Shadow Banking and the Great Recession: Evidence from an Estimated DSGE Model

Patrick Fève[a]* Alban Moura[b] Olivier Pierrard[b]

[a] *Toulouse School of Economics and University of Toulouse I - Capitole*

[b] *Banque Centrale du Luxembourg*

January 25, 2019

Abstract

We argue that shocks to credit supply by shadow and retail banks were key to understand the behavior of the US economy during the Great Recession and the Slow Recovery. We base this result on an estimated DSGE model featuring a rich representation of credit flows. Our model selects the two banking shocks as the most important drivers of the crisis because they account simultaneously for the fall in real activity, the decline in credit intermediation, and the rise in lending-borrowing spreads. On the other hand, in contrast with the existing literature, our results assign only a moderate role to productivity and investment efficiency shocks.

KEYWORDS: Shadow Banking, Great Recession, Slow Recovery, estimated DSGE models.

JEL CODES: C32, E32.

*Correspondence: Patrick Fève, Toulouse School of Economics, 21 Allée de Brienne, 31000 Toulouse, France. Email: patrick.feve@tse-fr.eu. This paper has been produced in the context of the partnership agreement between the BCL and TSE. We thank colleagues at the BCL and TSE, as well as participants at several conferences and seminars, for helpful comments. This paper should not be reported as representing the views of the BCL or the Eurosystem. The views expressed are those of the authors and may not be shared by other research staff or policymakers at the BCL or in the Eurosystem.

1 Introduction

Starting mid-2007, a run on the US shadow banking system triggered a widespread financial crisis that soon turned into a deep economic downturn. The resulting Great Recession was marked by dramatic contractions in economic activity and financial flows and, ten years after, the subsequent Slow Recovery appears best characterized as a permanent negative shift in GDP (Guerron-Quintana and Jinnai, Forthcoming). Recently, a number of authors have studied the forces at play during the crisis and the recovery through the lens of estimated New-Keynesian models. Notable examples include Christiano et al. (2015), Lindé et al. (2016), Gust et al. (2017), and Cuba-Borda (2018). A common finding in these papers is the prominent role of shocks to the marginal efficiency of investment (MEI), or more broadly to capital accumulation, which proxy for disturbances affecting financial intermediation in standard DSGE models (see the discussion in Justiniano et al., 2011). Other important disturbances usually include preference shocks and total factor productivity (TFP) shocks, with the latter explaining the absence of marked deflation.

These attempts to construct a macroeconomic interpretation of the Great Recession provide a useful starting point. However, they also face important limitations. First and foremost, the papers typically consider models without explicit financial shocks nor frictions. As a result, they often have to interpret MEI and preference shocks as financial wedges, that lack the usual structural perspective of DSGE analysis. Second, the papers largely abstract from the behavior of banks and credit markets, whereas both policy makers (Bernanke, 2013) and academics (Gertler et al., 2016; Christiano et al., 2018) agree that disruptions to traditional and especially shadow banking were key to understand the crisis. This omission limits the ability of the models to generate a refined narrative about the events, for instance as regards the origins of the financial turmoil.

In this paper, we aim at closing these gaps. With this objective in mind, we build a DSGE model of the US economy featuring a rich representation of credit flows and a distinction between retail and shadow banking. Both types of banks intermediate funds between households and firms. However, traditional banks have access to deposits and are subject to macro-prudential regulation, while shadow banks finance on wholesale markets and operate unregulated. We introduce two credit supply shocks, one affecting the cost of extending traditional bank loans (the *loan cost shock*) and one driving the risk associated with shadow banking (the *shadow wedge*). This structure seems especially suited to account for the potential comovements between economic activity and traditional and shadow bank credit before, during, and after the Great Recession. The rest of our economy has the usual New-Keynesian structure. In particular, it features standard MEI and preference shocks.

We apply Bayesian techniques to estimate our model on a pre-crisis sample ending in 2007, including traditional and shadow bank loans as well as a spread measure among our observables to strengthen the identification of financial factors. The model attributes a substantial share of aggregate fluctuations to the two credit supply shocks, which explain about 40% of recurring movements in investment (32% for the loan cost shock and 10% for the shadow wedge). Then, we recover the sequence of shocks that explained the Great Recession and the Slow Recovery and assess their individual contributions to these events.

We obtain two main results. First, according to our model the Great Recession and the Slow Recovery largely originated from negative credit supply shocks. We find that, absent loan cost shocks, investment would have been higher at the end of the Great Recession by 15% with respect to its pre-crisis level, and by 20% absent shadow wedge shocks. Moreover, the recovery would have been much stronger absent banking shocks, as investment would have recovered its pre-crisis level as soon as 2010. In addition, our model associates the start of the Great Recession with negative shadow banking shocks, whereas shocks to traditional banks became important only after mid-2008. The resulting narrative of the crisis aligns well with the historical evidence, according to which the disruption started with a run on shadow banks before extending to all credit markets (see, e.g., Mishkin, 2011).

Second, our model assigns a negligible role to MEI shocks during the recession, and a largely positive one during the recovery. This key difference with respect to the literature reflects the ability of our framework to identify financial shocks from non-financial disturbances. It emphasizes the "catch-all" flavor of MEI shocks in standard DSGE models and warns against structural interpretations attributing the crisis to a drop in investment efficiency. Moreover, our model attributes little role to TFP and preference shocks during the recession, even though TFP shocks explain an increasingly important share of the Slow Recovery as time goes by.

Overall, our paper is the first to estimate a New-Keynesian DSGE model with traditional and shadow banking and to apply it to study the last recession and its aftermath. As such, it complements the literature reviewed above by tracing the origins of the crisis to bank credit supply shocks rather than generic MEI or preference disturbances. It also adds to an early strand of papers incorporating shadow banks in general equilibrium models, such as Verona et al. (2013), Gertler et al. (2016), Fève et al. (2017), and Meeks et al. (2017).

We organize the paper as follows. Section 2 develops the model, while Section 3 discusses the data and presents our estimation results. In Section 4, we apply the model to study the Great Recession and the Slow Recovery in order to identify the key forces at play. Finally, Section 5 concludes.

2 A Model with Traditional and Shadow Banks

This section details the model and the decision problems faced by the agents. Our economy resembles a standard medium-sized monetary DSGE model (Christiano et al., 2005; Smets and Wouters, 2007), augmented by financial intermediation between a saving household sector and a borrowing productive sector. We adopt a rich representation of the intermediation process, with both direct (household) and indirect (bank) credit intermediation. We further decompose the banking sector into traditional retail banks and shadow banks. Traditional banks have access to household deposits and are subject to macro-prudential regulation. In contrast, shadow banks have no access to deposits and operate outside the regulatory framework.

2.1 New-Keynesian block

First, we describe the standard New-Keynesian block of our economy. It features competitive producers of the homogeneous final good, monopolistically competitive producers of differentiated intermediate goods, capital producers which transform the final good into investment, a representative household, and fiscal and monetary authorities. Both prices and wages adjust sluggishly.

2.1.1 Final producers

Final producers are perfectly competitive. They purchase a continuum of differentiated intermediate goods $f_t(j)$ and produce the final good in quantity F_t according to a standard CES technology:

$$F_t = \left[\int_0^1 f_t(j)^{\frac{1}{1+\lambda_{p,t}}} \, dj \right]^{1+\lambda_{p,t}},$$

where $\lambda_{p,t}$ is a price markup shock with steady state $\overline{\lambda}_p > 0$, persistence $\rho_p \in [0,1)$, and innovation u_t^p. Letting $p_t(j)$ and P_t denote the price of intermediate good j and of the final good, cost minimization implies the usual demand function

$$\frac{f_t}{F_t} = \left(\frac{p_t}{P_t} \right)^{-\frac{1+\lambda_{p,t}}{\lambda_{p,t}}}, \tag{1}$$

where symmetry allows dropping the j index.

2.1.2 Intermediate producers

Monopolistically competitive firms hire labor in quantity h_t and combine it with capital to produce the intermediate goods. Capital is supplied by traditional banks, shadow banks, and households in quantities l_{t-1}, s_{t-1}, and b_{t-1}. Following Iacoviello (2015), we assume imperfect substitution between funding sources, as embodied in the production function

$$f_t = \epsilon_t^e \left(l_{t-1}^{\chi_l \epsilon_t^\chi} \, s_{t-1}^{\chi_s \epsilon_t^\chi} \, b_{t-1}^{1-(\chi_l - \chi_s)\epsilon_t^\chi} \right)^\alpha \; h_t^{1-\alpha}, \tag{2}$$

where ϵ_t^e is a productivity shifter with persistence $\rho_e \in [0,1)$ and innovation u_t^e. ϵ_t^χ is a stochastic processes that changes the relative productivity of bank-intermediated capital over time, which we interpret as a shock to the demand for bank credit. Bocola et al. (2014) use a similar relative productivity shock shifting the demand for production factors. It has persistence $\rho_\chi \in [0,1)$ and innovation u_t^χ. In steady state, χ_l, $\chi_s \in (0,1)$ pin down the levels of traditional and shadow bank credit relative to household credit. Finally, $\alpha \in (0,1)$ denotes the elasticity of output with respect to capital.

The typical intermediate firm rents capital at real rates r_t^{kl}, r_t^{ks}, and r_t^{kb} and pays a real wage rate W_t. To help the model reproduce the positive comovement between loans and GDP observed in the data, we introduce a working capital channel (Christiano et al., 2005): the firm must borrow a fraction $\psi_w \in [0,1]$ of its wage bill in advance of production at the interest rate r_t^w. Finally, as in Rotemberg (1982), the firm bears a quadratic cost parametrized by $\kappa_p \geq 0$ when changing its price.

Overall, the firm maximizes

$$E_0 \sum_{t=0}^{\infty} \beta^t \Lambda_t \left[\frac{p_t}{P_t} f_t - r_t^{kl} l_{t-1} - r_t^{ks} s_{t-1} - r_t^{kb} b_{t-1} - (1 + \psi_w r_t^w) \, W_t h_t - \frac{\kappa_p}{2} \left(\frac{p_t}{\overline{\pi}^{1-\gamma_p} \pi_{t-1}^{\gamma_p} p_{t-1}} - 1 \right)^2 F_t \right],$$

subject to constraints (1) and (2). Here, Λ_t denotes the Lagrange multiplier on the representative household's budget constraint, $\beta \in (0,1)$ is the household's discount factor, $\gamma_p \in (0,1)$ is an indexation coefficient, and $\pi_t = P_t / P_{t-1}$ is price inflation with steady state $\overline{\pi}$. The associated first-order optimality conditions (FOCs) are

$$\begin{aligned}
r_t^{kl} L_{t-1} &= \alpha \chi_l \epsilon_t^\chi \chi_l MC_t F_t, \\
r_t^{ks} S_{t-1} &= \alpha \chi_s \epsilon_t^\chi MC_t F_t, \\
r_t^{kb} B_{t-1} &= \alpha \left[1 - (\chi_l - \chi_s) \epsilon_t^\chi \right] MC_t F_t, \\
(1 + \psi_w r_t^w) W_t H_t &= (1 - \alpha) MC_t F_t,
\end{aligned}$$

and

$$\frac{1}{\lambda_{p,t}}+\kappa_p\left(\frac{\pi_t}{\overline{\pi}^{1-\gamma_p}\pi_{t-1}^{\gamma_p}}-1\right)\frac{\pi_t}{\overline{\pi}^{1-\gamma_p}\pi_{t-1}^{\gamma_p}}=\frac{1+\lambda_{p,t}}{\lambda_{p,t}}MC_t+\kappa_p E_t\Lambda_{t,t+1}\left(\frac{\pi_{t+1}}{\overline{\pi}^{1-\gamma_p}\pi_t^{\gamma_p}}-1\right)\frac{\pi_{t+1}}{\overline{\pi}^{1-\gamma_p}\pi_t^{\gamma_p}}\frac{F_{t+1}}{F_t},$$

where MC_t represents the real marginal cost of production and $\Lambda_{t,t+1}=\beta\Lambda_{t+1}/\Lambda_t$ is the household's stochastic discount factor between dates t and $t+1$. These FOCs take into account that all intermediate firms are identical in equilibrium.

2.1.3 Capital producers

Capital producers operate under perfect competition and combine the $(1-\delta)K_{t-1}$ installed capital goods with investment goods I_t to create new capital goods in quantity K_t. Their technology is given by

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

where $\delta\in(0,1)$ denotes the depreciation rate. Producing I_t units of investment goods requires

$$Y_{i,t}=\epsilon_t^i\left[1+\frac{\phi_i}{2}\left(\frac{I_t}{I_{t-1}}-1\right)^2\right]I_t$$

units of the final good, where ϵ_t^i is a shock to the marginal (in)efficiency of investment (MEI) with persistence $\rho_i\in[0,1)$ and innovation u_t^i. Finally, $\phi_i\geq 0$ measures the strength of investment adjustment costs.

Letting Q_t denote the price of capital, producers maximize

$$E_0\sum_{t=0}^{\infty}\beta^t\Lambda_t\left[Q_tK_t-Q_t(1-\delta)K_{t-1}-Y_{i,t}\right]$$

subject to the above two equations. The associated FOC is

$$Q_t=\epsilon_t^i\left[1+\frac{\phi_i}{2}\left(\frac{I_t}{I_{t-1}}-1\right)^2+\phi_i\left(\frac{I_t}{I_{t-1}}-1\right)\frac{I_t}{I_{t-1}}\right]-\phi_iE_t\Lambda_{t,t+1}\epsilon_{t+1}^i\left(\frac{I_{t+1}}{I_t}-1\right)\frac{I_{t+1}^2}{I_t^2}.$$

2.1.4 Household

The representative household owns the whole economy and maximizes

$$U_0=E_0\sum_{t=0}^{\infty}\beta^t\left[\ln(c_t-hC_{t-1})+\epsilon_t^d\ln D_t-\frac{m}{1+\psi}h_t^{1+\psi}\right],$$

where c_t is individual consumption, $h \in (0,1)$ measures habit formation defined in terms of lagged aggregate consumption, $\psi \geq 0$ is the curvature in labor disutility, h_t are individual hours worked, and $m > 0$ is a preference weight. Deposits D_t provide utility through a standard liquidity motive, which varies over time due to the preference shock ϵ_t^d with steady state $\bar{\epsilon}^d \geq 0$, persistence $\rho_d \in [0,1)$, and innovation u_t^d. This shock shifts the arbitrage between consumption and savings and plays a role similar to the risk-premium shock in Gust et al. (2017) or the preference shock in Cuba-Borda (2018).

On top of the income received from labor supply, deposits at the bank, and direct loans to the production sector, the household receives profits Π_t from intermediate firms, as well as traditional and shadow banks. It uses this income to consume, save in new deposits and loans, and pay lump-sum taxes T_t as well as different costs. For calibration purposes, we introduce a marginal management cost $\gamma_h \geq 0$ for deposits and loans.[1] To smooth the dynamics of the model, we also introduce quadratic costs on deposits and loans, $\Phi_{D,t}$ and $\Phi_{B,t}$:

$$\Phi_{D,t} = \frac{\phi_d}{2}\left(\frac{D_t}{D_{t-1}} - 1\right)^2, \qquad \Phi_{B,t} = \frac{\phi_b}{2}\left(\frac{B_t}{B_{t-1}} - 1\right)^2,$$

with ϕ_b, $\phi_d \geq 0$. Finally, the household faces a quadratic cost when changing its nominal wage rate, parametrized by $\kappa_w \geq 0$.[2] Overall, the flow budget constraint is given by

$$\begin{aligned} C_t + (1+\gamma_h+\Phi_{D,t})\,D_t + (1+\gamma_h+\Phi_{B,t})\,Q_t B_t + \frac{\kappa_w}{2}\left(\frac{P_t w_t}{\bar{\pi}^{1-\gamma_w}\pi_{t-1}^{\gamma_w} P_{t-1} w_{t-1}} - 1\right)^2 H_t + T_t \\ = w_t h_t + \left(1 + r_{t-1}^d\right) D_{t-1} + \left[(1-\delta)Q_t + r_r^{kb}\right] B_{t-1} + \Pi_t, \end{aligned}$$

where $\gamma_w \in (0,1)$ is an indexation coefficient.

Taking equilibrium symmetry into account, utility maximization with respect to consumption, deposits, loans, and wages yields

$$\begin{aligned} \Lambda_t &= \frac{1}{C_t - hC_{t-1}}, \\ 1+\gamma_h+\Phi_{D,t}+\Phi'_{D,t}\frac{D_t}{D_{t-1}} &= \frac{\epsilon_t^d}{\Lambda_t D_t} + E_t\Lambda_{t,t+1}\left(1 + r_t^d + \Phi'_{D,t+1}\frac{D_{t+1}^2}{D_t^2}\right), \\ 1+\gamma_h+\Phi_{B,t}+\Phi'_{B,t}\frac{B_t}{B_{t-1}} &= E_t\Lambda_{t,t+1}\frac{r_{t+1}^{kb} + Q_{t+1}(1-\delta+\Phi'_{B,t+1}B_{t+1}^2/B_t^2)}{Q_t}, \end{aligned}$$

[1] We could introduce different management costs for deposits and loans. However, our calibration strategy only requires a single cost, so we prefer to remain parsimonious. The same remark applies to the banking cost γ_b introduced in Section 2.2.1.

[2] We keep implicit the usual CES demand structure for individual labor services.

and

$$\frac{W_t}{\lambda_{w,t}} + \kappa_w \left(\frac{\pi_t W_t}{\overline{\pi}^{1-\gamma_w} \pi_{t-1}^{\gamma_w} W_{t-1}} - 1 \right) \frac{\pi_t W_t}{\overline{\pi}^{1-\gamma_w} \pi_{t-1}^{\gamma_w} W_{t-1}} = \frac{1+\lambda_{w,t}}{\lambda_{w,t}} \frac{m H_t^{\psi}}{\Lambda_t}$$
$$+\kappa_w E_t \Lambda_{t,t+1} \left(\frac{\pi_{t+1} W_{t+1}}{\overline{\pi}^{1-\gamma_w} \pi_t^{\gamma_w} W_t} - 1 \right) \frac{\pi_{t+1} W_{t+1}}{\overline{\pi}^{1-\gamma_w} \pi_t^{\gamma_w} W_t} \frac{H_{t+1}}{H_t},$$

where $\lambda_{w,t}$ is a wage markup shock with steady state $\overline{\lambda}_w > 0$, persistence $\rho_w \in (-1, 1)$, and innovation u_t^w.

2.1.5 Public authorities

The fiscal authority purchases an exogenous amount G_t of the final good, driven by a stochastic process with persistence $\rho_g \in [0, 1)$ and innovation u_t^g. It finances itself through the lump-sum tax $T_t = G_t$ levied on households.

The monetary authority sets the nominal interest rate according to the Taylor-type rule

$$\log \frac{R_t}{\overline{R}} = \rho_r \log \frac{R_{t-1}}{\overline{R}} + (1-\rho_r) \left(r_\pi \log \frac{\pi_t}{\overline{\pi}} + r_y \log \frac{Y_t}{\overline{Y}} \right) + u_t^r,$$

with $\rho_r \in (0, 1)$, $r_\pi > 1$, and $r_y \geq 0$. GDP is given by $Y_t = C_t + I_t + G_t$ and u_t^r is an iid. disturbance.

2.2 Financial block

We now turn to the financial block of the economy, which features traditional and shadow banks.

2.2.1 Traditional bank

The representative traditional bank resembles a retail credit institution. It extends loans of physical capital $Q_t L_t$ and working-capital loans $L_{w,t}$, and finances through own capital N_t and household deposits. In addition, we assume that the traditional bank can invest in asset-backed securities ABS_t issued by shadow banks. Therefore, the bank balance sheet verifies

$$Q_t L_t + L_{w,t} + ABS_t = N_t + D_t. \tag{3}$$

The traditional bank is also subject to a Basel-like macro-prudential regulation. The Basel framework requires that bank capital N_t should not be lower than a fraction $\eta \in (0, 1)$ of risk-weighted assets. We assume that risk-weighted assets include all loans to the non-financial sector, that is

$Q_t L_t + L_{w,t}$, but exclude the ABS issued by shadow intermediaries. This setup roughly reproduces the Basel I regulation, which was in force during most of our estimation sample.[3] Then, we define excess capital as

$$X_t = N_t - \eta(Q_t L_t + L_{w,t})$$

and capture the regulation faced by traditional banks through the decreasing and convex cost function

$$\mathcal{C}(X_t) = -p_1 \ln(1 + p_2 X_t),$$

with p_1, $p_2 \geq 0$. This setup is borrowed from Enders et al. (2011) and Kollmann (2013) and conveniently circumvents the numerical issues related to the non-differentiability of the real-world regulatory constraint $X_t \geq 0$.

Finally, we assume that the traditional bank incurs both a marginal management cost $\gamma_b \geq 0$ and quadratic adjustment costs $\Phi_{L,t}$, $\Phi_{N,t}$, and $\Phi_{A,t}$ related to intertemporal loans, own capital, and ABS holdings. The adjustment costs are given by

$$\Phi_{L,t} = \frac{\phi_l}{2}\left(\frac{L_t}{L_{t-1}} - 1\right)^2, \qquad \Phi_{N,t} = \frac{\phi_n}{2}\left(\frac{N_t}{N_{t-1}} - 1\right)^2, \qquad \Phi_{A,t} = \frac{\phi_a}{2}\left(\frac{ABS_t}{ABS_{t-1}} - 1\right)^2,$$

with ϕ_a, ϕ_l, $\phi_n \geq 0$. We do not introduce costs on intratemporal working-capital loans, nor on household deposits. Overall, the traditional bank's flow profit verifies

$$\begin{aligned} \left[r_t^{kl} + (1-\delta)Q_t\right] L_{t-1} - Q_t L_t + (1 + r_{t-1}^a)ABS_{t-1} - ABS_t + r_t^w L_{w,t} + D_t - (1 + r_{t-1}^d)D_{t-1} \\ -\epsilon_t^x \mathcal{C}(X_t) - \epsilon_t^l(\gamma_b + \Phi_{L,t})Q_t L_t - (\gamma_b + \Phi_{N,t})N_t - (\gamma_b + \Phi_{A,t})ABS_t. \end{aligned}$$

The date-t return on ABS, r_{t-1}^a, is predetermined.[4] ϵ_t^l and ϵ_t^x are two disturbances affecting the costs of physical loan extension and of bank capital shortage. We discuss them in more detail below.

The traditional bank maximizes the expected net present value of its current and future flow profits, taking into account its balance sheet constraint (3). Letting ν_t denote the multiplier on this

[3] The Basel I regulation fixed a risk weight of 100% for traditional loans and of 20% of securities with the highest rating, as were most ABS before the crisis. Here, we assume an even more dichotomous regulation with a 100% weight on loans and a 0% weight on ABS.

[4] From a technical perspective, the return on ABS must be predetermined to avoid indeterminacy. Otherwise, the free-entry condition in shadow banking (5) would only determine variables in expectations.

constraint, the associated FOCs are

$$
\begin{aligned}
1+\nu_t &= (1+r_t^d)E_t\Lambda_{t,t+1}, \\
1+\nu_t+\epsilon_t^l\left(\gamma_b+\Phi_{L,t}+\Phi'_{L,t}\frac{L_t}{L_{t-1}}\right) &= \epsilon_t^x\eta\mathcal{C}'(X_t)+E_t\Lambda_{t,t+1}\frac{r_{t+1}^{kl}+Q_{t+1}(1-\delta+\epsilon_{t+1}^l\Phi'_{L,t+1}L_{t+1}^2/L_t^2)}{Q_t}, \\
\nu_t-\epsilon_t^x\eta\mathcal{C}'(X_t) &= r_t^w, \\
1+\nu_t+\gamma_b+\Phi_{A,t}+\Phi'_{A,t}\frac{ABS_t}{ABS_{t-1}} &= E_t\Lambda_{t,t+1}\left[\epsilon_{t+1}^a(1+r_t^a)+\Phi'_{A,t+1}\left(\frac{ABS_{t+1}}{ABS_t}\right)^2\right], \\
\nu_t-\epsilon_t^x\mathcal{C}'(X_t) &= \gamma_b+\Phi_{N,t}+\Phi'_{N,t}\frac{N_t}{N_{t-1}}-E_t\Lambda_{t,t+1}\Phi'_{N,t+1}\left(\frac{N_{t+1}}{N_t}\right)^2.
\end{aligned}
$$

As in Gerali et al. (2010), we close the model by assuming that the traditional bank has access to unlimited finance from the monetary authority at the policy rate R_t. By arbitrage, this yields the additional condition

$$1+\nu_t=R_tE_t\frac{\Lambda_{t,t+1}}{\pi_{t+1}}.$$

Before moving forward, we discuss in more details the economic interpretation of the banking shocks in our model. First, we consider the loan cost shock ϵ_t^l, with persistence $\rho_l\in(0,1)$ and innovation u_t^l. Abstracting from adjustment costs and capital requirement for simplicity, and assuming that the price of capital and the discount factor remain constant, we obtain

$$E_tr_{t+1}^{kl}-\delta=\frac{\gamma_b}{\beta}\epsilon_t^l+r_t^d \tag{4}$$

when subtracting the FOC with respect to deposit from the FOC with respect to loans. The left-hand side is the marginal return of extending intertemporal loans and the right-hand side measures the marginal cost of doing so. The latter includes a borrowing cost r_t^d and a loan management cost γ_b, which is subject to the shock ϵ_t^l. It follows that the time-varying loan cost directly translates into the lending-borrowing spread in our model, making traditional bank intermediation more costly. It may arise from changes in the monitoring intensity due to non-modeled borrower-related risk, or from a time-varying markup in retail banking (Gerali et al., 2010).

Second, we introduce a shock ϵ_t^a, with persistence $\rho_a\in(0,1)$ and innovation u_t^a, in the FOC with respect to ABS holdings. In Appendix A, we demonstrate that this disturbance has a structural interpretation as a shadow wedge shock encompassing the risk associated with shadow banking. Under similar simplifications as before (no adjustment costs, no capital requirement, $Q=1$, constant discount factor, and $\epsilon_t^l=1$ for all periods), and subtracting the FOC with respect to ABS from the FOC with respect to intertemporal loans, we obtain

$$E_t\epsilon_{t+1}^a(1+r_t^a)=E_t(r_{t+1}^{kl}+1-\delta).$$

Thus, the shock ϵ_t^a creates a wedge between the returns on loans and ABS holdings. More precisely, we see that, *ceteris paribus*, the traditional bank will ask for a relatively higher return on ABS when $E_t \epsilon_{t+1}^a$ decreases, that is when the risk associated with shadow banking increases. As a result, shadow bank intermediation should decline.

Finally, our model features a shock to the cost of bank capital shortage ϵ_t^x, with persistence $\rho_x \in (0,1)$ and innovation u_t^x. Assuming no adjustment cost and a constant discount factor β, we obtain

$$1 + \phi + \epsilon_t^x \mathcal{C}'(X_t) = \beta(1 + r_t^d)$$

when subtracting the FOC with respect to deposits from the FOC with respect to bank capital. This condition implies that in equilibrium the bank is indifferent between financing through capital or deposits. Given that $\mathcal{C}' \leq 0$, an increase in ϵ_t^x makes own financing cheaper, pushing the bank to build more capital. As such, the bank capital shock plays a similar role in our model as the capital requirement shock in Kollmann (2013).

2.2.2 Shadow bank

Like the traditional bank, the representative shadow bank extends intertemporal loans to firms. However, it has no access to household deposits and finances on wholesale markets by issuing tradable securities.[5] Moreover, it operates outside the macro-prudential regulatory framework, in line with the pre-crisis setup. In the model, this implies that the shadow bank has zero own capital. Since empirical evidence suggests that shadow banking bears low entry/exit costs and little frictions, we also assume that the shadow bank lives for 2 periods and operates in a frictionless and free-entry market (see Fève et al., 2017, for a longer discussion).

More precisely, at any given period t, new shadow banks enter the market without capital, finance by issuing ABS_t, and extend loans S_t to firms. For calibration purposes, we introduce a marginal issuing cost for ABS, denoted $a \in [0,1)$. Hence, the budget constraint of the representative new shadow bank is

$$(1-a)ABS_t = Q_t S_t.$$

At date $t+1$, the representative shadow bank's profit is

$$\left[r_{t+1}^{ks} + (1-\delta)Q_{t+1}\right] S_t - (1 + r_t^a) ABS_t.$$

[5]Since these securities are held by traditional banks in our model, the shadow bank has the flavor of a special-purpose vehicle (SPV) created to achieve off-balance sheet accounting. The Basel Committee on Banking Supervision (2009) provides a comprehensive presentation of SPV.

This profit is rebated in a lump-sum fashion to the household. Under free entry, an expected zero-profit condition pins down the size of the shadow banking sector:

$$E_t \Lambda_{t,t+1} \left[\frac{r^{ks}_{t+1} + (1-\delta) Q_{t+1}}{Q_t} - \frac{1 + r^a_t}{1-a} \right] = 0. \tag{5}$$

This equation equates the expected marginal return on ABS with the marginal cost of issuance.

2.3 Closing the model

We close the model by the market-clearing conditions for capital, working-capital loans, and the final good:

$$\begin{aligned} K_t &= L_t + S_t + B_t, \\ L_{w,t} &= \psi_w W_t H_t, \\ F_t &= C_t + Y_{i,t} + G_t + \text{costs}_t, \end{aligned}$$

where cost_t encompasses all costs related to (i) changes in prices and wages, (ii) changes in household deposits and loans, and in bank loans, capital, and ABS holdings, (iii) the excess capital cost on traditional banks, (iv) the management of household deposit and loans, as well as of bank loans, capital, and ABS holdings, and (v) ABS issuance.[6]

Finally, we postulate standard AR(1) processes in logs for ten forcing processes of our model economy: the price markup shock ϵ^p_t, the TFP shock ϵ^e_t, the credit demand shock ϵ^χ_t, the MEI shock ϵ^i_t, the deposit preference shock ϵ^d_t, the wage markup shock ϵ^p_t, the government spending shock G_t, the bank excess capital shock ϵ^x_t, the loan cost shock ϵ^l_t, and the shadow wedge ϵ^a_t (in order of appearance). The last driving force of our model is the shock in the monetary policy rule.

3 Econometric Analysis

We solve the model with standard linearization techniques and estimate it using Bayesian methods on quarterly US data. This section discusses the data and the estimation results.

[6] In the linear approximation used to solve the model, only costs (iii) to (v) matter as the other ones vanish near the steady state.

3.1 Data

We estimate the model using eleven observables. The first seven are the macro variables often used to estimate DSGE models: real consumption, real investment, real government expenditures, hours worked, price inflation, wage inflation, and the nominal interest rate. In addition, we exploit data on four financial variables to strengthen the identification of financial shocks and frictions. These variables are real loans by retail banks, real loans by shadow banks, the leverage of traditional banks, and a measure of credit spread. In model notation, these observables correspond to

$$\left[\ln C_t,\ \ln I_t,\ \ln G_t,\ \ln H_t,\ \pi_t,\ \frac{W_t \pi_t}{W_{t-1}},\ R_t,\ \ln(Q_t L_t + L_{w,t}),\ \ln(Q_t S_t),\ \ln \frac{Q_t L_t + L_{w,t}}{N_t},\ r_t^{kl} - r_t^d\right].$$

For all but four observables, we detrend the logarithm of each variable independently with a quadratic trend.[7] The exceptions are price inflation, wage inflation, the interest rate, and the spread, for which we simply remove the sample mean.

In line with the literature reviewed in the introduction, we estimate our model on pre-crisis data to avoid issues related to large shocks and to the zero lower bound on interest rates. In particular, our estimation sample runs from 1985Q1 to 2007Q4. Appendix B provides details about the data. Here, we briefly discuss our measurement of the loans extended by traditional and shadow banks. We proceed in two steps. First, we build on Gertler et al. (2016) to assign financial intermediaries to the traditional and shadow banking sectors. We consider private depository institutions as traditional banks and we assign government-sponsored enterprises, GSE mortgage pools, issuers of ABS, finance companies, real estate investment trusts, security brokers and dealers, holding companies, and funding corporations to the shadow banking sector. Second, we measure the credit supplied to the private sector by each type of banks as the sum of their asset positions in corporate bonds, mortgages, consumer credit, and other types of loans, extracted from the US Financial Accounts.[8]

3.2 Parameter estimates

We partition the parameters into two sets. The first set contains 18 parameters or targets kept fixed during estimation and listed in Table 1. Regarding standard parameters, the capital share α, the household discount factor β, the depreciation rate δ, and the two markups λ_p, λ_w are fixed at 0.33, 0.995, 0.025, and 0.25, respectively. We calibrate $\overline{G}/\overline{Y}$, $\overline{\pi}$, and $\overline{R}$ by matching the sample averages

[7] This procedure, which follows Iacoviello (2015), limits the effects of the trend divergences observed between real and financial variables in the data.

[8] In line with the model, we exclude credit to public entities from our observables.

Table 1: Calibrated parameters

Parameter	Value	Description	Parameter	Value	Description
Standard parameters			*Financial parameters*		
α	0.33	Capital share	$\overline{B}/\overline{K}$	0.66	Non-financial capital
β	0.995	Discount factor	$\overline{S}/\overline{L}$	0.89	Shadow vs. traditional bank credit
δ	0.025	Depreciation rate	$\overline{\eta}$	0.09	Capital requirement
$\overline{G}/\overline{Y}$	0.19	Government spending	ψ_w	1	Working capital
$\overline{H}$	0.20	Hours	$\overline{r}^{kl} - \overline{r}^{d}$	0.005	Lending-borrowing spread
$\overline{\lambda}_p, \overline{\lambda}_w$	0.25	Price and wage markups	$\overline{r}^{kb}$	$\overline{r}^{kl}$	Return to household capital
$\overline{\pi}$	1.006	Inflation	$\overline{r}^{ks}$	$\overline{r}^{kl}$	Return to shadow bank capital
ψ	2	Inverse Frisch elasticity	$\overline{X}$	0	Bank excess capital
$\overline{R}$	1.012	Nominal interest rate			

Notes. In this table, we treat steady-state targets as implicit parameters.

for the government spending to output ratio, price inflation, and the policy rate. We normalize steady-state hours worked at 0.20, pinning down m, and impose an inverse Frisch elasticity of 2, in line with the value estimated by Smets and Wouters (2007).

Regarding financial parameters, we set the Cobb-Douglas coefficients $\overline{\chi}_l$ and $\overline{\chi}_s$ to 0.18 and 0.16 respectively. This allows to reproduce two data targets: (i) a ratio between intermediated credit and total capital of about 1/3 in the US (Christiano et al., 2014), and (ii) a ratio between shadow and traditional bank credit of about 0.90 (sample average over the estimation sample). We impose that all types of capital have the same return in steady state ($\overline{r}^{kb} = \overline{r}^{kl} = \overline{r}^{ks}$), pinning down the ABS issuance cost a and the household management cost γ_h. We also calibrate the bank management cost γ_b to match the average spread in the data and we follow Kollmann (2013) in assuming that excess bank capital is zero in steady state. Finally, we suppose as in Christiano et al. (2005) that firms must borrow the totality of the wage bill in advance, resulting in $\psi_w = 1$, and we set the capital adequacy ratio to $\overline{\eta} = 9\%$, implying a leverage of about 11 for traditional banks.

The second set contains 36 parameters estimated from the data. Table 2 reports our prior choices, as well as the posterior mode and 90% credible intervals constructed using standard MCMC techniques. For usual New-Keynesian parameters (habits, investment cost, nominal frictions), we adopt distributions largely in line with the DSGE literature. Our estimates signal a standard degree of consumption habits and moderate investment costs (Smets and Wouters, 2007; Lindé et al., 2016). The estimated Rotemberg parameters suggest that prices are slightly more sticky than wages, even though the posterior distributions largely overlap. The estimates of the Taylor rule coefficients take plausible values.

Table 2: Estimation results

Parameter	Description	Prior distribution			Posterior distribution	
		Distribution	Mean	SD	Mode	[5%, 95%]
h	Consumption habits	Beta	0.60	0.15	0.66	[0.59, 0.76]
ϕ_i	Investment adjustment cost	Normal	5.00	1.00	1.71	[1.10, 2.72]
ρ_r	Taylor rule: Smoothing	Beta	0.65	0.15	0.89	[0.86, 0.92]
r_π	Taylor rule: Inflation response	Normal	1.50	0.15	1.76	[1.53, 1.99]
r_y	Taylor rule: Output response	Normal	0.25	0.05	0.09	[0.04, 0.14]
κ_p	Price adjustment cost	Normal	150.00	25.00	192.14	[145.39, 236.31]
γ_p	Price indexation	Beta	0.50	0.15	0.04	[0.01, 0.10]
κ_w	Wage adjustment cost	Normal	150.00	25.00	176.27	[142.28, 213.13]
γ_w	Wage indexation	Beta	0.50	0.15	0.28	[0.12, 0.54]
$\mathcal{C}''(0)$	Convexity of excess capital cost	Gamma	0.50	0.25	0.71	[0.37, 1.26]
ϕ_a	ABS adjustment cost	Inv. Gamma	1.00	2.00	1.08	[0.74, 2.10]
ϕ_b	Bond adjustment cost	Inv. Gamma	1.00	2.00	4.91	[2.03, 11.34]
ϕ_d	Deposit adjustment cost	Inv. Gamma	1.00	2.00	0.27	[0.20, 0.38]
ϕ_l	Loan adjustment cost	Inv. Gamma	1.00	2.00	1.13	[0.72, 2.01]
ϕ_n	Bank capital adjustment cost	Inv. Gamma	1.00	2.00	0.26	[0.21, 0.37]
ρ_e	Technology shock	Beta	0.65	0.15	0.83	[0.76, 0.87]
ρ_i	Investment shock	Beta	0.65	0.15	0.88	[0.79, 0.98]
ρ_g	Government spending shock	Beta	0.65	0.15	0.96	[0.94, 0.98]
ρ_p	Price markup shock	Beta	0.65	0.15	0.44	[0.22, 0.70]
ρ_w	Wage markup shock	Normal	0.00	0.15	0.10	[-0.05, 0.23]
ρ_d	Deposit preference shock	Beta	0.65	0.15	0.92	[0.87, 0.95]
ρ_χ	Credit demand shock	Beta	0.65	0.15	0.94	[0.90, 0.97]
ρ_l	Loan cost shock	Beta	0.65	0.15	0.93	[0.87, 0.95]
ρ_a	Shadow wedge	Beta	0.65	0.15	0.92	[0.87, 0.95]
ρ_x	Bank capital shock	Inv. Gamma	0.65	0.15	0.32	[0.17, 0.49]
$100\sigma_e$	SD technology shock	Inv. Gamma	1.00	3.00	0.99	[0.89, 1.22]
$100\sigma_i$	SD investment shock	Inv. Gamma	1.00	3.00	1.25	[0.95, 1.91]
$100\sigma_g$	SD government spending shock	Inv. Gamma	1.00	3.00	0.79	[0.71, 0.91]
$10\sigma_p$	SD price markup shock	Inv. Gamma	1.00	3.00	3.59	[1.29, 5.59]
σ_w	SD wage markup shock	Inv. Gamma	1.00	3.00	1.85	[1.40, 2.45]
$1000\sigma_r$	SD monetary shock	Inv. Gamma	1.00	3.00	1.15	[1.02, 1.33]
$10\sigma_d$	SD deposit preference shock	Inv. Gamma	1.00	3.00	3.99	[2.98, 5.35]
$10\sigma_\chi$	SD credit demand shock	Inv. Gamma	1.00	3.00	0.73	[0.61, 1.03]
σ_l	SD loan cost shock	Inv. Gamma	1.00	3.00	3.52	[2.50, 6.01]
$1000\sigma_a$	SD shadow wedge	Inv. Gamma	1.00	3.00	3.06	[2.29, 5.60]
$0.10\sigma_x$	SD bank capital shock	Inv. Gamma	1.00	3.00	1.11	[0.89, 1.60]

Notes. The posterior distribution is constructed from the random-walk Metropolis-Hastings algorithm with a single chain of 250,000 draws, after a burn-in period of 250,000 draws. The acceptance rate is 27% and standard tests confirm convergence.

Turning to the parameters defining the adjustment costs on financial variables, we use inverse gamma distributions allowing for a strictly positive density at zero. Posterior estimates indicate that the model needs large adjustment costs on household credit to fit the data, with a posterior mode of ϕ_b well above its prior mean. This is not surprising: since household credit accounts for 2/3 of the capital stock on average in our model, its dynamics must be slowed down to generate smooth dynamics. Adjustment costs are also relatively important for traditional bank loans and ABS holdings, while they seem less relevant for deposits and bank capital. Finally, we follow Kollmann (2013) in using a Gamma prior centered at 0.50 for $\mathcal{C}''(0)$, which defines the curvature of the bank capital cost function and controls the transmission of bank capital shocks to the equilibrium spread. We obtain a slightly larger posterior estimate of 0.71.

3.3 Model properties

In the next section, we apply our estimated model to shed light on macroeconomic dynamics in the US during the Great Recession and the Slow Recovery. Before doing so, we find it interesting to discuss some of its properties, in particular as regards the role of financial factors in business cycles. With this objective in mind, Table 3 reports the variance decomposition for seven key variables: consumption, investment, hours, traditional bank loans, shadow bank loans, and the lending-deposit spread. To increase readability, the table focuses on the most relevant shocks.[9] Two results stand out.

First, shocks to the efficiency of investment and to the cost of traditional loans are the most important drivers of consumption and investment in our model. The leading role of MEI shocks is consistent with results from the DSGE literature (Justiniano et al., 2011; Moura, 2018), while the empirical relevance of loan supply shocks has been documented by Gambetti and Musso (2017) using structural VARs.[10] While both shocks affect the transformation of foregone consumption into productive capital, the decomposition emphasizes an important difference between these disturbances:

[9] That is, the table omits the contributions of the government spending shock u^g, the price and wage markup shocks u^p and u^w, the preference shock u^d, the credit demand shock u^χ, the monetary shock u^r, and the bank capital cost shock u^x. These are reported in Appendix C.

[10] The loan cost shock from our model verifies most of the sign restrictions Gambetti and Musso (2017) impose on their loan supply shock (for GDP, loan volumes, and lending rates). According to their estimates, loan supply shocks account for about 20% of GDP movements at a 5-year horizon in the US. In our model, loan cost shocks explain 27% of GDP fluctuations at 5 years, which is broadly comparable. Gambetti and Musso also emphasize that loan supply shocks have been especially important during the Great Recession, but less so during the ensuing Slow Recovery. We show below that our structural model attributes an important role to loan cost shocks during both the Great Recession and the Slow Recovery.

Table 3: Variance decomposition

Variable	Shocks			
	TFP u^e	MEI u^i	Loan cost u^l	Shadow u^a
Consumption	9	11	24	2
Investment	5	36	32	10
Hours	31	4	3	5
Traditional loans	1	1	88	1
Shadow loans	1	2	4	74
Spread	3	2	56	0

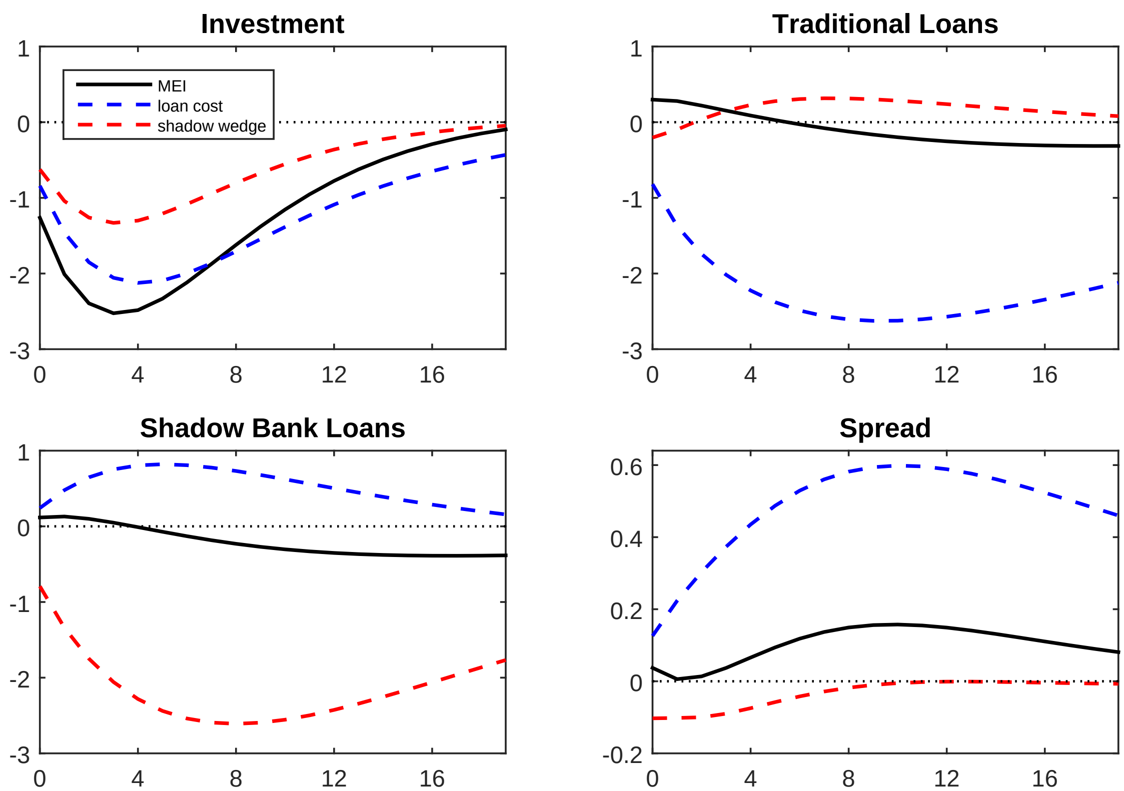
Notes. Statistics computed at the posterior mode. TFP (u^e) is the technology shock, MEI (u^i) is the investment efficiency shock, Loan cost (u^l) is the loan cost shock, and Shadow (u^a) is the shadow wedge. Results for the remaining shocks and variables are in Appendix C.

the loan cost shock largely explains bank credit and the spread on top of real variables, whereas the MEI shock has little effect on financial variables.

Second, shocks to financial intermediation by both traditional and shadow banks account for a substantial share of aggregate fluctuations. Together, the loan cost shock and the shadow wedge cause 26% of the movements in consumption and 42% of those in investment. This is largely due to the loan cost shock, as the shadow wedge is quite specialized into explaining shadow bank credit in the model. However, it still explains a non-negligible 10% of investment cycles. Overall, we conclude that our model embeds sufficient propagation to ensure the transmission of financial shocks to the real sphere.

Figure 1 provides further information about the dynamics triggered by the MEI, loan cost, and shadow wedge shocks in our model. To make comparison easier, we focus on shocks that all induce similarly negative responses of investment (and real activity more broadly), as shown in Panel (a). Panel (b) demonstrates that only the loan cost shock is able to generate positive comovement between investment and traditional bank credit, which is a strong feature of the data. In particular, the MEI shock triggers a counterfactual negative correlation between investment and loans during the first periods. Panel (c) shows that the shadow wedge shock generates positive comovement between investment and shadow bank loans, which is not the case for the MEI and loan cost shock. This is not surprising, as a rise in the cost of traditional bank loans is associated with a shift in intermediation toward shadow banks. Finally, Panel (d) reports the response of the lending-deposit spread. It makes clear that only the loan cost shock triggers significant countercyclical movements

Figure 1: Selected impulse response functions to the MEI, loan cost, and shadow wedge shocks



Notes. Deviations from steady states are expressed in percent for investment, traditional bank loans, and shadow bank loans, and in annualized percentage points for the spread. Computations realized at the posterior mode.

in the cost of borrowing. Overall, these responses suggest that our structural estimation exercise identifies a leading role for the loan cost shock because it is the only disturbance generating both procyclical bank credit and a countercyclical spread.

4 Accounting for the Great Recession and the Slow Recovery

This section characterizes the shocks explaining macroeconomic dynamics in the US during the Great Recession and the Slow Recovery through the lens of our estimated model. We proceed in three steps. First, we extend our dataset to include the period 2008Q1-2016Q4. Second, we apply the Kalman smoother to the model solution in order to recover from the data the sequence of shocks that began in 2008Q1 and drove the US economy from there on. Third, we construct counterfactual paths for investment and GDP by removing a single disturbance at a time in order to isolate the role of each shock. Gust et al. (2017) and Cuba-Borda (2018) follow very similar procedures. Throughout, we keep the parameter estimates obtained from the 1985-2007 sample.

One particular challenge related to the crisis period is the binding ZLB on nominal interest rates and the implementation of non-standard monetary policy measures, which both are difficult to handle within linearized DSGE models. Because the literature is divided about the empirical relevance and the best way to address these issues,[11] we opt for what we consider the most transparent approach and replace the Fed Funds rate after 2008 by the "shadow" interest rate estimated by Wu and Xia (2016). This alternative index of the monetary policy stance, equal to the Fed Funds rate in normal times and negative when the ZLB on the policy rate binds, has been shown empirically to capture well non-conventional measures. In our view, using the shadow rate conveniently avoids taking a stance about how to deal with the ZLB and/or to model non-standard measures. Moreover, Zhang and Wu (2017) demonstrate that the shadow rate can be mapped meaningfully into an equilibrium object in DSGE models.[12]

4.1 The paths of estimated shocks

We start our analysis by looking at the realization of the forcing processes during the crisis episode and its aftermath. Figure 2 reports the smoothed estimates of the TFP, MEI, loan cost, and shadow wedge shocks over the period 2007-2016. The series are normalized by their standard deviations, so that a value of 2 signals a shock two standard deviations above its mean. We focus on these shocks because they are the most important drivers of GDP and investment during the recession and the recovery according to our model.[13]

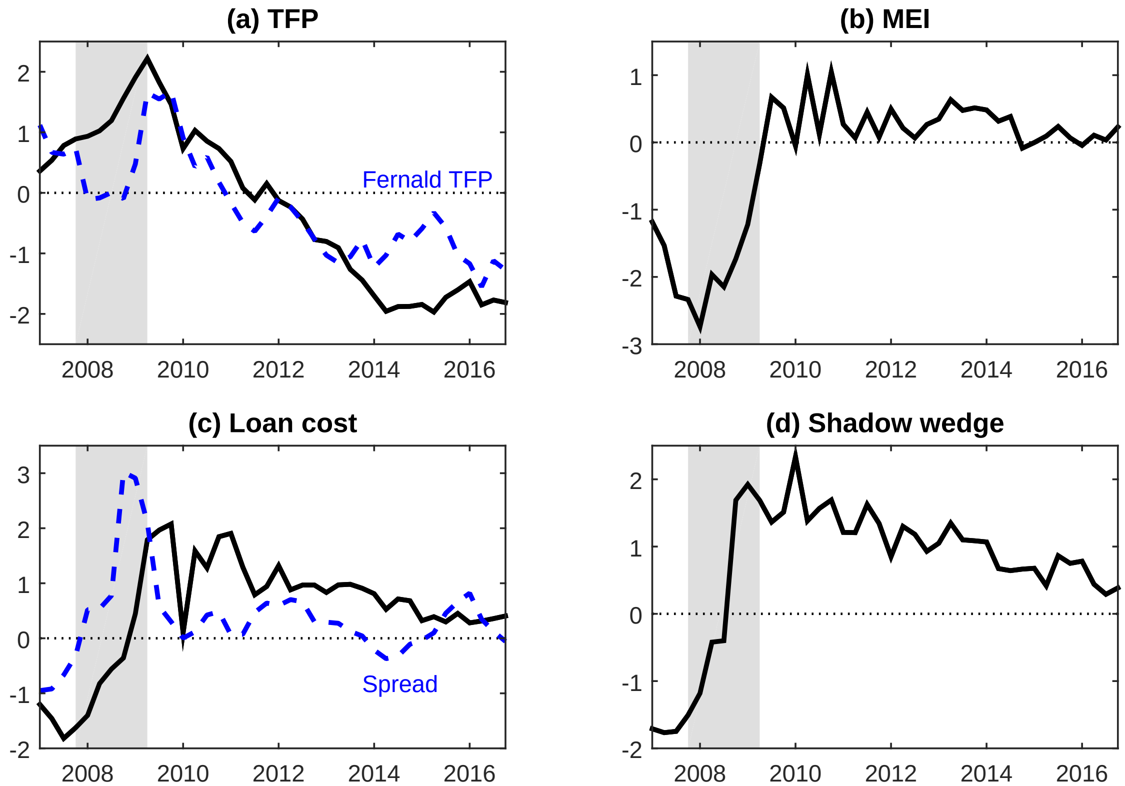
As shown in Panel (a), our estimates suggest that TFP was above its mean at the start of the recession and kept increasing until mid-2009. Then, it started a sustained fall that lasted until 2014. This pattern implies that technology shocks are unlikely to account much of the Great Recession, but might be important to understand the Slow Recovery. To assess the plausibility of these insights, the chart

[11]Some authors (see, e.g. Christiano et al., 2015; Lindé et al., 2016; Gust et al., 2017; Cuba-Borda, 2018) suggest that the ZLB on interest rates was a key feature of the crisis that modelers must take into account using non-linear methods. However, their framework abstracts from the effects of non-standard policy measures. Other authors ignore the ZLB altogether (Galí et al., 2012; Brzoza-Brzezina and Kolasa, 2013), or find that unconventional policy measures such as forward guidance and asset purchases allowed to bypass it (Debortoli et al., 2018).

[12]Nevertheless, we also verified that our conclusions hold when using the Fed Funds rate as the observable interest rate and ignoring the ZLB.

[13]We report the smoothed estimates of the other seven shocks in Appendix C, in which we also discuss their role during the Great Recession and the Slow Recovery.

Figure 2: Paths of estimated shocks



Notes. The figure shows the smoothed series (computed at the posterior mode) of the TFP shock $\ln \epsilon_t^e$, the MEI shock $\ln \epsilon_t^i$, the loan cost shock $\ln \epsilon_t^l$, and the shadow wedge $\ln \epsilon_t^a$, all normalized by their unconditional standard deviations. The shaded area corresponds to the NBER Great Recession dates. Signs are such that positive TFP and MEI shocks are expansionary, while positive loan cost and shadow wedge shocks are contractionary.
Panel (a) also includes the log deviation of Fernald's (2014) utilization-adjusted TFP series from its quadratic trend, while Panel (c) includes the credit spread measure used in estimation. Both series are rescaled for comparison purposes.

also displays the behavior of Fernald's (2014) utilization-adjusted TFP series, widely considered as the best available measure of aggregate technology.[14] It broadly confirms our findings: TFP was positive before the crisis, ended up higher in 2009 than at the onset of the recession, and began a persistent downward drift in 2010. Moreover, the correlation between our smoothed estimate and Fernald's TFP is as high as 0.83 between 2007 and 2016.

Our finding that technology did not sharply fall during the Great Recession contrasts with the conclusions of a number of papers, including Christiano et al. (2015) and Cuba-Borda (2018). These authors argue that negative TFP shocks are needed for DSGE models to explain the absence of

[14]With the obvious caveat that Fernald's TFP measure is constructed from a much broader output definition than the one we consider, which excludes inventories as well as net exports.

marked deflation during the crisis: these shocks trigger a rise in marginal costs, which counteract deflationary forces in the model. Financial shocks play the exact same role in our model, as they increase the costs of labor and capital and thus the marginal cost of production. Simultaneously, they are consistent with the behavior of the credit spread. We also note that Lindé et al. (2016) found positive TFP innovations during the recession when estimating a standard Smets-Wouters model.

Panel (b) reports the estimated path for the MEI shock. Our results indicate that investment efficiency was low before the crisis. It then increased steadily between 2008 and 2010, before stabilizing at positive values and supporting economic activity. Clearly, this behavior makes it difficult for the MEI shocks filtered by our model to explain the deep recession or the weak recovery. This finding differs sharply from the results obtained by Lindé et al. (2016), Gust et al. (2017), and Cuba-Borda (2018), who find that the Great Recession largely originated from negative MEI shocks. Again, we explain this difference by our explicit consideration of credit supply shocks. In these authors' framework, the MEI shock is a proxy for disturbances affecting financial intermediation (Justiniano et al., 2011), which is driven out in our model by the explicit loan cost and shadow wedge shocks.

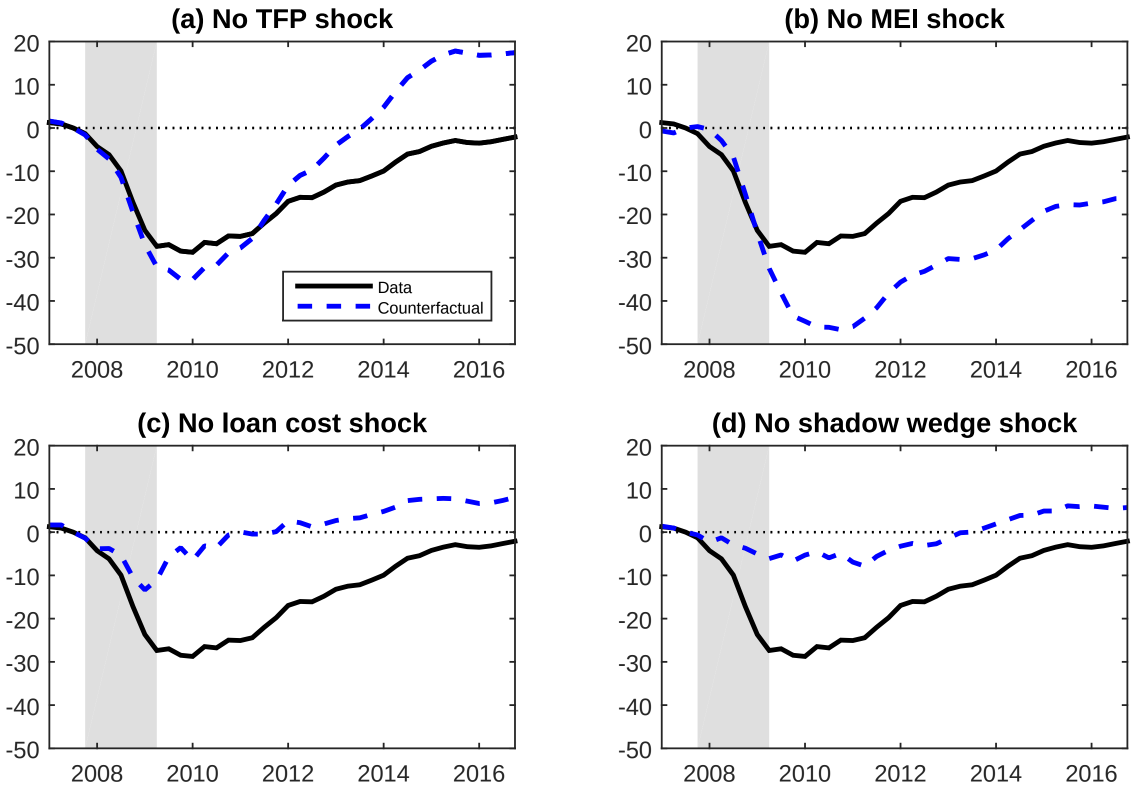
Indeed, Panels (c) and (d) signal that the loan cost shock and the shadow wedge have the potential to account for a substantial part of aggregate dynamics between 2007 and 2016. The marked rise in the cost of traditional loans and in the risk associated with shadow banks (in both cases, by about 4 standard deviations between 2008 and 2010) coincided with the Great Recession. It also mirrored the jump in credit spreads during the recession, shown in blue in the chart, confirming that our banking shocks drive out MEI shocks as the main sources of financial disturbances in crisis time. In addition, the very gradual normalization of the loan cost shock and the shadow wedge, which both remained largely positive between 2010 and 2016, coexisted with the Slow Recovery and suggests a causal effect. We corroborate this view in the next section.

4.2 Contributions to the Great Recession and Slow Recovery

Finally, we characterize the contributions of the shocks to the Great Recession and the Slow Recovery. Figures 3 and 4 compare the data and the counterfactual paths for investment and GDP obtained when shutting down the TFP, MEI, loan cost, and shadow wedge shocks one at a time. In each panel, the title indicates what shock is being shut down.

The main finding that emerges from Figure 3 is the overwhelming role of banking shocks, originating in both traditional and shadow banks, in the contraction of investment during the Great Recession and its subsequent protracted recovery. In particular, at the end of the recession in 2009Q2

Figure 3: Counterfactual paths – Investment

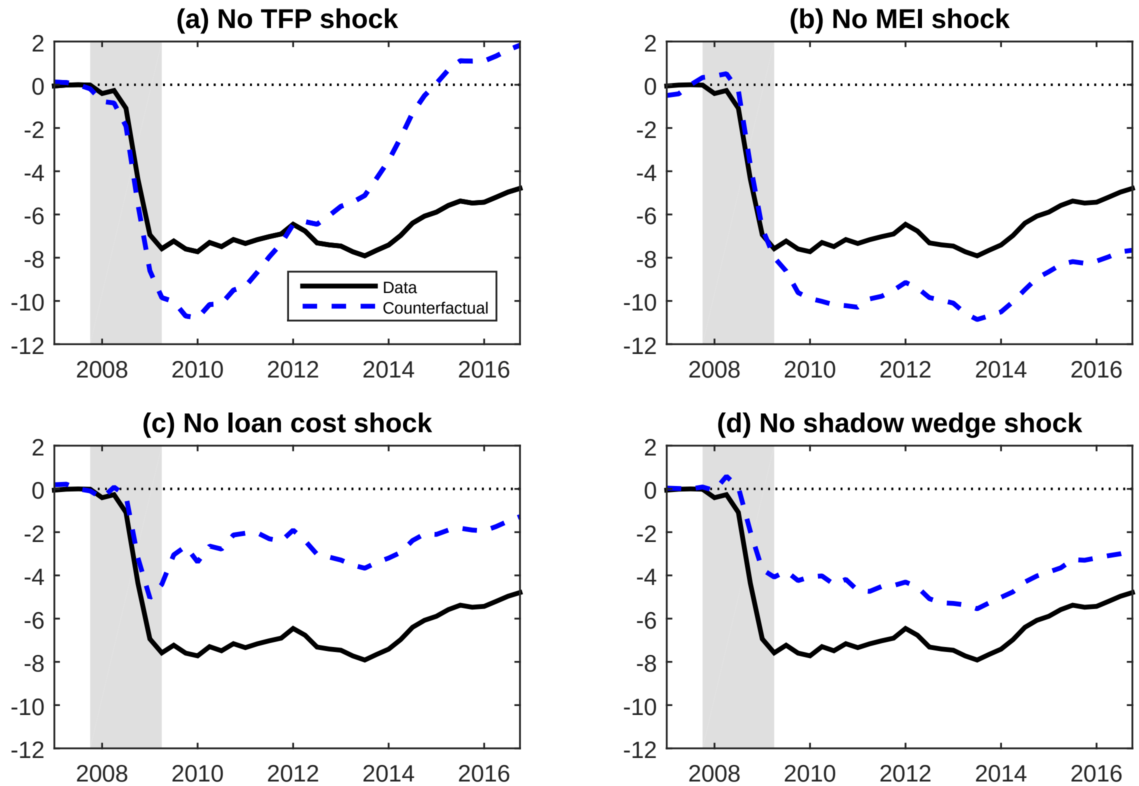


Notes. All series are detrended, normalized to zero in 2007Q3, and expressed in percent. The shaded area corresponds to the NBER Great Recession dates. The solid black line represents the data and the dashed blue line represents the counterfactual paths. A counterfactual path above (resp. below) the data means the shock has a negative (resp. positive) contribution.

investment would have been higher by about 15% absent loan cost shocks and by about 20% absent shadow wedge shocks. Moreover, the weak recovery is largely explained by the persistence of the banking shocks. Indeed, in 2016, seven years after the Great Recession ended, both loan cost and shadow wedge shocks still have a 10% negative effect on investment. The decomposition for GDP, reported in Figure 4, conveys a similar picture. Therefore, we confirm the insight derived from the paths of smoothed shocks that banking disturbances were key to both the Great Recession and the Slow Recovery.

Our results also suggest a narrative of the financial crisis that squares well with historical evidence. For instance, Mishkin (2011) identifies two successive phases within the US financial crisis. The first phase, between 2007Q2 and 2008Q2, was relatively mild as losses in subprime markets coexisted with weak GDP growth and forecasts of only a mild recession. The second phase was much more

Figure 4: Counterfactual paths – GDP



Notes. All series are detrended, normalized to zero in 2007Q3, and expressed in percent. The shaded area corresponds to the NBER Great Recession dates. The solid black line represents the data and the dashed blue line represents the counterfactual paths. A counterfactual path above (resp. below) the data means the shock has a negative (resp. positive) contribution.

virulent: starting in 2008Q3 with the simultaneous collapses of Lehman Brothers and AIG, it deepened the financial crisis and strengthened its transmission to the real economy. The decompositions reported in Figures 3 and 4 align well with this interpretation, as our model associates the start of the recession with negative shocks to shadow banking, whereas cost shocks affecting traditional banks play an important role only from 2008Q3 on.

Another important finding is that the contribution of MEI shocks was negligible during the Great Recession and strongly positive during the Slow Recovery, as can be seen from Panel (b) in Figures 3 and 4. This result corroborates that, in our model, the MEI shock is driven out by the two banking shocks. In our view, this eviction signals that our model successfully identifies financial disturbances from non-financial shocks to investment efficiency, and attributes a key role only to the former. Our ability to disentangle these shocks explain why our conclusions differ from those reported in the literature, based on models in which the MEI shock is a catch-all disturbance capturing both financial and non-financial forces.

Finally, Panel (a) in Figures 3 and 4 demonstrates that TFP shocks played little role during the Great Recession but explain an important and increasing share of the Slow Recovery after 2011. This finding is consistent with the view that real GDP experienced a permanent level shift during the crisis (see, e.g., Guerron-Quintana and Jinnai, Forthcoming, and the references therein), which can only be rationalized in DSGE models by a persistent technological regression.

5 Conclusion

In this paper, we argue that shocks to retail and shadow banks were key to understand the behavior of the US economy during the Great Recession and the Slow Recovery. We base this conclusion on an estimated DSGE model featuring a rich representation of credit flows. Our model selects the two banking shocks as the most important drivers of the crisis because they account simultaneously for the fall in real activity, the decline in credit intermediation, and the rise in lending-borrowing spreads. On the other hand, our results assign only a moderate role to TFP or MEI shocks, confirming the leading role of financial factors in the crisis and its aftermath.

One important question that has been debated recently is, what type of policy intervention would have prevented the boom-bust cycle associated with the Great Recession? Addressing this question in a quantitative fashion requires a framework able to account for the key asymmetries between traditional and shadow banks, in terms of regulation, frictions, and shocks altogether. We believe that our model meets these requirements and constitutes an attractive environment to study macroprudential policy in presence of shadow banks. We plan to explore this topic in future research.

References

Basel Committee on Banking Supervision (2009). Report of Special Purpose Entities. September.

Bernanke, B. (2013). Monitoring the Financial System. Speech at the 49th Annual Conference on Bank Structure and Competition, Federal Reserve Bank of Chicago.

Bocola, L., M. Hagedorn, and I. Manovskii (2014). Identifying Neutral Technology Shocks. Mimeo.

Brzoza-Brzezina, M. and M. Kolasa (2013). Bayesian Evaluation of DSGE Models with Financial Frictions. *Journal of Money, Credit and Banking 45*(8), 1451–1476.

Christiano, L., M. Eichenbaum, and C. Evans (2005). Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy. *Journal of Political Economy 113*(1), 1–45.

Christiano, L. J., M. S. Eichenbaum, and M. Trabandt (2015). Understanding the Great Recession. *American Economic Journal: Macroeconomics 7*(1), 110–167.

Christiano, L. J., M. S. Eichenbaum, and M. Trabandt (2018). On DSGE Models. *Journal of Economic Perspectives 32*(3), 113–140.

Christiano, L. J., R. Motto, and M. Rostagno (2014). Risk Shocks. *American Economic Review 104*(1), 27–65.

Corsetti, G., K. Kuester, A. Meier, and G. Mueller (2013). Sovereign Risk, Fiscal Policy, and Macroeconomic Stability. *The Economic Journal 123*, F99–F132.

Cuba-Borda, P. (2018). What Explains the Great Recession and Slow Recovery? Mimeo, Federal Reserve Board.

Debortoli, D., J. Galí, and L. Gambetti (2018). On the Empirical (Ir)Relevance of the Zero Lower Bound Constraint. Mimeo, Barcelona Graduate School of Economics.

Enders, Z., R. Kollmann, and G. Muller (2011). Global Banking and International Business Cycles. *European Economic Review 55*, 407–426.

Fernald, J. G. (2014). A Quarterly, Utilization-Adjusted Series on Total Factor Productivity. Working Paper Series 2012-19, Federal Reserve Bank of San Francisco.

Fève, P., A. Moura, and O. Pierrard (2017). Financial Regulation and Shadow Banking: A Small-Scale DSGE Perspective. TSE Working Papers 17-829, Toulouse School of Economics (TSE).

Galí, J., F. Smets, and R. Wouters (2012). Slow Recoveries: A Structural Interpretation. *Journal of Money, Credit and Banking 44*, 9–30.

Gambetti, L. and A. Musso (2017). Loan Supply Shocks and the Business Cycle. *Journal of Applied Econometrics 32*(4), 764–782.

Gerali, A., S. Neri, L. Sessa, and F. M. Signoretti (2010). Credit and Banking in a DSGE Model of the Euro Area. *Journal of Money, Credit and Banking 42*(s1), 107–141.

Gertler, M., N. Kiyotaki, and A. Prestipino (2016). Wholesale Banking and Bank Runs in Macroeconomic Modeling of Financial Crises. In J. Taylor and H. Uhlig (Eds.), *Handbook of Macroeconomics*, Volume 2, Chapter 16, pp. 1345–1425. Elsevier.

Guerron-Quintana, P. A. and R. Jinnai (Forthcoming). Financial Frictions, Trends, and the Great Recession. *Quantitative Economics*.

Gust, C., E. Herbst, D. López-Salido, and M. E. Smith (2017). The Empirical Implications of the Interest-Rate Lower Bound. *American Economic Review 107*(7), 1971–2006.

Iacoviello, M. (2015). Financial Business Cycles. *Review of Economic Dynamics 18*(1), 140–164.

Justiniano, A., G. Primiceri, and A. Tambalotti (2011). Investment Shocks and the Relative Price of Investment. *Review of Economic Dynamics 14*(1), 101–121.

Kollmann, R. (2013). Global Banks, Financial Shocks, and International Business Cycles: Evidence from an Estimated Model. *Journal of Money, Credit and Banking 55*(2), 159–195.

Lindé, J., F. Smets, and R. Wouters (2016). Challenges for Central Banks' Macro Models. In J. Taylor and H. Uhlig (Eds.), *Handbook of Macroeconomics*, Volume 2, Chapter 28, pp. 2185–2262. Elsevier.

Meeks, R., B. Nelson, and P. Alessandri (2017). Shadow Banks and Macroeconomic Instability. *Journal of Money, Credit and Banking 49*(7), 1483–1516.

Mishkin, F. S. (2011, Winter). Over the Cliff: From the Subprime to the Global Financial Crisis. *Journal of Economic Perspectives 25*(1), 49–70.

Moura, A. (2018). Investment Shocks, Sticky Prices, and the Endogenous Relative Price of Investment. *Review of Economic Dynamics 27*, 48–63.

Rotemberg, J. (1982). Sticky Prices in the United States. *Journal of Political Economy 90*(6), 1187–1211.

Smets, F. and R. Wouters (2007). Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach. *American Economic Review 97*(3), 586–606.

Verona, F., M. Martins, and I. Drumond (2013). (Un)anticipated Monetary Policy in a DSGE Model with a Shadow Banking System. *International Journal of Central Banking 9*(3), 73–117.

Wu, J. C. and F. D. Xia (2016). Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound. *Journal of Money, Credit and Banking 48*(2-3), 253–291.

Zhang, J. and J. C. Wu (2017). A Shadow Rate New Keynesian Model. 2017 Meeting Papers 11, Society for Economic Dynamics.

Appendix

A Micro-founding the shadow wedge

This appendix provides some micro-foundation for the shadow wedge introduced in Section 2.2.1 to capture the risk associated with shadow banking intermediation.

Consider modifying our model along two dimensions. First, assume that existing shadow banks default on an exogenous and random fraction $1-\epsilon_t^a$ of their ABS in each period, so that they effectively repay a fraction ϵ_t^a of their debt. Second, assume that shadow banks must pay a transfer T_{t+1}^s in the second period of their life. This transfer is rebated lump sum to traditional banks.

In this alternative setup, free entry in shadow banking implies the following expected zero-profit condition:

$$E_t\Lambda_{t,t+1}\left[\left(r_{t+1}^{ks}+[1-\delta]Q_{t+1}\right)S_t-\epsilon_{t+1}^a(1+r_t^a)ABS_t-T_{t+1}^s\right]=0.$$

The traditional bank's profit function becomes

$$\begin{aligned}\left[r_t^{kl}+(1-\delta)Q_t\right]L_{t-1}-Q_tL_t+\epsilon_t^a(1+r_{t-1}^a)ABS_{t-1}-ABS_t+r_t^wL_{w,t}+D_t-(1+r_{t-1}^d)D_{t-1}+T_t^s\\ -\epsilon_t^x\mathcal{C}(X_t)-\epsilon_t^l(\gamma_b+\Phi_{L,t})Q_tL_t-(\gamma_b+\Phi_{N,t})N_t-(\gamma_b+\Phi_{A,t})ABS_t.\end{aligned}$$

Assume now that the lump-sum transfer exactly compensates the loss incurred by the traditional bank because of the partial default on ABS, so that

$$T_t^s=(1-\epsilon_t^a)(1+r_{t-1}^a)ABS_{t-1}.$$

In that case, the alternative setup with partial default in shadow banking is strictly equivalent to the model presented in Section 2. Therefore, it is possible to microfound the shadow wedge ϵ_t^a as a default ("risk") shock originating in shadow banking and compensated with a lump-sum transfer. Corsetti et al. (2013) use a similar specification in a model of sovereign default.

B Data

This appendix describes the sources and the construction of the observables used in estimation.

Consumption. Consumption expenditures on nondurable goods and services (BEA, NIPA Table 1.1.5, lines 5 and 6).

Investment. Sum of consumption expenditures on durable goods and fixed investment (BEA, NIPA Table 1.1.5, lines 4 and 8).

Government spending. Government consumption expenditures and gross investment (BEA, NIPA Table 1.1.5, line 22).

Hours worked. Hours of all persons in the nonfarm business sector (BLS, available as series HOANBS in FRED).

Inflation. Rate of change in the GDP deflator (BEA, NIPA Table 1.1.4, line 1).

Wage inflation. Rate of change in the compensation per hour in the nonfarm business sector (BLS, available as series COMPNFB in FRED).

Interest rate. Effective Federal Funds rate, expressed in quarterly terms (series FEDFUNDS in FRED). In our analysis of the Great Recession and Slow Recovery, we use instead the shadow interest rate estimated by Wu and Xia (2016) to avoid issues related with the ZLB.

Traditional credit. Asset positions in corporate bonds, depository institution loans, other loans, mortgages, and consumer credit of private depository institutions (Z1 release, Table L110, sum of lines 10, 12, 13, 14, and 15).

Shadow credit. Asset positions in corporate bonds, depository institution loans, other loans, mortgages, and consumer credit of government-sponsored enterprises, GSE mortgage pools, issuers of ABS, finance companies, real estate investment trusts, security brokers and dealers, holding companies, and funding corporations (Z1 release, sum of Table L125 lines 10 and 11, Table L126 line 1, Table L127 line 5, Table L128 lines 4 and 5, Table L129 lines 4 and 6, Table L130 lines 9 and 10, Table L131 lines 7 and 8, and Table L132 lines 6 and 7).

Leverage. Computed as $\text{Credit}/(\text{Assets} - \text{Liabilities})$ using series for US commercial banks (series TLAACBW027SBOG, TLBACBM027SBOG, and TOTLL in FRED).

Credit spread. Moody's seasoned Baa corporate bond yield relative to the yield on 10-year treasury bonds, expressed in quarterly terms (series BAA10YM in FRED).

We seasonally adjust all series extracted from the Financial Accounts Z1 release using the X-12 algorithm implemented in IRIS. We deflate all nominal series by the GDP deflator (BEA, NIPA Table 1.1.4, line 1) to obtain quantity series, which we express in per-capita terms using the population series from the BEA (NIPA, Table 2.1, line 40).

C The role of other shocks (NOT FOR PUBLICATION)

To save on space, in the body of the paper our discussion focused on a few important shocks, namely the TFP, MEI, loan cost, and shadow wedge shocks. In this appendix, we provide the results for the other seven shocks of the model, namely the government spending, price markup, wage markup, monetary policy, credit demand, deposit preference, and bank capital shocks. We report their unconditional contributions to the variance of our observables, as well as to the path of investment during and after the financial crisis. Our main message is that none of these shocks can explain the Great Recession nor the Slow Recovery.

Table 4 shows the contributions of the shocks to the variance of our observables. For completeness, we report the results for all shocks but we only discuss here those ignored in the paper. It is clear that some shocks are very specialized in explaining one variables, with little effects on the others. This is the case of the government spending shock, the two markup shocks, and the bank capital shock. The monetary policy shock explains about 10% of movements in hours worked and in the credit spread. Finally, the shocks to credit demand and to deposit preferences have more important effects, as they account for approximately 20% of fluctuations in consumption, hours, and inflation. However, both have little impact on investment and are thus unlikely candidates to explain the

Table 4: Variance decomposition

Variable	Shocks										
	u^e	u^i	u^l	u^a	u^g	u^p	u^w	u^r	u^χ	u^d	u^x
Consumption	9	11	24	2	4	2	1	6	18	23	0
Investment	5	36	32	10	0	2	1	5	6	3	0
Government spending	0	0	0	0	100	0	0	0	0	0	0
Hours	31	4	3	5	1	5	2	13	21	15	0
Price inflation	15	4	9	1	0	19	2	4	22	22	0
Wage inflation	4	2	3	1	0	1	65	6	5	14	0
Policy rate	8	3	6	2	0	3	1	10	19	48	0
Traditional loans	1	1	88	1	0	1	0	1	3	4	0
Shadow loans	1	2	4	74	0	0	0	0	6	12	0
Bank leverage	0	0	0	0	0	0	0	0	0	13	87
Spread	3	2	56	0	0	3	1	10	20	4	0

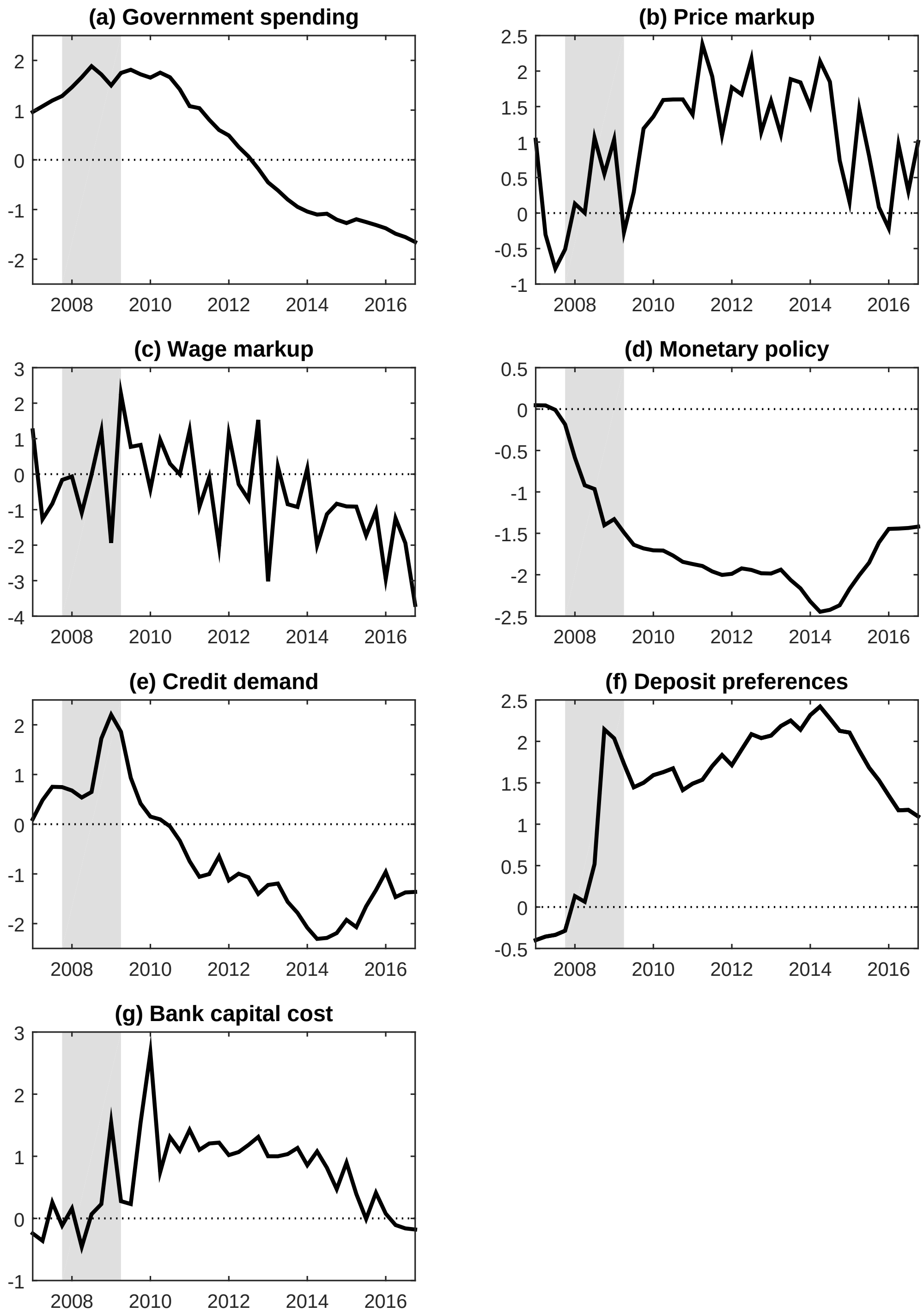
Notes. Statistics computed at the posterior mode. u^e is the TFP shock, u^i is the MEI shock, u^l is the loan cost shock, u^a is the shadow wedge shock, u^g is the government spending shock, u^p is the price markup shock, u^w is the wage markup shock, u^r is the monetary policy shock, u^χ is the credit demand shock, u^d is the deposit preference shock, and u^x is the bank excess capital shock.

Great Recession.

Figure 5 displays the smoothed estimates of the shocks over the period 2007-2016. As in the body of the paper, the series are normalized by their standard deviations. We note that fiscal policy was supportive during the Great Recession, as government spending increased between 2007 and 2009. On the other hand, it decreased significantly during the ensuing recovery period. Price and wage markups exhibit no clear behavior during the recession, even though the sustained rise in the price markup during the Slow Recovery may have penalized aggregate demand. The shadow rate captures the expansionary nature of the non-standard measures implemented during the crisis and suggests that monetary policy remained very accomodative over the Slow Recovery. We also observe a marked rise in credit demand and deposit preference during the recession, but we show below that these movements do not account for much of the crisis. Finally, the cost of bank capital experienced important spikes in 2009 and 2010, when US banks issued significant amounts of additional equity.

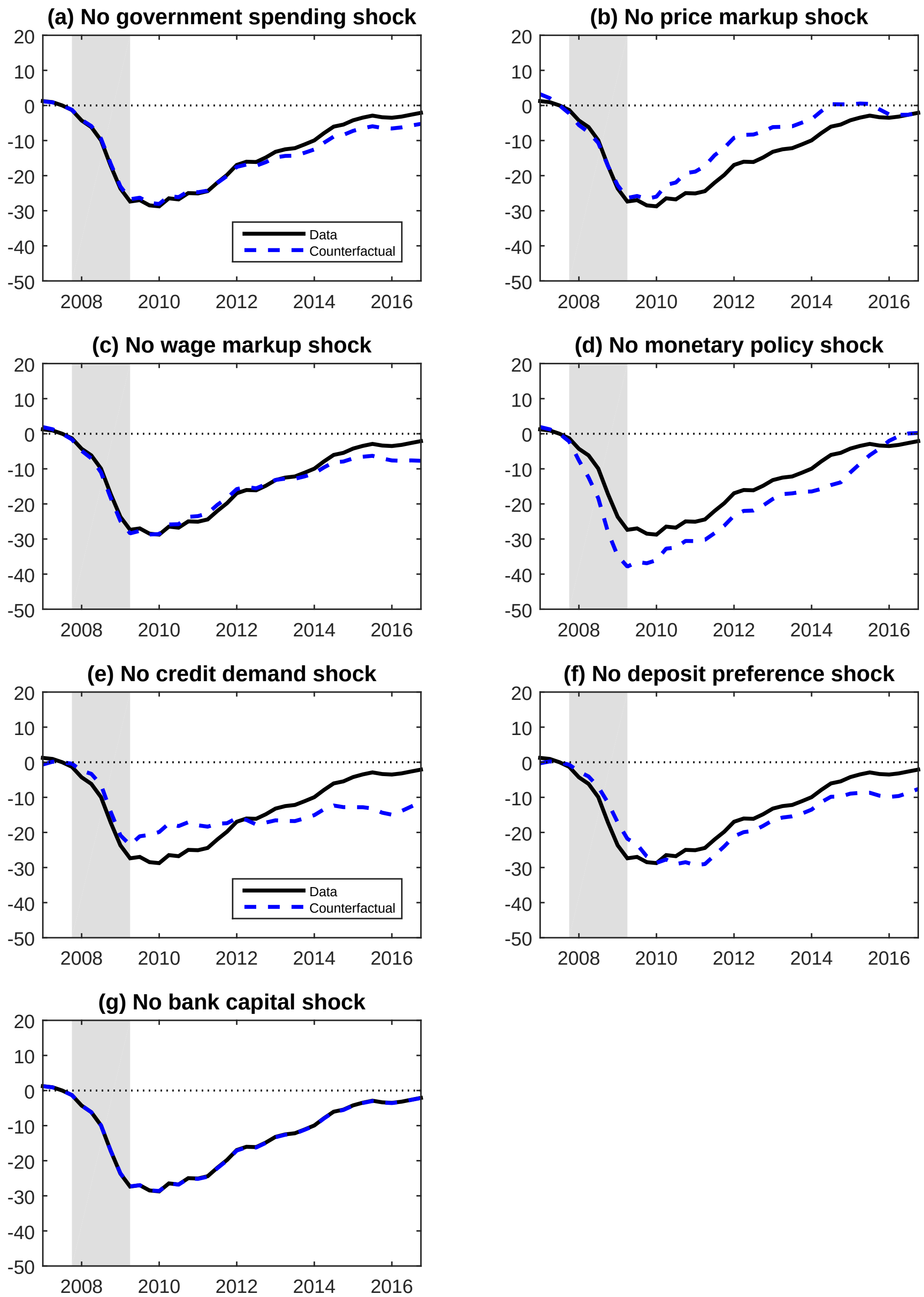
Figure 6 compares the data and the counterfactual path for investment obtained when shutting down the shocks one at a time. We focus on investment because a shock has to be able to account for an important part of its dynamics to be a credible explanation of the Great Recession and the Slow Recovery. The charts make it clear that none of these shocks had a noticeable effect on investment during the recession, with the exception of the monetary policy shock which strongly supported activity. This justifies our choice to exclude these shocks from our main discussion in the paper. For the Slow Recovery, the picture is less clear-cut. For instance, the price markup shock, probably proxying for weak demand conditions, had a negative 10% impact on investment between 2011 and 2015. Still, this contribution remains much lower than those from the loan cost and shadow wedge shocks.

Figure 5: Paths of estimated shocks



Notes. The figure shows the smoothed series (computed at the posterior mode) of the government spending shock $\ln(G_t/\overline{G})$, price markup shock $\ln(\lambda_{p,t}/\overline{\lambda}_p)$, wage markup shock $\ln(\lambda_{w,t}/\overline{\lambda}_w)$, monetary policy shock $\ln(R_t/\overline{R})$, credit demand shock $\ln(\epsilon_t^X)$, deposit preference shock $\ln(\epsilon_t^d/\overline{\epsilon}^d)$, and excess bank capital shock $\ln \epsilon_t^x$, all normalized by their unconditional standard deviations. The shaded area corresponds to the NBER Great Recession dates.

Figure 6: Counterfactual paths – Investment



Notes. All series are detrended, normalized to zero in 2007Q3, and expressed in percent. The shaded area corresponds to the NBER Great Recession dates. The solid black line represents the data and the dashed blue line represents the counterfactual paths. A counterfactual path above (resp. below) the data means the shock has a negative (resp. positive) contribution.