(\hat{y}_t\right)^{\kappa_y(1-\rho_r)} e_{t,R}, \tag{23}$$

where $\hat{y}_t$ is the log of the output gap, i.e., the percentage deviation of output from natural output, which we proxy through the inverse of the markup gap. $e_{t,R}$ is a monetary policy shock and parameter $0 < \rho_r < 1$ determines the degree of interest rate smoothing. Parameters κ_π and κ_y determine the central bank responsivenss to inflation and output gap, respectively.

A well known Fisher equations links the nominal rate to the real rate and inflation,

$$R_t = \frac{R_t^n}{E_t \Pi_{t+1}}. \tag{24}$$

The technology shock follows an autoregressive process given by

$$\ln A_t = \rho_a \ln A_{t-1} + e_{t,A}, \tag{25}$$

where $\rho_A \in (0,1)$ and $e_{t,A}, \sim iid(0, \sigma_x^2)$.

4 Solution and Calibration

4.1 Solution Method

We solve the model using perturbation techniques. Compared to projection methods, perturbation, in general, allows for solving and estimating larger models, i.e., models with more state variables. A commonly used perturbation technique in the context of regime-switching models is to linearize the model, assuming all parameters were constant, and then add switching to certain parameters. In this case, the solution and estimation of larger models is straightforward, however, this linear technique ignores that agents know about the possibility of regime switches and take this knowledge into account when optimizing. Therefore, we resort to a non-linear perturbation technique, which allows for the consideration of higher-order terms and endogenous regime-switching. It has been developed by Maih and Waggoner (2018).[5] [6] The technique will be briefly described in the following paragraph, for a more detailed description, the reader is referred to Chang et al. (2021).

The system of equilibrium equations to be solved – including the switching functions – can be cast into the following form

$$\mathbb{E}_t \left[\sum_{r_{t+1}=1}^{h} p_{r_t r_{t+1}}(\mathscr{I}_t) f_{r_t}(x_{t+1}(r_{t+1}), x_t(r_t), x_{t-1}, \theta_{r_t}, \theta_{r_{t+1}}, \epsilon_t) \right] = 0, \tag{26}$$

where x_t is a vector of model variables, r_t represents the switching process with h different states, θ_{r_t} is the vector of parameters in state r_t and $p_{r_t r_{t+1}}(\mathscr{I}_t)$ is the transition probability for going from state r_t to state r_{t+1} which depends on $\mathscr{I}_t$,

[5]It is embedded in the Matlab toolbox RISE developed by Junior Maih. The toobox is freely available under https://github.com/jmaih/RISE_toolbox.

[6]The perturbation approach proposed by Barthélemy and Marx (2017) also allows to solve models with endogenous regime-switching.

the information at time t. The aim is to find a regime-specific policy function which expresses the variables of the model as a function of the states, z_t.

$$x_t = \mathscr{T}_{r_t}(z_t). \tag{27}$$

A key property of $\mathscr{T}_{r_t}$ is, that it es a function of the solution in other regimes, i.e.,

$$\mathscr{T}_{r_t} = \tau_{r_t}(\mathscr{T}_1, \mathscr{T}_2, ..., \mathscr{T}_{r_t}, ..., \mathscr{T}_h)$$

As there is no analytical solution to the above system of equations, Maih and Waggoner (2018) propose a perturbation solution,

$$x_t(r_t) \approx x(r_t) + \mathscr{T}_{r_t,z}(z_t - z(r_t)) + \frac{1}{2!}\mathscr{T}_{r_t,zz}(z_t - z(r_t))^{\otimes}2 + ...,$$

where $z_t \equiv [x'_{t-1}, \sigma, \epsilon'_t]$, the vector of state variables, is augmented by an auxiliary argument, the perturbation parameter σ. The perturbation parameter has the property, that if $\sigma = 1$ the system of equations to be solved becomes the original one (26), while if $\sigma = 0$ it reduces to tractable system from which any stochastic disturbances are eliminated – including the randomness resulting from possible regime changes. The system of equations is perturbed around the point where $\sigma = 0$, i.e., around regime-specific steady states.Regime-specific steady states can be interpreted as resting points at which the economy would stay in the absence of shocks if it happened to start at of these points.

For solving the quadratic matrix equations, RISE relies on efficient functional iterations and Newton algorithms which allow for the solution of relatively large models (see, e.g., Maih, 2015).

4.2 Calibration of Regime-Invariant Parameters

Table 2 shows the invariant model parameters and their corresponding values. Most values are taken from Gertler and Karadi (2011) and Akinci and Queralto (2020) who calibrate their model to match important regularities of US business and financial cycles.

4.3 Calibration of Regime-Dependent Parameters and Switching Functions

As stated above, we assume that there are two regimes between which the economy switches, denoted by $r_t \in (\textit{normal}, \textit{stress})$. Three of the parameters defining the size of the financial friction, $\omega(r_t)$, $\theta(r_t)$ and $\kappa(r_t)$, are calibrated to distinguish the high from the low financial friction (FF) regime. The probabilities

Parameter	Description	Value	Source/Target
Households			
β	subjective discount factor	0.99	Gertler and Karadi (2011)
ϕ_L	inverse of Frisch elast.	0.276	Gertler and Karadi (2011)
Capital producing firms			
η_I	inverse elast. of invest. with respect to price of capital	1.728	Gertler and Karadi (2011)
Intermediate goods firms			
α	output elast. of capital	0.33	standard value
δ	capital depreciation rate	0.025	standard value
Final goods firms			
θ^p	probability of keeping prices fixed	0.779	Gertler and Karadi (2011)
ϵ	elast. of subst. between varieties	4.167	Gertler and Karadi (2011)
Financial intermediaries			
λ	fraction of divertable assets	0.35	Gertler and Karadi (2011)
Monetary policy			
κ_y	feedback coeff. on output gap	0.125	Gertler and Karadi (2011)
κ_π	feedback coeff. on inflation	1.500	Gertler and Karadi (2011)
ρ_r	interest rate smoothing coeff.	0.800	Gertler and Karadi (2011)
Exogenous processes			
ρ_A	persistence of technology shock	0.97	Gertler and Karadi (2011)
σ_N	std. dev. of net wealth shock	0.001	Gertler and Karadi (2011)
σ_A	std. dev. of technology shock	0.00246	Akinci and Queralto (2020)
σ_R	std. dev. of monetary policy shock	0.0014	Akinci and Queralto (2020)

Table 2: Regime-Invariant Parameters

of switching from the low-FF regime (i.e., normal times) to the high-FF regime (i.e., stress times) in period t and vice versa are denoted as $p_{lh,t}$ and $p_{hl,t}$, respectively. They are assumed to depend on the deviation of bank leverage from its steady state value in the following form,[7]

$$p_{lh,t} = \frac{\alpha_{lh}}{\alpha_{lh} + exp(-\psi_{lh}(\phi_t - \bar{\phi}_l))} \tag{28}$$

$$p_{hl,t} = \frac{\alpha_{hl}}{\alpha_{hl} + exp(\psi_{hl}(\phi_t - \bar{\phi}_h))} \tag{29}$$

where $\bar{\phi}_l$ and $\bar{\phi}_h$ denote the regime-specific steady state values of the leverage ratio. Parameters ψ_{lh}, ψ_{hl}, α_{lh} and α_{hl} govern the form of the switching function.

[7] We also considered alternative regime-switching indicators such as the deviation of the spread from its steady state values or of net worth from its steady state value. However, these alternative indicators generated either too much or too little volatility of the economy, making it difficult to match data on the frequency of financial crises.

We calibrate the three regime-specific parameters $\omega(r_t)$, $\theta(r_t)$ and $\kappa(r_t)$ jointly with the parameters of the switching functions in order to hit the following targets: a ratio of the BAA-AAA spread of tranquil times to turbulent times of approximately 60%, the proportion of the time spent in financially turbulent times of approximately 25%, and a mean duration of financially turbulent times of about 3.5 years.

Table 3 gives an overview of the chosen regime-specific parameters and parameters of the switching function. The high-FF regime is characterized by a combination of a shorter lifetime horizon of a banker ($\theta(h) < \theta(l)$), higher start-up funds ($\omega(h) > \omega(l)$) and higher costs of equity issuance ($\kappa(h) > \kappa(l)$). A shorter lifetime horizon of the banker (lower $\theta(r_t)$) worsens balance sheet conditions, as bankers have less time to accumulate net worth. Therefore, the multiplier on the incentive constraint becomes larger on average. Assuming a higher cost of equity issuance in the high friction regime is motivated by recent empirical evidence by Gertler et al. (2020a), who find that the cost of equity issuance of financial institutions peaked during the Great Recession, reaching 2.4%. Higher start-up funds on average loosen the financial constraint, however, we found it necessary to assume $\omega(h) > \omega(l)$ to render the model stable. We conjecture, that it is necessary to increase the fraction of the assets $Q_t S_{t-1}$ provided to new bankers in the high-friction regime, due to the massive drop in Q_t.

The table also shows, that in the deterministic steady state, the chosen combination of the three financial parameter values is associated with a higher spread and lower leverage in the high-FF regime. It should be noted, however, that in a model with endogenous regime-switches the regime-specific mean values of certain variables can differ quite a bit from their respective steady state values, even if the model is only approximated up to first-order. The reason is that with endogenous regime-switches the model economy reacts differently to positive and negative shocks. These non-linearities are to a large extend governed by the functional form and calibration of the switching functions. Furthermore, the switching functions have an important effect on the time spent in each regime. Table 4 reports the regime-specific average values of certain variables, stemming from a simulation of the model. Comparing the values to the ones reported in table 3, it can be seen that, for example, the average values of the spreads in the two regimes are much further apart than their respective deterministic steady state values. Regarding leverage, its mean value is higher in the high-FF regime, whereas its deterministic steady-state-value is higher in the low-FF regime.

Figure 2 shows how the switching functions behave for the given choice of parameter values. The solid lines reflect the switching probability as a function of leverage, whereas the dashed lines reflect the regime-specific steady state

	“Normal Times” (**l**ow-FF)	“Financially Turbulent Times” (**h**igh-FF)
quart. survival prob. of banker, $\theta(r_t)$	0.97	0.955
start-up funds for new bankers, $\omega(r_t)$	0.001	0.005
equity issuance cost parameter, $\kappa(r_t)$	28	30
det. st. st. spread	63bps	100bps
det. st. st. leverage	3.8	3.7
α_{lh}	0.01	-
α_{hl}	-	0.06
ψ_{lh}	10	-
ψ_{hl}	-	20

Table 3: Regime-Specific Parameters

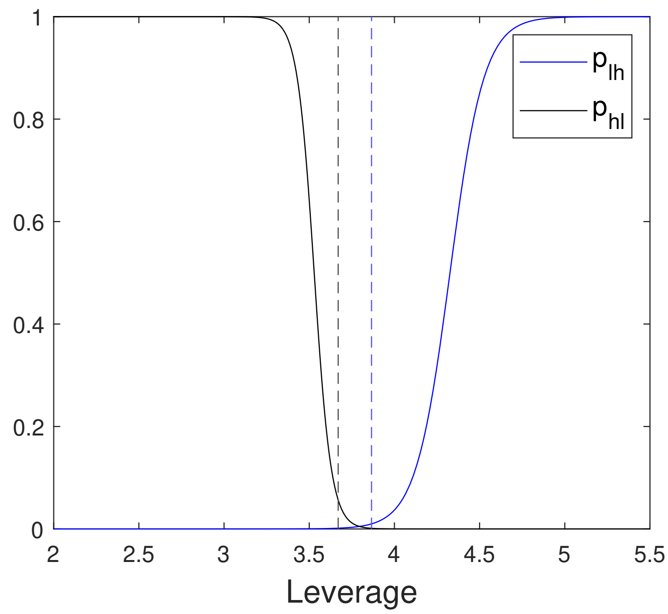
values. The likelihood of switching from the low-FF to the high-FF regime (blue graph) increases when banks start leveraging up. The switching probability is quite low when leverage is at its steady state value, but starts to increase exponentially when passing a value of four. The likelihood of switching from the high-FF to the low-FF regime (black graph) increases when banks reduce their leverage. It is around 7% when leverage is at its deterministic steady state value of 3.7. However, note that mean leverage in the high-FF regime amounts to 3.9 and for this value the probability to switch back to the tranquil regime is much lower which creates some more persistence of financially turbulent times.

5 Analysis of the Benchmark Model

5.1 Model Moments

Table 4 provides the moments of some important model variables obtained from a first-order approximation of the model. The first column contains the regime-specific mean values of obtained from simulating the model, approximated at first-order, for 100,000 periods, the second column shows the respective standard deviations and the third columns the deterministic, regime-specific steady state values.

As mentioned above, the assumption of endogenous regime-switching introduces non-linearities even in a first-order approximation of the model. While in the deterministic steady state, the spread of the low-FF regime takes the value of 63bp and the spread of the high-FF regime amounts to 100bp, in the regime-switching model they change to 67bp and 118bp, respectively. Average



Notes: The y-axis gives the probability of a regime switch. The x-axis represents banking sector leverage (ϕ_t). Regime-specific steady states are represented by dashed lines.

Figure 2: Switching Functions

leverage in the high-FF regime even increases to a larger value than in the low-FF regime, as a result of endogenous regime-switching. The intuition behind this is that, in general, leverage increases considerably when financial conditions worsen, which is the case when moving from the low-FF to the high-FF regime. Furthermore, higher leverage itself increases the probability to switch from the low-FF to the high-FF regime and to stay in the high-FF regime, i.e., in general, when the economy enters financially turbulent times, the spread is already higher than on average.

We find that the mean of the key variables of the real economy (output, consumption, capital, labor) is higher in the low-FF regime, as would be expected. Regarding the standard deviation of the variables, it can be seen, that the economy fluctuates more in the high-FF regime than in the low-FF regime, which is also a realistic feature of the model. The reason for this is, that in the low-FF regime the established trust in the banking sector allows banks to adjust their balance sheets more easily in response to shocks, which reduces the volatility of the entire economy. Moreover, the high-FF regime is dominated by the dynamics around the regime-switch, which display very high volatility. The regime-switch to the high-FF regime will be discussed in more detail in the next section.

	Mean	**Std. Dev.** (∗100)	**Det. St. St.**
Spread (l)	0.672	1.102	0.640
Spread (h)	1.187	1.722	1.000
Leverage (l)	3.718	16.155	3.761
Leverage (h)	3.860	22.639	3.695
Output (l)	0.852	1.749	0.851
Output (h)	0.833	1.769	0.836
Consumption (l)	0.702	1.179	0.703
Consumption (h)	0.696	1.192	0.695
Labor (l)	0.331	0.510	0.330
Labor (h)	0.325	0.616	0.329
Inflation (l)	0.003	0.200	0.000
Inflation (h)	-0.008	0.245	0.000
Time in h-regime (in %)	21.364		
Mean length in quart. (l)	63.467		
Mean length in quart. (h)	17.257		
Prob. l to h (in %)	1.511		
Prob. h to l (in %)	3.921		

Table 4: Simulation Statistics

5.2 Average Dynamics around a Switch to the Crisis Regime

Figure 3 shows the average dynamics around a switch from tranquil to financially turbulent times, which takes place between period -1 and 0 in the figure. The results are obtained from a simulation of the model economy over 1,000,000 quarters with a burn-in period of 100,000 quarters. We restrict our attention to episodes where the tranquil regime had lasted at least 20 quarters before the economy switched to the financially turbulent regime and where the subsequent turbulent regime lasted for at least eight periods. By doing so, we aim to exclude effects from previous crisis on the tranquil regime and to focus our analysis to financially turbulent episodes which are usually also considered as financial crises in the related literature. All variables, except for the switching probability, the inflation rate and the shocks, are reported in %-deviations from their simulation means. The upper part of table 5 summarizes the change in GDP, investment, leverage, net worth, the spread and credit around the regime switch and contrasts it with the corresponding data.

Figure 3 shows that up to approximately one year before a crisis starts, the real economy finds itself above average. This boom phase is especially pronounced for investment and output. Around five quarters before the switch,

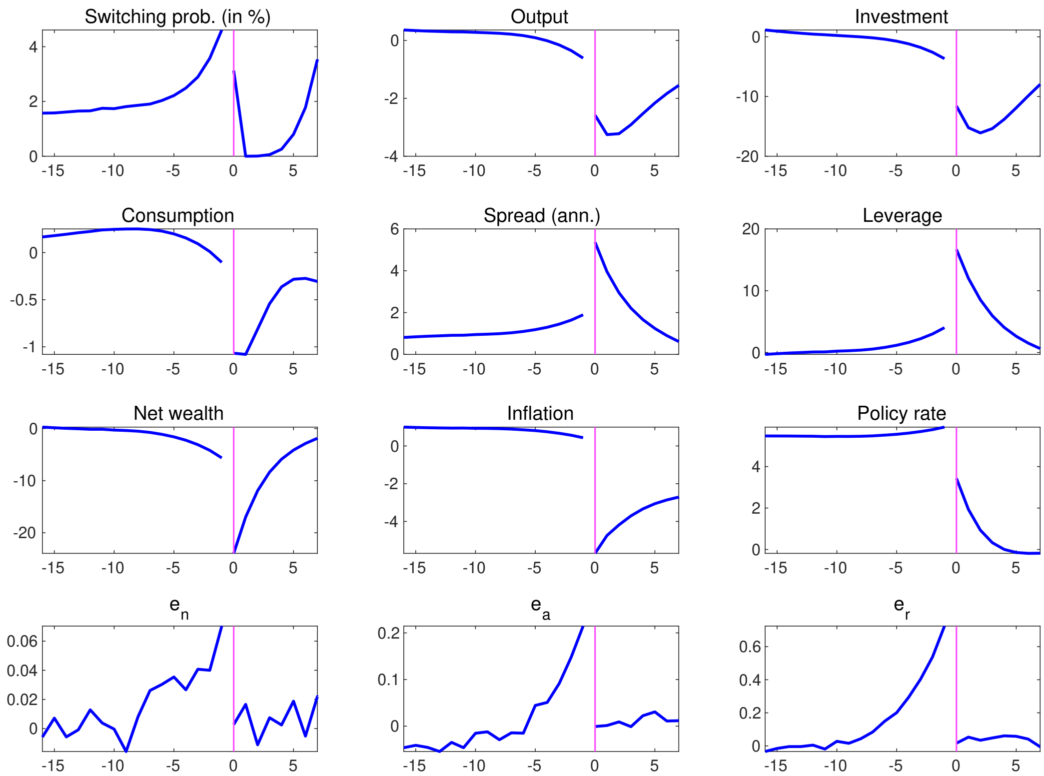


Figure 3: Average Dynamics around Financial Crises (in %-deviation from simulation mean, except for switching probability, inflation rate and shocks)

economic conditions start to worsen. This slowdown can also be observed in the financial sector, where leverage and the spread increase and net wealth drops faster than before. The drop in net wealth reflects the drop in capital returns. The switching probability, which is a function of leverage, increases rapidly, indicating the buildup of financial risks in the banking sector.

The onset of the crisis is ultimately triggered by a negative sequence of net wealth and technology shocks and an unexpected increase in policy rates. Note, however, that the realizations of the shocks that trigger the crisis are not abnormally large, they are all within approximately one standard deviation of the shock.

The average switch to the crisis regime is characterized by a soaring credit spread (+350bps), a drastic fall in bank net worth by about 20pp and – due to the latter – a dramatic rise in leverage by about 10pp. To meet balance sheet constraints, banks are forced to deleverage by selling off assets, i.e., cutting credit, which is reflected by a large drop in investment, by about 15pp. The crisis in the banking sector and the induced decline in credit have large effects on output, which declines by about 3pp in the first crisis quarters.

Approximately one year after the crisis started, leverage ratio and net worth are back to their pre-crisis levels. At this time, also the probability to switch back to normal times starts to increase considerably. However, about two years after the beginning of the crisis, investment is still low, which explains the slow recovery of output.

Comparing the model to the data, the model overpredicts the increase in spreads and leverage. The increase in the spread is comparable to the one seen during the Great Financial Crisis in isolation. The model manages to match the fall of the real economy, i.e., in output and investment. While the time spent in the crisis regime in our model is similar to the one found according to the classification of crisis by Lopez-Salido and Nelson (2010), the regimes in our model are much more persistent than the ones defined by Lopez-Salido and Nelson (2010).

	Model	**Data (LSN, 2010)**
Dynamics around crisis:		
GDP	-3pp	-3pp
Investment	-15pp	-11pp
Leverage	10pp	4pp
Net worth	-20pp	-4pp
Spread	350bps	170bps
Crises times:		
Time in crisis (in %)	21.36	25.60
Mean length in quart. (l)	63.46	33.75
Mean length in quart. (h)	17.26	13.25

Table 5: Average Dynamics around Regime Switch – Model versus Data

6 Macroprudential Policy

6.1 Equity Issuance and Macroprudential Policy

The assumption of equity issuance (e.g. Akinci and Queralto, 2020; Gertler et al., 2020a,b) provides households, as the owners of banks, with some control over the strength of banks' balances sheets. By deciding to pay out less earnings and turn it into equity instead, bank owners can increase their net wealth and, hence, enable more intermediation currently and in the future. With more solid balance sheets, the economy enters less frequently into crises and crises are less powerful. However, due to equity issuance costs, too little equity is issued – from a financial stability standpoint. Furthermore, since the present net value of an equity transfer from the household to the bank, $v_{e,t}$, increases when financial conditions worsen, banks issue more equity during financially turbulent times than during tranquil times – even though equity issuance cost is higher during financially turbulent times. Table shows mean equity issuance during each regime and its overall correlation with certain model variables. First, it can be seen that equity issuance is substantially higher in the high-FF regime. This can be explained with the very high correlation between equity issuance and the multiplier on the incentive constraint. The constraint becomes more binding in financially turbulent times, when net worth drops and, hence, leverage increases.

Mean (l) (in %)	1.049
Mean (h) (in %)	1.271
Std.*100 (l)	0.164
Std.*100 (h)	0.293
Corr. w/ mult.	0.946
Corr. w/ N	-0.844
Corr. w/ Y	-0.419
Corr. w/ C	-0.062

Table 6: Moments of x_t (share of equity in net worth)

The observed relationship with the financial cycle – i.e., the capital ratio is lowered during normal times and built up during turbulent times – is the opposite of what macroprudential policy aims for. Therefore, we introduce macroprudential policy as an instrument which promotes the buildup of bank capital during good times, i.e., a policy in the spirit of a countercyclical capital buffer.

In our model, such an instrument can be implemented in the form of a regulatory capital requirement. Note that the incentive constraint given in equation (3), states that the ratio of the franchise value of the bank to asset holdings needs to be larger or equal to λ, which denotes the fraction of assets bankers could potentially divert from their creditors. Hence, λ can be interpreted as the minimum capital ratio required by the stakeholders of the bank. To implement macroprudential policy, we assume that the regulator requires banks to hold a higher capital ratio than what would be required by the stakeholders of the bank, i.e.,

$$\frac{V_t}{(Q_t s_t + (1-(R_{L,t}-R_{t-1}))s_{W,t})} \geq \lambda^{\text{reg}}(r_t) > \lambda.$$

We analyze two different designs of the minimum capital requirement,

1. constant capital buffer: $\lambda^{\text{reg}}(l) = \lambda^{\text{reg}}(h) > \lambda$ and

2. countercyclical capital buffer: $\lambda^{\text{reg}}(l) > \lambda$, $\lambda^{\text{reg}}(h) = \lambda$.

Note that the constant capital buffer incentivizes the buildup of bank capital during *all* times, while the coumntercyclical capital buffer incentivizes equity issuance in the low-FF regime. In the following subsections, we analyze how the design and strength of the given macroprudential policies affects the time spend in one of the two regimes, the duration of financial crises, the overall volatilty of the economy and the mean of certain important variables.

6.2 Effects of a Regulatory Capital Buffer

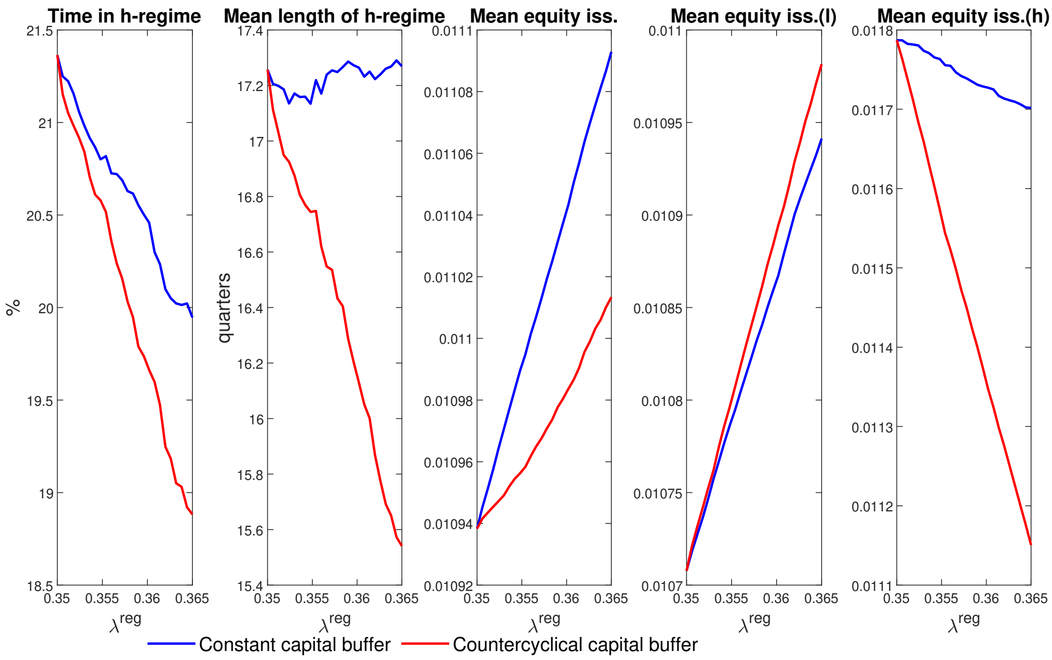


Figure 4: Effects of Regulatory Capital Buffers on the Frequency and Duration of Crises

Figure 4 shows how the introduction of a capital buffer affects the time in the high-FF regime by affecting equity issuance, x_t (equity issuance over total net worth). The blue line reflects the case of a constant buffer, which is required regardless of the regime, and the red line reflects the case of a countercyclical buffer requiring the bank to fullfill a higher capital ratio only in the low-FF regime. The size of $\lambda^{\text{reg}}(r_t)$ is shown on the x-axis. Note that when comparing the red and the blue line at a certain $\lambda^{\text{reg}}(r_t)$, on average, less capital is tight up in the financial sector when regarding the countercyclical buffer. This is reflected in the lower mean equity issuance in the case of the countercyclical buffer. Any value of $\lambda^{\text{reg}}(r_t)$ reduces the time in the high-FF regime more when a regime-dependent capital buffer is in place. Also the length of the high FF-regime is considerably reduced when the countercyclical policy is in place. This can be explained with a much more solid balance sheet when entering crisis times and – additionally – a looser capital requirement during financially turbulent times compared to the case of the constant capital requirement.[8] These effects of the countercyclical capital buffer in our model exactly resemble the purpose of a countercyclical capital buffer in practice.

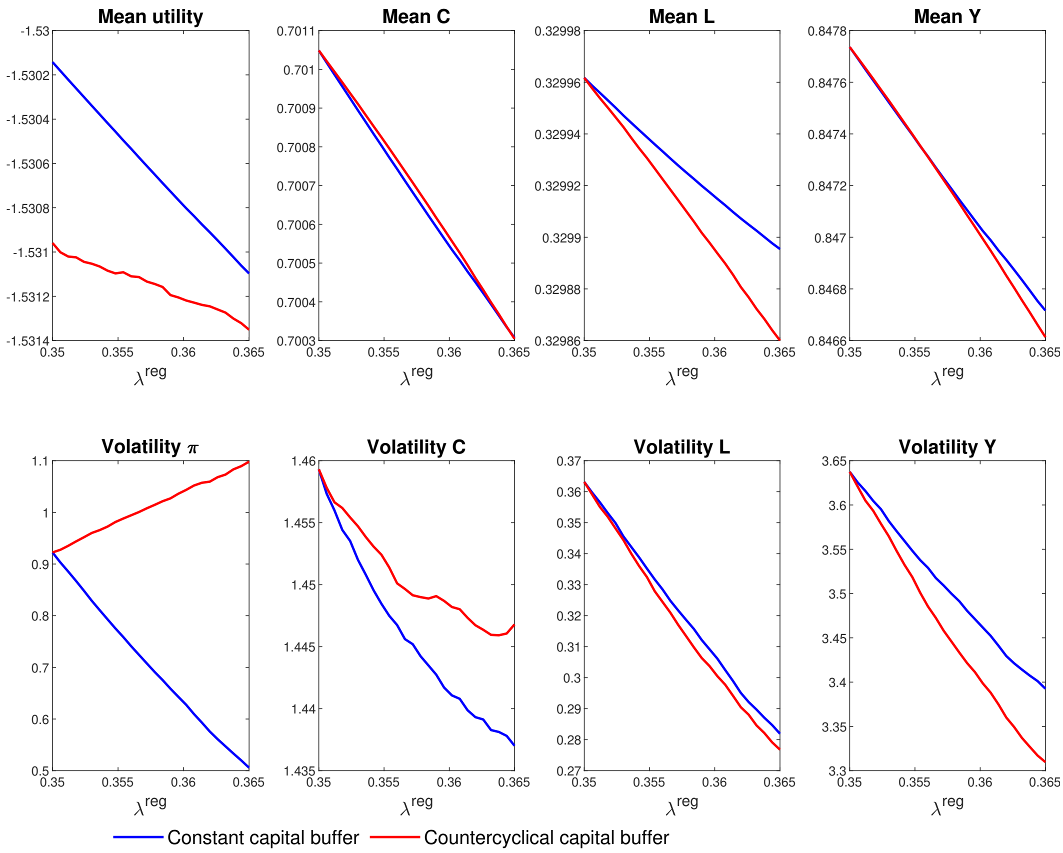


Figure 5: Effects of Regulatory Capital Buffers on the Macroeconomy

Next we turn to understanding effects of macroprudential policy on the mean and volatility of some important and potentially welfare-relevant variables of the model. In Figure 5, the blue line shows the respective value considering a constant capital buffer and the red line shows the case when the capital buffer is activated only during times of financial tranquility.

[8]In Appendix, Figure 6 shows the dynamics around the financial crisis for policies with capital buffers and without capital buffers. We find that the recovery of the economy is faster under the scenario with the countercyclical capital buffer (e.g., output and investment rebound).

First of all, note that mean utility, consumption, labor and output drop with the capital buffer. This is a result of the capital buffer tying up more funds in the financial sector which cannot be used for productive purposes instead. However, by significantly lowering the probability of entering financially turbulent times, the volatility of all variables is considerably reduced. Note that the effects of the countercyclical capital buffer and the constant capital buffer on the mean of consumption and output are very similar. Interestingly, mean utility is smaller in the case of the countercyclical capital buffer, even though the time spent in the high friction regime is significantly reduced. We conjecture, that this result is brought about by the small welfare cost of relatively large fluctuations in our model. Note in figure 3 that the drop in consumption caused by the onset of a financial crisis is quite small.

We plan to conduct a proper welfare analysis, in order to quantify how the opposing developments of mean and volatility of welfare-relevant variables affect total welfare.

7 Monetary Policy and Financial Stability

By estimating a Marko-switching DSGE model for the USA and the Euro area, Maih et al. (2021) find that during the last two decades, the Fed reacted more strongly to deteriorating macroeconomic conditions during times of financial distress. Our framework allows to analyze the implications of adjusting the coefficients of the Taylor rule depending on financial market conditions. Table 7 shows the results for differenct monetary policy scenarios. Column 1 represents model moments for the benchmark case in which κ_y and κ_π are regime-independent. The remaining columns show the same model moments for scenarios in which either κ_y or κ_π or both are higher in the low-FF regime, the high-FF regime or both regimes.

In the given model, a policy which resembles the policy of the Fed found by Maih et al. (2021), i.e., a stronger reaction to the output gap (column 2) or to inflation and the output gap (column 8) during times of financial distress reduces the time spent in the high friction regime and slightly increases mean consumption and output.

	$\kappa_y = 0.125$ $\kappa_\pi = 1.5$ 1	higher $\kappa_y(h)$ 2	higher $\kappa_y(l)$ 3	higher κ_y 4	higher $\kappa_\pi(h)$ 5	higher $\kappa_\pi(l)$ 6	higher κ_π 7	higher $\kappa_y(h)$,$\kappa_\pi(h)$ 8	higher $\kappa_y(l)$,$\kappa_\pi(l)$ 9
Time in h-reg.	21.8360	21.6160	21.9200	20.6340	26.2730	26.2730	20.5340	15.9210	28.8880
Length l-reg.	68.5649	67.5142	68.7930	71.6947	55.5173	55.5173	57.3762	68.2459	50.0084
Length h-reg.	19.1544	18.6184	19.3128	18.6396	19.7839	19.7839	14.8367	12.9229	20.3150
Spread (mean)	0.7266	0.6891	0.7754	0.7437	1.0036	1.0036	0.9183	0.5888	1.2088
Leverage (mean)	3.7466	3.7420	3.7520	3.7478	3.7649	3.7649	3.7576	3.7332	3.7828
Y (mean)	0.8414	0.8419	0.8413	0.8413	0.8408	0.8408	0.8406	0.8421	0.8397
Y (var)	0.0003	0.0003	0.0003	0.0003	0.0004	0.0004	0.0004	0.0004	0.0004
C (mean)	0.6957	0.6961	0.6956	0.6956	0.6952	0.6952	0.6950	0.6962	0.6943
C (var)	0.0002	0.0002	0.0001	0.0001	0.0002	0.0002	0.0002	0.0002	0.0002
L (mean)	0.3274	0.3275	0.3273	0.3273	0.3271	0.3271	0.3271	0.3275	0.3268
L (var)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
i (mean)	1.0104	1.0102	1.0107	1.0106	1.0115	1.0115	1.0118	1.0105	1.0124
i (var)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Π (mean)	1.0002	1.0001	1.0004	1.0004	1.0008	1.0008	1.0012	1.0003	1.0015
Π (var)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 7: Simulation Statistics for scenarios with monetary policy rules

8 Conclusion

We built a state-of-the-art financial frictions model, which endogenously transitions between a high and a low financial friction regime. It can replicate the fact that when entering financially turbulent times, volatility increases strongly, spreads surge and the production economy suffers from larger repercussions than in relatively tranquil times. It should be noted that these dynamics are found without resorting to exogenous disturbances of extraordinary size. Therefore, our model provides us with a laboratory well suited to analyze the effects of macroprudential policy.

The analysis of macroprudential policy showed that, in our model, a policy which promotes equity issuance, modelled through a minimum capital requirement, can be used as a tool to reduce the frequency of financial crisis and also the volatility of the economy. Policies which are not always in place, but which are used pre-emtively in the low financial frictions regime turn out to be much more effective in that sense than policies neglecting the current state of the economy. On the other hand, such regime-dependent policies have adverse affects on some welfare-relevant variables of the model, suggesting that the policy which is better able to reduce time spent in financial crises is not necessarily the optimal policy with respect to welfare. A full-fletched welfare analysis is still in the process.

The solution method we use, is well suited to accomodate further state-variables. We plan to extend the analysis in different directions, one being the role of non-Ricardian consumers for the severity of financial crises.

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9 Appendix

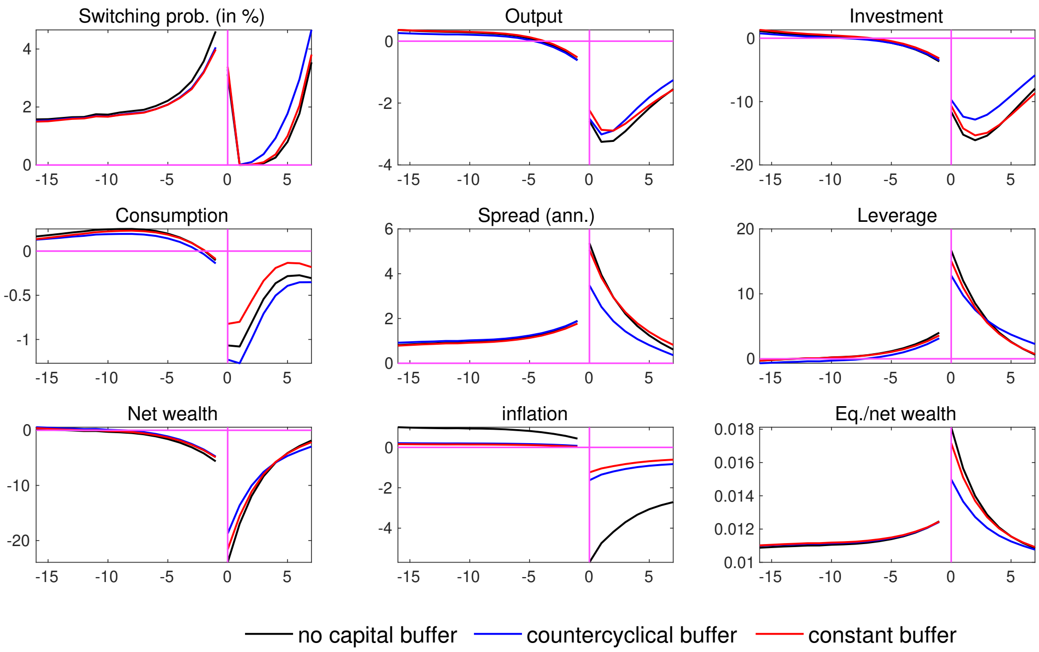

Figure 6: Average Dynamics around Financial Crisis