Collateral Shocks*
Preliminary and Incomplete

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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 nonfinancial firms. We find that fluctuations in collateral requirements, or collateral shocks, are the most important force driving the business cycle. In particular, we are able to match the dynamics of investment and consumption with this unique disturbance, something rarely seen in previous studies. Our model correctly replicates movements in the balance sheets of banks, households, and businesses, and allows us to reproduce the narrative of the 2008-2009 recession.
JEL Codes: E21, E22, E32, E44, G21.

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1 Introduction

In the years preceding the 2007-2008 financial crisis, the US economy witnessed an unprecedented rise in domestic credit to the private sector. The rise, which was much faster than the growth in output, was primarily directed towards households but also went to businesses. This formidable debt boom was followed by an equally formidable bust, which led to the worst economic recession in over half a century.

Banks played a major role in both the boom and the bust. They lent relentlessly in the good years, regardless of fundamental improvements in productivity or income, and often to untrustworthy borrowers. This massive expansion in the credit supply was the primary cause behind the housing market bubble. When mortgage markets stumbled in 2007, banks panicked and froze lending to all types of borrowers (households and firms alike), even to trustworthy ones. A large and growing literature backs this "credit supply view", in which financial institutions are seen as the main cause behind boom and bust debt cycles.[1]

In this paper, we study the impact of bank lending requirements on economic fluctuations. If the credit supply view is correct, a relaxing in lending standards should lead to an expansion in credit to households and firms, a rise in consumption and investment, and ultimately an economic expansion. The mechanism works in reverse if banks suddenly increase collateral requirements and credit dries up.

To this end, we develop a macroeconomic model where a banking sector extends loans to households and nonfinancial firms. Banks impose fluctuating collateral requirements on their borrowers: We define the exogenous tightening or loosening of these requirements as the collateral shock ν_t. This shocks is meant to capture a broad set of developments in the financial sector and should not be seen as the ultimate cause of crises. For example, in the recent financial crisis the first spark originated in the housing market, when subprime mortgages defaults began to rise in early 2007.[2] But it turned into a full-fledged crisis when financial institutions realized mortgage-backed assets were no longer safe and lost confidence. Hence, our starting point in the analysis is when banks lose confidence and they restrict lending.

We ask whether a restriction in bank lending can generate dynamics that resemble business cycles. The answer is yes. Using US financial and macroeconomic data, we estimate our model with Bayesian techniques, and we find that the collateral shock is the main driver of economic fluctuations 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 nonfinancial firm credit. To the best of our knowledge, no paper in the DSGE literature has managed to put forward a single shock that drives investment and consumption si-

[1] Chief examples include Mian and Sufi (2009, 2011, 2016), Duca, Muellbauer, and Murphy (2012), Mian, Rao, and Sufi (2013), and Justiniano, Primiceri Tambalotti (2015). On bank lending to firms, see Ivashina and Scharfstein (2010) and Basset, Chosak, Driscoll, and Zakrajsek (2014).

[2] The subprime mortgage market was relatively small compared to the value of all mortgages in the US. Find figures.

multaneously, let alone financial variables.[3] In most cases, these papers match the dynamics of output and investment well, but consumption is driven by a separate disturbance, typically a change in preferences. Given that real-world consumption always comoves with output and investment, a candidate driving force of the business cycle should be able to explain it as well.[4]

To be more precise, our core framework is the medium-scale dynamic stochastic general equilibrium (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. Both patient and impatient households purchase housing and consume. We also add a meaningful banking sector a la Jakab and Kumhof (2015). In particular, banks collect deposits from patient households and they combine these funds with their own net worth to extend secured loans to impatient households and entrepreneurs. Banks are subject to capital requirements imposed by the macroprudential regulator. Entrepreneurs use the loans to purchase raw capital and rent it as effective capital to productive firms. Impatient households use the loans to invest in housing and consumption goods; both goods are complementary. The collateral shock ν_t is defined as the fraction of assets impatient households and entrepreneurs can pledge as collateral in the debt contract. This corresponds to the amount that can be seized in case of default.

The reason why our collateral shock is able to drive consumption as well as investment is the following. When banks lose confidence, they restrict collateral requirements. But 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 firms' ability to purchase capital, which causes investment to fall. On the other hand, impatient households are forced to cut back on their goods and housing purchases, causing aggregate consumption to fall. Note that because of a shrinking economy, patient households also reduce their consumption, but this effect is relatively small. The direct link between credit and consumption that our model displays is documented by recent empirical studies, which we briefly survey in the next section.

Our model has interesting implications for leverage. In the financial sector, the reduction in bank credit is accompanied by a large deleveraging. This is because bank net worth is rather sticky and all the adjustment is made through bank debt, *i.e.* deposits. In the real sector, the steep fall in the price of capital depresses the net worth of entrepreneurs and their leverage jumps. The price of housing also falls, making impatient households more leveraged on impact. We document the cyclical properties of leverage in the US and show that our framework factually

[3] One exception is Angeletos et al. (2015) with their confidence shocks, which we discuss briefly below.

[4] Many empirical studies, using dynamic principal component analysis and dynamic factor models, find that US macroeconomic dynamics are driven by one or two shocks at most. Examples include Sargent and Sims (1977), Giannone et al. (2005), Stock and Watson (2010) and Andrle et al. (2016). These studies confirm the quote by Cochrane (1994) that business cycles are "all alike in many ways". Hence the search for a single force that moves all the main aggregate variables in the right direction.

generates procyclical bank leverage, countercyclical firm leverage, and acyclical household leverage.

We also provide three out-of-sample exercises, as a way to test the empirical validity of our model. We look successively at self-reported bank lending requirements, delinquency rates among households and firms, and marginal propensities to consume across households. Our model does a fairly good job at matching these, and we believe this strengthens our case. In addition, we conduct a small counterfactual experiment. In a hypothetical world with stronger macroprudential rules, we find that the business cycle would have been tamed. If the rules had been in place at the start of the century, per capita GDP as of 2015 would have been 3% higher than it actually was.

Our paper contributes to two main strands of the literature. The first one is the role of financial factors in business cycles. Early seminal contributions of Bernanke and Gertler (1989), Kiyotaki and Moore (1997), and Bernanke, Gertler, and Gilchrist (1999) focus on the demand side of credit and the balance sheets of borrowers. We follow their lead by embedding a (double) financial accelerator in our model. More recently, the crisis has sparked a myriad of papers that study the supply of credit by financial institutions.[5] In particular, the fact that these institutions are highly leveraged and their leverage is procyclical has received a lot of attention, because this acts as a powerful amplification mechanism. Gorton and Ordoñez (2014) write: "One link between small shocks and large crisis is leverage". Adrian and Shin (2010a,b,c, 2014) document these phenomena extensively,[6] and we complement their empirical findings in the next section. Other researchers, such as Iacoviello (2005), Iacoviello and Neri (2010), and Clerc et al. (2015), have included housing in their models with credit frictions. We are directly inspired by them, although we find that without a banking sector that redirects credit to both households *and* firms, housing shocks alone are not able to account fully for the dynamics of consumption and investment.

Our work is also related to a number of articles that use Bayesian econometrics to estimate quantitative models designed to fit the data.[7] 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 whatsoever.[8] 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

[5]See, for example, Gerali et al. (2010), Gertler and Kiyotaki (2010), Gertler and Karadi (2011), Brunnermeier and Sannikov (2014), Jakab and Kumhof (2015), Nuño and Thomas (2016), and Gertler, Kiyotaki, and Prestipino (2016).

[6]See also Geanakoplos (2009) and He, Khang, and Krishnamurthy (2010).

[7]Smets and Wouters (2003, 2007) show that DSGE 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).

[8]Jermann 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 financials 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).

the dispersion of entrepreneurs' productivity, or risk shocks, seem to be the main driver of economic fluctuations. Again, the risk shock is not able to account for the movements in consumption. We build on their approach, but we complement it by introducing bank lending to households as well, which allows us to match consumption. Our collateral shock is very similar to CMR's risk shock on the entrepreneurial side, but it differs on the household side. We believe it is easier to interpret, it is easier to identify using series of credit to households and firms, and the story behind it nicely fits the narrative of the recent crisis. Finally, our findings echo those of Angeletos, Collard, and Dellas (2016). They argue that agents' heterogeneous beliefs about their trading partners' future productivity can generate dynamics that resemble business cycles. Waves of pessimism cause recessions. Even if their setup is more general and extends beyond the financial sector, we interpret our collateral shock as a loss of confidence by banks about the quality of their borrowers' collateral.

The rest of the article is organized as follows. The next section lays out some preliminary facts that help motivate and clarify our endeavor. Section 3 presents the model. Section 4 discusses the data and the estimation of the parameters. In section 5 we analyze how and why the collateral shock is so important. Section 6 offers out-of-sample evidence in support of our model, while Section 7 proposes a small macroprudential application. We conclude in section 8.

2 Motivating Evidence

This section shows some preliminary evidence in line with our account of economic fluctuations. We note that credit cycles are vast in amplitude and their peak coincides with economic recessions. We then suggest that these cycles are very much linked to lending standards by banks. An important element in our story is the link between household debt and consumption; we report recent findings from the empirical literature. Finally, we document the cyclical properties of leverage in the three levered sectors of the economy: households, nonfinancial firms, and banks.

2.1 Boom and Bust Debt Cycles

Within the private sector, banks extend credit to households and businesses. Figure 1 displays both types of credit as a share of GDP. We make two observations. First, household debt is significantly larger than nonfinancial business sector debt (although the difference has been narrowing lately). This was not always the case: Prior to the 1990s corporate debt represented the bulk of total credit. Second, both household and business debt increased at a faster pace than output in the five to ten years preceding the Great Recession, and then dropped massively as the bubble burst. This indicates the existence of boom and bust cycles of debt, where the peak is associated with an economic recession.

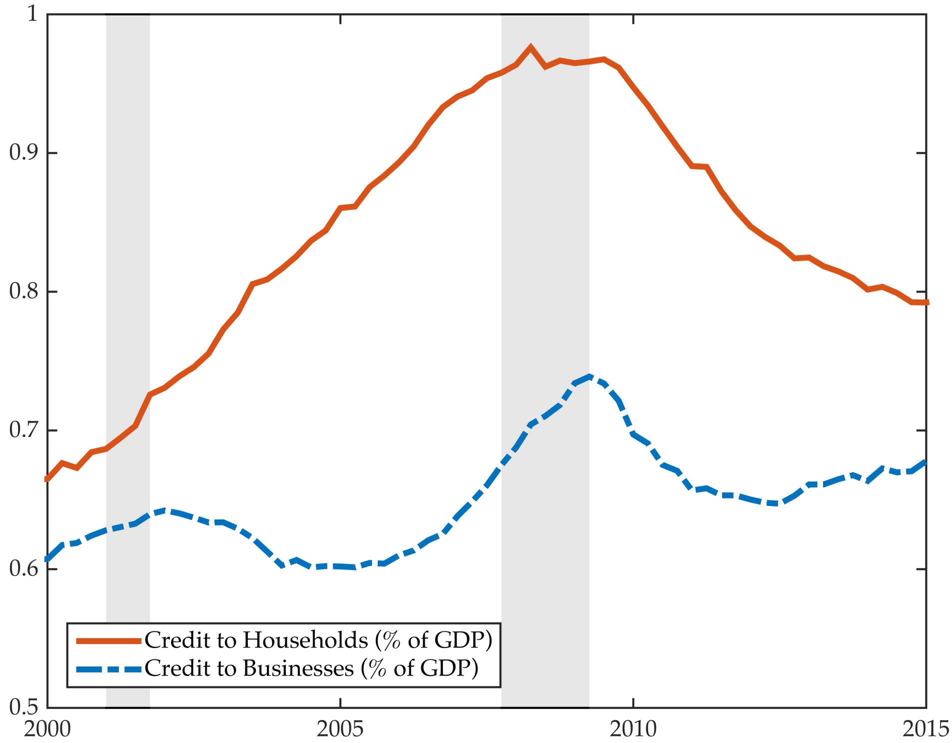

Figure 1: Credit to Households and Nonfinancial Businesses

Notes: The solid line corresponds to the ratio of total liabilities of households and nonprofit organizations to GDP. The dashed line is the ratio of total liabilities of nonfinancial businesses to GDP. The grey areas indicate NBER recessions.

2.2 Bank Lending Standards

What causes these boom and bust cycles? Evidence abounds that the willingness of banks to make loans plays a major role. In Figure 2 we plot two measures of bank lending standards coming from the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. The first one corresponds to the net percentage of US banks having tightened standards on credit card consumer loans in the last quarter. The second series is the net percentage of US banks having increased collateral requirements on commercial and industrial loans for large and middle-market firms, also in the last quarter.

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—the boom period—banks were relaxing standards quarter after quarter (values are negative). Again, prior to the Great Recession, in the first quarter of 2008, banks abruptly increased lending requirements on households and firms. It is remarkable that both the timing and the amplitude of the tightening is almost exactly the same for loans destined to very different types of borrowers.[9]

[9] Note that the interest rates on these loans behaved very differently. When banks started to

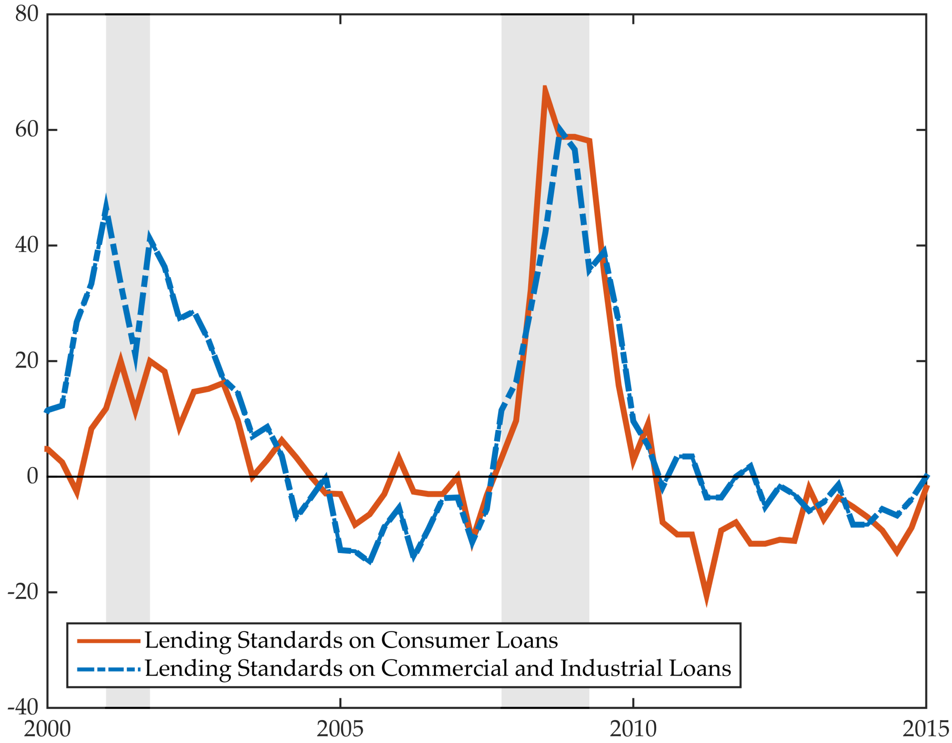

Figure 2: Bank Tightening

Notes: The solid line corresponds to the net percentage of domestic banks tightening standards on credit card consumer loans. The dashed line is the net percentage of domestic banks increasing collateral requirements on commercial and industrial loans for large and middle-market firms.

This suggests that whatever the original disturbance was, banks were affected and reacted by restricting credit to everyone of their borrowers, regardless of their type. In fact in the last financial crisis, there is more or less a consensus about the source of the initial shock. It occurred in the housing market in early 2007, when defaults among subprime borrowers began to rise, and mortgage-backed securities were suddenly no longer perceived as safe. But this shock was relatively small.[10] However, it was greatly amplified by highly leveraged—and suddenly panicking—financial institutions. Our view, therefore, is that as soon as a shock is potent enough to affect banks, there are chances that this shock will be magnified and sometimes result in an economic downturn. The fact that banks are highly leveraged is crucial, and we discuss this point further below.

tighten rates on business loans shot up, while mortgage rates remained rather flat. We plot these in the technical appendix.

[10]*Compare size of subprime market to total market.*

Table 1: Marginal Propensity to Consume out of Housing Wealth

	MPC out of Housing Wealth
Households with Income < \$35,000	0.024
Households with Income > \$200,000	0.008
Households with Leverage > 90%	0.032
Households with Leverage < 30%	0.010

Notes: These figures come from Mian, Rao, and Sufi (2013). The authors compute the MPC for auto spending at the ZIP code level, out of a negative housing wealth shock. The data is annual and spans the period 1998-2012.

2.3 The Link between Credit and Consumption

As mentioned in the introduction, most existing DSGE models of the business cycle overlook the link between credit markets and consumption by private agents in the economy. In recent years this link has been carefully examined empirically. In particular, Mian and Sufi (2011) use micro data to study the behavior of existing homeowners overtime. They find that as their house prices appreciate, homeowners borrow vast amount of debt through cash-out refinancing and home equity loans. This "home-equity-based borrowing channel" explains most of the rise in the household debt to GDP ratio from 2000 to 2007 documented in Figure 1. Interestingly, Mian and Sufi (2011) show that consumers do not use home equity-based borrowing to buy more real estate or financial assets, nor do they use borrowed funds to pay down costly credit card debt. Rather, the authors conclude that "a large fraction of home-equity borrowing is used for consumption or home improvement." Other studies, using survey data, comfort these results.[11]

What happens when households are hit by negative shocks? Mian, Rao, and Sufi (2013), using micro data at the ZIP code level, examine the consequences of the 2006-2009 housing collapse on consumption. They estimate households' marginal propensity to consume (MPC) following a negative net worth shock and show that the MPC differs by household wealth and leverage. In Table 1 we report some of their findings. The main takeaway is the following. The poorest and most levered households have MPCs three times as large as the richest and least levered households. The relation is monotonous across all categories (unreported here). Why is that so? Mian, Rao, and Sufi (2013) find that a decline in home values leads to tighter credit constraints, in the form of reduced home equity and credit card limits and more difficulties refinancing into lower interest rates. They also argue that credit constraints bind more for highly levered and poorer households.

In short, these findings point to a simple link between credit and consumption. Financially-constrained households, sometimes called hand-to-mouth, use credit to consume more. In bad times, when house prices fall, credit dries up and these households are forced to cut back on their consumption. Leverage is very important in this story because it amplifies the initial fall in net worth.

[11] See Brady, Canner, and Maki (2000) and Canner, Dynan and Passmore (2002).

2.4 The Cyclicality of Leverage

In this paper we emphasize the credit relationship between banks and their borrowers. As mentioned above, when either banks or their borrowers are highly levered, initial shocks are amplified and can have nasty consequences. In what follows we provide basic facts about leverage of banks, households, and firms.

Our definition of the household sector is simply what the Federal Reserve Board refers to as households and nonprofit organizations. We define an aggregate nonfinancial business sector as the sum of nonfinancial noncorporate businesses and nonfinancial corporate businesses. Finally, we construct an aggregate financial sector by adding up US-chartered depository institutions, which include commercial banks and savings institutions, security broker-dealers, and finance companies. These three subsectors represent the bulk of assets of the US levered financial sector.[12] For each of the three sectors we collect data on assets and equity. Details can be found in the technical appendix. Leverage is defined as the ratio of total assets to equity capital:

$$L_t = \frac{A_t}{N_t}.$$

Table 2 reports business cycle statistics about leverage for our three sectors, from 1985Q1 to 2015Q1.[13] Consider first households. On average, their leverage is low, at 1.18. This is because the whole US population is accounted for: over time as people pay back their (mainly mortgage) debt they move from being net borrowers to net savers (their leverage equals one). Household leverage is not very volatile either (0.37 as volatile as GDP), because most assets owned by people are in the form of real estate, and house prices vary less than other assets prices. Finally, while assets and equity are positively correlated with GDP (house prices are procylical), leverage is not significantly correlated with GDP.

The case of nonfinancial firms is somewhat similar. Again, their leverage is not very high (1.75) nor volatile (87% as GDP), although higher and more volatile than household leverage. Importantly though, leverage is strongly countercyclical with respect to assets and mildly countercyclical with respect to GDP. This outcome is what one would expect from passive investors. In the face of falling asset prices, firms holding their assets see their net worth decrease. As the amount of debt they owe is unchanged, leverage shoots up. Hence, firms become more leveraged (riskier) in bad times.

[12] We exclude government-sponsored enterprises because they are partly controlled by the state and may not reflect the behavior of financial markets. We also leave out funding corporations, insurance companies, and issuers of asset-backed securities because of lack of data on equity and hence leverage.

[13] Although the behavior of leverage hast been studied extensively, most notably by Adrian and Shin (2010a,b,c, 2014), and Nuño and Thomas (2016), we find useful to reproduce here because we believe it is a key element in our story. Indeed, at the time when the whole financial system was about to collapse, many banks were forced to deleverage in order to meet their collateral constraints. This caused fire sales in many asset categories, thus depressing their price. As these assets were often used as collateral in repos (especially asset-backed securities), a lower value meant higher haircuts and further develeraging, and so on and so forth. So the effect of tighter collateral requirements was amplified by the deleveraging process.

Table 2: US Business Cycle Statistics, 1985Q1–2015Q1

	Household Sector	Nonfinancial Business Sector	Financial Sector
Mean Leverage	1.18	1.75	8.76
Relative Standard Deviation[a]			
Assets	1.96	2.15	2.46
Equity	2.03	2.82	1.15
Leverage	0.37	0.87	2.03
Correlations			
Leverage – Assets	−0.10	−0.69***	0.89***
Leverage – Equity	−0.27***	−0.83***	0.13*
Leverage – GDP	0.09	−0.17**	0.72***
GDP – Assets	0.90***	0.54***	0.50***
GDP – Equity	0.85***	0.46***	−0.19**
Assets – Equity	0.98***	0.97***	0.57***

Notes: All series are logged and linearly detrended. Three asterisks indicate the 1 percent confidence level, two asterisks the 5 percent confidence level, and one asterisk the 10 percent confidence level.
[a] Standard deviation relative to the standard deviation of GDP.

Banks behave completely differently. First, their leverage is high, at 8.76 in our sample. Second, leverage comoves strongly with assets and GDP. An interpretation is that banks actively manage their balance sheets, and they do so mainly through debt. When times are bad they seek to reduce their balance sheet by selling assets on a massive scale, thus reducing their leverage. Banks leave their equity largely unchanged: Indeed, bank equity is almost three times less volatile than nonfinancial firm equity. One reason is that raising equity in bad times is costly and sends a wrong signal to investors about the bank's health.

To summarize, we establish three stylized facts. Household leverage is low and acyclical. Nonfinancial business sector leverage is low and countercyclical. Bank sector is high and procyclical. Based on this preliminary evidence, we want to address the following question. Can stricter lending constraints by banks trigger a massive deleveraging in the financial sector, a collapse in credit to households and firms, an increase in the riskiness of these two borrowers, a drop in consumption and investment, and ultimately a severe economic recession? We believe this question can be addressed using a quantitative model featuring three key ingredients—a borrowing household sector with acyclical leverage, a nonfinancial business sector with counteryclical leverage, and a banking sector with procyclical leverage. We now turn to the presentation of this model.

3 The Model

We extend the CMR model in two directions. First, we differentiate between two types of households, lenders and borrowers. Following Iacoviello (2005) we call them patient and impatient. Second, we incorporate a non trivial banking sector. 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

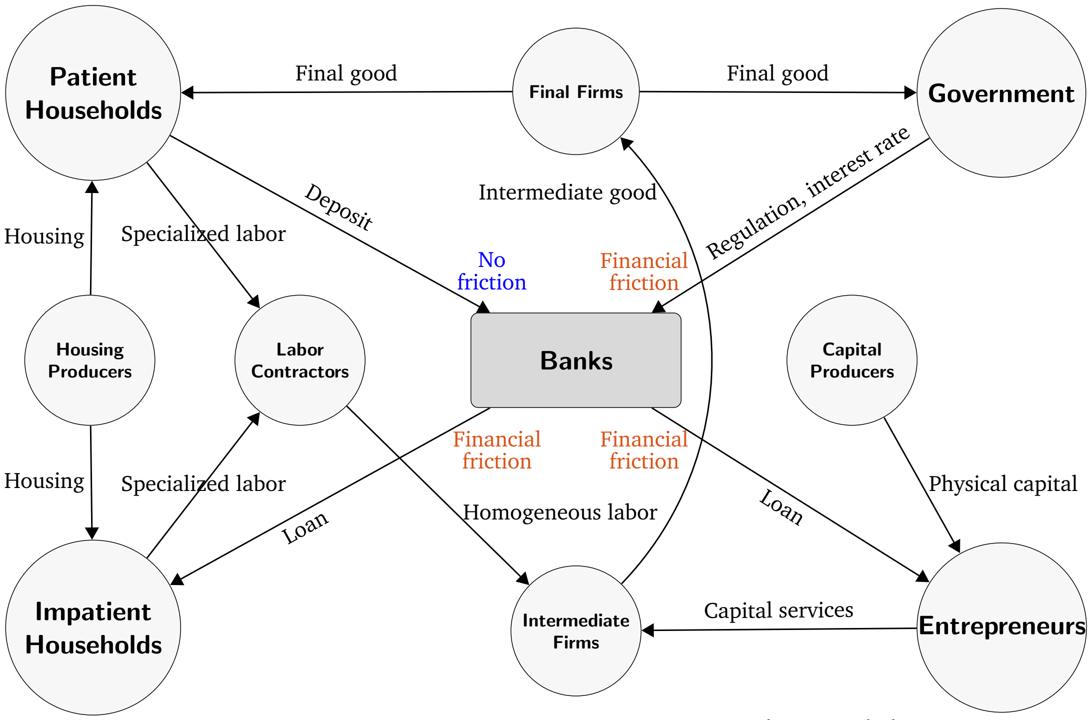

Figure 3: Interactions Among Agents in the Model

overview of the model, in Figure 3. The key agents are households, banks, and entrepreneurs.

3.1 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

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

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 an homogeneous labor input, u_t is the utilization rate of capital, and ε_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, $\mu_{\Upsilon,t}$, that changes the rate at which final goods are converted into $\Upsilon^t \mu_{\Upsilon,t}$ investment goods, with $\Upsilon > 0$. As in CMR, the fixed cost Φ is proportional to z_t^*, which combines the two trends

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

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

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

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

Labor Contractors Perfectly competitive labor contractors combine specialized labor services $h_{i,t}$ into homogeneous labor l_t sold to intermediate firms using the following technology

$$l_t = \left[\int_0^1 h_{i,t}^{\frac{1}{\lambda_w}} di \right]^{\lambda_w},$$

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

Monopoly Unions Unions represent workers by type i and set their wage rate $W_{i,t}$. 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

$$W_{i,t} = \left(\mu_{z,t}^*\right)^{\iota_\mu} \left(\mu_z^*\right)^{1-\iota_\mu} \left(\pi_t^*\right)^{\iota_w} \left(\pi_{t-1}\right)^{1-\iota_w} W_{i,t-1},$$

where $0 < \iota_\mu < 1$, $0 < \iota_w < 1$, and $\mu_{z,t}^*$ 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

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

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.

Patient Households A representative patient household consumes, purchases housing, and works to maximize its utility

$$E_0 \sum_{t=0}^{\infty} (\beta^p)^t \zeta_{c,t} \left\{ \log(C_t^p - b_c^p C_{t-1}^p) + \psi_H \log(H_t^p - b_h^p H_{t-1}^p) - \psi_L \int_0^1 \frac{(l_{i,t}^p)^{1+\sigma_L}}{1+\sigma_L} di \right\},$$

where $\sigma^L > 1$, b_c^p and b_h^p are habit parameters, C_t^p is consumption, H_t^p is housing, and $\zeta_{c,t} > 0$ is a preference shock. Its budget constraint writes

$$(1+\tau^c) P_t C_t^p + Q_t^h H_t^p + P_t D_t \leq (1-\tau^L) \int_0^1 W_{i,t}^p l_{i,t}^p di$$
$$+ (1+R_t^d) P_{t-1} D_{t-1} + Q_t^h H_{t-1}^p + \Omega_t.$$

Patient households spend on consumption, housing and bank deposits. The market price for capital is Q_t and the market price for housing is Q_t^h. Households' revenues come from labor income $W_{i,t}^p$, previous-period deposits, the sale of previous-period housing, and profit from firms, banks, and entrepreneurs, which is represented by Ω_t. The tax rates on consumption and labor, τ^c and τ^l, are exogenous.

Impatient Households Impatient households have the exact same preferences as patient ones, except for their discount factor, which is $\beta^i < \beta^p$. This implies that they borrow in equilibrium. At the end of period $t-1$, they obtain a loan B_{t-1}^i from the bank, at the net interest rate R_{t-1}^i, in order to purchase housing H_t^i and final goods C_t^i. At the beginning of period t, impatient households are subject to an idiosyncratic shock ω^i which converts the value of their housing stock $Q_{t-1}^h H_{t-1}^i$ into $\omega^i Q_{t-1}^h H_{t-1}^i$. In analogy to CMR, ω^i is a unit-mean lognormal random variable distributed independently over time and across impatient households. We denote by σ_t^i the standard deviation of $\log \omega_t^i$. This variable is exogenous and we refer to it as the housing risk shock.[14] Households can default if they are hit by a bad enough shock, in which case their assets are seized by the banks. The default threshold $\bar{\omega}_t^i$ is defined by

$$(1+R_t^h) \bar{\omega}_t^i \nu_{t-1} Q_{t-1}^h H_{t-1}^i = (1+R_{t-1}^i) B_{t-1}^i,$$

where R_t^h is the net rate of return on housing

$$1 + R_t^h = \frac{Q_t^h}{Q_{t-1}^h}.$$

The exogenous object ν_{t-1} is the fraction of households' housing capital that they 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 households' assets. This may reflect increased loan-to-value ratios for subprime mortgages once it became clear many of these mortgages would have not been repaid.

[14] Clerc 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).

Based on the preceding, the budget constraint writes

$$\begin{aligned}(1+\tau^c)P_tC_t^i + Q_t^hH_t^i \le (1-\tau^L)&\int_0^1 W_{i,t}^i l_{i,t}^i di \\ &+ \int_0^\infty \left[(1+R_t^h)\omega^i\nu_{t-1}Q_{t-1}^hH_{t-1}^i - (1+R_{t-1}^i)B_{t-1}^i\right] dF(\omega^i) \\ &+ B_t^i.\end{aligned}$$

A representative impatient household maximizes its utility

$$E_0\sum_{t=0}^\infty (\beta^i)^t\zeta_{c,t}\left\{\log(C_t^i - b_c^iC_{t-1}^i) + \psi_H\log(H_t^i - b_h^iH_{t-1}^i) - \psi_L\int_0^1 \frac{(l_{i,t}^i)^{1+\sigma_L}}{1+\sigma_L}di\right\},$$

subject to the budget constraint and a bank participation constraint, defined below.

Entrepreneurs We follow CMR, who themselves draw on Bernanke, Gertler, and Gilchrist (1999). At the end of period $t-1$, entrepreneurs 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 subject to an idiosyncratic shock ω^e, which converts raw capital K_{t-1} into efficiency units ω^eK_{t-1}. As in CMR, ω^e is a unit-mean lognormal random variable distributed independently over time and across entrepreneurs. We denote by σ_t^e the standard deviation of $\log\omega_t^e$. 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 $u_t\omega^eK_{t-1}$ to firms at the rental rate r_t^k. After production, entrepreneurs sell their depreciated capital to households at price Q_t. Their rate of return is

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

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

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

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, ν_{t-1} is the fraction of entrepreneurs' capital that they 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, they tighten lending to individuals and firms alike.

If entrepreneurs draw $\omega^e < \bar{\omega}_t^e$ 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

$$E_t \left\{ \int_{\bar{\omega}_{t+1}^e}^{\infty} \left[(1+R_{t+1}^k)\omega^e Q_t K_t - (1+R_t^e) B_t^e \right] dF(\omega^e) \right\}$$
$$= E_t[1-\nu_t \Gamma_{t+1}(\bar{\omega}_{t+1}^e)](1+R_{t+1}^k) L_t^e N_t^e,$$

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

$$\Gamma_{t+1}(\bar{\omega}_{t+1}^e) \equiv [1-F_{t+1}(\bar{\omega}_{t+1}^e)]\bar{\omega}_{t+1}^e + G_{t+1}(\bar{\omega}_{t+1}^e), \;\; G_{t+1}(\bar{\omega}_{t+1}^e) = \int_0^{\bar{\omega}_{t+1}^e} \omega^e dF(\omega^e),$$

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

Finally, entrepreneurs are required to pay dividends δ^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

$$N_t^e = [1-\nu_{t-1}\Gamma_t(\bar{\omega}_t^e)](1+R_t^k)Q_{t-1}K_{t-1} + \Lambda_t^L - \delta^e N_t^e,$$

where Λ_t^L corresponds to entrepreneurial gains, and thus bank losses, from the borrowing process. We define it in the next subsection.

3.2 Banking Sector

We draw closely on Jakab and Kumhof (2015). It is convenient to divide the banking sector 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 $0 \le j \le 1$ of monopolistic retail deposit banks. Each bank j receives deposit money $D_{j,t}$ to loan funds $O_{t,j}$ 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

$$D_t = \left[\int_0^1 D_{j,t}^{\frac{\sigma^d+1}{\sigma^d}} dj \right]^{\frac{\sigma^d}{\sigma^d+1}},$$

where $\sigma > 1$ 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

$$[1 - F_{t+1}(\bar{\omega}_{t+1}^i)](1 + R_t^i) B_t^i + (1 - \mu^i) \int_0^{\bar{\omega}_{t+1}^i} \omega^i dF(\omega^i)(1 + R_{t+1}^h) \nu_t Q_t^h H_t^i \geq (1 + R_{t+1}^a) B_t^i,$$

and

$$[1 - F_{t+1}(\bar{\omega}_{t+1}^e)](1 + R_t^e) B_t^e + (1 - \mu^e) \int_0^{\bar{\omega}_{t+1}^e} \omega^e dF(\omega^e)(1 + R_{t+1}^k) \nu_t Q_t K_t \geq (1 + R_{t+1}^a) B_t^e,$$

where μ^i and μ^e are the cost paid by banks to monitor defaulting households and entrepreneurs, respectively, and R_t^a is the return on bank assets. As mentioned above, the fraction ν_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 which it is therefore able to recover in case of bankruptcy. The first term on the left-hand side represents the return from nondefaulting 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 the 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

$$\begin{aligned} \Lambda_t^L = {} & (1 + R_t^a)(B_{t-1}^e + B_{t-1}^i) - \nu_{t-1} Q_{t-1}^h H_{t-1}^i (1 + R_t^h)[\Gamma_t(\bar{\omega}_t^i) - \mu^i G_t(\bar{\omega}_t^i)] \\ & - \nu_{t-1} Q_{t-1} K_{t-1} (1 + R_t^k)[\Gamma_t(\bar{\omega}_t^e) - \mu^e G_t(\bar{\omega}_t^e)]. \end{aligned}$$

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 $N_{j,t}^b$ to make funds available for the retail lending branch. The balance sheet of the whole group writes

$$B_{j,t}^i + B_{j,t}^e = D_{j,t} + N_{j,t}^b.$$

At the beginning of each period, wholesale banks receive an idiosyncratic shock ω_t^b such that the return on their assets equals $(1 + R_t^a)\omega_t^b$. As with households and entrepreneurs, ω^b has a unit-mean lognormal distribution independently drawn over time and across banks. We denote by σ_t^b the standard deviation of $\log \omega_t^b$ and we call it the bank risk shock. Banks are subject to a Basel III-type regulatory framework. In particular, they must hold a fraction γ 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 $\chi B_{j,t}^e$. The penalty cutoff condition writes

$$\begin{aligned}&(1+R_{t+1}^a)(B_{j,t}^i+B_{j,t}^e)\bar{\omega}_{t+1}^b-(1+R_{t+1})P_tD_{j,t}+\Pi_{j,t+1}^R-\Lambda_{j,t+1}^L\\&\quad\leq\gamma(1+R_{t+1}^a)(B_{j,t}^i+B_{j,t}^e)\bar{\omega}_{t+1}^b,\end{aligned}$$

where $\Pi_{j,t+1}^R$ denotes the share of profits of retail deposit banks received by bank j, and $\Lambda_{j,t+1}$ 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

$$\begin{aligned}E_t\big[&(1+R_{t+1}^a)(B_{j,t}^i+B_{j,t}^e)-(1+R_{t+1})P_tD_{j,t}\\&+\Pi_{j,t+1}^R-\Lambda_{j,t+1}^L-\chi(B_{j,t}^i+B_{j,t}^e)F_{t+1}^b(\bar{\omega}_{t+1}^b)\big],\end{aligned}$$

subject to the penalty cutoff condition and the equations for $\Pi_{j,t+1}^R$ and $\Lambda_{j,t+1}^L$. 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 δ^b to households at each period. Accordingly, the accumulation of bank net worth is given by

$$\begin{aligned}N_{j,t}^b=&(1+R_t^a)(B_{j,t-1}^i+B_{j,t-1}^e)-(1+R_t)P_{t-1}D_{t-1}\\&+\Pi_{j,t}^R-\lambda_{j,t}^L-\chi(B_{j,t-1}^i+B_{j,t-1}^e)F_t^b(\bar{\omega}_t^b)-\delta N_{j,t}^b.\end{aligned}$$

3.3 Government, Constraint, Adjustment Costs and Shocks

The monetary authority follows a standard Taylor rule

$$\frac{1+R_t}{1+R}=\left(\frac{1+R_{t-1}}{1+R}\right)^{\rho_p}\left[\left(\frac{\pi_t^*}{\pi}\right)\left(\frac{\pi_{t+1}}{\pi_t^*}\right)^{\alpha_\pi}\left(\frac{g_{y,t}}{\mu_z^*}\right)^{\alpha_{\Delta y}}\right]^{1-\rho_p}\varepsilon_t^p,$$

where ρ_p is a smoothing parameter and ε_t^p is a monetary policy shock. As mentioned earlier, π_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

$$Y_t = G_t + C_t + \frac{I_t}{\Upsilon^t \mu_{\Upsilon,t}} + a(u_t)\Upsilon^{-t}K_{t-1} + D_t^i + D_t^e + D_t^b.$$

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

$$D_t^i = \nu_{t-1}\mu^i G_t(\bar{\omega}_t^i)\left(1 + R_t^h\right)\frac{Q_{t-1}^h H_{t-1}^i}{P_t},$$

and

$$D_t^e = \nu_{t-1}\mu^e G_t(\bar{\omega}_t^e)\left(1 + R_t^k\right)\frac{Q_{t-1} K_{t-1}}{P_t},$$

and D_t^b represents regulatory penalties on banks

$$D_t^b = \chi F_t(\bar{\omega}_t^b)\frac{B_{t-1}^i + B_{t-1}^e}{P_t}.$$

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 $x_t \equiv \zeta_{I,t} I_t / I_{t-1}$. Note that $S(x) = S'(x) = 0$ and $S''(x) = S''$ 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 σ_a.

Shocks We consider 14 shocks: ε_t, g_t, γ_t^e, $\lambda_{f,t}$, $\mu_{\Upsilon,t}$, $\mu_{z,t}^*$, ν_t, π_t^*, η_t, ε_t^p, σ_t^i, σ_t^e, $\zeta_{c,t}$, and $\zeta_{i,t}$. All have the same structure and follow a standard AR(1) process. Let x_t be a generic shock, then

$$\log\left(\frac{x_t}{x}\right) = \rho_x \log\left(\frac{x_{t-1}}{x}\right) + \epsilon_t^x, \qquad \epsilon_t^x \sim N(0, {\sigma_x}^2).$$

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

4 Bayesian Inference

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

4.1 Data

We estimate our model on US quarterly data, covering the period from 1985Q1 to 2015Q1. We include 8 standard macroeconomic variables: GDP, consumption, investment, hours worked, inflation, wage, the relative price of investment goods, and the federal funds rate. Our framework also features two borrowing sectors, impatient households and entrepreneurs. Because we wish to assess the impact of bank credit on on the real economy, we use credit data for these two sectors. In particular, we include two financial series: total credit of households and nonprofit organizations, and total credit of the nonfinancial business sector. The technical appendix gives a full description of the data, including its sources and treatment.

4.2 Calibrated Parameters

There are 65 parameters, including 41 economic parameters and 24 related to shocks. Table 3 reports the values for the parameters we fix *a priori*. The calibration is standard for the well-known parameters. We set the capital share α to 0.38, the depreciation rate δ to 0.025, and the labor supply elasticity σ_L to 1. The discount factor β is fixed at 0.9993, which pins down the annualized fed funds rate R to 4.5%. Following Christiano, Eichenbaum, and Evans (2005), we calibrate the steady-state price markup λ_f at 1.20 and the steady-state wage markup λ_w at 1.05. The disutility weight on labor ψ_L is fixed so that total hours worked are normalized to one in steady state. The rest of the calibrated parameters are

Table 3: Calibrated Parameters

Par.	Description	Value	Target / Source
α	Capital share in production	0.38	Feenstra *et al.* (2015)
β^p	Discount factor patient	0.9993	$R = 4.5\%$ annual
δ	Depreciation rate of capital	0.025	10% annual
σ_L	Labor supply elasticity	1.00	Kimball and Shapiro (2010)
λ_f	Steady state price markup	1.20	Christiano *et al.* (2005)
λ_w	Steady state wage markup	1.05	Christiano *et al.* (2005)
η_g	Steady state gov. spending-GDP ratio	0.178	Our data
π^*	Steady state inflation (APR)	2.198	Our data
μ_{z^*}	Growth rate of the economy (APR)	1.454	Our data
Υ	Trend rate of IST change (APR)	1.337	Our data
δ^b	Bank dividend share	0.012	leverage $L^b = 8.76$
δ^e	Entrepreneurial dividend share	0.039	leverage $L^e = 1.75$
ψ_L	Disutility weight on labor	0.837	hours $l = 1$
τ^c	Tax rate on consumption	0.047	CMR
τ^k	Tax rate on capital income	0.32	CMR
τ^l	Tax rate on labor income	0.241	CMR
σ^d	Deposit variety elasticity of substitution	800	$R - R^d = 0.5\%$ annual
γ^b	Basel III minimum capital adequacy ratio	0.08	Basel III

set to match their empirical counterpart over the sample period. The steady-state government spending-to-GDP ratio η_g equals 0.178, the average in our data set. Annualized steady-state inflation π^* is set to 2.20%. The mean growth rate of per capita real GDP μ_z^* is fixed at 1.45% on an annual basis. We set the annualized rate of investment-specific technological change Υ to 1.337%, which corresponds to the average rate of decline in the relative price of investment goods. The dividends paid by banks and entrepreneurs, δ^b and δ^e, are calibrated to match the average bank and entrepreneurial leverage in our sample, of 8.76 and 1.75, respectively. We follow CMR for the calibration of the different tax rates. The tax rates on consumption τ^c, capital income τ^k, and labor income τ^l, are fixed at 0.047, 0.32 and 0.241, respectively. The elasticity of substitution for bank deposits σ^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 γ^b equals 8%, in accordance with the Basel Committee.

4.3 Estimated Parameters

We estimate 44 parameters using Bayesian methods. Their prior and posterior are reported in Table 4. Many of these parameters are standard in the DSGE literature, and we apply similarly standard priors.[15] These include the Taylor rule coefficients, $a_{\Delta y}$, a_π, and ρ_p, the Calvo price and wage stickiness parameters, ξ_p and ξ_w, the indexation coefficients, ι_p, ι_μ, and ι_w, and the curvature parameters for utilization and investment, σ_a and S''. For most of these parameters we find posterior modes close to those of CMR. We estimate a less persistent Taylor rule (the mode of ρ_p is 0.67 compared to their 0.85). Our lower value for the utilization cost function curvature (0.36 compared to their 2.54) implies higher fluctuations in capital utilization over the period. Another exception is the Calvo price stickiness, which we estimate at the relatively high value of 0.89. This entails a rather flat Phillips curve, with a slope coefficient of 0.012.[16] Note that our value does not imply that prices stay unchanged for $1/(1-0.89) = 9$ quarters, because at each period prices that are not re-optimized are indexed to past inflation.

We now discuss the less habitual parameters. We set the same prior for the four habit coefficients. The estimation reveals a much larger housing habit for impatient households ($b_h^i = 0.98$) than for patient ones ($b_h^p = 0.67$). This follows from the necessity to match household credit series. Without high habit in housing, impatient households would simply cut their demand for housing drastically in the face of an adverse shock. This would cause credit to plummet, much more than what we observe in the data. This constraint does not apply to patient households, who do not borrow, and that explains the discrepancy between the two parameters. Next, we choose the prior mean of the steady-state probability of household default $F(\omega^i)$ and entrepreneurial default $F(\omega^e)$ so that the annualized default rate is 3%.[17] We find larger values for both, implying our model slightly over-

[15] We refer to Smets and Wouters (2007), Justiniano, Primiceri, and Tambalotti (2010), and CMR.

[16] In a recent paper, Mavroeidis, Plagborg-Møller, and Stock (2014) find that the slope coefficient of the New Keynesian Philips curve varies from 0.001 to 0.018 according to different specifications and estimation methods. But in most cases the estimates are not significantly different from zero. Kim (2010) demonstrates that when New Keynesian models are estimated at a quarterly frequency, the Calvo parameter is upward biased and hence implies longer average price duration.

[17] Deliquency rates on consumer loans average 3.2% over the period 1987-2015. Deliquency rates on commercial and industrial loans average 2.95% over the same period.

Table 4: Estimated Parameters

		Prior			Posterior	
Param.	Description	Dist.	Mean	SD	Mode	SD
$a_{\Delta y}$	Taylor rule output coefficient	normal	0.25	0.1	0.4054	0.0857
a_{π}	Taylor rule inflation coefficient	normal	1.5	0.25	2.3772	0.1382
ρ_p	Taylor rule smoothing	beta	0.85	0.1	0.6674	0.0464
ξ_p	Calvo price stickiness	beta	0.6	0.1	0.8858	0.0163
ξ_w	Calvo wage stickiness	beta	0.6	0.1	0.8823	0.0169
ι_p	Price indexation on inflation target	beta	0.5	0.15	0.8080	0.0716
ι_μ	Wage indexation on tech. growth	beta	0.5	0.15	0.5631	0.1544
ι_w	Wage indexation on inflation target	beta	0.5	0.15	0.7262	0.0988
σ_a	Utilization cost curvature	normal	1	1	0.3612	0.118
S''	Invest. adjustment cost curvature	normal	5	3	4.6066	1.0468
β^i	Discount factor impatient	beta	0.94	0.01	0.9634	0.0073
b_c^p	Consumption habit patient	beta	0.65	0.1	0.9381	0.0163
b_c^i	Consumption habit impatient	beta	0.65	0.1	0.7499	0.0638
b_h^p	Housing habit patient	beta	0.65	0.1	0.9829	0.0048
b_h^i	Housing habit impatient	beta	0.65	0.1	0.6668	0.1064
$F(\omega^i)$	Probability of default impatient	beta	0.007	0.004	0.0149	0.0089
$F(\omega^e)$	Probability of default entrepreneur	beta	0.009	0.004	0.0129	0.004
μ^i	Monitoring cost impatient	beta	0.25	0.1	0.2043	0.082
μ^e	Monitoring cost entrepreneur	beta	0.25	0.1	0.3558	0.0733
ψ_h	Housing weight in utility	normal	0.25	0.1	0.1693	0.0671
κ	Share of patient in total labor	beta	0.5	0.1	0.5342	0.0901
ρ_ε	Autocorr. stationary technology	beta	0.5	0.2	0.9392	0.0115
ρ_g	Autocorr. government spending	beta	0.5	0.2	0.9221	0.0665
ρ_{λ_f}	Autocorr. price markup	beta	0.5	0.2	0.9168	0.0225
ρ_{μ_Υ}	Autocorr. IST	beta	0.5	0.2	0.9818	0.0103
ρ_{μ_z}	Autocorr. technology trend	beta	0.5	0.2	0.9885	0.0031
ρ_ν	Autocorr. collateral	beta	0.5	0.2	0.9893	0.0075
ρ_{π^*}	Autocorr. inflation target	beta	0.5	0.2	0.4369	0.0517
ρ_{σ^i}	Autocorr. household risk	beta	0.5	0.2	0.5001	0.2774
ρ_{σ^e}	Autocorr. entrepreneur risk	beta	0.5	0.2	0.5001	0.2773
ρ_{ζ_c}	Autocorr. preference	beta	0.5	0.2	0.2313	0.1328
ρ_{ζ_i}	Autocorr. MEI	beta	0.5	0.2	0.1519	0.0972
σ_ε	SD stationary technology	invg2	0.002	0.003	0.0042	0.0003
σ_g	SD government spending	invg2	0.002	0.003	0.0155	0.0011
σ_{γ^e}	SD equity	invg2	0.002	0.003	0.0010	0.0005
σ_{λ_f}	SD price markup	invg2	0.002	0.003	0.0083	0.0023
σ_{μ_Υ}	SD IST	invg2	0.002	0.003	0.0036	0.0002
σ_{μ_z}	SD technology trend	invg2	0.002	0.003	0.0004	0.0001
σ_ν	SD collateral	invg2	0.002	0.003	0.0169	0.0022
σ_{π^*}	SD inflation target	invg2	0.002	0.003	0.0023	0.0003
σ_{σ^e}	SD household risk	invg2	0.002	0.003	0.0010	0.0005
σ_{σ^e}	SD entrepreneur risk	invg2	0.002	0.003	0.0010	0.0005
σ_{ε^p}	SD monetary policy	invg2	0.002	0.003	0.1581	0.0321
σ_{ζ_c}	SD preference	invg2	0.002	0.003	0.0148	0.0046
σ_{ζ_i}	SD MEI	invg2	0.002	0.003	0.0167	0.002

Notes: invg2 corresponds to the inverse gamma distribution, type 2.

Table 5: Steady-State Properties, Model Versus Data

Variable	Description	Model	Data
c/y	Consumption to GDP ratio	0.64	0.60
i/y	Investment to GDP ratio	0.18	0.22
g/y	Government spending to GDP ratio	0.18	0.18
k/y	Productive capital to GDP ratio	1.38	1.25
h/y	Housing capital to GDP ratio	5.32	1.31
b/y	Bank assets to GDP ratio	1.05	1.34
d/y	Bank deposits to GDP ratio	0.93	1.09[a]
b^i/b	Household debt to total debt ratio	0.43	0.54
π	Inflation (APR)	2.20	2.20
R	Fed funds rate (APR)	4.50	3.97
L^b	Bank leverage	8.76	8.76
L^e	Entrepreneurial leverage	1.75	1.75
L^h	Household leverage	1.09	1.18

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.
[a] We define bank deposits as the sum of M3 (M2 + large and long-term deposits), Treasury Bills, and Treasury Notes.

shoots the actual default rates of firms and households. The two monitoring costs, μ^i and μ^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 relatively close to these values for both parameters. Another important coefficient is the share κ 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.[18] We find a posterior of 0.60, implying a larger large of patient households. The housing weight in utility ψ_h has a prior of 0.25, following Clerc et al. (2015) and we find a posterior of 0.17.

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 0.99. We think this is very high. Only the autoregressive coefficients of trend technology, inflation target, and consumption preference have a posterior mean below their prior mean. The estimated standard deviation of the collateral shock is quite large, with a value of 0.017, followed by that of the marginal efficiency of investment, at 0.032. We show the effect these shocks have on the economy in the next section.

4.4 Model Fit

We assess whether our estimated model is a reliable representation of the US economy by comparing its steady-state properties to the data. Table 5 reports selected

[18] According to Pew Charitable Trusts (2015), 8 in 10 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.

model variables and ratios evaluated at the posterior mode, along with their empirical counterpart.[19] Overall, the model and the data match well. Note that 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 housing capital to GDP, which is way too high in the model. This is because we deliberately abstract from housing producers (housing supply is fixed) because they are not central to our paper. A more elaborate housing construction sector would probably account for this difference. 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.

5 The Role of the Collateral Shock

In this section, we analyze the prominent role of the bank collateral shock. We first present quantitative evidence supporting our claim that this shock is the main driver of economic fluctuations. We then attempt to explain why this is the case. Finally, we discuss the disparities between our collateral shock and CMR's risk shock.

5.1 Quantifying the Role of the Collateral Shock

We start with our main result. Table 6 reports the percentage of the variance in key variables explained by our different shocks. By business cycle frequency we mean variations comprised between 6 and 32 quarters. The collateral shock accounts for more than half of the variance in output and investment, almost half of

Table 6: Variance Decomposition at Business Cycle Frequency

Shock	Collateral ν_t	M.E.I. $\zeta_{I,t}$	Technology ε_t, $\mu_{z,t}$, $\mu_{\Upsilon,t}$	Markup $\lambda_{f,t}$	Pref. $\zeta_{c,t}$	M.P. ϵ_t^p, π_t^*	Gov. ε_t^g	Equity γ_t^e
GDP	57	7	11	10	4	0	7	0
Consumption	47	1	19	8	21	0	0	0
Investment	63	18	6	11	0	0	0	0
Hours	38	10	24	12	5	0	9	0
Household Credit	44	0	46	3	0	0	0	0
Entrep. Credit	77	3	6	7	0	0	0	1
Bank leverage	54	2	17	15	0	6	1	0
Entrep. leverage	78	3	2	3	0	0	0	2

Notes: The variance decomposition is computed for the parameters evaluated at their posterior mode. The two risk shocks, σ_t^i and σ_t^e, contribute negligibly to the variance decomposition of all variables and are therefore omitted from the table. Shares are in percent. Numbers in each row need not add up to 100 due to rounding.

[19] We also compare our model's dynamic properties to the data, which we report in the last section of the technical appendix.

the variance in consumption, and over a third of the variance in employment. This is more than any other shock. To the best of our knowledge, no paper in the DSGE literature puts forward a shock able to drive simultaneously output, investment, and consumption. Regarding financial variables, the drive is even more substantial. Note that the marginal efficiency of investment shock contributes non negligibly to the evolution of investment, whereas the preference shock explains almost a quarter of consumption. Also, the four supply shocks combined (TFP, trend, investment-specific technology, and price markup) drive a significant 20% to 30% of the variance in the main macroeconomic variables. This stands in contrast to the other demand shocks (monetary policy, government spending, equity), which have virtually no 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, credit to households and entrepreneurs. 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 GDP, consumption, investment, household credit, and entrepreneurial credit, both 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. Regarding investment, the collateral shock is not able to account fully for the huge drop in 2009. As mentioned above we suspect that other factors are at play, including the MEI shock, which helps explain the difference between the two series. In the case of bank assets, we find that the collateral shock overshoots the actual data by a significant margin. The reason is probably that in the model banks have only one type of assets, the loans they make to entrepreneurs. Hence a shock on ν_t provokes a large fall in banks' balance sheet. However, in the real world, banks hold many different types of assets, including long-term illiquid loans, which will not adjust immediately to the new lending conditions. Also, following the turmoil in financial markets the US banking sector experienced a consolidation. Commercial banks purchased large amounts of assets from distressed shadow banks. Thus, the fall in assets in aggregate was less pronounced and this is what our data captures. A more detailed model with various types of assets or an heterogeneous sector would be better suited to address this phenomenon. Still, overall, the match is good, and we see this counterfactual exercise as supporting our claim that the collateral shock is the most important shock driving the economy.

5.2 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 strong comovements between output and investment on the one hand, and consumption on the other.

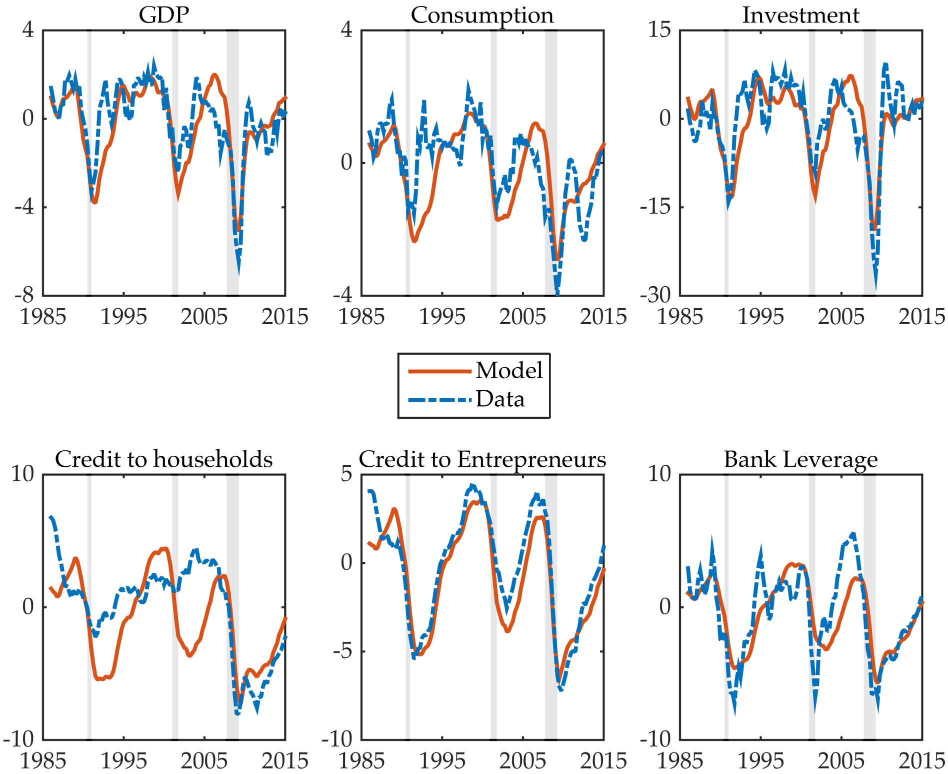

Figure 4: Isolating the Collateral Shock

Notes: The solid line is the result of simulating the model with only the estimated collateral shock, while shutting off all other shocks. The dashed line is the simulation of the model with all estimated shocks. By construction, this corresponds almost exactly to the data, up to some measurement errors. Variations are expressed in annual percentage rate.

Dynamic Responses Let us consider first impulse response functions. What we refer to as a negative collateral shock, *i.e.* a fall in ν_t, is the fact that at some point banks realize that the collateral they hold is going to depreciate in the next period.[20] Think of a sudden awareness to risks 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 macro, banking, and entrepreneurial variables to such an event, while Figure 8 focuses on the household sector.

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.

[20] 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. More specifically, the reduction in lending leads to a fall in the demand of capital and housing, which depresses asset prices.

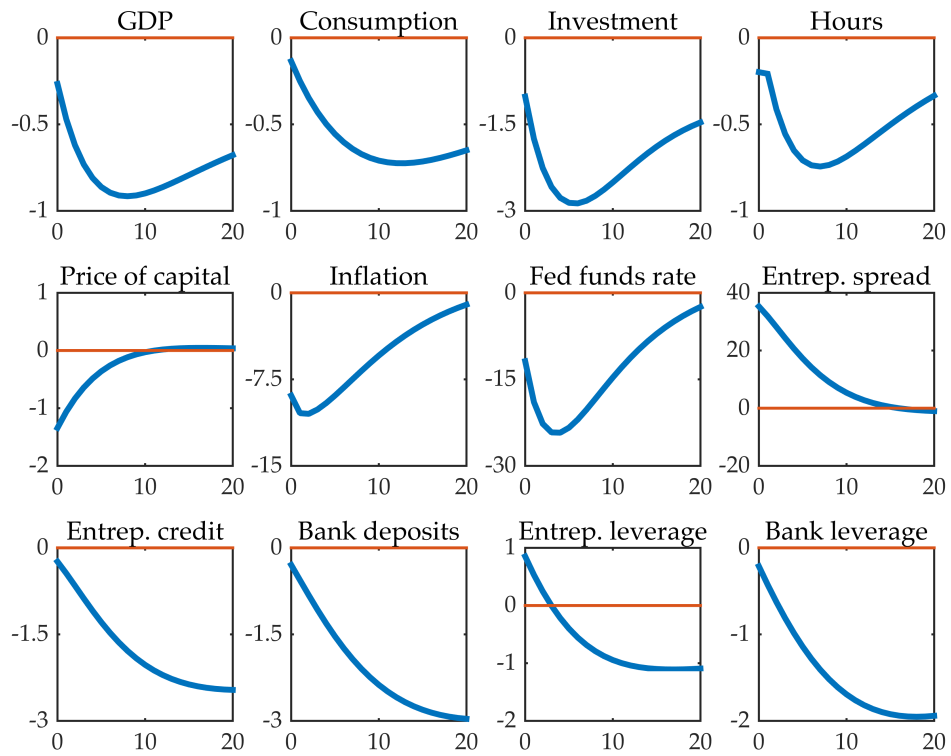

Figure 5: Dynamic Responses to a Collateral Shock, Main Variables

Notes: All variables are expressed in percentage deviation from their steady state, except for Inflation, Fed funds rate, and Credit spread, which are expressed in annual basis points.

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 entrepreneurial credit spread, *i.e.* the difference between the interest rate on loans to entrepreneurs and the fed funds rate, from going up.

In the banking sector, net worth is not immediately affected and adjusts rather slowly. This reflects the observation by Adrian and Shin (2010) that "bank equity is sticky". The reduction in credit translates into a drop in deposits. 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 leveraged 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

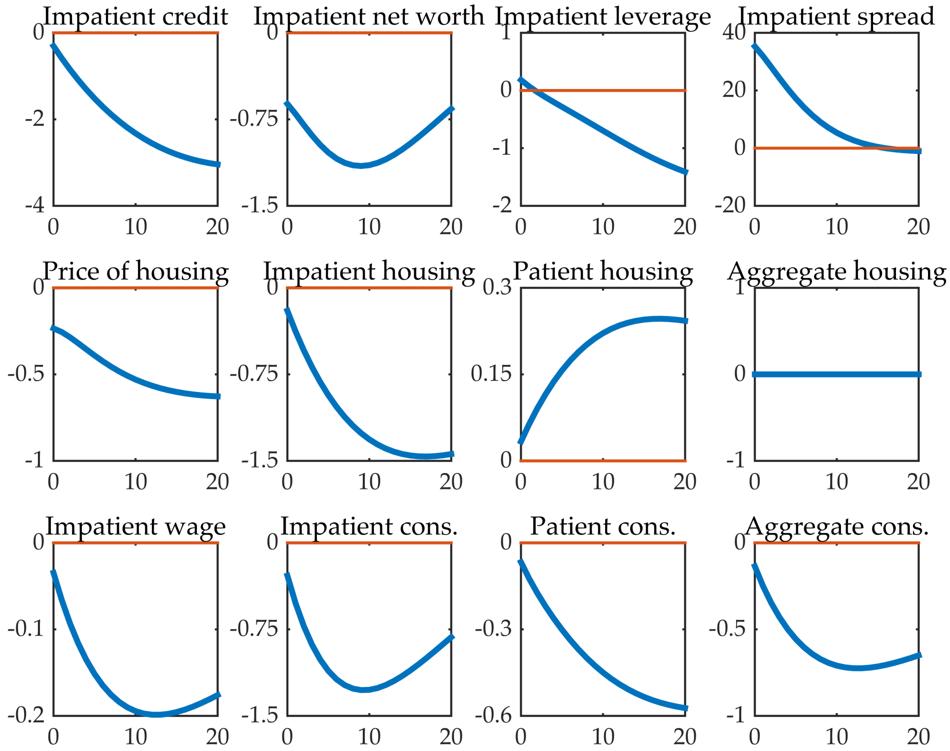

Figure 6: Dynamic Responses to a Collateral Shock, Household Variables

Notes: All variables are expressed in percentage deviation from their steady state, except for Impatient spread, which is expressed in annual basis points.

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 also falls, although less than the price of capital, because patient households take advantage of the situation by buying cheap housing, which stabilizes demand. 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 house prices and net worth, financially-constrained impatient households are forced to deleverage. This slow and painful process, sometimes referred to as debt deflation, is a stark feature of the recent financial crisis. One associated consequence is that indebted households cut their consumption drastically. Indeed, on impact, consumption of impatient workers drops by over six times as much as that of patient ones. As a result, aggregate consumption also 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; countercylical household net worth, nonfinancial firm net worth and leverage, and credit spreads. We believe this is the main reason why the data favors our shock.

Dynamic Correlation with GDP Following CMR's lead, we compute the cross-correlations between today's GDP and a number of 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. Note that contemporaneous consumption and investment are highly correlated with output, as is well known. The two lines display the correlations implied by our estimated model: the one with circles is the result of the model simulated with all shocks, while the one with stars is the result of the model fed only with the collateral shock. Figure 7 allows us to make two observa-

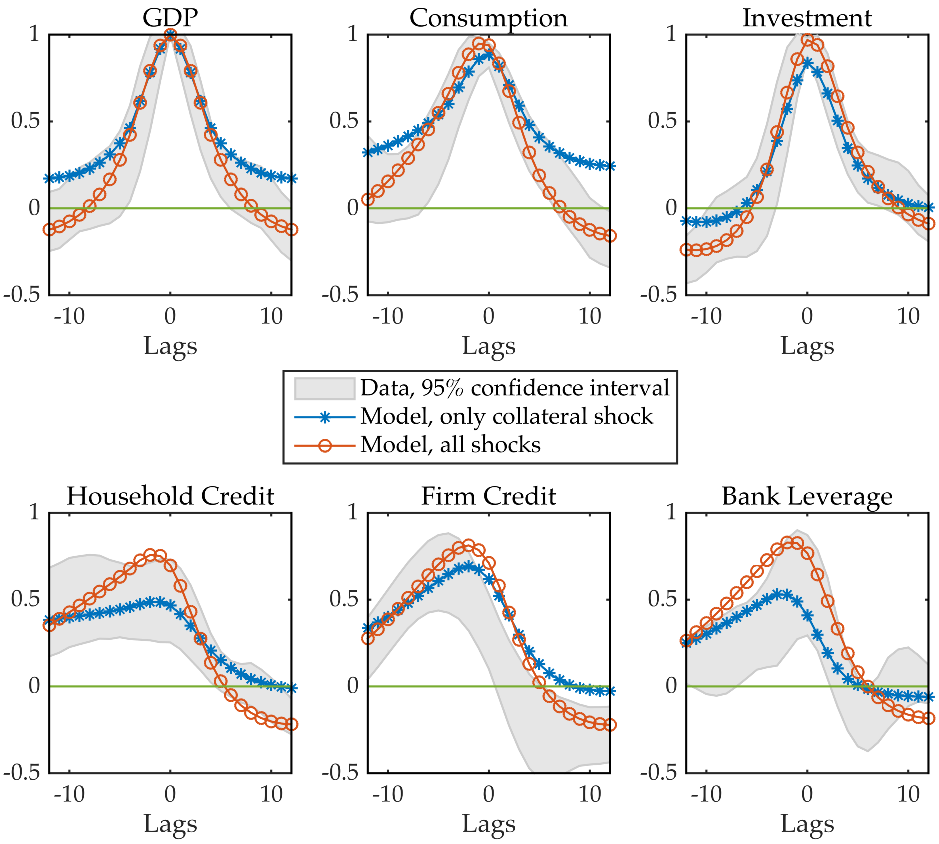

Figure 7: Cross Correlations with GDP, Model Versus Data

Notes: The x-axis corresponds to lags (one period is a quarter). For example, output is perfectly correlated with itself contemporaneously, that is, at lag zero.

tions. First, for all variables bar credit to firms, the two lines implied by the model lie within the range implied by the data. This means our model is successful at matching empirical correlations. Second, and perhaps more interestingly, the line with stars tracks the line with circles closely, meaning the model with only the estimated collateral shock is able to capture most of the actual correlations. We think this is another reason why our econometric estimation attributes such a large role to the collateral shock in the account of business cycles.

5.3 The Collateral Shock Versus the Risk Shock

In their influential paper, CMR claim that the risk shock, an idiosyncratic disturbance to the productivity of entrepreneurs, is the main driver of the business cycle. Our analysis is a continuation of their work: We reinterpret this 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.

Let us be clear, the risk shock and the collateral shock share many qualitative properties. They are both aggregate demand shocks, because they affect the volume of credit, the demand for capital, and ultimately investment and consumption. But there are some important differences. Figure 8 plots the responses of selected variables to both shocks. For this exercise, we equalize the autocorrelation

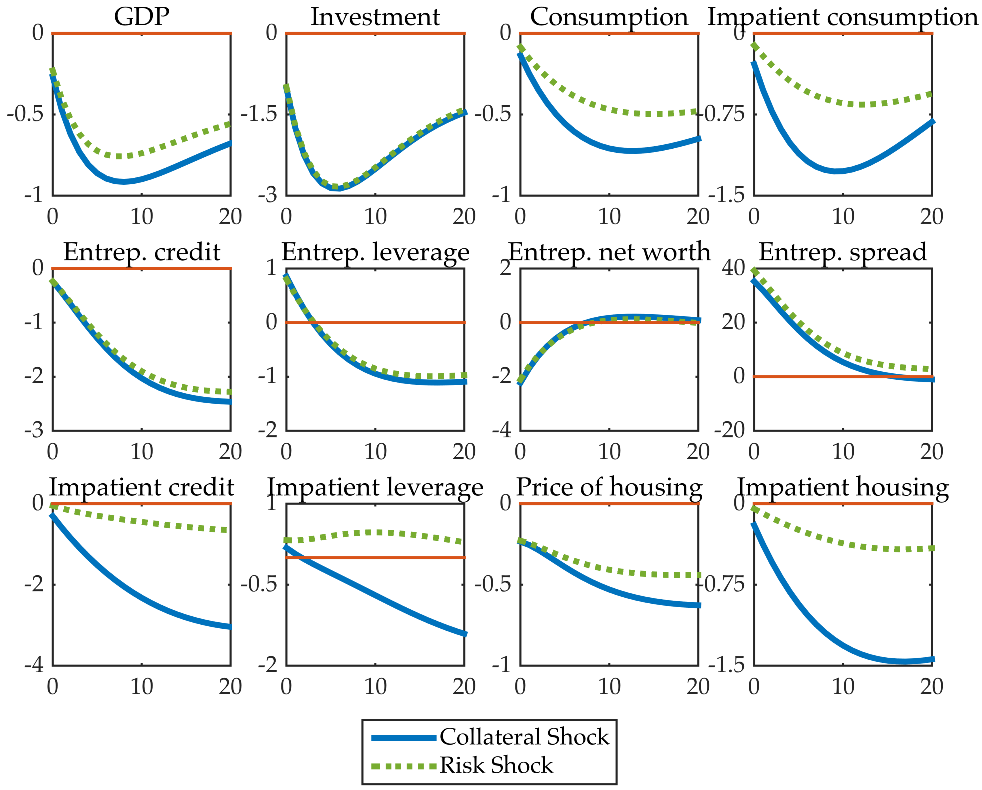

Figure 8: Dynamic Responses to Two Shocks

Notes: All variables are expressed in percentage deviation from their steady state, except for Entrep. spread, which is expressed in annual basis points.

parameters of the two shocks: $\rho_\nu = \rho_{\sigma^e} = 0.987$. We calibrate the standard deviation of σ_t^e such that the response of credit to entrepreneurs b_t^e is exactly the same for both shocks. In effect, this requires a larger value for the risk shock: $\sigma_\nu = 0.0176$ and $\sigma_{\sigma^e} = 0.021$. As the second row in the figures makes clear, all variables related to entrepreneurs exhibit almost exactly the same dynamics. This is also the case for investment. However, the third row tells another story. Credit to impatient households drops significantly more following a collateral shock. This is, of course, a direct effect of the shock. As a result, impatient households are forced to reduce their housing and consumption expenditures by a much larger amount. One consequence is a steeper fall in the price of housing, leading to larger housing crisis. In the case of the risk shock, impatient households are indirectly affected. Credit does fall but this is due to general equilibrium effects. Indeed, the drop in credit to entrepreneurs causes a fall in investment and hence in output. As a consequence of a weaker economy and a lower demand for labor, impoverished households reduce their demand for housing and consumption goods. But the effect is much more subdued. The drop in housing is about three times smaller then in the case of a collateral shock. The drop in consumption is about twice as small.

To further compare the two shocks, we remove the collateral shock from our model and we estimate it again. The full results are reported in the technical appendix. We make two observations. First, the model with collateral shocks has a higher marginal likelihood. Second, in the model without collateral shocks, the risk shock becomes the main driver of the business cycle, but its effect on consumption is not as strong.

To conclude this subsection, we note that although the collateral and the risk shocks have many features in common, the collateral shock clearly dominates, mainly by generating a greater response in household credit, housing price and demand, and consumption.

6 External Performance

We wish to provide additional evidence that our model is a sensible framework to study the role of lending standards on the US economy. We investigate how two measures of credit conditions in the model evolve relative to their proxy in the data. We emphasize that none of the data presented in this section was used in the econometric estimation.

6.1 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 the demand for loans and increase 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 ν_t. Figure 9 shows the results. The observation period is shorter than the one in our analysis, because the survey starts in 1991Q3 for business loans and 1995Q3 for consumer loans. Sill that 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 0.56 and 0.47 for the top and bottom panels, respectively. It is notable that our unique shock is able to match these two series. We conclude that it accurately

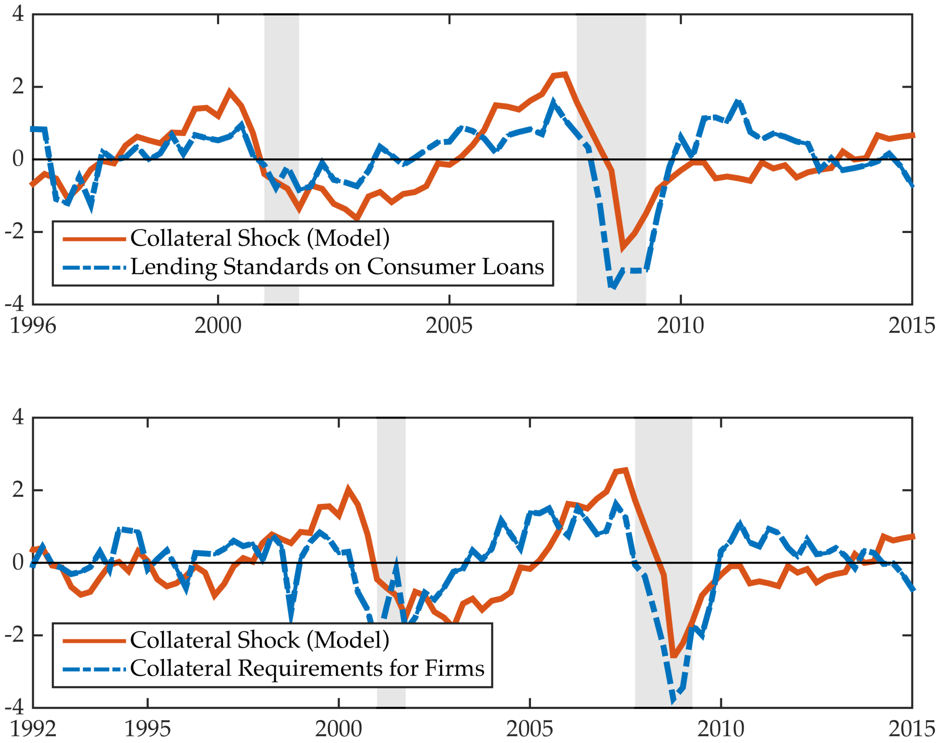

Figure 9: Bank Tightening, Model Versus Data

Notes: In both panels the solid line corresponds to the smoothed estimated process for the collateral shock. In the top panel the dashed line is the net percentage of domestic banks tightening standards on credit card consumer loans. In the bottom panel the dashed line plots 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. All three series are HP-filtered and normalized by their standard deviation.

reflects bank lending conditions, irrespective of the borrower, and we believe this provides further support to our story.

6.2 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. In Figure 10, we compare 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 0.65 for households and 0.72 for firms. We don't match the levels exactly, and the model series tend to overshoot the data, both in expansions and recessions. But contrary to the previous graph,

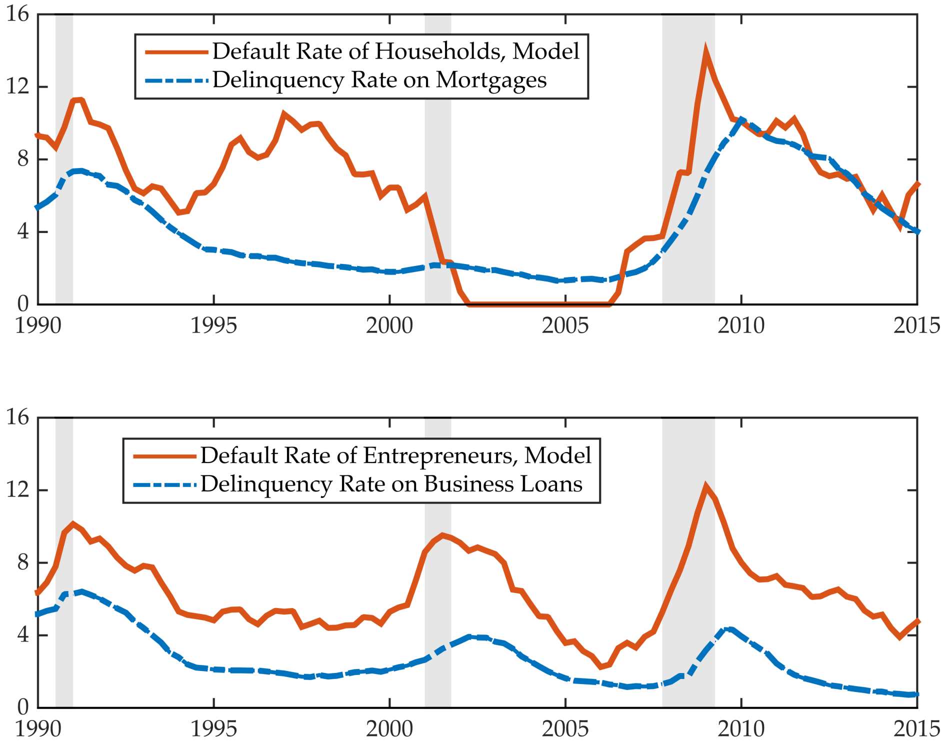

Figure 10: Delinquency Rates, Model Versus Data

Notes: In the top panel the solid line corresponds to the model-implied default rate of impatient households $F_t(\omega_t^i)$. The dashed line is the delinquency rate on loans secured by real estate for all commercial banks. In the bottom panel the solid line corresponds to the model-implied default rate of entrepreneurs $F_t(\omega_t^e)$. The dashed line is the delinquency rate on commercial and industrial loans for all commercial banks. The vertical axis is in percentage points.

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 have been a long period when defaults were continuously falling, from 1991 to 2006, despite the burst of the dot-com bubble in 2001. But then there was a huge increase in 2007 when the housing market collapsed.

Overall, notwithstanding some imperfections, we think our model does a good job at capturing the cyclical variations in default rates, especially given that these data did not play a role in the estimation. We see it as another test that validates our framework.

6.3 Marginal Propensity to Consume

Our model offers a limited degree of heterogeneity: households are either borrowers or savers. One could call them hand-to-mouth and Ricardian, subprime and prime, or even poor and rich. Yet this dual heterogeneity enables us to compare the behavior of each type following, say, an adverse shock. In Section 2 we report estimates of MPCs by Mian, Rao, and Sufi (2013).

The MPC out of wealth over a period τ is defined as

$$\begin{aligned} \mathrm{MPC}_\tau^i &= \frac{\partial C_\tau^i}{\partial N_\tau^i} \\ &= \frac{\partial C_\tau^i}{\partial \nu_\tau} \frac{\partial \nu_\tau}{\partial N_\tau^i}. \end{aligned}$$

To be completed.

7 Macroprudential Application

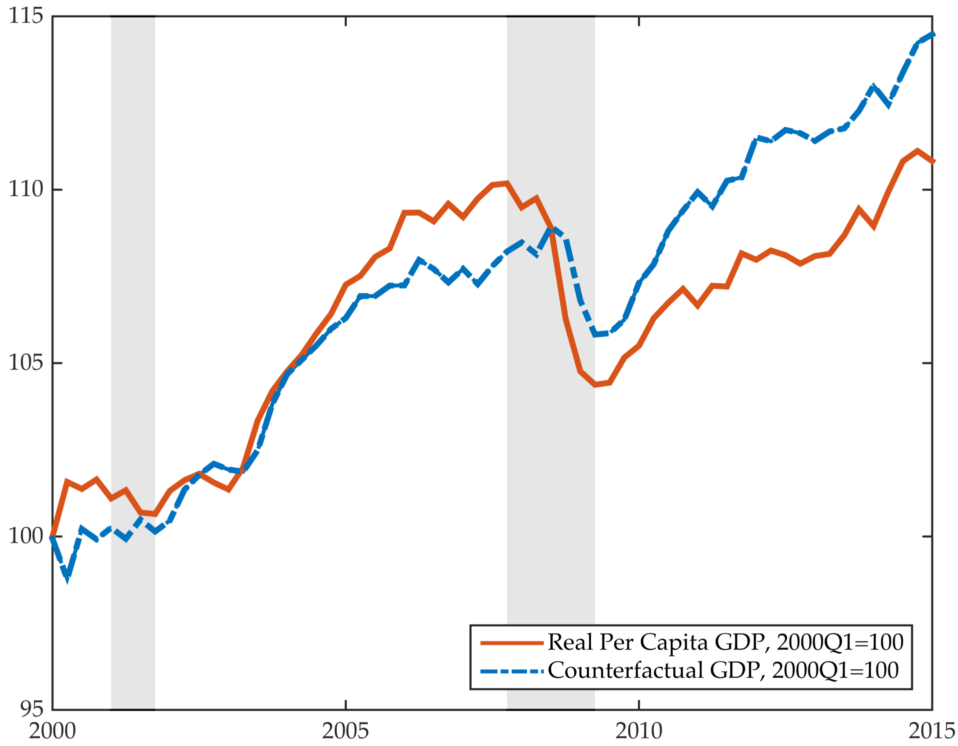

Figure 11: Output in a World with Macroprudential Regulation

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

To be completed.

8 Conclusion

We study the impact of bank collateral requirements on the economy. Tighter requirements mean less credit flowing to both households and the productive sector. We start by documenting the rise and fall in household and business debt over the past fifteen years. We suggest the origin of this boom and bust debt cycle has a lot to do with banks' adjustment of lending standards over time. We acknowledge the empirical evidence on the link between bank credit and household consumption, and we present stylized facts on the leverage of banks, households, and firms.

Equipped with this preliminary evidence, we build a macroeconomic model with two main ingredients. First, banks provide loans to entrepreneurs who use these loans to invest in physical capital. Second, banks also provide loans to a fraction of households who use these loans to invest in housing capital *and* consume. We define the collateral shock as the exogenous movement in collateral requirements imposed by banks on their borrowers. We estimate our model with US financial and macroeconomic data from 1985 to 2015. We find that the collateral shock is the main driver of the business cycle. The double credit relationship—bank-household and bank-entrepreneur—is the main reason why the collateral shock is able to jointly match the dynamics of aggregate consumption and investment. Our model replicates the aforementioned stylized facts, by implying procyclical bank leverage, countercyclical firm leverage, and acyclical household leverage.

We show that the series for collateral requirements generated by the model tracks two corresponding empirical series constructed by the Fed, which were not used in the inference of parameters. This gives extra credit to the collateral shock. In addition, our model matches the evolution of delinquency rates on household and business loans fairly well. Finally, we calculate the path of a hypothetical economy where we assume that banks would have been subject to strict capital requirements of the type of Basel 3 regulation. For what it is worth, we find that had the regulation been in place in 2000, real GDP per capita would have been 3% higher than it actually was in 2015. This is because the crisis would have been much less severe.

Our analysis treats collateral requirements as an exogenous disturbance. It is clear, however, that banks respond to changes in economic conditions by endogenously adjusting their lending standards. Therefore, an important question is to understand and model how banks react to these changes. Our understanding is that the economy is constantly hit by shocks coming from all different corners. The small ones have little or no effect on the macroeconomy or they average out in the aggregate. But the bigger ones can potentially cause trouble. Once they are caught up by the financial sector, they are amplified and essentially become collateral shocks, able to generate business cycle-like movements. The fact that banks and borrowers are more levered makes it more likely that these shocks will have large effects.

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