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Financial crises and shadow banks: A quantitative analysis☆

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ABSTRACT

Motivated by the build-up of shadow bank leverage prior to the financial crisis of 2007–2008, I develop a nonlinear macroeconomic model featuring excessive leverage accumulation and endogenous runs to capture the dynamics and quantify the build-up of instability. Incorporating monetary policy, I demonstrate that the zero lower bound increases the crises frequency and lowers welfare. The model is taken to U.S. data to estimate the run probability around the financial crisis of 2007–2008. The estimated run risk was already considerable in 2005 and kept increasing. Counterfactual simulations evaluate whether monetary interventions boost welfare and could have averted the financial crisis.

1. Introduction

The financial crisis of 2007–2008 was, at the time, the most severe economic downturn in the US since the Great Depression. Although the origins of the financial crisis are complex and various, the financial distress in the shadow banking sector has been shown to be one of the key factors.[1] The shadow banking sector, which consists of financial intermediaries operating outside normal banking regulation, expanded considerably before the crisis. Crucially, there was an excessive build-up of leverage (asset to equity ratio) for these unregulated banks. The collapse of the highly leveraged major investment bank Lehman Brothers in September 2008 intensified then a run on the short-term funding of many financial intermediaries, with very severe repercussions for the real economy in the fourth quarter of 2008. Fig. 1 documents these stylized facts about GDP growth and shadow bank leverage.

In this paper, I build a new nonlinear quantitative macroeconomic model with financial intermediaries and endogenous runs to capture the observed dynamics and to quantify the build-up of financial fragility. The model features endogenous boom-bust dynamics, which rely on the interaction among two features that correspond well to the shadow banking sector.

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[1] See e.g. Adrian and Shin (2010), Bernanke (2018), Brunnermeier (2009) and Gorton and Metrick (2012).

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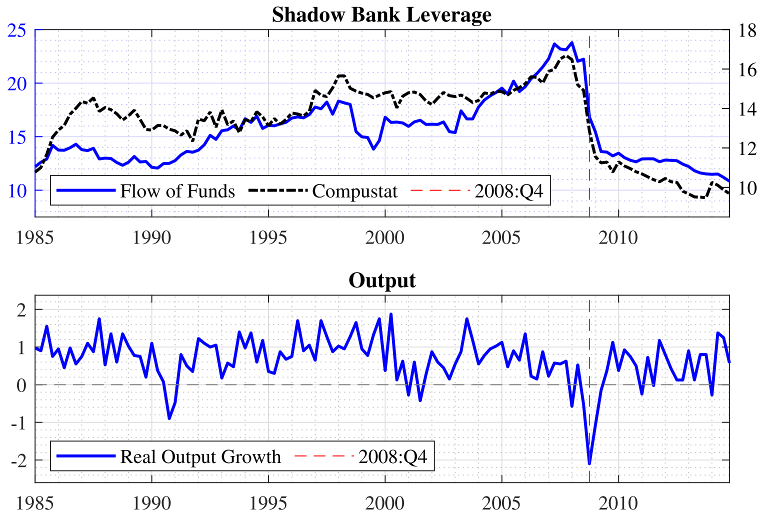

Fig. 1. The upper graph shows two measures of U.S. shadow bank book leverage. The first measure is based on balance sheet data from the Flow of Funds (left axis). The alternative one uses Compustat data (right axis). The leverage series rely on the book value of equity. Appendix A shows the details. The lower graph shows the quarter-on-quarter real output growth rate in percent.

First, the financial intermediaries face risk-shifting incentives and volatility shocks, which allow to account for extensive leverage accumulation similar to Adrian and Shin (2014) and Nuño and Thomas (2017). Second, the runs on the financial sector depend on economic and financial circumstances, as in Gertler et al. (2020b).

The boom-bust dynamics originate from a volatility paradox, in the spirit of Brunnermeier and Sannikov (2014). A period of low volatility reduces the risk-shifting incentives of financial intermediaries. This results in substantially elevated leverage, which implies low loss absorbing capacities, but also boosts credit and output. An increase in volatility can then trigger a self-fulfilling abrupt stop to the roll over of deposits, which triggers firesales and pushes the highly levered intermediaries into bankruptcy. This run on the financial sector causes a sharp contraction in output as observed in the great financial crisis in the fourth quarter of 2008. Importantly, the dynamics reconcile key empirical observations concerning financial crises since a run is preceded by a credit boom (Schularick and Taylor, 2012), low pre-crisis credit spreads (Krishnamurthy and Muir, 2017) and elevated shadow bank leverage as observed around 2008 (Adrian and Shin, 2010).

The model is embedded in a New Keynesian setup to study inflation dynamics and the zero lower bound (ZLB) in connection with financial crises. Financial fragility creates extensive downside risk for inflation. The ZLB increases the frequency and severity of financial crises substantially because it restricts the interventions of the monetary authority during a run. The ZLB also results in a considerable welfare loss of 0.3% in consumption equivalents.

The model is then taken to the data to obtain a structural estimate of the endogenous build-up of financial fragility in the U.S. around the great financial crisis. However, an estimation is very challenging because it requires to repeatedly solve the nonlinear model with global methods and then to filter it. To overcome this challenge, I apply a two-step procedure that reduces the computational burden, while still providing an estimate of financial fragility through the lens of a structural nonlinear model. In the first step, the nonlinear model is calibrated to key features of the U.S. and the shadow banking sector. The calibrated model is used as input for a nonlinear filter in the second step. The filter extracts the sequence of shocks and estimates the endogenous run probability over time conditional on the paths of selected data (shadow bank leverage and real output growth). In particular, I employ a particle filter to account for the nonlinear setup with endogenous financial crisis and the ZLB. This general approach provides a model-based growth-at-risk estimate.

According to the estimation, the run probability starts to increase significantly from 2005 onwards and peaks in 2008 due to rising shadow bank leverage. The estimation selects a run to explain the data in 2008:Q4. The run itself accounts for 70% of the severe output drop in this period. In addition to this, the results highlight the importance of low volatility because it causes the rise in leverage and makes the financial system prone to instability. As an external validation, the estimated path of volatility is also compared to a data proxy.

The model and estimation lend itself for a joint welfare analysis and counterfactual simulation of monetary and macroprudential strategies. Specifically, the focus is on a monetary policy rule that responds to the financial situation. The monetary policy response to financial conditions can be classified into interventions before (ex-ante) and after (ex-post) the crisis. Monetary policy can act in advance and lean against the wind through tightening measures, such as raising interest rates. Conversely, the ex-post component captures the monetary authority committing to a loose policy after the crisis. The welfare-maximizing rule enhances welfare by 0.6% (expressed in consumption equivalents) and succeeds in avoiding almost all runs. Most of these gains stem from the credible ex-post commitment, while ex-ante leaning provides only small, albeit positive, effects. To evaluate the policy, I compare it with a comparable macroprudential policy. Even though macroprudential policy would be preferable from a welfare perspective, monetary policy can in some cases serve as a good substitute that is easier to implement in practice, especially with respect to shadow banks.

Using the results from the estimation, the counterfactual paths for economic activity and financial fragility under alternative policies can be constructed. I demonstrate that the described welfare-maximizing rule would have mitigated the estimated build-up of financial fragility and averted the run in 2008. This outcome, however, hinges on a credible commitment to a loose ex-post policy, as ex-ante leaning alone would have not been sufficient.

Related Literature

Gertler et al. (2020b) and Gertler et al. (2020a) pioneer the incorporation of self-fulfilling runs into macroeconomic models to explain financial crises.[2] My paper contributes to this literature in three ways. First, I introduce volatility shocks as a new channel to quantify the financial crisis. This mechanism captures key macroeconomic and financial series, in particular the build-up of leverage prior to 2008 and endogenous boom-bust dynamics.[3] Second, I outline an approach to estimate the endogenous probability of a financial crisis through the lens of a microfounded nonlinear model. Taking the model to the data, I provide a novel nonlinear structural estimate of financial fragility around the financial crisis in 2008. Finally, I evaluate the economic and welfare implications of monetary policy with a special emphasis on the zero lower bound and responding to the financial situation. Combining the estimation with the policy analysis allows to show under what conditions a monetary interventions could have avoided the run on the financial sector in 2008. Other papers that incorporate runs into quantitative macro frameworks are Amador and Bianchi (2021), Faria-e Castro (2019), Ferrante (2018), De Groot (2021), Ikeda and Matsumoto (2021), Hakamada (2021), Mikkelsen and Poeschl (2019), Paul (2020) and Poeschl (2020).[4]

I also contribute to the large large growing body of empirical work on growth-at-risk that was inspired by Adrian et al. (2019). Their work links macrofinancial conditions and the future distribution of output growth using quantile regressions. More recently, Adrian et al. (2020) develop a semi-structural macroeconomic model with an ad-hoc specific vulnerability function to capture downside risk. My paper provides a novel structural empirical perspective on growth-at-risk through the combination of a fully microfounded nonlinear model and the particle filter. Based on the estimation, I also conduct (policy) counterfactuals on the estimated build-up of financial fragility and the occurrence of a financial crisis.

To obtain an estimate for the probability of a financial crisis through the lens of nonlinear model, I build on the literature that empirically assesses models with multiple equilibria. Following Aruoba et al. (2018), I use a particle filter (Fernández-Villaverde and Rubio-Ramírez, 2007) that is adapted to account for the multiplicity of equilibria.[5] A considerable difference to Aruoba et al. (2018) is the nature of the sunspot shock, which helps to select the equilibrium. While they use a Markov-switching sunspot shock to capture a switch in the inflation environment, I rely on an iid sunspot shock to capture the one-time event of a run. Furthermore, Bocola and Dovis (2019) use a particle filter to estimate the likelihood of a government default. Faria-e Castro (2019) applies a particle filter to conduct a counterfactual with countercyclical capital requirements in a model with bank runs.

2. Model

The setup is a dynamic stochastic general equilibrium model with a financial sector that faces endogenous runs. It is embedded in a New Keynesian setup with a zero lower bound (ZLB). Financial intermediaries have risk-shifting incentives based on Adrian and Shin (2014) and Nuño and Thomas (2017), which microfounds their leverage constraint. The financial sector occasionally faces system-wide runs, which are state-dependent, or in other words endogenous, similar to Gertler et al. (2020b). The occurrence of a run depends jointly on fundamentals and a self-fulfilling element. The intermediaries can be best thought of as shadow banks, as they are unregulated and not protected by deposit insurance.[6] The model featuring runs and the ZLB is solved in its nonlinear specification with global methods.

2.1. Household

There is a continuum of identical households. The representative household consists of workers and financial intermediaries that have perfect insurance for their consumption C_t. Workers supply labor L_t and earn the wage W_t. Intermediaries die with a probability of $1-\theta$ and return their net worth to the household to avoid self-financing. Simultaneously, new

[2] Gertler and Kiyotaki (2015) and Gertler et al. (2016) are important preceding contributions that integrate bank runs in the spirit of Diamond and Dybvig (1983) into standard macro models. Cooper and Corbae (2002) is an early study with runs that can be interpreted as roll-over crises.

[3] The risk-shifting incentives have a very different impact on leverage compared to that of a run-away constraint, where an intermediary can divert a fraction of assets that cannot be reclaimed, as used in Gertler et al. (2020b). Risk-shifting incentives combined with the volatility shock generate procyclical leverage, while leverage is normally countercyclical with the run-away constraint. The run-away constraint can be reconciled with the evidence for credit booms that generate busts if intermediaries are overly optimistic about future news. An alternative approach to obtain procyclical leverage is to have sticky net worth accumulation of financial intermediaries (Ikeda and Matsumoto, 2021).

[4] Other approaches to capture boom-bust dynamics are asymmetric information, optimistic beliefs and learning (e.g. Boissay et al., 2016; Bordalo et al., 2018; Boz and Mendoza, 2014). Other studies (e.g. Justiniano et al., 2019; Guerrieri and Lorenzoni, 2017) emphasize the role of housing.

[5] I adjust the filter to handle equilibrium probabilities that are endogenously time-varying.

[6] While assuming the absence of deposit insurance is a characteristic in line with shadow banks, a run could also occur in the presence of a deposit insurance system provided that the insurance is imperfect.

intermediaries enter each period and receive a transfer from the household. The household owns the non-financial firms and receives the profits. The variable Ξ_t captures all transfers.

The household is a net saver and holds two different assets. The first asset are one-period deposits D_t for which the financial intermediaries promise to pay a predetermined gross interest rate $\bar{R}_t$. However, the occurrence of a run alters the intermediary's ability to honor its commitment. Households receive then only a fraction $x_t^\star$, which is the recovery ratio, of the promised return. The gross rate R_t is thus state-dependent:

$$R_t = \begin{cases} \bar{R}_{t-1} & \text{if no run takes place in period } t \\ x_t^\star \bar{R}_{t-1} & \text{if a run takes place in period } t \end{cases} \tag{1}$$

The other asset are securities. I distinguish between beginning-of-period securities K_t that are used to produce output and end-of-period securities S_t. The end of period securities S_t^H give them an ownership in the non-financial firms. The household earns the stochastic rental rate Z_t and can trade the securities with other households as well as intermediaries at the market price Q_t. The securities of households and intermediaries, where the latter are denoted as S_t^B, are perfect substitutes. Total end-of-period securities S_t are $S_t = S_t^H + S_t^B$.

The households are less efficient in managing capital holdings, as in the framework of Brunnermeier and Sannikov (2014). Following the shortcut of Gertler et al. (2020b), capital holdings are costly in terms of utility. The utility function is given as:

$$U_t = E_t\left\{ \sum_{\tau=t}^{\infty} \beta^{\tau-t}\left[\frac{(C_\tau)^{1-\sigma^h}}{1-\sigma^h} - \frac{\chi L_\tau^{1+\varphi}}{1+\varphi} - \frac{\Theta}{2}\left(\frac{S_\tau^H}{S_\tau} - \gamma^F\right)^2 S_\tau \right]\right\}, \tag{2}$$

where $\Theta > 0$ and $\gamma^F > 0$. Thus, holding a share of securities share above γ^F becomes increasingly costly. The households maximize their utility subject to the budget constraint:

$$C_t = W_t L_t + D_{t-1}R_t - D_t + \Xi_t - Q_t S_t^H + (Z_t + (1-\delta)Q_t)S_{t-1}^H. \tag{3}$$

2.2. Financial intermediaries

The financial intermediaries' leverage decision depends on the risk-shifting incentives and the possibility of a run on the financial system. The intermediaries face a moral hazard problem due to risk-shifting incentives that limits their leverage. They can invest in two different securities with distinct risk profiles. Limited liability protects the intermediaries' losses in case of default and creates incentives to choose a strategy that is too risky from the depositors' point of view.[7] This results in an incentive and a participation constraint for the intermediaries' maximization problem, which also accounts for the threat of runs.

There is a continuum of financial intermediaries indexed by j, who intermediate funds between households and non-financial firms. The intermediaries hold net worth N_t^j and collect deposits D_t^j to buy securities S_t^B from the goods producers: $Q_t S_t^{Bj} = N_t^j + D_t^j$. Their leverage is defined as $\phi_t^j = Q_t S_t^{Bj}/N_t^j$. The intermediary chooses its security and deposit holdings to maximize the value of its franchise V_t. The maximization problem also depends on the run because the intermediary can only continue operating or return its net worth in the absence of a run. The probability that the intermediary defaults due to a run next period is denoted as p_t, which is derived in the next subsection. The value V_t^j is:

$$V_t^j(N_t^j) = (1-p_t)E_t^N\left[\Lambda_{t,t+1}\left(\theta V_{t+1}^j(N_{t+1}^j) + (1-\theta)(R_{t+1}^K Q_t S_t^{Bj} - R_{t+1}D_t^j)\right)\right], \tag{4}$$

where net worth accumulates as the return on assets net the cost of deposits: $N_t^j = R_t^K Q_{t-1} S_{t-1}^{Bj} - R_t D_{t-1}^j$. $E_t^N[\cdot]$ is the expectation conditional on no run in $t+1$. A superscript denotes if the expectations are conditioned on the absence (N) or occurrence of a run (R). The intermediary maximizes V_t subject to an incentive and participation constraint due to risk-shifting incentives, as described now. Appendix B.3 contains the formal derivation.

Risk-Shifting Incentives and Volatility After purchasing the securities, the financial intermediary converts, at the end of the period, the securities into efficiency units ω_{t+1} that are subject to idiosyncratic volatility similar to Christiano et al. (2014). The arrival of the idiosyncratic shock is iid over time and intermediaries. The intermediary has to choose between two different conversions - a good security ω and a substandard security $\tilde{\omega}$ - that differ in their cross-sectional idiosyncratic volatility. They have the following distinct distributions:

$$\log \omega_t = 0, \qquad \text{and} \qquad \log \tilde{\omega}_t \overset{iid}{\sim} N\left(\frac{-\sigma_t^2 - \psi}{2}, \sigma_t\right), \tag{5}$$

where $\psi < 1$. σ_t affects the idiosyncratic volatility and is an exogenous driver specified below. I abstract from idiosyncratic volatility for the good security so that its distribution is a dirac delta function with $\Delta_t(\omega)$ denoting the cumulative distribution function. The substandard one follows a log normal distribution, where $F_t(\tilde{\omega}_t)$ is the cumulative distribution function.

[7] This formulation microfounds a value-at-risk constraint - a common risk management approach for shadow banks - and corresponds to a contracting problem from corporate finance theory. Adrian and Shin (2010) provide evidence on the value-at-risk constraint and the leverage decision of security broker-dealers.

The good security is superior as it has a higher mean and a lower variance due to $\psi < 1$:[8]

$$E(\omega) = \omega = 1 > e^{-\frac{\psi}{2}} = E(\tilde{\omega}), \quad \text{and} \quad Var(\omega) = 0 < [e^{\sigma^2} - 1]e^{-\psi} = Var(\tilde{\omega}). \tag{6}$$

However, the substandard security features a higher upside risk due to the possibility of a large idiosyncratic shock $\tilde{\omega}$.[9] Appendix B.2 contains a graphical characterization.

The variable σ_t is labeled as volatility since it affects the relative cross-sectional idiosyncratic volatility of the securities. In particular, it changes the upside risk, while preserving the mean spread $E(\omega) - E(\tilde{\omega})$. Volatility σ_t is exogenous and follows an AR(1) process:

$$\sigma_t = (1 - \rho^\sigma)\sigma + \rho^\sigma \sigma_{t-1} + \sigma^\sigma \epsilon_t^\sigma, \qquad \text{where } \epsilon_t^\sigma \sim N(0, 1). \tag{7}$$

The intermediary earns the return $R_t^{K,j}$ on its securities that depends on the stochastic aggregate return R_t^K and the realized idiosyncratic shock conditional on its conversion choice. While the return for the good type $R_t^{Kj} = \omega_t^j R_t^K = R_t^K$ is independent of the idiosyncratic shock, the shock affects the return for the substandard type $R_t^{Kj} = \tilde{\omega}_t^j R_t^K$. The aggregate return depends on price Q_t and the profits per unit of effective capital Z_t: $R_t^K = [(1-\delta)Q_t + Z_t]/Q_{t-1}$. Based on this, a threshold value $\overline{\omega}_t^j$ for the idiosyncratic shock defines when the intermediary can exactly cover the face value of the deposits:

$$\overline{\omega}_t^j = (\bar{R}_{t-1} D_{t-1}^j)/(R_t^K Q_{t-1} S_{t-1}^{Bj}). \tag{8}$$

As it stands so far, the financial entities would choose to invest in the good security as it has a higher mean and lower variance. However, limited liability protects the financial entities, which distorts the choice between the securities. If the realized idiosyncratic volatility is below $\overline{\omega}_t^j$, the financial intermediary declares bankruptcy. The households seize then all assets, but they do not receive the promised repayment. This limits the downside risk of the substandard security, while the upside risk is unaffected. The gain from limited liability is:

$$\tilde{\pi}_t^j = \int^{\overline{\omega}_{t+1}^j} (\overline{\omega}_{t+1}^j - \tilde{\omega}) dF_t(\tilde{\omega}) > 0. \tag{9}$$

In contrast to this, the gain from limited liability due to idiosyncratic risk is zero for the good technology. This creates a trade-off between the good securities' higher mean return versus the gains from limited liability for the substandard security.

To ensure an investment in the good security, the intermediary faces an incentive constraint that deals with the risk-shifting incentives resulting from limited liability. The incentive constraint ensures that the good security is the only equilibrium choice.[10] The constraint limits the leverage of the intermediaries to force them to have enough "skin in the game" because the gain from limited liability increases in leverage. The microfoundation behind the leverage constraint is very different to the incentive constraint in Gertler et al. (2020b) and the collateral constraint in Jermann and Quadrini (2012). One crucial strength is that this financial friction in combination with the volatility shock accounts for procyclical leverage dynamics and other key empirical observations concerning financial crises, as shown later.

The incentive constraints is as follows, as derived in Appendix B.3:

$$(1 - p_t)E_t^N \Lambda_{t,t+1} R_{t+1}^K (\theta \lambda_{t+1}^j + (1-\theta))[1 - e^{\frac{-\psi}{2}} - \tilde{\pi}_{t+1}^j] \geq p_t E_t^R \Lambda_{t,t+1} R_{t+1}^K (e^{-\frac{\psi}{2}} - \overline{\omega}_{t+1}^j + \tilde{\pi}_{t+1}^j), \tag{10}$$

The LHS shows the trade-off between the higher mean return $(1 - e^{\frac{-\psi}{2}})$ and the upside risk $\tilde{\pi}_{t+1}^j$. This is the relevant consideration if there is no run next period. The RHS displays an additional gain of investing in the substandard security in case of a run. The substandard security offers the possibility to have positive net worth despite a run if the realized shock satisfies $\tilde{\omega}_t^i > \overline{\omega}_t$.[11] λ_t^j is the multiplier on the participation constraint, which is derived next.

The return on deposits needs to be sufficient such that households provide deposits to the intermediaries. While the households earn the predetermined interest rate $\bar{R}_t$ in normal times, the households recovers the gross return of the securities if a run takes place. As the return in a run is lower, an increase in p_t augments the funding costs to compensate for the run risk. The participation constraint can be written as:

$$(1 - p_t)E_t^N[\beta \Lambda_{t,t+1} \bar{R}_t^D D_t^j] + p_t E_t^R[\beta \Lambda_{t,t+1} R_{t+1}^K Q_t S_t^{Bj}] \geq D_t^j. \tag{11}$$

[8] More formally, I assume that $\Delta_t(\omega)$ cuts $F_t(\tilde{\omega})$ once from below to ensure this property. This means that there is a single ω^*, such that $(\Delta_t(\omega) - \tilde{F}_t(\omega))(\omega - \omega^*) \geq 0 \;\; \forall \omega$.

[9] Ang et al. (2006) find empirically that stocks with high idiosyncratic variance have low average returns.

[10] This also implies the absence of idiosyncratic default in equilibrium. However, the risk-shifting is not affected by the choice to not have idiosyncratic default in equilibrium. In that regard, idiosyncratic default in equilibrium, as e.g. in Ferrante (2019) or Nuño and Thomas (2017), can be seen as an additional element.

[11] Investing in substandard securities is an outside equilibrium strategy, which allows financial intermediaries to survive a run in the event of a very high realization of the idiosyncratic shock. It is assumed that the surviving intermediaries repay their depositors fully and return their remaining net worth to the households.

Both constraints are assumed to be binding in equilibrium. This implies for their respective multipliers $\kappa_t > 0$ and $\lambda_t > 1$ in all periods. I verify these assumptions numerically using a simulation and show that these conditions are satisfied in more than 99.5% periods.[12]

Aggregation

The participation and incentive constraint do not depend on intermediary-specific characteristics so that the optimal choice of leverage is independent of net worth as shown in Appendix B.3. Therefore, I can sum up across individual intermediaries to obtain the aggregate values. Their asset demand depends on leverage and net worth: $Q_t S_t^B = \phi_t N_t$.

The net worth evolution is as follows. In the absence of a run, surviving intermediaries retain their earnings. A run eradicates the net worth of the surviving intermediaries ($N_{S,t} = 0$), so that they stop operating. New intermediaries, which receive their net worth $N_{N,t}$ as a transfer from households, enter each period (independent of a run taking place or not):

$$N_{S,t} = \max\{R_t^K Q_t S_{t-1}^B - R_t^D D_t, 0\}, \qquad \text{and} \qquad N_{N,t} = (1-\theta)\zeta S_{t-1}. \tag{12}$$

Aggregate net worth N_t is given as $N_t = \theta N_{S,t} + N_{N,t}$.

2.3. Endogenous runs and multiple equilibria

There are occasional runs, in which depositors stop rolling over their deposits. Importantly, the possibility of such a run is endogenous because the existence of this equilibrium depends on economic circumstances, following Gertler et al. (2020b). In these states, the model features multiple equilibria in the spirit of Diamond and Dybvig (1983). The multiplicity of equilibria originates from heterogeneous asset demand of households and intermediaries.[13] During normal times households roll over their deposits. Financial intermediaries and households demand securities and the market clears at the fundamental price Q_t. The intermediary can cover the promised repayments for Q_t, that is $[(1-\delta)Q_t + Z_t]S_{t-1}^B > \bar{R}_{t-1}D_{t-1}$.

In contrast to this, a run wipes out the entire existing financial sector, so that $N_{S,t} = 0$. Households cease to roll over their deposits in a run, forcing intermediaries to liquidate their entire assets to repay the households. However, this eliminates their demand for securities. Households plus the newly entering financial intermediaries are the only remaining agents to buy the securities. Subsequently, the asset price falls to clear the market at a firesale price. The drop is particularly severe because it is costly for households to hold large amounts of securities. This firesale price $Q_t^\star$ depresses the potential liquidation value of intermediaries' securities. The run can then occur in the first place if the intermediaries do not have sufficient means to cover the claims of the households under $Q_t^\star$. This is the case if the recovery ratio $x_t^\star$, that is the firesale liquidation value relative to the promised repayments, is below 1:

$$x_t^\star \equiv \frac{[(1-\delta)Q_t^\star + Z_t^\star]S_{t-1}^B}{\bar{R}_{t-1}D_{t-1}} < 1. \tag{13}$$

The recovery ratio $x_t^\star$ partitions the state space into a safe region without runs ($x_t^\star \geq 1$) and a fragile region with multiple equilibria ($x_t^\star < 1$). Appendix B.4 contains more details and a graphical characterization. There is also a third scenario, in which the intermediaries cannot repay the depositors even under the fundamental price, which is the case if $[(1-\delta)Q_t + Z_t]S_{t-1}^B < \bar{R}_{t-1}D_{t-1}$. While this third case is accounted and checked for, this scenario is neglected because its probability is infinitesimally small in the quantitative model.

If there exists multiple equilibria, a sunspot shock selects the equilibrium, following Cole and Kehoe (2000).[14] The sunspot ι_t takes the value 1 with probability Υ and 0 with probability $1-\Upsilon$. A run takes place if $\iota_t = 1$ and $x_t^\star < 1$ is jointly the case. If $x_t^\star > 1$, then the sunspot shock has no impact on the equilibrium choice. Taken together, the probability for a run in period $t+1$ is endogenous because it depends on the probability of being in the crisis region in $t+1$ and of drawing a sunspot shock:

$$p_t = \text{prob}(x_{t+1}^\star < 1)\Upsilon. \tag{14}$$

2.4. Production, monetary policy and resource constraint

The non-financial firms sector consists of intermediate goods producers, final goods producers and capital goods producers. The central bank follows a Taylor rule with a ZLB.

There is a continuum of competitive intermediate goods producers. The representative producer produces the output Y_t with labor L_t and working capital K_t as input: $Y_t^j = A_t (K_{t-1}^j)^\alpha (L_t^j)^{1-\alpha}$.$A_t$ is total factor productivity (TFP), which follows an AR(1) process.

The firm pays the wage W_t to the households. The firm purchases in period $t-1$ capital S_{t-1} at the market price Q_{t-1}. The firm finances the capital with securities S_{t-1}^B from the financial sector and the households S_{t-1}^H, so that $K_{t-1} = S_{t-1}^H +$

[12] The reason for these rare violations is that the intermediaries accumulate too much net worth. This could be addressed, for instance, by allowing for state-dependent dividend payments. The payments could be modeled as an occasionally binding constraint similar to the equity injections of Gertler et al. (2020a). Appendix B.3.3 contains more details and shows the dynamics of the multipliers in a boom-bust scenario.

[13] There is no explicit distinction between households and typical lenders on the wholesale market.

[14] An alternative way could be global games, as used in Ikeda and Matsumoto (2021).

S^B_{t-1}. The intermediate firm pays the state-contingent return $R_{K,t}$. After using the capital in period t for production, the firm sells the undepreciated capital at the market. The intermediate output is sold at price M_t, which turns out to be equal to the marginal costs φ^{mc}. The firm problem is given as:

$$\max_{K_{t-1},L_t} \sum_{i=0}^{\infty} \beta^i \Lambda_{t,t+i}\big(M_{t+i}Y_{t+i} + Q_{t+i}(1-\delta)K_{t-1+i} - R_{k_{t+i}}Q_{t-1+i}K_{t-1+i} - W_{t+i}L_{t+i}\big).$$

The final goods retailers buy the intermediate goods and transform them into the final good using a CES production technology:

$$Y_t = \left[\int_0^1 (Y_t^j)^{\frac{\epsilon-1}{\epsilon}} df\right]^{\frac{\epsilon}{\epsilon-1}}. \tag{15}$$

The price index and intermediate goods demand are given by:

$$P_t = \left[\int_0^1 (P_t^j)^{1-\epsilon} df\right]^{\frac{1}{1-\epsilon}}, \quad \text{and} \quad Y_t^j = \left(P_t^j/P_t\right)^{-\epsilon} Y_t. \tag{16}$$

The final retailers are subject to Rotemberg price adjustment costs:

$$E_t\left\{\sum_{i=0}^{T} \Lambda_{t,t+i}\left[\left(\frac{P_{t+i}^j}{P_{t+i}} - \varphi_{t+i}^{mc}\right)Y_{t+i}^j - \frac{\rho^r}{2}Y_{t+i}\left(\frac{P_{t+i}^j}{\Pi P_{t+i-1}^j} - 1\right)^2\right]\right\}, \tag{17}$$

where Π is the inflation target of the monetary authority.

Competitive capital goods producers produce new end of period capital using final goods. They create $\Gamma(I_t/S_{t-1})S_{t-1}$ new capital out of an investment I_t, which they sell at price Q_t:

$$\max_{I_t} Q_t\Gamma(I_t/S_{t-1})S_{t-1} - I_t, \tag{18}$$

where the functional form is $\Gamma(I_t/S_{t-1}) = a_1(I_t/S_{t-1})^{1-\eta} + a_2$. The FOC gives a relation for the price Q_t. The law of motion for capital is $S_t = (1-\delta)S_{t-1} + \Gamma(I_t/S_{t-1})S_{t-1}$.

The monetary authority sets the interest rate R_t^I using a Taylor Rule subject to the ZLB:

$$R_t^I = \max\left\{R^I\left(\frac{\Pi_t}{\Pi}\right)^{\kappa_\Pi}\left(\frac{\varphi_t^{mc}}{\varphi^{mc}}\right)^{\kappa_y}, 1\right\}, \tag{19}$$

where deviations of marginal costs from its deterministic steady state φ^{mc} capture the output gap.[15] To connect this rate to the household, there exists one-period bond in zero net supply that pays the riskless nominal rate R_t^I. The associated Euler equation reads as follows: $\beta\Lambda_{t,t+1}R_t^I/\Pi_{t+1} = 1$. The resource constraint is $Y_t = C_t + I_t + G + \frac{\rho^r}{2}(\Pi_t/\Pi - 1)^2 Y_t$, where G is government spending. The equilibrium description can be found in Appendix B.1.

2.5. Multiple equilibria, ZLB and global solution method

The model features an occasionally binding constraint and multiplicity of equilibria. The main focus is on the role of multiplicity that is generated by runs. The occasionally binding constraint originates from the ZLB. On top of that, the ZLB introduces many equilibria such as the targeted-inflation equilibrium, deflation equilibria as well as sunspot equilibria (see Benhabib et al., 2001; Aruoba et al., 2018). This paper focuses on the targeted-inflation equilibrium, in which inflation fluctuates around the central bank's inflation target.

The model is solved with global methods, specifically policy function iteration, to account for all nonlinear features. Within the class of policy function iteration methods, I use time iteration with linear interpolation, as (Richter et al., 2014). Additionally, I use a piecewise representation of the policy functions to account for the multiplicity of equilibria generated by the runs on the financial sector in the spirit of Aruoba et al. (2018) and Aruoba et al. (2021). In particular, the numerical approximation of the policy functions has distinct functions for the run equilibrium and the no run equilibrium, which allows to locate the run equilibrium with a high precision. The details of the numerical solution are left to Appendix C.

3. Model dynamics: Volatility, endogenous runs and the ZLB

This section explains how the model is mapped to the data and analyzes the dynamics.

[15] The model could be extended to assess negative interest rates, e.g. following Darracq Pariès et al. (2020).

Table 1
Calibration and Targeted Moments.

a) Conventional Parameters		Value	Target / Source		
Discount factor	β	0.9975	Risk free rate = 1.0% p.a.		
Frisch labor elasticity	$1/\varphi$	0.75	Chetty et al. (2011)		
Risk aversion	σ^H	1	Log utility for consumption		
TFP level	A	0.407	Output = 1		
Government spending	G	0.2	Govt. spending to output = 0.2		
Capital share	α	0.33	Capital income share = 33%		
Capital depreciation	δ	0.025	Depreciation rate = 10% p.a.		
Price elasticity of demand	ϵ	10	Markup = 11%		
Rotemberg adjustment costs	ρ^r	178	Calvo duration of 5 quarters		
Elasticity of asset price	η_i	0.25	Bernanke et al. (1999)		
Investment Parameter 1	a_1	0.530	Asset Price Q = 1		
Investment Parameter 2	a_2	-.008	$\Gamma(I/K) = I$		
Target inflation	Π	1.005	Inflation Target of 2%		
MP response to inflation	κ_π	2.0	Standard		
MP response to output	κ_y	0.125	Standard		
(b) Financial Sector & Shocks		**Value**	**Moment**	**Data**	**Model**
Parameter asset share HH	γ^F	0.33	Share shadow banking sector	33%	35%
Mean Substandard Security	ψ	0.01	Mean shadow bank leverage	15.5	15.5
Intermediation cost HH	Θ	0.04	Financial crisis probability	2.0%	1.9%
Survival rate	ζ	0.88	Mean credit spread	2.3%	3.0%
Persistence volatility	ρ^σ	0.96	Persistence of leverage	0.96	0.95
Std. dev. volatility shock	σ^σ	0.0031	Std. dev. of leverage	3.0	2.9
Persistence TFP	ρ^A	0.95	Persistence TFP	0.95	0.95
Std. dev. TFP shock	σ^A	0.0026	Std. dev. of output growth	0.6	0.5
Sunspot Shock	Υ	0.50	Output drop during run	2.8%	2.8%

3.1. Model parameterization and selected key moments

The emphasis of the calibration is on the recent financial crisis in the U.S. and the shadow banking sector. The financial sector variables and shock processes are set to match selected moments, while the conventional parameters are chosen based on the literature. The focus is mostly on quarterly data from 1985:Q1 to 2014:Q4 to accommodate the changing regulation of shadow banking activities. The starting point coincides with major changes in the contracting conventions of the repurchasement agreement (repo) market - an important source of funding for shadow banks - that took place after the failure of a number of dealers in the early 1980s (Garbade, 2006). It also captures the period after the Great Inflation. After the financial crisis, new regulatory reforms such as Basel III and the Dodd-Frank overhauled the financial system, suggesting to end the sample a few years after 2008. Table 1 summarizes the calibration and the match with targeted moments in the data.

The discount factor is set to 0.9975, which corresponds to a low rate environment with an annualized long-run real interest rate of 1%. The Frisch elasticity is set to match an elasticity of 0.75. Risk aversion is parameterized to 1. TFP A normalizes output to 1 in the deterministic steady state (DSS). Government spending G is 20% of total GDP in the DSS. The production parameter α matches a capital income share of 33%. The depreciation rate is 10% annually. The price elasticity of demand is set to 10. The Rotemberg adjustment costs correspond to a five-quarter average duration of resetting prices in the related Calvo framework. The elasticity of the asset price ρ^r is 0.25. The parameters of the investment function normalize the asset price to $Q = 1$ and the investment $\Gamma(I/K) = I$ in the DSS. Monetary policy responds to deviations of marginal costs ($\kappa_y = 0.125$) and inflation ($\kappa_\pi = 2.0$), where the target inflation rate is normalized to 2% per annum.

The parameters related to the financial sector and the shock processes are set to target selected moments of the shadow banking sector, the frequency of financial crises and the dynamics of output. The financial sector represents the shadow banking sector. Specifically, I define these as entities that rely on short-term deposits that are not protected by the Federal Deposit Insurance Corporations and do not have access to the FED's discount window.[16] The share of total assets held directly by the shadow banking sector was 37.1% in 2006 and dropped to 28.3% in 2012, as shown by Gallin (2015). Thus, the parameter γ^F specifies that the shadow banking sector holds 33% of total assets on average. The leverage measure combines balance sheet data from security broker dealers and finance companies using the U.S. Flow of Funds data, as discussed in Appendix A. The leverage series relies on book equity, which is the difference between the market value of the portfolio and the liabilities.[17] The return of $\psi = 0.01$ for the substandard security is used to target a mean leverage ratio

[16] This definition applies to the following entities: Money market mutual funds, government-sponsored enterprises, agency- and GSE-backed mortgage pools, private-label issuers of asset-backed securities, finance companies, real estate investment trusts, security brokers and dealers, and funding corporations.

[17] An alternative measure is the intermediaries' market capitalization, as emphasized in He et al. (2010) and He et al. (2017). However, the appropriate concept here is book equity (net worth) since the run depends on it. Market capitalization would be relevant for the issuance of shares or acquisitions (Adrian et al., 2013).

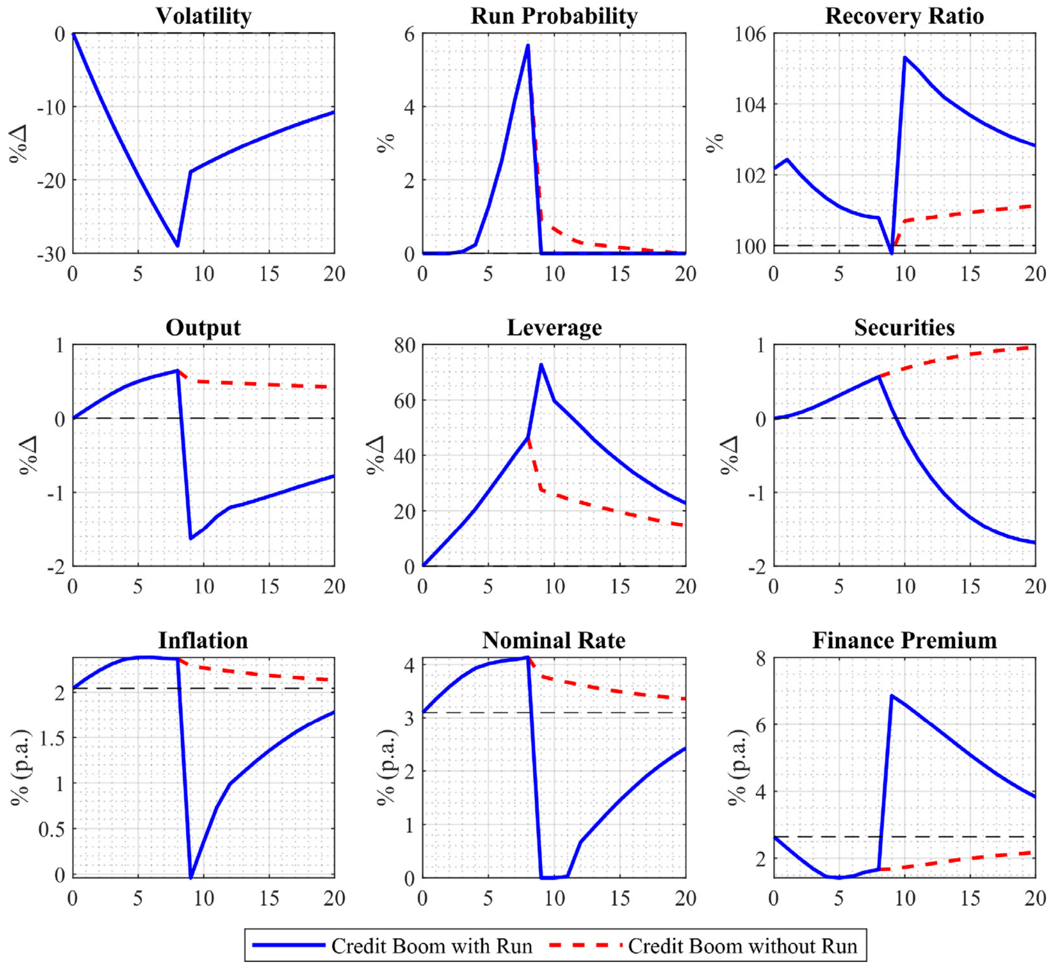

Fig. 2. The role of volatility for a credit boom with a run. The simulation shows the impulse responses for a sequence of volatility shocks. The economy is initially at its stochastic steady state (SS). From period 1 until period 8, the economy is hit by a one-standard-deviation negative volatility shock in every period. In period 9, a two-standard-deviation positive volatility shock materializes. Afterwards, no more shocks occur. The scenario is shown for two cases: a) a boom with a run, which implies that the sunspot shock occurs in period 9 (blue solid line); b) a boom without a run, which implies that the sunspot shock does not materialize in period 9 (red dashed line). The scales are either percentage deviations from the stochastic SS (%Δ), annualized percent (% (p.a.)) or percent (%). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

of 15.5. The intermediation costs Θ are set to match an annual run probability of 2.0% (every 50 years on average). This moment is based on the historical database of Jordà et al. (2017), in which the crisis probability is around 2.7% for the U.S. and 1.9% for a sample of advanced economies since World War II. The survival rate θ is set such that the finance premium targets an average spread of 2.3% as observed between the BAA bond yield and a 10 year Treasury bond. The start capital parameter ζ is implied from the other parameters.

The volatility shock's persistence ρ^{σ} and standard deviation σ^{σ} are set to match its counterpart for shadow bank leverage. The standard deviation of the TFP shock σ^{A} targets the standard deviation of real quarterly GDP growth. The persistence is aligned with the persistence of the TFP series of Fernald (2014). Finally, the sunspot shock materializes with a probability of 50% to help to match the demeaned GDP growth of -2.8% in 2008:Q4.

3.2. Financial crises dynamics: Endogenous runs, volatility and leverage

The model enables to study the vulnerability to a financial crisis. In particular, I evaluate how the combination of the volatility shock and the risk-shifting incentives can account for the key empirical observations that a financial crisis is preceded by a credit boom (Schularick and Taylor, 2012), low pre-crisis credit spreads (Krishnamurthy and Muir, 2017) and elevated shadow bank leverage as observed around 2008 (Adrian and Shin, 2010).

Fig. 2 shows the impulse response of the economy to a sequence of volatility shocks. Starting from the steady state, one-standard-deviation negative shocks hit the economy in period 1 until period 8. The reduction in volatility lowers the risk-

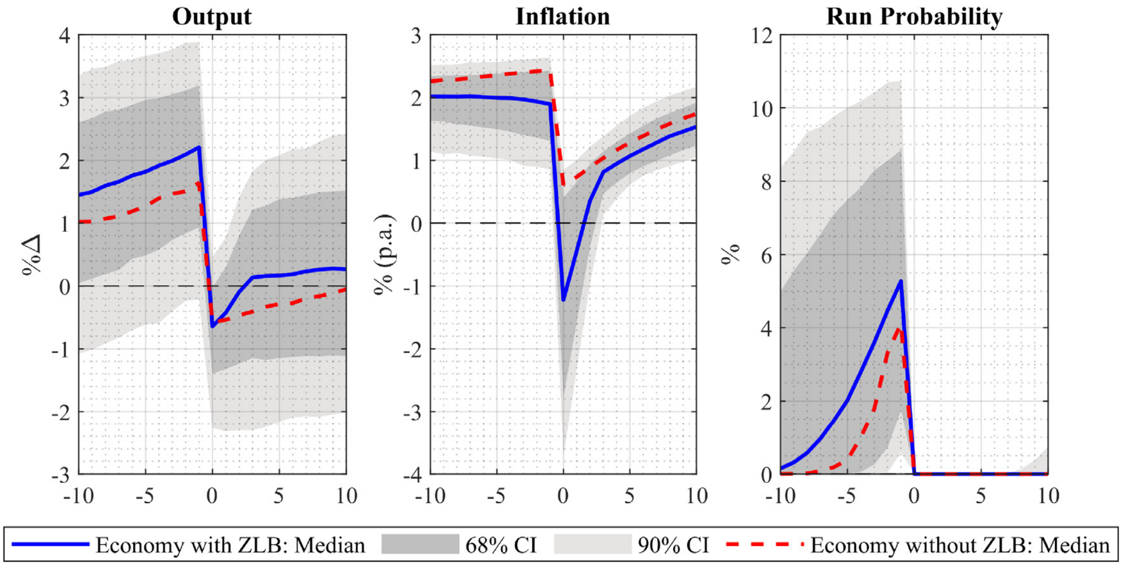

Fig. 3. Event window around run episodes for an economy with and without a ZLB. Based on a simulation of 500,000 periods, the median path (blue solid) and the 68% as well as 90% confidence intervals of all runs are displayed ten quarters before and after a run in period 0 for the economy with the ZLB. For the economy without the ZLB, only the median is displayed. The scales are either percentage deviations from the simulated mean (%Δ), annualized percent, or percent. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

shifting incentives so that intermediaries increase leverage and extend their security holdings. This results in a credit boom and boosts output. The finance premium also falls. To capture the increase in financial fragilities during a boom, the leverage dynamics are key. The run probability does initially not respond because leverage is still rather low and the economy is still in the safe zone. However, once leverage increases further, the run probability rises considerably. The intermediaries have too low equity buffers to cover potential large losses from a run.

During the ongoing boom, the economy is hit by a two-standard-deviation positive volatility shock in period 9. This realization pushes the highly levered economy into the fragile region, as shown by a recovery ratio below 1. It is important to note that a large contractionary shock is necessary to push the economy in the fragile zone. If then the sunspot shock materializes simultaneously, a run on the financial sector occurs. Depositors stop to roll over their deposits so that intermediaries, which are forced to sell the securities at a firesale price, do not have enough equity to cover their losses. While the solid line shows a scenario with a sunspot shock and thus a run in period 9, the dashed line shows a credit boom without a run. The run results in a severe drop in output, increase in the finance premium and also a substantial fall in inflation. The economy also faces the ZLB during the run. This feature will be explored in Section 3.3. Finally, leverage is quite high in the run period, exceeding the prediction in the data. The returns for new intermediaries is very large so that they lever up. While this is a common problem in the literature, the model already better aligns with the data. As seen later, the model can actually track the leverage data in the estimation.

The reason for the boom-bust dynamics is the leverage-constraint via risk-shifting incentives, which provides procyclical leverage dynamics. On the contrary, an incentive constraint, which generates countercyclical leverage, can not reconcile these boom-bust dynamics.

While extensive leverage raises the vulnerability to a run, the relationship is complex and highly nonlinear. If leverage is below some varying threshold value, which depends on the economic state, the run probability is zero. Once leverage increases above the threshold, then the run probability starts to respond nonlinearly. Additionally, the same level of leverage can result in different run probabilities depending on the economic circumstances. Thus, the relationship is not mechanic, and leverage alone is not a sufficient statistic to get the mapping to the probability of a run. Appendix D provides more details on this relationship.

The next step is to show that the discussed dynamics also represent a typical financial crisis in the model. I conduct an event analysis around a financial crisis, which is based on a simulation over 500,000 periods with 2,384 runs. Fig. 3 displays the run dynamics using an event window approach, where the window contains the path for ten quarters before and after a run. The dynamics are very similar as before, as shown for output for instance. The median run probability peaks in the period before the run with a median value of 5%, corresponding to a substantial 20% in terms of an annualized rate. At the same time, the upper bound of financial fragility is limited as it peaks around 10%. Agents' awareness of potential runs endogenously limits the leverage of the financial sector, preventing scenarios with an excessive run probability. Furthermore, the economy sometimes returns back to the safe zone without a crisis, aligning with the observation that not every boom ends in a bust (Gorton and Ordonez, 2020).

3.3. The role of the zero lower bound

The previous simulations have shown that the ZLB restricts the level of potential interest rate cuts during a financial collapse. Consequently, the ZLB can be an important amplification mechanism for financial fragility in a low rate environment.

To investigate this connection, I compare the run frequency and the run dynamics of the economy with and without the ZLB. The annual probability of a financial crisis drops significantly from 1.9% to 0.8% in the absence of the ZLB. This key moment emphasizes the relevance of the ZLB. The dynamics for the run itself are shown in Fig. 3, which compares an economy with a ZLB (blue solid) and without a ZLB (red dashed). Due to the ZLB, the output fall is more severe, e.g around 0.6 percentage points in the initial run period. While the threat financial crisis is associated with a strong downside risk in inflation - as also empirically found in López-Salido and Loria (2020) - the ZLB exacerbates the downside risk of inflation even further. The fall in inflation is much more severe. Furthermore, the threat of encountering the ZLB creates deflationary pressure in periods of high financial fragility. This constitutes a further deflationary channel of the lower bound, in addition to the one which has already been studied in the literature, as e.g. in Bianchi et al. (2021).

A welfare comparison between the economy with and without the ZLB allows to capture the total costs of the interaction between the ZLB and endogenous runs. Welfare is measured as the utility of representative household, as in equation (2). The welfare gains of not having the ZLB correspond to 0.32% in consumption equivalents. In other words, agents would be willing to give up 0.32% of their consumption in each period to avoid facing the ZLB. These costs are substantial, especially considering that runs are rare events.

4. Estimation of financial fragility

I estimate the build-up of financial fragility around the financial crisis in 2008.

4.1. Estimation approach, particle filter and data

The model is taken to the data to obtain a structural estimate of the endogenous build-up of financial fragility and economic downside risk in the U.S. around the great financial crisis. However, an estimation is very challenging because it requires to repeatedly solve the nonlinear model with global methods and then to filter it. The time to solve and filter the model only once is around 2h55m using an Intel Xeon W-2295 processor with 18 cores.

To overcome this challenge, I apply a two-step procedure for the estimation. In the first step, the nonlinear model is calibrated to key moments, as already done in Section 3.1. Targeting key moments in the calibration results in a model that is well equipped to be taken to the data, while lowering the number of times that the model needs to be solved. The calibrated model is then used as input for the particle filter in the second step. The estimation strategy employs a particle filter to account for the nonlinear setup with endogenous runs and the ZLB. The filter retrieves the sequence of the shocks including the sunspot shock using the parameterized model. This sequence can, in turn, be used to obtain other objects of interest such as the estimated probability of a run. Importantly, this approach provides an estimate of financial fragility, while reducing the computational burden significantly.

I adapt the particle filter to specifically take into account the multiplicity of equilibria similar to Aruoba et al. (2018).[18] To account for endogenous runs, I extend their approach to handle not only multiplicity of equilibria, but also the state-dependence of the equilibria probabilities. The filter estimates the hidden states and shocks based on a set of observables. It is convenient to cast the model in a nonlinear state-space representation as a starting point:

$$\mathbb{X}_t = f(\mathbb{X}_{t-1}, \nu_t, \iota_t), \qquad \text{and} \qquad \mathbb{Y}_t = g(\mathbb{X}_t) + u_t. \tag{20}$$

The first set of equations contains the transition equations that depend on the state variables $\mathbb{X}_t$, the structural shocks ν_t and the sunspot shock ι_t. In particular, the state variables and shocks determine endogenously the selected equilibrium of the model. The nonlinear functions f are obtained from the model that is solved with time iteration. The second set of equations contains the measurement equations, which connect the state variables with the observables $\mathbb{Y}_t$. It also includes an additive measurement error u_t.[19] The particle filter extracts a sequence of conditional distributions for the structural and sunspot shocks, which provides the empirical implications of the model. Thereby, the filter evaluates when a run occurs and provides the run probability. The algorithm is laid out in Appendix E.

The considered horizon stretches from 1985:Q1 to 2014:Q4. The observables are real GDP growth and shadow bank leverage, as used in the calibration. The observation equation is:

$$\begin{bmatrix} \text{Output Growth}_t \\ \text{Leverage}_t \end{bmatrix} = \begin{bmatrix} 100 \ln\left(\frac{Y_t}{Y_{t-1}}\right) \\ \phi_t \end{bmatrix} + u_t, \tag{21}$$

[18] The filter algorithm is also based on Atkinson et al. (2020) and Herbst and Schorfheide (2015).

[19] The particle filter requires a measurement error to avoid a degeneracy of the likelihood function. Another advantage is that it can take into account noisy data, which might be a concern for shadow bank leverage.

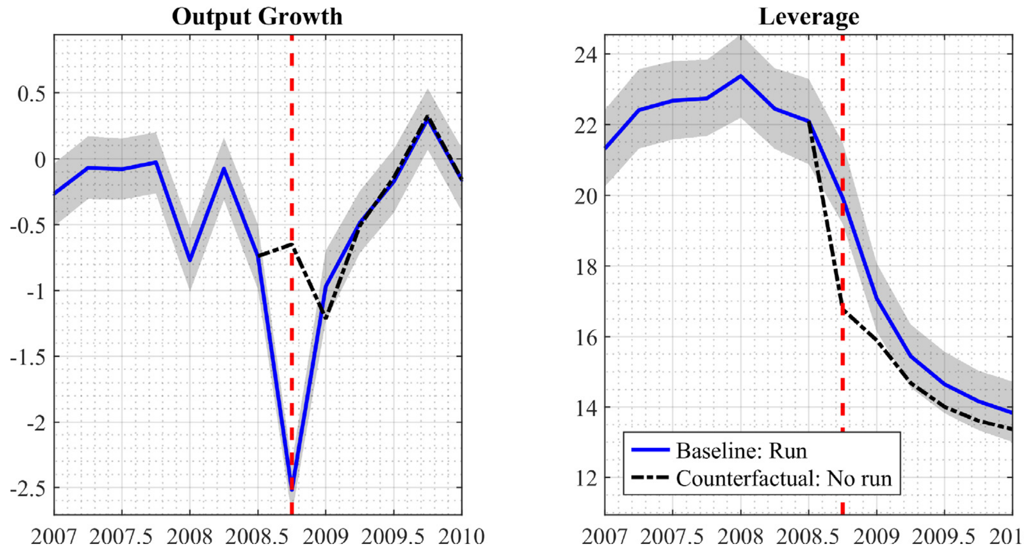

Fig. 4. Comparison of baseline estimate to a counterfactual scenario without a run. The baseline median (blue line with its 68% confidence interval) is compared to the counterfactual median, where no sunspot shock materializes in 2008:Q4. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

where GDP growth is quarterly and demeaned. The measurement error is $u_t \sim N(0, \Sigma_u)$. Its variance Σ_u is set to 25% of the sample variance, similar to Gust et al. (2017). Appendix F.1 establishes that the filtered model captures the fluctuations in the observables.

4.2. Results

Leverage increases substantially prior to the financial crisis. The peak comes in 2008:Q1, with leverage close to 24. The filtered path also takes account of the strong decrease in output and leverage in the fourth quarter of 2008. Crucially, the model can account for this sharp drop in the fourth quarter of 2008 via two different channels: a run on the financial sector or large contractionary shocks. As the equilibria are not exogenously imposed, the particle filter selects the regime depending on the fit with the data. This gives an assessment if a run took place. The model clearly favors a run. The filter assigns a weight of 98% to a run in 2008:Q4, while the weight of the run regime is almost 0% in all other periods.

Bernanke (2018) and Gorton and Metrick (2012) argue that the run on the financial sector is behind the sharp and large economic contraction. To assess this through the lens of the model, a counterfactual shown in Fig. 4 compares the estimated path to a hypothetical scenario without a run (no sunspot shock in 2008:Q4). The main take-away is that the contraction would have been much smaller since the run alone accounts for 70% of the drop.

Fig. 5 shows the filtered series for key variables. The estimation predicts a credit boom gone bust, a countercyclical finance premium and a period of low inflation after the run, which is line with the empirical evidence. The dynamics of volatility and TFP allow to inspect the economic drivers behind the run in 2008:Q4. A series of shocks reduces volatility σ_t prior to the financial crisis. In the spirit of the volatility paradox, this period sows the seed of a crisis as leverage and financial fragility increase. In 2008:Q4, contractionary volatility and TFP shocks in combination with a sunspot shock trigger the run.

The approach provides a novel model-implied estimate of financial fragility. Figure 6 shows the path of the estimated run probability p_t. While there is a slight increase around 1998, fragility starts to surge from 2005 onwards considerably. Thus, the model suggests that there had already been a substantial build-up of fragilities a few years prior to the outbreak of the financial crisis. The median one-quarter-ahead forecast peaks in 2007:Q4 at around 8%, which is more than 25% in annualized terms. Note that the run probability is going down in shortly before the run as the level of leverage is slightly lower than at its peak.

A counterfactual analysis can disentangle the structural sources of financial fragility. The estimated series of TFP and volatility are evaluated in isolation by setting the other shock to zero for the entire horizon. While the volatility shock is the main driver, explaining most of the fragility in 2008, TFP causes no financial fragility. But, there are relevant nonlinear interaction between the shocks that can increase or decrease financial fragility. Importantly, financial fragility induces substantial macroeconomic downside risk. In fact, the multiplicity of equilibria due to the run characterizes macroeconomic risk as a multimodal distribution as in the empirical papers of Adrian et al. (2021), Caldara et al. (2021) and Mitchell et al. (2021). Appendix F.4 elaborates more on tail risk and multimodality.

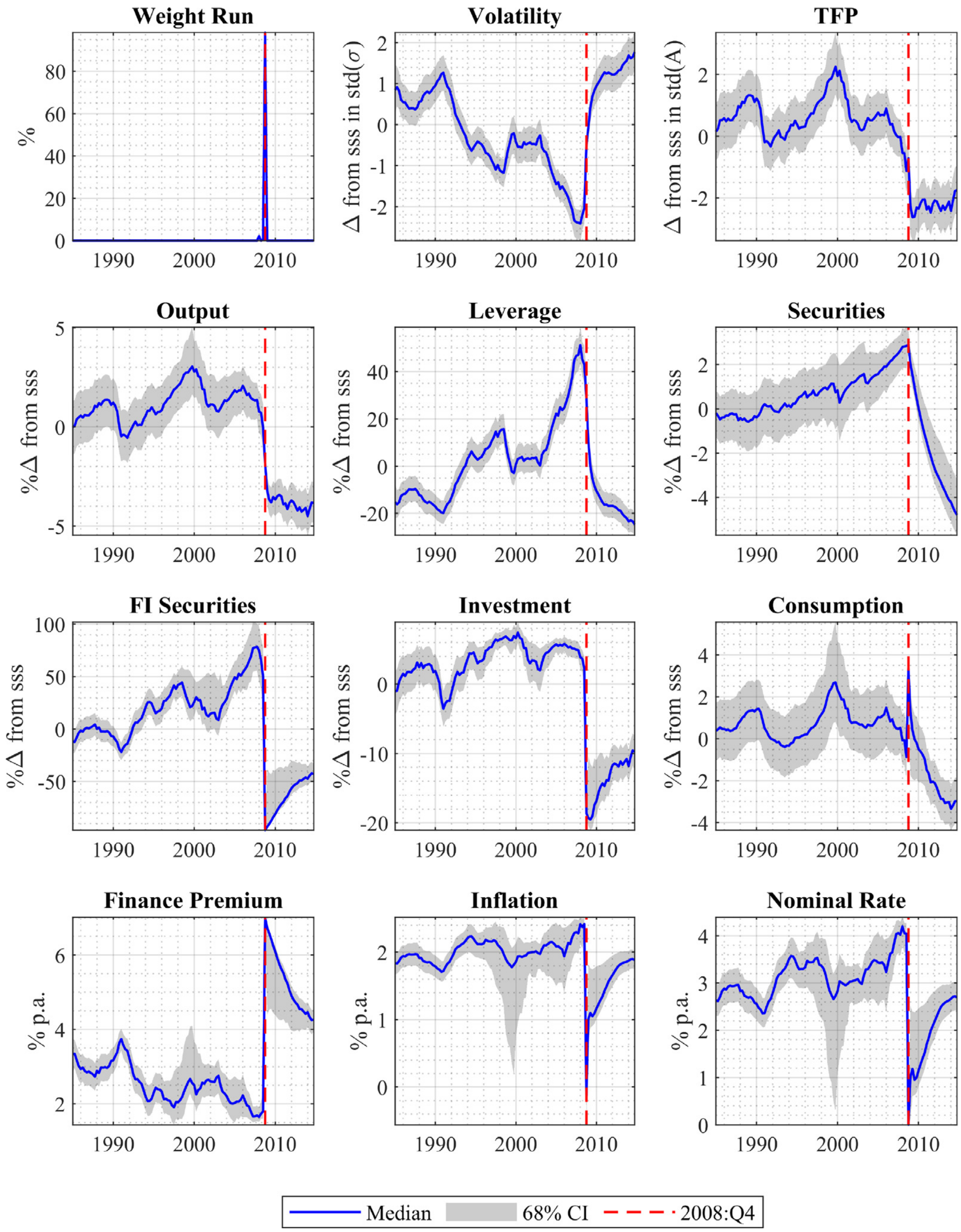

Fig. 5. Filtered median with its 68% confidence interval for selected variables. The first plot shows the regime selection. The second and third plot show the exogenous drivers volatility and TFP. The remaining plots show other key variables. Note that for the third plot the weight of the run regime is shown. The red line indicates the fourth quarter of 2008. The scales are either percentage deviations from the stochastic SS, deviations from the stochastic SS measured in the unconditional variance of the variables for the two shocks, annualized percent, percent, or the level. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

As external validation, I compare the model-implied filtered volatility series with a data proxy taken from Nuño and Thomas (2017). The key result is that both series comove most of the time. More details are in Appendix F.2.

I also include three alternative specifications. First, I include the credit spread as additional observable in the observation equation. One advantage of the particle filter is that it can handle more observables than shocks. Second, I use a lower measurement error of 10% for the particle filter. The dynamics are quite similar for both checks. Importantly, the estimated probability of a run still predicts a strong build-up before 2008 and that the run itself occurred in 2008:Q4. The third check is a scenario, in which no shocks hit the economy after 2009. The details are in Appendix F.3.

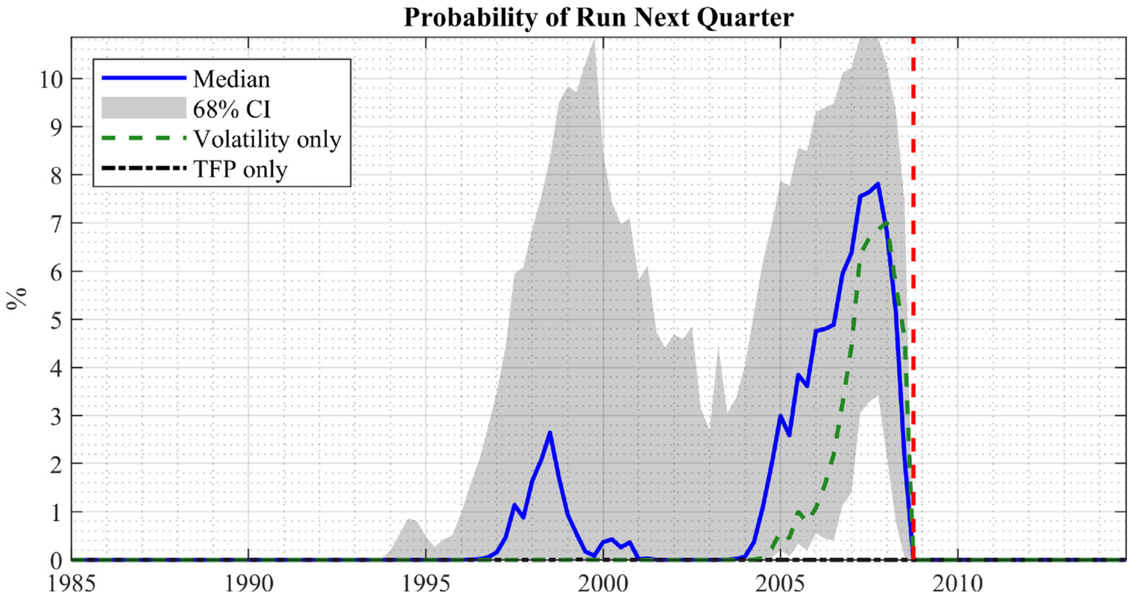

Fig. 6. Figure shows the filtered median run probability p_t for t+1 with its 68% confidence interval measured in percent (%). To disentangle the impact of the structural shocks, the realizations of the volatility shock and TFP shock are set to 0 one at a time. The dashed green line and black dash-dotted line show the scenario using only the extracted volatility shocks and TFP shocks, respectively. The red line indicates the fourth quarter of 2008. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5. Monetary and macroprudential policies

There is an active debate about the costs and benefits of alternative monetary and macroprudential policies. I provide a novel perspective through the lens of the nonlinear model.

5.1. Monetary policy and financial stability

Monetary policy can respond to financial conditions, which can be distinguished in interventions before (ex-ante) and after (ex-post) the crisis. Monetary policy can act in advance and lean-against-the-wind by raising rates during a boom. The second element is that monetary policy can commit to respond after the crisis by being more loose to "clean up". To begin with, the considered monetary policy rule features both elements. The central bank responds deviations of the level of security holdings relative to a target value. The monetary rule responding to financial conditions can be expressed as:

$$R_t^I = \max\left\{ R^I \left(\frac{\Pi_t}{\Pi}\right)^{\kappa_\Pi} \left(\frac{\varphi_t^{mc}}{\varphi^{mc}}\right)^{\kappa_y} \left(\frac{S_t^B}{S^B}\right)^{\kappa_s}, 1 \right\}, \tag{22}$$

where κ_s is the response to deviations from the target value S^B. The target value S^B is set to the median level of the intermediaries' security holdings in the baseline economy.

The financial stability and welfare impact is theoretically ambiguous. A rate hike during a boom can lead to a substitution towards more equity. The hike also reduces total securities and lowers the intermediaries' share of securities, resulting in enhanced financial resilience. At the same time, the increased funding cost due to higher rates can also result in less loss absorbing capacities, creating financial fragility. A rate cut during or after a run can stabilize the economy. If the central bank can credibly commit to a loose policy stance ex-post, such a commitment can even alter the existence of the run equilibrium. However, this commitment can also incentivize risk-taking and the accumulation of assets in the first place.

The welfare impact of this rule is illustrated in the upper plot of Fig. 7, where the response strength (κ_s) is varied. The welfare-maximizing rule, located at $\kappa_s^{opt} = 0.0102$, implies a substantial welfare gain of 0.57% in terms of consumption equivalents. The optimal rule is so effective that it reduces the run frequency to nearly zero.[20] Initially, a higher κ_s increases welfare because the monetary interventions reduce the financial risk. However, the gains start to reverse after reaching the peak at κ_s^{opt}. Raising κ_s further results in a too large accumulation of total securities, which makes the economy again more prone to runs and lowers welfare. This creates a hump-shaped welfare curve.

[20] The model does not include some shocks (e.g. markup), which could reduce κ_s^{opt} and the rule's impact.

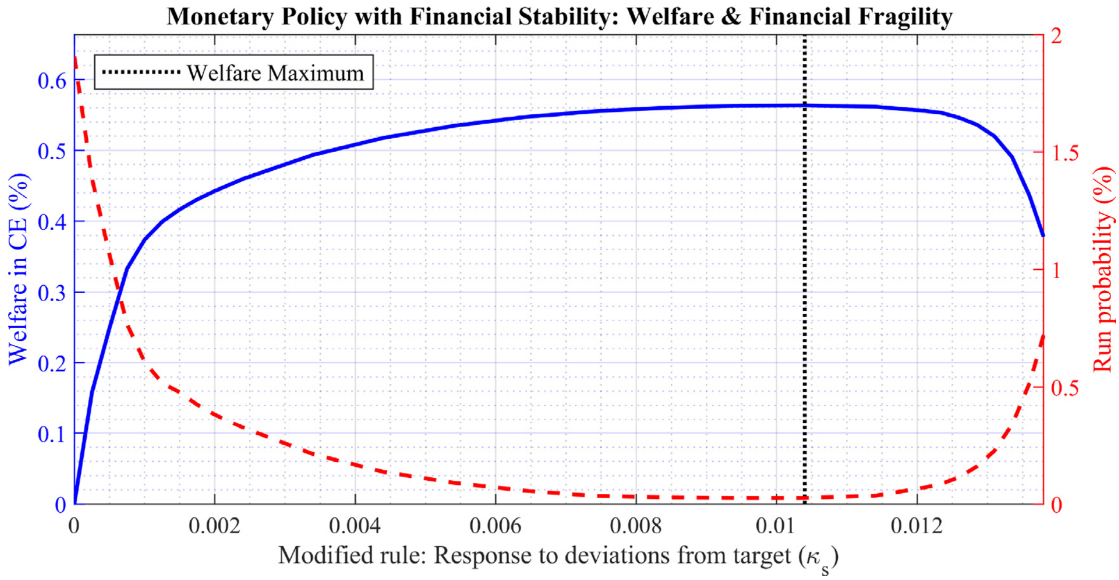

Fig. 7. The figure shows the impact of varying the response of monetary policy with financial stability considerations (κ_s) on welfare (left axis) and the annual run probability (right axis). The dashed black line indicates the welfare-maximizing rule (κ_s^{opt}).

While the rule succeeds in increasing financial stability and welfare, the source is not yet explored. Does the financial gain stem mostly from leaning-against-the-wind or a credible commitment ex-post? To shed light on this, I analyze the ex-ante and ex-post interventions separately. I model leaning-against-the-wind in advance as:

$$R_t^I = \max\left\{R^I\left(\frac{\Pi_t}{\Pi}\right)^{\kappa_\Pi}\left(\frac{\varphi_t^{mc}}{\varphi^{mc}}\right)^{\kappa_y}\left[\mathbf{1}_{S_t^B>S^B}\left(\frac{S_t^B}{S^B}\right)^{\kappa_s}+\left(1-\mathbf{1}_{S_t^B>S^B}\right)\right],1\right\}, \tag{23}$$

where $\mathbf{1}_{S_t^B>S^B}$ is an indicator function that is equal to one when intermediaries' security holdings are above target ($St^B > S^B$). In this specification, the monetary authority only raises rates in response to financial stability consideration.[21]

The commitment to a loose policy ex-post is modeled analogously as:

$$R_t^I = \max\left\{R^I\left(\frac{\Pi_t}{\Pi}\right)^{\kappa_\Pi}\left(\frac{\varphi_t^{mc}}{\varphi^{mc}}\right)^{\kappa_y}\left[\mathbf{1}_{S_t^B<S^B}\left(\frac{S_t^B}{S^B}\right)^{\kappa_s}+\left(1-\mathbf{1}_{S_t^B<S^B}\right)\right],1\right\}, \tag{24}$$

where the indicator functions captures now that the securities are below target ($S_t^B < S^B$).

To analyse the impact of the different components, Table 2 compares the welfare, financial stability and economic outcomes for various rules. The baseline MP rule (column 1) represents the scenario, in which the monetary authority only responds to inflation and output deviations. The modified monetary policy that responds to financial conditions is shown in column 2. The parameter κ_s is set to its welfare maximizing value. I then dissect the rule in its ex-ante and ex-post interventions using the same value for κ_s. While the impact of ex-ante leaning in isolation is shown in column 3, the credible ex-post commitment to loose monetary policy is displayed in column 4.

There are two key results from the analysis. First, leaning-against-the-wind has a small, albeit positive, impact on financial stability and welfare. When the central bank only leans against the wind by raising rates, the run probability is slightly reduced to 1.80% (from 1.91%) and welfare increases by 0.05% in terms of consumption equivalents. It also has a rather small effect on the mean and standard deviation of most variables. In contrast to this, a credible commitment to loose policy ex-post provides a very large substantial and basically explain almost all of the welfare gains, as can be seen when comparing column 2 and column 4. However, this requires a credible commitment from the central bank. This finding relates to Devereux et al. (2019), who show in the context of sudden stops the gains of having the ability to credibly commit to ex-post policies. Appendix G.1 includes robustness checks for the results related to the ex-ante and ex-post components that underline the main findings.

The impact of the ex-ante leaning policy is limited, albeit positive, in the model, while the empirical study of Schularick et al. (2021) even suggests that rate hikes may actually increase crisis risk. To delve deeper, I also examine how an unanticipated monetary policy shock affects financial stability during a boom. The key take-away is that a trade-off between

[21] One challenge with implementing this policy is that the solution procedure can easily explode. To solve the model with an interestingly strong leaning component, the ex-ante leaning component is only imposed at the relevant parts of the state space. The details are in Appendix G.1.

Table 2
Welfare, financial stability and economic outcomes of various policies.

	Baseline MP rule	Modified MP rule (κ_s^{opt})	Leaning ex-ante	Loosening ex-post	Leverage tax (τ_s^{opt})
Selected key moments					
Welfare W (CE)[a]	–	0.56	0.05	0.52	0.64
Run Probability[b]	1.91	0.02	1.80	0.05	0
Mean of selected variables[c]					
Consumption C	0.58	0.40%	0.04%	0.37%	0.39%
Labor L	1.01	0.08%	0.02%	0.07%	0.07%
Leverage ϕ	15.5	−0.82%	0.09%	−0.99%	−3.99%
Assets S	8.48	1.63%	0.20%	1.48%	1.51%
Share Financial S^B/S	0.35	4.57%	0.37%	4.28%	4.37%
Standard deviation of selected variables[d]					
Consumption C	0.01	0.22%	−1.36%	1.58%	−3.19%
Labor L	0.006	−46.4%	−5.05%	−33.0%	−48.3%
Leverage ϕ	2.92	−9.86%	0.04%	−11.3%	−48.6%
Assets S	0.14	32.9%	−0.11%	35.3%	8.70%
Share Financial S^B/S	0.10	−24.8%	−1.67%	−22.4%	−53.6%

[a] Welfare gain/loss expressed as consumption equivalent relative to baseline rule in %.
[b] Annual run probability in %.
[c] The level is shown for the baseline economy. The other scenarios display the mean as percentage deviations relative to the baseline economy.
[d] The level is shown for the baseline economy. The other scenarios display the standard deviation as percentage deviations relative to the baseline economy.

triggering a crisis in the short-term versus financial stability gains in the medium-term, which is also supported empirically by Ajello and Pike (2022). Appendix G.2 contains the details.

5.2. Macroprudential policy and financial stability

To put the gains of monetary policy in context, I analyze the stability and welfare implications of a corresponding macroprudential policy. The focus is on a state-dependent leverage tax, which taxes or subsidizes the intermediaries' deposit holdings. Even though regulating the unregulated part of the financial sector is in practice potentially extremely difficult, the tax outlines the gains of macroprudential policy targeted at shadow banks. Furthermore, the gains of the macroprudential instrument provide a benchmark for monetary policy.

The leverage tax τ_t^{ϕ} requires the banker to pay a tax or receive a subsidy at the end of the period for its borrowings from households: $N_t = R_t^K Q_{t-1} S_{t-1}^B - R_{t-1}^D D_{t-1} - \tau_t^{\phi} D_{t-1} + \tau_t^L$. The intermediaries receive a lump sum transfer τ_t^L, which is chosen in a way that the leverage tax is budget neutral for each intermediary. Even though the tax is budget neutral in the end, the leverage tax still alters the intermediaries' problem and thus leverage decision.

The macroprudential authority responds to the security holdings of intermediaries similar to monetary rule. If the securities are above a target value, the central bank raises the tax. If the intermediaries hold only few securities, it increases the subsidy. The rule τ_t^{ϕ} is:

$$\tau_t^{\phi} = \left(\frac{S_t^B}{S^B}\right)^{\tau_s} - 1, \qquad (25)$$

where τ_s is the response to deviations from the target value S^B set by the macroprudential authority. The target value S^B is calibrated to the same value as in the monetary rule.

The last column of Table 2 shows the outcomes for the leverage tax. The parameter τ_s is the lowest value that reduces the run frequency to zero. A forceful leverage tax can reduce the run probability to exactly zero. Furthermore, the macroprudential policy has a superior stabilization-welfare combination as the welfare gains are slightly larger. Nevertheless, monetary policy can be a good substitute. This is especially important because the advantage of monetary policy is that it gets in all of the cracks that macroprudential policy and supervision fail to reach in reality.

However, there is an import caveat to this result. Ex-ante macroprudential policy in isolation can be quite effective in increasing financial stability, which is discussed in Appendix G.3 and aligns with Gertler et al. (2020a). This result contrasts

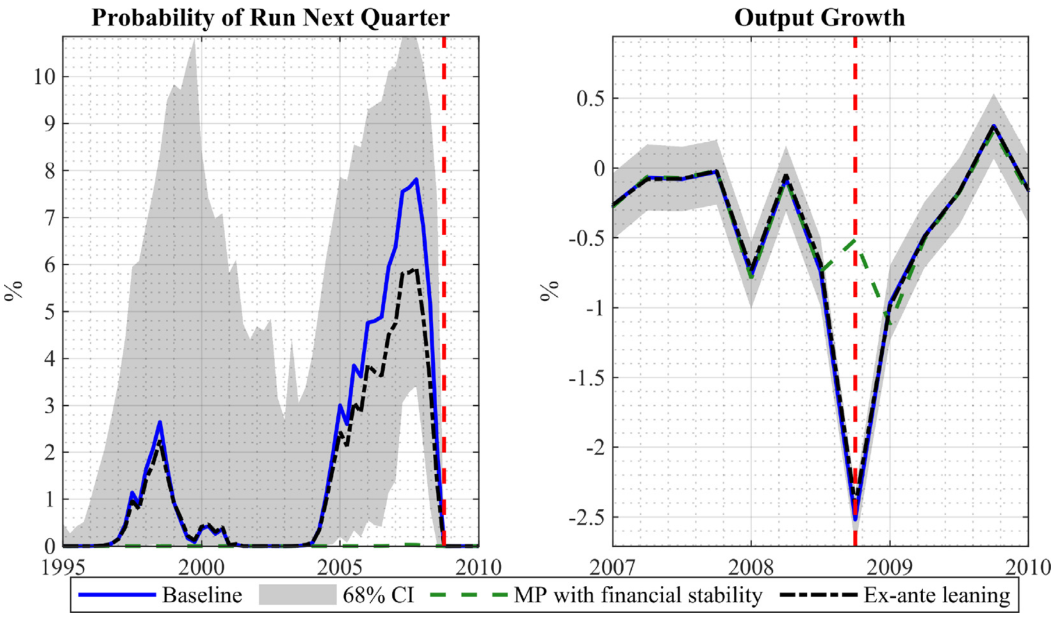

Fig. 8. Counterfactual policy analysis of monetary policy with financial considerations. The filtered median probability of a run in the next quarter and output growth (solid blue) with its 68% confidence interval is shown for the baseline scenario. Using the estimated shocks, the median for the counterfactual scenario of the modified monetary policy with monetary policy with financial considerations (dashed green) and the scenario with only ex-ante leaning is shown (dash-dotted black). The red line indicates the fourth quarter of 2008. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

with the findings for monetary policy, where the ex-ante effects were considerably smaller. Thus, monetary policy can be a good substitute for macroprudential policy only if the authorities can credibly commit to an ex-post looser policy stance.

5.3. Counterfactual policy analysis and the financial crisis in 2008

The policies can now be used to conduct a counterfactual scenario based on the estimation. In the previous section, the model is estimated under the assumption that monetary policy did not respond to financial conditions before or after the Great Recession.[22] Using the estimation results, I can construct the counterfactual paths for economic activity and financial fragility under alternative policies. This requires that the filtered shocks are fed into the model with the different policy to calculate the counterfactual evolution of the economy. The outlined strategy is general and can be used for a range of alternatives policies.

Specifically, I evaluate if the welfare-maximizing monetary rule that responds to financial conditions (κ_s^{opt}) would have mitigated the estimated run probability and prevented the run in 2008. Fig. 8 summarizes the counterfactual path. The build-up of financial fragility is now almost completely contained as it stays basically at zero. Furthermore, the run does not take place so that output decreases now only by 0.5% instead of 2.5% in 2008:Q4. Thus, the counterfactual scenario underlines the large financial stability gains and suggests that monetary policy could have helped to avoid the run. However, this result depends again on the ex-post commitment. A scenario with only ex-ante leaning does not succeed in averting the financial crisis as the stabilization impact is insufficient. The run probability peaks at a slightly lower level, but output still declines by around 2.5% due to the occurrence of the run. Thus, an ex-ante leaning policy alone would likely have had only a limited impact.

6. Conclusion

I investigate the endogenous build-up of financial fragility with a new nonlinear macroeconomic model. The combination of volatility shocks and risk-shifting incentives accounts for key macroeconomic and financial features. I then take the model to data to obtain a novel structural estimate of financial fragility. The estimation suggests a considerable increase in financial fragility from 2005 onwards that ends up in a run in 2008. Finally, I show that the zero lower bound entails substantial welfare costs and use counterfactual simulations to assess whether monetary policy could have averted the run in 2008.

[22] This means that the central bank follows a standard Taylor rule, which responds to output and inflation deviations. Additionally, I assume the absence of macroprudential policy in the estimation.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used ChatGPT partly for proofreading purposes. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Data availability

Data will be made available on request.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2023.06.006.

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