

Understanding Bank and Nonbank Credit Cycles: A Structural Exploration*

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Abstract

We explore the structural drivers of bank and nonbank credit cycles using a medium-scale DSGE model with two types of financial intermediation. We posit economy-wide and sectoral disturbances in both macro and financial sectors. We estimate that sectoral shocks to the balance sheets of entrepreneurs are important for fluctuations in bank and nonbank credit growth at the business cycle frequency. Economy-wide entrepreneurial risk shocks gain predominance for explaining the lower frequency co-movement between the two series. Macro shocks play very little role in explaining financial cycles.

JEL Classification: *E3, E44, G01, G21*

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1 Introduction

The increasing role of nonbank sector activity in the last three decades has significantly changed the U.S. financial intermediation system. Since the late 1990s, nearly 60 percent of total credit extended

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to the nonfinancial business sector has been from nonbanks as opposed to traditional bank sources. Additionally, nonbanks may have important implications for financial stability both directly and through their linkages with the banking system, considering that the current regulatory toolkit does not directly apply to these entities. The rapid rise of nonbank intermediation and its importance for financial stability make it critical to understand what drives credit in this sector, how these drivers relate to the drivers of traditional bank credit, and how fluctuations in nonbank credit propagate to the wider macroeconomy. To date, the macro literature has lacked an analysis of these issues.

We aim to fill this gap using an estimated dynamic equilibrium model that accounts for bank and nonbank lending to the nonfinancial business sector. Specifically, we ask what the structural sources of bank and nonbank credit cycles are, and how these disturbances propagate to the wider economy. Our model posits two main classes of structural shocks that could drive the credit cycles. First, we allow for the usual economy-wide disturbances such as technological progress, aggregate demand, or financial shocks that most of the extant literature on business cycles have considered¹. Second, on top of the economy-wide shocks, we also allow for sector-specific shocks, which only directly impact either bank or nonbank lending. These sectoral shocks—examples include the disturbances to commercial banking in the savings and loan crisis, the collapse of shadow banking in the Great Recession, or changes in bank regulatory policy—could play an important role alongside aggregate shocks in understanding the macro-financial cycles.²

Our model builds off the previous contributions of Bernanke et al. (1999); Sandri and Valencia (2013); Clerc et al. (2015) and Begenau and Landvoigt (2020). It allows for two types of financial intermediaries: banks and nonbanks. Both financial institutions intermediate credit between saving households and borrowing entrepreneurs. Following Begenau and Landvoigt (2020), deposits from both institutions produce partially substitutable liquidity services and there is competition for deposit funds. Both institutions combine deposits with inside equity accumulated through retained earnings to make loans to entrepreneurs. Banks and nonbanks have the option to default. The key difference is that upon default, banks have access to deposit insurance while nonbanks do not. Further, banks face capital requirements set by a regulator while nonbanks set leverage based on market forces.

¹See Smets and Wouters (2007); Justiniano et al. (2010); Jermann and Quadrini (2012); Christiano et al. (2014); Iacoviello (2015).

²One feature that our model does not include, however, is shifts in regime that may change structural parameters within the model along the lines of Bianchi (2013). Therefore, we do not capture potential switches in the structure of the economy that may impact the propagation of the structural shocks. Part of the reason for this is computational; since we are already estimating a rich structural model, it would be computationally challenging to allow for regime shifts as well.

We estimate our model using financial and macro data at the sectoral and aggregate levels. To construct our bank and nonbank lending data, we follow Gallin (2013) and allocate all lending passing through the long intermediation chains in the U.S. financial sector to institutions that, broadly speaking, borrow from households and lend to the productive nonfinancial sector. We think of bank lending as encompassing all lending to the nonfinancial business sector from commercial banks, savings institutions, and credit unions. We think of nonbank lending as encompassing all other providers of nonfinancial business credit outside of banks, including money market mutual funds, mutual funds, pension funds, and insurance companies. We use Bayesian methods to match macro aggregates and lending quantities and rates in the bank and nonbank sectors on quarterly U.S. data from 1987 to 2015.

We find a quantitatively dominant role for sectoral financial shocks in driving bank and nonbank lending growth. Over 70 percent of bank and nonbank lending growth is driven by sectoral shocks. Especially important are shocks to the net worth position of the entrepreneurs who borrow from banks and nonbanks. A decline in the net worth of entrepreneurs in one sector impairs their ability to take on debt and purchase capital, which leads to further declines in net worth and the price of capital. These fire sale dynamics encourage entrepreneurs in the other sector to demand loans to take advantage of the low capital prices. Indeed, without the unimpaired entrepreneurs from stepping in, capital prices would tumble even further. We find this dynamic to be the main mechanism that drives lending growth dynamics in the estimated model. Interestingly, the single most important structural shock driving lending growth in the banking sector is the shock to the net worth position of entrepreneurs borrowing from the nonbank sector, and vice versa. Historical decompositions show that entrepreneur net worth shocks are important in understanding the deep decline in bank lending growth in the early 1990s and the dynamics of bank and nonbank lending entering into the Great Recession. Together, they account for around half of the declines in bank and nonbank lending growth during the Great Recession.

All this is not to say, however, that aggregate shocks within the model are estimated to be unimportant for bank and nonbank lending growth. We find an important frequency dimension to our results on the importance of sectoral versus aggregate shocks. Specifically, at lower frequencies, economy-wide fluctuations in the variance of idiosyncratic risks that entrepreneurs face (risk shocks) become important, especially in driving the low-frequency positive co-movement between the bank and nonbank credit cycles. At business cycle frequencies, however, their effects are negligible. Historically, this entrepreneurial risk operating at low frequencies helps us understand the slow

lending growth recoveries following the three credit growth downturns – the savings and loan crisis, the early 2000s recession, and the Great Recession – found in the data. Additionally, entrepreneur risk shocks are the most important driver of investment growth dynamics among the financial shocks, accounting for close to 30% of its movements, and play an important role for nonfinancial lending spreads and deposit rate movements.

Our estimated model is consistent with three empirical facts on bank and nonbank lending growth in the United States. First, the model can generate that nonbank lending growth is less volatile than bank lending growth over the cycle. Second, despite the important role of sectoral shocks in driving lending growth dynamics, the model can replicate the positive correlation between bank and nonbank lending growth. Third, the model-generated data are also consistent with the low observed correlation between lending growth and investment growth.

Finally, we externally validate our estimated model in three ways. First, we compare model-generated series of bank and nonbank entrepreneur default to delinquency rates of commercial and industrial loans from all commercial banks and nonfinancial corporate bond default rates, respectively. As our model largely utilizes the aggregate entrepreneur risk shocks to generate the entrepreneur default rate series, this check provides support for our estimated risk shock dynamics. Second, we validate our modeling choice for the nonbank financial sector by comparing the model-implied nonbank sector default to corporate bond default rates in the financial sector excluding banks. Finally, we compare our model-implied financial sector credit supply shocks to the excess bond premium (Gilchrist and Zakrajsek, 2012) data, respectively. All of these data were not used in the estimation of the model, lending further external credence to the model structure and estimates.

Literature Review. Our work closely relates to the literature on macro models with a financial sector. Jermann and Quadrini (2012); Christiano et al. (2014); Ajello et al. (2018) estimate medium-scale macro models on macro and financial data. They all find important roles for financial shocks in driving business cycle fluctuations. Different from our work, these papers do not model a separate financial intermediation sector. Gerali et al. (2010); Sandri and Valencia (2013); Iacoviello (2015); Clerc et al. (2015); Ajello (2016); Hiraakata et al. (2017); Afanasyeva and Guntner (2018) all formulate models with financial intermediaries, but they do not distinguish between bank and nonbank lending.

A burgeoning literature incorporates unregulated or shadow banking into macroeconomic models. Begenau and Landvoigt (2020) and Moreira and Savov (2017) are focused on modeling shadow banks that introduce financial fragility into the macroeconomy in the form of run risk or liquidity

crunches, respectively. Gertler et al. (2016); Meeks et al. (2017); Nelson et al. (2017); Fève and Pierrard (2017) focus on the wholesale funding aspect of shadow banks. The shadow banks are either modeled as borrowing funds primarily from retail banks funded by the households as in Gertler et al. (2016), or as securitizers of bank loans that relax regulatory constraints on commercial banks as in Meeks et al. (2017); Nelson et al. (2017); Fève and Pierrard (2017). Adrian and Boyarchenko (2013) presents a model with banks and nonbanks that can generate the procyclicality of bank leverage and acyclicity of nonbank leverage. Mendicino et al. (2018) studies the optimal dynamic capital requirements in a model that allows for bank lending and direct household financing of investment. Dempsey (2020) analyzes optimal capital requirements in a model that distinguishes between banks and nonbanks through capital requirements and deposit insurance as well as the banks' market power and ability to monitor loans. While we share certain modeling elements with these works, none of them look at structurally understanding the drivers of bank and nonbank credit cycles.

Other papers have also considered a dichotomy between bank versus bond finance but without estimating the structural shocks driving bank versus nonbank credit cycles. Fiore and Uhlig (2011, 2015) present models that can endogenously generate a division between firms using market-based bond finance versus bank finance. Firms trade off more information about their idiosyncratic shocks at a cost via bank finance with the more uncertain but costless market-based finance. Crouzet (2018) studies a model where firms have the option to substitute between bank and bond finance, thereby speaking to both the extensive and intensive margin of firm finance. Bank finance allows restructuring in times of stress at a higher cost during normal times.

Finally, there have been more empirical studies measuring the bank and nonbank credit cycles Becker and Ivashina (2014); Herman et al. (2017); Kemp et al. (2018); FSB (2018). These papers take an entirely reduced-form approach in measuring bank and nonbank lending and in investigating their financial and macro effects. They do not attempt to model these fluctuations.

Plan for the Paper. The rest of the paper is organized as follows. Section 2 describes how we measure the bank and nonbank credit cycles and key empirical facts that we find in the data. Section 3 describes the model environment in detail. Section 4 discusses our estimation strategy. Section 5 presents our main results decomposing bank and nonbank credit cycles with the estimated model. Section 6 presents three model external validation exercises. Finally, Section 7 summarizes our conclusions.

2 Empirical Facts on the Bank and Nonbank Credit Cycles

We begin by documenting the empirical regularities on the bank and nonbank credit cycles in the U.S. from 1987:Q2 to 2015:Q1. We focus on lending to the nonfinancial business sector and from domestic private financial entities to be consistent with our modeling approach.

2.1 Defining Bank and Nonbank Lending

We define bank lending as all loans from commercial banks, savings institutions, and credit unions. We take a broad approach in thinking about nonbank lending. Our definition includes all lending to the nonfinancial business sector outside of the traditional banking sector, government, and foreign entities. This is comprised of a mix of financial institutions such as mutual funds, pension funds, insurance companies, and money market mutual funds.

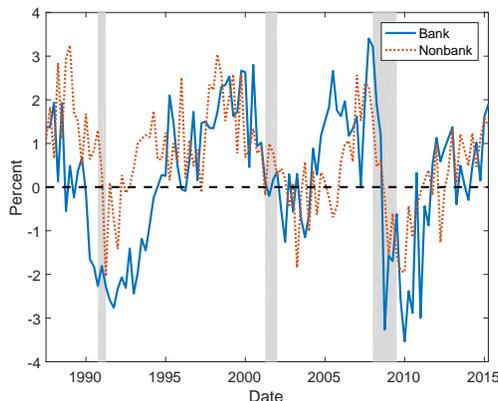
Before moving on, it is important to emphasize that, in measuring nonbank credit cycles, we consider a larger class of financial intermediaries than what several authors have referred to as shadow banks (Pozsar et al., 2010; Gallin, 2013). For example, Gallin (2013) is careful to distinguish between shadow bank and nonbank lending, of which the former is defined as institutions relying on short-term funding and have "inherent susceptibility to runs." Our definition of nonbank lending is closer to the "Monitoring Universe of Non-bank Financial Intermediation" as defined in the FSB (2018), which contains all nonbank financial intermediation. This broad definition is also in line with recent papers measuring the nonbank credit cycle, such as Kemp et al. (2018).

2.2 Measurement Issues

We use the Federal Reserve Board's Z.1 statistical release to construct our measures of bank and nonbank lending. Our goal is to decompose a measure of total nonfinancial business sector lending into that done by banks and nonbanks. Pozsar et al. (2010) and Gallin (2013) emphasize the difficulty of this exercise, as there are complex intermediary chains within financial sector institutions that may lead to a drastic overstatement of the size of nonbank lending.

To overcome this issue, we follow a procedure outlined in Gallin (2013) for netting out the financial intermediary chains. Gallin (2013) decomposes the credit from nonfinancial sector lenders to nonfinancial sector borrowers as flowing through five categories of financial intermediaries: traditional banks (commercial banks, savings institutions, and credit unions), government (federal government and the monetary authority), foreign entities, long-term funders (mutual funds, pen-

Figure 1: Growth Rates of Bank and Nonbank Lending



NOTE: This figure shows per capita bank and nonbank lending growth. The data are constructed using the methodology of Gallin (2013) and cover the period from 1987:Q2 to 2015:Q1. Gray shaded areas denote NBER recessions.

sion funds, and insurance companies), and short-term funders (money market mutual funds). He calls these financial intermediaries "terminal funders." Broadly speaking, these terminal funders borrow from the nonfinancial sector and fund both other financial intermediaries and nonfinancial sector borrowers. There are also intermediate funders, such as private-label issuers of asset-backed securities, funding corporations, and real estate investment trusts, which are entities along the intermediation chain.³

The objective of Gallin (2013) is to trace each unit of debt provided to nonfinancial sector borrowers through the intermediation chains in the financial system back to one of these terminal funders. The paper does so by assigning all nonfinancial sector debt listed in the Z.1 tables as held by the intermediate funders to terminal funders proportional to the holders of the intermediate funders' liabilities. For our purpose, this measure is appropriate as it resolves any double counting in the amount of credit provided by the financial system to the nonfinancial sector from grossing up the aggregate debt holdings of different financial intermediary entities.

We define banks as the traditional banks in Gallin (2013). Nonbanks are the sum of long-term funders and short-term funders. An important additional distinction to make is that while Gallin (2013) is interested in total nonfinancial sector lending, we are focused on lending to the nonfinancial business sector.⁴

Table 1: Key Summary Statistics on Bank and Nonbank Lending Growth

Statistic	Data
Std. bank gr.	1.59
Std. nonbank gr.	1.12
Corr. bank and nonbank gr.	0.48
Corr. bank and inv. gr.	0.16
Corr. nonbank and inv. gr.	0.17

NOTE: This table shows the standard deviations and correlations statistics for a selected set of variables. The data run from 1987:Q2 to 2015:Q1.

2.3 Empirical Facts

Figure 1 shows the bank (blue) and nonbank (orange) lending growth dynamics in the United States. Both bank and nonbank lending growth tend to comove over the credit cycle. Since the late-1980s, they have gone through three distinct swings. In the early- to mid-1990s, bank lending growth persistently declined following the savings and loan crisis. This decline was steeper and much longer lasting than the corresponding slowdown in nonbank lending growth. A second milder credit crunch occurred following the early-2000s recession. This decline in lending, in contrast, led to a more sluggish nonbank lending growth recovery. Finally, the Great Recession produced sharp declines and sluggish recovery in both bank and nonbank lending growth to the nonfinancial business sector, although again the depths of the decline in bank lending growth was more severe.

Table 1 shows several statistics that highlight the empirical regularities that we would like to investigate with our structural model. We are interested in three facts of the bank and nonbank credit cycles. First, nonbank lending growth is less volatile than bank lending growth. The standard deviation of bank lending growth fluctuations is 1.59, while it is 1.12 for nonbank lending growth. Second, bank and nonbank lending growth are positively correlated, with a correlation of nearly 0.5. Finally, both bank and nonbank lending growth are at best weakly positively correlated with real activity, which we measure in this case with investment growth.⁵

2.4 Discussion

Our empirical facts largely align with the literature. Kemp et al. (2018) measures the bank and nonbank credit extended to the entire nonfinancial sector for many developed and emerging markets.

³A full list of the definitions for each category can be found in Table 4.1 of Gallin (2013).

⁴Further details about our implementation of the procedure can be found in the Online Appendix Section A.

⁵As we are focusing on credit extension to the nonfinancial business sector, we find it most useful to use investment growth as our real indicator. Our exact definition of investment growth and the other variables we use in estimating the model can be found in Section 4.

Their results on the coherence and relative magnitudes of the bank and nonbank credit cycles differ across countries, but they do find that, for the United States, bank and nonbank credit growth are positively correlated with bank lending growth more volatile than nonbank lending growth. Becker and Ivashina (2014) examines bank and bond credit growth in the United States, and finds that bank debt is more volatile than bond debt.

At face value, the second empirical fact—that bank and nonbank credit growth is strongly positively correlated—points to the importance of an economy-wide factor in driving fluctuations. As emphasized in Foerster et al. (2011), however, inter-sectoral linkages may propagate sectoral shocks to the wider system as a whole, potentially allowing them to also explain positive sectoral co-movement. This issue necessitates the development of a structural model through which to filter the data, as discussed in the next section.

3 Model Environment

Our goal is to examine the structural drivers of bank and nonbank lending growth. To this end, we employ a medium-scale model that allows for bank and nonbank lending and can be taken to the data. The model builds off of the previous contributions of Bernanke et al. (1999); Sandri and Valencia (2013); Clerc et al. (2015); Begenau and Landvoigt (2020). At the heart of our model is a friction driven by asymmetric information that prevents the direct flow of funds from the saving households to the borrowing entrepreneurs. Financial intermediaries have the technology to monitor the entrepreneurs at a cost, and they take deposits from households and lend to entrepreneurs.

Importantly, our model specifies financial frictions that operate in both the productive nonfinancial sector and the financial sector. This feature implies that the net worth positions of the financial intermediaries and the nonfinancial sector both matter, allowing our paper to speak to the literature on the relative importance of nonfinancial versus financial sector net worth—Sandri and Valencia (2013); Clerc et al. (2015); Hirakata et al. (2017). In contrast to those papers, in our model, there are two types of intermediaries: banks whose deposits are insured and face capital requirements and nonbanks whose deposits are risky and have leverage ratios governed by market discipline.

We allow for a rich set of interactions between banks and nonbanks that can propagate sectoral shocks to the wider economy. First, on the funding side, banks and nonbanks compete for deposits from households and inside equity from investor agents. Second, the entrepreneurs who borrow from

banks and nonbanks compete in common capital goods and final goods markets. Therefore, financial conditions of banks and nonbanks are important in the determination of the overall equilibrium.

Our model is populated by households, entrepreneurs, investors, two types of credit intermediaries, and final goods and capital goods producers. We first give a brief summary of the economy. Then, we provide further details about the characteristics of the agents.

3.1 Structure of the Economy

In our economy, households are the main saving agents. They have an option to save in riskless bank deposits or risky nonbank deposits. We assume that households derive utility from both types of deposits, motivated by the benefits from liquidity services. Banks and nonbanks are two-period lived agents funded by deposits and inside equity capital provided by investor agents. Banks and nonbanks lend out funds to entrepreneurs, who then combine these funds with inside net worth to purchase capital to rent to final goods producers. We assume that a certain class of entrepreneurs borrow from banks exclusively and another class borrow from nonbanks exclusively.

There are aggregate and idiosyncratic shocks that hit the economy. The aggregate shocks can be economy-wide or sectoral in nature. The idiosyncratic shocks impact the capital returns of entrepreneurs and the portfolio returns of the financial intermediaries and generate an asymmetric information problem between the borrowers and lenders. Upon realization of the aggregate and idiosyncratic shocks, payoffs from the borrowers to lenders occur. We allow for limited liability and strategic default of entrepreneurs and intermediaries.

3.2 Agents in the Economy

Households. Households are risk-averse, infinitely-lived agents, who derive utility from consumption and liquidity services and disutility from working. They can save in deposits in banks and nonbanks. Households maximize

$$\begin{aligned}
& \max_{c_t, l_t, d_t^B, d_t^N} E_t \sum_{i=0}^{\infty} \beta^{t+i} \left[\tilde{\beta}_{t+i} \log(c_{t+i} - hc_{t+i-1}) - \frac{\chi}{1+\psi} l_{t+i}^{1+\psi} + \chi_h \log(h_{t+i}) \right] \\
& \text{s.t. } c_t + d_t^B + d_t^N \leq w_t l_t + R_{t-1}^D d_{t-1}^B + \tilde{R}_t^{D,N} d_{t-1}^N - T_t + \Pi_t \\
& h_t = \left[\Lambda_{N,t} (d_t^N)^{\alpha_h} + (d_t^B)^{\alpha_h} \right]^{1/\alpha_h},
\end{aligned} \tag{1}$$

where c_t denotes consumption, l_t denotes labor supply, and h_t denotes the liquidity services derived from credit intermediary deposits. The deposits can take two forms: d_t^B and d_t^N , representing deposits in banks and nonbanks, respectively, with corresponding returns R_{t-1}^D and $\tilde{R}_t^{D,N}$. Because of the presence of deposit insurance, the return from holding deposits in banks is risk-free from the perspective of the households and R_{t-1}^D is predetermined, whereas the return from holding deposits in nonbanks are risky and therefore $\tilde{R}_t^{D,N}$ may be affected by contemporaneous shocks. T_t denotes lump-sum taxes paid to the government, Π_t denotes profits from the capital good producers, which are owned by households, and dividend transfers from the investors and entrepreneurs who borrow from banks and nonbanks.

The liquidity services h_t is a CES function of deposits at the banks and nonbanks. The parameter ψ is the inverse of the Frisch elasticity of labor supply. The parameters χ and χ_h are respective utility parameters for labor and liquidity services. The parameter α_h denotes the elasticity of substitution between bank and nonbank deposits.⁶

There are two shocks: $\tilde{\beta}_t$ are consumption preference shocks, and $\Lambda_{N,t}$ are nonbank liquidity demand shocks. Positive nonbank liquidity demand shocks increase the liquidity service provided by nonbank deposits while decreasing the liquidity service provided by bank deposits.

Entrepreneurs. There are two classes of entrepreneurs, which we call B -sector and N -sector entrepreneurs. Each class of entrepreneurs belongs to a sequence of overlapping generations of two-period-lived risk-neutral agents who own and maintain the capital stock for each sector. Within each generation of entrepreneurs, there is an ex-ante identical continuum of agents. We specify that the B -sector entrepreneurs only borrow from banks and that the N -sector entrepreneurs only borrow from nonbanks. We need this assumption to ensure that there is a well-defined portfolio of borrowing from banks and nonbanks.

Within each class of entrepreneurs, the modeling of their problem closely follows Clerc et al. (2015), which, in turn, follows Bernanke et al. (1999) and Townsend (1979). Each generation of entrepreneurs inherits net worth in the form of bequests, $n_t^{e,i}$, where $i \equiv B, N$. They purchase capital from capital goods producers in a common market and then rent it to the producers of the consumption good in each of the B and N sectors frictionlessly. Entrepreneurs finance the capital holdings with their initial net worth and loans b_t^i for each of the B and N sectors. In line with

⁶We have also tried specifications of the liquidity aggregator that allow the amount of liquidity service provided by nonbank deposits to be a function of the amount of nonbank default. Estimates set the elasticity of that relationship to 0, so we did not pursue that extension further.

previous work such as Clerc et al. (2015); Sandri and Valencia (2013); Bernanke et al. (1999), we assume that entrepreneurs have all the bargaining power in the contractual relationship. In addition to aggregate shocks, each entrepreneur is also hit by private idiosyncratic productivity shocks that the intermediary cannot observe in the second period and faces a default decision. As discussed in Clerc et al. (2015), the idiosyncratic shocks are a simple way to generate an asymmetric information problem between lenders and borrowers in the model, rationalize the existence of differences in the entrepreneurs' performance, and generate a nontrivial default decision on entrepreneurial loans. Upon default, the lending intermediary monitors the entrepreneur at a cost.

An entrepreneur in each sector born in time- t therefore has a sequence of decisions over the two dates. At time- t , the entrepreneur is endowed with the previous generation's bequests and takes out loans to purchase capital to maximize expected time $t + 1$ wealth. After aggregate and idiosyncratic shocks realize, each entrepreneur has a default decision with limited liability. If the entrepreneur defaults, her time $t + 1$ wealth level is 0 with no additional penalty. Finally, conditional on a time $t + 1$ wealth level, each entrepreneur must allocate the resources into dividends to households and bequests to the future generation of entrepreneurs.

It is convenient to work backwards to solve the entrepreneur's problem. Given a wealth level $W_{t+1}^{e,i}$, the time $t + 1$ optimization problem for an entrepreneur born in period t in each of the $i \in \{B, N\}$ sector is given by

$$\begin{aligned} \max_{c_{t+1}^{e,i}, n_{t+1}^{e,i}} & \left(c_{t+1}^{e,i}\right)^{\chi_{t+1}^{e,i}} \left(n_{t+1}^{e,i}\right)^{1-\chi_{t+1}^{e,i}} \\ \text{s.t.} & c_{t+1}^{e,i} + n_{t+1}^{e,i} \leq W_{t+1}^{e,i}. \end{aligned} \quad (2)$$

Optimizing behavior yields the following dividend payment and earnings retention rules

$$\begin{aligned} c_{t+1}^{e,i} &= \chi_{t+1}^{e,i} W_{t+1}^{e,i}, \\ n_{t+1}^{e,i} &= (1 - \chi_{t+1}^{e,i}) W_{t+1}^{e,i}. \end{aligned} \quad (3)$$

$\chi_{t+1}^{e,i}$ are entrepreneur dividend policy shocks. These shocks change the fraction of overall wealth allocated as dividends to households ($c_{t+1}^{e,i}$) versus bequeathed to the following generation of entrepreneurs. Positive entrepreneur dividend policy shocks therefore reduce the net worth passed on to the future generation. These shocks can account for the unmodeled investor equity flows into

and out of the nonfinancial sector.⁷

Taking one step back, we look at the default decision of the entrepreneur. Conditional upon the realization of aggregate variables and idiosyncratic shocks, as well as the previously-made time- t decisions on the amount of capital to purchase, amount of borrowing, and contractual borrowing rate, the entrepreneur faces the following default decision:

$$W_{t+1}^{e,i} = \max \left[\omega_{t+1}^{e,i} \left(r_{t+1}^{k,i} + (1 - \delta)q_{t+1}^K \right) k_t^i - R_t^i b_t^i, 0 \right], \quad (4)$$

where q_t^K is the price of capital, k_t^i is the capital stock held by the entrepreneur, b_t^i is the amount borrowed from the corresponding type of financial intermediary, $r_t^{k,i}$ is the rental rate of capital, and R_t^i is the contractual gross interest rate of loans. The term $\omega_t^{e,i}$ denotes the idiosyncratic shocks to the entrepreneur's efficiency units of capital. If the entrepreneur's revenues from holding capital are exceeded by the promised payment to the financial intermediary, she defaults and ends up with a wealth of 0.

The time- t decision problem of the entrepreneur can be written as

$$\begin{aligned} \max_{k_t^i, b_t^i, R_t^i} & E_t \left(W_{t+1}^{e,i} \right) \\ \text{s.t.} & q_t^K k_t^i - b_t^i = n_t^{e,i} \end{aligned} \quad (5)$$

Bank or nonbank participation constraint.

The entrepreneur chooses the amount of capital to purchase k_t^i , amount of loans to take on b_t^i , and contractual interest rate on the loans R_t^i to maximize expected wealth subject to the budget constraint and incentive compatibility of the intermediary from which the entrepreneur borrows. The structure of this optimization problem comes from the assumption that the entrepreneur has all of the bargaining power in the contractual relationship. The intermediary participation constraint will be specified below.

To compute the expected value of wealth $W_{t+1}^{e,i}$, we must specify the distribution of the idiosyncratic shocks. These shocks are independently and identically distributed across entrepreneurs and follow a log-normal distribution with an expected value of one and a density and cumulative distribution function denoted $f^{e,i}(\cdot)$ and $F^{e,i}(\cdot)$, respectively. Following Christiano et al. (2014), we

⁷Modeling dividend policy shocks is further motivated by evidence from the Senior Loan Officer Opinion Survey on Bank Lending Practices, which shows that on average from 1996:Q2 to 2015:Q1, 33% of survey respondents believed that increases in firm loan demand were due to declines in the firms' internally generated funds.

allow for risk shocks $\sigma_t^{e,i}$ that impact the cross-sectional volatility of the idiosyncratic shocks.

The entrepreneurs face limited liability if they default on their loans. In case of default, the intermediary can only recover a fraction, $1 - \mu^{e,i}$ of the gross return of capital, where $\mu^{e,i}$ denotes verification costs. Defining the gross return per efficiency unit of capital as

$$R_{t+1}^{K,i} = \frac{r_{t+1}^{K,i} + (1 - \delta)q_{t+1}^K}{q_t^K},$$

the cutoff threshold above which the entrepreneur repays the loan equals

$$\bar{\omega}_{t+1}^{e,i} = \frac{R_t^i b_t^i}{R_{t+1}^K q_t^K k_t^i}. \quad (6)$$

As in Bernanke et al. (1999) and Clerc et al. (2015), we can define the expected gross fraction (not including intermediary monitoring costs on defaulted loans) of entrepreneurial returns from capital going to intermediaries as:

$$\Gamma^{e,i}(\bar{\omega}_{t+1}^{e,i}) = \int_0^{\bar{\omega}_{t+1}^{e,i}} \omega_{t+1}^{e,i} f^{e,i}(\omega_{t+1}^{e,i}) d\omega_{t+1}^{e,i} + \bar{\omega}_{t+1}^{e,i} \int_{\bar{\omega}_{t+1}^{e,i}}^{\infty} f^{e,i}(\omega_{t+1}^{e,i}) d\omega_{t+1}^{e,i}. \quad (7)$$

Intuitively, this term depends on the expected values of the idiosyncratic shock, taking into account the entrepreneur's default decision. The first term in this expression is the component of the expected value conditional on entrepreneurial default, whereas the second term in this expression is the component of the expected value conditional on entrepreneurial repayment.

We define the share of gross return for each intermediary that comes from defaulted loans as:

$$G^{e,i}(\bar{\omega}_{t+1}^{e,i}) = \int_0^{\bar{\omega}_{t+1}^{e,i}} \omega_{t+1}^{e,i} f^{e,i}(\omega_{t+1}^{e,i}) d\omega_{t+1}^{e,i}. \quad (8)$$

The net share of the total gross returns that each bank appropriates then becomes $\Gamma^{e,i}(\bar{\omega}_{t+1}^{e,i}) - \mu^{e,i} G^{e,i}(\bar{\omega}_{t+1}^{e,i})$.

With these definitions, we can reformulate the entrepreneurs' optimization problem as follows:

$$\begin{aligned} \max_{k_t^i, b_t^i, R_t^i} E_t & \left[\left(1 - \Gamma^{e,i} \left(\frac{x_t^{e,i}(\cdot)}{R_{t+1}^{K,i}} \right) \right) R_{t+1}^{K,i} q_t^K k_t^i \right] \\ \text{s.t.} & \quad q_t^K k_t^i - b_t^i = n_t^{e,i} \\ E_t & \left[(1 - \Gamma^i(\bar{\omega}_{t+1}^i)) \left(\Gamma^{e,i} \left(\frac{x_t^{e,i}(\cdot)}{R_{t+1}^{K,i}} \right) - \mu^{e,i} G^{e,i} \left(\frac{x_t^{e,i}(\cdot)}{R_{t+1}^{K,i}} \right) \right) R_{t+1}^{K,i} q_t^K k_t^i \right] \geq \rho_t \phi_t^i b_t^i, \end{aligned} \quad (9)$$

where $x_t^{e,i}(\cdot) = \frac{R_t^i b_t^i}{q_t^K k_t^i}$. The intermediary participation constraint contains an additional term $1 - \Gamma^i(\bar{\omega}_{t+1}^i)$ that represents the expected fraction of total intermediary loan returns going to the inside equity investors. This value depends on a yet to be specified term $\bar{\omega}_{t+1}^i$, which is the threshold between default and repayment for the idiosyncratic shock that hits the intermediary. The entrepreneur takes this value as given.

The intermediary participation constraint says that the total expected return to intermediary inside equity investment must be greater than or equal to a required return to equity ρ_t that the entrepreneur takes as given. There is no superscript on ρ_t because of the presence of a no-arbitrage condition that equalizes expected returns across the two sectors. The term ϕ_t^i is the equity-to-assets ratio of the intermediary, so $\phi_t^i b_t^i$ is the total inside equity position of the investors in the intermediary.

We next define \tilde{R}_{t+1}^i , which is the time $t + 1$ realized return of loans from the intermediary of type i .

$$\tilde{R}_{t+1}^i = \frac{\left(\Gamma^{e,i} \left(\frac{x_t^{e,i}(\cdot)}{R_{t+1}^{K,i}} \right) - \mu^{e,i} G^{e,i} \left(\frac{x_t^{e,i}(\cdot)}{R_{t+1}^{K,i}} \right) \right) R_{t+1}^{K,i} q_t^K k_t^i}{b_t^i} \quad (10)$$

Finally, before we move on, we discuss our modeling assumptions on the financing structure of entrepreneurs. For some firms, equity financing might be more important than debt financing and its relative importance might change over the business cycle. Indeed, a strand of the literature analyzes debt and equity issuance decisions by firms in the nonfinancial sector (Jermann and Quadrini, 2012; Covas and Den Haan, 2011, 2012; Begenau and Salomao, 2018).

If we think of the entrepreneurs in our model who borrow from banks as private nonfinancial firms that cannot access the external capital markets, we view our model assumption that these entrepreneurs can only build net worth through accumulating retained earnings as reasonable. Brav (2009), for example, finds that private equity is more expensive than public equity and that private firms issue much less new equity than their public counterparts.

Moreover, as documented in Covas and Den Haan (2011, 2012); Begenau and Salomao (2018), there is a high degree of heterogeneity in the cyclicity properties of debt and equity issuance by public nonfinancial firms. Specifically, smaller firms have procyclical debt and equity issuance while large firms have procyclical debt issuance and countercyclical equity issuance. This heterogeneity is important at the aggregate level as well, and can help explain the conflicting empirical stylized facts at the aggregate level that papers in the literature find (Covas and Den Haan, 2011). Both Covas and

Den Haan (2012) and Begenau and Salomao (2018) rely on decreasing returns to scale to generate heterogeneity of firm size. Begenau and Salomao (2018) find that their model can successfully replicate the stylized facts with a reasonable parameterization, but they rely on a global solution.⁸ These issues preclude our ability to incorporate these elements into our model. As our aim is to solve and estimate our medium-scale model with many structural shocks and latent state variables, accounting for a large degree of firm heterogeneity along with a nonlinear solution method would not be feasible computationally. Therefore, we leave this important dimension for future research.

Investors. There are an ex-ante identical continuum of investors belonging to a sequence of overlapping generations of risk-neutral, two-period-lived agents. Investors are the only agents who can invest net worth as bank and nonbank equity capital. Each generation of investors inherits net worth, n_t^b , in the form of bequests, and has the utility function $(c_{t+1}^b)^{\chi_{t+1}^b} (n_{t+1}^b)^{1-\chi_{t+1}^b}$. This form of the utility function implies that, at time $t+1$, conditional on a level of investor wealth, the agents allocate a fraction χ_{t+1}^b of total wealth to household dividends (c_{t+1}^b) and the rest as bequests to the next period of investors.

As investors only allocate funds between inside equity of bank and nonbank credit intermediaries, they equalize the expected returns of investing in both sectors.

$$\rho_t = E_t \tilde{\rho}_{t+1}^B = E_t \tilde{\rho}_{t+1}^N \quad (11)$$

Hence, investors' net worth evolves according to the following law of motion

$$n_{t+1}^b = \left(1 - \chi_{t+1}^b\right) \left(\tilde{\rho}_{t+1}^B e_t^B + \tilde{\rho}_{t+1}^N e_t^N\right), \quad (12)$$

where $\tilde{\rho}_{t+1}^B$ denotes ex-post return on bank equity, and $\tilde{\rho}_{t+1}^N$ denotes ex-post return on nonbank equity.

There are investor dividend policy shocks χ_{t+1}^b . These shocks shift around the fraction of wealth allocated to consumption versus bequests, similar to the redistribution shocks considered in Iacoviello (2015). The shocks can be interpreted as capturing unmodeled investor inside equity flows or unmodeled housing loan losses from default, as in Iacoviello (2015). They are a simple way to allow for a credit supply shock.

⁸Covas and Den Haan (2012) find that they can match the stylized facts only with a counterfactually large movement in equity issuance costs.

Intermediaries. There are an ex-ante identical continuum of two types of intermediaries: banks (B) and nonbanks (N). The B intermediaries lend to a well-diversified portfolio of B entrepreneurs, and N intermediaries lend to a well-diversified portfolio of N entrepreneurs. Both banks and nonbanks are two-period lived projects financed by inside equity provided by the investors as well as deposits from the households.⁹ The shareholders of the intermediaries—the investor agents—have limited liability, hence the payoffs from investing into intermediaries are nonnegative. Both banks and nonbanks receive idiosyncratic private portfolio return shocks, creating an asymmetric information problem between intermediaries and households.

There are two key differences between the banks and nonbanks. First, banks have deposit insurance, whereas nonbanks do not. Second, banks face capital requirements, whereas nonbanks do not. The monitors of the banks are the deposit insurance fund, whereas the monitors of the nonbanks are the households.

It is worth clarifying our motivation in keeping the heterogeneity in bank and nonbank financing relatively simple. In reality, there might a richer set of heterogeneity between bank and nonbank financing along with heterogeneity in the entrepreneur sector. In practice, however, our review of the literature suggests that papers developing macroeconomic models of bank and nonbank finance generally focus on either modeling heterogeneity within the financial sector or heterogeneity within the entrepreneurial sector, but almost never combine the two. For instance, papers that focus on financial sector heterogeneity but keep the entrepreneur side relatively standard include Begenau and Landvoigt (2020); Gertler et al. (2016); Meeks et al. (2017); Fève and Pierrard (2017). Conversely, papers that take the opposite approach of modeling richly the heterogeneity of firms in obtaining bank versus nonbank funding include Fiore and Uhlig (2011, 2015); Crouzet (2018). These papers, however, make simplifying assumptions on the funding side of financial intermediaries.¹⁰

We view our paper as squarely within the former category. Our modeling choices particularly follow Begenau and Landvoigt (2020). Nevertheless, we should note that our model does allow for some forms of heterogeneity in the borrowers. In particular, we allow for different steady state standard deviations of idiosyncratic shocks hitting the entrepreneurs who borrow from the banks versus the nonbanks.

⁹Raising new equity might be important in modeling bank and nonbank financial intermediation. To this end, we do a robustness check by allowing banks and nonbanks to issue outside equity in Online Appendix Section D, following the modeling strategy of Covas and Den Haan (2012). We find that the results from the benchmark model continue to hold.

¹⁰Dempsey (2020) is a recent paper that tries to make progress by introducing rich heterogeneity in both the financial and nonfinancial sectors.

We next discuss the problem of the banks and then move on to the nonbanks. For the problem of banks, we begin with the $t+1$ decision problem after the realization of the aggregate and idiosyncratic shocks, the time- t lending and borrowing levels, and the previously agreed upon contractual deposit rate. Conditional on those variables, the banks have the following default decision:

$$\pi_{t+1}^B = \max \left[\omega_{t+1}^B \tilde{R}_{t+1}^B b_t^B - R_t^D d_t^B, 0 \right], \quad (13)$$

where \tilde{R}_{t+1}^B is the aggregate return on B entrepreneurial loans, b_t^B is the quantity of entrepreneurial loans held by the banks, R_t^D is the contractual deposit rate, d_t^B is the amount of bank deposits, and ω_{t+1}^B is the idiosyncratic portfolio return shock. In the event of a default, the deposit insurance fund monitors the banks.

Now we move on to the time- t decision. Because of deposit insurance, the deposit rate the banks face is not sensitive to their leverage positions, which is defined as

$$\phi_t^B = \frac{e_t^B}{b_t^B}. \quad (14)$$

Therefore, the banks always find it optimal to lever up to the maximum leverage allowed by the capital requirements, which is set on ϕ_t^B . The capital requirement directly determines the leverage position of the banks. They take the amount of equity invested, e_t^B , by the investor agents as given.

The nonbanks face the same default decision as the banks at time $t + 1$:

$$\pi_{t+1}^N = \max \left[\omega_{t+1}^N \tilde{R}_{t+1}^N b_t^N - R_t^{D,N} d_t^N, 0 \right], \quad (15)$$

where the definitions of the variables are the same, except now with an N instead of B superscript to denote that the N intermediaries take nonbank deposits from households and lend to N -sector entrepreneurs. $R_t^{D,N}$ is the contractual deposit rate agreed at time- t (specified below), which distinguishes it from the realized deposit rate $\tilde{R}_{t+1}^{D,N}$ that the household receives taking into account nonbank default.

The time- t decision problem of the nonbanks is more involved. Although the government does not impose a capital requirement, a leverage constraint arises endogenously from a contractual problem between the households and the nonbanks. We assume that the nonbanks have all of the bargaining power in setting the contract with the household.

$$\begin{aligned}
& \max_{x_t^N, b_t^N} E_t \left[\left(1 - \Gamma^N \left(\frac{x_t^N}{\tilde{R}_{t+1}^N} \right) \right) \tilde{R}_{t+1}^N b_t^N \right] \\
& s.t. \\
& \lambda_t - \chi_h \frac{\Lambda_{N,t} (d_t^N)^{\alpha_h - 1}}{\Lambda_{N,t} (d_t^N)^{\alpha_h} + (d_t^B)^{\alpha_h}} = \dots \\
& \beta E_t \left[\lambda_{t+1} \left(\left(\Gamma^N \left(\frac{x_t^N}{\tilde{R}_{t+1}^N} \right) - \mu^N G^N \left(\frac{x_t^N}{\tilde{R}_{t+1}^N} \right) \right) \tilde{R}_{t+1}^N \frac{b_t^N}{b_t^N - e_t^N} \right) \right],
\end{aligned} \tag{16}$$

where $x_t^N = \frac{R_t^{D,N} (b_t^N - e_t^N)}{b_t^N}$. Here we have already substituted out the balance sheet constraint of the intermediaries $b_t^N = e_t^N + d_t^N$.

Given an amount of inside equity e_t^N , the N intermediaries choose the amount of lending b_t^N and leverage position x_t^N (implicitly the contractual deposit rate $R_t^{D,N}$) to maximize the expected returns to the inside equity holders, making sure to satisfy the incentive compatibility constraint of the household. The incentive compatibility constraint comes from the first order condition of the household with respect to the nonbank deposits. It says that the discounted expected return the nonbanks offer the household on their deposits must at least make up for the foregone cost of consumption today. Relative to a standard Euler equation, there is an extra term on the left hand side of the equality that accounts for the fact that households have direct utility services from holding deposits, which the intermediaries take into account.

The time- t return to households from depositing in the N -type intermediaries is the following:

$$\tilde{R}_t^{D,N} d_{t-1}^N = (\Gamma^N (\bar{\omega}_t^N) - \mu^N G^N (\bar{\omega}_t^N)) \tilde{R}_t^N b_{t-1}^N, \tag{17}$$

where $\bar{\omega}_t^N$ is the idiosyncratic shock default threshold for the nonbanks. We can rewrite this return in terms of nonbank deposits, d_{t-1}^N . Using the balance sheet constraint $b_t^N = e_t^N + d_t^N$ and the definition for nonbank leverage $e_t^N = \phi_t^N b_t^N$, where ϕ_t^N is determined by the contract and households take it as given, b_t^N is nonbank intermediary lending, e_t^N is nonbank intermediary equity, we can derive

$$\begin{aligned}
b_t^N &= \frac{d_t^N}{1 - \phi_t^N} \\
\tilde{R}_t^{D,N} &= (\Gamma^N (\bar{\omega}_t^N) - \mu^N G^N (\bar{\omega}_t^N)) \frac{\tilde{R}_t^N}{1 - \phi_{t-1}^N}.
\end{aligned}$$

Capital Good Production. The capital good producers purchase all undepreciated capital from the old generation of entrepreneurs and combine it with the new capital from investment to sell to the new generation of B - and N -sector entrepreneurs in a common market. Therefore, they solve the following maximization problem

$$\max_{I_{t+i}} E_t \sum_{i=0}^{\infty} \beta^i \frac{\lambda_{t+i}}{\lambda_t} \left\{ q_{t+i}^K I_{t+i} - EK_t \left[1 + g \left(\frac{I_{t+i}}{I_{t+i-1}} \right) \right] I_{t+i} \right\}. \quad (18)$$

The optimality condition would yield

$$q_t^K = EK_t \left(1 + g_t + \frac{I_t}{I_{t-1}} g'_t \right) - \beta E_t \left[\frac{\lambda_{t+1}}{\lambda_t} \left(\frac{I_{t+1}}{I_t} \right)^2 EK_{t+1} g'_{t+1} \right], \quad (19)$$

where $g_t = g \left(\frac{I_t}{I_{t-1}} \right)$.

EK_t denotes marginal efficiency of investment (MEI) shocks, as in Justiniano et al. (2010). Positive MEI shocks increase the price of capital by making it more expensive to produce.

Final Good Production. The homogeneous final good is produced by both the B and N sectors, indexed by the type of entrepreneur from which they rent capital. Each sector i has its respective following production function

$$y_t^i = (k_{t-1}^i)^{\alpha^i} (A_t l_t^i)^{1-\alpha^i}. \quad (20)$$

A_t is a total factor productivity (TFP) shock, which is common across sectors and drives long-run growth in the model.

The optimality conditions for each sector implies the following rental rate and the wage rate

$$\begin{aligned} r_t^{K,i} &= \alpha^i \frac{y_t^i}{k_{t-1}^i}, \\ w_t^i &= (1 - \alpha^i) \frac{y_t^i}{l_t^i}. \end{aligned} \quad (21)$$

Market Clearing Conditions. In the interest of space, we discuss the market clearing conditions in Online Appendix Section B.

Capital Requirements. In addition to the market clearing conditions highlighted so far, a capital requirement also needs to be satisfied by banks. We consider the following capital requirement:

$$\phi_t^B = \bar{\phi}_0^B + \eta_{\phi,t}, \quad (22)$$

where $\eta_{\phi,t}$ is the capital requirements shock, meant to capture bank regulatory capital changes.

3.3 Shocks

We specify several candidate drivers of the bank and nonbank credit cycles. These shocks can be divided along two dimensions. The first dividing line is between macro and financial shocks. The second is between economy-wide and sectoral shocks.

Let us begin with the economy-wide macro shocks in the model. We specify aggregate TFP shocks that affect both sectors.¹¹ The TFP shocks are an $AR(1)$ in growth rates.

$$\Delta \log A_t = \Lambda_A(1 - \rho_A) + \rho_A \Delta \log A_{t-1} + \epsilon_{A,t}, \epsilon_{A,t} \sim N(0, \sigma_A^2). \quad (23)$$

MEI shocks are specified as $AR(1)$:¹²

$$EK_t = (1 - \rho_{EK}) + \rho_{EK} EK_{t-1} + \epsilon_{EK,t}, \epsilon_{EK,t} \sim N(0, \sigma_{EK}^2). \quad (24)$$

Preference shocks are also specified as $AR(1)$:

$$\tilde{\beta}_t = (1 - \rho_\beta) + \rho_\beta \tilde{\beta}_{t-1} + \epsilon_{\beta,t}, \epsilon_{\beta,t} \sim N(0, \sigma_\beta^2). \quad (25)$$

Financial shocks in the model can be economy-wide or sectoral. The economy-wide shocks are the economy-wide components of the entrepreneur risk and dividend policy shocks and the investor dividend policy shocks. The sectoral shocks are the nonbank liquidity demand shocks, the sectoral components of the entrepreneur risk and dividend policy shocks, and the capital requirements shocks.

The nonbank liquidity demand shocks are specified as $AR(1)$:

$$\begin{aligned} \tilde{\Lambda}_{U,t} &= (1 - \rho_{\Lambda,U}) + \rho_{\Lambda,U} \tilde{\Lambda}_{U,t-1} + \epsilon_{\Lambda,U,t}, \epsilon_{\Lambda,U,t} \sim N(0, \sigma_{\Lambda,U,t}^2) \\ \Lambda_{U,t} &= \Lambda_U \tilde{\Lambda}_{U,t}. \end{aligned} \quad (26)$$

¹¹In our explorations, we also tried specifications with sectoral TFP level shocks. They ended up being estimated as unimportant.

¹²The $1 - \rho_{EK}$ term ensures that the shocks are centered around a mean of 1.

We decompose entrepreneur risk shocks and entrepreneur dividend policy shocks into an aggregate and sectoral component. Our specification for the entrepreneur risk shocks is as follows:

$$\begin{aligned}
\sigma_t^{e,i} &= \sigma^{e,i} \sigma_t^{e,Agg} \sigma_t^{e,i} \\
\sigma_t^{e,Agg} &= (1 - \rho_{\sigma,e,Agg}) + \rho_{\sigma,e,Agg} \sigma_{t-1}^{e,Agg} + \epsilon_{\sigma,e,Agg,t}, \epsilon_{\sigma,e,Agg,t} \sim N(0, \sigma_{\sigma,e,Agg}^2) \\
\sigma_t^{e,i} &= (1 - \rho_{\sigma,e,i}) + \rho_{\sigma,e,i} \sigma_{t-1}^{e,i} + \epsilon_{\sigma,e,i,t}, \epsilon_{\sigma,e,i,t} \sim N(0, \sigma_{\sigma,e,i}^2).
\end{aligned} \tag{27}$$

Our entrepreneur dividend policy shocks are specified as follows:

$$\begin{aligned}
\chi_t^{e,i} &= \chi^{e,i} + \chi_t^{e,Agg} + \chi_t^{e,i} \\
\chi_t^{e,Agg} &= \rho_{\chi,e,Agg} \chi_{t-1}^{e,Agg} + \epsilon_{\chi,e,Agg,t}, \epsilon_{\chi,e,Agg,t} \sim N(0, \sigma_{\chi,e,Agg}^2) \\
\chi_t^{e,i} &= \rho_{\chi,e,i} \chi_{t-1}^{e,i} + \epsilon_{\chi,e,i,t}, \epsilon_{\chi,e,i,t} \sim N(0, \sigma_{\chi,e,i}^2).
\end{aligned} \tag{28}$$

The investor dividend policy shocks are specified as $AR(1)$:

$$\begin{aligned}
\chi_t^b &= \chi^b + \tilde{\chi}_t^b \\
\tilde{\chi}_t^b &= \rho_{\chi,b} \tilde{\chi}_{t-1}^b + \epsilon_{\chi,b,t}, \epsilon_{\chi,b,t} \sim N(0, \sigma_{\chi,b}^2).
\end{aligned} \tag{29}$$

Finally, the capital requirements policy shocks are also $AR(1)$:

$$\eta_{\phi,t} = \rho_{\eta} \eta_{\phi,t-1} + \epsilon_{\eta,t}, \epsilon_{\eta,t} \sim N(0, \sigma_{\eta}^2). \tag{30}$$

4 Empirical Strategy

To measure the importance of the structural shocks for the bank and nonbank credit cycles, we estimate our model using Bayesian methods. In this section, we discuss the additional data we use to inform the model and our estimation strategy.

4.1 Data

We use the following data to inform our empirical analysis: per capita consumption and investment growth, commercial bank and money market mutual fund deposit rates, BAA 10-year spreads, bank

equity-to-lending ratio, and per capita bank and nonbank debt growth. With the exception of the bank equity-to-lending ratio data, all of the data are quarterly from 1987:Q1 to 2015:Q1. The bank equity-to-lending ratio data are available at an annual frequency from 1987 to 2015. Further details about the data can be found in Online Appendix Section A.

4.2 Calibration and Estimation Procedure

We take a two-step approach to setting the parameters in the model. For a block of parameters that have important implications for steady state values, we either set them to commonly accepted values in the literature or use them to target important moments of interest.

The parameters we calibrate based on the past literature are the discount factor, Frisch elasticity of labor, substitutability between bank and nonbank deposits in the utility function, depreciation rate, entrepreneur and bank monitoring costs, and the persistence of the capital requirements shock. We set the substitutability between bank and nonbank deposits to be near 1, implying that the two types of deposits are perfect substitutes, in line with the benchmark value used by Krishnamurthy and Vissing-Jorgensen (2012).¹³ We follow Clerc et al. (2015) and calibrate the monitoring costs to be 0.3.¹⁴ We fix the persistence of the capital requirements shock to be 0.999 as we think of these policy changes as permanent.

The rest of the parameters we calibrate are chosen to target important moments of interest. Table 2 shows the moments that we target. We target the mean levels of our two deposit rate data to set the steady states for the contractual deposit rates charged to the households in each sector. The spread between bank and nonbank entrepreneur lending rates targets the spread between bank and bond borrowing rates used by Fiore and Uhlig (2011). The size of bank to nonbank lending targets the mean relative sizes implied by our constructed sectoral lending growth data. Nonbank sector entrepreneur default rates come from Bernanke et al. (1999). We leave the bank sector entrepreneur default rate untargeted. It is disciplined in part by information on the average spreads between the lending rates to bank and nonbank sector entrepreneurs. Our justification for this choice is that Bernanke et al. (1999) was focused more on the default of entrepreneurs borrowing from the corporate debt markets, not the traditional banking markets. For bank default rates, we

¹³We have experimented with values below 1, implying that the two deposits are imperfect substitutes. This makes it more difficult for the model to match the amount of nonbank leverage we see in the data. This is because the cost of nonbank deposits rises as the share of nonbank deposits in total deposits rise, limiting the amount of leverage the nonbanks can maintain.

¹⁴The nonbank monitoring cost parameter is set to 0.2, on the low side of the range recommended from Carlstrom and Fuerst (1997). A lower value for this parameter helps the model generate higher levels of nonbank leverage.

Table 2: Calibration Targets

$R^D(N)$	B(N) intermediary deposit rate (Bank time and Inst only MMF rates)	1.003(1.004)
$R^B - R^N$	B and N entrepreneur lending spreads (Fiore and Uhlig (2011))	0.000675
L	Labor share	1/3
$\frac{b^B}{b^N}$	Size B to N intermediary lending (Z.1. Tables)	0.72
$\text{def}_{e,N}^B$	Qtrly. default rates of N entrepreneur (Bernanke et al., 1999)	0.75%
$\text{def}_{B(N)}^B$	Qtrly. default rates of B (N) intermediary (FDIC, S&P)	0.17(0.17)%
ρ	Qtrly. return investor equity (U.S. Commercial bank equity returns, FRED)	2.87%
ϕ_B	Equity-to-lending ratio B intermediary (FDIC data)	0.088
ϕ_N	Equity-to-lending ratio N intermediary (Hirakata et al. (2017))	0.1084

NOTE: These are the calibration targets for the model. The first column shows the variable in the model being targeted, the middle column shows the source of the target, and the last column shows the value of the target. Numbers in parentheses are the corresponding values for the N sector.

use the average percentage of assets defaulted in the commercial banking sector from the FDIC for our sample period. For nonbank default, we look at Vazza and Kraemer (2017), who report that the average default rates for financial institutions as a whole is around the same as those we calculate from the Federal Deposit Insurance Corporation (FDIC) data for banks from 1981 to 2016. We target an average inside investor equity return of 2.87 percent quarterly, in line with U.S. commercial bank equity return data from 1987:Q1 to 2015:Q1 from the Federal Reserve Economic Data (FRED). The steady state equity-to-lending ratio of banks is calculated from the mean equity-to-lending ratio data we obtained from the FDIC. For the steady state equity-to-lending ratio of the nonbanks, we use the value computed by Hirakata et al. (2017) for financial intermediaries.

We then linearize the model around the nonstochastic steady state and estimate the rest of the parameters using Bayesian methods (An and Schorfheide, 2007), which include the parameters governing the exogenous shocks, degree of habits, and investment adjustment costs.¹⁵ We use the following data to estimate the model: three-month rates of commercial bank time deposits; three-month rates of institutional only money market funds to inform the annualized contractual bank and nonbank deposit rates, $400(R_t^D - 1)$ and $400(R_t^{D,N} - 1)$; BAA 10-year spreads to inform the annualized spread of the N -sector entrepreneur borrowing rates over the risk-free rate, $400(R_t^N - R_t^f)$;¹⁶ per capita consumption growth and investment growth data; equity-to-lending ratio data to inform the level of the capital requirements (ϕ_t^B); and per capita bank and nonbank lending growth data. As the equity-to-lending ratio data are only available at the annual frequency, there is an

¹⁵The full set of equilibrium conditions can be found in Online Appendix Section C.

¹⁶ R_t^f is the risk-free rate in the model, which is derived from the Euler equation of the household over a hypothetical risk free asset that does not have liquidity services. We demean the BAA 10-year spread data and match it to model-based deviations of $400(R_t^N - R_t^f)$ from steady state.

Table 3: Standard Deviations of Observables in the Data and the Model at Posterior Mode Parameters

Variable	Data	Model
B Deposit rates	2.05	1.69
N Deposit rates	2.40	1.66
N Ent. lending spreads	0.75	0.99
Cons. gr.	0.51	0.62
Inv. gr.	2.29	2.80
B Lending gr.	1.59	1.70
N Lending gr.	1.12	1.26

NOTE: These are the standard deviations of the observables in the data and implied by the model.

issue of a mixed frequency of observations. We follow work by Del Negro and Eusepi (2011) on estimating DSGE models allowing for missing observations. We assume that the equity-to-lending ratio data informs the fourth quarter observation of the corresponding year.

4.3 Estimated Parameters and Model Fit

Table 8 in Appendix A lists the parameters and their calibrated or estimated values. We focus our empirical results on the posterior mode parameters.¹⁷ We estimate a high degree of habits and a lower level of investment adjustment costs. Our estimates for the macro shocks are in line with the literature. We estimate a fairly low degree of persistence for the TFP growth shock. Relative to Justiniano et al. (2010), our MEI shocks are less important because of the inclusion of financial data, more in line with the results of Christiano et al. (2014). Among the financial shocks, we estimate highly persistent economy-wide entrepreneur risk and nonbank liquidity demand shocks. The sectoral entrepreneur risk shocks are estimated to be much less important. However, the sectoral entrepreneur dividend policy shocks are estimated to be important while the economy-wide entrepreneur dividend policy shocks are estimated to be unimportant. Therefore, in looking at the estimates, it seems both economy-wide and sectoral shocks could play an important role in understanding the macro-financial cycle in this model.

In Table 9 in Appendix A, we list the model-implied steady state values. Overall, we think the model does a good job at matching our calibration targets. One issue that is worth pointing out is that the model implies too high of a return to investor equity. This high amount of investor equity payout is required for the model to generate the elevated levels of leverage for the banks and nonbanks.

¹⁷Additional estimation details, including on the prior specifications and posterior distributions, can be found in Appendix Sections B and C.

Table 4: Autocorrelation of Observables in the Data and the Model at Posterior Mode Parameters

Variable	Data	Model
B Deposit rates	0.90	0.65
N Deposit rates	0.92	0.62
N Ent. lending spreads	0.89	0.87
Cons. gr.	0.43	0.40
Inv. gr.	0.53	0.45
B Lending gr.	0.74	0.43
N Lending gr.	0.59	0.37

NOTE: These are the autocorrelations of the observables in the data and implied by the model.

Tables 3 and 4 show model-implied standard deviations and autocorrelations for our observable variables and compare them with the data. Our model does a decent job at matching both the volatility and persistence of the macro and financial data. It accurately generates that bank lending growth is more volatile than nonbank lending growth. The model underpredicts the volatility in deposit rates. It also understates the persistence of the deposit rates and lending growth. All in all, however, we believe that the model does do a good job at simultaneously matching moments for macro and financial data, given the well-known difficulties DSGE models have in simultaneously matching macro quantities and asset prices—Rouwenhorst (1995); Fernández-Villaverde (2010).

5 Decomposing Bank and Nonbank Credit Cycles

With our estimated model in hand, we are now in a position to decompose the bank and nonbank credit cycles. We first look at simulations of our model to determine the main drivers of bank and nonbank credit growth. Then, we move on to a historical decomposition of the two credit cycles. Finally, we close by looking at the relationship between credit and business cycles implied by the model.

5.1 Which Shocks are Important in Driving Bank and Nonbank Lending Growth?

Table 5 shows an unconditional variance decomposition of bank and nonbank lending growth at the posterior mode parameters. Several interesting results emerge. First, it is clear that our model interprets credit cycles, in general, as primarily driven by financial shocks. Indeed, for both bank and nonbank credit cycles, the macro shocks make up at most 10 percent of fluctuations. The most important among the macro shocks is the TFP growth shock, which drives around 2 percent of bank lending growth and 6 percent of nonbank lending growth, respectively. The muted importance

Table 5: Unconditional Variance Decomposition of Bank and Nonbank Lending Growth

Variable	TFP gr.	Liq. N	Ent. risk EW	Ent. risk N	Ent. div B	Ent. div N	Cap. req.
Bank lending gr.	2	9	14	13	19	40	0
Nonbank lending gr.	6	8	15	16	42	6	1

NOTE: This table shows the unconditional variance decomposition of bank and nonbank lending growth at the posterior mode parameters for a selected set of structural shocks. EW denotes economy-wide. The shocks which are not included here were estimated to be unimportant.

of macro shocks for credit cycles should not be surprising given the lack of empirical co-movement between investment growth and lending growth in either sector.

Second, among the financial shocks, it seems that sector-specific, as opposed to economy-wide shocks play a dominant role. The sector-specific shocks, which are the nonbank liquidity demand, nonbank entrepreneur risk shocks and dividend policy shocks, drive over 80 percent of bank lending growth and over 70 percent of nonbank lending growth. In contrast, the economy-wide shocks, most importantly the entrepreneur risk shock, play less of a role. Nevertheless, the model can still generate positive correlation between bank and nonbank lending growth. Model-simulated bank and nonbank lending growth has a correlation of 0.13. At business cycle frequencies, which we define as cycles between 6 and 32 quarters, this correlation rises to 0.36.

Third, the sectoral entrepreneur dividend policy shocks seem to be the most important drivers of bank and nonbank lending growth. Interestingly, our results suggest that exogenous shocks to the balance sheet conditions of entrepreneurs who borrow from banks mainly drive nonbank lending growth dynamics and vice versa. In the next subsection, we will give some intuition as to why this is the case.

There is an important frequency dimension to our second and third results mentioned above. This can be seen from comparing variance decompositions at business cycle frequencies, 6-32 quarters, and medium-frequency cycles, 32-200 quarters as in Comin and Gertler (2006), as shown in Table 6.¹⁸ At business cycle frequencies, the sectoral shocks—and specifically the bank and nonbank entrepreneur dividend policy shocks—gain even more importance. The bank and nonbank entrepreneur dividend policy shocks drive over 70 percent of fluctuations in both sectors. The economy-wide entrepreneur risk shocks become more important at longer horizons, driving 53 percent of credit fluctuations in the bank sector and 38 percent in the nonbank sector at medium frequencies. A persistent rise in economy-wide entrepreneurial risk increases entrepreneurial default, which leads to lending spreads rising, investment growth declining, and both bank and nonbank

¹⁸The frequency decomposition is done by applying a bandpass filter to isolate the fluctuations at the relevant frequencies.

Table 6: Variance Decompositions at Business Cycle (6-32 qtrs.) and Medium-Frequency Cycle (32-200 qtrs.) Frequencies

	Variable	Ent. risk EW	Ent div B	Ent div N
6-32 qtrs	Bank lending gr.	9	23	54
	Nonbank lending gr.	5	71	2
32-200 qtrs	Bank lending gr.	53	13	25
	Nonbank lending gr.	38	27	19

NOTE: This table shows the variance decompositions at the posterior mode parameters at business cycle (6-32 quarters) and medium-frequency cycle (32-200 quarters) frequencies. The isolation of the frequencies is done by applying a bandpass filter. EW means economy-wide.

lending growth persistently falling.¹⁹ Therefore, in our model, credit fluctuations at business cycle frequencies are best characterized as responses to sectoral financial shocks, but an important economy-wide financial shock drives their lower frequency co-movement.

Finally, a point of independent interest is the importance of bank capital requirement changes on bank and nonbank lending growth behavior. We find in our estimated model that this effect is negligible, mainly because of the fact that free investor equity flows between financing banks and nonbanks can largely undue the credit supply restrictions or loosening from the capital requirements shocks.

5.2 Understanding the Mechanism Behind Sectoral Entrepreneur Dividend Policy Shocks

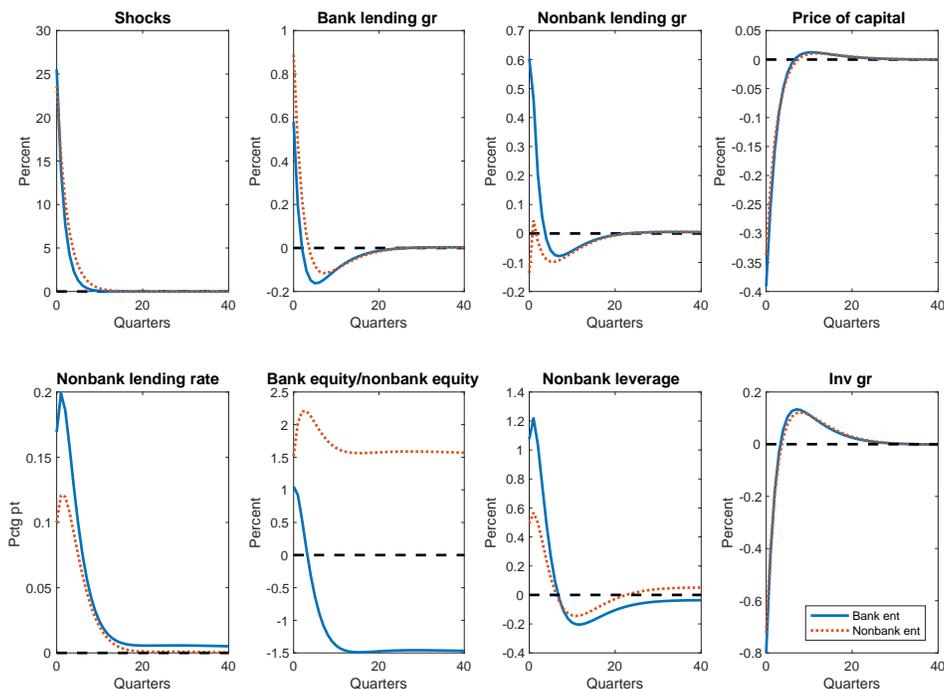
Figure 2 shows the responses of bank and nonbank lending growth, as well as other quantities of interest, to positive bank and nonbank sector entrepreneur dividend policy shocks, which lowers the net worth of the respective entrepreneur.²⁰

Let us first begin with the bank sector entrepreneur dividend policy shocks. Positive bank entrepreneur dividend policy shocks decrease the amount of wealth bank entrepreneurs allocate to net worth and increase the amount allocated as dividends for households. This decline in net worth impairs the ability of the bank sector entrepreneurs to purchase capital. Therefore, in the short run, they purchase less capital but borrow more from banks to partially make up for the lost purchasing power. Investor equity flows into the bank sector from the nonbank sector to support this extra lending. Nonbank lending growth increases at an even faster pace than bank lending growth. This is because the lack of capital purchasing power from bank sector entrepreneurs decreases the price of capital, making it a good time to invest in capital to take advantage of the expected capital

¹⁹As this shock is a more standard financial shock in the literature, we discuss its effects in more detail in Appendix Section D.

²⁰Figure 9 shows the corresponding IRFs including the 80% credible sets.

Figure 2: Impulse Responses of Bank and Nonbank Sectoral Entrepreneur Dividend Policy Shocks



NOTE: These are the responses to one standard deviation bank (blue solid) and nonbank (orange dashed) positive entrepreneur dividend policy shocks at the posterior mode parameters. The y-axis is in percent and the x-axis is in quarters.

appreciation. Therefore, the nonbank sector entrepreneurs borrow to finance their capital purchases. Despite their sectoral nature, bank sector entrepreneur shocks can generate positive comovement between bank and nonbank lending growth. Nonbank leverage rises as a result of the relaxed constraints from higher lending rates. Overall, these shocks generate a deep short-run decline in investment growth. In the longer run, investor inside equity shifts towards the nonbank sector, as bank lending is persistently lower than nonbank lending as bank sector entrepreneurs build back their inside net worth.

Nonbank sector entrepreneur dividend policy shocks have much the same effects, except operating in the opposite direction. Bank lending growth greatly increases, as bank sector entrepreneurs have stronger net worth positions. Indeed, the nonbank lending growth response is a muted decline on impact, as a combination of the weak net worth positions of the nonbank entrepreneurs and weak financial position of nonbanks interferes with the free flow of credit. Nonbanks continue to lever up on impact because of the fire-sale prices of capital, but once the price of capital returns to near its steady state by quarter 10, nonbank leverage declines below its steady state as nonbank sector entrepreneurs continue to build back their net worth. In the longer run, investor equity is

tilted towards the bank sector as the nonbank entrepreneurs build back up their net worth.

Taken together, these shocks are important drivers of bank and nonbank credit cycles, especially at business cycle frequencies. The combined shocks lead to bank lending growth being more volatile than nonbank lending growth and a positive co-movement between bank and nonbank lending growth. A negative co-movement between lending growth and investment growth is an important driver of the dynamics, but as we saw in Section 2, this lack of co-movement between real and debt quantities is not inconsistent with the data.²¹

The amplification of bank relative to nonbank lending growth primarily comes from two sources: one exogenous and one endogenous. The estimated nonbank sector entrepreneur dividend policy shocks are more persistent than the bank sector entrepreneur ones. This fact, along with a similar estimated volatility of the innovations, does mechanically lead to a more volatile bank lending growth series.

The endogenous factor is important as well. As can be seen in Figure 2, troubles in the balance sheets of the entrepreneurial sector always lead to investor flows to the bank sector initially. This is because in response to the two shocks, the bank sector entrepreneurs always demand more loans, which the banks must fund by extra equity. The negative effects on nonbank lending of the resulting outflows of inside equity from the nonbank sector are partially offset by an increase in nonbank leverage. When the shocks originate with the bank sector entrepreneurs, the investor equity inflows help to support the modest rise in bank lending growth and limit the rise in nonbank lending growth. When the shocks originate with the nonbank sector entrepreneurs, however, the equity flows from the nonbank to bank sector amplifies the increase in bank lending growth and adds further distress to the nonbank sector, which counteracts the positive demand for loans from the nonbank sector entrepreneurs. Therefore, even if the two shocks were of the same magnitude, the nonbank sector entrepreneur balance sheet shocks would have larger effects on bank lending growth compared to the bank sector entrepreneur balance shocks' effects on nonbank lending growth.

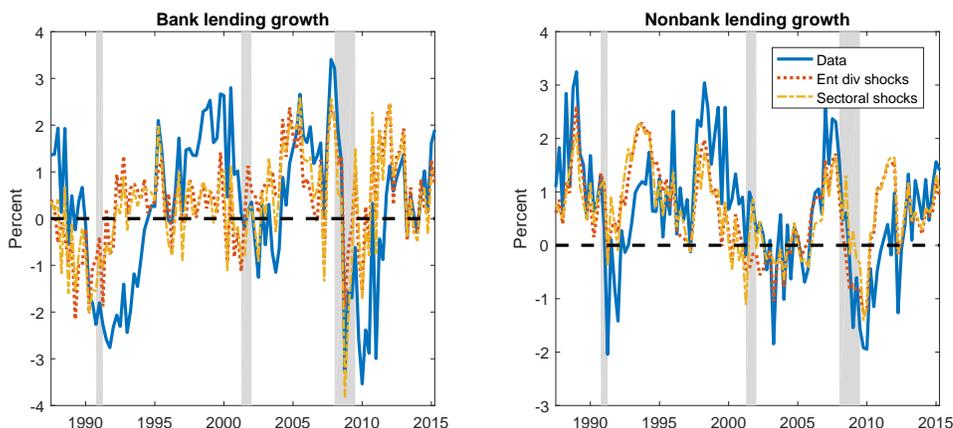
5.3 Historical Decomposition of Bank and Nonbank Credit Cycles

We now give a historical perspective on the drivers of bank and nonbank credit cycles. Figure 3 shows the historical movements of bank and nonbank lending growth implied by just the entrepreneurial dividend shocks (red) and all sectoral shocks in yellow. As was alluded to in the

²¹In addition, the entrepreneur dividend policy shocks help the model replicate the negative comovement between firm leverage and investment, as documented by Lang et al. (1996).

variance decomposition results, the entrepreneur dividend policy shocks are by far the most important sectoral shocks in driving bank and nonbank lending growth. This can be seen by noting that the red and yellow lines co-move very closely.

Figure 3: Bank and Nonbank Credit Growth Implied by Only Sectoral Shocks

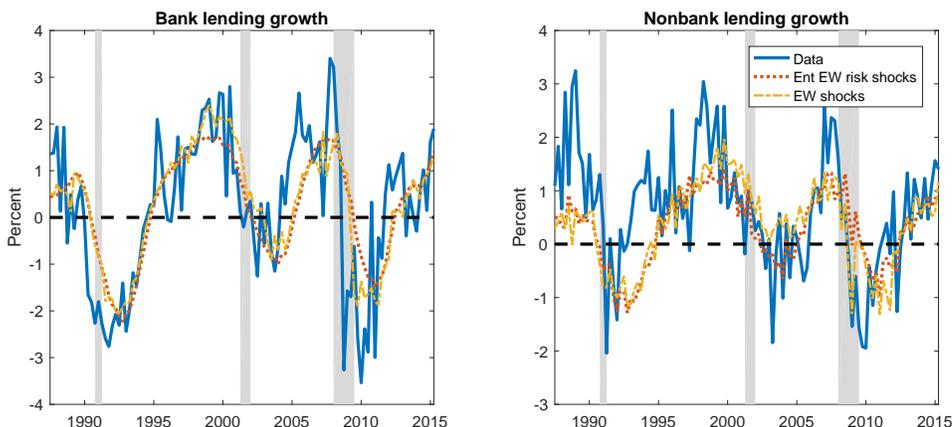


NOTE: These figures show the historical bank (left) and nonbank (right) lending growth series implied by only entrepreneurial dividend shocks as well as all sectoral shocks from 1987:Q2 to 2015:Q1. We use the simulation smoother for these calculations. Gray shaded areas denote NBER recessions.

The sectoral shocks are most important in understanding the higher frequency movements in bank and nonbank lending growth, in line with the observation that they are most important at the business cycle frequencies. Entrepreneur dividend policy shocks can help to explain much of the early drop of bank lending growth entering the savings and loan crisis and around half of the drop in bank and nonbank lending growth during the Great Recession. They can also explain much of the strong lending growth before the Great Recession. For understanding all three dips in lending growth found in the data, however, an important part of the story is missing. This fact is most evident when looking at the slow recoveries in lending growth following the savings and loan crisis and the Great Recession.

Figure 4 shows the credit cycle movements implied by just economy-wide shocks. The economy-wide shocks drive the lower frequency movements in bank and nonbank lending growth, capturing the three distinct waves in lending growth that we see in the data. They do a better job at explaining the slower recoveries in lending growth, especially after the savings and loan crisis and the Great Recession. Among the economy-wide shocks, the entrepreneur risk shocks are by far the most important for the bank and nonbank credit cycles.

Figure 4: Bank and Nonbank Credit Growth Implied by Only Economy-Wide Shocks



NOTE: These figures show the historical bank (left) and nonbank (right) lending growth series implied by only entrepreneurial economy-wide risk shocks as well as all economy-wide shocks from 1987:Q2 to 2015:Q1. We use the simulation smoother for these calculations. Gray shaded areas denote NBER recessions.

Table 7: Unconditional Variance Decomposition of Investment Growth

Variable	TFP gr.	Ent. risk EW	Ent. div. B	Ent. div. N
Inv. gr.	37	27	13	11

NOTE: This table shows the unconditional variance decomposition of investment growth at the posterior mode parameters for interesting structural shocks. EW means economy-wide. The shocks not on this list were estimated to be unimportant.

5.4 The Relationship Between Credit Cycles and Business Cycles

Finally, we discuss the linkages between financial fluctuations and their real effects. The variance decompositions show that the credit cycles estimated by the model are almost entirely a financial phenomenon. Even at lower frequencies, structural macro shocks do not have much of a role. Therefore, we focus on the effects of our important sectoral and economy-wide financial shocks on real aggregates.

Table 7 shows the unconditional variance decomposition of investment growth. Investment growth is primarily driven by four shocks: a TFP growth shock and three financial shocks. In line with Christiano et al. (2014), the entrepreneur risk shocks play an important role in understanding investment growth fluctuations. The sectoral dividend policy shocks play a factor as well, together accounting for 24 percent of fluctuations. The model is consistent with the low observed correlation between lending growth in both sectors and investment growth. Model simulations at the posterior mode parameters produce a correlation between bank lending growth and investment growth of -0.33 and a correlation between nonbank lending growth and investment growth of -0.02 .

6 Validating the Estimated Model

In this section, we present some external evidence supporting the validity of the estimated model. First, we compare model-implied default rates for bank and nonbank sector entrepreneurs to commercial and industrial loan and nonfinancial corporate bond default rates. Second, we compare nonbank default rates to the financial sector default rates excluding banks. Finally, we look at the model-implied investor dividend policy shocks to the excess bond premium.

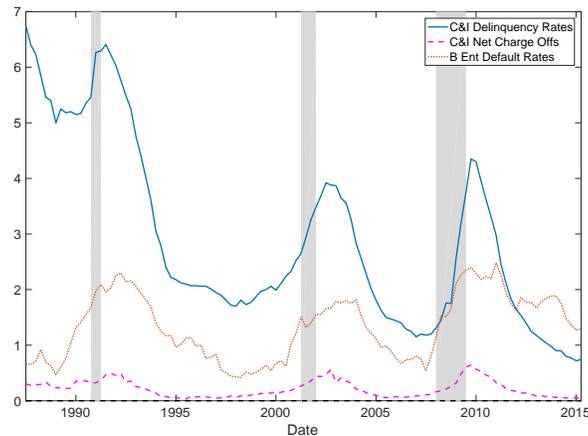
We begin by discussing the model-implied entrepreneurial default in the two sectors. The estimated model assigns a large role for the aggregate entrepreneurial risk shock in driving entrepreneurial default, so this validation exercise would help alleviate any concerns regarding the plausibility of the estimated risk shock dynamics.²² Figure 5 compares commercial and industrial loan delinquency (solid blue line) and net charge off (dashed magenta line) rates from all commercial banks to the model-implied bank entrepreneur default. The model does a good job at accurately replicating the timing of the increases and decreases of delinquencies in commercial and industrial loans across all three recessions and recoveries. Similar to Christiano et al. (2014), however, the model does understate on average bank entrepreneur default when compared to delinquency rates. Moreover, the model also does not do as good of a job in replicating the delinquency rates at the beginning of the sample in the late 1980s. On the other hand, net charge offs – a more stringent characterization of bank loan default – are on average below the model-predicted default rates. Moreover, net charge offs do not exhibit the same decline from high levels in the late 1980s that the delinquency rate data does.

Figure 6 compares the one-year ahead expected default rate on nonfinancial corporate bonds to our model-implied one-year ahead expected nonbank entrepreneur default. Our comparison starts in 2004:Q2 due to data limitations. In this case, the model accurately predicts the timing and magnitude of expected nonfinancial corporate bond default dynamics heading into and during the Great Recession. Specifically, the model can replicate the decline in expected corporate bond default entering into the recession and its rapid rise during the recession. However, the model implies a more sluggish recovery in terms of expected default relative to the data.

Second, we validate our modeling choice for the nonbank sector by comparing the model-implied nonbank default rates to the corporate bond default rates in the financial sector excluding banks as defined by the Moody’s Annual Default Study 1920-2017. The results are shown in Figure 7.

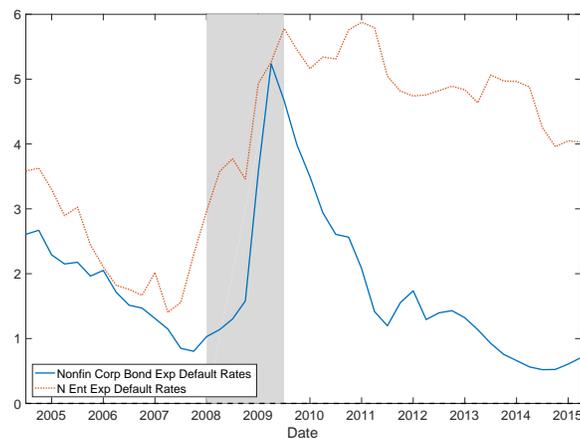
²²At the posterior mode parameters, the aggregate entrepreneurial risk shock drives over 60% of the variance in bank and nonbank entrepreneur default.

Figure 5: Empirical Measures of C&I Loan Defaults from Commercial Banks Versus Bank Entrepreneur Default



NOTE: This figure shows the delinquency rate on commercial and industrial loans from all commercial banks (mneumonic DRBLACBS from FRED and produced by the Board of Governors of the Federal Reserve System) in solid blue, net charge offs on commercial and industrial loans from all commercial banks (mneumonic CORBLACBS from FRED) in dashed magenta, and our model-implied bank entrepreneur default rates in broken red from 1987:Q2 to 2015:Q1. We use the simulation smoother for these calculations. Gray shaded areas denote NBER recessions.

Figure 6: One-Year Ahead Expected Default Rate on Nonfinancial Corporate Bonds Versus One-Year Ahead Expected Nonbank Entrepreneur Default



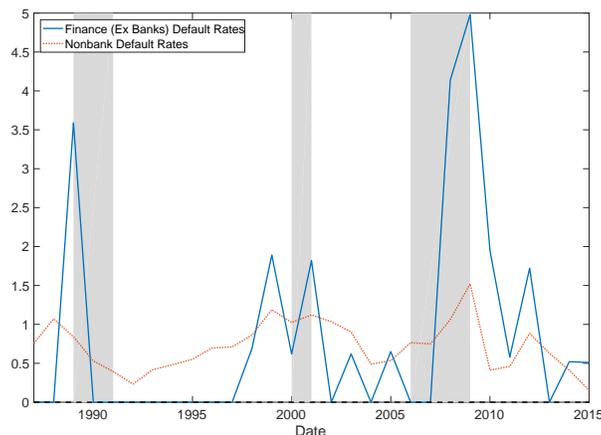
SOURCE: Calculated using firm-level data from Moody's KMV. Firm-level estimates of default weighted by firm liabilities as a percent of total liabilities.

NOTE: This figure shows the one-year ahead expected default rate on nonfinancial corporate bonds in solid blue and our model-implied one-year ahead expected nonbank entrepreneur default rates in broken red from 2004:Q2 to 2015:Q1. We use the simulation smoother for these calculations. Gray shaded areas denote NBER recessions.

While our model cannot replicate the magnitude of the increases in financial sector default during recessions, we do a good job at matching the timing of the increases and declines in default over the business cycle. The correlation of the two series is 0.57.

Finally, Figure 8 shows a comparison of the excess bond premium data from Gilchrist and Zakrajsek (2012) (blue) and our model's smoothed investor dividend shocks (orange). The excess

Figure 7: Annual Default Rate for Financial Sector Excluding Banks Versus Nonbank Default



SOURCE: Obtained from the Moody’s Annual Default Study 1920-2017. The data is issuer-weighted.

NOTE: This figure shows the annual corporate bond default rates in the FIRE: Finance industry group as defined by Moody’s in solid blue and our annual model-implied nonbank default rates in broken red from 1987 to 2015. We use the simulation smoother for these calculations and sum the default rates in each quarter to come up with an annual rate. Since we only have 3 quarters in 1987 and 1 quarter in 2015 in our model estimation, our model-implied results for those years are artificially lower. Gray shaded areas denote NBER recessions.

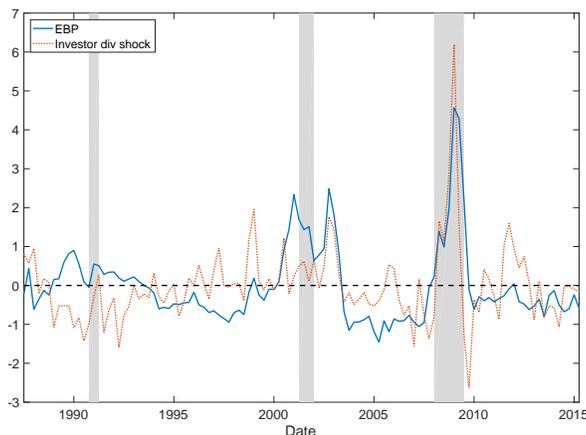
bond premium measures the willingness to provide credit to nonfinancial sector borrowing firms over and above the expected default conditions of those firms. It is generally a credit supply indicator and viewed as a proxy for exogenous financial sector shocks. The investor dividend shock in the model is the key credit supply shock. A positive investor dividend policy shock reduces the amount of inside equity available for banks and nonbanks to draw from, thereby raising lending spreads and contracting credit. The two series move especially close around the Great Recession. The model correctly estimates the relative magnitude and timing of the credit supply contraction. Overall, the correlation is 0.51.

All in all, we view these checks as important validations of several key mechanisms in the model, especially considering the fact that we do not use any of these data in our estimation.

7 Conclusion

In this paper, we examined drivers of bank and nonbank credit cycles through the lens of a medium-scale DSGE model. We considered various macro, financial, economy-wide, and sectoral structural shocks in our estimation. Overall, we find that sectoral financial shocks are the predominant drivers of both bank and nonbank lending growth, especially at business cycle frequencies. The shocks to the net worth position of the entrepreneurs who borrow from banks and nonbanks (e.g., entrepreneur dividend policy shocks) are especially important. In spite of the predominant role of sectoral

Figure 8: Excess Bond Premium Versus Smoothed Investor Dividend Shock



NOTE: This figure shows normalized excess bond premium from Gilchrist and Zakrajsek (2012) and our model-implied investor dividend shock from 1987Q2 to 2015Q1. We use the simulation smoother for these calculations. Gray shaded areas denote NBER recessions.

financial shocks at the higher frequencies, the aggregate entrepreneur risk shocks become more important at the medium-frequency cycle frequencies. For instance, these aggregate entrepreneurial risk shocks can help explain the slow leading growth recoveries following credit downturns as well as investment growth dynamics.

Our findings provide important insights on the role of macro versus financial shocks in driving economic fluctuations. In line with earlier studies, we found an important role for financial shocks in driving fluctuations in both macro and financial variables. Differently from existing studies, by explicitly modeling two different financial intermediaries, we uncovered an important role for sectoral financial shocks that has been overlooked by the previous literature. Further, based on variance decomposition analysis, we found a minor role for traditional macro shocks (i.e., TFP shocks) in driving both bank and nonbank credit cycles. For external validation of our model, we showed that the model-implied default rates for the bank and nonbank entrepreneurs, default rates for the nonbank financial sector, and the investor dividend policy shocks—broadly speaking credit supply shocks—largely cohere with their data counterparts.

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Appendix

A Calibration Parameters and Steady State Values

In this section, we present the baseline parameters and implied steady state values used in Section 4.3. These are shown in Tables 8 and 9.

β	Discount factor**	0.9965
h	Habits	0.79
η	Frisch elasticity of labor**	1
α_h	Substitutability between bank and nonbank deposits**	0.999
χ	Importance of labor disutility*	7.77
χ_h	Importance of liquidity service*	0.013
Λ_N	Importance of nonbank deposits in liquidity*	0.90
$\chi_{e,B}(N)$	Entrepreneur dividend policy*	0.02(0.026)
χ_b	Banker dividend policy*	0.042
$\alpha^B(N)$	Capital share in production**	0.33
δ_K	Depreciation rate**	0.025
Φ_I	Investment adj. cost	1.03
$\mu_{e,B}(N)$	Monitoring cost entrepreneur B(N)**	0.30(0.30)
$\mu_B(N)$	Monitoring cost B(N) intermediary**	0.30(0.20)
$\sigma_{e,B}(N)$	Std. of idio. shock B(N) entrepreneurs*	0.57(0.30)
$\sigma_B(N)$	Std. of idio. shock B(N) bank*	0.033(0.043)
$\bar{\phi}_0^B$	B Bank capital requirement*	0.088
Λ_A	Steady state TFP growth**	0.004
ρ_A	Persistence TFP growth	0.27
ρ_{EK}	Persistence MEI	0.59
ρ_β	Persistence pref.	0.35
$\rho_{\Lambda,N}$	Persistence nonbank liquidity demand shock	0.90
$\rho_{\sigma,e,Agg}$	Persistence economy-wide entrepreneur risk shock	0.99
$\rho_{\sigma,e,B}(N)$	Persistence bank (nonbank) sector entrepreneur risk shock	0.50(0.50)
$\rho_{\chi,e,Agg}$	Persistence aggregate entrepreneur dividend policy shock	0.5
$\rho_{\chi,e,B}(N)$	Persistence bank (nonbank) sector entrepreneur dividend policy shock	0.55(0.66)
$\rho_{\chi,b}$	Persistence investor dividend policy shock	0.39
ρ_η	Persistence capital requirements shock**	0.999
σ_A	Std. TFP	0.01
σ_{EK}	Std. MEI	0.006
σ_β	Std. preference	0.025
$\sigma_{\Lambda,N}$	Std. nonbank liquidity demand shock	0.10
$\sigma_{\sigma,e,Agg}$	Std. aggregate entrepreneur risk shock	0.019
$\sigma_{\sigma,e,B}(N)$	Std. bank (nonbank) sector entrepreneur risk shock	0.0(0.012)
$\sigma_{\chi,e,Agg}$	Std. aggregate entrepreneur dividend policy shock	0.0
$\sigma_{\chi,e,B}(N)$	Std. bank (nonbank) sector entrepreneur dividend policy shock	0.005(0.006)
$\sigma_{\chi,b}$	Std. investor dividend policy shock	0.02
σ_η	Std. capital requirements shock	0.002

Table 8: Baseline Parameters: * denotes that the parameter is calibrated from the data moments. ** denotes that the parameter is calibrated from the previous literature. The rest of the parameters are estimated.

Table 9: Implied steady state Values for Selected Variables

$R^D(N)$	B(N) intermediary deposit rate	1.003(1.004)
$R^B(N)$	B(N) intermediary lending rate	1.012(1.011)
$R^B - R^N$	B and N entrepreneur lending spreads	0.000672
L	Labor share	1/3
$\frac{b^B}{b^N}$	Size B to N intermediary lending	0.74
$\text{def}_{e,B(N)}$	Qtrly. default rates of B (N) ent.	1.28(0.75)%
$\text{def}_{B(N)}$	Qtrly. default rates of B (N) inter (FDIC)	0.17(0.16)%
ρ	Qtrly. return investor equity	4.43%
$\phi_{B(N)}$	Equity-to-lending ratio B (N) intermediary	0.088(0.115)

NOTE: This table shows the steady state values implied by the model for a selected set of variables. Numbers in parentheses denote the corresponding values for the N sector.

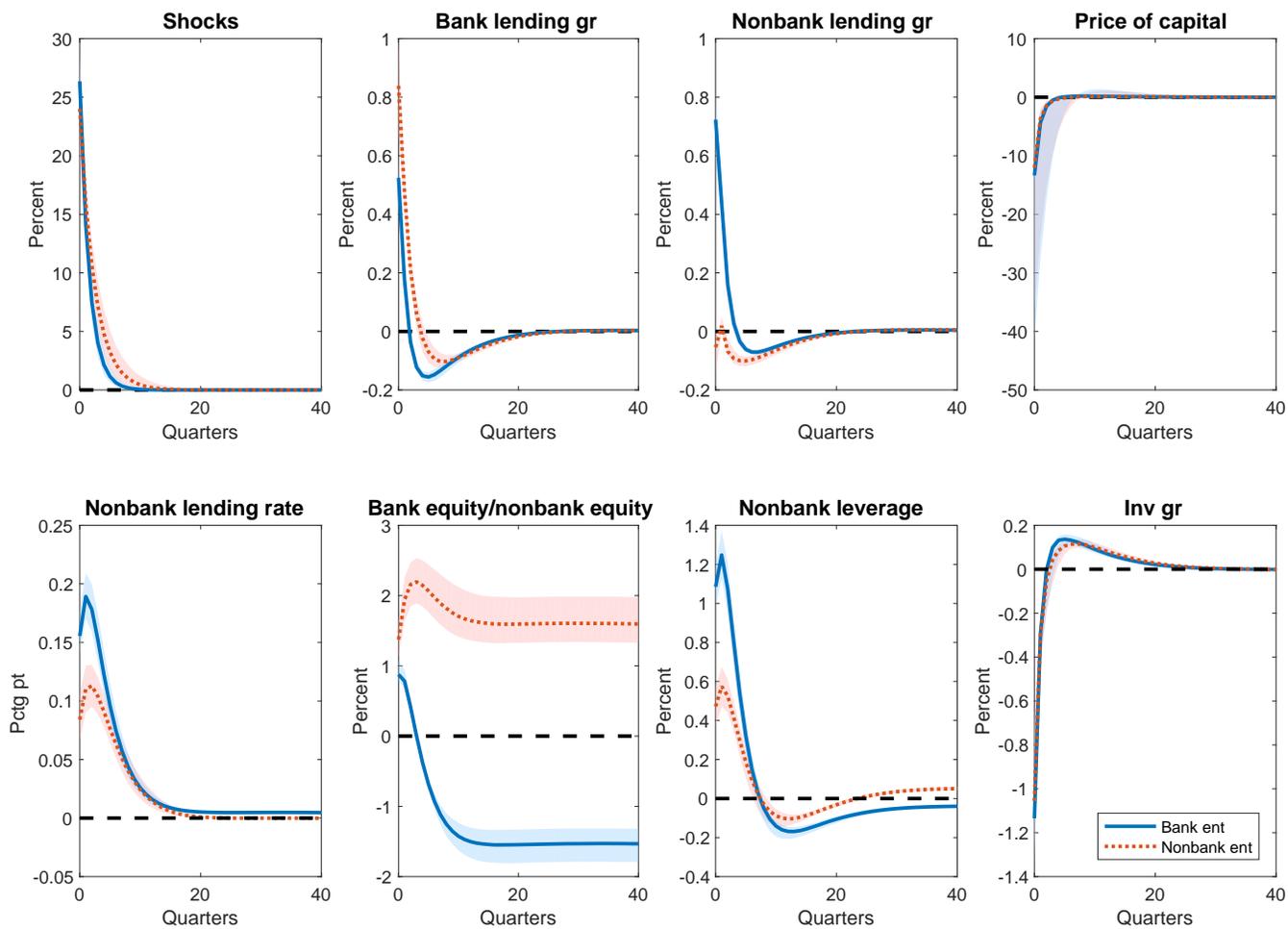
B Prior Distributions

Our prior for the habits parameter is Beta with mean of 0.5 and standard deviation of 0.2. For the investment adjustment costs, it is normal with a mean of 4 and a standard deviation of 1.5. For the exogenous processes, we use normal distributions centered at 0.5 and with standard deviation of 0.1. The exception is the TFP growth persistence parameter, which we center around 0. For the standard deviations of the shocks, we use exponential distributions with mean and variance of 0.1. As we specify more structural shocks than observables, we think it is important for us to allow for negligible effects from certain structural shocks, as discussed in Ferroni et al. (2019).

C Posterior Distributions

We use a two-step procedure to estimate the model. In the first step, we find the posterior mode parameters. There are several shocks that are estimated to be negligible, which means that the standard deviations of the innovations on these shocks are estimated to be near 0. In the second step, we shut off all of the shocks estimated to be unimportant and take 750,000 draws from the posterior distribution of the parameters. We take the first 375,000 as burn in. Table 10 shows the resulting 10 percent and 90 percent quantiles of the estimated parameters. We find that the nonbank sectoral entrepreneur risk shocks and aggregate entrepreneur dividend policy shocks are unimportant. Figure 9 shows the IRFs of the bank and nonbank entrepreneur dividend policy shocks along with their associated 80% credible sets.

Figure 9: Impulse Responses of Bank and Nonbank Sectoral Entrepreneur Dividend Policy Shocks with 80% Credible Sets



NOTE: These are the responses to one standard deviation bank (blue solid) and nonbank (orange dashed) positive entrepreneur dividend policy shocks. The shaded areas are 80% credible sets. The y-axis is in percent and the x-axis is in quarters.

Table 10: Posterior Distribution Parameters

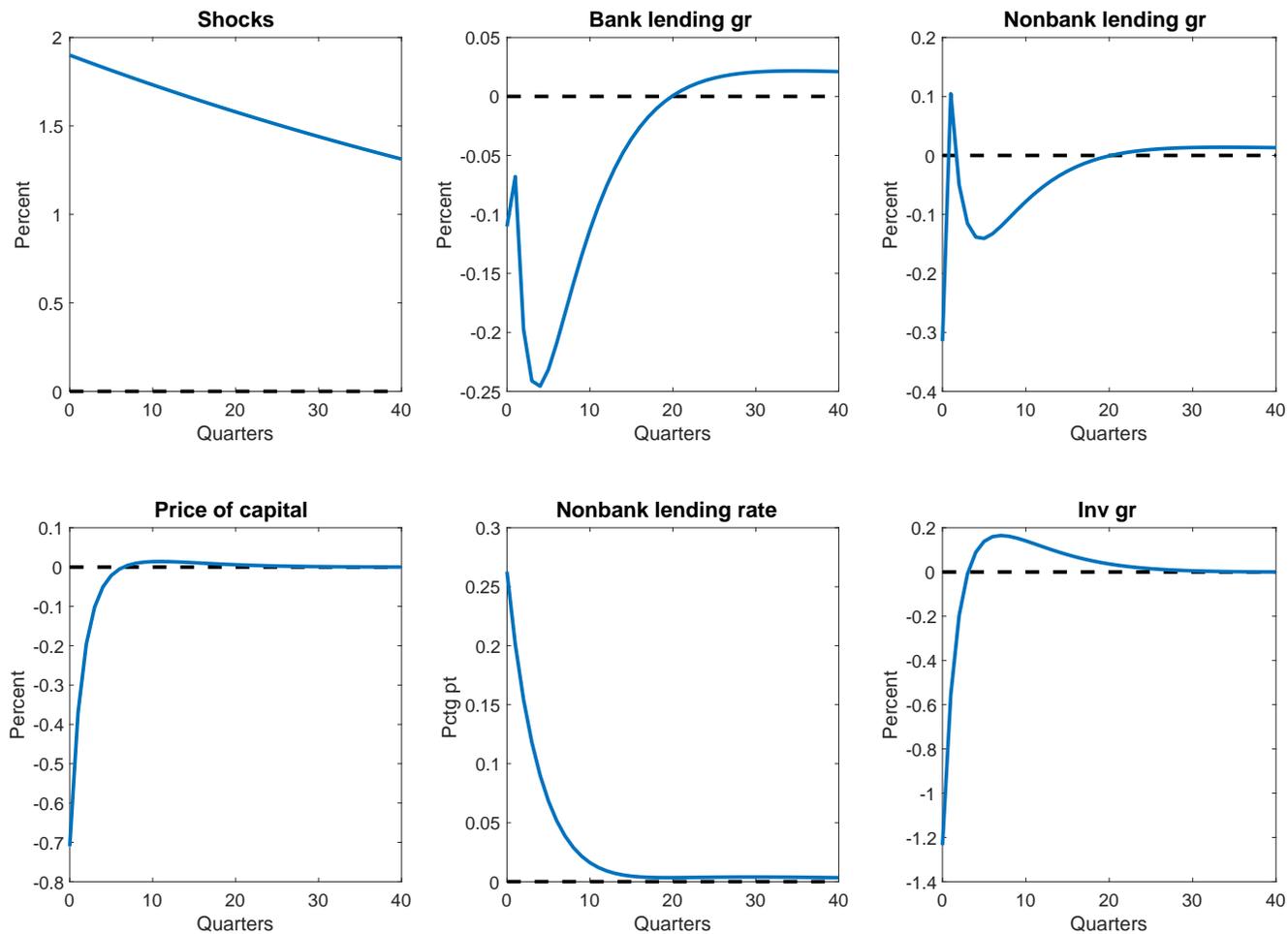
Parameter	10%	90%
h	0.76	0.92
Φ_I	0.09	1.18
ρ_A	0.23	0.38
ρ_{EK}	0.50	0.69
ρ_β	0.25	0.48
$\rho_{\Lambda,N}$	0.86	0.94
$\rho_{\sigma,e,Agg}$	0.89	0.99
$\rho_{\sigma,e,N}$	0.39	0.64
$\rho_{\chi,e,B}$	0.48	0.59
$\rho_{\chi,e,N}$	0.59	0.75
$\rho_{\chi,b}$	0.32	0.53
σ_A	0.009	0.012
σ_{EK}	0.006	0.011
σ_β	0.022	0.055
$\sigma_{\Lambda,N}$	0.095	0.113
$\sigma_{\sigma,e,Agg}$	0.018	0.025
$\sigma_{\sigma,e,N}$	0.008	0.014
$\sigma_{\chi,e,B}$	0.005	0.006
$\sigma_{\chi,e,N}$	0.005	0.007
$\sigma_{\chi,b}$	0.013	0.022
σ_η	0.002	0.003

NOTE: This table shows the 10% and 90% quantiles of the posterior distribution.

D Effects of Economy-Wide Entrepreneur Risk Shocks

Figure 10 shows the effects of a one standard deviation economy-wide entrepreneur risk shock. An increase in economy-wide entrepreneurial risk increases the probability of default for both bank and nonbank entrepreneurs. This leads to a spike in both the bank and nonbank lending rates, which depresses lending in both sectors. The resulting decline in credit decreases the price of capital. Investment growth therefore declines as well.

Figure 10: Impulse Responses of Economy-Wide Entrepreneur Risk Shocks



NOTE: This figure shows the responses to one standard deviation economy-wide entrepreneur risk shocks at the posterior mode parameters. The y-axis is in percent and the x-axis is in quarters.