Abstract

We investigate the impact of changes in lending conditions by banks on economic fluctuations. Using US financial and macroeconomic data we estimate a dynamic stochastic general equilibrium model where a banking sector extends loans to households and businesses. We find that fluctuations in collateral requirements, or collateral shocks, are the most important force driving the business cycle. In particular, our model quantitatively reproduces the joint dynamics of output, consumption, investment, employment, and household and business debt with this unique disturbance. The estimated collateral shock turns out to track actual measures of bank lending standards and generates empirically accurate default rates and interest rate spreads for both households and businesses.


\textit{Key Words}: business cycles, comovements, bank lending, household debt.
1 Introduction

Business cycles in the United States are characterized by the positive comovement among output, consumption, investment, and employment. To understand what drives these comovements, a strand of the literature develops and estimates quantitative dynamic stochastic general equilibrium (DSGE) models where a number of candidate exogenous forces compete to generate responses that mimic actual business cycles. In particular, in the aftermath of the 2008 recession, a number of influential papers have come to the conclusion that financial shocks, and more broadly financial factors, play a key role in driving economic fluctuations. These findings are important because they are consistent with other strands of the empirical literature, and can ultimately help understand how the economy functions.

But despite the recent progress, none of these studies proposes a single shock that generates the comovements observed in the data. Typically in these papers, the main impulse (whether it is a financial shock or a real shock amplified by financial frictions) drives a large share of the variance in output, investment, and hours worked, but has very small impact on the dynamics of consumption. Because consumption is procyclical in the data, these papers must resort to a distinct source, generally a preference shock, to explain the movements in consumption. This is not satisfactory because to fit the data, the financial shock and the preference shock need to be correlated, which is at odds with their structural exogenous nature.

In this paper, we identify a single disturbance that produces the comovements in all four aggregate variables, including consumption. We argue the source of this disturbance is bank lending. Although the idea is not new, we think two key aspects of bank lending have been overlooked by the DSGE literature. The first one is that the lion’s share of bank lending goes to households, not firms. Figure 1 illustrates this point clearly. Yet the majority of papers with financial frictions have instead focused on bank lending to firms. So while business credit is indeed important to explain the dynamics of investment, we believe household credit is similarly important to explain the dynamics of consumption.

The second key aspect of bank lending is the following. When banks tighten or loosen their lending standards, they do so for both types of borrowers—households and firms alike. This can be seen in Figure 2, which plots two measures of lending standards—one for consumer loans and the other for business

---


3 A few papers do study bank lending to households, but they either abstract from lending to firms or they overlook the common bank lending component that affects households and firms simultaneously. See Iacoviello (2005, 2015), Gerali et al. (2010), Clerc et al. (2015), and Justiniano, Primiceri, and Tambalotti (2015).
loans. The two series exhibit largely the same pattern. Right before the 2001 recession, standards tightened, especially for firms. They subsequently eased and from 2004 to 2007 banks were relaxing standards quarter after quarter (values are negative). Again, prior to the Great Recession, banks abruptly increased lending requirements on both households and firms.

Motivated by this preliminary evidence, we develop a macroeconomic model with two main ingredients: i) banks lend to households and firms, and ii) banks adjust their lending requirements simultaneously on both types of loans. More precisely, our core framework is the medium-scale DSGE model of Christiano, Motto, and Rostagno (2014)—hereafter CMR. We augment this model by introducing heterogeneity among households. Following Iacoviello (2005), households are either “patient”, meaning they are net savers in equilibrium, or “impatient”, in which case they are net borrowers. We also add a banking sector subject to capital requirements imposed by the macroprudential regulator, as in Jakab and Kuhnhof (2015). Banks collect deposits from patient households and combine these funds with their own net worth to extend secured loans to impatient households and entrepreneurs. Entrepreneurs use the loans to purchase raw capital and rent
it as effective capital to productive firms. Impatient households use the loans to purchase housing and consume.

Banks impose fluctuating collateral requirements on their borrowers: we define the exogenous tightening or loosening of these requirements as the collateral shock $\nu_t$. More specifically, $\nu_t$ corresponds to the fraction of assets impatient households and entrepreneurs can pledge as collateral in the debt contract. In case of default, this fraction is seized by the bank. The collateral shock is meant to capture a broad set of developments in the financial sector. For instance, in the boom years preceding the last financial crisis, securitization enabled banks to demand lower downpayments. This is captured as a positive collateral shock. Conversely, the sudden downgrading of securities used as collateral led banks to require higher haircuts. This is captured as a negative collateral shock.

We ask whether a collateral shock, i.e. a change in bank lending standards, can generate dynamics that resemble US business cycles. The answer is yes. Using financial and macroeconomic data, we estimate our model with Bayesian techniques, and find that the collateral shock is the main driver of economic fluctuation.

Figure 2: Bank Tightening

Notes: The solid line corresponds to the net percentage of domestic banks tightening standards for consumer loans (excluding credit card loans). The dashed line is the net percentage of domestic banks increasing collateral requirements for commercial and industrial loans to large and middle-market firms. Both series come from the Senior Loan Officer Opinion Survey on Bank Lending Practices conducted by the Federal Reserve.
ons over the past three decades. In particular, the collateral shock accounts for the bulk of the variance in output, consumption, investment, employment, household credit, and business credit. To the best of our knowledge, our paper is the first to put forward a shock that explains the movements in all four main macroeconomic variables as well as in two financial series.\footnote{A recent paper by Angeletos, Collard, and Dellas (2016) argues that agents’ heterogeneous beliefs about their trading partners’ future productivity can generate dynamics that resemble business cycles. Their confidence shock is able to explain a large share of the movements in the main macroeconomic variables, but is silent on financial variables, as the authors abstract from financial frictions.}

The reason why our collateral shock is able to drive consumption as well as the other macro variables is the following. Imagine banks lose confidence and decide to restrict collateral requirements (a negative collateral shock). They do so regardless of the type of borrowers. As a result, both impatient households and entrepreneurs are allocated fewer loans. On the one hand, this limits entrepreneurs’ ability to purchase capital, which causes investment to fall, thus generating a drop in output and employment. On the other hand, impatient households are forced to cut back on their goods and housing purchases, causing aggregate consumption to fall, and further reducing output. The relatively small initial effect of the shock is amplified by two financial accelerators present in the model. The first one is well known. Less demand for capital means capital prices fall, which further limits the ability of entrepreneurs to borrow, and thus provokes an even larger fall in investment. The second financial accelerator is peculiar to our model. Less demand for housing means housing prices fall, which further limits the ability of impatient households to borrow, and thus provokes an even greater fall in consumption.

To test the importance of the lending channel between banks and households, we shut it down, by setting the share of impatient households to zero, and we re-estimate our model. We find the collateral shock has a much lower impact on consumption. To test the importance of the collateral shock, we remove it and re-estimate our model. We find the risk shock of CMR, a disruption to credit conditions of entrepreneurs only, takes over and becomes the main driving force. This is not surprising because the collateral shock and the risk shock are similar in many respects. However, while the risk shock drives a large share of the variance in output, investment, and hours, it does not explain consumption much.\footnote{These results are very close to those of CMR.} These two tests confirm that the presence of both the channel and the shock are key to our results.

We also perform three out-of-sample exercises. First, we plot the estimated collateral shock process against the series of bank lending standards presented in Figure 2. The two match well, thus providing a real-world counterpart to our theoretical object. Second, we compare default rates implied by the model with actual delinquency rates of households and firms. The correlation is high: our single disturbance is able to generate realistically different patterns for households and firms. Third, we look at cyclical properties of household, firm, and bank leverage. Again, our model does a good job at matching the data for each of the three agents, even though we don’t include leverage in the observable variables.
These three exercises strengthen the case of the collateral shock.

Lastly, we conduct a small counterfactual experiment. We consider a hypothetical world with stronger macroprudential rules, in the spirit of Basel III regulation. Specifically, we assume that higher capital requirements and a higher penalty for not complying with the rule were put in place in the first quarter of 2000, instead of after the financial crisis. We simulate the model with our sequence of estimated shocks and this stricter regulation and we find that the business cycle would have been tamed. Importantly, per capita GDP as of 2015 would have been two percent higher than it actually was.

Our paper contributes to the literature that estimates DSGE models with Bayesian methods to understand the sources of business cycles. Justiniano, Primiceri, and Tambalotti (2010, 2011) demonstrate that shocks to the marginal efficiency of investment (MEI) can explain a large chunk of the business cycle, except for consumption. Their findings suggest that financial factors might be at play, even though their model features no financial frictions. CMR show that once they add a financial accelerator to this setup and estimate it using financial series, the importance of the MEI shock nearly vanishes. Instead, shocks to the dispersion of entrepreneurs’ productivity, or risk shocks, become the main driver of economic fluctuations. But as we emphasize above, the risk shock is not able to account for the movements in consumption. We build on their approach and complement it by introducing bank lending to households. Our collateral shock is very similar to CMR’s risk shock on the entrepreneurial side, but it differs on the household side, which allows us to match consumption. The collateral shock fits the narrative of the recent crisis, which saw a contraction in both types of credit, due in part to credit tightening by ailing banks.

Our work is also related to two recent and growing lines of research. First, the “credit supply view” argues that an increase in the credit supply by banks, often unrelated to fundamental improvements in productivity or income, is the cause of debt booms. We interpret our collateral shock as a credit supply shock because it hits households’ and firms’ credit conditions simultaneously and must therefore come from their common interlocutor, the banks. Second, several studies provide empirical support for the direct causal link between household credit and household consumption that our model displays. Using micro data, Mian and Sufi (2011) show that homeowners borrow a vast amount of debt through refinancing and home equity loan as their house appreciates; a large fraction of this home-equity borrowing is used for consumption or home improvement. Furthermore, Mian, Rao, and Sufi (2013) find that the poorest and most credit-constrained hou-

---

6Smets and Wouters (2003, 2007) show that DSGE models compete well against less restricted VAR models, and this makes them attractive for researchers and policy makers. Other references include Schorfheide (2000), An and Schorfheide (2007), and Gilchrist, Ortiz, and Zakrajšek (2009).

7Jermann and Quadrini (2012) estimate a model where firms raise intra-period loans to finance working capital. They find that the tightening of the enforcement constraint by lenders, the so-called financial shocks, are the most important factor driving US business cycles—excluding consumption. However, Pfeifer (2016) disputes their result and argues that a more reliable estimation reproduces the findings of Justiniano, Primiceri, and Tambalotti (2010).

seholds reduce consumption by the largest amount in bad times.

The rest of the article is organized as follows. The next section presents the model. Section 3 discusses the data and the calibration and estimation of the parameters. In section 4 we analyze the collateral shock and discuss why it is so important. Section 5 offers out-of-sample evidence that supports our model and the collateral shock. Section 6 proposes a simple macroprudential application. We conclude in section 7.

2 The Model

We extend the CMR model in two directions. First and most importantly, we introduce a type of borrowing households along with the usual type of saving households. Following Iacoviello (2005) we call them impatient and patient, respectively. Second, we incorporate a banking sector subject to capital requirements. This regulatory friction is not crucial to our main results but we use it to study macroprudential policy. Subsection 1 outlines the real sector of the economy. Its core includes a standard monetary model of the business cycle, as in Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007), augmented with the Bernanke, Gertler, and Gilchrist (1999) financial accelerator. Subsection 2 describes the banking sector, which is based on Jakab and Kumhof (2015). In subsection 3, we discuss monetary policy, the government, the resource constraint, adjustment costs, and the exogenous processes. We try to keep the presentation brief. A full derivation of the model can be found in the technical appendix. We find it useful to draw an overview of the model, in Figure 3. The key agents are the two types of households, banks, and entrepreneurs.
2.1 Real Sector

**Final Good Producers** Perfectly competitive final good firms produce the final consumption good $Y_t$ combining a continuum of intermediate goods $Y_{j,t}$ according to the following Dixit-Stiglitz technology

$$Y_t = \left[ \int_0^1 Y_{j,t} \frac{1}{\lambda} dj \right]^{\lambda f,t},$$

where $\lambda f,t \geq 1$ is an exogenous price markup shock.

**Intermediate Good Producers** A monopolist produces the intermediate good $j$ according to the production function

$$Y_{j,t} = \max \left\{ \varepsilon_t(u_t K_{j,t-1})^\alpha (z_t l_{j,t})^{1-\alpha} - \Phi z^*_t; 0 \right\},$$

where $0 < \alpha < 1$, $K_{j,t-1}$ represents capital services, $l_{j,t}$ is a homogeneous labor input, $u_t$ is the utilization rate of capital, and $\varepsilon_t$ is a covariance stationary technology shock. There are two sources of growth in the model. The first one is $z_t$, a shock to the growth rate of technology. The second one is an investment-specific shock $\mu_{t-1}$ that changes the rate at which final goods are converted into investment goods, with $\mu > 0$. As in CMR, the fixed cost $\Phi$ is proportional to $z^*_t$, which combines the two trends

$$z^*_t = z_t \Upsilon \left( \frac{\alpha}{1-\alpha} \right)^t.$$

The intermediate good producer faces standard Calvo frictions. Every period, a fraction $1 - \xi_p$ of intermediate firms set their price $P_{j,t}$ optimally. The remaining fraction follows an indexation rule

$$P_{j,t} = (\pi_t^*)^{1-i} (\pi_{t-1})^{1-i} P_{j,t-1},$$

where $0 < i < 1$, $\pi_{t-1} = P_{t-1}/P_{t-2}$ is actual inflation, $P_t$ is the price of the final good $Y_t$, and $\pi_t^*$ is the central bank’s target inflation rate, which is a shock.

**Labor Contractors** Perfectly competitive labor contractors combine specialized labor services from patient households $l_{i,t}^p$ and impatient households $l_{i,t}^i$ into homogeneous labor $l_t^p$ and $l_t^i$, respectively, using the following technology

$$l_t^p = \left[ \int_0^1 (l_{i,t}^p) \frac{1}{\lambda} di \right]^{\lambda_p}; \quad l_t^i = \left[ \int_0^1 (l_{i,t}^i) \frac{1}{\lambda} di \right]^{\lambda_i},$$

where $\lambda_w \geq 1$ is a wage markup.

**Monopoly Unions** Unions represent patient workers by type $i$ and set their wage rate $W_{i,t}^p$. They do the same for impatient workers and their wage $W_{i,t}^i$. They are subject to Calvo frictions in a similar fashion to intermediate firms. A fraction
\(1 - \xi_w\) of monopoly unions chooses their wage optimally. The remaining fraction follows an indexation rule

\[
W^p_{i,t} = (\mu^*_z)^{1-\nu} (\mu^*_z)^{\nu} (\mu^*_t)^{1-\nu} (\mu^*_t)^{\nu} W^p_{i,t-1}
\]

\[
W^i_{i,t} = (\mu^*_z)^{1-\nu} (\mu^*_z)^{\nu} (\mu^*_t)^{1-\nu} (\mu^*_t)^{\nu} W^i_{i,t-1}
\]

where \(0 < \nu < 1\), \(0 < \nu < 1\), and \(\mu^*_z\) is the growth rate of \(z_t^*\). Throughout the paper, a variable without the subscript \(t\) denotes its steady state value.

**Capital Producers** Capital producers build raw capital \(K_t\) according to a standard technology

\[
K_t = (1 - \delta) K_{t-1} + \left[ 1 - S\left( \frac{I_t}{I_{t-1}} \right) \right] I_t,
\]

where \(0 < \delta < 1\) is the depreciation rate of capital, \(I_t\) is investment, \(S\) is an increasing function (defined below), and \(\zeta_{i,t}\) is a shock to the marginal efficiency of investment.

**Housing Producers** For simplicity, housing is in fixed supply and does not depreciate. Total housing writes

\[
H^p_t + H^i_t = H,
\]

where \(H^p_t\) and \(H^i_t\) are the housing stock owned by patient and impatient households, respectively.

**Patient Households** A representative patient household (superscript \(p\)) consumes, purchases housing, and works to maximize its utility

\[
E_0 \sum_{t=0}^{\infty} (\beta^p)^t \left\{ \zeta_{c,t} \log(C^p_t - b^p c_{t-1}^p) + \psi^p_H \log H^p_t - \psi_L \int_0^t \left( \frac{P^p_{i,t}}{1 + \sigma L} \right) d \nu \right\},
\]

where \(\sigma_L > 1\), \(\psi^p_H\) and \(\psi_L\) are weight parameters, \(C^p_t\) is consumption, and \(\zeta_{c,t} > 0\) is a preference shock. Its budget constraint writes

\[
(1 + \tau^c) P_t C^p_t + Q^h_t H^p_t + P_t D_t \leq (1 - \tau^L) \int_0^1 W^p_{i,t} L^p_{i,t} d \nu + (1 + R^b_t) P_{t-1} D_{t-1} + Q^h_t H^p_{t-1} + \Omega_t.
\]

Patient households spend on consumption, housing and bank deposits \(D_t\). The market price for housing is \(Q^h_t\). Households’ revenues come from labor income, previous-period deposits, the sale of previous-period housing, and profits from firms, banks, and entrepreneurs, which is represented by \(\Omega_t\). The tax rates on consumption and labor, \(\tau^c\) and \(\tau^l\), are exogenous.
**Impatient Households** Impatient households (superscript $i$) have the same utility function as patient ones, except that the parameters $b^i_t$, $b^i_{t-1}$, $\psi^i_H$, and $\beta^i$ have different values. The condition $\beta^i < \beta^p$ implies that impatient households borrow in equilibrium. At the end of period $t - 1$, they obtain a loan $B^i_{t-1}$ from the bank, at the net interest rate $R^i_{t-1}$, in order to purchase housing $H^i_t$ and final goods $C^i_t$ in the next period. At the beginning of period $t$, impatient households are hit by an idiosyncratic shock $\omega^i$ which converts the value of their housing stock $Q^h_{t-1}H^i_{t-1}$ into $\omega^i Q^h_{t-1}H^i_{t-1}$. In analogy to CMR, $\omega^i$ is a unit-mean lognormal random variable distributed independently over time and across impatient households. We denote by $\sigma^i_t$ the standard deviation of $\log \omega^i$. This variable is exogenous and we refer to it as the housing risk shock. Households can default if they are hit by a bad enough shock, in which case their pledged assets are seized by the banks. The default threshold $\bar{\omega}^i_t$ is defined by

$$ (1 + R^h_t) \bar{\omega}^i_t \nu_{t-1} Q^h_{t-1} H^i_{t-1} = (1 + R^i_{t-1}) B^i_{t-1}, $$

where $R^h_t$ is the net rate of return on housing

$$ 1 + R^h_t = \frac{Q^h_t}{Q^h_{t-1}}. $$

The exogenous object $\nu_{t-1}$ is the fraction of their housing capital households can pledge as collateral. This shock is key to our analysis and we refer to it as the collateral shock. Intuitively, as banks lose faith in borrowing households, they are willing to lend against a smaller fraction of these households’ assets. This may reflect increased down payments for subprime mortgages once banks realize many of these mortgages will not be repaid.

Based on the preceding, the budget constraint writes

$$ (1 + \tau^c) P^i_t C^i_t + \left[ 1 + S^h \left( \frac{H^i_t}{H^i_{t-1}} \right) \right] Q^h_t H^i_t \leq (1 - \tau^L) \int_0^1 W^i_{t,t-1} F^i_{t,t-1} \, di $$

$$ + \int_{\bar{\omega}^i_t}^{\infty} \left[ (1 + R^h_t) \omega^i Q^h_{t-1} H^i_{t-1} - (1 + R^i_{t-1}) B^i_{t-1} \right] F^i_{t-1} (\omega^i) $$

$$ + (1 - \nu_{t-1}) \int_0^{\bar{\omega}^i_t} (1 + R^h_t) \omega^i Q^h_{t-1} H^i_{t-1} \, dF^i_{t-1} (\omega^i) + B^i_t, $$

where $S^h$ is an adjustment cost function, defined below. A representative impatient household maximizes its utility

$$ E_0 \sum_{t=0}^{\infty} (\beta^i)^t \left\{ \zeta_{c,t} \log(C^i_t - b^i_{t-1} C^i_{t-1}) + \zeta_{h,t} \psi^i_H \log H^i_t - \psi^i \int_0^1 \frac{(R^h_t)^{1+\sigma_L}}{1 + \sigma_L} \, di \right\}, $$

subject to the budget constraint and a bank participation constraint, defined below. Here, $\zeta_{h,t}$ is a housing preference shock.

---

9Clerc et al. (2015) interpret this shock as changing conditions in the neighborhood (a nearby factory closes, neighbors sell and move out), new social equipment (public transportation, broadband), or cost of maintaining the property (natural disasters, lack of qualified workers in the area).
Entrepreneurs We follow CMR, who themselves draw on Bernanke, Gertler, and Gilchrist (1999). At the end of period $t-1$, entrepreneurs (superscript $e$) receive loans $B_{t-1}^e$ from banks, which they combine with end-of-period’s net worth $N_{t-1}^e$, to purchase raw capital $K_{t-1}$ from households at price $Q_{t-1}$.

$$Q_{t-1}K_{t-1} = N_{t-1}^e + B_{t-1}^e.$$ At the beginning of period $t$, entrepreneurs are hit by an idiosyncratic shock $\omega^e$, which converts raw capital $K_{t-1}$ into efficiency units $\omega^e K_{t-1}$. As in CMR, $\omega^e$ is a unit-mean lognormal random variable distributed independently over time and across entrepreneurs. We denote by $\sigma^e_t$ the standard deviation of $\log \omega^e$. This variable is exogenous and we refer to it as the capital risk shock. Entrepreneurs choose the utilization rate $u_t$ of capital and rent out capital services $u_t \omega^e K_{t-1}$ to firms at the rental rate $r_k^t$. After production, entrepreneurs sell their depreciated capital to households at price $Q_t$. Their rate of return is

$$1 + R_{t}^{k} = \frac{(1 - \tau^k)[u_t r_k^t - a(u_t)] Y^{-t} P_t + (1 - \delta)Q_t + \tau^k \delta Q_t}{Q_{t-1}},$$

where $a$ is an utilization adjustment cost function, defined below. The default threshold $\tilde{\omega}^e_t$ is defined by

$$(1 + R_{t-1}^{k})\tilde{\omega}^e_t \nu_{t-1} Q_{t-1} K_{t-1} = (1 + R_{t-1}^{e})B_{t-1}^e,$$

where $R_{t-1}^{e}$ is the net interest rate paid by entrepreneurs on their debt. Note that this rate is predetermined in period $t-1$, and therefore not contingent on period $t$ state. Here, $\nu_{t-1}$ is the fraction of capital entrepreneurs can pledge as collateral. As their confidence drops, banks are willing to lend against a smaller fraction of entrepreneurs’ assets. This may capture the fact that in the real world capital is heterogeneous, and in bad times banks tend to consider only the safer and more liquid assets of their borrowers. Note that this is the same $\nu_{t-1}$ present in the problem of impatient households. The rationale is that when banks lose faith in the economy and want to restrict lending, they do so regardless of the type of borrower.

If entrepreneurs draw $\omega^e < \tilde{\omega}^e_t$ they become bankrupt, in which case their pledged assets are seized by the banks. The problem of entrepreneurs is to maximize expected pre-dividend net worth

$$E_t \left\{ \int_0^\infty [(1 + R_{t+1}^k)\omega^e Q_t K_t - (1 + R_{t}^{e})B_{t}^e] dF_t^e(\omega^e) + (1 - \nu_t) \int_0^{\tilde{\omega}^e_t} (1 + R_{t+1}^k)\omega^e Q_t K_t dF_t^e(\omega^e) \right\} = E_t[1 - \nu_t \Gamma_t^e(\tilde{\omega}^e_t)](1 + R_{t+1}^k) L_t^e N_{t}^e,$$

subject to a bank participation constraint, defined below. Note that $N_t^e$ corresponds to entrepreneurial net worth, and entrepreneurial leverage $L_t^e$ is defined as

$$L_t^e = \frac{Q_t K_t}{N_t^e}.$$
Also, as in CMR, the expected gross share in pledged assets’ earnings going to banks is

\[ \Gamma_t^e(\tilde{\omega}_{t+1}) \equiv [1 - F_t^e(\tilde{\omega}_{t+1})] \tilde{\omega}_{t+1} + G_t^e(\tilde{\omega}_{t+1}), \quad G_t^e(\tilde{\omega}_{t+1}) = \int_0^{\tilde{\omega}_{t+1}} \omega^e dF_t^e(\omega), \]

where \(1 - F_t^e(\tilde{\omega}_{t+1})\) represents the share of entrepreneurs who repay their debt, and \(G_t^e(\tilde{\omega}_{t+1})\) represents the monitoring returns when entrepreneurs default. Thus, \(1 - \nu_t \Gamma_t^e(\tilde{\omega}_{t+1})\) represents the share of earnings entrepreneurs keep to themselves, and this is what they maximize.

Finally, entrepreneurs are required to pay dividends \(\delta^e\) to households at the end of each period. This is to ensure that they never accumulate enough net worth to the point that they stop relying on banks for funding. Entrepreneurial net worth writes

\[ N_t^e = [1 - \nu_t \Gamma_t^e(\tilde{\omega}_{t})](1 + R_t^k)Q_{t-1}K_{t-1} - \delta^e N_t^e. \]

### 2.2 Banking Sector

We draw closely on Jakab and Kumhof (2015). It is convenient to divide the banking sector (superscript \(b\)) into three units. The retail deposit branch issues deposits to households. The retail lending branch deals with loans to impatient households and entrepreneurs. Finally, the wholesale branch manages the capital position of the group.

**Retail Deposit Banks** There is a continuum \(0 \leq j \leq 1\) of monopolistic retail deposit banks. Each bank \(j\) receives deposit money \(D_{j,t}\) to loan funds \(O_{j,t}\) to wholesale banks, at the nominal interest rate \(R_t\). Different varieties are combined into a homogeneous deposit composite \(D_t\) according to the following technology

\[ D_t = \left[ \int_0^1 D_{j,t}^{\sigma_d+1} \sigma_d dj \right]^{1/\sigma_d+1}, \]

where \(\sigma_d > 1\) is the elasticity of substitution between deposit varieties. In the technical appendix, we derive the optimal price setting condition, which is identical for all retail deposit banks, and stipulates that the deposit rate \(R_t^d\) is a markdown over the policy rate

\[ 1 + R_t^d = \frac{\sigma_d}{\sigma_d + 1}(1 + R_t). \]

Retail deposit banks make the following aggregate profit

\[ \Pi_t^R = (R_t - R_t^d) P_{t-1} D_{t-1}. \]

**Retail Lending Banks** Banks lend to impatient households and entrepreneurs. In both cases, a participation constraint requires that retail lending banks make no
ex-ante loss when providing funds to risky borrowers. The two constraints write

\[
\begin{align*}
E_t \left\{ [1 - F^i_t(\tilde{\omega}_{t+1}^i)](1 + R^i_t)B^i_t \\
+ (1 - \mu^i) \int_0^{\tilde{\omega}_{t+1}^i} \omega^i dF^i_t(\omega^i)(1 + R^h_{t+1})\nu_t Q^h_t H^i_t \geq (1 + R^n_{t+1})B^i_t \right\},
\end{align*}
\]

and

\[
\begin{align*}
E_t \left\{ [1 - F^e_t(\tilde{\omega}_{t+1}^e)](1 + R^e_t)B^e_t \\
+ (1 - \mu^e) \int_0^{\tilde{\omega}_{t+1}^e} \omega^e dF^e_t(\omega^e)(1 + R^k_{t+1})\nu_t Q^e_t K^e_t \geq (1 + R^n_{t+1})B^e_t \right\},
\end{align*}
\]

where \(\mu^i\) and \(\mu^e\) are the cost paid by banks to monitor defaulting households and entrepreneurs, respectively, and \(R^n_t\) is the interest rate demanded by the wholesale bank. As mentioned above, the fraction \(\nu_t\) represents the value of underlying asset (housing or capital) against which the bank, at the time of setting its interest rate, is willing to lend, and therefore able to recover in case of bankruptcy. The first term on the left-hand side represents the return from non-defaulting borrowers. The second term on the left-hand side is the return on assets from defaulting borrowers whose assets are seized by the bank. In equilibrium these two constraints hold with equality.

If too many households or entrepreneurs default, banks could be in a situation in which the interest rate on loans is not high enough to compensate for bankruptcies. Ex-post loan losses would occur. They are given by

\[
\Lambda^L_t = (1 + R^n_t) (B^i_{t-1} + B^e_{t-1}) - \nu_{t-1} Q^h_{t-1} H^i_{t-1}(1 + R^h_t)[\Gamma^i_{t-1}(\tilde{\omega}^i_{t-1}) - \mu^i G^i_{t-1}(\tilde{\omega}^i_{t-1})] \\
- \nu_{t-1} Q^e_{t-1} K^e_{t-1}(1 + R^k_t)[\Gamma^e_{t-1}(\tilde{\omega}^e_{t-1}) - \mu^e G^e_{t-1}(\tilde{\omega}^e_{t-1})].
\]

**Wholesale Banks**  There is a continuum \(0 \leq j \leq 1\) of wholesale banks. Each bank combines the loan it obtains from the retail deposit branch with its own net worth \(N^b_{j,t}\) to make funds available for the retail lending branch. The balance sheet of the whole group writes

\[
B^i_{j,t} + B^e_{j,t} = D_{j,t} + N^b_{j,t}.
\]

At the beginning of each period, wholesale banks are hit by an idiosyncratic shock \(\omega^b\) such that the return on their assets equals \((1 + R^n_t)\omega^b\). As with households and entrepreneurs, \(\omega^b\) has a unit-mean lognormal distribution independently drawn over time and across banks. Banks are subject to a Basel III-type regulatory framework. In particular, they must hold a fraction \(\gamma^b\) of their total assets as capital, or net worth. This parameter represents the Basel minimum capital adequacy ratio. If banks violate this rule they pay a penalty in the next period, equal to the share \(\chi\) of their total assets \(B^i_{j,t} + B^e_{j,t}\). The penalty cutoff condition writes

\[
(1 + R^n_{t+1})(B^i_{j,t} + B^e_{j,t})\omega^b_{t+1} - (1 + R^n_{t+1})P_tD_{j,t} + \Pi^R_{j,t+1} - \Lambda^L_{j,t+1} \\
\leq \gamma^b(1 + R^n_{t+1})(B^i_{j,t} + B^e_{j,t})\omega^b_{t+1},
\]
where Π^{R}_{j,t+1} denotes the share of profits of retail deposit banks received by bank \( j \), and Λ^{L}_{j,t+1} represents the share of losses of retail lending banks paid by bank \( j \). Banks select the amount of loans to maximize their pre-dividend net worth

\[
E_t \left[ (1 + R_{t+1}^e)(B^e_{j,t} + B^e_{j,t+1}) - (1 + R_{t+1}^i)P_i D_{j,t} + \Pi^{R}_{j,t+1} - \Lambda^{L}_{j,t+1} - \chi(B^i_{j,t} + B^e_{j,t})F^b(\bar{\omega}_{t+1}) \right],
\]

subject to the penalty cutoff condition and the equations for Π^{R}_{j,t+1} and Λ^{L}_{j,t+1}. Banks have two sources of revenues, namely the return on their loans and the profits from retail deposit operations. Banks’ costs include the rate on deposits, net losses on retail lending operations, and for those banks that do not comply with macroprudential regulation, penalties. Note that banks take into account this potential (large) fine in their optimization problem. At every point in time in equilibrium, a fraction of banks will be under-capitalized and thus pay the fine.

Similarly to entrepreneurs, banks distribute dividends \( \delta^b \) to households at each period. Accordingly, the accumulation of bank net worth is given by

\[
N^b_{j,t} = (1 + R_{t}) (B^i_{j,t} - 1 + B^e_{j,t} - 1) - (1 + R_{t}^i) P_{t} - \delta^b N^b_{j,t-1} + \Pi^{R}_{j,t} - \Lambda^{L}_{j,t} - \chi(B^i_{j,t} + B^e_{j,t})F^b(\bar{\omega}_{t}) - \delta^b N^b_{j,t}.
\]

### 2.3 Government, Constraint, Adjustment Costs, and Shocks

The monetary authority follows a standard Taylor rule

\[
R_t - R = \rho_p (R_{t-1} - R) + (1 - \rho_p) \left[ \alpha_x (E_t \pi_{t+1} - \pi^*_t) + \alpha_{\Delta_y} (g_{y,t} - \mu^*_y) \right] + \varepsilon^p_t,
\]

where \( \rho_p \) is a smoothing parameter and \( \varepsilon^p_t \) is a monetary policy shock. As mentioned earlier, \( \pi^*_t \) is the central bank’s inflation target. The variable \( g_{y,t} \) is quarterly growth in GDP. Government expenditure \( G_t \) is given by

\[
G_t = z^*_t g_t,
\]

where \( g_t \) is a government-spending shock.

**Resource Constraint** Clearing in the goods market imposes

\[
Y_t = G_t + C_t + \frac{I_t}{1 + \mu Y_{t,t}} + a(R_t) K_{t-1} + D_t^i + D_t^e + D_t^h.
\]

Here, \( D_t^i \) and \( D_t^e \) represent aggregate resources used by banks to monitor households and entrepreneurs, respectively

\[
D_t^i = \nu_{t-1} \mu^i G^i_{t} (\tilde{\omega}_{t}^i) (1 + R^h_t) \frac{Q^h_{t-1} H_{t-1}^i}{P_t},
\]

and

\[
D_t^e = \nu_{t-1} \mu^e G^e_{t} (\tilde{\omega}_{t}^e) (1 + R^h_t) \frac{Q^h_{t-1} K_{t-1}}{P_t},
\]

and \( D_t^h \) represents regulatory penalties on banks

\[
D_t^h = \chi F^h(\bar{\omega}_{t}) B^i_{t-1} + B^e_{t-1}.
\]
Adjustment Costs  We follow CMR for the investment adjustment cost function

\[ S(x_t) = \exp \left[ \sqrt{S''/2}(x_t - x) \right] + \exp \left[ -\sqrt{S''/2}(x_t - x) \right] - 2, \]

where \( x_t \equiv \zeta_{I,1}I_t/I_{t-1} \). Note that \( S(x) = S'(x) = 0 \) and \( S''(x) = S'' \) is a parameter. The housing adjustment cost function takes a similar form

\[ S^h(x^h_t) = \exp \left[ \sqrt{(S^h)''/2}(x^h_t - x^h) \right] + \exp \left[ -\sqrt{(S^h)''/2}(x^h_t - x^h) \right] - 2, \]

where \( x^h_t \equiv H^i_t/H^i_{t-1} \) and \((S^h)''\) is a parameter. The utilization adjustment cost function is standard

\[ a(u) = r^k(\exp[\sigma_a(u - 1)] - 1) \frac{1}{\sigma_a}, \]

where \( \sigma_a > 0 \) and \( r^k \) is the steady-state rental rate of capital. In the steady state, utilization is equal to one, independently of the value of the parameter \( \sigma_a \).

Shocks  We consider 14 shocks: \( \varepsilon_{t_i}, g_t, \gamma_{e_t}, \lambda_{f,t}, \mu_{\Upsilon,t}, \mu^*_{s,t}, \nu_{t}, \pi^*_t, \varepsilon^*_p, \sigma^*_t, \sigma^*_e, \zeta_{e,t}, \zeta_{h,t}, \) and \( \zeta_{i,t} \). All have the same structure and follow a standard AR(1) process. Let \( x_t \) be a generic shock, then

\[ \log \left( \frac{x_t}{x} \right) = \rho_x \log \left( \frac{x_{t-1}}{x} \right) + \epsilon^*_t, \quad \epsilon^*_t \sim N(0, \sigma_x^2). \]

All the equations of our model are listed in the technical appendix.

3 Bayesian Inference

This section describes the data used in the estimation, the calibrated parameters, the priors and posteriors for the estimated parameters, and a measure of model fit.

3.1 Data

We estimate our model on US quarterly data, covering the period from 1985Q1 to 2015Q1. We include eight standard macroeconomic variables: GDP, consumption, investment, hours worked, inflation, wages, the federal funds rate, and the relative price of investment goods. In addition, we use the two financial series introduced in Section 2: bank loans to households and nonprofit organizations, and bank loans to the nonfinancial business sector. Finally, we add a series on house prices: the S&P Case-Shiller home price index. The reason is that house prices are a key determinant in household net worth and access to credit. The technical appendix gives a full description of the data,\(^{10}\) including its sources and treatment, and plots the 11 observed variables.

\(^{10}\)We use other data to calibrate some parameters, match steady-state ratios, and perform out-of-sample exercises.
3.2 Calibrated Parameters

There are 66 parameters, including 40 economic parameters and 26 related to shocks. Table 1 reports the values of the parameters we fix a priori. For those

<table>
<thead>
<tr>
<th>Par. Description</th>
<th>Value</th>
<th>Target / Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameters Calibrated with Data Set</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha$ Capital share in production</td>
<td>0.38</td>
<td>Sample mean</td>
</tr>
<tr>
<td>$\eta_g$ Steady state gov. spending-GDP ratio</td>
<td>0.178</td>
<td>Sample mean</td>
</tr>
<tr>
<td>$\pi^*$ Steady state inflation (APR)</td>
<td>2.198</td>
<td>Sample mean</td>
</tr>
<tr>
<td>$\mu_z$ Growth rate of the economy (APR)</td>
<td>1.454</td>
<td>Sample mean</td>
</tr>
<tr>
<td>$\Upsilon$ Trend rate of IST change (APR)</td>
<td>1.337</td>
<td>Sample mean</td>
</tr>
<tr>
<td>$\delta^b$ Bank dividend share</td>
<td>0.037</td>
<td>$L^b = 8.76$</td>
</tr>
<tr>
<td>$\delta^e$ Entrepreneurial dividend share</td>
<td>0.033</td>
<td>$L^e = 1.75$</td>
</tr>
<tr>
<td>Other Parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta$ Depreciation rate of capital</td>
<td>0.025</td>
<td>10% annual</td>
</tr>
<tr>
<td>$\sigma_L$ Labor supply elasticity</td>
<td>1.00</td>
<td>Kimball and Shapiro (2010)</td>
</tr>
<tr>
<td>$\beta^p$ Patient discount factor</td>
<td>0.9993</td>
<td>$R = 4.5%$ annual</td>
</tr>
<tr>
<td>$\beta^i$ Impatient discount factor</td>
<td>0.985</td>
<td>Krusell and Smith (1998)</td>
</tr>
<tr>
<td>$\lambda_f$ Steady state price markup</td>
<td>1.20</td>
<td>Christiano et al. (2005)</td>
</tr>
<tr>
<td>$\lambda_w$ Steady state wage markup</td>
<td>1.05</td>
<td>Christiano et al. (2005)</td>
</tr>
<tr>
<td>$\psi_L$ Disutility weight on labor</td>
<td>0.837</td>
<td>hours $l = 1$</td>
</tr>
<tr>
<td>$\tau^c$ Tax rate on consumption</td>
<td>0.047</td>
<td>CMR</td>
</tr>
<tr>
<td>$\tau^k$ Tax rate on capital income</td>
<td>0.32</td>
<td>CMR</td>
</tr>
<tr>
<td>$\tau^l$ Tax rate on labor income</td>
<td>0.241</td>
<td>CMR</td>
</tr>
<tr>
<td>$\sigma^d$ Deposit variety elasticity of substitution</td>
<td>800</td>
<td>$R - R^d = 0.5%$ annual</td>
</tr>
<tr>
<td>$\gamma^b$ Basel II-III minimum capital adequacy ratio</td>
<td>0.08</td>
<td>Basel II and Basel III</td>
</tr>
</tbody>
</table>

in the top panel, we use our data set directly. The share of capital in production is 0.38. The steady-state government spending-to-GDP ratio $\eta_g$ equals 0.178, the average in our sample. Annualized steady-state inflation $\pi^*$ is set to 2.20%. The mean growth rate of per capita real GDP $\mu_z$ is fixed at 1.45% on an annual basis. We set the annualized rate of investment-specific technological change $\Upsilon$ to 1.337%, which corresponds to the average rate of decline in the relative price of investment goods over the period. The dividends paid by banks and entrepreneurs, $\delta^b$ and $\delta^e$, are set to match the average bank and entrepreneurial leverage in our sample, of 8.76 and 1.75, respectively.

We calibrate the remaining parameters, in the bottom panel, as follows. We set the depreciation rate $\delta$ to 0.025 and the labor supply elasticity $\sigma_L$ to 1. The patient household discount factor $\beta^p$ is fixed at 0.9993, which pins down the annualized fed funds rate $R$ to 4.5%. The impatient household discount factor $\beta^i$ must be lower than $\beta^p$, so we put it at 0.985, which is between the values used by Iacoviello (2005) and Krusell and Smith (1998). Following Christiano, Eichenbaum, and Evans (2005), we calibrate the steady-state price markup $\lambda_f$ at 1.20 and the steady-state wage markup $\lambda_w$ at 1.05. The disutility weight on labor $\psi_L$ is fixed so that total hours worked are normalized to one in steady state. Following CMR, the tax rates on consumption $\tau^c$, capital income $\tau^k$, and labor income $\tau^l$, are fixed at 0.047, 0.32 and 0.241, respectively. The elasticity of substitution for bank
deposits $\sigma^d$ is set to match a 0.5% spread between the central bank’s policy rate and the aggregate deposit rate, consistent with the evidence presented in Ashcraft and Steindel (2008). Finally, the minimal capital adequacy ratio $\gamma^b$ equals 8%, in accordance with Basel II and III.

### 3.3 Estimated Parameters

We estimate 46 parameters using Bayesian methods. Their prior and posterior are reported in Table 2. Many of these parameters are standard in the DSGE literature, and we apply similarly standard priors.\(^\text{11}\) These include the Taylor rule coefficients, $a_{\Delta y}, a_{\pi}$, and $\rho_p$, the Calvo price and wage stickiness parameters, $\xi_p$ and $\xi_w$, the indexation coefficients, $\xi_{\pi}, \xi_{\mu}$, and $\xi_w$, and the curvature parameters for utilization and investment, $\sigma_a$ and $S''$. For most of these parameters we find posterior modes close to those of CMR. One exception is the lower utilization cost function curvature (0.46 compared to their 2.54) which implies higher fluctuations in capital utilization over the period. We also find a smaller investment adjustment cost curvature $S''$ (3.84 compared to their 10.78), but our value lies between those of Justiniano, Primiceri, and Tambalotti (2010) and Smets and Wouters (2007). Our estimate of the Calvo price stickiness, at 0.80, entails a Phillips curve with a slope coefficient of 0.048.\(^\text{12}\)

We now discuss the less habitual parameters. The cost of adjusting housing $S''_h$ is essential to smooth the dynamics of impatient household housing and therefore impatient household debt, which we observe. The posterior mode, at 8.6, is higher than the prior mean, at 6. Because it is very costly to sell housing on a massive scale, impatient households will react to adverse shocks by reducing their consumption, which is precisely what we want. Next, we choose the prior mean of the steady-state probability of household default $F^1(\omega^i)$ and entrepreneurial default $F^e(\omega^e)$ so that the annualized default rate is 3%.\(^\text{13}\) We find values a little higher for both, implying our model slightly overshoots the actual default rates of firms and households. The two monitoring costs, $\mu^i$ and $\mu^e$, have a prior mean of 0.25. It is difficult to measure precisely the cost of bankruptcy. Cagan (2006) puts it at 14% regarding home foreclosures, while Alderson and Betker (1995) estimate it at 36% for firms. Our posterior estimates are remarkably close to these values for both parameters. Another important coefficient is the share $\kappa$ of patient labor in total labor. We set its prior to 0.5 based on the observation that at least half of households in the US hold a form of collateralized debt.\(^\text{14}\) We find a posterior mode of 0.25, implying a large share of impatient households. We interpret this

---

\(^\text{11}\)We refer to Smets and Wouters (2007), Justiniano, Primiceri, and Tambalotti (2010), and CMR.
\(^\text{12}\)Mavroeidis, Plagborg-Møller, and Stock (2014) find that the slope coefficient of the New Keynesian Phillips curve varies from 0.001 to 0.141 according to different model specifications and estimation methods. This is a wide range and the authors warn of specification uncertainty and weak identification issues.
\(^\text{13}\)Delinquency rates on consumer loans average 3.2% over the period 1987-2015. Delinquency rates on commercial and industrial loans average 2.95% over the same period.
\(^\text{14}\)According to The Pew Charitable Trusts (2015), eight in ten Americans hold some form of debt. The most frequently held forms are mortgage debt (44%), unpaid credit card balances (39%), car loans (37%), and student loans (21%). In our model debt is backed by collateral, so that corresponds to all mortgage debt as well as a large share of auto loans.
Table 2: Estimated Parameters

<table>
<thead>
<tr>
<th>Param. Description</th>
<th>Prior Distribution</th>
<th>Mean</th>
<th>SD</th>
<th>Mode</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Economic Parameters</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( a_{\Delta y} ) Taylor rule output coefficient</td>
<td>normal</td>
<td>0.25</td>
<td>0.1</td>
<td>0.4792</td>
<td>0.0713</td>
</tr>
<tr>
<td>( a_\pi ) Taylor rule inflation coefficient</td>
<td>normal</td>
<td>1.5</td>
<td>0.25</td>
<td>1.9491</td>
<td>0.1851</td>
</tr>
<tr>
<td>( \rho_p ) Taylor rule smoothing</td>
<td>beta</td>
<td>0.85</td>
<td>0.1</td>
<td>0.8233</td>
<td>0.0194</td>
</tr>
<tr>
<td>( \xi_p ) Calvo price stickiness</td>
<td>beta</td>
<td>0.6</td>
<td>0.1</td>
<td>0.8033</td>
<td>0.0338</td>
</tr>
<tr>
<td>( \xi_w ) Calvo wage stickiness</td>
<td>beta</td>
<td>0.6</td>
<td>0.1</td>
<td>0.8805</td>
<td>0.026</td>
</tr>
<tr>
<td>( \tau_p ) Price indexation on inflation target</td>
<td>beta</td>
<td>0.5</td>
<td>0.15</td>
<td>0.9095</td>
<td>0.0425</td>
</tr>
<tr>
<td>( \tau_{\mu} ) Wage indexation on tech. growth</td>
<td>beta</td>
<td>0.5</td>
<td>0.15</td>
<td>0.5507</td>
<td>0.1393</td>
</tr>
<tr>
<td>( \tau_w ) Wage indexation on inflation target</td>
<td>beta</td>
<td>0.5</td>
<td>0.15</td>
<td>0.7259</td>
<td>0.1096</td>
</tr>
<tr>
<td>( \sigma_d ) Utilization cost curvature</td>
<td>normal</td>
<td>1</td>
<td>1</td>
<td>0.4649</td>
<td>0.2733</td>
</tr>
<tr>
<td>( S'' ) Investment adjust. cost curvature</td>
<td>normal</td>
<td>3</td>
<td>2</td>
<td>3.8431</td>
<td>1.0609</td>
</tr>
<tr>
<td>( S'' ) Housing adjust. cost curvature</td>
<td>normal</td>
<td>6</td>
<td>2</td>
<td>8.6026</td>
<td>1.6978</td>
</tr>
<tr>
<td>( b^c ) Consumption habit patient</td>
<td>beta</td>
<td>0.65</td>
<td>0.1</td>
<td>0.7952</td>
<td>0.0779</td>
</tr>
<tr>
<td>( b^i ) Consumption habit impatient</td>
<td>beta</td>
<td>0.65</td>
<td>0.1</td>
<td>0.8771</td>
<td>0.0286</td>
</tr>
<tr>
<td>( F^i(\bar{\omega}^i) ) Probability of default impatient</td>
<td>beta</td>
<td>0.007</td>
<td>0.004</td>
<td>0.0083</td>
<td>0.0044</td>
</tr>
<tr>
<td>( F^e(\bar{\omega}^e) ) Probability of default entrepreneur</td>
<td>beta</td>
<td>0.009</td>
<td>0.004</td>
<td>0.0097</td>
<td>0.0036</td>
</tr>
<tr>
<td>( \mu^i ) Monitoring cost impatient</td>
<td>beta</td>
<td>0.25</td>
<td>0.1</td>
<td>0.1123</td>
<td>0.0323</td>
</tr>
<tr>
<td>( \mu^e ) Monitoring cost entrepreneur</td>
<td>beta</td>
<td>0.25</td>
<td>0.1</td>
<td>0.3575</td>
<td>0.0878</td>
</tr>
<tr>
<td>( \kappa ) Share of patient in total labor</td>
<td>beta</td>
<td>0.5</td>
<td>0.1</td>
<td>0.2467</td>
<td>0.0721</td>
</tr>
<tr>
<td>( \psi^p ) Housing weight in patient utility</td>
<td>normal</td>
<td>0.05</td>
<td>0.05</td>
<td>0.0207</td>
<td>0.025</td>
</tr>
<tr>
<td>( \psi^i ) Housing weight in impatient utility</td>
<td>normal</td>
<td>0.4</td>
<td>0.1</td>
<td>0.3712</td>
<td>0.1019</td>
</tr>
<tr>
<td>( F^b(\bar{\omega}^b) ) Probability of bank paying fine</td>
<td>beta</td>
<td>0.007</td>
<td>0.005</td>
<td>0.0113</td>
<td>0.007</td>
</tr>
<tr>
<td>( \chi ) Bank penalty coefficient</td>
<td>beta</td>
<td>0.01</td>
<td>0.005</td>
<td>0.0139</td>
<td>0.0056</td>
</tr>
<tr>
<td><strong>Shock Parameters</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \rho_e ) Autocorr. stationary technology</td>
<td>beta</td>
<td>0.5</td>
<td>0.2</td>
<td>0.9163</td>
<td>0.0179</td>
</tr>
<tr>
<td>( \rho_g ) Autocorr. government spending</td>
<td>beta</td>
<td>0.5</td>
<td>0.2</td>
<td>0.9127</td>
<td>0.0401</td>
</tr>
<tr>
<td>( \rho_{aT} ) Autocorr. price markup</td>
<td>beta</td>
<td>0.5</td>
<td>0.2</td>
<td>0.9165</td>
<td>0.0252</td>
</tr>
<tr>
<td>( \rho_{aT} ) Autocorr. IST</td>
<td>beta</td>
<td>0.5</td>
<td>0.2</td>
<td>0.9848</td>
<td>0.0108</td>
</tr>
<tr>
<td>( \rho_{aT} ) Autocorr. technology trend</td>
<td>beta</td>
<td>0.5</td>
<td>0.2</td>
<td>0.6572</td>
<td>0.0959</td>
</tr>
<tr>
<td>( \rho_{aC} ) Autocorr. collateral</td>
<td>beta</td>
<td>0.5</td>
<td>0.2</td>
<td>0.9729</td>
<td>0.0089</td>
</tr>
<tr>
<td>( \rho_{aE} ) Autocorr. entrepreneur risk</td>
<td>beta</td>
<td>0.5</td>
<td>0.2</td>
<td>0.5021</td>
<td>0.2774</td>
</tr>
<tr>
<td>( \rho_{cC} ) Autocorr. cons. preference</td>
<td>beta</td>
<td>0.5</td>
<td>0.2</td>
<td>0.1437</td>
<td>0.0968</td>
</tr>
<tr>
<td>( \rho_{cH} ) Autocorr. housing preference</td>
<td>beta</td>
<td>0.5</td>
<td>0.2</td>
<td>0.9274</td>
<td>0.0499</td>
</tr>
<tr>
<td>( \rho_{cI} ) Autocorr. MEI</td>
<td>beta</td>
<td>0.5</td>
<td>0.2</td>
<td>0.1176</td>
<td>0.0761</td>
</tr>
<tr>
<td>( \sigma_z ) SD stationary technology</td>
<td>invg2</td>
<td>0.002</td>
<td>0.003</td>
<td>0.0038</td>
<td>0.0004</td>
</tr>
<tr>
<td>( \sigma_g ) SD government spending</td>
<td>invg2</td>
<td>0.002</td>
<td>0.003</td>
<td>0.0153</td>
<td>0.001</td>
</tr>
<tr>
<td>( \sigma_{aT} ) SD equity</td>
<td>invg2</td>
<td>0.002</td>
<td>0.003</td>
<td>0.0009</td>
<td>0.0004</td>
</tr>
<tr>
<td>( \sigma_{aT} ) SD price markup</td>
<td>invg2</td>
<td>0.002</td>
<td>0.003</td>
<td>0.0101</td>
<td>0.0027</td>
</tr>
<tr>
<td>( \sigma_{aT} ) SD IST</td>
<td>invg2</td>
<td>0.002</td>
<td>0.003</td>
<td>0.0036</td>
<td>0.0002</td>
</tr>
<tr>
<td>( \sigma_{aT} ) SD technology trend</td>
<td>invg2</td>
<td>0.002</td>
<td>0.003</td>
<td>0.0026</td>
<td>0.001</td>
</tr>
<tr>
<td>( \sigma_{aT} ) SD collateral</td>
<td>invg2</td>
<td>0.002</td>
<td>0.003</td>
<td>0.0215</td>
<td>0.0037</td>
</tr>
<tr>
<td>( \sigma_{aT} ) SD household risk</td>
<td>invg2</td>
<td>0.002</td>
<td>0.003</td>
<td>0.0010</td>
<td>0.0005</td>
</tr>
<tr>
<td>( \sigma_{aT} ) SD entrepreneur risk</td>
<td>invg2</td>
<td>0.002</td>
<td>0.003</td>
<td>0.0010</td>
<td>0.0005</td>
</tr>
<tr>
<td>( \sigma_{aT} ) SD monetary policy</td>
<td>invg2</td>
<td>0.002</td>
<td>0.003</td>
<td>0.0012</td>
<td>0.0001</td>
</tr>
<tr>
<td>( \sigma_{cC} ) SD consumption preference</td>
<td>invg2</td>
<td>0.002</td>
<td>0.003</td>
<td>0.0166</td>
<td>0.0048</td>
</tr>
<tr>
<td>( \sigma_{cH} ) SD housing preference</td>
<td>invg2</td>
<td>0.002</td>
<td>0.003</td>
<td>0.0967</td>
<td>0.0982</td>
</tr>
<tr>
<td>( \sigma_{cI} ) SD MEI</td>
<td>invg2</td>
<td>0.002</td>
<td>0.003</td>
<td>0.0177</td>
<td>0.0018</td>
</tr>
</tbody>
</table>

Notes: invg2 corresponds to the inverse gamma distribution, type 2. MEI stands for marginal efficiency of investment, and IST for investment-specific technology.


Table 3: Steady-State Properties, Model Versus Data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Model</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>c/y</td>
<td>Consumption-to-GDP ratio</td>
<td>0.64</td>
<td>0.60</td>
</tr>
<tr>
<td>i/y</td>
<td>Investment-to-GDP ratio</td>
<td>0.18</td>
<td>0.22</td>
</tr>
<tr>
<td>g/y</td>
<td>Government-spending-to-GDP ratio</td>
<td>0.18</td>
<td>0.18</td>
</tr>
<tr>
<td>k/(4y)</td>
<td>Productive-capital-to-GDP ratio</td>
<td>1.41</td>
<td>1.49</td>
</tr>
<tr>
<td>h/(4y)</td>
<td>Housing-capital-to-GDP ratio</td>
<td>2.47</td>
<td>2.41</td>
</tr>
<tr>
<td>b/(4y)</td>
<td>Debt-to-GDP ratio</td>
<td>1.68</td>
<td>1.09</td>
</tr>
<tr>
<td>d/(4y)</td>
<td>Bank-deposits-to-GDP ratio</td>
<td>1.49</td>
<td>1.08&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>b/b&lt;sup&gt;i&lt;/sup&gt;</td>
<td>Household-debt-to-total-debt ratio</td>
<td>0.64</td>
<td>0.64</td>
</tr>
<tr>
<td>b/h&lt;sup&gt;i&lt;/sup&gt;</td>
<td>Loan-to-value ratio</td>
<td>0.52</td>
<td>0.58&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>π</td>
<td>Inflation (APR)</td>
<td>2.20</td>
<td>2.20</td>
</tr>
<tr>
<td>R</td>
<td>Fed funds rate (APR)</td>
<td>4.50</td>
<td>3.97</td>
</tr>
<tr>
<td>L&lt;sup&gt;b&lt;/sup&gt;</td>
<td>Household leverage</td>
<td>1.37</td>
<td>1.18</td>
</tr>
<tr>
<td>L&lt;sup&gt;e&lt;/sup&gt;</td>
<td>Entrepreneurial leverage</td>
<td>1.75</td>
<td>1.75</td>
</tr>
<tr>
<td>L&lt;sup&gt;b&lt;/sup&gt;</td>
<td>Bank leverage</td>
<td>8.76</td>
<td>8.76</td>
</tr>
</tbody>
</table>

Notes: All data values are computed as the sample average over the period 1985Q1–2015Q1. Model values are computed for the parameters evaluated at their posterior mode.

<sup>a</sup> We define bank deposits as the sum of M3 (M2 + large and long-term deposits) and outstanding domestic public debt securities.


as our channel being validated by the data. As a robustness check, we re-estimate the model by fixing \( \kappa = 0.5 \) and we find very similar results. The housing weight in impatient utility \( \psi_H^i \) has a prior of 0.4, in order to match a steady-state share of household debt in total debt of approximately two thirds. The housing weight in patient utility \( \psi_H^p \) is set to a lower value to match a total housing-to-GDP ratio of 2.4. In both cases posterior estimates remain close to their prior. We set a low prior to the bank penalty coefficient \( \chi \) to reflect the fact that macroprudential rules were not stringent over most of the 1985-2015 period. This coefficient and the other banking parameter \( F(b, \omega^b) \) have low impact on the model’s dynamics but will turn out to be important in the macroprudential policy section.

Finally, we turn to the exogenous processes. We find that several shocks are highly persistent, including the collateral shock, with an estimated autocorrelation coefficient of 0.972. Only the autoregressive coefficients of consumption preference and the marginal efficiency of investment have a posterior mean below their prior mean. The estimated standard deviation of the collateral shock is relatively high, at 0.02. We show the effect of this shock on the economy in Section 4.

### 3.4 Model Fit

We ask whether our estimated model is a reliable representation of the US economy by comparing its steady-state properties to the data. Table 3 reports selected model variables and ratios evaluated at the posterior mode, along with their em-
empirical counterpart.\textsuperscript{15} Overall, the model and the data match well. Note this is the case by construction for the ratio of government spending to GDP, the inflation rate and the two leverage ratios for nonfinancial firms and banks. One exception to the good fit is the ratio of debt to GDP, which is a bit too high in the model. But bear in mind that to construct the data object, we abstract from the (large) fraction of business credit that is not bank-based. Including this fraction would yield a ratio of 1.49, much closer to our model ratio. Another discrepancy lies in the steady-state fed funds rate, which is lower in the data. This can be explained by a regime switch since the recent financial crisis, with rates close to zero for an extended period of time. Our model is not suited to account for the zero lower bound, but we suspect that the collateral shock would have an even more pronounced effect on the cycle if the constraint were binding.

4 The Collateral Shock

In this section, we analyze the prominent role of the collateral shock. We first present quantitative evidence showing that this shock is the main driver of economic fluctuations. We then explain the reasons why this is the case. Finally, we discuss the importance of the model’s two key ingredients, and in doing this we highlight the disparities between our collateral shock and CMR’s risk shock.

4.1 Quantifying the Role of the Collateral Shock

We start with our main result. Table 4 reports the percentage of the variance in key variables explained by the different shocks. By business cycle frequency we mean frequency comprised between 6 and 32 quarters. The collateral shock accounts for more than half of the variance in output, consumption, investment, and business credit, over a third of the variance in employment, and close to a third of the variance in household credit. This is more than any other shock. To the best of our

\textsuperscript{15} We also compare our model’s dynamic properties to the data, which we report in the last section of the technical appendix.
knowledge, no paper in the DSGE literature puts forward a shock able to drive simultaneously the main four macroeconomic variables and two financial series. Note that the combined effect of the two preference shocks on consumption is only 14%, well below what most previous studies find. The marginal efficiency of investment shock contributes non negligibly to the evolution of investment. Also, the four supply shocks combined (TFP, trend, investment-specific technology, and price markup) drive a significant 18% to 35% of the variance in the main aggregate variables, and have large effects on the two credit variables. This stands in contrast to the other demand shocks (monetary policy, government spending, equity, household and firm risk), which have low effect on the cycle. We interpret this finding as the result of the dominance of the collateral shock, which dwarfs its demand-side competitors.

Another way to measure the importance of the collateral shock is to conduct the following experiment. We simulate our model with all the estimated shocks at once. By construction, this replicates the data exactly, with the exception of small measurement errors on the two financial series, household and business credit. Next, we simulate the model again, but we shut down all shocks except our collateral shock. Figure 4 plots the results. In the case of consumption, investment and business credit, the two lines track each other closely. This is true both in downturns and upturns. The 2008-2009 recession, in particular, highlights the leading role of the collateral shock. But the other two recessions in our sample are also closely associated with a restriction in bank lending. Regarding household credit, the collateral shock predicts a drop in 2001 that did not occur, but it captures the Great Recession particularly well. Overall, this counterfactual exercise supports our claim that the collateral shock is the most important shock driving the economy.

4.2 Explaining the Dominance of the Collateral Shock

The reason why our empirical analysis singles out the collateral shock is the following. When hit by a collateral shock, our model generates responses that mimic actual business cycles. We place special emphasis on the behavior of consumption, because previous studies have failed to generate comovements between consumption and the other main aggregate variables.

Let us consider impulse response functions. What we refer to as a negative collateral shock, \( i.e. \) a fall in \( \nu_t \), is the fact that at some point banks realize that the collateral they hold is going to depreciate in the next period.\(^{16}\) Think of a sudden awareness to risk in the housing market and a correction in the value of mortgage-backed securities. As a result, banks adjust their lending conditions by tightening collateral requirements. This affects all their borrowers, households and entrepreneurs alike. Figure 5 displays the responses of key macroeconomic,

\(^{16}\)In a sense, this could be seen as a news shock. The difference is that the collateral shock is not a signal about future fundamentals. It is rather the bank’s impression, or sentiment, that the collateral will lose its value. The fact that it indeed does is a consequence of general equilibrium effects. Indeed, the reduction in lending leads to a fall in the demand of capital and housing, which depresses asset prices.
banking, and entrepreneurial variables to such an event, while Figure 6 focuses on households.

The first consequence is a fall in the volume of loans. In the production sector, entrepreneurs are forced to reduce their capital purchases. Capital producers, facing a lower demand for physical capital, reduce investment. Output drops. The lower demand for capital generates a contraction in its price, which reduces entrepreneurial net worth. This delivers the standard financial accelerator effect. The fall in net worth implies a rise in leverage, making entrepreneurs riskier. This, in turn, prevents them from borrowing, further reducing capital expenditures and hurting the economy. Because output falls, firms cut down employment. As the economy shrinks, production costs go down and inflation decreases. The central bank tries to mitigate the crisis by cutting down its policy rate. But this does not prevent the interest rate on loans to entrepreneurs from going up. As a result, the spread between the two rates shoots up.

In the banking sector, net worth is not immediately affected and adjusts rather slowly. This reflects the observation by Adrian and Shin (2011, 2014) that bank equity is "sticky”. The reduction in credit translates into a drop in depo-
sits. Therefore, bank leverage plunges. The liquidity dry out our model displays is comparable to what Gorton and Metrick (2010, 2012) refer to as modern bank runs. When creditors in the financial markets lose confidence in the collateral of their borrowers, haircuts increase and highly levered institutions are forced to deleverage massively. This leads to fire sales, declines in asset prices, a reduction in lending and ultimately reduction in real activity. In a related paper, Singh (2011) argues that another component of deleveraging is the reduction in the reuse of pledged collateral between banks and nonbanks. He shows that the velocity of collateral has dropped from 3 at the 2007 peak to 2.4 in 2010. Although our model does not feature collateral rehypothecation, a way to interpret the collateral shock is to see it as reduction in the use of pledgeable collateral.

Consider now what happens in the household sector, in Figure 6. As loans are cut back, impatient consumers are forced to reduce their housing purchases. The price of housing falls. The second financial accelerator of the model, similar to the one on entrepreneurs, kicks in. As their housing net worth depreciates, impatient households become riskier and thus are even more constrained in their borrowing. Note that because of fixed supply, all housing sold by impatient households is necessarily taken over by patient ones. After an initial spike in leverage due to falling net worth and higher cost of credit, financially-constrained impa-
patient households are forced to deleverage. The slow and painful debt deflation process is a stark feature of the recent financial crisis. A major consequence is that indebted households cut their consumption drastically. Indeed, on impact, consumption of impatient workers drops by over five times as much as that of patient ones. As a result, aggregate consumption plummets.

To sum up, the dynamics triggered by the collateral shock exhibit many key features of US business cycles: procyclical consumption, investment, employment, inflation, credit, bank assets, and bank leverage; countercyclical household net worth, nonfinancial firm net worth and leverage, and credit spreads. This is the reason why the data favors our shock.

4.3 The Importance of the Channel and the Shock

Our model features two key ingredients: i) a lending channel between banks and households and ii) a single collateral shock that hits households and entrepreneurs at once. In this subsection we show that both are crucial to our results. We do this by removing each one separately and comparing to the baseline model.
The Importance of the Channel: Case with No Impatient Households

Our model with two types of households nests the representative household case. By setting the share of patient households $\kappa = 1$, we get rid of borrowing households in the economy. We now re-estimate the model, with the same set of observable variables, except for household credit, which we remove because households don’t borrow. Parameter estimates are reported in the technical appendix. Rows marked *no impatient* in Table 5 show the variance decomposition at business cycle frequency in this specification.

Table 5: Variance Decomposition, Two Alternative Model Specifications

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP</td>
<td>$\nu_t$</td>
<td>$\sigma^2_t$</td>
<td>$\zeta_f,t$</td>
<td>$\varepsilon_t, \mu_z,t, \mu_Y,t$</td>
<td>$\lambda_f,t$</td>
<td>$\zeta_c,t, \zeta_h,t$</td>
<td>$\varepsilon_t^p, \pi_t^*$</td>
<td>$\varepsilon_t^q$</td>
</tr>
<tr>
<td><em>no impatient</em></td>
<td>32</td>
<td>0</td>
<td>0</td>
<td>25</td>
<td>15</td>
<td>19</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td><em>no collateral</em></td>
<td>-</td>
<td>53</td>
<td>2</td>
<td>11</td>
<td>12</td>
<td>10</td>
<td>6</td>
<td>3</td>
</tr>
<tr>
<td>Consumption</td>
<td>$\nu_t$</td>
<td>$\sigma^2_t$</td>
<td>$\zeta_f,t$</td>
<td>$\varepsilon_t, \mu_z,t, \mu_Y,t$</td>
<td>$\lambda_f,t$</td>
<td>$\zeta_c,t, \zeta_h,t$</td>
<td>$\varepsilon_t^p, \pi_t^*$</td>
<td>$\varepsilon_t^q$</td>
</tr>
<tr>
<td><em>no impatient</em></td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>37</td>
<td>10</td>
<td>48</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td><em>no collateral</em></td>
<td>-</td>
<td>9</td>
<td>4</td>
<td>26</td>
<td>14</td>
<td>41</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>Investment</td>
<td>$\nu_t$</td>
<td>$\sigma^2_t$</td>
<td>$\zeta_f,t$</td>
<td>$\varepsilon_t, \mu_z,t, \mu_Y,t$</td>
<td>$\lambda_f,t$</td>
<td>$\zeta_c,t, \zeta_h,t$</td>
<td>$\varepsilon_t^p, \pi_t^*$</td>
<td>$\varepsilon_t^q$</td>
</tr>
<tr>
<td><em>no impatient</em></td>
<td>83</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>8</td>
<td>0</td>
<td>5</td>
<td>0</td>
</tr>
<tr>
<td><em>no collateral</em></td>
<td>-</td>
<td>79</td>
<td>7</td>
<td>1</td>
<td>5</td>
<td>1</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>Hours</td>
<td>$\nu_t$</td>
<td>$\sigma^2_t$</td>
<td>$\zeta_f,t$</td>
<td>$\varepsilon_t, \mu_z,t, \mu_Y,t$</td>
<td>$\lambda_f,t$</td>
<td>$\zeta_c,t, \zeta_h,t$</td>
<td>$\varepsilon_t^p, \pi_t^*$</td>
<td>$\varepsilon_t^q$</td>
</tr>
<tr>
<td><em>no impatient</em></td>
<td>27</td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>24</td>
<td>30</td>
<td>7</td>
<td>5</td>
</tr>
<tr>
<td><em>no collateral</em></td>
<td>-</td>
<td>41</td>
<td>3</td>
<td>9</td>
<td>18</td>
<td>17</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Household Credit</td>
<td>$\nu_t$</td>
<td>$\sigma^2_t$</td>
<td>$\zeta_f,t$</td>
<td>$\varepsilon_t, \mu_z,t, \mu_Y,t$</td>
<td>$\lambda_f,t$</td>
<td>$\zeta_c,t, \zeta_h,t$</td>
<td>$\varepsilon_t^p, \pi_t^*$</td>
<td>$\varepsilon_t^q$</td>
</tr>
<tr>
<td><em>no impatient</em></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td><em>no collateral</em></td>
<td>-</td>
<td>5</td>
<td>2</td>
<td>53</td>
<td>17</td>
<td>21</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>Business Credit</td>
<td>$\nu_t$</td>
<td>$\sigma^2_t$</td>
<td>$\zeta_f,t$</td>
<td>$\varepsilon_t, \mu_z,t, \mu_Y,t$</td>
<td>$\lambda_f,t$</td>
<td>$\zeta_c,t, \zeta_h,t$</td>
<td>$\varepsilon_t^p, \pi_t^*$</td>
<td>$\varepsilon_t^q$</td>
</tr>
<tr>
<td><em>no impatient</em></td>
<td>68</td>
<td>0</td>
<td>0</td>
<td>26</td>
<td>4</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td><em>no collateral</em></td>
<td>-</td>
<td>67</td>
<td>6</td>
<td>12</td>
<td>4</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Notes: The variance decomposition is computed for the parameters evaluated at their posterior mode. Results in the rows marked *no impatient* correspond to a model with no impatient households, that is $\kappa = 1$. Results in the rows marked *no collateral* correspond to the baseline model where the collateral shock is switched off. Shares are in percent. Numbers in each row need not add up to 100 due to rounding.

The main results are as follows. The collateral shock remains the most important force driving GDP, investment, and business credit. It accounts for 32%, 83%, and 68% of the variance in these three variables, respectively. But the collateral shock is no longer able to explain consumption: it accounts for a meager 2% of its variance. Instead, the preference shock, at 48%, becomes the main driver of consumption (and also hours). These findings are in line with the previous literature, where the main financial shock does a good job at replicating the dynamics of output and investment (and sometimes hours) but has virtually no effect on consumption. The reason for this is well known. The financial shock, in our case the collateral shock, limits the ability of entrepreneurs to purchase capital. Because

17In this model specification with no impatient households, the collateral shock only affects the disruption in credit between banks and entrepreneurs. Therefore, it is observationally equivalent with the risk shock.
of a lower demand for capital, the return on capital falls. This makes investment less profitable.\textsuperscript{18} Therefore, saving households, who are the only type of households in the economy, will turn to consumption instead. This substitution effect makes it very difficult to generate the strong comovement between consumption and investment we see in the data.

The rise of the consumption preference shock is not innocuous. Suppose the estimation procedure attributes a given downturn (such as the last recession) to a series of negative collateral shocks. These shocks drive output, investment, and hours down. But to match the fall in consumption, the negative collateral shocks must be accompanied by negative preference shocks. This implies these two innovations are correlated. Indeed, we find a correlation coefficient of 0.81, significant at the one percent confidence level. This conflicts with the fact that the collateral and preference shocks are supposed to be structural, exogenous shocks. In our baseline estimation, however, we don’t face this issue because the correlation is 0.13 and not statistically significant at the ten percent confidence level.

To summarize, when impatient households that borrow from banks are absent, the collateral shock cannot account for the dynamics in consumption over the bu-

\textsuperscript{18}The collateral shock in this setting is essentially like a negative tax on capital.
The Importance of the Shock: Case with No Collateral Shock

We now turn to the second key aspect of our model, a common shock with a dual effect on households and firms. What if borrowing households are present in the economy, but the financial shock only disrupts credit between banks and businesses? This is precisely what the risk shock of CMR is about, a dispersion in the productivity of entrepreneurs that limits their ability to borrow. CMR claim the risk shock is the main driver of the business cycle. Our work is a continuation of theirs: we reinterpret their disturbance by broadening its effect. We argue that during the crisis, banks not only cut credit to businesses but also to households, and this had a large effect on aggregate consumption. To verify this, we remove the collateral shock and we re-estimate the model. Again, parameter estimates are reported in the technical appendix. Rows marked no collateral in Table 5 show the variance decomposition at business cycle frequency in this alternative specification.

Not surprisingly, the risk shock takes over the collateral shock and becomes the main impulse. It explains the bulk of the variance in GDP (53%), investment (79%), hours (41%), and business credit (67%), but not in consumption (9%) and household credit (5%). With these results, we confirm CMR’s findings, without having to resort to a number of anticipated, or news, components on the risk shock. Note the risk shock has more impact on consumption than the collateral shock in the previous case with no impatient households. This is due to general equilibrium effects. The risk shock prevents firms from purchasing capital. They respond by cutting employment and wages, which reduces the income of impatient households. Impatient households, in turn, must reduce consumption. But this indirect effect is not large enough to account for the full dynamics of consumption. As in the previous case with no impatient households, there needs to be another disturbance, and again, the consumption preference shock fills the gap.

To further illustrate the difference between the collateral and the risk shocks, we follow CMR’s lead by computing dynamic cross-correlations between today’s GDP and selected variables, for $-12 \leq L \leq 12$, where $L$ is the number of lags. We plot the results in Figure 7. The grey area corresponds to a 95 percent confidence interval centered around the actual correlations in the data. The line with stars is the correlation implied by the estimated baseline model when only the collateral shock is active, and all other shocks are switched off. The line with circles is the correlation implied by the alternative estimated model with no collateral shock when only the risk shock is active, and all other shocks are switched off.

Figure 7 allows us to make two observations. On the one hand, for all four variables the collateral shock generates correlations that lie within the range implied the data, at almost every lag. In the case of consumption and investment the match is nearly perfect. On the other hand, the risk shock is incapable of generating

---

19CMR add eight anticipated components, one for each quarter, from one quarter to two years ahead. These news shocks improve the fit of the model, but they also boost the impact of the risk shock artificially, which becomes in effect the sum of nine innovations, the unanticipated one and the eight news.
empirically plausible correlations for consumption and household credit. This is because the risk shock only affects the credit relation between firms and banks, and thus has not much to say about variables affecting households.

To conclude this subsection, we note that neither the collateral shock in a model with no impatient households nor the risk shock in a model with impatient households are able to account for the joint dynamics of consumption and other aggregate variables. Both the borrowing household channel and the common collateral shock are essential.

5 External Performance

We provide additional evidence in support of the collateral shock. We confront the shock process itself against a proxy in the data, and we compare default rates implied by the shock with actual delinquency rates. Finally, we look at the implications of our model for leverage. We emphasize that none of the data presented in this section is used in the econometric estimation.

5.1 Lending Standards and Collateral Requirements

Our analysis stresses the role of collateral shocks on economic fluctuations. In good times lax lending conditions by banks increase credit and boost consumption and investment. This mechanism works in reverse in bad times. One way to validate this story is to find a possible proxy in the data for our shock. In Section 2 we discuss bank lending standards from the Senior Loan Officer Opinion Survey on Bank Lending Practices. We reuse these series and plot them against our single estimated collateral process \( \nu_t \). Figure 8 shows the results. The observation period is shorter than the one in our analysis, because the survey starts in 1995Q3. Still it embeds two crises, the Internet bubble and the Great Recession.

In both cases, the model and data series track each other fairly well. The correlation is 0.42 and 0.43 for the top and bottom panels, respectively. Lending standards tighten during each of the two recessions, especially for firms. It is notable that our unique shock is able to match these two series. We conclude that the collateral shock accurately reflects bank lending conditions, irrespective of the borrower type, and this provides further support to our story.

5.2 Delinquency Rates

Our second out-of-sample exercise looks at delinquency rates. In the model, when a negative collateral shock occurs, this weakens the balance sheet of borrowers through a decline in the price of capital and housing. Hence both impatient households and entrepreneurs become riskier. As a result, the share of these borrowers unable to repay their debt at each period increases sharply. Figure 9 compares default rates on households and entrepreneurs implied by our model with actual delinquency rates on mortgages and commercial and industrial loans, respectively. The correlations are pretty high, at 0.68 for households and 0.32 for firms. In the case of households we even match the levels well. But contrary to the previous
Figure 8: Bank Tightening, Model Versus Data

Notes: In both panels the solid line corresponds to the scaled estimated process for the collateral shock. In the top panel the dashed line is the net percentage of domestic banks tightening standards for consumer loans (excluding credit card). In the bottom panel the dashed line is the net percentage of domestic banks increasing collateral requirements on commercial and industrial loans for large and middle-market firms. Negative values mean banks tighten lending standards.

dograph, where we suggest that the tightening of standards by banks is more or less the same regardless of the type of borrower, here there is a clear distinction between the default rates of households and firms. In particular, firm defaults shoot up in each recession, before returning to low levels. For households, there seems to be a long period from 1991 to 2006 when defaults continuously fall, despite the burst of the dot-com bubble in 2001. But then there is a huge increase in 2007 when the housing market collapses.

Overall, notwithstanding some imperfections, our shock alone does a good job at capturing the cyclical variations in default rates, especially given that these data do not play a role in the estimation. We see it as another test that validates our framework.
5.3 Leverage Cyclicality

There has been a focus on leverage since the crisis. The reason is it acts as a powerful amplifier: when banks or their borrowers are highly levered, small losses lead to failures and endanger the whole system. Gorton and Ordoñez (2014) write: "One link between small shocks and large crisis is leverage".

Our model is interesting in that it features three types of leverage, for households, firms, and banks. We look at the prediction of the model for these three variables and we compare them to the data. Table 6 reports the results. Our models successfully replicates two well known stylized facts about leverage. First, bank leverage is significantly more volatile than firm leverage, which in turn is more volatile than household leverage. Second, while household and firm leverage are mildly countercyclical, bank leverage is procyclical. This is because firms and households tend to act rather passively to changes in asset prices. When prices go

---

Table 6: Leverage Statistics, 1985Q1–2015Q1

<table>
<thead>
<tr>
<th></th>
<th>Households</th>
<th>Firms</th>
<th>Banks</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Relative Standard Deviation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model</td>
<td>0.25</td>
<td>1.29</td>
<td>1.66</td>
</tr>
<tr>
<td>Data</td>
<td>0.38</td>
<td>0.91</td>
<td>2.12</td>
</tr>
<tr>
<td><strong>Correlation with GDP</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model</td>
<td>–0.14</td>
<td>–0.13</td>
<td>0.33</td>
</tr>
<tr>
<td>Data</td>
<td>0.03</td>
<td>–0.12</td>
<td>0.65</td>
</tr>
</tbody>
</table>

Notes: All series are logged and linearly detrended. P-values are in parentheses.

*a* Standard deviation relative to the standard deviation of GDP.

down and debt is unchanged, leverage mechanically goes up. Banks, on the other hand, manage their balance sheet much more actively: in bad times they sell assets on a massive scale in order to lower their risk profile. Our model captures these movements. The collateral shock engineers a rise in household and entrepreneurial leverage trough a fall in capital and house prices and a rise in loan interest rates. Banks reduce their balance sheet by cutting loans, and because their net worth is more sticky, leverage goes down and is thus procyclical. The next section explores what happens if a regulator forces banks to reduce their leverage.

6 Macroprudential Analysis

A natural question emerges from the study of business cycles: how can these cycles be dampened? In other words, how can we prevent unsustainable expansions and, more importantly, costly recessions? The view developed in this paper is that bank lending is too lax in good times and too tight in bad times. If this view is correct, then the answer to the question lies in limiting reckless lending by banks. This is precisely what macroprudential policy is about.

Our model incorporates capital requirements, the main regulatory friction put in place by the Bank for International Settlements’ Basel Committee on Banking Supervision. Specifically, if banks do not maintain a ratio $\gamma^b$ of their assets as equity, they pay a penalty $\chi$ of their assets. For simplicity we consider that the risk weight for all bank assets is the same and equals one.\(^{21}\) In the estimation, we set $\gamma^b = 8\%$, which is the initial ratio established in Basel I in 1988 and kept for Basel II in 2004.\(^{22}\) We estimate $\chi$ the penalty coefficient around a relatively low prior of $0.01$, and find a posterior mode at $0.014$. The idea is that although the Basel accords were in place, their enforcement was not stringent, because banks were allowed to develop their own model to quantify required regulatory capital.\(^{23}\)

\(^{21}\)According to Basel III, loans secured by commercial real estate have a risk weight of 100%. Loans secured by residential property have a risk weight ranging from 25% to 100% based on the loan-to-value ratio.


\(^{23}\)This is known as the internal ratings-based (IRB) approach.
We now ask the following question. What would have happened if a stricter rule, in the spirit of Basel III, had been introduced at the start of the century? To provide an answer, we take our estimated model and recover the sequence of shocks from 2000Q1 to 2015Q1. We then change the two regulatory parameters. We set the minimum capital adequacy ratio $\gamma^b$ to 10% and the penalty coefficient $\chi$ to 3.1%. Next, we simulate the model by feeding the sequence of shocks and we look at the evolution of output. Figure 10 plots this counterfactual against actual GDP.

Unsurprisingly, the ups and downs are less pronounced. In the years preceding the financial crisis, starting from 2004, hypothetical output grows less than actual output. Banks cannot lend as much and this prevents constrained households from consuming more. During the crisis, however, the drop in activity is considerably smaller than what we actually observe. Actually output falls by 6.7% from peak to trough whereas hypothetical output drops by 3.4%. It’s interesting to note that the recovery is also faster in a world with more regulation. One explanation is that banks are not willing to lend in the ‘hangover’ period, which our estimation captures with low or negative collateral shocks.

![Figure 10: Output in a World with Stricter Macroprudential Rules](image)

*Notes:* The solid line is the result of simulating the model for real per capita GDP with the estimated shocks if Basel III-type regulation had been put in place in the first quarter of 2000. The dashed line corresponds to actual real per capita GDP. Both series are normalized to equal 100 in 2000Q1.

To conclude, this section shows that there is room for policies aimed at stabi-
lizing the financial system and the economy as a whole. It is important to better understand how banks adjust their collateral requirements over time, in order to identify early on when their behavior becomes problematic. Recessions are not inevitable.

7 Conclusion

We study the impact of bank collateral requirements on the economy. Looser requirements mean more credit flowing to households and businesses. We start by documenting the increasing predominance of household debt over business debt in the past thirty years. Both types of credit rose sharply in the years preceding the 2007-2008 financial crisis, and fell dramatically during the crisis. We suggest the origin of this boom and bust debt cycle has a lot to do with banks’ adjustment of credit conditions over time. We show evidence that banks loosen and tighten lending standards in the same way regardless if the borrower is a household or a business.

Equipped with these preliminary observations, we build a macroeconomic model with two main characteristics. First, banks provide loans to households and entrepreneurs. Households use the funds to invest in housing capital and consume. Entrepreneurs use the funds to invest in productive capital. Second, we allow banks lending requirements to fluctuate over time. We call these fluctuations collateral shocks: their particularity is they affect credit conditions simultaneously on households and businesses.

We estimate our model using Bayesian methods on US financial and macroeconomic data from 1985 to 2015. We find that the collateral shock is the main driver of the business cycle. In particular, it accounts for the bulk of variance in GDP, consumption, investment, employment, household credit, and business credit. To the extent of our knowledge, this is the first study where a single shock explains the dynamics of the four aggregate variables, including consumption, as well as two key financial series. The double credit relationship—bank-household and bank-entrepreneur—is the main reason why the collateral shock is able to jointly match the movements in consumption and investment.

We show that the series for collateral requirements generated by the estimated model tracks two corresponding empirical series on household and business loans, which were not used in the inference of the parameters. This gives extra credit to the collateral shock. In addition, our model simulated with only the collateral shock matches well the evolution of delinquency rates and credit spreads on household and business loans. Finally, our model replicates key stylized facts on borrowers’ balance sheets: it generates countercyclical household and firm leverage and procyclical bank leverage.

How can we prevent future recessions? If we take the results of this paper seriously, then one possibility would be to limit over-lending in the boom years. We calculate the path of a hypothetical economy in which we assume banks are subject to stricter capital requirements, of the type of Basel III regulation. For what it is worth, we find that had the regulation been in place in 2000, real GDP per capita would have been two percent higher than it actually was in 2015. Importantly, this
would have halved the drop in output during the 2008-2009 recession.

Our analysis treats collateral requirements as an exogenous disturbance. Banks, however, respond to changes in economic conditions by endogenously adjusting their lending standards. Therefore, an important question is to understand how banks react to sudden changes and why they sometimes tighten to the point that they asphyxiate the economy. Our understanding is that the economy is constantly hit by shocks coming from all corners. Most have little or no effect on banks or wash out in the aggregate. But some shocks, once caught up by the financial sector, are amplified and essentially become like collateral shocks, generating a fall in credit and a subsequent drop in macroeconomic variables. The fact that banks and borrowers are more levered makes it more likely that these shocks will have large effects.

References


34


Singh, Manmohan 2011. “Velocity of Pledged Collateral; Analysis and Implications”.


38