Understanding Bank and Nonbank Credit Cycles: A Structural Exploration*

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Jun 2019

Abstract

We explore the structural drivers of bank and nonbank credit cycles using an estimated medium-scale macro model that allows for bank and nonbank financial intermediation. We posit economy-wide aggregate and sectoral disturbances that can drive bank and nonbank credit growth. 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.

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

Keywords: banks, nonbanks, credit cycles, leverage, DSGE models, capital requirements

1 Introduction

The increasing role of nonbank sector activity in the last three decades has significantly changed the U.S. financial intermediation system. Indeed, since the late 1990s, nearly 60 percent of total credit extended to the nonfinancial business sector has been from nonbanks as opposed to traditional

*We would like to thank Elena Afanasyeva, Levent Altinoglu, Luca Guerrieri, Jose Lopez, Shannon Luk, Caterina Mendicino, Wayne Passmore, Pau Rabanal, Alex Vardoulakis, and seminar participants at the Federal Reserve Board, Federal Reserve Research Scrum 2018, IAAE 2018, NASMES 2018, SED 2018, and the Federal Reserve Board/IMF Mini-Conference on Bank Capital Regulation and Credit Provision, for helpful discussions and Holt Dwyer, Alex Martin, and Skeet Singleton for excellent research assistance. All remaining errors are exclusively our responsibility. Correspondence: `bora.durdu@frb.gov` and `molin.zhong@frb.gov`, mailing address: 20th Street and Constitution Ave. NW, Washington, DC 20551, phone numbers: 202-452-3755 (Bora Durdu) and 202-973-6126 (Molin Zhong). The views expressed in this paper are those of the authors and should not be attributed to the Board of Governors of the Federal Reserve System or its staff.

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 are the structural sources of bank and nonbank credit cycles, and how do 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 considered[1]. 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 cycle.[2]

Our model builds off the previous contributions of **???** and **?**. It allows for two types of financial intermediaries: banks and nonbanks. Both financial institutions intermediate credit between saving households and borrowing entrepreneurs. Following **?**, 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.

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 **?** and allocate all lending passing through the long intermediation chains in the U.S. financial sector to institutions that, broadly speaking,

[1] See **?????**.

[2] One feature that our model does not include, however, is shifts in regime that may change structural parameters within the model along the lines of **?**. 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.

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 those two periods.

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 around 30 percent 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 by comparing historical model-implied series of nonbank leverage and financial sector credit supply shocks to broker-dealer leverage (**?**) and the excess bond premium (**?**) data, respectively. Both of these data were not used in the estimation of the model, lending further external credence to the model estimates.

Literature Review. Our work closely relates to the literature on macro models with a financial sector. **???** 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. **???????** 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. **?** and **?** are focused on modeling shadow banks that introduce financial fragility into the macroeconomy in the form of run risk or liquidity crunches, respectively. **????** 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 **?**, or as securitizers of bank loans that relax regulatory constraints on commercial banks as in **???**. **?** studies the optimal dynamic capital requirements in a model that allows for bank lending and direct household financing of investment. 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. **??** 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. **?** 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 **????**. 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 **??** describes how we measure the bank and nonbank credit cycles and key empirical facts that we find in the data. Section **??** describes the model environment in detail. Section **??** discusses our estimation strategy. Section **??** presents our main results decomposing bank and nonbank credit cycles with the estimated model. Section **??** presents two model external validation exercises. Finally, Section **??** summarizes our conclusions.

2 Empirical Facts on the Bank and Nonbank Credit Cycle

We begin by documenting the empirical regularities on the bank and nonbank credit cycle 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 the nonbank credit cycle, we consider a larger class of financial intermediaries than what several authors have referred to as shadow banks (**??**). For example, **?** 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 **?**, which contains all nonbank

financial intermediation. This broad definition is also in line with recent papers measuring the nonbank credit cycle, such as **?**.

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. **?** and **?** 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 **?** for netting out the financial intermediary chains. **?** 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, pension 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]

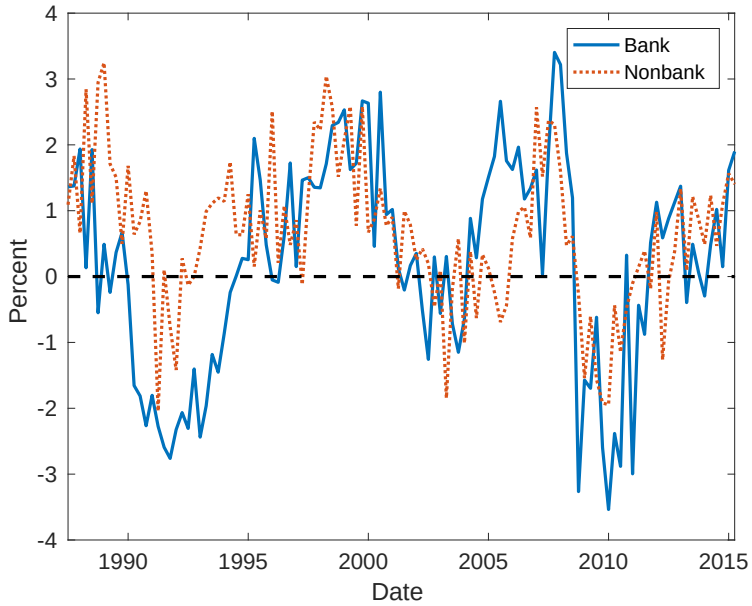
The objective of **?** is to trace each unit of debt provided to nonfinancial sector borrowers through the intermediation chains in the financial system back to one of these terminal funders. The paper does so by assigning all nonfinancial sector debt listed in the Z.1 tables as held by the intermediate funders to terminal funders proportionate to the holders of the intermediate funders' liabilities. For the purposes of our paper, 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 **?**. Nonbanks are the sum of long-term funders and short-term funders. An important additional distinction to make is that while **?** is interested in total nonfinancial sector lending, we are focused on lending to the nonfinancial business sector.[4]

[3] A full list of the definitions for each category can be found in Table 4.1 of **?**.

[4] Further details about our implementation of the procedure can be found in the appendix.

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 **?** and cover the period from 1987Q2 to 2015Q1.

2.3 Empirical Facts

Figure **??** 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 **??** 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. In the data, 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

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.

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. **?** measures the bank and nonbank credit extended to the entire nonfinancial sector for many developed and emerging markets. 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. **?** looks at bank and bond credit growth in the United States, finding 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 **?**, 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 structurally decompose fluctuations in 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 **????**. At the heart of our model is a friction driven by asymmetric information that prevents the direct flow of funds from the saving

[5] As 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 **??**.

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 on 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–**???**. 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

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

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 banks and nonbanks deposits.[6]

There are two shocks: $\tilde{\beta}_t$ are 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

[6]We 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.

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 **?**, which, in turn, follows **?** and **?**. 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 previous work such as **???**, 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 **?**, 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

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

Optimizing behavior yields the following dividend payment and earnings retention rules

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

$\chi_{t+1}^{e,i}$ 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.

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:

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

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

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

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 **?**, we 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

$$\overline{\omega}_{t+1}^{e,i} = \frac{R_t^i b_t^i}{R_{t+1}^K q_t^K k_t^i}. \tag{6}$$

As in **?** and **?**, we can define the expected gross fraction (not including intermediary monitoring costs on defaulted loans) of entrepreneurial returns from capital going to intermediaries as:

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

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:

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

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

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

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

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 $1 - \Gamma^i\left(\overline{\omega}_{t+1}^i\right)$ 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 $\overline{\omega}_{t+1}^i$, 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.

Finally, before we move on, we define $\tilde{R}_{t+1}^i$, which is the time $t+1$ realized return of loans from the intermediary of type i.

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

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 $\left(c_{t+1}^b\right)^{\chi_{t+1}^b}\left(n_{t+1}^b\right)^{1-\chi_{t+1}^b}$. 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.

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

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

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

where $\tilde{\rho}_{t+1}^B$ denotes ex post gross 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 **?**. The shocks can be interpreted as capturing unmodeled investor inside equity flows or unmodeled housing loan losses from default, as in **?**.

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. 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.

We first 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:

$$\pi_{t+1}^{B} = \max\left[\omega_{t+1}^{B}\tilde{R}_{t+1}^{B}b_{t}^{B} - R_{t}^{D}d_{t}^{B}, 0\right], \tag{13}$$

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

$$\phi_{t}^{B} = \frac{e_{t}^{B}}{b_{t}^{B}}. \tag{14}$$

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 $t+1$:

$$\pi_{t+1}^{N} = \max\left[\omega_{t+1}^{N}\tilde{R}_{t+1}^{N}b_{t}^{N} - R_{t}^{D,N}d_{t}^{N}, 0\right], \tag{15}$$

where the definitions of the variables are the same, except now with a 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.

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

where $x_t^N = \frac{R_t^{D,N}\left(b_t^N - e_t^N\right)}{b_t^N}$. 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:

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

where $\overline{\omega}_t^N$ 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

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

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

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

The optimality condition would yield

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

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

EK_t denotes marginal efficiency of investment (MEI) shocks, as in **?**. 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

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

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

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

Market Clearing Conditions. The following market clearing conditions must be satisfied in equilibrium. The consumption good market clearing implies

$$\begin{aligned} y_t =& c_t + \left[1 + g\left(\frac{I_t}{I_{t-1}}\right)\right] I_t + \mu^{e,B} G^{e,B}\left(\overline{\omega}_t^{e,B}\right) R_t^{K,B} q_{t-1}^K k_{t-1}^B + \mu^{e,N} G^{e,N}\left(\overline{\omega}_t^{e,N}\right) R_t^{K,N} q_{t-1}^K k_{t-1}^N + \\ & \mu^B G^B\left(\overline{\omega}_t^B\right) \tilde{R}_t^B b_{t-1}^B + \mu^N G^N\left(\overline{\omega}_t^N\right) \tilde{R}_t^N b_{t-1}^N. \end{aligned} \tag{22}$$

The consumption good market clearing implies that total output must equal total consumption, total investment taking into account adjustment costs, and monitoring costs from the defaulting entrepreneurs and intermediaries in both the B and N sectors.

Labor market clearing implies

$$\begin{aligned} (1-\alpha^B)\frac{y_t^B}{w_t^B} &= l_t^B \\ (1-\alpha^N)\frac{y_t^N}{w_t^N} &= l_t^N \\ l_t^B + l_t^N &= l_t. \end{aligned} \tag{23}$$

Capital market clearing implies

$$\begin{aligned} \alpha^B \frac{y_t^B}{r_t^B} &= k_t^B \\ \alpha^N \frac{y_t^N}{r_t^N} &= k_t^N \\ k_t^B + k_t^N &= k_t \\ k_t &= (1-\delta)k_{t-1} + I_t. \end{aligned} \tag{24}$$

Market clearing in the bank and nonbank deposit markets implies the following conditions

$$\begin{aligned} d_t^B &= (1-\phi_t^B) b_t^N \\ d_t^N &= b_t^N - e_t^N. \end{aligned} \tag{25}$$

Market clearing in the entrepreneurial loan markets implies

$$\begin{aligned} q_t^K k_t^B - b_t^B &= n_t^{e,B} \\ q_t^K k_t^N - b_t^N &= n_t^{e,N}. \end{aligned} \tag{26}$$

The intermediary equity market clearing condition implies

$$\left(1 - \chi_t^b\right) W_t^b = \phi_t^B b_t^B + b_t^N - d_t^N. \tag{27}$$

Finally, the deposit insurance agency needs to have a balanced budget, hence the taxes collected from households need to be equal to the insurance provided to the regulated intermediary deposits, e.g.,

$$T_t = \left[\overline{\omega}_t^B - \Gamma^B\left(\overline{\omega}_t^B\right) + \mu_t^B G^B\left(\overline{\omega}_t^B\right)\right] \tilde{R}_t^B b_{t-1}^B. \tag{28}$$

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:

$$\phi_t^B = \overline{\phi}_0^B + \eta_{\phi,t}, \tag{29}$$

where η_{ϕ_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 interesting 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.[7] The TFP shocks are an $AR(1)$ in growth rates.

$$\Delta \log A_t = \Lambda_A(1 - \rho_A) + \rho_A \Delta \log A_{t-1} + \epsilon_{A,t}, \epsilon_{A,t} \sim N(0, \sigma_A^2). \tag{30}$$

MEI shocks are specified as $AR(1)$:[8]

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

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

$$EK_t = (1 - \rho_{EK}) + \rho_{EK} EK_{t-1} + \epsilon_{EK,t}, \epsilon_{EK,t} \sim N(0, \sigma^2_{EK}). \tag{31}$$

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

$$\tilde{\beta}_t = (1 - \rho_\beta) + \rho_\beta \tilde{\beta}_{t-1} + \epsilon_{\beta,t}, \epsilon_{\beta,t} \sim N(0, \sigma^2_\beta). \tag{32}$$

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 $AR(1)$:

$$\begin{aligned} \tilde{\Lambda}_{U,t} &= (1 - \rho_{\Lambda,U}) + \rho_{\Lambda,U} \tilde{\Lambda}_{U,t-1} + \epsilon_{\Lambda,U,t}, \epsilon_{\Lambda,U,t} \sim N(0, \sigma^2_{\Lambda,U,t}) \\ \Lambda_{U,t} &= \Lambda_U \tilde{\Lambda}_{U,t}. \end{aligned} \tag{33}$$

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:

$$\begin{aligned} \sigma^{e,i}_t &= \sigma^{e,i} \sigma^{e,Agg}_t \sigma^{e,i}_t \\ \sigma^{e,Agg}_t &= (1 - \rho_{\sigma,e,Agg}) + \rho_{\sigma,e,Agg} \sigma^{e,Agg}_{t-1} + \epsilon_{\sigma,e,Agg,t}, \epsilon_{\sigma,e,Agg,t} \sim N(0, \sigma^2_{\sigma,e,Agg}) \\ \sigma^{e,i}_t &= (1 - \rho_{\sigma,e,i}) + \rho_{\sigma,e,i} \sigma^{e,i}_{t-1} + \epsilon_{\sigma,e,i,t}, \epsilon_{\sigma,e,i,t} \sim N(0, \sigma^2_{\sigma,e,i}). \end{aligned} \tag{34}$$

Our entrepreneur dividend policy shocks are specified as follows:

$$\begin{aligned} \chi^{e,i}_t &= \chi^{e,i} + \chi^{e,Agg}_t + \chi^{e,i}_t \\ \chi^{e,Agg}_t &= \rho_{\chi,e,Agg} \chi^{e,Agg}_{t-1} + \epsilon_{\chi,e,Agg,t}, \epsilon_{\chi,e,Agg,t} \sim N(0, \sigma^2_{\chi,e,Agg}) \\ \chi^{e,i}_t &= \rho_{\chi,e,i} \chi^{e,i}_{t-1} + \epsilon_{\chi,e,i,t}, \epsilon_{\chi,e,i,t} \sim N(0, \sigma^2_{\chi,e,i}). \end{aligned} \tag{35}$$

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

$$\begin{aligned}\chi_t^b &= \chi^b + \tilde{\chi}_t^b \\ \tilde{\chi}_t^b &= \rho_{\chi,b}\tilde{\chi}_{t-1}^b + \epsilon_{\chi,b,t}, \epsilon_{\chi,b,t} \sim N(0, \sigma_{\chi,b}^2).\end{aligned} \tag{36}$$

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

$$\eta_{\phi,t} = \rho_\eta \eta_{\phi,t-1} + \epsilon_{\eta,t}, \epsilon_{\eta,t} \sim N\left(0, \sigma_\eta^2\right). \tag{37}$$

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 the appendix.

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 household liquidity utility function, depreciation rate, and the persistence of the capital requirements shock. One important calibrated parameter to discuss is α_h, or the substitutability between bank and nonbank deposits in the household utility function. We use the same value of 0.745 as in **?**. 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 **??** 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 **?**. 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 **?**. 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 **?** was focused more on the default of entrepreneurs borrowing from the corporate debt markets, not the traditional banking markets. For bank default rates, we 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 **?**, 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 **?** for financial intermediaries.

Finally, we discuss our nonbank lending rate target. We target a quarterly value of 1.0093 percent in our calibration. This is below the mean of the BAA rate of 1.0135 percent (quarterly) in our sample, which is our proxy for the nonbank lending rates. It is difficult for our model to simultaneously match the high leverage in the financial sector, net worth levels implied by the return to investor inside equity, and high lending spreads. This is because the combination of the net worth and high leverage of the financial sector imply high levels of lending, which make it difficult to square with a high lending rate.[9]

We then linearize the model around the nonstochastic steady state and estimate the rest of the parameters using Bayesian methods (**?**), which include the parameters governing the exogenous shocks, degree of habits, and investment adjustment costs.[10] We use the following data to

[9] One in theory could match a high lending rate by assuming an unreasonably high level of entrepreneur default monitoring cost. We check to ensure our entrepreneur default monitoring is within the range deemed reasonable by **?**.

[10] The full set of equilibrium conditions can be found in the appendix.

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 (**?**)	0.000675
R^N	N intermediary lending rate	1.0093
L	Labor share	1/3
$\frac{b^B}{b^N}$	Size B to N intermediary lending (Z.1. Tables)	0.72
$\text{def}_{e,N}$	Qtrly. default rates of N entrepreneur (**?**)	0.75%
$\text{def}_{B(N)}$	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 (**?**)	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.

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, $400(R_t^N - R_t^f)$;[11] 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 issue of a mixed frequency of observations. We follow work by **?** 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 **??** lists the parameters and their calibrated or estimated values. We focus our empirical results on the posterior mode parameters.[12] We estimate a high degree of habits and a moderate amount of investment adjustment costs. Our estimates for the macro shocks are fairly in line with the literature. We estimate a low degree of persistence for the TFP growth shock. Relative to **?**, our MEI shocks are less important because of the inclusion of financial data, more in line with the results

[11] 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. This is because of the aforementioned issue that the model has with matching the average BAA rate.

[12] Additional estimation details, including on the prior specifications and posterior distributions, can be found in the appendix.

of **?**. Among the financial shocks, we estimate highly persistent economy-wide entrepreneur risk and nonbank liquidity demand shocks. The sectoral 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 **??**, 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 has a hard time simultaneously matching the equity-to-lending ratio values in the bank and nonbank intermediary sectors. We choose to hit the equity-to-lending ratio in the bank sector exactly at the cost of calibrating the equity-to-lending ratio in the nonbank sector at slightly too low of a value.

Tables **??** and **??** 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. In terms of volatility, the variable that the model does not do well in matching is the N-sector entrepreneur lending spread volatility, although it does do a good job at matching the volatility of the deposit rates in both sectors. The estimated model understates the persistence of the deposit rates and lending growth. All in all, 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–**??**.

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 **??** 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

β	Discount factor*	0.9965
h	Habits	0.9693
η	Frisch elasticity of labor*	1
α_h	Substitutability between bank and nonbank deposits*	0.745
χ	Importance of labor disutility*	8.32
χ_h	Importance of liquidity service*	0.013
Λ_N	Importance of nonbank deposits in liquidity*	1.04
$\chi_{e,B}(N)$	Entrepreneur dividend policy*	0.019(0.020)
χ_b	Banker dividend policy*	0.024
$\alpha^B(N)$	Capital share in production*	0.33
δ_K	Depreciation rate*	0.025
Φ_I	Investment adj. cost	3.09
$\mu_{e,B}(N)$	Monitoring cost entrepreneur B(N)*	0.31(0.36)
$\mu_B(N)$	Monitoring cost B(N) intermediary*	0.3(0.35)
$\sigma_{e,B}(N)$	Std. of idio. shock B(N) entrepreneurs*	0.54(0.41)
$\sigma_B(N)$	Std. of idio. shock B(N) bank*	0.032(0.035)
$\overline{\phi}_0^B$	B Bank capital requirement*	0.088
Λ_A	Steady state TFP growth*	0.004
ρ_A	Persistence TFP growth	0.12
ρ_{EK}	Persistence MEI	0.52
ρ_β	Persistence pref.	0.49
$\rho_{\Lambda,N}$	Persistence nonbank liquidity demand shock	0.93
$\rho_{\sigma,e,Agg}$	Persistence economy-wide entrepreneur risk shock	0.99
$\rho_{\sigma,e,B}(N)$	Persistence bank (nonbank) sector entrepreneur risk shock	0.51(0.5)
$\rho_{\chi,e,Agg}$	Persistence aggregate entrepreneur dividend policy shock	0.5
$\rho_{\chi,e,B}(N)$	Persistence bank (nonbank) sector entrepreneur dividend policy shock	0.58(0.65)
$\rho_{\chi,b}$	Persistence investor dividend policy shock	0.58
ρ_η	Persistence capital requirements shock*	0.999
σ_A	Std. TFP	0.013
σ_{EK}	Std. MEI	0.005
σ_β	Std. preference	0.15
$\sigma_{\Lambda,N}$	Std. nonbank liquidity demand shock	0.11
$\sigma_{\sigma,e,Agg}$	Std. aggregate entrepreneur risk shock	0.02
$\sigma_{\sigma,e,B}(N)$	Std. bank (nonbank) sector entrepreneur risk shock	0.01(0.0)
$\sigma_{\chi,e,Agg}$	Std. aggregate entrepreneur dividend policy shock	0.0
$\sigma_{\chi,e,B}(N)$	Std. bank (nonbank) sector entrepreneur dividend policy shock	0.005(0.005)
$\sigma_{\chi,b}$	Std. investor dividend policy shock	0.016
σ_η	Std. capital requirements shock	0.002

Table 3: Baseline Parameters: * denotes that the parameter is calibrated. The rest of the parameters are estimated.

Table 4: 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	1.0099(1.0093)
L	Labor share	1/3
$\frac{b^B}{b^N}$	Size B to N intermediary lending	0.72
$\text{def}_{e,B(N)}$	Qtrly. default rates of B (N) ent.	1.18(0.74)%
$\text{def}_{B(N)}$	Qtrly. default rates of B (N) inter (FDIC)	0.17(0.17)%
$\phi_B(N)$	Equity-to-lending ratio B (N) intermediary	0.088(0.097)

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.

Table 5: Standard Deviations of Observables in the Data and the Model at Posterior Mode Parameters

Variable	Data	Model
B Deposit rates	2.05	2.10
N Deposit rates	2.40	2.76
N Ent. lending spreads	0.75	1.39
Cons. gr.	0.51	0.55
Inv. gr.	2.29	2.03
B Lending gr.	1.59	1.77
N Lending gr.	1.12	1.37

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

Table 6: Autocorrelation of Observables in the Data and the Model at Posterior Mode Parameters

Variable	Data	Model
B Deposit rates	0.90	0.69
N Deposit rates	0.92	0.81
N Ent. lending spreads	0.89	0.80
Cons. gr.	0.43	0.51
Inv. gr.	0.53	0.43
B Lending gr.	0.74	0.45
N Lending gr.	0.59	0.31

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

Table 7: Unconditional Variance Decomposition of Bank and Nonbank Lending Growth

Variable	TFP gr.	Liq. N	Ent. risk EW	Ent. risk B	Ent. div B	Ent. div N	Cap. req.
Bank lending gr.	4	13	9	13	11	49	0
Nonbank lending gr.	10	9	19	9	37	8	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.

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 less than 15 percent of fluctuations. The most important among the macro shocks is the TFP growth shock, which drives around 4 percent of bank lending growth and 10 percent of nonbank lending growth, respectively. The lack of importance 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, bank entrepreneur risk shocks and dividend policy shocks, and nonbank entrepreneur dividend policy shocks, drive over 80 percent of bank lending growth and nearly 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 0.22.

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 **?**, as shown in Table **??**. [13] At business cycle frequencies, the sectoral shocks–and specifically the bank and nonbank entrepreneur dividend policy shocks–gain even more importance, driving over 70 percent of fluctuations in both sectors. The economy-wide entrepreneur risk shocks become more important at longer horizons, driving over

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

Table 8: 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.	4	13	66
	Nonbank lending gr.	4	61	11
32-200 qtrs	Bank lending gr.	34	13	40
	Nonbank lending gr.	34	30	15

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.

30 percent of credit fluctuations in both sectors 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 lending growth persistently falling.[14] 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 loosenings from the capital requirements shocks.

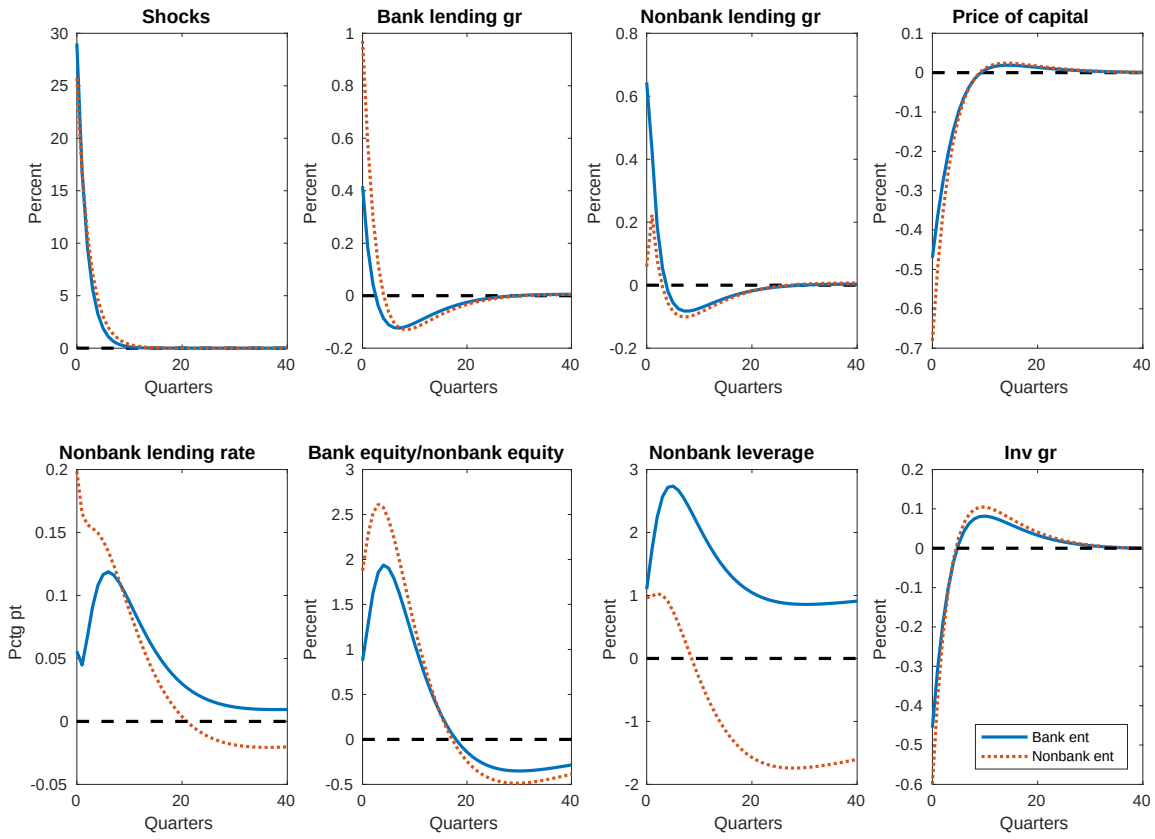
5.2 Understanding the Mechanism Behind Sectoral Entrepreneur Dividend Policy Shocks

Figure **??** 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. Interestingly, despite the sectoral nature of the shocks, both disturbances lead to positive co-movement between bank and nonbank lending growth.

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

[14] As this shock is a more standard financial shock in the literature, we discuss its effects in more detail in the appendix.

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.

power. Investor equity flows into the banking sector from the nonbanking 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 appreciation. Therefore, the nonbank sector entrepreneurs borrow to finance their capital purchases. Nonbank leverage rises as a result of the relaxed constraints from higher lending rates. In the longer run, nonbank leverage continues to be high as bank sector entrepreneurs build back their net worth. Overall, these shocks generate a short-run decline in investment growth.

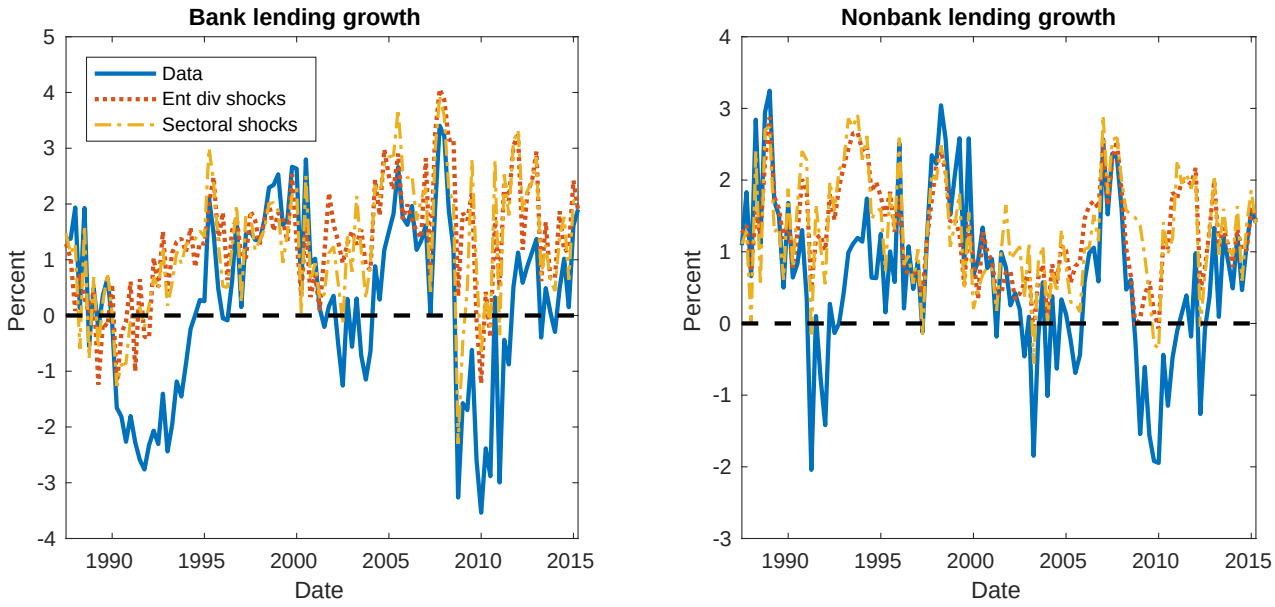
Nonbank sector entrepreneur dividend policy shocks have much the same effects, except operating in the opposite direction. Now, it is the bank lending growth that increases more than the nonbank lending growth, as bank sector entrepreneurs have stronger net worth positions. Indeed, the nonbank lending growth response is muted on impact, as a combination of the weak net worth positions of the nonbank entrepreneurs and weak financial position of nonbanks interfere 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.

Taken together, these shocks are important drivers of bank and nonbank credit cycles. 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 **??**, this lack of co-movement between real and debt quantities is not inconsistent with the data.

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 slightly 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 **??**, troubles in the balance sheets of the entrepreneurial sector always lead to investor flows to the bank sector. 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.

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.

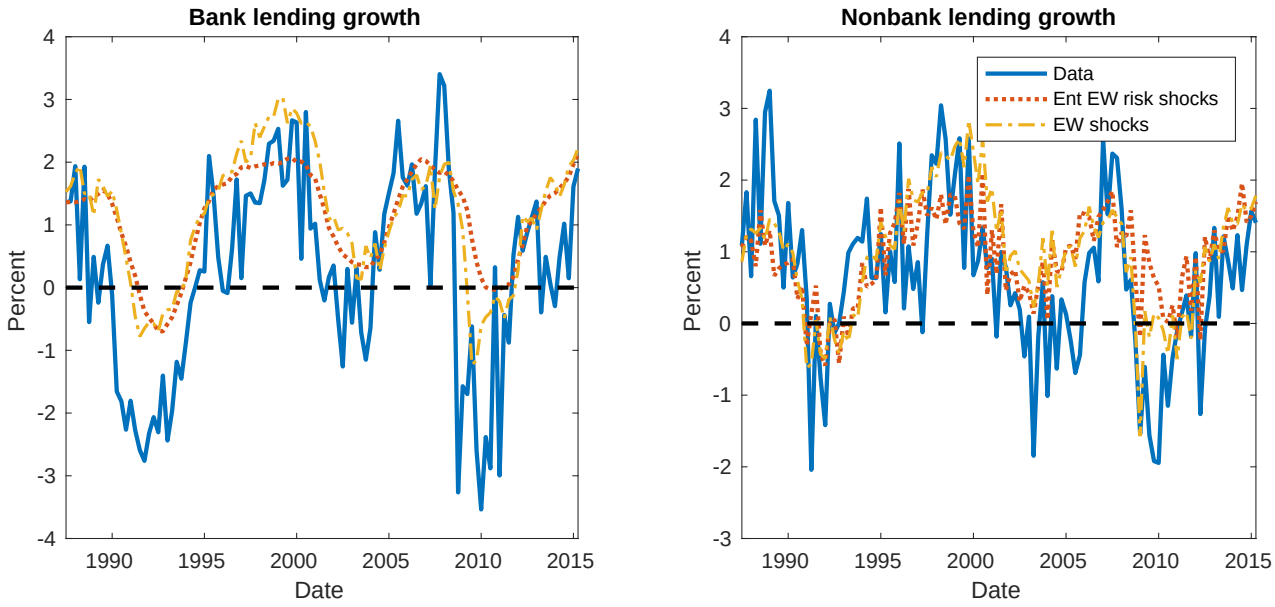
When the shocks originate with the bank sector entrepreneurs, the investor equity inflows help to support the modest rise in bank lending growth and limit the rise in nonbank lending growth. When the shocks originate with the nonbank sector entrepreneurs, however, the equity flows from the nonbank to 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 Historically Decomposing Bank and Nonbank Credit Cycles

We now give a historical perspective on the drivers of bank and nonbank credit cycles. Figure **??** 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 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 closely hug each other.

The sectoral shocks are most important in understanding the higher frequency movements in

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.

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 around half of the drop in bank and nonbank lending growth during the savings and loan crisis and the Great Recession. They can also explain almost all of the strong lending growth in the late 1990s and 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 **??** 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.

Table 9: Unconditional Variance Decomposition of Investment Growth

Variable	TFP gr.	Ent. risk EW	Ent. div. B	Ent. div. N
Inv. gr.	27	30	16	24

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.

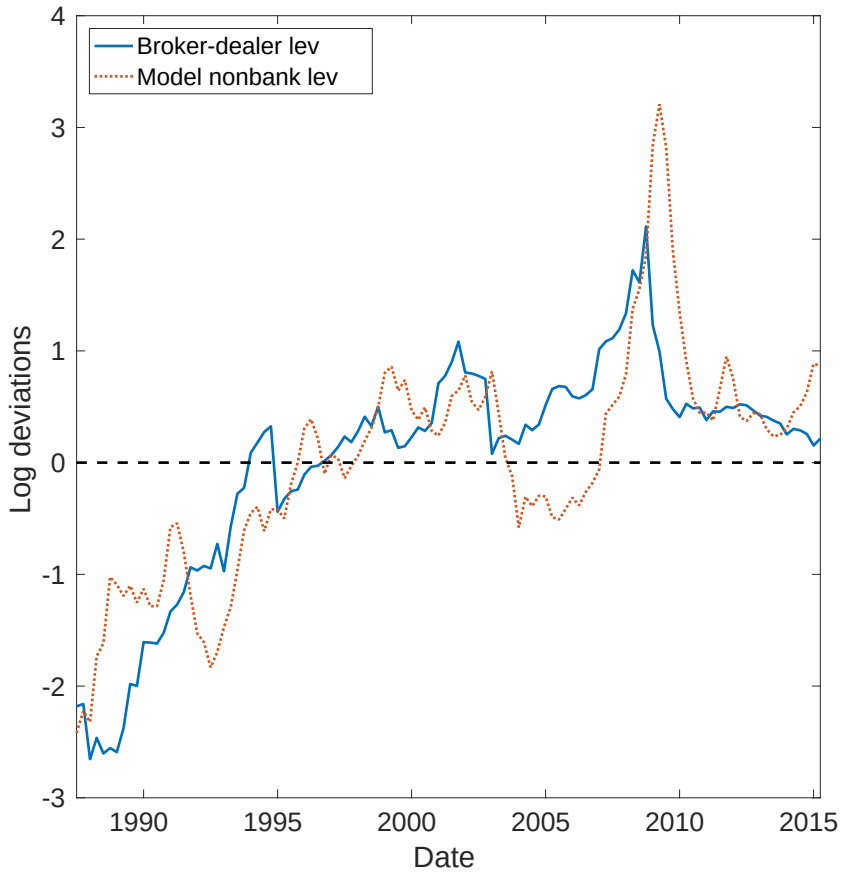
Table **??** shows the unconditional variance decomposition of investment growth. Investment growth is primarily driven by four shocks: a TFP growth shock and three financial shocks. In line with **?**, the entrepreneur risk shocks play an important role in understanding investment growth fluctuations. The sectoral dividend policy shocks play a factor as well, together accounting for 40 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 -0.34 and a correlation between nonbank lending growth and investment growth of -0.14.

6 Validating the Estimated Model

In this section, we present some external evidence supporting the validity of the estimated model. First, we compare the measure of broker-dealer leverage computed in **?** to our smoothed nonbank leverage series in Figure **??**. Although our nonbank sector covers a larger group of nonbank intermediaries, collecting leverage data for the nonbank intermediaries as a whole is difficult. We follow **?** and use broker-dealer leverage to proxy for overall nonbank leverage. Our model can capture several important features of the data, including the rise in nonbank leverage from the late 1980s to 2003 as well as the drop in 2004 and subsequent peak in the Great Recession. Overall, the correlation between the two series is 0.77. We view this as an important validation of a key mechanism of the model, especially considering we do not use this data to inform nonbank leverage in our estimation.

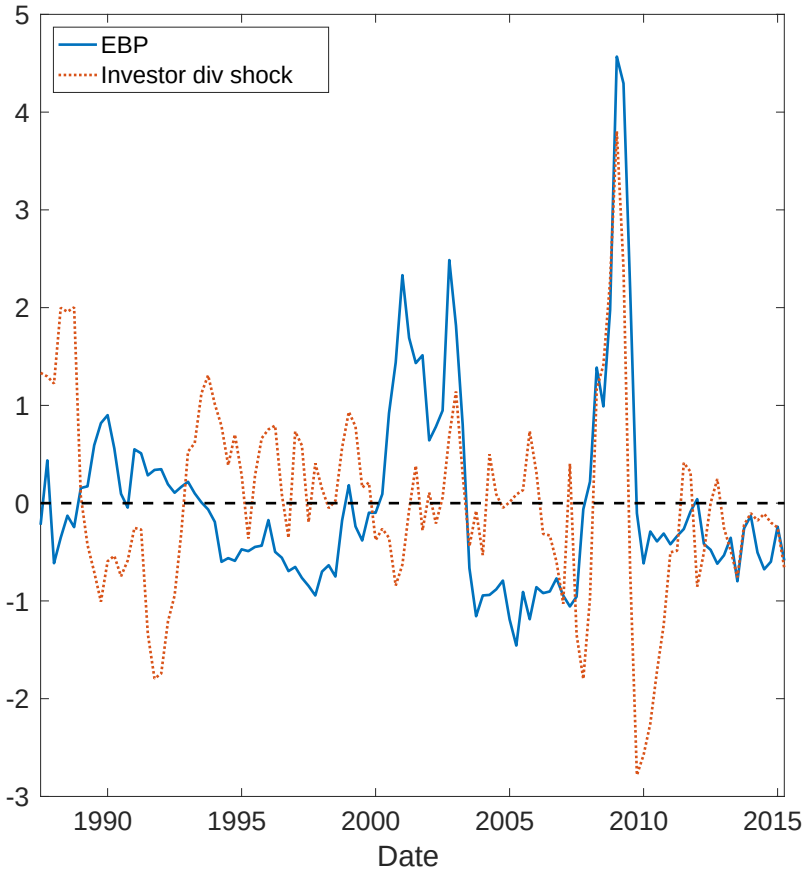
Figure **??** shows a comparison of the excess bond premium data from **?** (blue) and our model's smoothed investor dividend shocks (orange). The excess bond premium measures the willingness to

Figure 5: Broker-Dealer Leverage Versus Smoothed Nonbank Leverage



NOTE: This figure shows normalized log broker-dealer leverage from **?** and our model-implied nonbank leverage from 1987:Q2 to 2015:Q1. We use the simulation smoother for these calculations.

Figure 6: Excess Bond Premium Versus Smoothed Investor Dividend Shock



NOTE: This figure shows normalized excess bond premium from **?** and our model-implied investor dividend shock from 1987Q2 to 2015Q1. We use the simulation smoother for these calculations.

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 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. Indeed, the two series co-move more closely after 2000, with a correlation of 0.53. Before 2000, the series co-move less closely. Overall, the correlation is 0.29.

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. Despite the predominant role of sectoral 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 lending growth recoveries following credit downturns as well as investment growth dynamics.

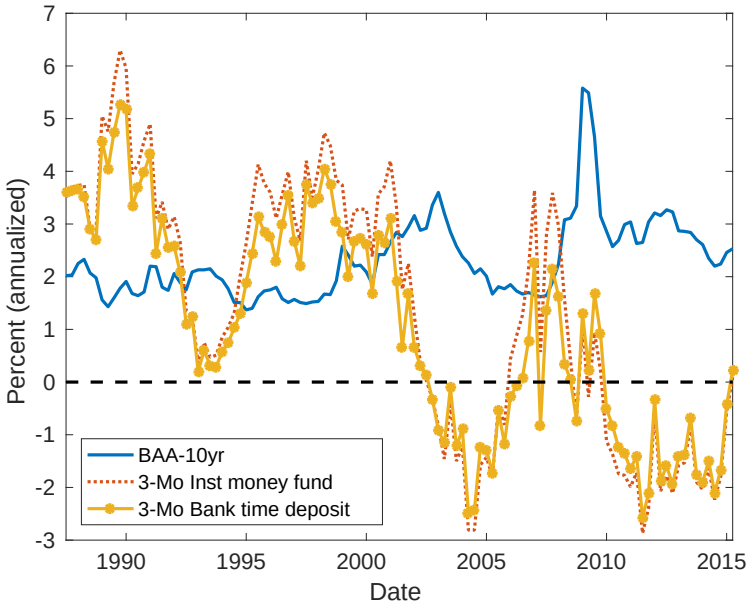
Our findings provide important insights on the role of macro versus financial shocks in driving economic fluctuations. In line with earlier studies, we found an important role for financial shocks in driving fluctuations in both macro and financial variables. Differently from existing studies, by explicitly 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-series of nonbank leverage closely mimic broker-dealer leverage of Adrian et al. (2014), and the model implied investor dividend policy shocks–broadly speaking credit supply shocks–largely follow the excess bond premium estimates of Gilchrist and Zakraksek (2012).

Appendix

A Data

For our deposit rate data, we use three-month deposit rates for commercial bank time deposits collected from call reports and three-month rates of institutional only money market funds from iMoneyNet. We turn these nominal rates to real rates by subtracting the GDP price deflator inflation from FRED. We use the Moody's Seasoned BAA Corporate bond yield over the 10-year Treasury constant maturity data from FRED to inform our unregulated intermediary lending spreads (see Figure **??**).[15]

Figure 7: Spreads on Entrepreneurial Loans and Real Rates on Deposits

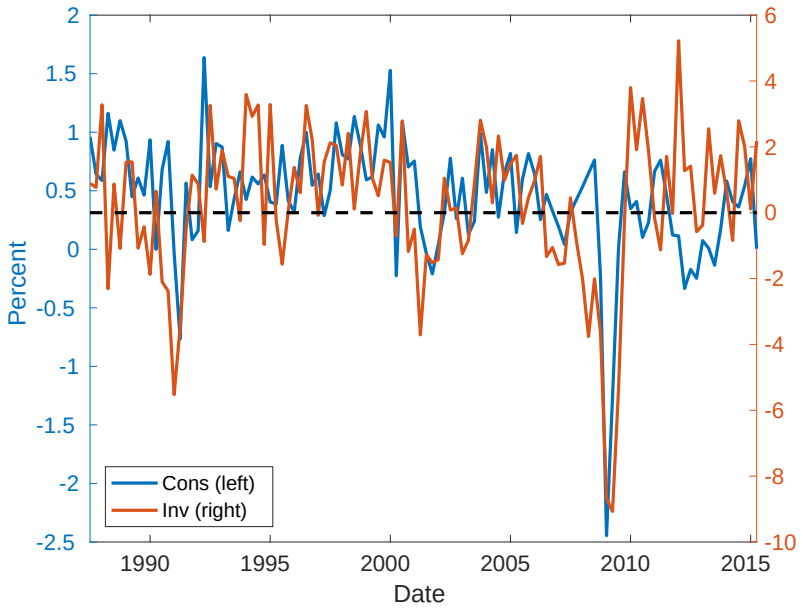


SOURCE: MMF: iMoneyNet, Inc., iMoneyNet Bulk Data - Offshore Analyzer and Gold Analyzer, BAA: Moody's, Moody's Seasoned Baa Corporate Bond Yield [BAA], Commercial bank time deposits: Board of Governors of the Federal Reserve System (US), Call report data.
NOTE: Our deposit rate data is a real rate, as we subtract the GDP price deflator inflation.

Our consumption and investment growth data both come from FRED. Consumption is defined as the sum of personal consumption expenditures (PCE) services and nondurables whereas investment is the sum of PCE durables and domestic private investment. We deflate the series using the GDP

[15]Note that as we are constructing real deposit rates, the three-month Inst money fund and three-month bank time deposit series can go negative.

Figure 8: Growth Rate of Consumption and Investment



NOTE: This data is the real per capita consumption and investment growth series from FRED. Consumption is defined as the sum of PCE services and nondurables, whereas investment is the sum of PCE durables and domestic private investment. We deflate the series using the GDP price deflator and turn them into per capita values by dividing by the civilian noninstitutionalized population aged 16 or over from FRED.

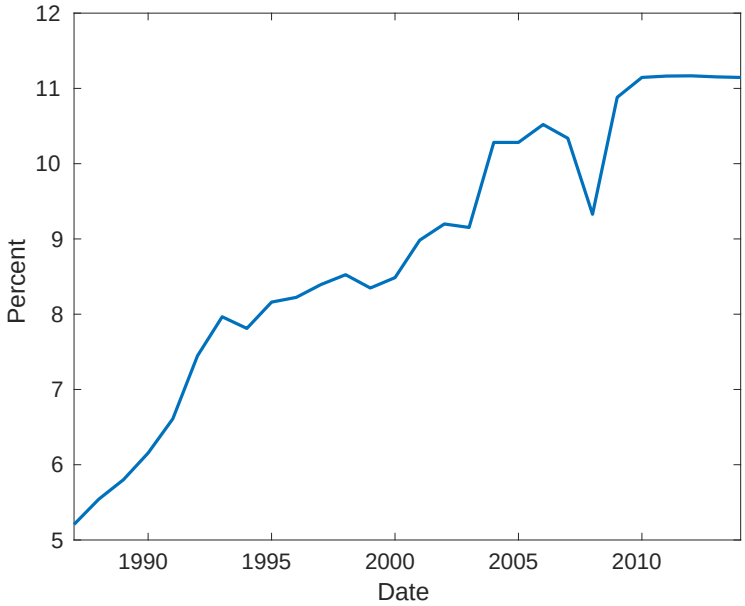
price deflator and turn them into per capita values by dividing by the civilian noninstitutionalized population aged 16 or over from FRED (see Figure **??**).

The bank equity-to-lending ratio data is constructed as the ratio between the total equity capital of commercial banks and savings institutions (defined as the sum of perpetual preferred stock, common stock, surplus, undivided profits, and other capital) and the total equity capital and liabilities (liabilities are the sum of total deposits, borrowed funds, subordinated notes, and other liabilities, see Figure **??**). This data are from the FDIC.

A.1 Details on the Calculation of Bank and Nonbank Debt Growth

The construction of our bank and nonbank nonfinancial business debt growth data closely follows the methodology of **?**, which uses the Z.1. Financial Accounts of the United States. **?** 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, pension funds, insurance companies), and short-term funders (money

Figure 9: Equity-to-Lending Ratio Commercial Bank Lending



NOTE: This figure is constructed using annual data of total equity capital of commercial banks and savings institutions (sum of perpetual preferred stock, common stock, surplus, undivided profits, and other capital) and the total equity capital and liabilities (liabilities are the sum of total deposits, borrowed funds, subordinated notes, and other liabilities). The data are from the FDIC.

market mutual funds).[16] He calls these financial intermediaries as "terminal funders." Broadly speaking, these terminal funders borrow from the nonfinancial sector and fund both other financial intermediaries and nonfinancial sector borrowers. The objective of **?** 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. For the purposes of our paper, this measure is especially appropriate as it attempts to resolve 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.

Relative to **?**, which constructs this decomposition for the nonfinancial sector as a whole, we do so for only the nonfinancial business sector. We define banks as the traditional banks in **?**. The nonbanks are the sum of long-term funders and short-term funders. As we are primarily concerned with the domestic private provision of credit, we exclude from our calculations the government and foreign entities.

In our paper, we provide a short description of our implementation of the empirical strategy of **?**.

[16] A full list of the definitions for each category can be found in Table 4.1 of **?**.

The Z.1. Tables give a breakdown of total nonfinancial sector liabilities into several instruments. They also provide information on the holders of each instrument. **?** allocates the holders of each instrument into terminal funders and intermediate funders. Intermediate funders include financial institutions that are generally thought of as borrowing from other financial institutions (e.g. government-sponsored enterprises, or private-label issuers of asset-backed securities). For the nonfinancial sector liabilities held by the intermediate funders, **?** uses information on the funding structure of the intermediate funders to allocate these liabilities further along the intermediation chain. Specifically, the nonfinancial sector liabilities held by the intermediate funders are allocated proportionally to the holders of the liabilities issued by the intermediate funders. The process abstracts away from the equity claims issued by the intermediate funders. It finishes when all nonfinancial sector liabilities are allocated to only terminal funders.

We follow the same strategy but focus on the nonfinancial business sector. A complication, however, is that we only have terminal and intermediate funders' holdings by instrument of the overall nonfinancial sector liabilities but not the nonfinancial business sector components of these instruments from the Z.1. tables. We do, however, have data on the total liabilities of the nonfinancial business sector broken down by instrument. Therefore, an assumption we make is that each type of funder (terminal and intermediate) holds the same fraction of each instrument for the nonfinancial business sector as it does for the overall nonfinancial sector. This allows us to back out the amount of nonfinancial business sector liabilities by instrument held by each funder from only the total nonfinancial business sector liabilities by instrument and terminal and intermediate funders' holdings of total nonfinancial sector liabilities by instrument.

Our bank and nonbank lending data therefore capture differences in the importance of terminal funders for the nonfinancial business sector relative to the nonfinancial sector due to the differing mix of the liability instruments issued. For example, the nonfinancial business sector is funded by commercial paper and corporate bonds, whereas the household sector is not. What our assumption misses, however, is any differences in the importance of terminal funders due to differing terminal funder holdings of nonfinancial business versus household debt instruments. For instance, we would not capture any relative differences in traditional bank holdings of household mortgages versus business mortgages.

B Model Equations

We list here the full set of detrended equilibrium conditions implied by the model. The variables that are trending are detrended by A_t.

Households

$$\lambda_t = \frac{\tilde{\beta}_t}{C_t - h\, C_{t-1}\, \exp\left(-\Delta \log A_t\right)} - h\beta E_t \left[\frac{\tilde{\beta}_{t+1}\, \exp\left(-\Delta \log A_{t+1}\right)}{C_{t+1} - h \exp\left(-\Delta \log A_{t+1}\right)\, C_t} \right]$$

$$UL_t = \chi\, \tilde{\beta}_t\, L_t^{\eta}$$

$$UL_t = w_t \lambda_t$$

$$\lambda_t = \chi_h \frac{\tilde{\beta}_t \left(d_t^B\right)^{\alpha_h - 1}}{\Lambda_{N,t} \left(d_t^N\right)^{\alpha_h} + \left(d_t^B\right)^{\alpha_h}} + \beta E_t \left[\tilde{\beta}_{t+1} \exp\left(-\Delta \log A_{t+1}\right) \lambda_{t+1} R_t^D \right]$$

$$\lambda_t = \chi_h \frac{\tilde{\beta}_t \Lambda_{N,t} \left(d_t^N\right)^{\alpha_h - 1}}{\Lambda_{N,t} \left(d_t^N\right)^{\alpha_h} + \left(d_t^B\right)^{\alpha_h}} + \beta E_t \left[\tilde{\beta}_{t+1} \exp\left(-\Delta \log A_{t+1}\right) \lambda_{t+1} \tilde{R}_{t+1}^{D,N} \right]$$

$$\lambda_t = \beta E_t \left[\tilde{\beta}_{t+1} \exp\left(-\Delta \log A_{t+1}\right)\, \lambda_{t+1} R_t^f \right]$$

$$R_t^{D,N} = \frac{\left(\Gamma_t^N - \mu^N\, G_t^N\right)\, \tilde{R}_t^N}{1 - \phi_{t-1}^N}$$

$$c_t + d_t^B + d_t^N = w_t l_t + R_{t-1}^D d_{t-1}^B + \tilde{R}_t^{D,N} d_{t-1}^N - T_t + \Pi_t$$

Entrepreneurs

$$W_t^{e,B} = \left(1 - \Gamma_t^{e,B}\right) \exp\left(-\Delta \log A_t\right)\, R_t^{K,B}\, q_{t-1}^K\, K_{t-1}^B$$

$$n_t^{e,B} = \left(1 - \chi_t^{e,B}\right) W_t^{e,B}$$

$$E_t\left[\left(1-\Gamma_{t+1}^{e,B}\right)\,R_{t+1}^{K,B}+\lambda_t^{e,B}\,\left(\frac{1-\Gamma_{t+1}^{B}}{\phi_t^B}\,\left(\Gamma_{t+1}^{e,B}-m_t^{e,B}\,G_{t+1}^{e,B}\right)R_{t+1}^{K,B}-\rho_{t+1}^{B}\right)\right]=0$$

$$E_t\left[-\Gamma_{t+1}^{e,B,1}\right]+\lambda_t^{e,B}\,E_t\left[\frac{1-\Gamma_{t+1}^{B}}{\phi_t^B}\,\left(\Gamma_{t+1}^{e,B,1}-m_t^{e,B}\,G_{t+1}^{e,B,1}\right)\right]=0$$

$$\rho_t^{e,B}=\frac{\left(1-\Gamma_t^B\right)\,\tilde{R}_t^B}{\phi_{t-1}^B}$$

$$\bar{\omega}_t^{e,B}=\frac{x_{t-1}^{e,B}}{R_t^{K,B}}$$

$$x_t^{e,B}=\frac{R_t^B\,\left(q_t^K\,K_t^B-n_t^{e,B}\right)}{q_t^K\,K_t^B}$$

$$R_t^{K,B}=\frac{r_t^{K,B}+q_t^K\,(1-\delta)}{q_{t-1}^K}$$

$$W_t^{e,N}=\exp\left(-\Delta\log A_t\right)\,\left(1-\Gamma_t^{e,N}\right)\,R_t^{K,N}\,q_{t-1}^K K_{t-1}^N$$

$$n_t^{e,N}=\left(1-\chi_t^{e,N}\right)W_t^{e,N}$$

$$E_t\left[\left(1-\Gamma_{t+1}^{e,N}\right)\,R_{t+1}^{K,N}+\lambda_t^{e,N}\,\frac{1-\Gamma_{t+1}^{N}}{\phi_t^N}\,\left(\Gamma_{t+1}^{e,N}-m_t^{e,N}\,G_{t+1}^{e,N}\right)\left(R_{t+1}^{K,N}-\rho_{t+1}^{N}\right)\right]=0$$

$$E_t\left[\left(-\Gamma_{t+1}^{e,N,1}\right)+\lambda_t^{e,N}\,\frac{1-\Gamma_{t+1}^{N}}{\phi_t^N}\,\left(\Gamma_{t+1}^{e,N,1}-m_t^{e,N}\,G_{t+1}^{e,N,1}\right)\right]=0$$

$$\rho_t^{e,N}=\frac{\tilde{R}_t^N\,\left(1-\Gamma_t^N\right)}{\phi_{t-1}^N}$$

$$\bar{\omega}_t^{e,N}=\frac{x_{t-1}^{e,N}}{R_t^{K,N}}$$

$$x_t^{e,N} = \frac{R_t^N \left(q_t^K \, K_t^N - n_t^{e,N} \right)}{q_t^K \, K_t^N}$$

$$R_t^{K,N} = \frac{r_t^{K,N} + q_t^K \, (1-\delta)}{q_{t-1}^K}$$

$$\tilde{R}_t^B = \frac{K_{t-1}^B \, q_{t-1}^K \, R_t^{K,B} \left(\Gamma_t^{e,B} - m_t^{e,B} \, G_eC_t \right)}{q_K_{t-1} \, KC_{t-1} - n_eC_{t-1}}$$

$$\tilde{R}_t^N = \frac{K_{t-1}^N \, q_{t-1}^K \, R_t^{K,N} \left(\Gamma_t^{e,N} - m_t^{e,N} \, G_t^{e,N} \right)}{q_{t-1}^K \, K_{t-1}^N - n_{t-1}^{e,N}}$$

$$\Gamma_t^{e,i} = \Phi \left(\frac{\log \left(\bar{\omega}_t^{e,i} \right) - \frac{\left(\sigma_t^{e,i} \right)^2}{2}}{\sigma_t^{e,i}} \right) + \bar{\omega}_t^{e,i} \left(1 - \Phi \left(\frac{\log \left(\bar{\omega}_t^{e,i} \right) + \frac{\left(\sigma_t^{e,i} \right)^2}{2}}{\sigma_t^{e,i}} \right) \right)$$

$$\Gamma_t^{e,i,1} = 1 - \Phi \left(\frac{\log \left(\bar{\omega}_t^{e,i} \right) + \frac{\left(\sigma_t^{e,i} \right)^2}{2}}{\sigma_t^{e,i}} \right) + \frac{\phi \left(\frac{\log \left(\bar{\omega}_t^{e,i} \right) - \frac{\left(\sigma_t^{e,i} \right)^2}{2}}{\sigma_t^{e,i}} \right) - \bar{\omega}_t^{e,i} \, \phi \left(\frac{\log \left(\bar{\omega}_t^{e,i} \right) + \frac{\left(\sigma_t^{e,i} \right)^2}{2}}{\sigma_t^{e,i}} \right)}{\bar{\omega}_t^{e,i} \sigma_t^{e,i}}$$

$$G_t^{e,i} = \Phi \left(\frac{\log \left(\bar{\omega}_t^{e,i} \right) - \frac{\left(\sigma_t^{e,i} \right)^2}{2}}{\sigma_t^{e,i}} \right)$$

$$G_t^{e,i,1} = \frac{\phi \left(\frac{\log \left(\bar{\omega}_t^{e,i} \right) - \frac{\left(\sigma_t^{e,i} \right)^2}{2}}{\sigma_t^{e,i}} \right)}{\bar{\omega}_t^{e,B} \sigma_t^{e,B}}$$

Investors

$$W_t^b = \exp \left(-\Delta \log A_t \right) \left(\rho_t^B \, \phi_{t-1}^B \, b_{t-1}^B + \rho_t^N \, e_{t-1}^N - n_{t-1}^b \right)$$

$$n_t^b = b_t^N + \phi_t^B b_t^B - d_t^N$$

$$n_t^b = \left(1 - \chi_t^b \right) W_t^b$$

$$E_t\left[\rho_{t+1}^N\right] = E_t\left[\rho_{t+1}^N\right]$$

Intermediaries

$$\bar{\omega}_t^B = \frac{R_{t-1}^D\ \left(1-\phi_{t-1}^B\right)}{\tilde{R}_t^B}$$

$$\bar{\omega}_t^N = \frac{R_{t-1}^{D,N}\ \left(1-\phi_{t-1}^N\right)}{\tilde{R}_t^N}$$

$$\phi_t^N = \frac{e_t^N}{b_t^N}$$

$$E_t\left[\Gamma_{t+1}^{N,1}\right] = \beta\lambda_t^N E_t\left[\tilde{\beta}_{t+1}\ \exp\left(-\Delta\log A_{t+1}\right)\ \lambda_{t+1}\ \left(\Gamma_{t+1}^{N,1} - \mu^N\, G_{t+1}^{N,1}\right)\right]$$

$$E_t\left[\left(1-\Gamma_{t+1}^N\right)\ \tilde{R}_{t+1}^N\right]+\lambda_t^N\left(\chi_h\ \Lambda_{N,t}\ \tilde{\beta}_t\ \frac{\left(-\Lambda_{N,t}\right)-\left(1-\alpha^h\right)\ \left(\frac{d_t^B}{d_t^N}\right)^{\alpha^h}}{\left(d_t^N\ \Lambda_{N,t}\ +d_t^N\ \left(\frac{d_t^B}{d_t^N}\right)^{\alpha^h}\right)^2}+\beta\ E_t\left[\frac{\tilde{R}_{t+1}^N\ \exp\left(-\Delta\log A_{t+1}\right)\ \tilde{\beta}_{t+1}\ \lambda_{t+1}^N\ \left(\Gamma_{t+1}^N-\mu^N\ G_{t+1}^N\right)\ \left(d_t^N\ -b_t^N\right)}{\left(d_t^N\right)^2}\right]\right)=0$$

$$\Gamma_t^i = \Phi\left(\frac{\log\left(\bar{\omega}_t^i\right)-\frac{\left(\sigma_t^i\right)^2}{2}}{\sigma_t^i}\right)+\bar{\omega}_t^i\ \left(1-\Phi\left(\frac{\log\left(\bar{\omega}_t^i\right)+\frac{\left(\sigma_t^i\right)^2}{2}}{\sigma_t^i}\right)\right)$$

$$\Gamma_t^{i,1} = 1-\Phi\left(\frac{\log\left(\bar{\omega}_t^i\right)+\frac{\left(\sigma_t^i\right)^2}{2}}{\sigma_t^i}\right)+\frac{\phi\left(\frac{\log\left(\bar{\omega}_t^i\right)-\frac{\left(\sigma_t^i\right)^2}{2}}{\sigma_t^i}\right)-\bar{\omega}_t^i\,\phi\left(\frac{\log\left(\bar{\omega}_t^i\right)+\frac{\left(\sigma_t^i\right)^2}{2}}{\sigma_t^i}\right)}{\bar{\omega}_t^i\,\sigma_t^i}$$

$$G_t^i = \Phi\left(\frac{\log\left(\bar{\omega}_t^i\right)-\frac{\left(\sigma_t^i\right)^2}{2}}{\sigma_t^i}\right)$$

$$G_t^{i,1} = \frac{\phi\left(\frac{\log\left(\bar{\omega}_t^i\right)-\frac{\left(\sigma_t^i\right)^2}{2}}{\sigma_t^i}\right)}{\bar{\omega}_t^i\,\sigma_t^i}$$

Final Good Production

$$Y_t^B = \exp\left(-\alpha^{y_B}\Delta\log A_t\right)\ \left(K_{t-1}^B\right)^{\alpha^{y_B}}\ \left(L_t^B\right)^{1-\alpha^{y_B}}$$

$$r_t^{K,B} = \alpha^{y_B} \exp\left(\Delta \log A_t\right) \frac{Y_t^B}{K_{t-1}^B}$$

$$w_t = \left(1 - \alpha^{y_B}\right) \frac{Y_t^B}{L_t^B}$$

$$Y_t^N = \exp\left(-\alpha^{y_N} \Delta \log A_t\right) \left(K_{t-1}^N\right)^{\alpha^{y_N}} \left(L_t^N\right)^{1-\alpha^{y_N}}$$

$$r_t^{K,N} = \alpha^{y_N} \exp\left(\Delta \log A_t\right) \frac{Y_t^N}{K_{t-1}^N}$$

$$w_t = \left(1 - \alpha^{y_N}\right) \frac{Y_t^N}{L_t^N}$$

Capital Good Production

$$g_t^I = \frac{\psi^i}{2} \left(\exp\left(\Delta \log A_t\right) \frac{I_t}{I_{t-1}} - \exp\left(\Delta \log A_t\right)\right)^2$$

$$g_t^{I,1} = \psi^i \left(\exp\left(\Delta \log A_t\right) \frac{I_t}{I_{t-1}} - \exp\left(\Delta \log A_t\right)\right)$$

$$K_t = I_t + (1 - \delta) \exp\left(-\Delta \log A_t\right) K_{t-1}$$

$$\tilde{\beta}_t \, q_t^K = \tilde{\beta}_t \, EK_t \left(1 + g_t^I + \exp\left(\Delta \log A_t\right) \frac{I_t}{I_{t-1}} g_t^{I,1}\right) - \beta E_t \left[\tilde{\beta}_{t+1} \exp\left(\Delta \log A_{t+1}\right) EK_{t+1} \frac{\lambda_{t+1}}{\lambda_t} \left(\frac{I_{t+1}}{I_t}\right)^2 g_{t+1}^{I,1}\right]$$

Market Clearing

$$d_t^B = \left(1 - \phi_t^B\right) b_t^B$$

$$d_t^N = b_t^N - e_t^N$$

$$b_t^B + b_t^N = b_t$$

$$Y_t = Y_t^B + Y_t^N$$

$$K_t = K_t^B + K_t^N$$

$$L_t = L_t^B + L_t^N$$

$$q_t^K \, K_t^B - b_t^B = n_t^{e,B}$$

$$q_t^K \, K_t^N - b_t^N = n_t^{e,N}$$

Deposit Insurance

$$-Tr_t + \exp\left(-\Delta \log A_t\right) \, b_{t-1}^B \, \tilde{R}_t^B \, \left(\bar{\omega}_t^B - \Gamma_t^B + \mu^B \, G_t^B\right) = 0$$

Observation Equations

$$Cgr_t = 100 \left(\Delta \log A_t + \log\left(C_t\right) - \log\left(C_{t-1}\right)\right)$$

$$Igr_t = 100 \left(\Delta \log A_t + \log\left(I_t\right) - \log\left(I_{t-1}\right)\right)$$

$$bCgr_t = 100 \left(\Delta \log A_t + \log\left(bC_t\right) - \log\left(bC_{t-1}\right)\right)$$

$$bSgr_t = 100 \left(\Delta \log A_t + \log\left(bS_t\right) - \log\left(bS_{t-1}\right)\right)$$

$$R_{obs,t}^{B,N,spr} = 400 \, \left(R_t^{B,N} - R_t^f\right)$$

$$R_{obs,t}^D = 400 \, \left(R_t^D - 1\right)$$

$$R^{D,N}_{obs,t} = 400 \left(R^{D,N}_{t} - 1 \right)$$

$$\phi^{C}_{obs,t} = 100 \, \phi^{C}_{t}$$

C 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 flat priors. As we specify more structural shocks than observables, we think it is important for us to allow for negligible effects from certain structural shocks.

D 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 0. In the second step, we shut off all of the shocks estimated to be unimportant and take $250,000$ draws from the posterior distribution of the parameters. The first $125,000$ we take as burn in. Table **??** 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.[17]

E Effects of Economy-Wide Entrepreneur Risk Shocks

Figure **??** 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

[17] Additionally, in the first stage estimates, the persistence of the economy-wide entrepreneur risk shocks was estimated to be near the upper bound of its stationary level at 0.998. Therefore, we fixed this persistence parameter at that level and did not draw from its posterior distribution.

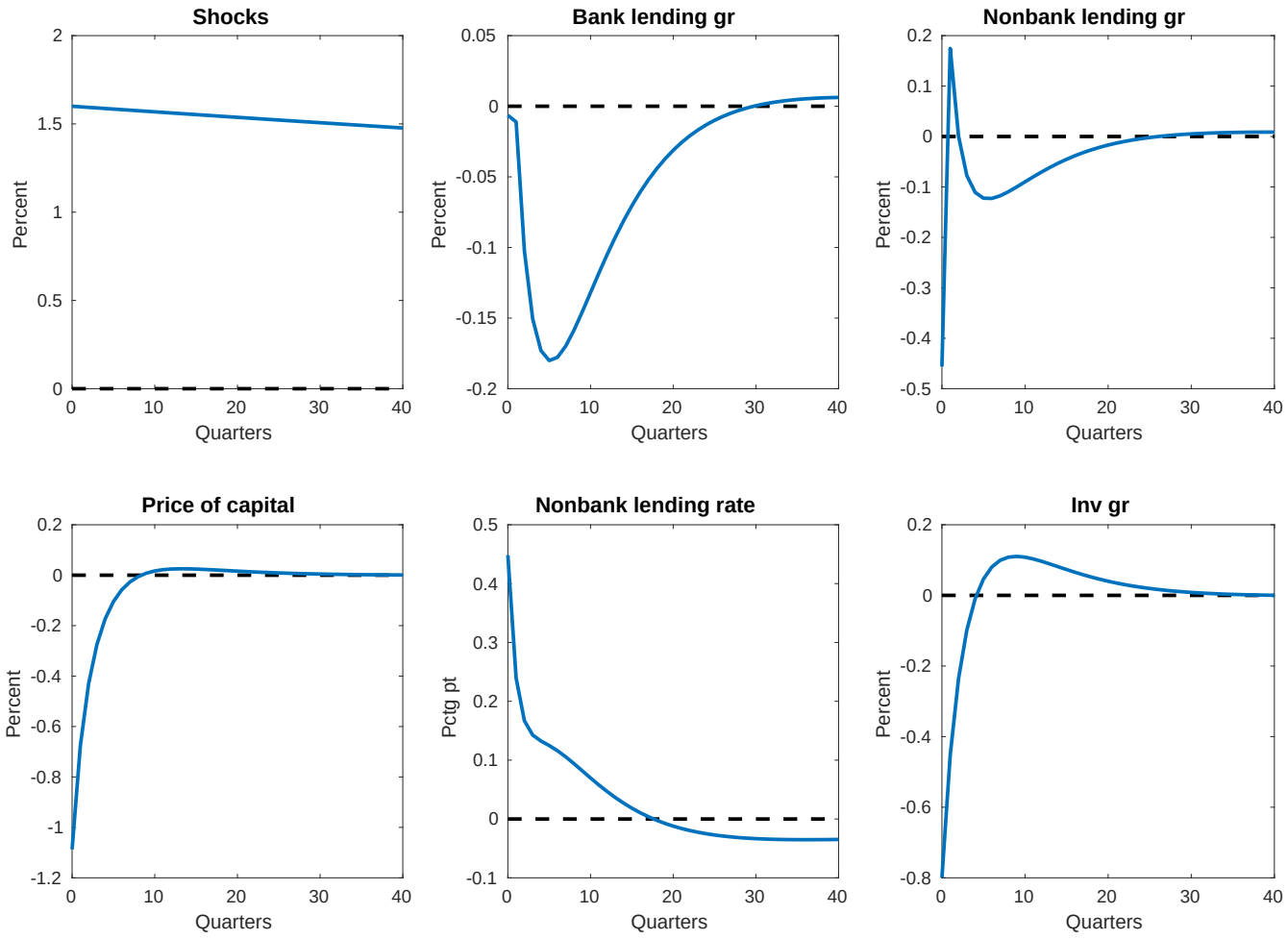
Table 10: Posterior Distribution Parameters

Parameter	10%	90%
h	0.95	0.98
Φ_I	2.15	4.22
ρ_A	0.10	0.15
ρ_{EK}	0.41	0.68
ρ_β	0.48	0.49
$\rho_{\Lambda,N}$	0.89	0.97
$\rho_{\sigma,e,B}$	0.37	0.63
$\rho_{\chi,e,B}$	0.50	0.64
$\rho_{\chi,e,N}$	0.58	0.71
$\rho_{\chi,b}$	0.49	0.66
σ_A	0.011	0.014
σ_{EK}	0.003	0.007
σ_β	0.10	0.19
$\sigma_{\Lambda,N}$	0.10	0.12
$\sigma_{\sigma,e,Agg}$	0.015	0.019
$\sigma_{\sigma,e,B}$	0.009	0.015
$\sigma_{\chi,e,B}$	0.005	0.006
$\sigma_{\chi,e,N}$	0.005	0.006
$\sigma_{\chi,b}$	0.014	0.019
σ_η	0.002	0.003

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

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.