Bank size and macroeconomic shock transmission: Are there economic volatility gains from shrinking large, too big to fail banks?*

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Abstract
This paper investigates the transmission of macroeconomic shocks to production in a model that includes a large and a small bank. The two banks are differentiated by parameters that govern their sensitivities to their own and their borrowers' balance sheets and simulations show that the large (small) bank responds more to demand/financial (supply) shocks. Bank-level evidence generally supports the model's assumptions but indicates that the large banks' sensitivities and the sensitivity to borrower balance sheets are more important. Incorporating U.S. macroeconomic shocks into the empirical model illustrates a stronger transmission through large bank lending. Shrinking banks can, therefore, decrease volatility.

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1. Introduction

Following the 08/09 financial crisis policymakers in the world have taken steps to restrict the risk taking behavior of large banks and to prevent the possible systematic consequences for the economy. These steps have started to take effect as large, global banks began shrinking their balance sheets to comply with the local and international regulations such as the Dodd-Frank Act and Basel III. The transition to stricter regulations has not been without resistance, however, and researchers and institutions have stressed the advantages of having large banks (some of which I mention below) including during financial crisis episodes.

I abstract from the dynamics governing these turbulent episodes and investigate how economic volatility is related to bank size in general. The overall conclusion I draw from my analysis is that the level of volatility is higher when there is more large bank lending and that an economy with smaller banks, therefore, not only becomes less vulnerable to the risks associated with large, too big fail banks but also has less severe business cycles.

I follow three sequential steps that, in the end, lead to this conclusion. As a first step, I build a closed economy general equilibrium model that includes a large and a small bank to predict how the two banks' lending reacts to macroeconomic shocks. Besides their share in total lending, the banks are differentiated by the degree of frictions (in the form of bankruptcy monitoring costs) that they face on the demand and the supply side of credit markets. These frictions, in turn, determine the banks' sensitivity to borrower and their own balance sheets and generate, together with other parameters, a difference in the banks' steady state characteristics (for example, the large bank borrows and lends more relative to its net worth).

The disparity in the banks' sensitivity to balance sheets, credit market shares and steady state characteristics causes them to react differently to macroeconomic shocks. The model simulations, corresponding to a reasonable calibration to U.S. data, show that the large (small) bank is more responsive to demand/financial (supply) shocks. These results can be explained as follows: In response to a positive demand/financial shock, for example, the firms' demand for loans increases. The large bank uses the higher revenue from lending to improve its borrowing conditions more aggressively compared to a small bank that does not rely as heavily on external finance. This prompts a more substantial drop in the large bank's lending spreads and a larger positive output response of its borrowers. This channel of transmission, operating through the supply side of credit markets, is reinforced by the financial frictions on the demand side. Given its larger bankruptcy monitoring costs (lower bad-loan recovery rates), the large bank chooses to keep lending rates and its borrowers' expected default rates lower. In response to a positive supply shock, conversely, the firms become less leveraged and their demand for loans is relatively smaller. The banks, in response to the lower revenue, decrease their net worth to smooth their owners' consumption and consequently face higher borrowing costs. The transmission from borrowing costs to lending spreads is stronger for the large bank and thus its borrowers produce less. Turning to the demand side, although both banks increase their lending rates to match the firms' higher returns to capital, the large bank increases its rate by more since it has higher balance sheet sensitivity and its borrowers' default probability is low initially.

These baseline results imply that if demand/financial (supply) shocks are more important and/or frequent then reducing bank size may make the economy less (more) volatile. The accuracy of this prediction depends on two assumptions: The disparity between the banks is observed even as the credit market share of the large bank is lowered (i.e., the large bank becomes smaller), and that the friction parameters, that are consistent with aggregate banking data, accurately reflect the balance sheet sensitivities of individual banks. Further simulations of the model demonstrate that the banks' responses are strongly related to their credit market share and the financial friction parameter values that govern the sensitivity to balance sheets. These relationships are important enough to reverse the baseline ordering of the small and large bank responses for some shocks. A natural way to proceed, therefore, is to check the validity of the two assumptions and the predictions of the model, given the findings.

As a second step, I take a closer look at the banking industry and empirically measure the large and small banks' sensitivities to their borrowers' and their own balance sheets using a bank-level panel dataset. To construct the dataset, I obtain quarterly data for U.S. chartered banks from the Federal Reserve's Call Reports of Condition and Income for the period 1986Q2 to 2012Q4. This allows me to use a large number of observations in my estimations. The main challenge in these estimations is identifying the two sensitivities or, in other words, determining whether banks lend more (less) because their borrowers' or their own balance sheets are improving (deteriorating). I use the internal capital markets present in the in the banking industry to help me identify the two sensitivities and control for bank (borrower) balance sheets when measuring the sensitivity to borrower (bank) balance sheets. To measure the sensitivity to borrower balance sheets, I compare the loan growth rates of banks that are the subsidiaries of the same parent bank holding company (BHC) but lend in different states. When investigating how these relative growth rates are related to local balance sheets, measured as state level personal income gaps, I am therefore able to control for the lending constraints that originate from the supply side of credit markets. Of course, the assumption here is that internal markets are functioning effectively (see the discussion below) and thus supply side restrictions are equally binding for sister subsidiaries. To measure the sensitivity to BHC balance sheets, I compare the loan growth rates of banks that have different parent BHC but are located in the same state. When investigating the relationship between these relative growth rates and BHC balance sheet ratios (e.g., the equity ratio in the baseline estimation) then, I am, similarly, able to control for the strength of borrower balance sheets.

The baseline results clearly demonstrate two aspects of lending. The large banks' sensitivity to their own and their borrowers' balance sheets is considerably larger than the small banks' sensitivities and the sensitivity to borrower balance sheets are much larger in magnitude and more economically significant compared to the sensitivity to BHC balance sheets. These results are robust to using different specifications and consistent with the model's assumption that the large bank faces a higher degree of friction in the demand side of credit markets. The results are also consistent with the models' supply side sensitivities. Although the large bank's supply side friction parameter is lower in the model, since it relies more on external finance, it is more sensitive to its borrowing costs and thus its balance sheets. Overall, the results imply that shock propagation and amplification through balance sheets is stronger for large banks and thus an economy with a higher share of large bank lending would be more volatile.

I test this prediction, as a third step, by comparing the lending responses of large and small banks to various macroeconomic shocks. I begin by identifying 9 time series of shocks in the U.S. economy. To do so, I estimate, with a Bayesian methodology, the widely-used DSGE framework of Smets and Wouters (2007) (embedded with the financial accelerator mechanism in Gilchrist et al. (2009) to measure the responses of banking-industry/financial shocks). Next, I include these shocks in the empirical model discussed above, interacting them with the balance sheet variables, to measure their effects on the banks' lending. The evidence and the support for the model predictions are mixed. While the large banks' borrower balance sheet sensitivities, consistent with the model, becomes smaller (larger) and they lend more (less) during most of the expansionary demand/financial (supply shocks), the small bank and BHC balance sheet regressions, consistent with earlier empirical results, produce considerably smaller and less significant coefficients. Incorporating different measures of market concentration, as the share of large bank lending, in this model has a negligible effect on the disparity between large and small banks' lending and balance sheet sensitivities. The overall conclusion from my analysis is, therefore, that shrinking banks can decrease economic volatility.

This paper is not a perfect fit for one specific strand of the literature but there are many studies, in different fields, whose results are closely related to mine. The propagation of macroeconomic shocks through balance sheets in my model, for example, has been the subject of a long-standing literature (Bernanke et al., 1999; Carlstrom and Fuerst, 1997; Townsend, 1979). The emphasis in this literature is on the demand side frictions and banks are, therefore, generally risk neutral and passive. I deviate from these studies to generate sensitivities to bank balance sheets. In my model, the banks are risk averse and their owners make active decisions in each period (i.e., how much to consume, lend, borrow and securitize). Bank balance sheets have similarly been incorporated into macroeconomic models by a recently and rapidly growing literature (e.g. Gertler and Karadi, 2011; Meh and Moran, 2010; Davis, 2011; Kollmann et al., 2011) a part of which directly studies the effects of the post-crisis banking regulations (e.g. Corbae and D'Erasmo 2013; Allen et al, 2011; Aliaga-Dias and Olivero, 2012). Combining the two frameworks allows me to investigate how shocks separately propagate through the demand and the supply side of credit markets.

Separating the demand side and supply side frictions empirically is an infamous challenge in the credit channel literature. Since it was first stated in Bernanke and Gertler (1995), studies (e.g. Ashcraft, 2006; Kashyap and Stein, 2000; Loutskina and Strahan, 2009; Morgan et al., 2004) have used various methodologies to mostly identify the independent effects of lender balance sheets on the transmission of monetary policy shocks (the lending channel) and there are a few number of studies (Ashcraft and Campello, 2007; Aysun and Hepp, 2012, 2013) that focus on borrower balance sheets (the balance sheet channel). The unique identification that I use in this paper allows me to focus on both channels and compare their relative strength. While the higher economic significance of the balance sheet channel (and the weakness of the lending channel) in the results is consistent with the earlier findings, I find, additionally, that this channel mostly operates through large bank lending. Furthermore, I find that borrower balance sheets and large bank lending not only have a significant impact on the transmission of monetary policy shocks but also on economic fluctuations in general.

The main disparity in my model, that large banks are more sensitive to balance sheets, is consistent with a well-documented literature on bank behavior and characteristics. The stylized facts in this literature are that large banks are more sensitive to their borrowers' balance sheets because they enter contracts with shorter maturity and do less relationship/house-bank lending, and that they rely more heavily on external finance (see Berger et al., 2000; Berger et al., 2001; Buch, 2005). A common finding here, that also validates my empirical methodology, is that BHCs use their internal capital markets effectively (e.g. Houston et al., 1997; De Haas and Van Lelyveld, 2010; Cetorelli and Goldberg, 2012) to transfer funds to their subsidiaries both domestically and internationally.

Turning to the relationship between economic stability and bank size, the literature provides mixed evidence. On the one hand, some studies (Hughes et al., 2001; Feng and Serletis, 2010; Stern and Feldman, 2004; Martinez-Miera and Repullo, 2010; Marcus, 1984; Jimenez et al,. 2013; Marquez, 2002; Besanko and Thakor, 1993; Diamond, 1984; Demsetz and Strahan, 1997; Allen and Gale, 2000; Stiroh, 2006; Morgan et al., 2004) suggest that having large banks can bring more stability because they take less risks to protect their franchise value, they have lower service costs, they enjoy higher informational rents and prevent informational dispersion, and they can more efficiently diversify risk. On the other hand, others (Wheelock, 2012; Boyd and De Nicoló, 2005; Stiglitz and Weiss; 1981) argue that the level of moral hazard, risk-taking, operational inefficiencies are higher for large banks and thus financial markets with smaller and more competitive banks are more stable. The international evidence is similarly mixed. While Beck et al. (2006) argues that countries with a higher share of large bank lending are less vulnerable to financial crisis and economic instability, the findings of Uhdea and Heimeshoff (2009), Canova and De Nicoló (2003) suggest otherwise. A majority of these studies either emphasize financial market stability, cost of lending or crisis periods. The emphasis in my paper, by contrast, is on the relationship between large bank lending and real economic volatility and my results suggest that the disparity between the characteristics of large and small banks mentioned above generate a net, adverse effect of large bank lending on economic fluctuations.

The next section describes the model and its calibration. Section 3 discusses the results. Section 4 presents empirical evidence. Section 5 concludes.

2. A general equilibrium model with heterogeneous banks

Below I describe the basic building blocks of the model, explain how I differentiate small and large banks and describe how I extend the baseline model to allow for bank competition.

2.1. Consumers

In the economy there is a continuum of households that consume, c_t and save in the form of bank deposits, d_t (that pay an interest rate, r_t). The households finance these with their wages, the returns from previous period's bank deposits and profit payments from firms. Here I assume that consumers own the firms and the firms' profits are transferred to the consumers at the end of each period. Let β, w_t, h_t, π_t and η denote the time-discount factor, wages, households' labor supply and the profit transfers and the parameter governing labor supply elasticity then the households' optimization problem can be represented as:

$$Max_{c_t,h_t}\ E_t\left[\sum_{k=0}^{\infty}\beta^k\left[\ln c_{t+k}+\eta\ln(1-h_t)\right]\right]\quad s.t.$$

$$c_t+d_t=w_t h_t+r_{t-1}d_{t-1}+\pi_{t-1} \tag{1}$$

2.2. Firms

The firms, indexed by *i*, combine capital k_{it} and labor h_{it} to produce consumption goods, y_{it}, according to the production function,

$$y_{it}=\varepsilon_t^a a_{it}\left(k_{it}\right)^{\alpha}\left(h_{it}\right)^{1-\alpha}, \tag{2}$$

where α is the share of capital income. During production, the firms face two productivity shocks: an idiosyncratic shock, a_{it} and a systematic shock, ε_t^a. I assume that a_{it} has a lognormal distribution and that ε_t^a, similar to the other systematic shocks in the model, follows an AR(1) process given by $\varepsilon_t^a=\rho_a\varepsilon_{t-1}^a+\sigma_{a,t}$ (ρ_a is the persistence parameter and $\sigma_{a,t}$ is the *i.i.d* normal shock innovation with a mean of 0 and standard deviation σ_a). Let δ, i_{it} and ε_t^k denote the depreciation rate, investment and a capital shock (common to both firms), the capital stock then evolves as follows:

$$k_{it}=(1-\delta)k_{it-1}+i_{it-1}+\varepsilon_t^k \tag{3}$$

Here, I assume that the capital stock is firm specific and the households supply their labor to both firms until the firms' returns to labor equals the real wage rate. At the end of each period, the amount produced is used to pay borrowing costs and labor. The amount produced, however, can fall short of these factor payments, if there is a sufficiently adverse productivity shock. In this case, the firm defaults and it is replaced by another that finances its factor payments and investment by borrowing. If the firm does not default, profits are positive and it borrows only to finance investment. Therefore, the budget constraint of the firms can be represented as,

$$l_{it} + y_t = i_{it} + r_{it-1}^{f} l_{it-1} + w_t h_{it}\,, \tag{4}$$

where l_{it} and r_{it-1}^{f} denote the borrowed funds and the borrowing costs (including principal).

2.3. Banks and the financial contract with the firms

The firms borrow from two banks, a small bank and a large bank. These banks are owned by two sets of agents that I refer to as small and large bank owners. Initially, I assume that the cost of switching from one bank to the other is large enough to ensure that the firms always borrow from the same bank. Thus, I use the superscripts *l* and *s* when referring to the firms that borrow from the large and the small bank. Within each group, the firms are identical except for their idiosyncratic productivity shock and given the constant returns to scale production function, it is straightforward to show (see Bernanke et al., 1999) that output, capital, labor and investment can be aggregated across firms. I thus drop the firm subscript when describing the model below.

The output of the two firms, y_t^l and y_t^s, are combined (with a share parameter of θ) to obtain the aggregate output in the economy, y_t, as,

$$y_t = \left(y_t^l\right)^{\theta} \left(y_t^s\right)^{1-\theta} \tag{5}$$

I proceed by describing the optimization problem of the large bank owners. Large bank owners, similar to consumers, maximize their discounted utility subject to a budget constraint. In doing so, they choose how much to consume, $c_t^{l,b}$, lend, l_t^l, and the share of loans they want to securitize, λ_t^l. Securitization, here, makes the model more realistic and allows me to analyze a way in which asset price shocks propagate.[1]

$$Max_{c_t^{l,b}, l_t^l, \lambda_t^l} \sum_{k=0}^{\infty} \beta^k \ln\left(c_{t+k}^{l,b}\right) \qquad s.t.$$

$$l_t^l + c_t^{l,b} + nb_t^l = rev_t^l + b_t^l - r_{t-1}^{l,b} b_{t-1}^l + d_t^l - r_{t-1} d_{t-1}^l + p_t \lambda_t^l l_t^l + r_{t-1}\left(nb_{t-1}^l\right)^{\phi} \tag{6}$$

[1] Securitization activity has declined after the 08-09 crisis. But it is agreed that the ability to transfer credit risk is the reason why it is still widespread (see Cetorelli and Peristiani (2012) for an informative discussion).

Bank owners finance their consumption, loans and the funds retained for the next period, nb_t^l (hereafter, net worth for simplicity) with their revenues from the previous period, rev_t^l, the funds borrowed from a wholesale credit market, b_t^l (net of previous period's interest and principal payments, $r_{t-1}^{l,b} b_{t-1}^l$), households deposits, d_t^l (net of previous periods' payments, $r_{t-1} d_{t-1}^l$), the sale of securitized loans, $p_t \lambda_t^l l_t^l$ and previous period's net worth. The latter earns the deposit rate r_{t-1} which also reflects the stance of monetary policy. The bank survival parameter ϕ (smaller than 1) ensures that the banks do not build enough net worth and that they always need external finance. If the bank does not survive it is replaced by an identical bank.

The price of securities, p_t, is determined in a securities market (see below). To simplify the model, I assume that the banks do not compete for deposits and receive a constant share.

It should be noted here that the bank keeps a positive amount as net worth in each period. Although this behavior could be motivated by banking regulations that require banks to keep a certain fraction of loans as capital, I instead model the bank's borrowing costs as a function of its leverage, b_t^l / nb_t^l, (see below) so that it always keeps a positive amount of nb_t^l. I do this to more dynamically investigate how supply side constraints affect the transmission of shocks.

The bank's revenues depend on the firms' default rate. If the idiosyncratic productivity shock is above the cutoff value of $\bar{a}_t^u$, the firm pays back the bank and its workers. If the shock is below $\bar{a}_t^u$, the firm pays wages and defaults on its loans. The bank keeps the firm's output net of labor income but they have to pay a monitoring cost, μ^l (the source of financial frictions). If the shock is below $\bar{a}_t^d$, the bank does not recover any funds and the labor payments are financed by borrowing. Here, I assume that either the bank rolls-over the debt or that the firm is replaced by an identical firm that finances its investment from the same bank. Given that the bank is only entitled to a $(1-\lambda_t^l)$ fraction of the returns, its expected revenue can then be represented as,

$$E_t\left(rev_{t+1}^l\right) = \left(1-\lambda_t^l\right)\left(\left[1-F(\bar{a}_t^u)\right] r_t^{l,f} l_t^l + \left(1-\mu^l\right)\int_{\bar{a}_t^d}^{\bar{a}_t^u}\left(a_t\left(k_t^l\right)^{\alpha}\left(h_t^l\right)^{1-\alpha} - w_t h_t^l\right) dF(a_t)\right) \tag{7}$$

where $F(\cdot)$ is the lognormal c.d.f with $\left[1-F\left(\bar{a}_t^u\right)\right]$ representing the probability that the firm does not default and the upper and the lower bounds of the productivity shock are given by, $\bar{a}_t^u = \left(r_t^{l,f} l_t^l + w_t h_t^l\right) / \left(k_t^l\right)^{\alpha}\left(h_t^l\right)^{1-\alpha} \varepsilon_t^u$, $\bar{a}_t^d = w_t h_t^l / \left(k_t^l\right)^{\alpha}\left(h_t^l\right)^{1-\alpha} = a_t(1-\alpha)$, where ε_t^u is a borrower default shock.[2]

The small bank's optimization problem and budget constraint are similar to those for the large bank. Therefore, I do not list these equations to save space. It is important to note however that the key difference between the banks, so far, is that they have different monitoring and unit borrowing costs. The calibration exercise below will make further distinctions between the banks.

2.4. The wholesale credit market and the closing conditions

I assume that both the small and the large bank owners borrow from a wholesale credit market at the rate of $r_t^{l,b}$ and $r_t^{s,b}$ respectively. These lending rates are determined according to the following financial contract (displayed only for the large bank again for brevity),

$$\left[1 - F\left(\bar{a}_t^w\right)\right] r_t^{l,b} b_t^l + \left(1 - \mu^{l,b}\right) \int_0^{\bar{a}_t^w} \left[nb_t^l + E_t\left(rev_{t+1}^l\right)\right] dF\left(a_t\right) = r_t b_t^l \ , \tag{8}$$

where the expected returns from lending to the banks is set equal to the risk free rate, r_t and $\mu^{l,b}$ represents the monitoring costs when there is default. The cutoff value of the productivity shock, $\bar{a}_t^{w,l}$, represents the value below which the bank is unable to pay back its debt and it is given by,

$$\bar{a}_t^{w,l} = \left[\left(r_t^{l,b} b_t^l - nb_t^l\right) / \left(1 - \lambda_t^l\right)\left(1 - \mu^l\right) + w_t h_t^l\right] / \left(k_t^l\right)^\alpha \left(h_t^l\right)^{1-\alpha} \varepsilon_t^w \ . \tag{9}$$

I assume that if there is default, the bank is replaced by a new one that finances its expenditures by borrowing from the wholesale credit market. The variable ε_t^w in equation (9) represents an economy-wide bank default shock that is common for both banks. Note also that the monitoring costs, factored into the contract, are not the same for the two banks.

I assume that the supply side of the wholesale credit market is controlled by a central bank which consequently determines the risk free rate. In doing so, the central bank targets output fluctuations according to the following rule:

$$r_t = r_{t-1}^{\pi_p} y_t^{\pi_y} \varepsilon_t^r \tag{10}$$

where π_p , π_y and ε_t^r denote the interest rate smoothing parameter, the output response coefficient and a monetary policy shock. Let ε_t^g and fr_t denote a government expenditure shock and the income losses due to bank and borrower bankruptcies, the following feasibility constraint ensures that the amount of production equals the demand for goods.[3]

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[2] The profits of the firm, given that it doesn't default is $\pi_t^l = \int_{\bar{a}_t^u}^{\infty} \left(\left(\alpha y_t^l + (1-\delta) k_t^l\right) - r_t^{l,f} l_t^l\right) dF\left(a_t\right)$.

[3] $fr_t = \mu^l f\left(\bar{a}^u\right) y^l / rev^l \left(y_t^l - a_t\right) + \mu^s f\left(\bar{a}^u\right) y^s / rev^s \left(y_t^s - a_t\right) + \mu^{b,l} f\left(\bar{a}^{w,l}\right) nb^l / y^l \left(\bar{a}_t^{w,l} - nb_t^l\right) + \mu^{b,s} f\left(\bar{a}^{w,s}\right) nb^s / y^s \left(\bar{a}_t^{w,s} - nb_t^s\right)$.

$$y_t = c_t + i_t^l + i_t^s + c_t^{l,b} + c_t^{s,b} + fr_t + \varepsilon_t^g \tag{11}$$

I assume that the demand side of the securities market is regulated by a government agency. This agency equates the next period expected returns from loans to the current period cost of buying the loans to determine the price of the securities according to:

$$\frac{rev^l}{p}\left(\lambda_t^l + E_t\left(rev_{t+1}^l\right)\right) + \frac{\lambda^s rev^s(1-\theta)}{p\lambda^l\theta}\left(\lambda_t^s + E_t\left(rev_{t+1}^s\right)\right) = \frac{\lambda^l\theta + \lambda^s(1-\theta)}{\lambda^l\theta} p_t + l_t^l + \lambda_t^l + \frac{\lambda^s(1-\theta)}{\lambda^l\theta}\left(l_t^s + \lambda_t^s\right) + \varepsilon_t^p \tag{12}$$

I also assume that the agency can independently alter its demand to exogenously affect the price of securities. The variable, ε_t^p, represents these shocks that I refer to as security price shocks.

2.5. First order conditions

Since it is very difficult to obtain a closed form solution to the model, I approximate a solution by linearizing the model around its steady state. I begin by obtaining the optimality conditions from the consumers', the firms' and the banks' maximization problems. I then linearize this model and discuss how I calibrate it to U.S. data. For consistency and to save space, I only list the conditions for the large bank and its borrowers. The linearized equations that describe the complete model are listed in Appendix A.

The households' optimization problem produces the following two, standard, intratemporal and intertemporal conditions,

$$(1-\alpha)y_t^l\left(1-h_t^l\right)/h_t^l = \eta c_t \varepsilon_t^h \tag{13}$$

$$c_t^{-1} = \beta E_t\left(c_{t+1}\right)^{-1} r_t \varepsilon_t^c \tag{14}$$

Equation (13) determines the demand for labor in the presence of a labor supply shock, ε_t^h, that is common for both types of borrowers and consumption shock, ε_t^c, affects the intertemporal allocation of consumption in equation (14). The demand for capital is inferred from the firms' optimization problem as,

$$E_{t-1}\left[\alpha y_t^l / \left((1-\delta)k_{t-1}^l + l_t^l\right)\right] + 1 - \delta = r_t^{l,f} \tag{15}$$

According to equation (15), the firms set their expected marginal returns from capital to their borrowing costs. Given that the next period's investment is financed by bank loans, by choosing the amount of lending, the banks therefore, determine the interest rate on the loans.

The amount that banks lend also affects their expected revenue, securitization proceeds and borrowing costs and current period consumption. The following condition, obtained by maximizing bank's utility with respect to l_t^l, demonstrates these tradeoffs

$$\left(c_t^{l,b}\right)^{-1}\left(1-p_t\lambda_t^l\right)=\beta E_t\left[c_{t+1}^{l,b}\right]^{-1}\left(\partial E_t\left(rev_{t+1}^l\right)/\partial l_t^l-b_t^l\partial r_t^{l,b}/\partial l_t^l\right) \tag{16}$$

where the two partial derivatives on the right hand side are given by,

$$\frac{\partial E_t\left(rev_{t+1}^l\right)}{\partial l_t^l}=\frac{\alpha^2\left(1-\lambda_t^l\right)y_t^l}{a_t k_t^l}\left(E\left(a_t\right)\left[\left(1-F\left(\bar{a}_t^u\right)\right)-\mu^l f\left(\bar{a}_t^u\right)l_t^l\left(\frac{\alpha E\left(a_t\right)-\bar{a}_t^u}{k_t^l}\right)\right]+\left(1-\mu^l\right)\int_{\bar{a}_t^d}^{\bar{a}_t^u}a_t dF(a_t)\right) \tag{17}$$

$$\frac{\partial r_t^{l,b}}{\partial l_t^l}=\frac{\alpha\mu^{l,b}r_t^{l,b}f\left(\bar{a}_t^{w,l}\right)/k_t^l}{\left[1-F\left(\bar{a}_t^{w,l}\right)-\bar{a}_t^{w,l}f\left(\bar{a}_t^{w,l}\right)\left(1+\mu^{l,b}\right)\right]} \tag{18}$$

The two expressions on the right hand side of equation (17), in parenthesis, are the expected returns when the firms do and do not pay back their debt. According to the first expression, returns from lending are higher if the firm does not default. By lending more, however, the probability of default increases. This is given by the negative term in the first expression. The recovered funds, in case of loan default, are given by the second expression. As expected, loan recovery depends negatively on the monitoring costs. Equation (18) indicates a positive relationship between the banks' borrowing rate and their loans. This is similarly due to a positive relationship between the amount of lending and the probability of bank default and the magnitude of this effect is amplified by the level of frictions in the wholesale credit market.

The bank decides how much to borrow and hold as net worth according to:

$$\left(c_t^{l,b}\right)^{-1}=\beta E_t\left(c_{t+1}^{l,b}\right)^{-1}\left(r_t^{l,b}+\partial r_t^{l,b}/\partial b_t^l\right) \tag{19}$$

$$\left(c_t^{l,b}\right)^{-1}=\beta E_t\left(c_{t+1}^{l,b}\right)^{-1}\left(r_t+b_t^l\partial r_t^{l,b}/\partial nb_t^l\right) \tag{20}$$

When banks borrow more today, they not only make interest payments the next period but they also incur higher borrowing costs since they become more leveraged. When they hold more net worth, by contrast, their leverage and cost of borrowing decreases. The bank chooses to hold a positive amount of net worth instead of lending it out or reducing the amount it borrows because the relationship between the borrowing rate and net worth is nonlinear. Specifically, when banks' net worth is at the lower values of the cumulative distribution, an increase in its value decreases the probability of default, $F\left(\bar{a}_t^{w,l}\right)$, by more than it does at higher values of net worth.

The borrowing rate's sensitivity to the amount borrowed and net worth are given by,

$$\frac{\partial r_t^{l,b}}{\partial b_t^l} = \frac{\left[\left(\left[1 - F\left(\overline{a}_t^{w,l}\right)\right]r_t^{l,b} - r_t\right) - \frac{\mu^{l,b}\left(r_t^{l,b}\right)^2 b_t^l f\left(\overline{a}_t^{w,l}\right)}{\left(1-\lambda_t^l\right)\left(1-\mu^l\right)y_t^l / a_t}\right]}{\left[1 - F\left(\overline{a}_t^{w,l}\right) - \overline{a}_t^{w,l} f\left(\overline{a}_t^{w,l}\right)\left(1+\mu^{l,b}\right)\right]b_t^l} \tag{21}$$

$$\frac{\partial r_t^{l,b}}{\partial nb_t^l} = -\frac{\mu^{l,b} r_t^{l,b} f\left(\overline{a}_t^{w,l}\right)}{\left[1 - F\left(\overline{a}_t^{w,l}\right) - \overline{a}_t^{w,l} f\left(\overline{a}_t^{w,l}\right)\left(1+\mu^{l,b}\right)\right]\left(1-\mu^l\right)\left(1-\lambda_t^l\right)y_t^l / a_t} \tag{22}$$

Here the impact of borrowing and holding more net worth on the borrowing rate is similarly amplified by the degree of financial frictions in the wholesale credit market. Although the second expression in the numerator of equation (21), the unit costs of default, indicates a mitigating effect, the first expression in the parenthesis, the unit returns if the bank does not default, is always larger for reasonable parameter values (see the calibration exercise below).

Finally, the banks choose the share of loans they want to securitize according to:

$$\left(c_t^{l,b}\right)^{-1} p_t l_t^l = \beta E_t \left(c_{t+1}^{l,b}\right)^{-1} \left(\partial E_t \left(rev_{t+1}^l\right) / \partial \lambda_t^l + b_t^l \partial r_t^{l,b} / \partial \lambda_t^l\right) \tag{23}$$

where the two partial derivatives are given by,

$$\frac{\partial E_t\left(rev_{t+1}^l\right)}{\partial \lambda_t^l} = -\frac{E_t\left(rev_{t+1}^l\right)}{1-\lambda_t^l} \tag{24}$$

$$\frac{\partial r_t^{l,b}}{\partial \lambda_t^l} = \frac{r_t^{l,b} \mu^{l,b} f\left(\overline{a}_t^{w,l}\right)\left(\overline{a}_t^{w,l} - \overline{a}_t^d\right)}{\left(1-\lambda_t^l\right)\left[1 - F\left(\overline{a}_t^{w,l}\right) - \overline{a}_t^{w} f\left(\overline{a}_t^{w,l}\right)\left(1+\mu^{l,b}\right)\right]} \tag{25}$$

In deciding how much to securitize, the banks take security prices as given and compare the proceeds from securitization today with the cost of securitization in the next period. With a higher share of securitization, the expected revenues from lending, as expected, are lower and the borrowing rate is higher. The latter relationship is due to the negative (positive) effect of securitization on banks' expected revenues (probability of default).

2.6. Calibration

I choose standard parameter values to calibrate the non-financial part of the model to quarterly data. I set the discount rate β to 0.99, the capital income share α to 0.35, the depreciation rate δ to 0.025, the labor supply elasticity η to 2, and the policy rule parameters π_p and π_r to 0.95 and 0.05, respectively.

To calibrate financial side of the economy, I use data from various sources. These sources and data definitions are provided in Appendix B. To distinguish between large and small banks, I obtain quarterly, BHC level data from the Federal Reserve's Call Reports of Condition and

Income. I then construct a dataset that spans the time period 1986Q2 to 2012Q4. For each quarter, BHCs (hereafter, referred to as banks for simplicity) are classified as large if their total assets are in the top 10 percent of the size distribution in that quarter. I should mention that, when calibrating the financial economy, I choose the parameter values relatively loosely since the focus of this part of the paper is to determine how the response of the economy to shocks depends on bank behavior/characteristics such as the sensitivity to borrower and bank balance sheets that are in turn governed by these parameters. Specifically, I will compare the response of the economy to different shocks for different values of these parameters. I do, however, attempt to match 3 stylized facts about the banking industry. Small banks fail more often than large banks, the sensitivity to borrower balance sheets (governed by the monitoring cost parameter) is higher for larger banks and small banks' costs of borrowing are larger.

I begin by setting the standard deviation of the idiosyncratic shock to 0.475 and the monitoring cost coefficients, μ^l and μ^s to 0.12 and 0.08, respectively. This generates an annual lending spread of 1.6 and 2.3 percent, respectively, for large and small banks, an annual failure rate of 3 percent for firms and allows me to approximate historical averages.[4]

Setting the monitoring cost coefficients, $\mu^{l,b}$ and $\mu^{s,b}$ to 0.12 and 0.47, the bank survival rate ϕ to 0.99 and the output share of firms that borrows from the large bank, θ, to 0.9 allows me to match the historical averages in the Call Report data. Specifically, the parameter values are consistent with a debt-to-loans ratio, debt-to-net-worth (debt-to-equity) ratio and securitized-loans-to-total-loans ratio of 1.05, 1.25, 0.16 for the large bank and 0.20, 3.62 and 0.07 for the small bank, and they imply a steady state borrowing spread, $r^b - r$ and an annual failure rate of 0.2517 and 0.98 percent for the large bank. The borrowing spread and the failure rate for the small bank are 1.89 and 2.12 percent, respectively. These steady state values allow for a reasonable, yet not perfectly accurate, representation of the data. For example, the average interest rate spread computed using the London Interbank Offered Rate (LIBOR, 3 month, U.S. Dollar), the rate at which large banks borrow, is 0.3019 percent between January, 1986 and February, 2013. The average interest rate spread computed using the bank prime loan rate, the

[4] The average BofA Merill Lynch US, BBB corporate bond spread was 2.13 percent between January 1997 and February 2013. The spread between the lending rates (Weighted-Average Effective Rate) of small and large banks was 0.6 percent during the same period (Source: FRED database). According to my computations based on Small Business Administration, Office of Advocacy data, annual business closure rates between 2000 and 2009 was 2.3 percent. The value in my baseline calibration is slightly higher but it is consistent with Bernanke et al. (1999). The time periods used here were determined by availability.

base lending rate for large banks (including loans to small banks), in the same period is 2.78 percent. Although data for failures are not available by bank size, the average annual bank failure rate was 0.76 between 1986 and 2012.[5] The price of securitized loans in this steady is 0.94.[6]

3. Simulation Results

Figure 1 displays the impulse responses (in deviations from steady state) to a positive 1 percent government expenditure shock. In response to the shock, there is initially an increase in the demand for labor and real wages. When households decide to work more, the level of output, the returns to capital and the demand for capital all increase. The higher returns to capital, in turn, generate a decrease in the probability of default. The banks react by raising lending rates to match the returns to capital. Despite a higher policy rate, this also causes the lending spread to increase. Turning to the supply side of the credit market, banks' revenues increase both because of larger lending and the decrease in the probability of default. Due to consumption smoothing and to reduce borrowing costs, the banks retain some of the higher levels of returns as net worth. This increase in net worth is larger than the increase in the funds borrowed from the credit market and thus there is a decrease in bank leverage and bank borrowing spreads. The higher expected loan returns also increase the price of securities and the banks increase the share of loans that they securitize.

Before comparing the responses for the two banks, I should mention that the responses are not weighted by the output and credit market shares. This allows for a more fair comparison and it is more consistent with the empirical analysis below. It should be noted, albeit, that the aggregate responses are very similar to those of the large bank borrowers given their high share.

Figure 1 illustrates a larger output response by large bank borrowers. One reason for this disparity is the sharper drop in the borrowing rate of the large bank. Specifically, since the large bank finances a higher share of its loans with external finance, it retains a higher fraction of its revenues as net worth to decrease its borrowing costs more aggressively. The lower borrowing rate is, therefore, one determinant of the lower lending spreads and the higher output response.

[5] To compute the failure rate, I obtained the annual number of bank failures from the Federal Deposit Insurance Corporation during 1986 to 2012 and divided this with the number of U.S. chartered banks in my Call Report dataset.

[6] To compare this value with the data, I first measure, using BHC level data, the average income on Mortgage-backed securities (BHCKB489) between 2001 and 2012. I then divide this by the amount of banks' total residential loans and compute the average ratio across banks to approximate the securitization revenues per unit of lending. Finally, I divide these revenues by a weighted share of securitized loans to obtain the price of securities, p (using the share of small and large bank loans as weights). I find that the price of securitized loans is approximately 0.6. The difference between this value and the steady value in my model, 0.94, is smaller when I omit real estate loans that are not considered as mortgages (construction, land development and other land loans).

The mechanism described here is reinforced by the larger bankruptcy costs that the large bank faces. Compared to the small bank, the large bank chooses to keep lending rates and thus the default rates lower since its bankruptcy recovery rates are smaller. At these low default rates of its borrowers and itself, the large bank becomes less sensitive to the strength of balance sheets.

3.1. Other Macroeconomic shocks

The disparity between the two banks, mentioned above, is not observed for every shock. The graphs in Figure 2 indicate that the large bank borrowers are, initially, more responsive to demand shocks such as government expenditure, consumption and a monetary policy shock (contractionary) and that they are less responsive to supply shocks such as positive labor, capital and systematic productivity shocks. In response to a positive supply shock, the firms' demand for loans and borrowing spreads, unlike their demand during a demand shock, decrease. Faced with lower revenue from lending activity, banks hold less net worth to smooth their consumption and increase their leverage. Higher leverage affects the banks asymmetrically since the transmission from borrowing costs to lending spreads is stronger for the large bank. Large bank borrowers, therefore, face higher lending spreads and their output response is smaller. The higher returns to capital allow the large bank to choose higher lending rates and increase its returns. As a result, though, the large bank becomes more sensitive to the borrowers' and its own balance sheets.

To further investigate the disparity between the banks, I consider three financial shocks: a positive bank and borrower default probability and a security price shock. Although one can include other shocks such as net worth, loan return, lending spread, bank consumption shocks, these would propagate through their effects on bank and borrower default probabilities. Focusing on default probability shocks, therefore, allows me to more concisely capture the effects of financial shocks. Finally, I consider a security price shock since it allows me to analyze the real effects of asset price shocks. The large bank borrowers' output responses in Figure 2 are larger in magnitude. This is because the large bank borrows more, it faces higher bankruptcy costs and it securitizes a larger share of its loans. These characteristics make the large bank more sensitive to shocks that affect its own and its borrowers' default probability and to security price shocks.

It is important to note here that the responses of small bank borrowers are in general more delayed, persistent and at times they have the opposite sign of the large bank responses. The mechanism that generates this asymmetric behavior is the impact of large bank borrowers' production on real wages, the higher persistence of small banks' net worth and small banks' lower sensitivity to borrowers' default probability. First, when there is an increase (a decrease) in large bank borrowers' output, there is an increase (a decrease) in real wages since large bank borrowers' account for a large share of total production. The increase (decrease) in wages, in turn, mitigates (amplifies) the positive response of small bank borrowers. Here, the small bank borrowers' response is more persistent since the small bank is not as sensitive to borrowers' and its own default probability and the countercyclical adjustment of its lending spreads is smaller.

3.2. Bank size and the amplitude of impulse responses

The results, so far, indicate that large banks are more sensitive to demand and financial shocks and small banks are more sensitive to supply shocks. If these results are accurate and if one can determine what type of shocks are more frequently observed in an economy, then it would be straightforward to make recommendations about bank size and mitigate fluctuations. Notice, however, that I have so far assumed that the output/credit market shares of the banks stay the same. This assumption could lead to false predictions about the effects of changing bank size on fluctuations if banks' respond very differently when their share changes. In this section, I therefore, investigate how the total output response is related to the credit market share of large banks, θ. These relationships are illustrated in Figure 3 for each shock. The vertical axis values are measured as the percent deviation of the maximum output responses from the maximum responses in the baseline simulations. The negative 2 percent output response to a government expenditure shock obtained by setting $\theta = 0.99$, for example, indicates that the maximum output response is 2 percent less than the baseline maximum response (when $\theta = 0.9$). The results generally suggest that a higher large bank share makes economic fluctuations smaller (larger) if the economy is faced with demand/financial (supply) shocks.

The conclusions drawn from these results are opposite of those drawn from Figure 2 and thus the predictions based on constant credit market shares can be misleading. Although the large bank's response to demand shocks, for example, is higher in the baseline model, when their credit market share is increased, the amplitude of the total amount of lending (and output) response actually decreases. The opposing force that produces this result is generated by the relationship between the credit market share and the sensitivity to returns to capital. When large banks have a lower share (θ is smaller) and large bank borrowers have a lower steady level of capital, return to capital becomes more sensitive to the amount borrowed. Therefore, when there is a positive demand shock, for example, large banks' lending rates (and the lending spreads) do not increase as much as they do when θ is larger. A similar relationship is observed when there is a financial shock. When there is a supply shock, similarly, large banks' lending rates do not decrease as much as they do when θ is larger and the positive output response is smaller.

Although the steady state with a smaller θ has a larger amount of small bank lending (or a larger number of small banks), it is also characterized by more volatile returns to capital. It is this latter feature that determines the negative (positive) relationship between the share of large bank lending and the amplitude of demand/financial (supply) shocks.

3.3. Different degrees of financial frictions and loan competition

Financial frictions, in the form of monitoring costs, play the key role of amplifying the responses through borrower/lender balance sheets. These frictions are also an aspect of the financial market that separates a large bank from a small bank. Although the results are, so far, obtained by setting the friction parameters to values that are reasonably consistent with aggregate lending spreads, given the difficulties in matching borrower/lender balance sheets with lending spreads in the data (especially for smaller banks), it would be a stretch to argue that these parameter values allow for a perfect representation. It is, thus, important to determine whether the different degrees of frictions substantially change the results.

Another potentially misrepresentation of credit markets in the model is that banks do not compete for loans. In other words, borrowers do not have to option to switch from one bank to the other in response to the changes in lending rates. In this section, I test whether allowing for bank competition (in the lending market) leads to a substantial deviation from the baseline results. Here, I make the opposite extreme assumption that there is perfect competition so that the large and small banks' lending rates are always the same.

The results displayed in Table 1 suggest that the degree of financial frictions and competition can both have a considerable effect on how the economy responds to shocks. To obtain the values in the first column, I set the firm-specific monitoring cost coefficients, μ^l and μ^s, equal to zero and then to values that are twice the baseline values. I then compute the percent change in the maximum/minimum output response when the financial friction coefficients are changed from low values to high values. I do the same for the bank-specific parameters, $\mu^{l,b}$ and $\mu^{s,b}$, to obtain the values in column 2.[7] The first row for each column shows by how much the steady state lending spread increases when I switch from the low to the high values of frictions. Comparing the two columns, it is not clear whether supply side frictions are important than demand side frictions or vice-versa. Notice, however, that the supply side frictions are more important for the amplification of financial shocks and that, consistent with the usual findings in the monetary transmission literature, demand side frictions (and the balance sheet channel of monetary transmission) have a larger impact on output responses (albeit, a relatively impact compared to other shocks) than supply side frictions (and the lending channel).

Next, I conduct a similar experiment but this time I compare the aggregate output responses when bank-specific financial friction parameters are low (equal to zero) and high (equal to two times their baseline values). These results in columns 3 and 4 similarly indicate that the different values of frictions, faced by the small or the large bank, can substantially change the economic impact of shocks. I also find that the bank-specific frictions are more important for the amplification of financial shocks and frictions faced by large and small banks are important for the amplification of demand and supply shocks, respectively.

In column 5, I report the percent deviation of the maximum output response from the baseline maximum response when there is competition for loans. The results suggest that, although competition substantially changes how output responds to shocks, the direction of the change is not always negative or positive.

4. Empirical evidence

The quantitative significance of the sensitivity results in the previous section implies that the model predictions could be inaccurate/reversed if the financial friction parameters that are consistent with aggregate banking data do not realistically capture the importance of demand and supply side frictions for individual banks. In this section I take a closer, look at the banking industry by focusing on bank and BHC level data to estimate the degree of financial frictions, I quantify the effect of these frictions on the transmission of various macroeconomic shocks and I measure the impact of financial frictions in a more/less concentrated banking market.

4.1. Estimating the degree of financial frictions

[7] I should note here that the amplitudes of the output responses when financial frictions were set equal to zero were always lower than when they were set equal to high values. This is why the numbers reported in the first 4 columns of Table 1 are all positive.

Although credit channel theory makes a clear distinction between the role that supply and demand side frictions play in the transmission of shocks through bank lending, empirically identifying the independent effects of these frictions has been a difficult task. The challenge here is to determine whether banks are lending more (less) because their borrowers' or their own balance sheets are improving (deteriorating). The identification is difficult, especially when using aggregate data, since shocks and characteristics that affect borrower balance sheets could be also be related to bank balance sheets or their cost of raising loanable funds.

In this section, I use the internal capital markets that are present in the banking system to control for the strength of borrower balance sheets when measuring the impact of bank balance sheets on lending and to control for the strength of bank balance sheets when measuring the impact of borrower balance sheets. When measuring the sensitivity of bank lending to borrower balance sheets, I compare the lending behavior of banks that have the same parent BHC but are located in different states. Conversely, when measuring the sensitivity to bank balance sheets, I compare the lending behavior of banks that are in the same state but have a different parent BHC. The implicit assumption in this identification is that BHCs effectively provide funds to their subsidiaries through internal capital markets. The subsidiaries of a BHC in different states, thus, face similar supply side constraints but different borrower balance sheets. Similarly, banks that have a different parent BHC but are located in the same state face similar borrower balance sheets but different supply side constraints. These assumptions is validated by the evidence in the literature (e.g. Cetorelli and Goldberg, 2012; Houston et al., 1997) showing that internal capital markets, both international and domestic are functioning effectively.

It is important to note here that I am identifying the demand and supply side financial frictions as the sensitivity of lending to borrower and bank balance sheets, respectively. This formulation is consistent with the theoretical findings in the previous section and with the well-documented theory of asymmetric information in lending markets (Bernanke, Gertler and Gilchrist, 1999; Carlstrom and Fuerst, 1997; Prescott and Townsend,1984; Townsend, 1979). These suggest that as balance sheets improve, financial frictions decrease and banks lend more. The following model illustrates how I identify the effects of demand side frictions on lending:

$$ld^{d}_{ijmt} = \alpha^{d} + \beta^{d} ld^{d}_{ijmt-1} + \sum_{k=1}^{4} \gamma^{d}_{k} bs^{d}_{ijmt-k} + \lambda^{d,b} c^{d,b}_{ijmt-1} + \lambda^{d,bhc} c^{d,bhc}_{ijmt-1} + \varepsilon^{d}_{ijmt} \tag{26}$$

where ld_{ijt}^{d} represents the relative period t loan growth rate of bank i that is affiliated with BHC j, and located in state m. This rate is measured as the deviation of bank i's loan growth, $\lg_{ijmt}$, from the mean value of loan growth measured across all the banks that are affiliated with BHC j, $\overline{\lg}_{jmt}$,

$$ld_{ijmt}^{d} = \lg_{ijmt} - \overline{\lg}_{jmt}. \tag{27}$$

The focus here is on the borrower balance sheet variables, bs_{ijmt}^{d}, measured as the negative value of the personal income gap (see the data section) in the state that bank i operates, y_{imt}, relative to the average personal income gap of all the states that BHC j has subsidiaries in, $\overline{y}_{jt}$, so that,

$$bs_{ijmt}^{d} = y_{imt} - \overline{y}_{jt}. \tag{28}$$

A positive (negative) value of this variable, therefore, indicates a relative expansion (recession). The reasonable assumption here is that if a state is experiencing an expansion, its borrowers' balance sheets are stronger. Thus, the summation $\gamma^{d} = \sum_{k=1}^{4} \gamma_{k}^{d}$ measures the sensitivity of loan growth to the strength of borrower balance sheets. I follow a similar methodology and construct the bank specific control variables, combined in the vector $c_{ijmt}^{d,b}$, as deviations from the BHC averages. This allows me to control for BHC variables that are omitted from equation (26) but may be correlated with the balance sheet variables. I also include the deviation of BHC j's balance sheet variables from the averages of all the BHC's that have subsidiaries in bank i's state in period t in the vector $c_{ijmt}^{d,bhc}$. I do this to account for the different supply side restrictions that bank i may be facing compared to the other banks in the same state.

I estimate a similar equation to measure the degree of supply side frictions:

$$ld_{ijmt}^{s} = \alpha^{s} + \beta^{s} ld_{ijmt-1}^{s} + \sum_{k=1}^{4} \gamma_{k}^{s} bs_{ijmt-k}^{s} + \lambda^{s,b} c_{ijmt-1}^{s,b} + \lambda^{s,bhc} c_{ijmt-1}^{s,bhc} + \varepsilon_{ijmt}^{s} \tag{29}$$

but this time the dependent variable is measured as the deviation of bank i's loan growth from the average loan growth of all the banks that are in the same state but have different BHCs, $\overline{\lg}_{mt}$.

$$ld_{ijmt}^{s} = \lg_{ijmt} - \overline{\lg}_{mt}. \tag{30}$$

The coefficients γ_{k}^{s} capture the sensitivity of lending to the strength of BHC balance sheets. The variables that quantify this strength, bs_{ijmt}^{s}, are the deviation of BHC j's balance sheet variable, bs_{ijmt}, from its average value, $\overline{bs}_{mt}$, across all the BHCs that have subsidiaries in state m,

$$bs_{ijmt}^{s} = bs_{ijmt} - \overline{bs}_{mt} \tag{31}$$

BHC specific control variables, $c_{ijmt}^{s,bhc}$, are similarly constructed in deviation form. I include the bank-specific control variables in equation (26) and the lag of the income gap variable to control for the relative strength of bank *i*'s balance sheet compared to the other affiliates of BHC *j* and to control for the effects of state income on bank lending that may still remain even after measuring the variables as deviations from state level averages. These variables form the vector $c_{ijmt}^{s,b}$.

After constructing the variables, and restricting the dataset as described below, I estimate equations (26) and (29) separately for banks that are affiliated with small and large BHCs and compare the sensitivity coefficients. It is important to note here that I am using BHC affiliation to classify the banks as small or large and that I am using BHC data to measure supply side frictions. This approach, of course, would be misleading if banks' lending decisions and are independently determined. The majority of the evidence in the finance literature, however, suggests otherwise. Studies such as Berger et al. (1995), Berger et al. (2000), Stiroh (2000) and De Haas and van Lelyveld (2010) find that using BHC data is a more accurate way of investigating business decisions such as the sensitivity to balance sheets and risk taking. These studies find that the activities of the subsidiaries are coordinated to increase performance and that there is strong parent BHC influence (both at home and abroad).

4.1.1. Data

Most of the data that I use in this paper are obtained from the Federal Reserve's Call Reports. The data definitions and acronyms are provided in Appendix B. These data are available, quarterly, for every U.S. chartered bank and BHC for the periods 1976Q1 to 2012Q4 and 1986Q3 to 2012Q4, respectively. I use the later period in my baseline estimation. I do, however, exclude periods corresponding to crisis/recession episodes later in the paper.

When measuring the dependent variables, the loan growth rates are measured over the previous quarter (in log-difference form). The loans include lease financing receivables in addition to the outstanding balances of loans. In computing the deviations from BHC averages in equation (26), I use the identifier RSSD9348 to link banks with their BHC. To construct the state income gap variable, I first identify, for every bank, the state in which it operates. I then obtain quarterly, seasonally adjusted, personal income data from the Bureau of Economic Analysis and compute income gaps by using a Hodrick-Prescott filter (smoothing parameter equal to 1600).

The bank specific control variables are the equity ratio, liquidity ratio (the share of liquid assets in total assets), return on assets, the share of tangible assets in total assets and total assets all measured as deviations from the BHC averages as explained above. Including the equity ratio allows me to control for the usual ways in which financial leverage may restrain bank lending (through default probability, cost of borrowing and by making capital restrictions more binding) and it is one key ratio that captures the strength of bank balance sheets. I include the liquidity ratio following the standard practice (e.g. Kashyap and Stein, 2000) of predicting banks' cost of raising loanable funds. In fact, this ratio is often used to measure the strength of the lending channel of monetary transmission instead of the equity ratio. I follow this practice in a sensitivity analysis when measuring supply side frictions. The return on assets is a commonly used right hand side variable that captures profitability (see Altman, 2000) and the share of tangible assets is included since the composition of a firm's assets, in addition to total assets, may impact its borrowing costs (a large share of tangible assets, for example may imply lower costs).

The baseline BHC specific variables are the deviation of the BHC *j*'s (bank *i*'s parent's) liquidity ratio and total assets from the average values computed across the BHCs that have subsidiaries in state *m*. When estimating equation (26), I include the lag of the dependent variable from equation (29) to account for the possibility that a banks' loan growth, relative to the banks located in the same state, can be related to its lending compared to its sister subsidiaries. The main independent variable of interest in equation (29) is the deviation of BHC *j*'s equity ratio from the average value in state *m*.

After constructing the panel dataset, I exclude banks that do not have a parent BHC and/or banks that have a parent BHC with subsidiaries in only one state. I do this to be consistent with the methodology described above. I then exclude entities that are not insured or are not commercial banks. Finally, I exclude banks whose variables (independent and dependent) are 3 standard deviations away from the average values in a given quarter and banks that are in the bottom 5 percent of the size distribution since their variables are very volatile. Despite these restrictions, the baseline dataset has a large number of observations. Table 2 reports the number of banks in the sample as well as other descriptive statistics. Notice that although the banks that are excluded from the sample are smaller, throughout the sample period they have very similar balance sheet characteristics compared with the banks in the sample. This observation can also be made when small and large BHCs are compared. Specifically, although large BHCs have larger equity and return on assets ratios, and a smaller liquidity ratio, the differences are not large.

I choose the general method of moments (GMM) estimation strategy of Arellano and Bond (1991) to estimate the dynamic panel models above (with time t-1 dated explanatory variables used as instruments). This methodology is designed for panel datasets that have a relatively large cross section dimension, similar to mine, and it allows me to remove time-invariant bank/BHC fixed effects, account for the potential endogeneity caused by including the lag of the dependent variable, to account for the potential nonstationarity of the dependent variable and obtain heteroskedasticity-consistent standard errors.

4.1.2. Baseline results, robustness

The baseline results are displayed in Table 3. The first and the last two columns report the results obtained from the estimation of equation (26) and equation (29), respectively. These equations are estimated separately by using data from banks that are affiliated with large and small BHCs, respectively. In each quarter, BHCs are classified as large if they are in the top 5 percent of the size distribution. Note that the number of observations is large and the p-values (reported at the bottom) do not suggest a second order serial correlation in the error term.

The central result in Table 3 is that the subsidiaries of large BHCs are more sensitive to their borrowers' and their parent BHC's balance sheets. Specifically, the coefficients of the balance sheet variables, state income gaps and BHC equity, are both more significant and larger in magnitude for banks affiliated with large BHCs. The numbers in the parentheses that correspond to the balance sheet variables are the chi-square statistics that test whether the summation of the coefficients is significant. A straightforward thought experiment illustrates the economic significance of the disparity in the first two columns. Assume that a state in which a large and a small bank (banks with a large and a small parent BHC) are located experiences a 1 percent increase in personal income, evenly distributed over the past 4 quarters, while the other states in which their parent BHC has subsidiaries do not. The coefficient values of 15.18 and 1.05 in the first columns then imply that the large and the small bank would increase their loans 15.18 and 1.05 percent more than their sister subsidiaries do. Similarly, if the parent BHCs of these two banks experience a 100 percent increase in their equity ratio relative to the other BHCs with subsidiaries in the same state, the large bank increases its loans by 40 percent more than the other banks in the same state. This change for the small bank is -0.3 percent. Notice, too, that the small bank coefficients mentioned here are both insignificant.

The bank specific control variables in the first two columns indicate that banks that are less leveraged (have a high equity ratio), more liquid and profitable, larger and that carry more intangible assets generally have a significantly higher loan growth compared to their sister subsidiaries. By contrast, the two coefficients for the BHC specific variables are insignificant implying that the residual impact of BHC variables that remain after controlling for BHC specific effects is small. The bank specific variable coefficients in the last two columns are mostly insignificant (albeit, less so for smaller banks). This suggests that bank specific variables are less important determinants of supply side constraints.

In Table 4, I report the balance sheet coefficients estimated by using different specifications for bank size and balance sheets. The control variable coefficient values were similar and thus are not reported in the table for brevity. The results indicate that when income growth rate deviations are used instead of HP detrended values and when BHC return on assets is used to capture the strength of balance sheets, the coefficient values are larger and more significant for large banks. When I use the BHC liquidity ratio, however, I find that the coefficient value, corresponding to small banks is more significant, albeit smaller in magnitude. This result is consistent with the stylized finding that the lending channel of monetary transmission is stronger for smaller banks. Overall, the results however suggest that the larger banks may be more sensitive to their own (or their parent BHC's) balance sheets when measures other than the liquidity ratio are used to approximate the supply side constraints in lending. When I use a broader size category to classify the banks (top and bottom 50 percent, respectively), I find that the coefficient values for both groups are insignificant. The results also show that excluding the 2001 and 2008 crisis/recession periods do not change the conclusions.

The results, so far, do not indicate whether borrower or BHC balance sheets have a larger impact on lending. A comparison of the BHC balance sheet coefficients with the income gap coefficients is confounded by the fact that BHC variables are substantially more volatile than the state income gaps. To make this comparison more meaningful, I standardize the two variables so that they have a mean of zero and a standard deviation of one. The estimated coefficient values are reported in columns (4) and (9). These coefficients can be interpreted as the impact of a one standard deviation change in the balance sheet variable on the dependent variable. The results indicate that lending is more sensitive to borrower balance sheets and that demand side frictions that depend on the strength of these balance sheets, may be much more important.

As a final robustness check, I test whether the disparity between the banks is only an aggregate result or whether they are consistently observed for each quarter. To do so, I estimate a cross section model separately for each quarter using OLS (the standard errors are adjusted for correlation across BHCs). The borrower and BHC balance sheet coefficients are displayed in Figure 4. These coefficient values suggest a similar disparity between the large and small banks' sensitivity to borrower and BHC balance sheets.

4.2. Lending response to shocks and the impact of market concentration

The model simulations in Section 3 illustrated that in response to demand and financial shocks, the large bank's lending spreads are less procyclical and that it is less sensitive to its borrower and its own balance sheets. In response to supply shocks, by contrast, the large bank became more sensitive to balance sheets. The comparison between small and large banks, as demonstrated by the analysis in Section 3.3 however, was highly sensitive to the financial frictions parameter values. Identifying these financial frictions as the sensitivity of lending to the strength of balance sheets, I then found that larger banks are more sensitive to the strength of both their borrowers' and their own balance sheets and that demand side frictions are more important for lending compared to supply side frictions. In view of this evidence, here I measure the effect of various shocks on the sensitivity of large and small banks' lending to borrower and their own balance sheets to determine if there is any empirical support for the results in Section 3.

I begin the investigation by first identifying the macroeconomic shocks in the U.S. economy between 1986Q3 and 2012Q4. To do so, I estimate a standard, closed economy DSGE model (including a financial accelerator mechanism) by using a Bayesian methodology. The model and the prior/posterior distributions of the behavioral parameters are similar to those in Smets and Wouters (2007) and Gilchrist et al. (2009). I, thus, defer the description of the model and the estimation results to Appendix C. Here, I describe the estimation of the shock processes.

The model has 9 shocks: 4 demand shocks (consumption, investment, government expenditure and monetary policy), 3 supply shocks (productivity, price and wage) and 2 financial shocks (returns to capital and borrower net worth). To estimate the model and identify the shocks, I obtain 9 quarterly data series for the 1986Q3-2012Q4 period from the Federal Reserve Bank of St. Louis, FRED database: the real gross domestic product, real personal consumption expenditures, real gross private domestic investment, index of aggregate weekly hours, average hourly earnings, gross domestic product price deflator, S&P 500 stock price index, Moody's seasoned Baa corporate bond yield and the effective federal funds rate. All data series are log-differenced except for the bond yield and the federal funds rate that are linearly detrended.

The prior and the posterior values of the parameters that govern the shock processes are displayed in Table 5. The posterior means of the parameters are often significantly different from the prior means and thus the data appear to be informative. Similar to Smets and Wouters (2007) and Gilchrist et al. (2009), I find that the cost push (price and wage), productivity and the government expenditure shocks have the largest persistence. I should note, however, that despite their high persistence, the historical contribution of the supply side shocks to quarterly GDP growth rates were not larger than the other types of shocks.[8] I should also mention that, the posterior mean of the net worth shock persistence parameter is considerably smaller, compared to the estimated value in Gilchrist et al. (2009). This difference may be due to the fact that I, unlike Gilchrist et al. (2009), include a stock market index amongst the observable variables. The stock market index (log-differenced) had a much lower persistence rate and a much higher variance compared to the other series. The estimated time series of shocks, measured in standard deviations, are displayed in Figure 5. The shocks illustrate the expansionary fiscal and monetary policies during the 1990, 2001 and 2008 recessions. As expected, during these downturns, the returns to capital (approximating credit spreads) and borrowers' net worth were countercyclical and procyclical, respectively. While the consumption and investment shocks are positive before the 2008 crisis, there is a more persistent increase in consumption shocks between 2001 and 2008. Compared to the other series, productivity displays a larger and a more immediate positive trend after every economic downturn. The price shocks are positive in the second and the first half of the 1980s and the 2000's, respectively and they are mostly negative in the 1990's.

I proceed by measuring the effects of the shocks on the balance sheet sensitivity of lending. I do so by including the estimated shock series into the models in Section 4.1 as follows,

$$ld_{ijmt} = \alpha_{sh} + \beta_{sh} ld_{ijmt-1} + \sum_{k=1}^{4} \gamma_{sh,k} bs_{ijmt-k} + \sum_{k=1}^{4} \mu_k sh_{jmt-k} + \sum_{k=1}^{4} \sum_{n=k}^{k+3} \chi_{k,n} bs_{ijmt-k} sh_{jmt-n} + \lambda_{sh}^{b} c_{ijmt-1}^{b} + \lambda_{sh}^{bhc} c_{ijmt-1}^{bhc} + \varepsilon_{sh,ijmt} \qquad (32)$$

where the shocks are represented by the variable sh_{jmt} and they enter the model as separate right hand variables and interactive variables – interacted with the balance sheet variable. Here the central focus is on the sum of the interactive variable coefficients that indicate whether the

[8] A simple average of the total historical contributions of productivity, price and wage shocks over the 1986Q3-2012Q4 period was 30.9%. The average contributions of the 4 demand and 2 financial shocks were 36.2% and 32.9%, respectively.

sensitivities to balance sheets are larger or smaller when the shock is observed.[9] To simplify the interpretation of the coefficients, I adjust the sign of the shocks so that they are all expansionary (for example, an increase in the monetary policy shock variable represents a negative shock to the policy rate). I estimate equation (32) separately for each shock and separately for borrower and lender balance sheets and I follow the same methodology in Section 4.1 and measure the same dependent and the independent variables as deviations from BHC averages. The sample period, the bank classification scheme and the estimation strategy are also the same.

The estimation results are reported in Table 6. These results provide a mixed support for the theoretical findings in Section 3 and they are mostly consistent with the empirical findings in Section 4.1. First, notice that the significant balance sheet sensitivity coefficients in column 2 are all positive, except for the wage and net worth shock regressions, and thus the balance sheet channel mechanism (lending more in states with higher personal income growth), described in Section 2 and that is empirically supported for the economy as a whole, is also observed when individual shock are taken into account. Consistent with the theoretical assumptions and the results in Section 4, the large banks' balance sheet sensitivity appears to be more significant and larger in magnitude. The interpretation of the shock coefficients in column 1 is not as straightforward since the variables, including the dependent variable, are measured as deviations from BHC averages in a given state and the systematic national shocks that I consider here affect both the average and the bank specific lending. The positive and significant large bank coefficients, albeit, indicate that the balance sheet mechanism may be reinforced by expansionary shocks. The opposite conclusions are drawn from the mostly negative small bank coefficients. These are, however, much smaller compared to the large bank coefficients.

The central focus in Table 6 is on the interactive coefficient values in column 3. If these are negative (positive) it implies that the sensitivity to balance sheets (income gap) becomes smaller (larger) when a shock is expansionary. The large banks' coefficients in column 3 then indicate that the sensitivity to balance sheets, consistent with the theoretical results, becomes smaller during 3 out of the 4 expansionary demand and 1 out of the 2 financial shocks and it becomes larger during all 3 of the supply shocks. The evidence from the small bank regressions is less convincing and the coefficient values in these regressions are considerably smaller.

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[9] I included 4 lags of the shock variable in equation (32) to consider the delayed effects that shocks may have on bank lending. The duration and the impact of these effects are, of course, different for each type of shock. I included 8 lags of the shocks as an alternative strategy. The results showed that the effects of the shocks were more significant but smaller in magnitude.

Turning to lender balance sheets, I find that the sensitivity coefficients are, in general, both statistically and economically less significant compared to the borrower balance sheet sensitivity coefficients (the disparity is more evident when the variables are standardized). Although small bank coefficients are slightly more significant compared to the large bank coefficients, they are much smaller. Consistent with the results in Tables 3 and 4, the equity ratio coefficients are positive only for large banks. The interactive variable coefficients are again less significant and the significant coefficients' signs do not appear to depend on the type of shock.

4.2.1. The impact of market concentration

The simulations in Section 3 showed that an increase in the concentration of the banking sector can either mitigate or amplify output responses depending on the type of shock. In this section, I investigate empirical evidence to determine the overall effect of market concentration on the sensitivity to balance sheets. I do so by replacing the shock variable in equation (29) with 3 different indicators of market concentration. The indicators are computed in each quarter and they are measured as the lending shares of the BHCs (more specifically, the total lending of their affiliates) that are in the top 1, 5 and 10 percent of their size distribution in that quarter. The interactive variable coefficients in equation (32) then indicate whether the degree of frictions measured by the sensitivity to balance sheets is higher when the banking sector is more concentrated. The main conclusion drawn from the results in Table 7 is that the market concentration has only a very small effect on the sensitivities to balance sheets. Nevertheless, the negative interactive variable coefficients obtained from the large bank, borrower balance sheet regressions, consistent with the theoretical findings, suggest that as the banking sector becomes more concentrated frictions on the demand side of credit markets decrease and the amplification mechanism becomes weaker. Conversely, the significant, positive (negative) interactive variable coefficients obtained from the large (small) bank, BHC balance sheet regressions imply a stronger amplification mechanism in periods with a more concentrated banking industry.

5. Conclusion

The theoretical framework in this paper uncovered a disparity between the responses of large and small banks to macroeconomics shocks (large (small) banks are more responsive to demand/financial (supply) shocks). The main determinant of this disparity, in the model, was the degree of credit market frictions. These frictions manifested themselves as the banks' sensitivity to their own and their borrowers' balance sheets with large banks displaying higher sensitivity to both balance sheets. Bank level empirical evidence provided support for the degree of frictions in the model and also indicated that the sensitivity to borrower balance sheets is much more important. Incorporating various macroeconomic shocks into the empirical, I then found that shock transmission operates mostly through large bank lending and borrower balance sheets.

The straightforward implication of these findings is that shrinking bank size may reduce economic volatility. It is important to note here, though, that for this prediction to be true, large banks would have to behave like small banks when their size decreases. In this paper, this would mean that large banks' sensitivity to borrower balance sheets, the main determinant of the disparity between the two types of banks, would have to decrease together with their size. It would, therefore, be highly informative for future work to determine empirically whether banks exhibit this transformation. An interesting challenge here would be to determine whether a decrease in size prompted by regulatory restrictions decrease or increase balance sheet sensitivity.

The conclusions in this paper were drawn from a closed economy framework. However, the relative change in the composition of international and domestic assets when shrinking large, global banks could also affect economic volatility. For example, there is a growing global banking literature (e.g. Cetorelli and Goldberg, 2012; Kollmann et al., 2011) that shows how global banks can either mitigate, by drawing liquidity from abroad during liquidity crunches, or amplify domestic volatility, as high loan default rates in one country can induce a recession globally as in the 08/09 crisis. It is therefore important to extend the scope of the analysis in this paper to more completely and globally capture the domestic impact of decreasing bank size.

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Appendix A. Linearized first order conditions

In this Appendix, I list the first order conditions that are obtained from the model described in Section 2. Before I do that, I should mention that for brevity I do not specify whether the equations, obtained from the bank optimization problem (equations A.13 to A.19), are for small or large banks (or for firms that borrow from small or large banks). The equations are identical for each bank except for the financial friction parameters, μ, μ^b and the bank specific steady state values. The variables with time subscripts in this appendix represent deviations from their steady state values.

$$y_t^l - h_t^l - c_t = h_t^l / \eta + \varepsilon_t^h \tag{A.1}$$

$$y_t^s - h_t^s - c_t = h_t^s / \eta + \varepsilon_t^h \tag{A.2}$$

$$c_t = E_t c_{t+1} - r_t + \varepsilon_t^c \tag{A.3}$$

$$E_{t-1} y_t^l - k_t^l = r_t^{l,f} \tag{A.4}$$

$$E_{t-1} y_t^s - k_t^s = r_t^{s,f} \tag{A.5}$$

$$k_t^l = (1-\delta) k_{t-1}^l + \delta l_t^l + \varepsilon_t^k \tag{A.6}$$

$$k_t^s = (1-\delta) k_{t-1}^s + \delta l_t^s + \varepsilon_t^k \tag{A.7}$$

$$y_t^l = a_t + \alpha k_t^l + (1-\alpha) h_t^l + \varepsilon_t^a \tag{A.8}$$

$$y_t^s = a_t + \alpha k_t^s + (1-\alpha) h_t^s + \varepsilon_t^a \tag{A.9}$$

$$y_t y = \theta y_t^l y + (1-\theta) y_t^s y = c_t c + c_t^{l,b} c^{l,b} + c_t^{s,b} c^{s,b} + i_t^l i^l + i_t^s i^s + fr_t fr + \varepsilon_t^g \tag{A.10}$$

$$r_t = \pi_p r_{t-1} + \pi_y y_t + \varepsilon_t^r \tag{A.11}$$

$$\begin{aligned} p\left(\lambda^l + \lambda^s (1-\theta)/\theta\right)\left(p_t + \varepsilon_t^p\right) + p\lambda^l \left(l_t^l + \lambda_t^l\right) + p\lambda^s (1-\theta)/\theta \left(l_t^s + \lambda_t^s\right) \\ = \lambda^l rev^l \left(\lambda_t^l + E_t rev_{t+1}^l\right) + \lambda^s rev^s (1-\theta)/\theta \left(\lambda_t^s + E_t rev_{t+1}^s\right) \end{aligned} \tag{A.12}$$

$$\begin{aligned} (1-p\lambda) c_t^b - p p_t + \lambda \lambda_t = E_t c_{t+1}^b + c_{11} c_{12} \left(y_t - a_t - k_t - \lambda_t\right) \\ + c_{13} \bar{a}_t^u + c_{14} \bar{a}_t^d + c_{15} \left(k_t - l_t\right) + c_{16} \left(b_t + r_t^b + c_{17} \bar{a}_t^w - k_t\right) \end{aligned} \tag{A.13}$$

$$c_{11} = \frac{\alpha^2 \beta (1-\lambda) y}{ak}, \quad c_{12} = -E(a)\left(1 - F\left(\bar{a}^u\right)\right) + \mu f\left(\bar{a}^u\right) E(a) l \left(\frac{\alpha E(a) - \bar{a}^u}{k}\right) - (1-\mu) \int_{\bar{a}^d}^{\bar{a}^u} a_t \, dF(a_t)$$

$$c_{13} = c_{11} f\left(\bar{a}^u\right) E(a) \bar{a}^u + \mu \beta E(a) l / k \left(f'\left(\bar{a}^u\right)\left(\alpha E(a) - \bar{a}^u\right) - f\left(\bar{a}^u\right)\right) - \beta (1-\mu) \bar{a}^u f\left(\bar{a}^u\right)$$

$$c_{14} = \beta(1-\mu)\bar{a}^d f(\bar{a}^d), \qquad c_{15} = -\beta\mu l / kf(\bar{a}^u)E(a)(\alpha E(a) - \bar{a}^u)$$

$$c_{16} = \frac{\alpha\beta\mu^b r^b f(\bar{a}^w)b/k}{1-F(\bar{a}^w) - \bar{a}^w f(\bar{a}^w)(1+\mu^b)} \quad , \quad c_{17} = -f'(\bar{a}^w)\frac{c_{16}\left(f(\bar{a}^w) + [\bar{a}^w f'(\bar{a}^w) + f(\bar{a}^w)](1+\mu^b)\right)}{[1-F(\bar{a}^w) - \bar{a}^w f(\bar{a}^w)(1+\mu^b)]}$$

$$c_t^b = E_t c_{t+1}^b + c_{21} r_t^b + c_{22} r_t + c_{23}\left(a_t - y_t + \lambda_t \lambda/(1-\lambda)\right) + c_{24} b_t + c_{25}\bar{a}_t^w \tag{A.14}$$

Let $cs_{21} = [1-F(\bar{a}^w) - \bar{a}^w f(\bar{a}^w)(1+\mu^b)]b$ and $cs_{22} = \frac{\mu^b (r^b)^2 bf(\bar{a}^w)}{(1-\lambda)(1-\mu)y/a}$ then,

$$c_{21} = -\beta\left(r^b + \frac{1-F(\bar{a}^w) - 2cs_{22}/r^b}{cs_{21}}\right), \; c_{22} = \frac{\beta}{cs_{21}} \quad , \; c_{23} = \beta\frac{cs_{22}}{cs_{21}} \quad , \; c_{24} = \beta\frac{[1-F(\bar{a}^w)]r^b - r}{cs_{21}}$$

$$c_{25} = \beta f(\bar{a}^w)\frac{r^b}{cs_{21}} + \frac{\beta f'(\bar{a}^w)cs_{22}}{f(\bar{a}^w)cs_{21}} - \frac{\beta}{cs_{21}^2}\left(f(\bar{a}^w) + [\bar{a}^w f'(\bar{a}^w) + f(\bar{a}^w)](1+\mu^b)\right)\left(1-F(\bar{a}^w)r^b - r - cs_{22}\right)$$

$$c_t^b = E_t c_{t+1}^b + c_{31}\left(b_t + a_t - y_t + \lambda_t\lambda(1-\lambda) + r_t^b\right) + c_{32}\bar{a}_t^w + c_{33} r_t \tag{A.15}$$

$$c_{31} = \beta\frac{cs_{22}}{cs_{21} r^b} \; , \; c_{32} = \frac{c_{31}\beta f'(\bar{a}^w)\bar{a}^w}{f(\bar{a}^w)} + \beta\left[f(\bar{a}^w) + (1+\mu^b)\left(f(\bar{a}^w) + \bar{a}^w f'(\bar{a}^w)\right)\right]\frac{c_{31}}{cs_{21}}, \;\; c_{33} = \beta r$$

$$c_t^b - p_t - l_t = E_t c_{t+1}^b + c_{41} E_t rev_{t+1} + c_{42}\lambda_t + c_{43}\left(b_t + r_t^b\right) + c_{44}\lambda_t + c_{45}\bar{a}_t^w + c_{46}\bar{a}_t^d \tag{A.16}$$

$$c_{41} = \beta\frac{rev}{pl(1-\lambda)} \; , \; c_{42} = -c_{41}\frac{\lambda}{1-\lambda} \; , \; c_{43} = -\beta\frac{r^b b\mu^b f(\bar{a}^w)(\bar{a}^w - \bar{a}^d)}{pl(1-\lambda)cs_{21}} \quad , \; c_{44} = c_{43}\frac{\lambda}{1-\lambda}$$

$$c_{45} = c_{43}\frac{1 + \bar{a}^w f'(\bar{a}^w)/f(\bar{a}^w)}{\bar{a}^w - \bar{a}^d} + \frac{c_{43}\left[f(\bar{a}^w) + (1+\mu^b)\left(f(\bar{a}^w) + \bar{a}^w f'(\bar{a}^w)\right)\right]}{cs_{21}}, \; c_{46} = -\frac{c_{43}}{\bar{a}^w - \bar{a}^d}$$

$$\bar{a}_t^u = (\bar{a}^u - \bar{a}^d)/\bar{a}^u\left(r_t^f + l_t^l + a_t - y_t^l\right) + (1-\alpha)\bar{a}^u a_t + \varepsilon_t^u \tag{A.17}$$

$$\bar{a}_t^w = \frac{\bar{a}^d}{\bar{a}^w} a_t + \frac{\left(r^b \frac{b}{y} - \frac{nb}{y}\right)}{(1-\mu)(1-\lambda)}\left(a_t + y_t + \frac{\lambda}{1-\lambda}\lambda_t\right) + \frac{\left(r^b \frac{b}{y}\left(r_t^b + b_t\right) - \frac{nb}{k} nb_t\right)}{(1-\mu)(1-\lambda)} + \varepsilon_t^w \tag{A.18}$$

$$\begin{aligned} nb_t nb = \phi nb_{t-1} - ll_t - c^b c_t^b + rev * rev_t + bb_t - rb\left(r_{t-1}^b + b_{t-1}\right) \\ + dd_t - rd\left(r_{t-1} + d_{t-1}\right) + p\lambda l\left(p_t + \lambda_t + l_t\right) \end{aligned} \tag{A.19}$$

Appendix B. Data

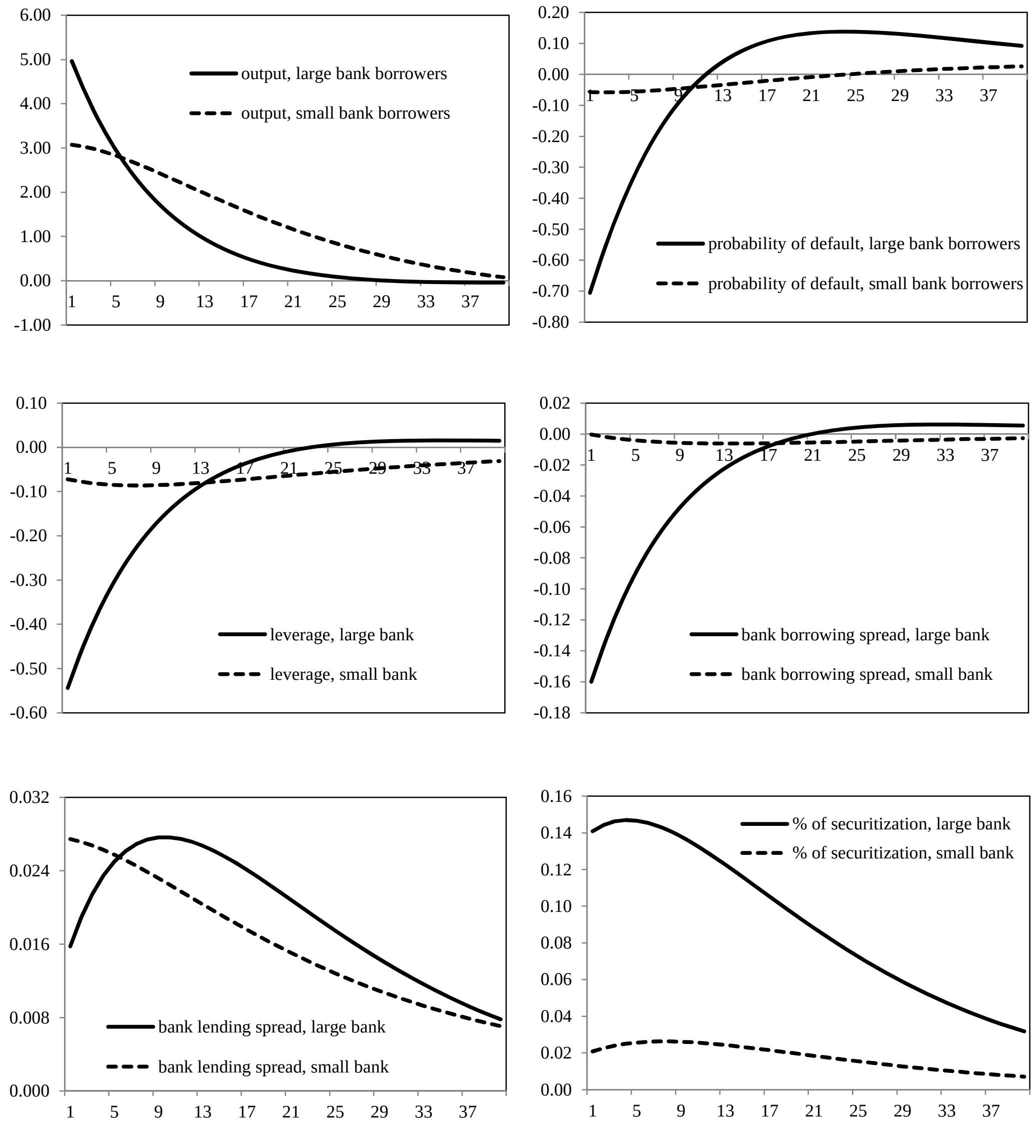
Table B.1. Data definitions and sources

Data	Variable	Acronym	Description
Call Report data. Source: Federal Reserve's Call Reports of Condition and Income			
	Bank ID	RSSD9001	The primary identifier of a bank.
	Date	RSSD9999	The quarter for which the report was filed.
	Bank type	RSSD9331	A two-digit code indicating the type of entity. This is used to identify
	Primary Insurer	RSSD9424	A code indicating the highest level of deposit-related insurance of the head office of a U.S. depository institution or U.S. branch of a foreign bank. This is used to determine whether a bank is insured or not
	MBHC Affiliation	RSSD9348	The five-digit code assigned to the principle holding company or the highest holding company in a tiered organization.
	State	RSSD9210	A two-digit code assigned to a state of the United States or a U. S. territory in which the entity is physically located or its mailing address.
	Total loans	RCFD1400, RCFD2165	The aggregate gross book value of total loans, before deduction of valuation reserves (RCFD1400) plus lease financing receivables (RCFD2165)
	Assets	RCFD 2170	The sum of all assets.
	Intangible Assets	RCFD2143	Includes the sum of Mortgage Servicing Rights, Purchased Credit Card Relationships, All Other Identifiable Intangibles and Goodwill.
	Equity	RCFD3210	The sum Perpetual Preferred Stock and Related Surplus, Common Stock, Surplus, Undivided Profits and Capital Reserves, Cumulative Foreign Currency Translation Adjustments, less Net Unrealized Loss on Marketable Equity Securities.
	Liquidity	RCFD0390, RCFD1350, RCFD2146, RCFD0400, RCFD0600, RCFD1754, RCFD3545	From 1986Q2 through 1993Q2 period, liquidity is the sum of U.S. Treasury and Government Agency securities (RCFD400, RCFD600), investment securities (RCFD0390, RCFD1350), and assets held in trading account (RCFD2146). From 1993Q3 trhough 2012Q4, liquidity is measured as the sum of RCFD1350, securities held to maturity (RCFD1754), and trading assets (RCFD3545).
	Net income	RCFD4340	Year-to-date value of net income (loss). This variable is used to compute
	Indicators of securitization	RCFDB705	1-4 Family Residential Loans
		RCFDB706	Home Equity Lines
		RCFDB707	Credit Card Receivables
		RCFDB708	Auto Loans
		RCFDB709	Other Consumer Loans
		RCFDB710	Commercial And Industrial Loans
		RCFDB711	All Other Loans
Local balance sheets. Source: Bureau of Economic Analysis			
	State personal income		Quarterly, seasonally adjusted, personal income in current dollars
U.S. macroeconomic data used in the DSGE Estimation. Source: FRED			
	Output		Real Gross Domestic Product, 1 Decimal
	Consumption		Real personal Consumption Expenditures
	Investment		Real Gross Private Domestic Investment, 1 Decimal
	Government expenditures		Real Government Consumption Expenditures & Gross Investment, 1 Decimal
	Employment		Index of Aggregate Weekly Hours: Production and Nonsupervisory Employees: Total Private Industries
	Wages		Average Hourly Earnings of Production and Nonsupervisory Employees: Total Private
	GDPDeflator		Gross Domestic Product: Implicit Price Deflator
	Net worth, stock market data		S&P 500 Stock Price Index, change from a year ago
	Bond Yield		Moody's Seasoned Baa Corporate Bond Yield
	Fed funds rate		Effective Federal Funds Rate
Additional data used in the calibration			
	Failure rate (Source: Office of Advocacy)		Annual business closure rates between 2000 and 2009
	Bank lending rate (Source: FRED)		London Interbank Offered Rate
	Bank borrowing rate (Source: FRED)		BofA Merill Lynch, BBB corporate bond rates (01/1997-02/2013)
	Bank debt		Total assets minus equity minus deposits (RCFD6631),RCFD(6636)

Note: Detailed definitions are available at the Federal Reserve, Bureau of Economic Analysis and Office of Advocacy websites.

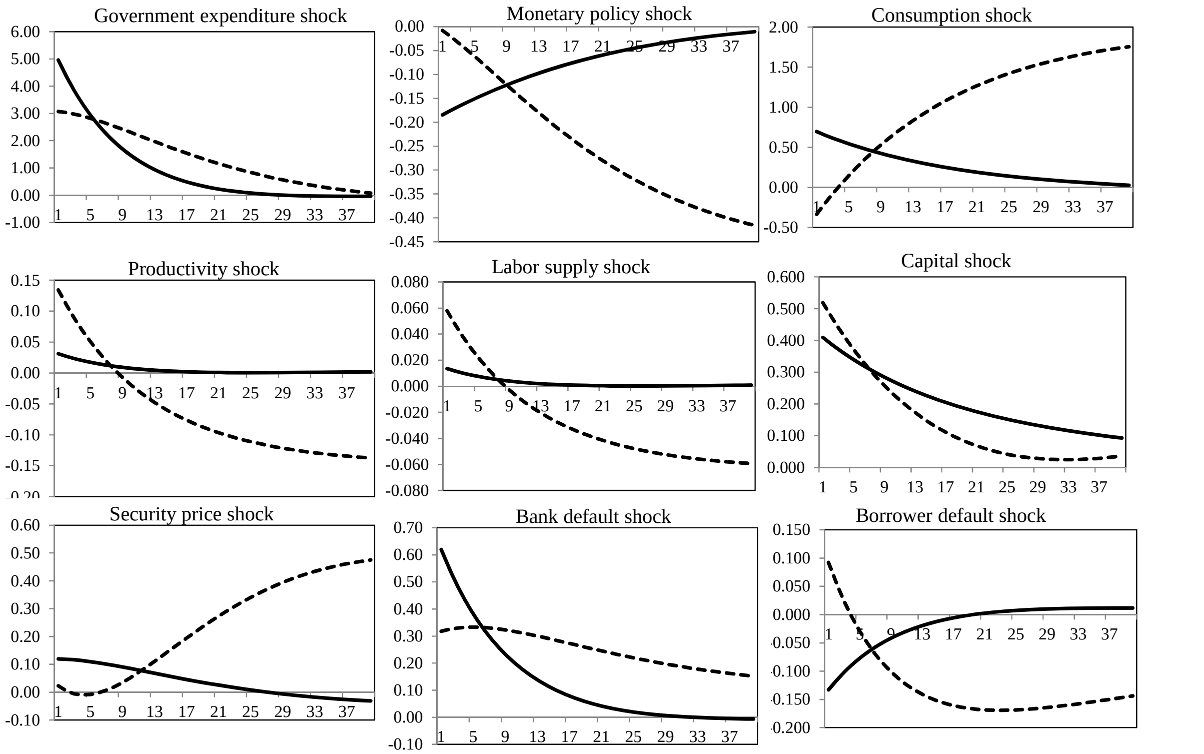
Appendix C. The DSGE model and the estimation methodology – available online at http://www.bus.ucf.edu/faculty/uaysun/file.axd?file=2013%2f8%2fAppendix_C.pdf

Figure 1. Responses to a government expenditure shock



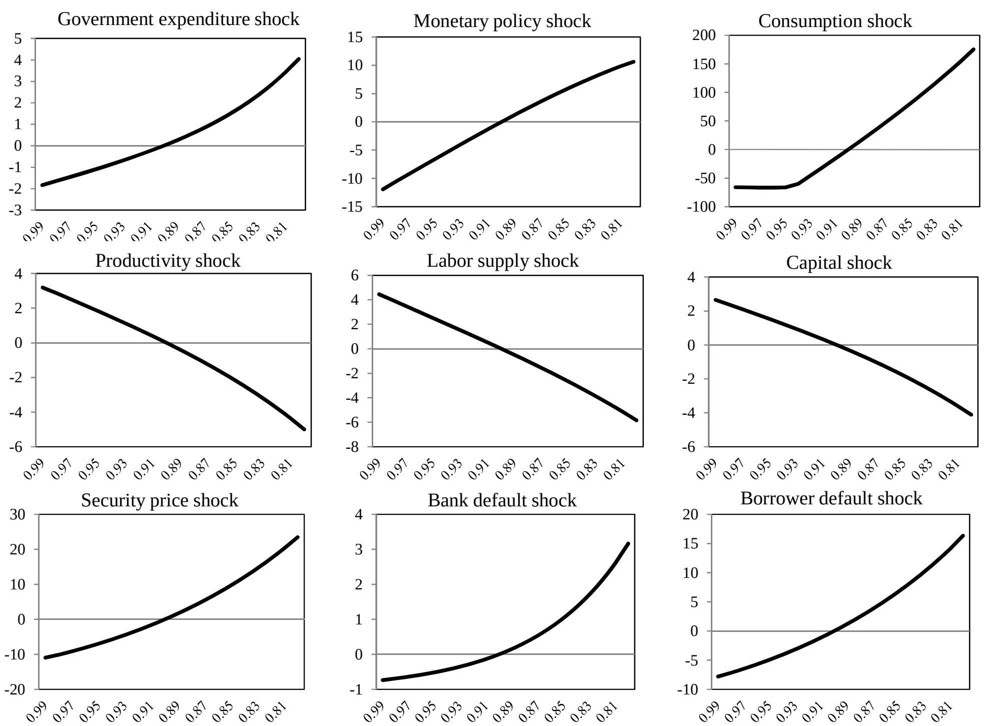
Note: The figure reports the impulse responses to a 1 percent government expenditure shock.

Figure 2. Output responses to other shocks



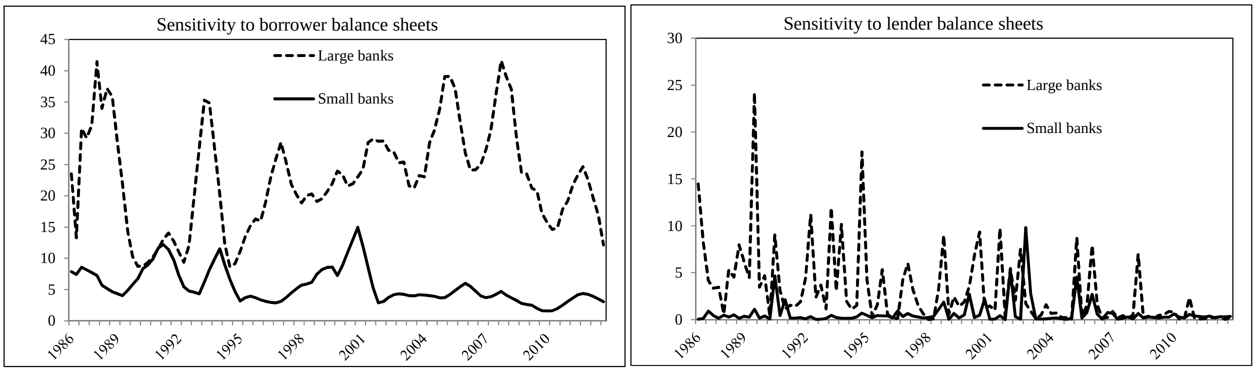
Note: The figures show the output responses to a 1 percent shock to 9 variables. ----- large bank lending —— small bank lending.

Figure 3. Bank size and the percent change in output responses



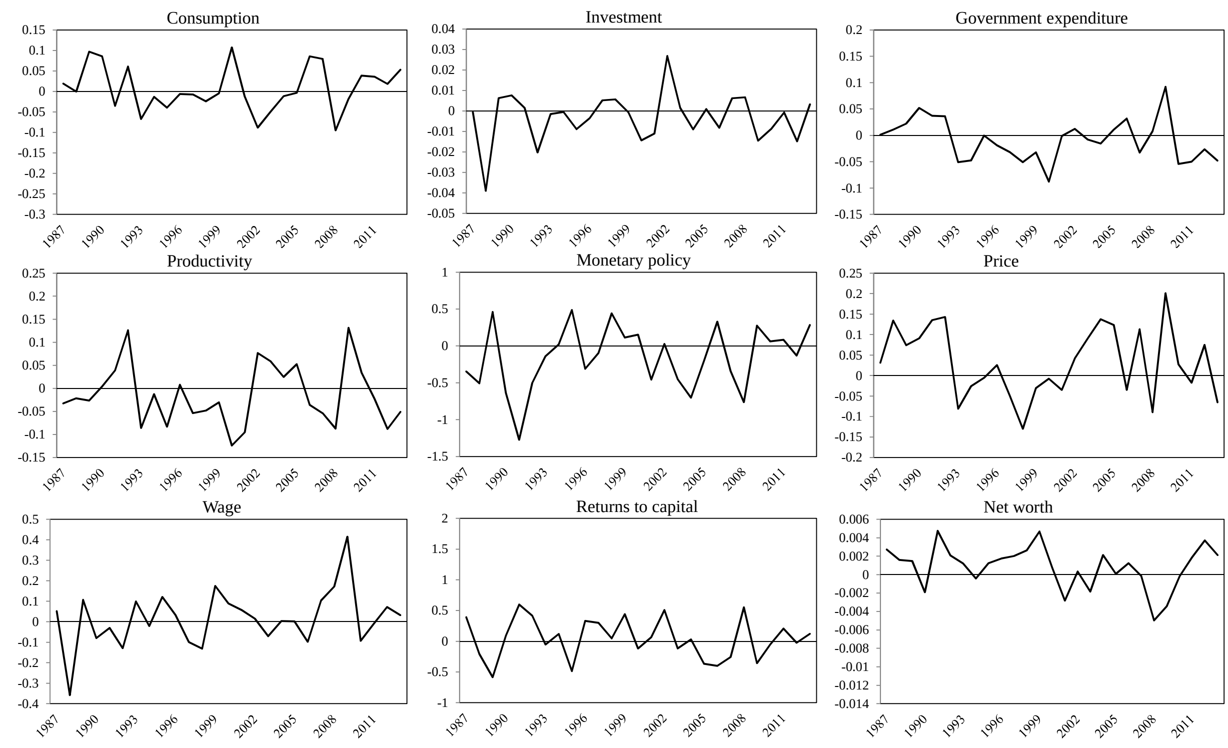
Note: The figure reports the percent deviations from the maximum/minimum output reponses to shocks when the share of large bank lending, the horizontal axis values, is changed in the calibration exercise.

Figure 4. Quarterly sensitivity coefficients



Note: This figure displays the balance sheet coefficient values obtained by estimating equations (26) and (29) using cross-section regression for each quarter.

Figure 5. Estimated macroeconomic shocks



Note: This figure reports the time series of U.S. shocks estimated in the dynamic New Keynesian DSGE model.

Table 1. Financial frictions, loan competition and output responses

	demand side frictions	supply side frictions	small banks frictions	large banks frictions	Competition
Lending spread	2.58	3.00	1.18	4.59	
Gov. expenditure shock	11.0	7.9	6.2	9.1	6.7
Monetary policy shock	4.5	2.4	9.1	15.3	15.6
Consumption shock	7.2	137.8	1.9	138.8	306.8
Productivity shock	44.6	15.7	34.0	0.1	-51.4
Labor supply shock	22.1	13.5	6.8	5.3	-23.0
Capital shock	7.0	10.5	3.0	1.0	-6.0
Security price shock	29.5	187.2	247.9	68.7	28.0
Bank default shock	13.7	502.2	295.0	73.7	-24.4
Borrower default shock	10.5	48.8	350.1	68.7	-58.8

Note: This table reports the percent change in the maximum/minimum output responses when the level of demand side, supply side, small bank and large bank financial frictions switch from low values to high values. The last column reports the percent change in the maximum/minimum output responses, relative to the baseline responses, when the two banks compete for loans. The first row reports the change in the steady state lending spread when the friction parameter values switch from low to high values.

Table 2. Bank/BHC characteristics

Banks			BHCs		
banks included			Small BHCs		
	number of observations	67,561		number of observations	11,490
	average size	2,858,237		average size	2,284,297
	equity ratio	9.8		equity ratio	8.5
	liquidity ratio	16.4		liquidity ratio	31.7
	return on assets	0.6		return on assets	0.5
banks excluded			Large BHCs		
	number of observations	199,379		number of observations	605
	average size	523,779		average size	103,864,279
	equity ratio	10.6		equity ratio	9.5
	liquidity ratio	18.6		liquidity ratio	24.9
	return on assets	0.5		return on assets	0.7

Note: The table reports descriptive statistics for the bank/BHC dataset used in Section 4.

Table 3. Sensitivity to borrower and BHC balance sheets

	Local income gaps		BHC equity	
	Large	Small	Large	Small
$\sum \gamma_k$	15.18	1.05	40.71	-0.30
	(26.92)***	(0.86)	(8.87)*	(5.93)
lag of loan deviations across states	0.37	0.45	-0.94	-0.00016
	(0.036)***	(0.089)***	(0.10)***	(0.00007)**
Bank equity ratio	5.55	6.34	-4.77	-0.58
	(1.27)***	(1.26)***	(8.68)	(0.60)
Bank liquidity ratio	3.44	1.78	-0.31	0.55
	(0.88)***	(0.47)***	(5.67)	(0.13)***
Bank return on assets	4.16	0.27	0.22	-0.43
	(1.29)***	(1.80)	(0.92)	(0.41)
Bank tangible assets	-9.38	-29.46	23.99	-3.09
	(4.21)**	(12.21)**	(25.32)	(1.69)*
Bank size	4.82	-10.10	-4.63	-6.94
	(1.95)**	(7.22)	(3.57)	(4.39)
lag of loan deviations within state	-0.63	-0.75	0.65	-0.12
	(0.03)***	(0.08)***	(0.08)***	(0.014)***
BHC liquidity	-0.07	0.15	-0.55	0.21
	(0.27)	(0.13)	(0.89)	(0.07)***
within state BHC asset deviation	0.23	-0.03	-0.70	-0.10
	(0.19)	(0.27)	(0.62)	(0.06)
Constant	-19.35	-5.73	2.17	-8.97
	(12.76)	(2.1)***	(32.15)	(0.63)***
Number of obs.	9,915	110,995	7,300	67,784
AR(2)	0.64	0.20	0.50	0.27

Note: The results are obtained by estimating equations (26) and (29). The numbers in the parenthesis in the first row are the chi-square statistics that test the joint significance of the balance sheet coefficients. The results in the columns entitled large (small) are obtained by using data for banks affiliated with large (small) BHCs. *, **, *** significant at 10%, 5%, 1%, respectively.

Table 4. Different specifications of BHC size and borrower/lender balance sheets

	Income gap	Income growth	Income gap excluding 2001, 2008	Income gap standardized	BHC equity ratio	BHC return on assets ratio	BHC liquidity ratio	BHC equity ratio excluding 2001, 2008	BHC equity ratio standardized
Large <5%	15.18	53.23	19.36	8.57	40.71	71.82	-3.05	40.74	1.20
	(26.92)***	(32.68)***	(27.62)***	(26.92)***	(8.87)*	(10.09)**	(6.08)	(12.33)**	(8.87)*
Small >5%	1.05	6.57	0.99	0.59	-0.30	-0.21	0.01	-0.32	-0.01
	(0.86)	(0.76)	(0.86)	(0.86)	(5.93)	(2.84)	(10.71)**	(6.31)	(6.25)
Large <50%	3.80	8.46	4.15	2.15	-0.39	-0.40	-0.13	-0.26	-0.01
	(2.83)	(3.58)	(2.94)	(2.83)	(1.14)	(2.30)	(9.15)*	(0.98)	(1.14)
Small >50%	0.41	-0.83	0.41	0.23	1.42	-0.56	0.13	1.41	0.04
	(0.75)	(5.35)	(0.75)	(0.75)	(1.89)	(4.46)	(5.27)	(1.97)	(1.89)

Note: The results are obtained from the estimation of equations (26) and equation (29) for different specifications of balance sheets and time periods. The numbers in the parenthesis are the chi-square statistics used to test the joint significance of the balance sheet coefficients. The results reported in the rows entitled large (small) are obtained by using data for banks affiliated with large (small) BHCs. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5. Prior distributions and posterior estimates of shock parameters

		Prior Distributions			Posterior Distributions			Prior Distributions			Posterior Distributions	
Shocks	Persistence	Distrib.	Mean	std. dev	Mean	std. dev	std. dev	Distrib.	Mean	std. dev	Mean	std. dev
Consumption	ρ_c	B	0.5	0.200	0.281	0.095	σ_c	IG	0.005	inf	0.00095	0.000110
Investment	ρ_i	B	0.5	0.200	0.633	0.080	σ_i	IG	0.005	inf	0.00440	0.000413
Gov. expenditure	ρ_g	B	0.5	0.200	0.954	0.020	σ_g	IG	0.005	inf	0.00640	0.000415
Monetary policy	ρ_r	B	0.5	0.200	0.456	0.062	σ_r	IG	0.005	inf	0.00091	0.000074
Productivity	ρ_a	B	0.5	0.200	0.902	0.031	σ_a	IG	0.005	inf	0.00210	0.000145
Price	ρ_h	B	0.5	0.200	0.960	0.019	σ_h	IG	0.005	inf	0.00079	0.000122
Wage	ρ_w	B	0.5	0.200	0.994	0.005	σ_w	IG	0.005	inf	0.00077	0.000107
Returns to capital	ρ_k	B	0.5	0.200	0.855	0.033	σ_k	IG	0.005	inf	0.00130	0.000086
Net worth	ρ_n	B	0.5	0.200	0.209	0.071	σ_n	IG	0.005	inf	0.06420	0.004100

Note: The posterior values in the table are obtained from the estimation of the dynamic New Keynesian, DSGE model.

Table 6. Impact of macroeconomic shocks and market concentration

		Borrower balance sheets			Lender balance sheets		
Shocks	size	shock	income gap	income gap * shock	shock	Equity ratio	Equity ratio * shock
Consumption	Large	3.04	1.46	-1.44	5.655	0.204	0.063
		(128.7)***	(14.0)***	(43.6)***	(7.5)	(2.4)	(42.8)***
	Small	0.70	-0.65	0.07	-0.002	-0.009	-0.001
		(77.2)***	(3.9)	(18.3)	(34.5)***	(1.7)	(20.7)
Investment	Large	2.39	0.41	-2.86	7.902	0.130	-0.271
		(153.2)***	(17.7)***	(61.3)***	(12.0)**	(4.6)	(22.0)
	Small	-0.20	0.36	2.39	-0.950	-0.001	0.007
		(66.2)***	(4.2)	(33.8)***	(23.3)***	(7.4)	(19.4)
Gov. expenditure	Large	0.19	0.02	1.25	1.977	0.216	0.047
		(54.9)***	(27.6)***	(80.8)***	(6.0)	(4.0)	(16.0)
	Small	-0.03	-0.18	-0.58	0.307	-0.010	0.001
		(27.2)***	(0.8)	(23.8)*	(82.8)***	(14.4)***	(31.0)**
Monetary policy	Large	1.17	19.24	-0.60	-0.884	1.426	0.011
		(193.0)***	(12.6)**	(70.8)***	(7.3)	(6.6)	(17.3)
	Small	-0.09	-1.65	-0.06	0.115	-0.022	0.0003
		(81.8)***	(6.3)	(19.8)	(95.7)***	(11.3)**	(21.3)
Productivity	Large	-1.35	3.85	0.23	-5.111	0.744	-0.137
		(60.1)***	(24.0)***	(64.1)***	(12.7)**	(5.6)	(36.4)***
	Small	-0.05	-1.80	-0.66	-0.010	-0.006	0.003
		(26.5)***	(2.3)	(11.8)	(33.5)***	(19.2)***	(31.6)**
Price	Large	9.75	15.17	1.41	1.908	1.422	0.076
		(63.9)***	(24.6)***	(77.3)***	(5.4)	(12.0)**	(47.4)***
	Small	-0.07	-3.55	0.93	0.224	-0.005	-0.0004
		(6.4)	(3.5)	(40.0)***	(11.8)**	(17.0)***	(30.9)**
Wage	Large	-4.30	-7.82	4.81	7.928	0.927	-0.076
		(100.1)***	(19.1)***	(84.2)***	(14.0)***	(9.7)**	(24.3)*
	Small	0.06	1.06	-0.66	0.252	-0.023	0.001
		(21.1)***	(1.7)	(19.9)	(45.8)***	(32.3)***	(43.9)***
Returns to capital	Large	0.12	0.68	-0.14	-0.074	0.061	-0.002
		(187.4)***	(12.6)**	(69.5)***	(7.3)	(3.8)	(15.7)
	Small	-0.01	0.33	0.01	0.005	-0.001	0.0001
		(105.1)***	(5.2)	(16.0)	(70.1)***	(5.8)	(17.9)
Net worth	Large	0.62	-0.01	1.19	-1.020	0.003	-0.007
		(84.0)***	(27.1)***	(111.7)***	(10.3)**	(10.7)**	(18.1)
	Small	0.03	0.005	-0.19	0.014	-0.0001	0.000002
		(62.7)***	(2.9)	(26.4)**	(37.7)***	(10.2)**	(17.5)

Note: The results are obtained by estimating equation (32). The numbers in the parenthesis are the chi-square statistics that test the joint significance of the balance sheet, shock and interactive variable coefficients. The results in the rows entitled large (small) are obtained by using data for banks affiliated with large (small) BHCs. *, **, *** significant at 10%, 5%, 1%, respectively.

Table 7. Market concentration

	MC, top 5%				MC, top 1%				MC, top 10%			
	Income gap	Income gap*MC	Equity ratio	Equity ratio*MC	Income gap	Income gap*MC	Equity ratio	Equity ratio*MC	Income gap	Income gap*MC	Equity ratio	Equity ratio*MC
Large	1.633	-0.049	0.975	0.004	0.802	-0.036	4.081	-0.160	1.601	-0.030	-0.412	0.024
	(15.9)***	(79.5)***	(15.8)***	(34.8)***	(8.5)*	(91.1)***	(4.1)	(23.1)	(26.2)***	(72.3)***	(5.7)	(35.5)***
Small	0.113	-0.005	0.184	-0.005	0.484	-0.002	0.174	-0.009	0.011	-0.001	0.306	-0.006
	(4.1)	(10.6)	(24.3)***	(31.8)***	(9.1)*	(23.4)	(27.4)***	(33.7)***	(2.9)	(9.4)	(25.9)***	(38.9)***

Note: The results are obtained by replacing the shock variable with the market concentration variables, MC, in equation (32). The numbers in the parenthesis are the chi-square statistics that test the joint significance of the balance sheet and the interactive variable coefficients. The results in the rows entitled large (small) are obtained by using data for banks affiliated with large (small) BHCs. *, **, *** significant at 10%, 5%, 1%, respectively.