How Much do Bank Shocks Affect Investment? Evidence from Matched Bank-Firm Loan Data

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Abstract

We show that supply-side financial shocks have a large impact on firms' investment. We do this by developing a new methodology to separate firm-borrowing shocks from bank supply shocks using a vast sample of matched bank-firm lending data. We decompose loan movements in Japan for the period 1990 to 2010 into bank, firm, industry, and common shocks. The high degree of financial institution concentration means that individual banks are large relative to the size of the economy, which creates a role for granular shocks as in Gabaix (2011). As a result, bank supply shocks—i.e., movements in the supply of bank loans net of borrower characteristics and general credit conditions—can have large impacts on aggregate loan supply and investment. We show that these bank supply shocks explain 40 percent of aggregate loan and investment fluctuations.

1 Introduction

Do bank-loan supply shocks matter for investment rates, and if so, how much? Since the principal reason firms borrow is to finance capital expenditures, this question stands at the center of debates on the importance of financial shocks for real economic activity. The dearth of empirical work on this issue reflects the difficulty of linking bank supply shocks to firm investment decisions. For example, while several studies have offered compelling bank-level evidence that bank shocks matter for loan supply and certain types of foreign investment (*cf.* Peek and Rosengren (1997), Peek and Rosengren (2000), Kashyap and Stein (2000), Klein, Peek, and Rosengren (2002), Paravisini (2008), and Khwaja and Mian (2008)), they have not addressed the central question of how important bank-loan supply shocks are in determining the overall investment rates of their borrowers or aggregate investment more generally. Our study answers this question by providing the first estimate of how much financial institution shocks matter for overall firm-level and aggregate investment rates and establishes that lender shocks are an important determinant of both.

We develop a new methodology that enables us to provide the first direct estimates of firm borrowing and bank supply shocks using a comprehensive, matched lender-borrower data set covering all loans received from all sources by every listed Japanese firm over the period 1990 to 2010. The data contain the values of total short- and long-term lending from hundreds of financial institutions to thousands of listed firms: 272,302 loans in total. A key difference between our approach and that of other studies is the imposition of an adding-up constraint on the estimation that ensures that the estimates obtained from the micro-lending data are consistent with aggregate lending and borrowing patterns.

A major advantage of our approach relative to earlier work is that we are able to identify the shocks directly from the loan data, and hence do not need to rely on instrumental variables that are correlated with firm-borrowing and bank supply shocks. These bank supply shocks measure idiosyncratic movements of loan supply at the financial-institution level that cannot be explained by common loan shocks hitting all financial institutions or even by movements in loan demand from the financial institutions' borrowers. Moreover, we provide extensive evidence of the external validity of our estimates. In particular, we show that our estimates capture the impact of idiosyncratic events such as bankruptcies, capital injections, regulatory interventions,

computer glitches, trading errors, and other proxy variables that previous researchers have thought important determinants of bank shocks.

Armed with these bank supply shocks estimated from micro data, we then exploit the heterogeneity in the sources of firm financing in order to identify time-varying bank-supply shocks hitting firms. We then use these bank shocks to demonstrate that firms that borrow heavily have investment rates that are very sensitive to their lenders' supply shocks. Moreover, we show that these loan supply channels are important determinants of investment not only in financial crisis years, but in non-crisis years as well.

The fact that our micro estimates are consistent with macro data allows us to develop a theoretically sound aggregation method that enables us to apply these estimates to national accounts data. Our approach builds on Gabaix (2011) to develop a method for estimating "granular" bank supply shocks, which measure the aggregate loan supply movements that arise from the supply shocks of large lenders.[1] We use these granular bank shocks to measure how important the bank shocks are for understanding aggregate lending and investment fluctuations. In particular, we show that granular bank shocks are both statistically and economically significant determinants of aggregate investment, accounting for 40 percent of the fluctuations in lending and investment.

Our work is related to a number of previous studies. One important strand of literature is the set of papers (*cf.* Fazzari, Hubbard, and Petersen (1988), Hoshi, Kashyap, and Scharfstein (1991), and Gan (2007)) that examine the cash-flow sensitivity of capital-constrained and unconstrained firms. While addressing a similar question, our methodology is quite different because we are not focused on the cash flow sensitivity of investment but rather on whether investment rates are determined by loan supply shocks. For example, it could be the case that firm investment is cash-flow sensitive, but bank-shocks do not decrease investment rates.

A related strand of the literature has investigated the financial accelerator with firm or industry data by examining the access to credit by borrowers that are deemed

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[1]Gabaix (2011) coined the term "granular" because it reflects the fact that firms are not infinitesimal in size. We use the term in the same sense here to refer to the macroeconomic impact of idiosyncratic bank shocks. If all banks were infinitesimally small and had uncorrelated idiosyncratic shocks, then these shocks would not be important for understanding aggregate fluctuations. However, if banks are large or "granular", idiosyncratic shocks in one or more large institutions can move aggregate lending.

to be more financially sensitive. For example, Gertler and Gilchrist (1994) found that small firms, which presumably are more constrained in their external finance options, and bank-dependent borrowers are more sensitive to monetary policy fluctuations. This sensitivity may reflect the financial accelerator at play, but it is also hard to rule out other unobserved characteristics of small firms and bank-dependent borrowers that may be driving the results.

A different strand of the literature has shown that firms or industries that depend more heavily on external finance or lending contract more severely during banking crises (e.g., Kashyap, Lamont, and Stein (1994), Dell'Ariccia, Detragiache, and Rajan (2008), Kalemli-Ozcan, Kamil, and Villegas-Sanchez (2010), and Chava and Purnanandam (2011)) but has not linked the contracting sectors or firms to the affected banks. Braun and Larrain (2005) have argued that sectors more dependent on external finance are more cyclical, and that this cyclicality may be particularly manifest during banking crises. Thus, it is difficult to know if there is a common factor driving financial dependence and cyclicality. Alternatively, it may be the case that people who invest in banks also invest in sectors that need a lot of external finance, so that the contraction in industrial output of financially dependent sectors is only associated with the credit contraction because investors pull back from both sectors simultaneously.

In order to deal with the inevitable issues arising from the use of aggregate data, several authors have worked with microdata and proxy variables for bank health to demonstrate that bank shocks can matter for bank lending and certain types of real economic activity. For example, the work of Peek and Rosengren (1997, 2000), Klein, Peek, and Rosengren (2002), Khwaja and Mian (2008), Paravisini (2008), Greenstone and Mas (2012), Amiti and Weinstein (2011), Jimenez et al. (2011), Santos (2012) and Chodorow-Reich (2013) provide bank-level or matched bank-firm level evidence that deteriorations in bank health or increases in the cost of raising capital cause banks to contract lending, raise rates, and/or have impacts on *foreign* markets or employment, but none of these papers address whether bank-supply shocks affect the overall investment rates of borrowers from these institutions at the firm or aggregate level. Thus, the question of how much these shocks matter for investment, and therefore GDP, remains unanswered. Moreover, while the existing literature makes use of instruments to identify the impacts of particular bank shocks, we are able to develop a methodology that identifies these bank shocks even in situations where it

may not be possible to have measures of bank health.

Our work is also able to address a major outstanding question in the literature regarding whether bank shocks matter only following extreme events or for small firms and firms without access to other sources of capital, or whether credit crunches are a phenomenon with broader implications. For example, although Ashcraft (2005) found that the failure of healthy bank subsidiaries affected county-level output in Texas, Ashcraft (2006) argues that "these effects are likely to be very small and unworthy of concern" because "while small firms might view bank loans as special, they are not special enough for the lending channel to be an important part of how monetary policy works." These concerns are particularly apt given the evidence that loans and other types of borrowing are substitutable. For example, Kashyap, Stein, and Wilcox (1993), Kroszner, Laeven, and Klingebiel (2007), and Adrian, Colla, and Shin (2012) show that some firms are able to substitute other forms of credit supply in the presence of loan supply shocks, and Khwaja and Mian (2008) show that bank shocks matter for small but not large firms. On the other hand, Hubbard, Kuttner, and Palia (2002) stress the difficulties that firms have substituting loans from one bank with loans from another. Consistent with both sets of studies, we find evidence that bank supply shocks do not matter for firms that borrow little to finance their capital expenditures. However, we also show that these bank-supply shocks affect investment rates of those firms that borrow heavily from banks.

Finally, our paper is also related to the work of Buch and Neugebauer (2011) and Bremus et al. (2013), who use aggregate bank loan data to construct granular bank shocks and regress them on cross-country GDP growth. However, our work differs from theirs in a number of respects. First, rather than ascribing bank shocks to loan growth rate differences across institutions, which may reflect differences due to heterogeneity in borrower characteristics across banks, our method allows us to econometrically isolate bank shocks from firm-borrowing shocks and time-varying common and industry shocks. This eliminates any worry that an observed correlation between granular bank shocks and GDP might arise from large banks lending to more procyclical sectors or any factor that would cause credit demand for large institutions to covary more with GDP than credit demand for small institutions. Second, since we separate firm-borrowing and bank-supply shocks, we show that the link from the banking sector to GDP flows directly from the affected banks to the investment decisions of their client firms. This enables us not only to be precise about the

mechanism through which GDP is affected, but also to show the relative importance of the bank-lending channel in understanding investment fluctuations.

The rest of the paper is structured as follows. Section 2 develops the empirical strategy. Section 3 describes and previews the data. Section 4 provides intuition about how our methodology generates bank shock estimates and investigates their plausibility. Section 5 presents the main results regarding the impact of bank shocks on firm-level investment as well as aggregate investment, and Section 6 concludes.

2   Empirical Strategy

Our econometric approach begins by specifying a fairly general empirical model that we can use to estimate the importance of each type of shock hitting the economy. In order to simplify the exposition, we will refer to financial institutions in our data as "banks" even though our data comprise banks, insurance companies, and holding companies.

2.1   Estimating Firm-borrowing and Bank Shocks

Let L_{fbt} denote borrowing by firm f from bank b in time t. We begin by considering a class of empirical models in which we can write the growth in lending as

$$\frac{L_{fbt} - L_{fb,t-1}}{L_{fb,t-1}} = \alpha_{ft} + \beta_{bt} + \varepsilon_{fbt}, \tag{1}$$

where α_{ft} denotes the "firm-borrowing channel" and β_{bt} the "bank-lending channel". Critically, we do not assume that the bank and firm shocks are independent. This equation has been widely used empirically and can be derived structurally.[2] For instance, Khwaja and Mian (2008) develop a model to obtain an estimating equation that is a special case of equation 1.[3] Following the literature, we assume that the

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[2]Examples include Chava and Purnanandam (2011) and Greenstone and Mas (2012).

[3]More specifically, Khwaja and Mian (2008) provide a structural interpretation of equation 1 based on a model in which the marginal cost of a bank raising financing (α_L) is positive and the firm's marginal return on capital (α_B) is a decreasing function of borrowing. They use this to derive their estimating equation (equation 2 in their paper), which in our notation becomes

$$\frac{L_{fbt} - L_{fb,t-1}}{L_{fb,t-1}} = \frac{1}{\alpha_L + \alpha_B} \left(\bar{\eta}_t + \eta_{ft} \right) + \frac{\alpha_B}{\alpha_L + \alpha_B} \left(\bar{\delta}_t + \delta_{bt} \right),$$

where $\left(\bar{\eta}_t + \eta_{ft} \right)$ denotes the economy-wide and firm-specific productivity shocks and $\left(\bar{\delta}_t + \delta_{bt} \right)$ denotes the economy-wide and bank-specific credit-supply shocks. This equation is isomorphic to

expectation of the error term is zero, *i.e.* $E\left[\epsilon_{fbt}\right] = 0$.

This empirical model can easily be understood by contemplating the standard explanations for what causes lending from a bank to a firm to vary. If lending varies because of firm-level productivity shocks, changes in other factor costs, changes in investment demand, firm-level credit constraints, etc., we will measure that as arising from the firm borrowing channel, α_{ft}. Similarly, if a bank cuts back on lending because it is credit constrained, we would capture that in the bank lending channel, β_{bt}.

While one approach to identifying these channels is to estimate equation 1 using a large set of time-varying firm and bank fixed effects, in practice this is inefficient because it ignores a large number of adding-up constraints. In particular, a firm cannot borrow more without at least one bank lending more, and a bank cannot lend more without at least one firm borrowing more. This implies that there must be general equilibrium linkages between the α_{ft}'s and the β_{bt}'s. As we will see, ignoring these linkages produces estimates of aggregate bank lending growth that are wildly different from the actual growth rates. Such an approach to estimating equation 1 thus fails to provide an exact decomposition of actual macro lending growth into the borrowing and lending channels.

We therefore adopt a different approach that exploits the adding-up constraints implicit in equation 1. In order to derive the formulas for the adding-up constraints, we multiply both sides of equation 1 by the lagged share of lending to firm f, $\phi_{fb,t-1}$, and sum across all firms to obtain,

$$D_{bt}^{B} \equiv \sum_{f} \left(\frac{L_{fbt} - L_{fb,t-1}}{L_{fb,t-1}} \right) \frac{L_{fb,t-1}}{\sum_{f} L_{fb,t-1}} = \beta_{bt} + \sum_{f} \phi_{fb,t-1}\alpha_{ft} + \sum_{f} \phi_{fb,t-1}\epsilon_{fbt}, \quad (2)$$

where

$$\phi_{fb,t-1} \equiv \frac{L_{fb,t-1}}{\sum_{f} L_{fb,t-1}}.$$

and D_{bt}^{B} equals the growth rate of lending of bank b to all of its client firms. Crucially, equation 2 provides the formula for the adding-up constraint linking each bank's

our equation 1. Khwaja and Mian (2008)'s estimating equation (rewritten in our notation) is $\frac{L_{fbt} - L_{fb,t-1}}{L_{fb,t-1}} = \alpha_{ft} + \beta\Delta DEP_{bt} + \varepsilon_{fbt}$, where ΔDEP_{bt} is the bank-specific change in deposits (and is assumed to be uncorrelated with ϵ_{fbt}). Note that this equation is a special case of equation 1 in which all bank shocks that are independent of deposits have been relegated to the error term.

loan growth, its loan supply shock and the borrowing shocks of each of it's clients. Similarly, these same shocks must also aggregate to yield a *firm's* aggregate borrowing:

$$D_{ft}^F \equiv \sum_b \left(\frac{L_{fbt} - L_{fb,t-1}}{L_{fb,t-1}} \right) \frac{L_{fb,t-1}}{\sum_b L_{fb,t-1}} = \alpha_{ft} + \sum_b \theta_{fb,t-1}\beta_{bt} + \sum_b \theta_{fb,t-1}\epsilon_{fbt}, \qquad (3)$$

where
$$\theta_{fb,t-1} \equiv \frac{L_{fb,t-1}}{\sum_b L_{fb,t-1}}.$$

and D_{ft}^F equals the growth rate of borrowing of firm f from all of its banks. Equation 3 will prove to be particularly important for our analysis of the impact of bank shocks on firm investment because the first summation term on the right-hand side captures the impact of bank supply shocks, β_{bt}, on the firm's ability to borrow from banks. Thus if we can identify the bank shocks, we will have a metric for measuring their importance for firm borrowing.

A key methodological contribution of this paper is to show that we can obtain identification of the α_{ft}'s and the β_{bt}'s that are consistent in the sense that the estimates match the growth rates of firm, bank, and aggregate lending. In particular, since $\phi_{fb,t-1}$ is a predetermined variable, we can impose the following moment conditions on the data: $E\left[\sum_f \phi_{fb,t-1}\epsilon_{fbt}\right] = \sum_f \phi_{fb,t-1}E\left[\epsilon_{fbt}\right] = 0$, and $E\left[\sum_b \theta_{fb,t-1}\epsilon_{fbt}\right] = \sum_b \theta_{fb,t-1}E\left[\epsilon_{fbt}\right] = 0$. These conditions imply that we can choose our parameters such that the following equations hold in our data:

$$D_{bt}^B = \beta_{bt} + \sum_f \phi_{fb,t-1}\alpha_{ft}. \qquad (4)$$

$$D_{ft}^F = \alpha_{ft} + \sum_b \theta_{fb,t-1}\beta_{bt}. \qquad (5)$$

As we show in Appendix A, it is possible to use these moment conditions to estimate the α_{ft}'s and β_{bt}'s. A key insight is that equations 4 and 5 provide a system of $F + B$ equations and $F + B$ unknowns in each time period enabling us to solve for a unique set of firm and bank shocks (relative to what is happening to the median bank and firm) in each time period.

We can obtain some intuition for the difference between estimating equation 1 using fixed effects and solving equations 4 and 5 by considering a simple example. Consider a case in which every bank's total loan growth is constant in every period (*i.e.*, $D_{bt}^B = D_b^B$) and every firm's total borrowing growth is also constant (*i.e.*, $D_{ft}^F = D_f^F$). In this case, we know that bank and firm shocks cannot be changing because

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every bank lends (and every firm borrows) the same amount in every period (*i.e.,* the left-hand sides of equations 4 and 5 are unchanging). Now suppose that loans from each bank to each firm are perturbed in such a way that *aggregate* lending by each bank and *aggregate* borrowing by each firm are unchanged (*i.e.,* the shocks satisfy our moment condition: $\sum_f \phi_{fb,t-1}\epsilon_{fbt} = \sum_b \theta_{fb,t-1}\epsilon_{fbt} = 0$ but $\epsilon_{fbt} \neq 0$ for some fb). In general, it will not be the case that $\sum_{f,b} \epsilon_{fbt} = 0$, which means that the fixed-effects estimates of bank and firm shocks will not be the same each period. The fact that the fixed-effects estimates can vary period to period even though there is no change in any bank's aggregate lending behavior or any firm's aggregate borrowing behavior highlights the inefficiency of using the fixed-effects estimator. Our approach is more efficient because it takes into account the fact that shocks to individual bank-firm pairs that do not lead to changes in the aggregate lending of any institution are not bank or firm shocks. Moreover, it is important to remember that this problem cannot be solved by running a weighted regression since a weighted regression implies setting $\sum_{f,b} \omega_{fbt}\epsilon_{fbt} = 0$ (where the weights are given by ω_{fbt}), which is a different equation than the moment condition written above and therefore will have a different solution in general.

The fact that we can solve for the firm and bank shocks enables us to obtain an exact decomposition of each bank's aggregate lending into four terms, as described in the equation below:

$$\boldsymbol{D_{Bt}} = \left(\bar{A}_t + \bar{B}_t\right)\mathbf{1_B} + \boldsymbol{\Phi_{t-1}}\boldsymbol{N_t} + \boldsymbol{\Phi_{t-1}}\boldsymbol{\tilde{A}_t} + \boldsymbol{\tilde{B}_t}, \qquad (6)$$

where $\boldsymbol{D_{Bt}}$ is a $B \times 1$ vector whose elements are each bank's total loan growth in year t; $\left(\bar{A}_t + \bar{B}_t\right)$ are the median firm and bank shocks in year t, which reflects any shocks that would affect all lending pairs identically in a year; $\mathbf{1_B}$ and $\mathbf{1_F}$ are $B \times 1$ and $F \times 1$ vectors of 1's; $\boldsymbol{N_t}$ is a vector containing the median firm shock in the industry containing the firm; $\boldsymbol{\Phi_t}$ is a matrix that contains as elements the weights of each loan to every borrower in time t, i.e.,

$$\boldsymbol{\Phi_t} \equiv \begin{pmatrix} \phi_{11t} & \cdots & \phi_{F1t} \\ \vdots & \ddots & \vdots \\ \phi_{1Bt} & \cdots & \phi_{FBt} \end{pmatrix};$$

$\boldsymbol{\tilde{A}_t}$ is a vector composed of each firm shock in year t less the median firm shock in that firm's industry in year t; and $\boldsymbol{\tilde{B}_t}$ is a vector composed of each bank shock in year

t less the median bank shock in year t.[4]

The key feature of equation 6 is that one can exactly decompose each bank's loan growth into four elements. The first term measures "common shocks": changes in lending that are common to all lending pairs. These shocks measure any force that would cause all lending to rise or fall (such as an interest rate change). The second term is the "industry shock": a bank-specific weighted average of the industry shocks affecting each of the bank's borrowers. It measures changes in lending that arise because a bank might have a loan portfolio that is skewed toward borrowers in certain industries. The industry shock captures forces that might cause a bank's lending to deviate from the typical bank's because it specialized in lending to particular industries. We refer to the third term as the "firm-borrowing shock" or firm shock because it captures changes in a bank's lending that arise due to the idiosyncratic changes in borrowing demand of their clients that cannot be attributed to changes in bank-loan supply.

Finally, the last term captures the bank-supply shock or "bank shock" because it measures changes in a bank's loan supply that is independent of anything related to the firms, industries, or common shocks hitting the economy. The elements of $\tilde{\boldsymbol{B}}_{\boldsymbol{t}}$ equal bank b's supply shock in year t less the supply shock of the median bank in that year, $i.e.$ $\tilde{\beta}_{bt} = \beta_{bt} - \bar{B}_t$. Thus, if all banks except bank b suffered a negative 10 percent shock while bank b had no shock, that would be isomorphic in our framework to bank b experiencing a 10 percent positive shock and all other banks experiencing no shock. Since the supply shocks are already purged of all factors affecting their borrowers, our measure of bank shocks reflects what is happening at each bank *relative* to the typical bank.

Now that we have developed a methodology for decomposing bank lending into firm, bank, industry and common shocks, we can turn our attention to the task of understanding how these shocks affect aggregate lending. In order to do this, we need a little more notation. Let $w_{b,t}^B$ be the average share of bank b in total lending in year t, $w_{f,t}^F$ be the share of firm f in total borrowing in year t, and define $\boldsymbol{W_{B,t}} \equiv \left[w_{1t}^B, \cdots, w_{Bt}^B \right]$. We can now use equation 6 to obtain

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[4]We could have defined the decompositions in equation 6 using the mean shock instead of the median. We believe the median more appropriate because it reflects the shocks affecting the typical bank and firm, and the mean shock is more sensitive to extreme shocks hitting small firms and banks. However, the results are qualitatively the same with both methods.

$$\boldsymbol{D_t} = \boldsymbol{W_{B,t-1}} \boldsymbol{D_{Bt}} = \left(\bar{A}_t + \bar{B}_t\right) + \boldsymbol{W_{B,t-1}} \boldsymbol{\Phi_{t-1}} \boldsymbol{N_t} + \boldsymbol{W_{B,t-1}} \boldsymbol{\Phi_{t-1}} \boldsymbol{\tilde{A}_t} + \boldsymbol{W_{B,t-1}} \boldsymbol{\tilde{B}_t}. \quad (7)$$

It is worth pausing a moment to contemplate the implications of equation 7. This equation decomposes aggregate loan growth, $\boldsymbol{D_t}$, into four terms based on the firm-borrowing and bank-lending channels. The first term captures the impact of common shocks on aggregate lending by measuring what happens to the lending of the typical bank-firm pair.[5] The second term represents the "granular industry shock" because it captures the interaction between industry shocks and the size of the industries. The size of this term will depend on the degree of aggregation used and the variance of shocks within an industry. The third term is the "granular firm shock" because it measures the importance of firm-borrowing shocks on aggregate lending. This term will be small if demand shocks are small or if the loan share of every borrower tends to be small. Finally, we refer to the last term as the "granular bank shock" because it is a weighted average of all the financial institution shocks.

Our decomposition of aggregate lending into the four channels differs in important ways from other studies. First, prior work on granular bank shocks has followed Gabaix (2011) and assumed that bank supply and firm-borrowing shocks are uncorrelated across and between firms and banks. Equations 6 and 7 are more general in that we only need to assume that these shocks are not perfectly correlated. Second, the estimates of the bank-lending and firm-borrowing channels are consistent with the aggregate borrowing by firms and lending by banks.

Granular bank supply shocks are likely to be particularly important for aggregate lending fluctuations if lending markets are concentrated. The reason stems from the fact that the magnitude of granular bank-supply shocks depends on two factors: the variance of bank shocks ($\boldsymbol{\tilde{B}_t}$) and the existence of large financial institutions (i.e. some of the elements of $\boldsymbol{W_{Bt}}$ are not small). As Gabaix (2011) has shown, if all institutions were sufficiently small or if their shocks were sufficiently small, then one should expect this term to be small because, on average, these shocks should cancel out due to the law of large numbers. However, as we will see in the next section, financial institutions are indeed quite large compared to the aggregate loan market and have loan shocks that are idiosyncratic. These facts explain why we find in

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[5]As we explain in Appendix A, our methodology does not let us separate how much of the common shock is due to firm-borrowing vs. bank-lending effects. We can only identify the sum of the two effects.

our econometric section that granular bank shocks matter enormously for aggregate fluctuations.

3   Data Description

3.1   Data Construction

Our data come from four sources. First, we use matched bank-firm loan data from Nikkei NEEDS FinancialQUEST for the period 1990 to 2010. Nikkei reports all short-term and long-term loans from each financial institution for every company on any Japanese stock exchange, which we sum to obtain total loans. Our definition of a "bank" covers all Japanese city, trust, regional, mutual banks, and insurance companies, as well as Japanese holding companies. We include loans from all financial institutions, except for the twelve that are government banks or cooperatives. We dropped loans from government institutions such as the Development Bank of Japan and the Export-Import Bank of Japan because we wanted to focus our results on the impact of bank-supply shocks arising from private institutions on aggregate lending. Our loan measure is the total borrowing from a given bank in a year, comprising all loans received from each bank for 870 to 1,633 firms per year. Our data cover all industries, including manufacturing, mining, agriculture, and services. We exclude only the firms in the financial and insurance industries to avoid endogeneity concerns. We divide the industries using the JSIC 2-digit codes, comprising 78 industries.

In general, the Japanese fiscal year runs from April in year t to March in year $t+1$. More than 80 percent of the firms report annual loan data for the fiscal year ending in March, and the rest of the firms report loans ending in one of the other months. For most of our analysis, we will include only firms that report for the year ending in March so that a year is defined over the same time period for all of our firms.[6] We will refer to years ending in March 31 as a "fiscal year" and denote such years by the prefix "FY" to distinguish them from calendar years. Because nine months of any fiscal year occur in the previous calendar year, one should remember that a fiscal year tends to refer to information that is lagged by one year relative to a calendar year. For example, Hokkaido Takushoku Bank, which failed in November 1997, fails in FY1998 because the 1998 fiscal year closes in March 1998.

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[6]Our results are robust to the inclusion of all months.

One difficulty working with these data is tracking mergers and restructurings. Whenever a bank ceases to exist, due to either bankruptcy or merger, firms will cease reporting that bank as a source of loans. We investigated every bank in order to see if there was any report in the media of a bankruptcy or merger. If we could not find any report, we assumed that the zero loan data were accurate, but if we could find evidence of a failure or a merger, we recorded the date. Since firms sometimes reported loans coming from a restructured bank as coming from the prior institution, we recoded these loans as coming from the restructured institution if they occurred after the restructuring. In order to compute the loan growth of a new institution, we had to keep track of all the institutions that predated it. Thus, if Banks 1 and 2 merged in year t to form Bank 3, Bank 3's loans in year $t-1$ would be set equal to the sum of the loans of Banks 1 and 2, and the growth rate would be computed accordingly. Since we could trace the evolution of hundreds of banks in our data, we did not have any gaps associated with mergers.

A related issue concerns the definition of a bank. In general, we erred on the side of assuming that institutions changed whenever an institution was nationalized or privatized. For example, Long-Term Credit Bank failed in 1998 and then, after an interval of nationalized control, reopened as Shinsei Bank in 2000, so the bank appears in our data as different institutions for each of these periods: LTCB, "Nationalized LTCB," and Shinsei Bank.

To ensure sufficient observations to estimate the bank shocks, we keep only bank-year pairs that have a minimum of five loans in both t and $t-1$. This procedure dropped 0.6 percent of the observations. The number of banks in the sample ranges from 101 to 166 depending on the year, with a smaller number of banks in the later period resulting from the wave of mergers in the 2000s.

The second source of data is the Development Bank of Japan (DBJ) database of unconsolidated reports, which provides information on a wide range of firm characteristics. We use information on investment, capital, total borrowings, bonds, cash, total assets, and the firm's book value for our analysis (while the market value is from Nikkei). Our measure of investment is constructed as the annual difference in total tangible fixed assets plus depreciation; and the market-to-book value is the ratio of market value to shareholder equity.

Finally, we draw on two sources of aggregate information on economy-wide borrowings and investment-to-capital ratios. The flow-of-funds data from the Bank of

Japan website provide data on the stock of lending to private nonfinancial corporations from private financial institutions.[7] The economy-wide investment-to-capital ratio data are measured in 2000 yen for fiscal years 1990 to 2010 from the National Accounts, Economic and Social Research Institute, Cabinet Office. The summary statistics are reported in Appendix B.

3.2 Data Preview

In this section, we highlight some key patterns in the data. First, we show that the pattern of aggregate lending from our firm-level data exhibits similar year-to-year fluctuations as those from the official economy-wide statistics, demonstrating the plausibility of using information on listed companies as a means of understanding aggregate fluctuations. Even though lending to listed nonfinancial firms in the Nikkei data accounts for only 17 percent of aggregate lending to nonfinancial enterprises in 1990 and 18 percent in 2010, the aggregate lending to listed companies from our firm-level data exhibits a similar pattern as commercial lending in the broad economy.

Figure 1 plots the annual percent change in loans to nonfinancial enterprises using the flow-of-funds lending data and the annual percent change in aggregate loans to nonfinancial enterprises from the Nikkei firm-level database. As can be seen from this graph, aggregate corporate loans track that of listed companies extremely closely, with a correlation of 0.8. The figure makes clear that corporate borrowing fell off sharply as the bubble burst in FY1990. By FY1995, the growth rate of lending became negative and remained so for a decade.

Second, we show a clear positive association between economy-wide nonfinancial corporate borrowing and economy-wide investment in the data. Figure 2 indicates that the growth rate in the stock of lending to private nonfinancial corporations from private financial institutions using the flow-of-funds data tracks the aggregate investment-to-capital ratio fairly closely. The correlation between the two series is 0.72, illustrating the tight relationship between borrowing and investment.
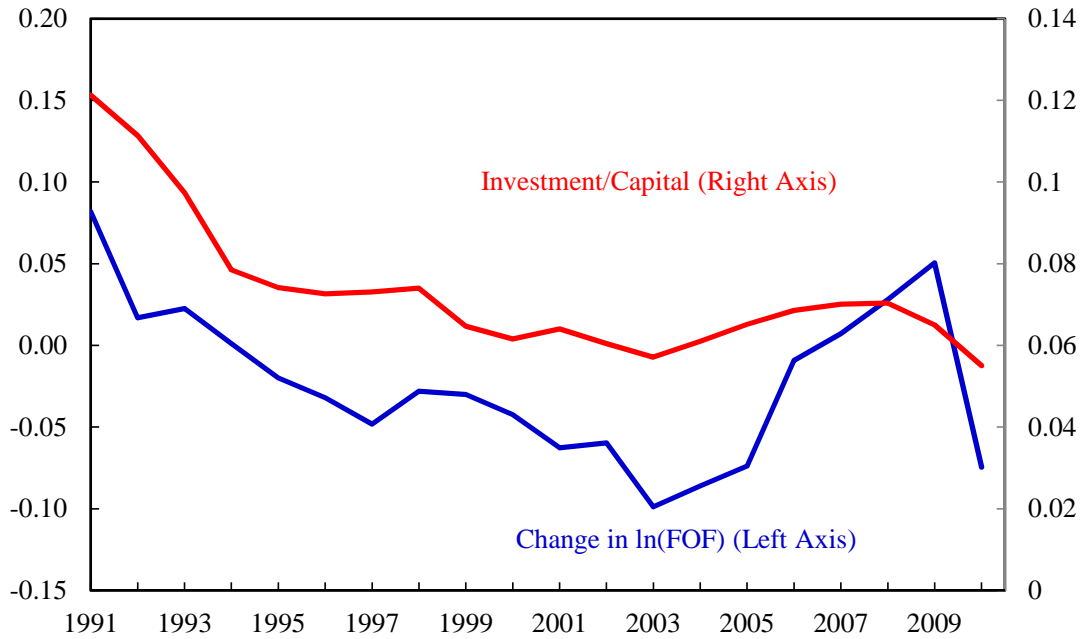
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[7]The borrowing data are from the Bank of Japan website. The series number is FF'FOF_FFYS411L240.
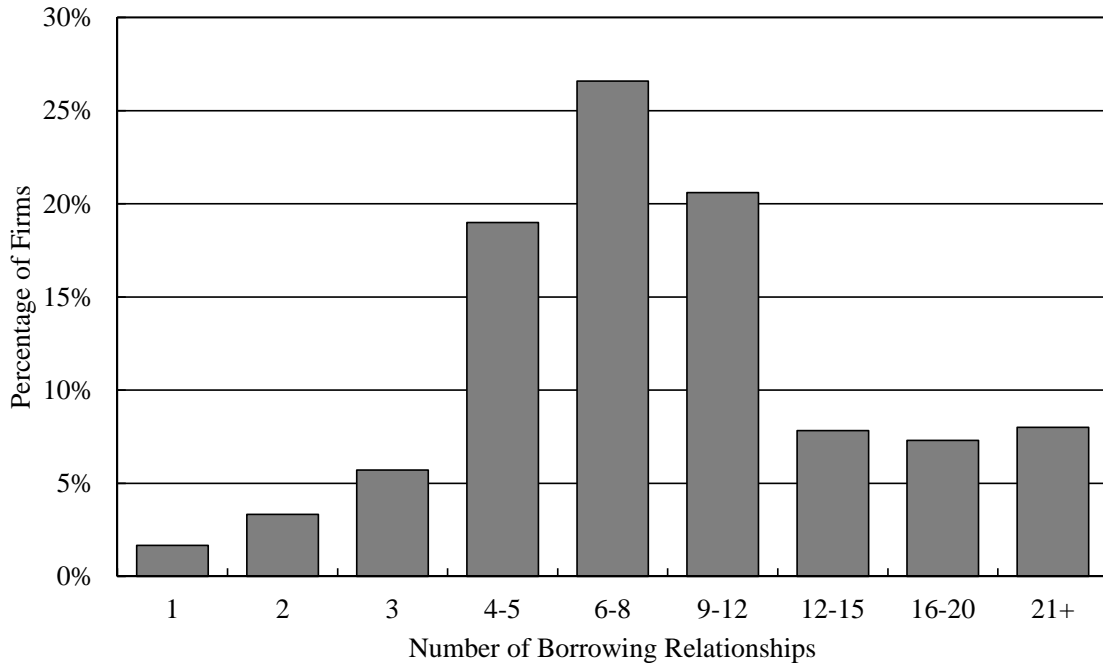
Figure 1: Flow of Funds and Nikkei Debt
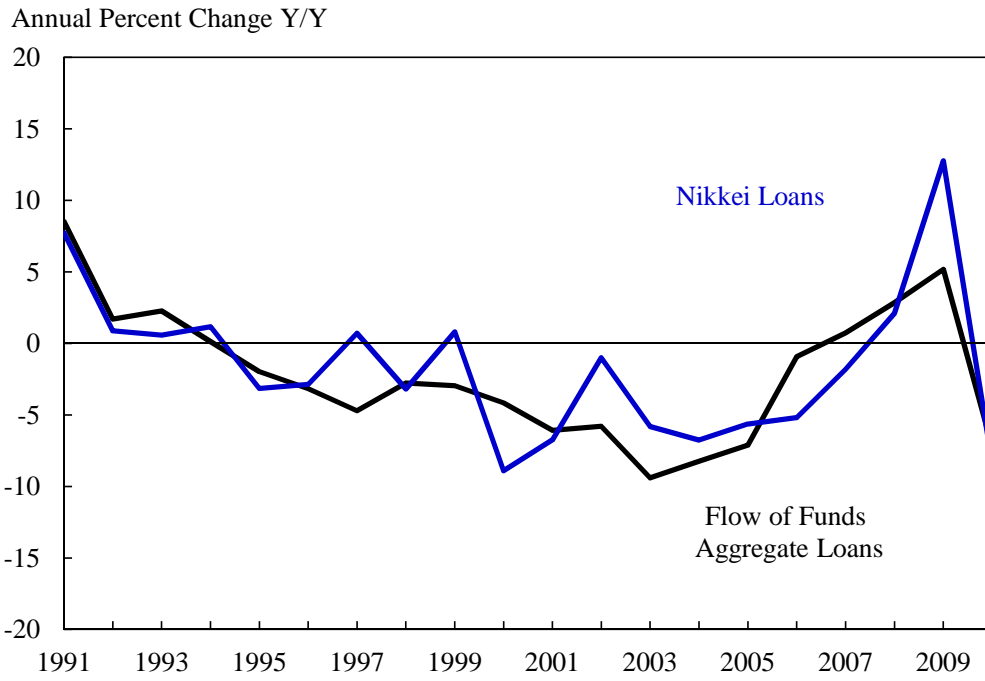
Note: Years are fiscal years, which roughly correspond to the calendar year plus one.

Figure 2: Flow of Funds and Aggregate Investment

Note: Years are fiscal years which roughly correspond to the calendar year plus one.

Figure 3: Distribution of Number of Loans per Firm

Third, a critical feature of our identification strategy is the exploitation of the fact that Japanese listed companies typically borrow from a large number of banks. Figure 3 presents a histogram of the number of institutions providing loans to each firm. The median firm borrowed from eight banks and 98 percent of the firms in our sample borrowed from more than one.[8] Moreover, since the average firm's borrowing Hefindahl index averaged 0.17, we know that the typical firm spread its borrowing out relatively evenly across many banks.[9]

Finally, we need to show sufficient "granularity" in the financial sector so it can plausibly be argued that shocks to major banks in Japan are large enough that an idiosyncratic shock at one of them, such as the failure of Long-Term Credit Bank, might actually move a macroeconomic aggregate. Figure 4 shows a breakdown of total lending by bank. For each year, we depict individual loan shares of every bank

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[8]This is in sharp contrast with the data underlying Khwaja and Mian (2008) in which only 10 percent of the firms borrowed from more than one bank.

[9]The firm borrowing Herfindahl index $\left(= \frac{1}{F_t} \sum_f \sum_b \left(L_{fbt} / \sum_b L_{fbt}\right)^2\right)$ measures how concentrated each firm's borrowing is on average. A Herfindahl index of 1 arises if a firm only borrows from one institution. A Herfindahl index of zero would arise if a firm spread its borrowing evenly across an infinite number of banks.

with a loan share exceeding one percent of aggregate lending to listed companies, and group those with a market share of less than one percent into the shaded region.

Figure 4: Bank Concentration
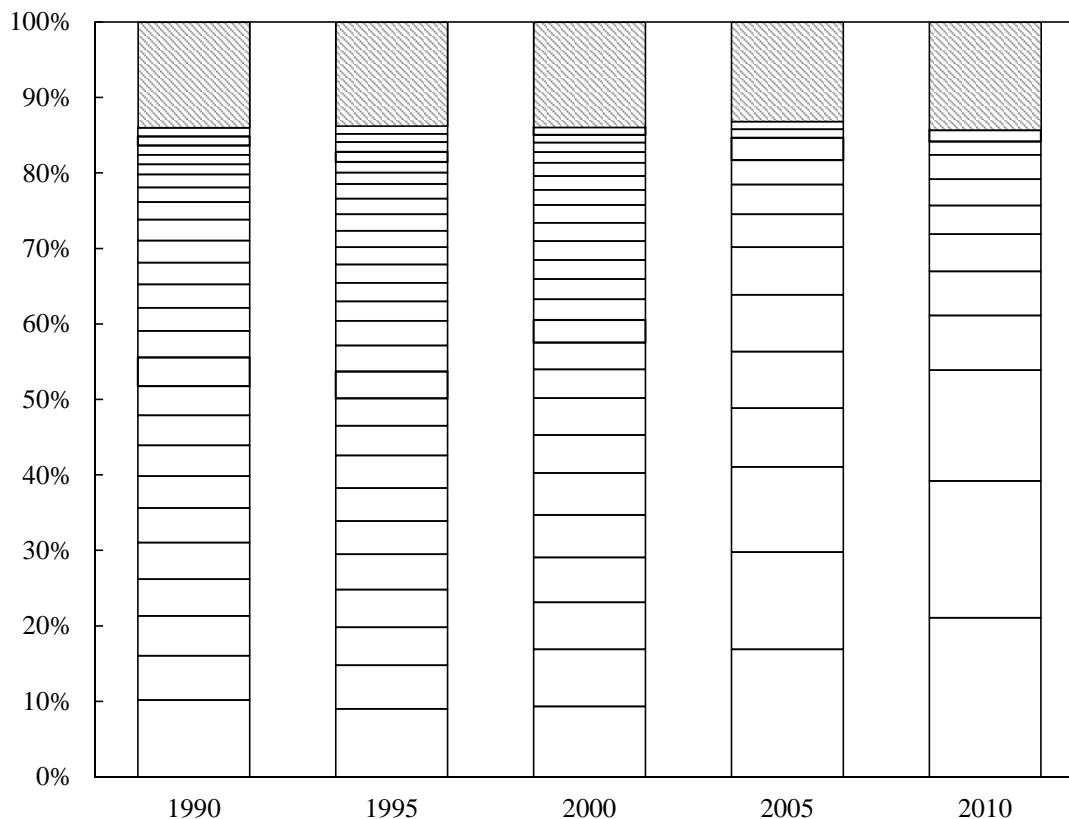
As the figure shows, Japanese finance has always been dominated by relatively few financial institutions. In FY1990, the three largest Japanese banks accounted for 23 percent of aggregate lending to listed companies, and this number rose to 54 percent in FY2010, with the largest financial institution, Mitsubishi UFJ Financial Group (MUFG), accounting for 21 percent of all Japanese lending.[10] The concentration in lending in the world's second largest economy at the time provides the basic motivation for our suggestion that bank shocks might have macroeconomic implications. If

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[10]As Amel et al. (2004) show, the growth in merger activity in Japan's banking and insurance industry was quite similar to that in other industrial countries. The increase in concentration in Japanese finance between FY2000 and FY2010 was driven by deregulating laws related to the formation of holding companies in 1997 and, as Sakuragawa and Watanabe (2009) argue, the 2002 "Takenaka Plan," which forced more disclosure of nonperforming loans (resulting in mergers of weak institutions).

banks are large relative to the size of the economy, idiosyncratic shocks to particular institutions could move macro aggregates if firms have difficulty substituting between different sources of finance.

Interestingly, Japan's high levels of concentration do not make the country an outlier. For example, in the U.S., most major lenders are bank holding companies, which in 2010 jointly accounted for 79 percent of all assets held by commercial banks, thrifts, and credit unions.[11] Federal Reserve data indicate that the three largest institutions in the U.S.—Bank of America, JP Morgan, and Citigroup—held 49 percent of all banking assets.[12] This number is remarkably close to the 54 percent number in our Japanese sample. Similarly, Buch and Neugebauer (2011) calculate bank Herfindahl indexes for many western European countries that are similar to those we obtain for Japan. Therefore, any observed large impact from bank shocks in Japan cannot be attributed to a more concentrated banking sector than in other countries. Rather, the high degree of financial market concentration appears to be a feature of many developed countries.

4   Estimating the Bank Shocks

Before turning to our main results on the impact of bank shocks on investment, we explore in this section the unique features of our methodology and conduct some external validation tests of our bank shock estimates to ensure that our point estimates are reasonable. The following three sections explore the properties of our bank shock estimates. We first examine the efficiency gains associated with imposing the adding-up constraints instead of using standard fixed-effects estimates. Next, we explore the external validity of our estimates by checking that they are correlated with conventional measures of bank shocks. Finally, we run some checks to make sure that the granular bank shock term is determined by idiosyncratic bank supply movements of large institutions.

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[11]Federal Financial Institutions Examination Council (2011) *Annual Report 2010*, March 31.

[12]The bank asset numbers come from the Bank Holding Company Performance Reports, which are available on the National Information Center website:

(http://www.ffiec.gov/nicpubweb/content/BHCPRRPT/BHCPR_Peer.htm).

4.1   The Importance of Adding-Up Constraints

We have argued that simply using fixed effects to estimate equation 1 is not efficient because that procedure ignores the adding-up constraints. However, the question of how important is this inefficiency remains. We can quantify this by first estimating equation 1 using fixed effects in order to obtain predicted values of loan growth to each client firm, $\hat{D}_{fbt}$ and then use these predicted values to generate estimates of bank lending growth as follows:

$$\hat{D}_{bt}^B \equiv \sum_f \frac{L_{fb,t-1}}{\sum_f L_{fb,t-1}} \hat{D}_{fbt}. \tag{8}$$

We then can see how well the fixed-effects procedure works by comparing a bank's actual loan growth, D_{bt}^B (obtained from equation 2) with $\hat{D}_{bt}^B$.

The results from this exercise suggest that using fixed effects to identify the bank-lending channel does not provide us with estimates that are highly correlated with actual lending patterns. If we regress the bank's actual loan growth, D_{bt}^B on $\hat{D}_{bt}^B$, we obtain an R^2 of only 0.08. By contrast, if we implement our methodology, which imposes the adding-up constraints given in equations 2 and 3, the R^2 is one by construction. We plot these data in Figure 5 to show that this result is not driven by a particular institution. In other words, the inefficiency of estimating the unconstrained fixed-effects model is so severe that it hardly explains any of the aggregate bank lending growth.

One potential explanation for this result is that we estimate the fixed-effects model with the dependent variable in percentage changes instead of log changes. A log change specification reduces outliers by forcing the econometrician to exclude observations where loans to a firm fall to zero. However, replacing the dependent variable with the log change in loans does not do much to improve the fit of equation 1—the R^2 rises to 0.25, which still leaves most of aggregate bank lending unexplained. Alternatively, one might be able to improve the fit by weighting the data by the size of the loan, $L_{fb,t-1}$, in order to take into account the possibility that the growth rates of large loans might be more informative about a bank's lending than the growth rate of small loans. However, using a log specification and this weighting structure only raises the R^2 to 0.36. Thus, the difficulty of identifying what is happening at the bank from individual loan information is not easily solved by using a log specification or weighting the regression.

Figure 5: Predicted Bank Loan Growth Using Fixed Effects vs. Actual
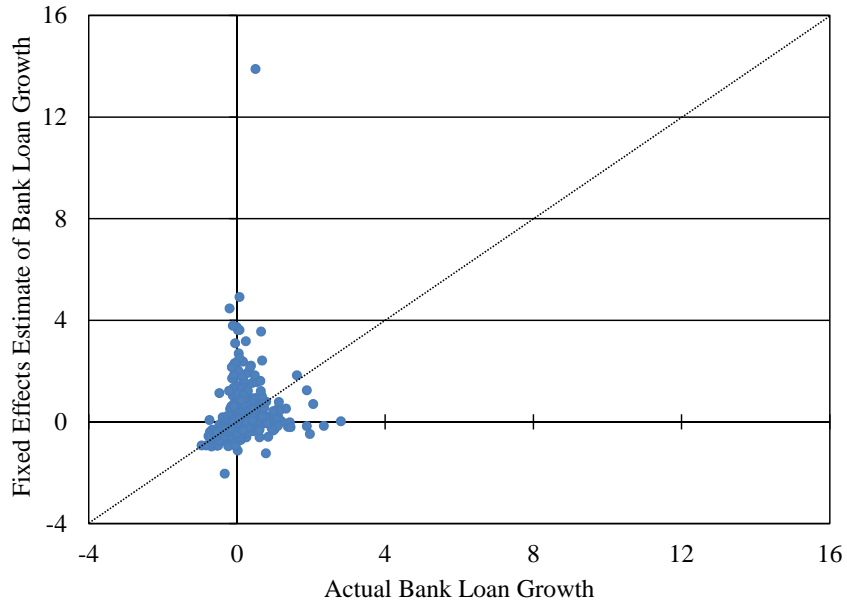
4.2 Estimating Firm-Borrowing and Bank Shocks

In Figure 6, we plot the median absolute value of the estimated firm and bank shocks, $\tilde{\alpha}_{ft}$ and $\tilde{\beta}_{bt}$, that form the elements of $\tilde{\boldsymbol{A}_t}$ and $\tilde{\boldsymbol{B}_t}$ in equation 6. The graph indicates substantial heterogeneity in the loan supply shocks of individual banks and the borrowing shocks experienced by firms. The figure suggests that the typical firm's borrowing shocks tend to fluctuate by ten to fifteen percent each year. There is an upward trend in the volatility of the firm shocks which may reflect the fact that capital market liberalizations enabled more small firms to become listed over this time period and these small firms may have been more volatile. Fluctuations in the bank supply channel are typically around 8 percent each year, which is about 30 percent smaller than the typical shock to firms.

4.3 External Validity of Bank Shock Estimates

While our methodology generates estimates that match aggregate data by construction, we also would like some reassurance that they make sense. One way to evaluate how reasonable our estimates are is to look at their values in situations where we have a strong prior for what they should be. We pursue this in three ways. First, we

Figure 6: Median Absolute Values of Bank and Firm-Borrowing Shocks
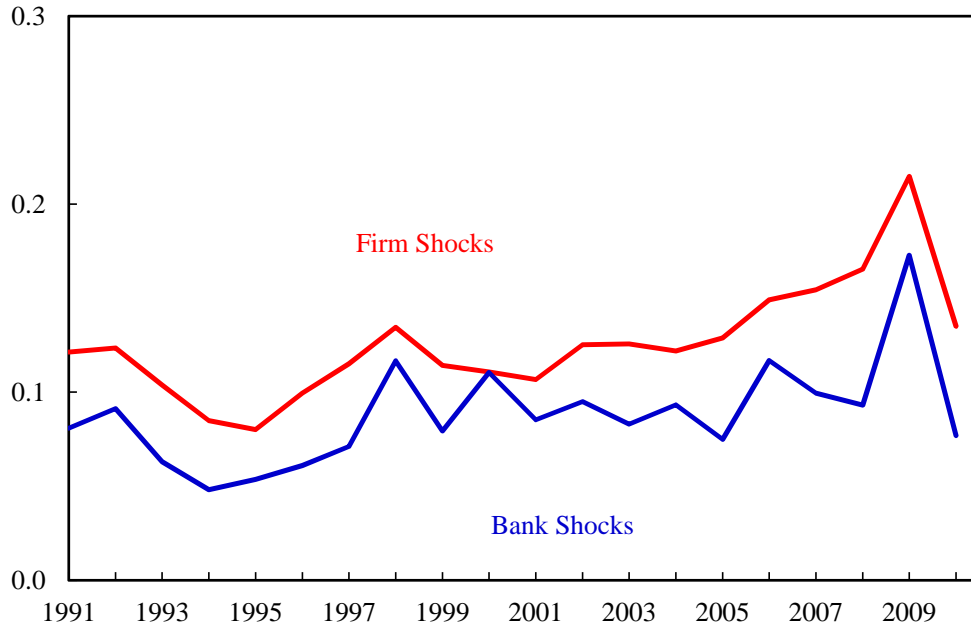
Notes: These are the median absolute values of the firm-borrowing shocks, removing the common and industry-specific component; and bank shocks, removing the common component, in each year. Years refer to fiscal years, which roughly correspond to the calendar year plus one.

look at extreme events. In particular, we examine the failures of financial institutions and see what types of shocks we estimate in the last year of their existence, and we look at extreme values and examine what happened to the institution immediately prior to them. Second, in order to provide systematic evidence for the validity of our bank shock estimates, we examine whether they are consistent with proxy measures of bank shocks used in prior studies. Finally, we show that the individual bank shocks are independent of aggregate shocks and that granular bank shocks are principally driven by shocks to large firms. We consider each in turn.

4.3.1 Extreme Events

We have a strong intuition that financial institutions dramatically curtail lending when they are on the verge of failure. This result is clearly apparent in the bank-shock measures. Financial institutions that entered bankruptcy, as opposed to merging or receiving capital injections when financially stressed, had a mean and median bank

shock in the year of their failure of -9 percent. Some of the major institutions that failed had even larger negative shocks. For example, we estimate Long-Term Credit Bank (at the time, the ninth largest bank in the world) and Nippon Credit Bank had bank shocks of -22 percent and -34 percent, respectively, in the years that they failed.

Another way of examining the plausibility of our estimates is to see what happened in the institutions with extreme bank shocks. Obviously, there are too many bank shocks to discuss each in detail, however, it is worthwhile examining the largest contributors to the granular bank shock. A financial institution's contribution to this channel is $w_{b,t-1}\tilde{\beta}_{bt}$ (see equation 7), which weights each bank's shock by its lagged share in lending. Thus, we looked for events that preceded the ten largest of these (in absolute value) to see if there were newsworthy events that plausibly could have caused them. It is interesting to note that all but one of these shocks represented lending contractions, which suggests that we should observe events that signaled either major mismanagement or some major piece of bad news shortly before most of the shocks. Fortunately, examples of these were easy to find.

Our estimates indicate that some of the largest bank-supply shocks to hit the Japanese economy occurred in 2008 and were experienced by Nippon Life, Sumitomo Life Insurance Co., Meiji Yasuda Life Insurance Co., and Dai-ichi Mutual Life Insurance Co. The timing of these shocks hardly appears coincidental—these shocks immediately followed the announcement of a widely reported investigation by the Japanese Financial Services Agency (FSA) that found that these four leading insurance companies had illegally denied ¥40 billion worth of benefits and payments in 700,000 cases.[13] This scandal forced the insurers to implement what they referred to as "drastic reforms."[14] Another insurance company, Dai-Ichi Mutual Life Insurance in 2006, was also responsible for one of the largest shocks, which occurred following a revelation that a computer error had resulted in the insurer failing to pay out dividends to 47,000 policyholders between 1984 and 2005.[15]

Bank holding companies were also major contributors to the top ten bank shocks. The negative shock in Japan's largest financial group Mitsubishi-UFJ in 2005 immediately followed what was a stormy merger between Japan's second and fourth largest banks. In the final stages of the merger negotiations, the Financial Services

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[13] *The Japan Times.* "Insurance Scandal Toll to Exceed ¥40 billion," September 30, 2007.

[14] http://www.nissay.co.jp/english/news/pdf/20070919_1.pdf

[15] "Dai-ichi Life failed to pay 115 million yen," *The Japan Times,* June 25, 2006

Agency charged one of the merger parties with obstructing FSA inspections by concealing documents that showed UFJ's nonperforming loan situation was worse than had been disclosed. This revelation on top of UFJ's losses of 403 billion yen the year before resulted in the FSA issuing UFJ four business improvement orders in the middle of the merger.[16] To make matters worse, Mitsubishi was forced to pay more money for UFJ than it had initially anticipated because Sumitomo Mitsui Financial Group attempted to disrupt the takeover by initiating its own hostile takeover bid.[17]

Mizuho Holdings, which started out as the world's largest bank in terms of assets, also appears to have major idiosyncratic impacts on the supply of credit in the years 2002, 2003, and 2005.[18] The events preceding these negative shocks were marked by enormous stresses placed on the bank. In late 2001, tighter reporting standards forced Mizuho to acknowledge twice the level of nonperforming loans that it had earlier revealed, which contributed to a 63 percent drop in its share price.[19] In 2002, Mizuho's share prices fell another 64 percent following a computer glitch that caused the bank's ATM system to collapse, rejecting millions of transactions and double-charging some of its customers. And in early 2003, Mizuho announced, according to *The New York Times,* that it was going to post "the biggest loss in Japanese corporate history."[20] The final shock in 2005 followed one of the most spectacular idiosyncratic errors in the history of finance: a trader at Mizuho intended to sell one share at ￥610,000 but mistyped the order and accidentally sold 610,000 shares at ￥1![21]

Finally, the tenth largest bank shock affecting Japan differed from the the other shocks in that it was positive. We estimate that the magnitude of Industrial Bank of Japan's positive shock raised aggregate Japanese lending 1.3 percent in 1999. Once again, this was a remarkable year for the bank following tremendous positive news for

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[16]Uranaka, Taiga. *The Japan Times.* "Misconduct, Bad Fortunes Hit: Investors Vent Spleen on Execs at UFJ Holdings, June 26, 2004.

[17]Zaun, Todd. "A Bank Takeover in Japan Breaks Tradition," *The New York Times.* August 25, 2004.

[18]Belson, Ken. "Mizuho Holdings Projects Biggest Loss Ever in Japan," *The New York Times,* January 21, 2003.

[19]"World Business Briefing | Asia: Japan: Bad Loans Reportedly Rising," *The New York Times,* November 8, 2001.

[20]Belson, Ken. "Mizuho Holdings Projects Biggest Loss Ever in Japan," *The New York Times,* January 21, 2003.

[21]"Botched stock trade costs Japan firm $225M,"
http://www.nbcnews.com/id/10394551/#.Ub9VMRZ1W5Q.

the institution. For much of the postwar period, Japanese regulations protected long-term credit banks from competition in the long-term lending market, but deregulation eliminated this protected status, resulting in the failures of every long-term credit bank except IBJ in the financial crisis of 1997–8. The troubled IBJ was only able to survive the crisis after receiving a large capital injection in 1998. It is hardly surprising that the year after receiving a large capital injection, the bank could once again begin lending more aggressively.

The point of these examples is that the major bank shocks that we estimate were typically preceded by major idiosyncratic events that could not easily be characterized as aggregate shocks. The results of FSA investigations into illegal activities, computer programming errors, capital injections, and rogue traders rocked major Japanese financial institutions. Moreover, the fact that our estimated extreme shocks followed these events, which really were some of the most memorable events in modern Japanese financial history, suggests that we are correctly identifying factors that moved financial institution's loan supply.

4.3.2 Consistency with Prior Research

This sort of validation is based on a small sample and hard to use as a general test of validity. Fortunately, much of the existing empirical literature analyzing bank channels is explicitly or implicitly based on the structure contained in equations 1 and 2, which lets us test whether our bank shock measures are significantly correlated with the proxy variables used in prior studies.[22] In other words, we can test whether our bank-shock estimates are in line with their hypotheses about what moves the bank-lending channel.

In order to see the link, we need to draw out the relationship between our framework and that in some previous studies. Since the econometrician does not observe β_{bt} and α_{ft}, prior studies have typically identified the bank channel by identifying a proxy variable, z_{bt}, which is assumed to be correlated with the bank channel, β_{bt}, but not with α_{ft} or ϵ_{fbt} in equation 1 in order to estimate $\Delta \ln L_{fbt} = \gamma z_{bt} + \alpha_{ft} + \epsilon_{fbt}$ or $D_{bt}^B = \gamma z_{bt} + \sum_f \phi_{fb,t-1} \alpha_{ft} + \sum_f \phi_{fb,t-1} \epsilon_{fbt}$. In both cases, the coefficient of interest is $\gamma = cov\left(z_{bt}, \beta_{bt}\right)/var\left(z_{bt}\right)$, and authors conclude that bank shocks matter if $\gamma \neq 0$. Although this method does not allow for the identification of β_{bt}, existing empirical papers tell us how much particular proxy variables (e.g., capital adequacy

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[22]For example, Chava and Purnanandam (2011) is explicitly based on equation 1.

ratios, market-to-book values, government credit supply, etc.) matter for lending, but the use of proxy variables may not tell us about the many other types of bank shocks—arising from revelations of illegal activities, good or bad management, computer errors, etc.—that could also matter for lending. Nevertheless, if our identification strategy is correct, bank shocks in our data should be correlated with the proxy variables proposed in other studies. To put this more concretely, since we have estimates of β_{bt} and can observe the proxy variables, we can estimate γ and test whether it has the predicted sign.

One of the most common proxy variables is the risk-based capital ratio (*cf.* Peek and Rosengren (1997, 2000, 2005) and Amiti and Weinstein (2011)). These authors argue that, in the aftermath of the bursting of the Japanese land and stock bubbles, banks with low levels of capital adequacy were forced to cut back on lending. In other words, these studies are based on the idea that $corr\left(\beta_{bt}, RCR_{bt}\right) > 0$, where RCR_{bt} denotes the risk-based capital ratio of a bank. Similarly, Montgomery and Shimizutani (2009) have argued that the capital injections implemented between 1997 and 1999 should have caused bank lending to rise in recipient banks (because they had more capital) and therefore should be positively correlated with bank shocks. In other words, their study is based on the assumption that $corr\left(\beta_{bt}, CapitalInjection_{bt}\right) > 0$. Finally, several of these studies have also argued that deteriorations in a bank's market-to-book value in a crisis, ΔMTB_{bt-1}, should lead to lower bank lending, and thus $corr\left(\beta_{bt}, \Delta MTB_{bt-1}\right) > 0$.

In Table 1, we examine each of these correlations using roughly the same time periods as the earlier papers. It is reassuring to see that our estimated bank shocks are correlated with proxy variables in just the way that previous authors have suggested: risk-based capital ratios, capital injections, and changes in market-to-book values are all positively correlated with our bank-supply shock measures. Thus, we can formally reject the hypothesis that our estimates of movements in the bank lending channel are uncorrelated with actual movements.

However, it is important to also realize that, while prior work was limited to tracing out the impacts of shocks that can be tied to these proxy variables, our methodology enables us to examine the magnitude and impacts of *all* bank-supply shocks.

Table 1: Validation of Bank-Supply Shocks

Dependent Variable: Bank Shock$_{b,t}$	(1)	(2)	(3)
Risk-Based Capital Ratio$_{b,t}$	0.015***		
	(0.004)		
Capital Injection$_{b,t}$		0.085***	
		(0.019)	
Δ ln(Market-to-Book Value$_{b,t-1}$)			0.075**
			(0.032)
Year Fixed Effects	Yes	Yes	Yes
Observations	657	405	843
R^2	0.037	0.030	0.012

Notes: The risk-based capital ratio in Column 1 is the combined Tier 1 and Tier 2 risk-based capital conforming to the Basel II agreement. These data are from Peek and Rosengren (2005). In Column 2, the regressor is a dummy variable equal to 1 if bank b received a capital injection in year t as in Montgomery and Shimizutani (2009). In Column 3, the market-to-book value is computed as the average of the monthly share price multiplied by the number of shares outstanding and divided by the book value of its equity. We take the 12-month log difference of this variable. We drop the top and bottom one percentiles for bank-supply shocks and log differences of market-to-book value. These data were taken from Nikkei and from the Pacific Basin Capital Markets database. Robust standard errors in parentheses. ***p<0.01, **p<0.05,*p<0.1.

4.3.3 Granular Bank Shocks and Aggregate Lending

One potential cause for concern about the granular bank shock is that instead of reflecting idiosyncratic shocks experienced by large financial institutions, it may just represent a simple correlation between large bank shocks and aggregate lending. For example, if the lending behavior of all large institutions mimics aggregate lending, we might think we are observing idiosyncratic shocks of large institutions—because the large lenders differ from the small ones—but really all we are observing is the fact that the lending behavior of a few large banks tracks aggregate lending.

We can formally test this conjecture by examining whether large bank shocks are independent of aggregate lending movements. We do this by splitting the sample into two groups, with one composed of data only from the banks that were among the

ten largest lenders in any year and the other comprising all of the other banks. We
then regress $\tilde{\beta}_{bt}$ for each subgroup on aggregate lending growth, D_t, to see whether
aggregate loan growth provides information about what we identified as bank-supply
shocks in particular institutions. In neither subsample did we obtain a significant
coefficient, which suggests that what we term bank-supply shocks are actually un-
correlated with aggregate loan growth.[23] Of course, this doesn't mean that there is
no link between the two variables—indeed, equation 7 provides the formula for the
link—but simply that one cannot reject the hypothesis that bank shocks, themselves,
and aggregate loan movements are statistically independent, and this is true even for
the largest institutions.

It also is instructive to demonstrate that the granular bank shocks are driven by
the behavior of the largest institutions and not by the (potentially highly-correlated)
shocks of smaller lenders. We demonstrate this by first regressing a granular bank
shock computed by only including the $\tilde{\beta}_{bt}$'s for the ten largest banks in that year on
the total granular bank shock. The slope coefficient from this regression is 0.81 (with
a standard error of 0.03), which indicates that the 10 largest banks accounted for 81
percent of the movement in the granular bank shock. Running the same regression
with a granular bank shocks computed using all banks except those in the top ten
produced a coefficient of 0.19—the coefficients must sum to one—which demonstrates
that smaller institutions account for a small role in the movement of granular bank
shocks.

5   Main Results

5.1   Bank-Supply Shocks and Firm-Level Investment

Having established the plausibility of our estimates of bank shocks, we now turn to
assessing whether these shocks matter for investment. Prior work in this area has
not had a firm-specific, time-varying measure of credit constraints and therefore has
focused on whether the cash-flow sensitivity of investment for some classes of firms
differs from that of others. As we have argued earlier, a major advantage of our
approach is that we have estimates of time-varying firm-borrowing and bank supply

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[23]The coefficient in the regression of bank shocks on aggregate lending was -0.10 with a standard
error of 0.11 in the sample of large banks and 0.01 with a standard error of 0.08 in the sample of
smaller banks.

changes. Moreover, equation A10 provides us with a way of decomposing each firm's loan growth into firm-borrowing shocks, bank-supply shocks, industry shocks, and common shocks. The fact that not all firms borrow from all banks means that if loans from different banks are not good substitutes, a bank-supply shock from one bank will have a bigger impact on a firm's investment if it is more dependent on that bank than if it is not. To put it concretely, we use equation 5 to define the aggregate bank-supply shock hitting a particular firm as

$$BankShock_{ft} = \sum_b \theta_{fbt-1} \tilde{\beta}_{bt}. \tag{9}$$

Table 2 presents our findings. In the first column of Table 2, we estimate a standard I/K regression on cash flow and the market-to-book value in which we also control for firm fixed effects and year fixed effects to sweep out any factors related to our sample of firms or correlations between firm-level investment and any common time-varying shock to the investment rate. Not surprisingly, we find the standard result that there is an association between a firm's investment and its cash flow and market-to-book value. In Column 2, we add in our industry shock variable to see if the variation in investment-to-capital ratios of a given firm is also associated with the typical change in firm-borrowing shocks within an industry. We find a positive and significant coefficient on the industry-borrowing shocks, which implies that many of the investment opportunities faced by individual firms are not economy-wide but are specific to firms in a particular industry. These might be exchange rate movements that affect firms in export sectors differently from those in other sectors, or any of a host of possible variables that matter at the industry level. The most interesting results, however, are those reported in Columns 3, 4, and 5 of Table 2, where we add our firm and bank shock variables to the specification. Since the firms in our sample are all listed nonfinancial firms that have access to both equity and bond markets, it makes sense to consider the impact of a firm-borrowing or bank-supply shock as having a different impact on a firm that borrows a lot from banks to finance its investment relative to a firm that finances investment through other means. In other words, a given bank shock is likely to have a much larger impact on the investment rate of a firm that finances, say, 80 percent of its capital through bank loans than on a firm that finances only 1 percent of its capital from loans. Therefore, in addition to including the firm and bank shocks in the specification, we also include their interaction with

Table 2: Firm-Level Investment

Dependent Variable: Investment$_{f,t}$/Capital$_{f,t-1}$	(1)	(2)	(3)	(4)	(5)
Cash Flow$_{f,t}$/Capital$_{f,t-1}$	0.048***	0.047***	0.047***	0.047***	0.048***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Market-to-Book Value$_{f,t-1}$	0.011***	0.011***	0.011***	0.011***	0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Bank Shock$_{f,t}$			-0.151***	-0.149***	-0.110**
			(0.044)	(0.048)	(0.044)
(Bank Shock$_{f,t}$)* (Mean Loan-to-Asset Ratio$_f$)			0.732***	0.730***	0.809***
			(0.192)	(0.192)	(0.190)
(Bank Shock$_{f,t}$)* (Mean Bond-to-Asset Ratio$_f$)				-0.040	
				(0.420)	
Firm Shock$_{f,t}$					0.013**
					(0.006)
(Firm Shock$_{f,t}$)* (Mean Loan-to-Asset Ratio$_f$)					0.245***
					(0.038)
Industry Shock$_{f,t}$			0.070***	0.069***	0.069***	0.067***
			(0.017)	(0.018)	(0.018)	(0.018)
Fixed Effects					
Year	yes	yes	yes	yes	yes
Firm	yes	yes	yes	yes	yes
Observations	21,701	21,701	21,701	21,701	21,701
R^2	0.307	0.307	0.308	0.308	0.323

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. We drop the top and bottom one percentiles of each variable. The mean loan-to-asset ratio is defined for each firm as its average ratio of loans to assets over the sample period. The mean bond-to-asset ration is similarly defined.

the firm's mean loan-to-asset ratio over the sample period.[24] Column 3 of Table 2 shows that the coefficient on the bank shock entering alone is negative and significant while that on the interaction term is positive and significant, indicating that loan-dependent firms' investments are affected by bank shocks. Interestingly, we find that negative bank shocks exert a positive impact on the investment of firms that do not rely much on loans for their financing needs, which may reflect the fact that firms that don't rely much on loans for finance actually benefit relative to other firms when credit conditions tighten.[25]

One concern about these results is that firms with access to forms of capital other than loans may be less susceptible to bank-supply shocks. To some extent we have already corrected for this by noting that the effect of bank-supply shocks is most keenly felt by firms that are, on average, larger borrowers. However, it might be the case that firms that also raise a lot of financing from bond markets are less susceptible to bank-supply shocks. In Column 4, we interact the bank shocks with the firm's mean bond-to-asset ratio to see if firms that rely more on bond financing have less sensitivity to bank shocks. If this were the case, one would expect to see a negative coefficient on the bond interaction term. The fact that we do not find a significant coefficient on the bond interaction term suggests that the firm's loan share is the critical determinant of a bank shock on a firm's investment. While access to the bond market might serve to lower the importance of loans as a source of finance, conditional on a given loan share of financing, we obtain equally strong estimates of the impact of bank-supply shocks on firms with and without high levels of bond finance.

Adding firm-borrowing shocks in Column 5 hardly affects the coefficients on the bank shocks. The positive coefficient on the firm shock interacted with the mean loan-to-asset ratio implies a strong association between firm-borrowing shocks and investment for firms that are highly loan dependent, but not for firms that do not finance much of their capital expenditures through loans. The positive association almost surely arises because, in equilibrium, factors that raise a firm's marginal product of capital also raise its demand for borrowing. However, whether we control for this factor or not does not affect the strong relationship between bank shocks and

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[24]We cannot include the mean loan-to-asset ratio independently because we are already using firm fixed effects.

[25]This result is a feature of the model in Buera, Fattal-Jaef, and Shin (2013).

firm-level investment.

The findings in the baseline specification in Column 5 of Table 2 imply a positive relationship between bank shocks and investment for firms with loan-to-asset ratios above 0.14 (around 60 percent of firms in our sample). Meanwhile, for firms below the 0.14 threshold there is either no relationship or, if anything, a negative relationship between bank shocks and investment.

These results therefore tend to bridge the gap between studies using matched bank-firm data and extreme events that find a strong relationship between bank shocks and real economic activity (e.g., Klein, Peek, and Rosengren (2002), Amiti and Weinstein (2011), Chodorow-Reich (2013)) and those that suggest firms can circumvent these shocks by accessing bond and other markets (e.g., Adrian, Colla, and Shin (2012)). Our results intuitively indicate that bank shocks matter for firms that are heavily dependent on loans, but less so for firms that are not dependent on loans. One implication of these findings is that loan-dependent firms cannot easily substitute towards other funding sources when the banks they rely on for financing cut back on their lending supply.

5.2 Robustness

5.2.1 Lagged Firm Shocks and Sample Periods

These results are robust to a number of alternative specifications. One concern might be that past firm-level shocks might be driving current bank shocks. In order to verify that this is not driving our results, in Column 1 of Table 3 we include lagged firm shocks and find that its coefficient is close to zero and its inclusion hardly affects the other coefficients. In Column 2, we include only the bank shock terms and the industry effects to see if the exclusion of all potentially endogenous variables affects the results. We find that the coefficients are almost the same.

Similarly, one might wonder if our results are driven only by crisis years. We therefore reran our regressions excluding the major financial crisis years (FY1991, FY1993, FY1998, and FY2009) to see if the results are robust to dropping these years.[26] The results reported in Column 3 indicate that the point estimates are

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[26] The first years are the same as those dropped in Amiti and Weinstein (2011) because they correspond to the year of the initial bursting of the Japanese stock market bubble, the year when the *jusen* (housing finance companies) began failing, and the year when the first major banks began failing. The last crisis year corresponds to the first year of the more recent financial crisis.

Table 3: Firm-Level Investment Robustness

Dependent Variable: Investment$_{f,t}$/Capital$_{f,t-1}$	(1) Full Sample	(2) Full Sample	(3) Crisis Years Excluded	(4) 1991-2000	(5) 2001-2010	(6) Full Sample
Cash Flow$_{f,t}$/Capital$_{f,t-1}$	0.045***		0.044***	0.164***	0.042***	0.047***
	(0.007)		(0.007)	(0.016)	(0.008)	(0.006)
Market-to-Book Value$_{f,t-1}$	0.013***		0.013***	0.009***	0.014***	0.012***
	(0.002)		(0.002)	(0.003)	(0.003)	(0.002)
Bank Shock$_{f,t}$	-0.112**	-0.148***	-0.114**	-0.086	-0.058	-0.099**
	(0.046)	(0.045)	(0.051)	(0.075)	(0.061)	(0.040)
(Bank Shock$_{f,t}$)* (Mean Loan-to-Asset Ratio$_f$)	0.760***	0.692***	0.902***	0.886***	0.624**	0.629***
	(0.203)	(0.192)	(0.209)	(0.298)	(0.260)	(0.170)
Firm Shock$_{f,t}$	0.015**		0.019***	-0.002	0.017**	0.014**
	(0.006)		(0.006)	(0.008)	(0.007)	(0.005)
Firm Shock$_{f,t-1}$	0.008***					
	(0.003)					
(Firm Shock$_{f,t}$)* (Mean Loan-to-Asset Ratio$_f$)	0.246***		0.192***	0.388***	0.227***	0.240***
	(0.041)		(0.042)	(0.072)	(0.047)	(0.038)
Industry Shock$_{f,t}$	0.075***	0.082***	0.088***	0.097***	0.050**	0.063***
	(0.021)	(0.017)	(0.021)	(0.026)	(0.022)	(0.017)
Fixed Effects						
Year	yes	yes	yes	yes	yes	yes
Firm	yes	yes	yes	yes	yes	yes
Observations	18,656	21,701	17,897	9,595	12,106	21,684
R^2	0.307	0.291	0.320	0.391	0.378	0.321

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Column (3) drops crisis years (1991, 1993, 1998, 2009). Column (4) uses a restricted sample from 1991-2000, and Column (5) uses a sample restricted to 2001-2010. We drop the top and bottom one percentiles of all the variables. Column (6) uses an alternative formulation of the bank shock in which we allow the same bank to supply credit differently to healthy and unhealthy firms. Distressed firms are defined as in Hoshi, Kashyap, and Scharfstein (1990) as firms with net interest payments above operating income in years t and t-1, but not in year t-2. The results are similar if we define distressed as just having operating income below net interest payments in the previous year.

hardly affected. Finally, in Columns 4 and 5, we divide the sample into two halves (FY1991–FY2000 and FY2001–FY2010) to see if the coefficients differ between the early years, when bank failures were frequent, and the later years. We find that bank shocks are significant determinants of investment in both periods and that the point estimates do not change significantly in the subsamples. Because we obtain our results for two non-overlapping subsamples, we can be confident that no single event or year is driving our results.

5.2.2 Differential Shocks to Healthy and Unhealthy Firms

A number of papers (e.g. Peek and Rosengren (2005) and Jimenez et al. (2011)) have found that weak banks not only lend less but lend relatively less to healthy firms in times of trouble, a practice known as "evergreening". Although this is not the main focus of our paper, we can also check if our results are robust to allowing banks to pass along their shocks more to healthy firms than to unhealthy ones. A simple way to nest the insights of these papers into our framework is to postulate that a bank's supply shock differs depending on whether the client is healthy or not. We follow Hoshi, Kashyap, and Scharfstein (1990) in defining unhealthy firms as previously healthy firms whose interest payments exceed their operating income for two consecutive years.

If we split our sample according to whether the firms are healthy or not, we can obtain different estimates of $\tilde{\beta}_{bt}$ for healthy firms and unhealthy ones. In order to keep the notation simple, let $\tilde{\beta}_{bt}^H$ be the bank shock we obtain using loan data for healthy firms and $\tilde{\beta}_{bt}^U$ to be the bank shock we obtain when we only include the unhealthy firms. Define L_{bt}^H and L_{bt}^U to be bank b's total lending to healthy and unhealthy firms, respectively. We now can define the overall bank shock to be

$$\bar{\beta}_{bt} \equiv \frac{L_{b,t-1}^H \tilde{\beta}_{bt}^H + L_{b,t-1}^U \tilde{\beta}_{bt}^U}{L_{b,t-1}^H + L_{b,t-1}^U}. \tag{10}$$

If we believe that evergreening causes unhealthy banks to lend more to unhealthy firms, then we should expect that $\tilde{\beta}_{bt}^U > \tilde{\beta}_{bt}^H$ when $\bar{\beta}_{bt} < 0$. This is, in fact, exactly what we find in the data. The mean value of $\tilde{\beta}_{bt}^U - \tilde{\beta}_{bt}^H$ for unhealthy banks is 0.058 (s.e. 0.11), indicating that troubled banks lent six percent more to unhealthy firms than healthy firms after controlling for their loan demand.[27] Interestingly, we also find

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[27]Because our bank shocks were estimated off a smaller sample (especially for the unhealthy firms), we had more outliers in our estimates. Therefore, we trimmed the top and bottom 5% of values of

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that healthy banks, i.e. those institutions with positive overall bank shocks lent 5.1 percent *less* to unhealthy firms (s.d. 1.2 percent), confirming the findings of Peek and Rosengren (2005) that the provision of more credit to unhealthy firms is something that unhealthy banks do, but healthy banks actually readjust their lending portfolios away from their worst clients.

Of course, our main concern is not whether we can use our methodology to replicate the results of other papers, but whether allowing banks to have different lending policies for healthy and unhealthy firms affects our main result. In order to do this, we redefined our bank shock variable to be $\sum_b \theta_{fbt-1} \tilde{\beta}_{bt}^h$, where $h = U$ if the firm is unhealthy and $h = H$ if the firm is healthy. This enables us to allow a bank's shock to vary depending on both the health of the bank and the health of the borrower. We report the result of using this regression in the last column of Table 3. The coefficient on the bank shock terms are not significantly different than those in our main specification, which indicates that our assumption that all of a bank's borrowers receive a common bank shock is not driving our results.

5.3   Bank Shocks and Aggregate Lending and Investment

As already noted, a key feature of our methodology is that our bank-shock estimates can be aggregated and applied to macro data. The lending data in our sample of firms account for only around 17 percent of total lending in Japan in an average year. However, our methodology allows us to identify a pure bank-supply shock that is independent of the borrowers. If these financial institutions were all small, then they would cancel at the aggregate level; however, as we have seen, financial institutions are large relative to the size of even the largest countries. The starting point for thinking about the aggregate impact is to realize that if we were to regress the left-hand side of equation 7 on each of the right-hand side terms, we would obtain coefficients of one on each term since the equation is an identity.

However, this need not be the case if we replace the dependent variable with economy-wide aggregate loan growth from the flow-of-funds data. In this case, we can write the relationship between the percentage change in aggregate lending and the percentage change in lending to listed companies as $D_t^{FOF} = \boldsymbol{W_{B,t-1}} \boldsymbol{D_{Bt}} + \epsilon_t$, or

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$\tilde{\beta}_{bt}^U$ and $\tilde{\beta}_{bt}^H$ before computing the mean.

$$D_t^{FOF} = \delta + \gamma_1 \left(\bar{A}_t + \bar{B}_t \right) + \gamma_2 \boldsymbol{W_{B,t-1}} \boldsymbol{\Phi_{t-1}} \boldsymbol{N_t} + \gamma_3 \boldsymbol{W_{B,t-1}} \boldsymbol{\Phi_{t-1}} \tilde{\boldsymbol{A}}_t + \gamma_4 \boldsymbol{W_{B,t-1}} \tilde{\boldsymbol{B}}_t + \epsilon_t.$$

(11)

If we estimate equation 11, we will only obtain coefficients of one on each term if each of the terms we measured using the Nikkei data equaled the terms for the whole economy and the error term is uncorrelated with any of the explanatory variables. Measurement error or economy-wide variables that moved more or less than the corresponding variables in the Nikkei data could cause the coefficients to differ from one. Moreover, to the extent that one thought that economy-wide lending behavior and loans to listed companies were uncorrelated, one might expect to see a low R^2 from estimating equation 11. Finally, even if we were to obtain coefficients equal to one using flow-of-funds data, it could be the case that bank shocks are sufficiently small that we obtain much smaller regression coefficients when executing a regression on standardized variables because a one-standard-deviation movement in granular bank supply might have a very small impact on aggregate lending. In other words, we can interpret the coefficients on each of these terms as the contribution of each variable to the flow-of-funds lending growth, while the error term corresponds to deviations in aggregate loan growth from loan growth for listed companies. Our interest is not in causality here, but in trying to understand how important the terms we identified in equation 7 are in determining aggregate loan fluctuations.

In Table 4, we regress aggregate lending growth from the flow-of-funds data on the various components of lending growth that we identified from the Nikkei matched bank-firm data. As one can see in the first two columns of the table, aggregate lending can only be well explained if we include the granular bank shocks.[28] Interestingly, while common, industry, and granular bank shocks have coefficients close to one in Column 3, the granular firm shock is attenuated, perhaps because while we have all of the large banks in our sample, we do not have large unlisted firms, and hence there is more measurement error in the granular firm shock variable.

Movements in aggregate lending are closely correlated with the forces we identified in the Nikkei sample. When we include all regressors in the sample, the R^2 is 0.8, suggesting that most of what drives aggregate commercial lending is explainable by the factors we identified in the Nikkei sample. Moreover, the coefficients on the

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[28]Alternatively, we could merge together the effects of the industry and firm shocks. This does not qualitatively affect the coefficients on the bank shock variable.

Table 4: Aggregate Effects

Dependent Variable:	Percentage Change in Flow of Funds$_t$			Investment$_t$/Capital$_{t-1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Common Shock$_t$	0.492*	1.212***	1.196***	0.206**	0.475***	1.274**
	(0.261)	(0.182)	(0.180)	(0.094)	(0.113)	(0.303)
Industry Shock$_t$	0.513	1.391***	0.595***	-0.117	0.211	0.246
	(0.329)	(0.275)	(0.118)	(0.183)	(0.192)	(0.223)
Firm Shock$_t$	0.215	0.318**	0.257**	-0.037	0.001	0.003
	(0.145)	(0.144)	(0.117)	(0.079)	(0.060)	(0.132)
Bank Shock$_t$		1.170***	1.042***		0.437***	1.057**
		(0.232)	(0.207)		(0.124)	(0.300)
Constant	-0.018*	-0.003	0.000	0.076***	0.081***	0.000
	(0.009)	(0.006)	(0.118)	(0.004)	(0.004)	(0.144)
Standardized Variables	No	No	Yes	No	No	Yes
Observations	20	20	20	20	20	20
R^2	0.420	0.782	0.782	0.303	0.675	0.675

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. All variables, including percentage change in the FOF and aggregate investment, are standardized in (3) and (6) with a mean of 0 and a standard deviation of 1. The sample is for the 1991-2010 period.

common shock, industry shock, and granular bank shock in Column 2 are statistically indistinguishable from one, which is the value that would obtain if these variables had been computed using data from all Japanese lending pairs. In other words, the data do not reject the hypothesis that the common, industry, and granular bank shocks identified in the Nikkei data are the same as those we would find in economy-wide data.

However, our main interest is in understanding the importance of the granular bank shock term. One metric of its importance is to consider how much of the variance in aggregate lending it explains. Comparing columns 1 and 2, we see that adding the granular bank shock term raises the R^2 of the regression by 0.36, indicating that bank shocks account for about 40 percent of the variance in aggregate lending. The fact that the granular bank shock term is highly significant and moves the R^2 of the

regression substantially strongly suggests that the idiosyncratic lending decisions of large financial institutions have a large impact on aggregate lending. In Column 3 of Table 4, we run a standardized regression in order to examine the relative importance of movements in the granular bank shock for understanding aggregate movements. Not surprisingly, we get a coefficient indistinguishable from one on the common shock term, indicating that a one-standard-deviation increase in lending observed in the Nikkei data is associated with a one standard-deviation-increase in lending in Japan. However, what is most surprising is the importance of the granular bank shock term: a one-standard-deviation movement in this term is also associated with a one-standard-deviation movement in *aggregate* lending. This indicates that aggregate loan supply is also highly sensitive to bank shocks. In an economy composed of small financial institutions, this term would likely be zero, but the fact that it is so large implies that much of aggregate lending is explainable by the loan supply movements of large institutions.

We have seen that the variation in the granular bank shock is an important component of aggregate lending volatility. We now turn to understanding the impact of bank shocks on aggregate investment activity in columns 4 through 6. Our results from the previous sections have already established exogeneity of the bank shocks, a strong relationship between firm-level investment and bank shocks, and that aggregate lending is tightly linked to granular loan shocks. Our next question is whether these granular bank shocks cause movements in aggregate investment. By construction, any common shock to a firm's investment demand will be captured in our common shock term; therefore, the granular bank shocks cannot be caused by these common shocks.

The granular bank shock term in Column 5 of Table 4 is strongly significant and raises the R^2 of the regression from 0.3 to 0.7, which indicates that these bank shocks also account for 40 percent of the fluctuations in aggregate investment. In terms of economic significance, we see in Column 6 of Table 4, where we run a standardized regression, that a one-standard-deviation movement in the granular bank shock moves the aggregate investment-to-capital ratio by one standard deviation—about as much as common shocks.

The importance of this result can be considered in comparison with those in Table 2. In that table, we learned that bank shocks matter for a firm's investment relative to the investment of other firms but that does not necessarily imply that these bank

shocks mattered overall. The results in Table 4 provide a way of answering the question of whether these same bank shocks matter at the aggregate level because we can isolate the granular bank shock from the common shocks affecting investment. Since we control for the firm-borrowing shocks when estimating the bank shocks, the granular bank shocks are macro variables that are not determined by fluctuations in borrower demand. The fact that they matter so much for investment suggests that the strong, causal link between loan supply and firm-level investment that we identified in Tables 2 and 3 matters at the aggregate level as well.

6 Conclusion

In this paper, we are the first to show that bank-supply shocks have large effects on firm-level and aggregate investment. We do this by developing a new methodology that enables us to estimate these effects using a fixed-effects approach that exploits general equilibrium adding-up constraints. This new methodology increases efficiency enormously compared to a standard fixed-effect estimation by producing estimates that can match macro aggregates, thus enabling us to not only estimate firm-level impacts but also to identify the aggregate effects.

We estimate time-varying bank shocks, firm-borrowing shocks, industry shocks, and common shocks using matched firm-bank loan data for Japan between 1990 and 2010. This decomposition enables us to establish a causal relationship between bank-supply shocks and firm-level investment for those firms that are loan dependent. We find that bank supply shocks are significant determinants of firm-level investment. This result is particularly surprising because our sample is comprised of listed companies that have, by definition, access to equity markets. Most importantly, we show that bank-supply shocks have large effects on firm-level and economy-wide investment.

The fact that banks are large even relative to the largest economies is at the heart of the underlying mechanism for these results. The bank data in most industrial countries show that the distribution of banks is highly skewed with a small number of large banks accounting for a large share of aggregate lending. For example, in Japan the three largest banks account for a 45 percent share of total banking assets.[29] Because there is "granularity" in the banking data, the law of large numbers does not apply, rendering firms vulnerable to the fates of individual banks. Indeed, we show

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[29]http://research.stlouisfed.org/fred2/series/DDOI01JPA156NWDB

that the bank shocks account for 40 percent of the variation in Japanese aggregate lending and 40 percent of the variation in aggregate investment.

There are a number of implications from this study. First, our results imply that it is difficult for firms to substitute between loan sources. Although the median number of bank loans per firm is eight in our sample, shocks to large banks still have significant effects on these firms' investment. Second, the fates of large financial institutions are an important determinant of investment and real economic activity. Although our study has relied on Japanese data, the key elements of the banking system that underlie these results are also prevalent in other industrialized countries, thus making it likely they would also be present in other countries. Analyzing the importance of bank shocks in other countries is potentially a fertile area for future research.

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Appendix A: Derivation of Equation 6

1.1 Identifying the Bank and Firm Shocks

Because we know that the loan shares must sum to one, i.e., $\sum_b \theta_{fbt} = 1$ and $\sum_f \phi_{fbt} = 1$, it must be the case that for any set of β_{bt}'s and α_{ft}'s that satisfy equations 4 and 5, $\beta_{bt} + k_t$ and $\alpha_{ft} - k_t$ must also be a solution. This means that we need to choose a *numéraire* in order to find a solution, and so we will impose that $\alpha_{1t} = 0$ (or equivalently $k_t = \alpha_{1t}$). This initial choice of *numéraire* is for mathematical convenience only as we renormalize the data in Section 1.2 relative to the median, and our results are unaffected by which firm we initially choose.

All shocks are defined as relative to this shock. Without loss of generality, we can rewrite equation 5 as

$$
\begin{aligned}
D_{ft}^F &\equiv \alpha_{ft} + \sum_b \theta_{fb,t-1} \left(\beta_{bt} - \beta_{1t} \right) + \beta_{1t} \\
&= \alpha_{ft} + \sum_{b \neq 1} \theta_{fb,t-1} \left(\beta_{bt} - \beta_{1t} \right) + \beta_{1t}.
\end{aligned} \tag{A1}
$$

Similarly, we can rewrite equation 4 as

$$
D_{bt}^B = \beta_{bt} + \sum_{f \neq 1} \phi_{fb,t-1} \alpha_{ft}. \tag{A2}
$$

Finally, for firm 1, we have

$$
D_{1t}^F = \sum_{b \neq 1} \theta_{1b,t-1} \left(\beta_{bt} - \beta_{1t} \right) + \beta_{1t} \tag{A3}
$$

or

$$
\beta_{1t} = D_{1t}^F - \sum_{b \neq 1} \theta_{1b,t-1} \left(\beta_{bt} - \beta_{1t} \right), \tag{A4}
$$

and for bank 1, we have

$$
D_{1t}^B = \beta_{1t} + \sum_{f \neq 1} \phi_{f1,t-1} \alpha_{ft}. \tag{A5}
$$

If we substitute equation A4 into equation A1, we obtain

$$
D_{ft}^F - D_{1t}^F = \left(\alpha_{ft} - \alpha_{1t} \right) + \sum_{b \neq 1} \left(\theta_{fb,t-1} - \theta_{1b,t-1} \right) \left(\beta_{bt} - \beta_{1t} \right) = \alpha_{ft} + \sum_{b \neq 1} \hat{\theta}_{fb,t-1} \hat{\beta}_{bt}, \tag{A6}
$$

where $\hat{\theta}_{fbt} = \left(\theta_{fbt} - \theta_{1bt} \right)$, and $\hat{\beta}_{bt} = \left(\beta_{bt} - \beta_{1t} \right)$. Substituting equation A5 into equation A2 gives us

$$D_{bt}^B - D_{1t}^B = (\beta_{bt} - \beta_{1t}) + \sum_{f \neq 1} (\phi_{fb,t-1} - \phi_{f1,t-1}) \alpha_{ft} = \hat{\beta}_{bt} + \sum_{f \neq 1} \hat{\phi}_{fb,t-1} \alpha_{ft}, \quad \text{(A7)}$$

where $\hat{\phi}_{fbt} = (\phi_{fbt} - \phi_{f1t})$.

For every year, equations A6 and A7 comprise a system of $F + B - 2$ equations and $F + B - 2$ unknowns, where F denotes the number of firms and B denotes the number of banks. *In other words, the moment conditions uniquely determine the bank and firm shocks up to the choice of numéraire.* To see this, we use some matrix algebra. We begin with a few definitions:

$$\hat{\boldsymbol{A}}_{\boldsymbol{t}} \equiv \begin{pmatrix} \alpha_{2t} \\ \vdots \\ \alpha_{Ft} \end{pmatrix}, \hat{\boldsymbol{B}}_{\boldsymbol{t}} \equiv \begin{pmatrix} \hat{\beta}_{2t} \\ \vdots \\ \hat{\beta}_{Bt} \end{pmatrix}, \hat{\boldsymbol{D}}_{\boldsymbol{Ft}} \equiv \begin{pmatrix} D_{2t}^F - D_{1t}^F \\ \vdots \\ D_{Ft}^F - D_{1t}^F \end{pmatrix}, \hat{\boldsymbol{D}}_{\boldsymbol{Bt}} \equiv \begin{pmatrix} D_{2t}^B - D_{1t}^B \\ \vdots \\ D_{Bt}^B - D_{1t}^B \end{pmatrix}$$

$$\hat{\boldsymbol{\Theta}}_{\boldsymbol{t}} \equiv \begin{pmatrix} \hat{\theta}_{22t} & \dots & \hat{\theta}_{2Bt} \\ \vdots & \ddots & \vdots \\ \hat{\theta}_{F2t} & \dots & \hat{\theta}_{FBt} \end{pmatrix}, \hat{\boldsymbol{\Phi}}_{\boldsymbol{t}} \equiv \begin{pmatrix} \hat{\phi}_{22t} & \dots & \hat{\phi}_{F2t} \\ \vdots & \ddots & \vdots \\ \hat{\phi}_{2Bt} & \dots & \hat{\phi}_{FBt} \end{pmatrix}$$

We now can rewrite equation A6 as

$$\hat{\boldsymbol{A}}_{\boldsymbol{t}} = \hat{\boldsymbol{D}}_{\boldsymbol{Ft}} - \hat{\boldsymbol{\Theta}}_{\boldsymbol{t-1}} \hat{\boldsymbol{B}}_{\boldsymbol{t}} \quad \text{(A8)}$$

and equation A7 as

$$\hat{\boldsymbol{B}}_{\boldsymbol{t}} = \hat{\boldsymbol{D}}_{\boldsymbol{Bt}} - \hat{\boldsymbol{\Phi}}_{\boldsymbol{t-1}} \hat{\boldsymbol{A}}_{\boldsymbol{t}}. \quad \text{(A9)}$$

If we use this fact and insert equation A8 into equation A9, we know that any solution to equations 5 and A9 must satisfy

$$\hat{\boldsymbol{B}}_{\boldsymbol{t}} = \hat{\boldsymbol{D}}_{\boldsymbol{Bt}} - \hat{\boldsymbol{\Phi}}_{\boldsymbol{t-1}} \left[\hat{\boldsymbol{D}}_{\boldsymbol{Ft}} - \hat{\boldsymbol{\Theta}}_{\boldsymbol{t-1}} \hat{\boldsymbol{B}}_{\boldsymbol{t}} \right].$$

This equation can be rewritten as

$$\left(\boldsymbol{I}_{\boldsymbol{B-1}} - \hat{\boldsymbol{\Phi}}_{\boldsymbol{t-1}} \hat{\boldsymbol{\Theta}}_{\boldsymbol{t-1}} \right) \hat{\boldsymbol{B}}_{\boldsymbol{t}} = \hat{\boldsymbol{D}}_{\boldsymbol{Bt}} - \hat{\boldsymbol{\Phi}}_{\boldsymbol{t-1}} \hat{\boldsymbol{D}}_{\boldsymbol{Ft}},$$

where $\boldsymbol{I}_{\boldsymbol{B-1}}$ is a $(B - 1) \times (B - 1)$ identity matrix. We can solve for $\boldsymbol{A}_{\boldsymbol{t}}$ and $\boldsymbol{B}_{\boldsymbol{t}}$ by inverting $(\boldsymbol{I}_{\boldsymbol{B}} - \boldsymbol{\Phi}_{\boldsymbol{t-1}} \boldsymbol{\Theta}_{\boldsymbol{t-1}})$ to yield[30]

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[30]One important assumption we make is that $(\boldsymbol{I}_{\boldsymbol{B}} - \boldsymbol{\Phi}_{\boldsymbol{t-1}} \boldsymbol{\Theta}_{\boldsymbol{t-1}})$ is invertible. This condition would be violated if, say, one firm only borrowed from one bank, and the bank had no other lending relationships. More generally, we cannot have a subset of firms borrow from a subset of banks, and this subset of banks not lend to any firms outside of this subset of firms. In practice, this condition is satisfied in the data.

$$\hat{\boldsymbol{B}}_t = \left(\boldsymbol{I}_{B-1} - \hat{\boldsymbol{\Phi}}_{t-1}\hat{\boldsymbol{\Theta}}_{t-1}\right)^{-1}\left(\hat{\boldsymbol{D}}_{Bt} - \hat{\boldsymbol{\Phi}}_{t-1}\hat{\boldsymbol{D}}_{Ft}\right)$$

and

$$\hat{\boldsymbol{A}}_t = \hat{\boldsymbol{D}}_{Ft} - \hat{\boldsymbol{\Theta}}_{t-1}\left(\boldsymbol{I}_{B-1} - \hat{\boldsymbol{\Phi}}_{t-1}\hat{\boldsymbol{\Theta}}_{t-1}\right)^{-1}\left(\hat{\boldsymbol{D}}_{Bt} - \hat{\boldsymbol{\Phi}}_{t-1}\hat{\boldsymbol{D}}_{Ft}\right).$$

We then can compute β_{1t} according to the following formula:

$$\beta_{1t} = D_{1t}^B - \sum_{f\neq 1}\phi_{f1,t-1}\alpha_{ft}.$$

1.2   Decomposing the Shocks

We now turn to using our parameter estimates to show how we can decompose aggregate lending growth into bank, firm, industry, and common shocks. Our choice of *numéraire* was necessary for solving the system, but it is not economically meaningful and has the unappealing property of expressing each shock relative to an arbitrary firm shock. In order to eliminate this problem, we will renormalize the system by expressing each shock relative to the median firm or bank shock. Specifically, we define the common firm shock, $\bar{A}_t$, as the median firm shock, and the common financial shock as the median bank shock, $\bar{B}_t$. We next define the firm-borrowing shock as the difference between the actual shocks and the median shock, i.e., $\dot{\boldsymbol{A}}_t \equiv \boldsymbol{A}_t - \bar{A}_t\boldsymbol{1}_F$, and similarly the financial institution loan shock as $\dot{\boldsymbol{B}}_t \equiv \boldsymbol{B}_t - \bar{B}_t\boldsymbol{1}_B$, where

$$\boldsymbol{A}_t \equiv \begin{pmatrix} \alpha_{1t} \\ \vdots \\ \alpha_{Ft} \end{pmatrix}, \boldsymbol{B}_t \equiv \begin{pmatrix} \beta_{1t} \\ \vdots \\ \beta_{Bt} \end{pmatrix}.$$

It will also be useful to define

$$\boldsymbol{D}_{Ft} \equiv \begin{pmatrix} D_{1t}^F \\ \vdots \\ D_{Ft}^F \end{pmatrix}, \boldsymbol{D}_{Bt} \equiv \begin{pmatrix} D_{1t}^B \\ \vdots \\ D_{bt}^B \end{pmatrix}, \boldsymbol{\Theta}_t \equiv \begin{pmatrix} \theta_{11t} & \dots & \theta_{1Bt} \\ \vdots & \ddots & \vdots \\ \theta_{F1t} & \dots & \theta_{FBt} \end{pmatrix}, \boldsymbol{\Phi}_t \equiv \begin{pmatrix} \phi_{11t} & \dots & \phi_{F1t} \\ \vdots & \ddots & \vdots \\ \phi_{1Bt} & \dots & \phi_{FBt} \end{pmatrix}.$$

We can rewrite the system of equations given

$$\begin{aligned} \boldsymbol{D}_{Ft} &= \boldsymbol{A}_t + \boldsymbol{\Theta}_{t-1}\boldsymbol{B}_t \\ &= \dot{\boldsymbol{A}}_t + \bar{A}_t\boldsymbol{1}_F + \boldsymbol{\Theta}_{t-1}\dot{\boldsymbol{B}}_t + \bar{B}_t\boldsymbol{\Theta}_{t-1}\boldsymbol{1}_B \end{aligned}$$

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$$= \dot{\boldsymbol{A}}_t + \boldsymbol{\Theta}_{t-1}\dot{\boldsymbol{B}}_t + \left(\bar{A}_t + \bar{B}_t\right)\boldsymbol{1_F}, \tag{A10}$$

where we move from the second line to the third by making use of the fact that the borrowing shares from each financial institution must sum to one.

Just as we can decompose firm borrowing into these three shocks, we can also decompose bank lending into a similar set of three elements. In particular, one can rewrite equation 4 as

$$\begin{aligned}
\boldsymbol{D_{Bt}} &= \dot{\boldsymbol{B}}_t + \boldsymbol{\Phi}_{t-1}\dot{\boldsymbol{A}}_t + \left(\bar{B}_t\boldsymbol{1_B} + \boldsymbol{\Phi}_{t-1}\bar{A}_t\boldsymbol{1_F}\right) \\
&= \dot{\boldsymbol{B}}_t + \boldsymbol{\Phi}_{t-1}\dot{\boldsymbol{A}}_t + \left(\bar{A}_t + \bar{B}_t\right)\boldsymbol{1_B}.
\end{aligned} \tag{A11}$$

We now turn to isolating the industry shocks. We define the firm shock as $\tilde{\boldsymbol{A}}_t \equiv \dot{\boldsymbol{A}}_t - median_{f\in n}(\dot{\boldsymbol{A}}_t)$, where n denotes the industry the firm is in. Similarly, we define the bank shock as $\tilde{\boldsymbol{B}}_t \equiv \dot{\boldsymbol{B}}_t - median(\dot{\boldsymbol{B}}_t) = \dot{\boldsymbol{B}}_t$ since $median(\dot{\boldsymbol{B}}_t) = 0$. Finally, we can define the vector of industry-level medians as $\boldsymbol{N_t}$; then we can rewrite firm and bank decompositions as

$$\boldsymbol{D_{Ft}} = \tilde{\boldsymbol{A}}_t + \boldsymbol{N_t} + \boldsymbol{\Theta}_{t-1}\tilde{\boldsymbol{B}}_t + \left(\bar{A}_t + \bar{B}_t\right)\boldsymbol{1_F}, \tag{A12}$$

and

$$\boldsymbol{D_{Bt}} = \tilde{\boldsymbol{B}}_t + \boldsymbol{\Phi}_{t-1}\tilde{\boldsymbol{A}}_t + \boldsymbol{\Phi}_{t-1}\boldsymbol{N_t} + \left(\bar{A}_t + \bar{B}_t\right)\boldsymbol{1_B}. \tag{A13}$$

Appendix B: Summary Statistics

By Year	Mean	Median	SD	Minimum	Maximum
Percent change in Flow-of-Funds$_t$	-0.022	-0.029	0.047	-0.094	0.085
Investment$_t$/Capital$_{t-1}$	0.073	0.069	0.017	0.055	0.121
Common Shock$_t$	-0.010	-0.010	0.047	-0.142	0.066
By Bank					
Bank Shock$_{b,t}$	0.010	0.000	0.182	-0.548	0.934
Capital Injection$_{b,t}$	0.096	0.000	0.295	0.000	1.000
Risk-Based Capital Ratio$_{b,t}$	8.796	9.120	1.766	2.820	13.610
$\Delta \ln$(Market-to-Book Value$_{b,t-1}$)	-0.099	-0.107	0.225	-0.684	0.572
By Firm					
Investment$_{f,t}$/Capital$_{f,t-1}$	0.118	0.080	0.167	-0.398	1.745
Cash-Flow$_{f,t}$/Capital$_{f,t-1}$	0.335	0.209	0.719	-1.569	15.410
Market-to-Book Value$_{f,t}$	1.696	1.295	1.377	0.234	10.367
Bank Shock$_{f,t}$	-0.011	-0.012	0.051	-0.173	0.151
Firm Shock$_{f,t}$	0.059	0.000	0.393	-0.760	3.252
Industry Shock$_{f,t}$	0.003	0.002	0.077	-0.658	2.492
Mean Loan-to-Asset Ratio$_f$	0.196	0.174	0.123	0.001	0.748
Mean Bond-to-Asset Ratio$_f$	0.048	0.029	0.057	0.000	0.359

Notes: The variables are defined as follows. By year: Percent change in Flow of Funds$_t$ is the year-on-year percent change in the stock of lending from private financial institutions to private nonfinancial corporations. Investment$_t$/Capital$_{t-1}$ is the total national investment in year t divided by the total capital stock in year $t-1$, both measured in 2000 yen. Common Shock$_t$ is the sum of the median firm shock and the median bank shock in each year. By bank: Bank Shock$_{b,t}$ is the idiosyncratic bank shock for each bank. Capital Injection$_{b,t}$ is a binary variable equal to 1 if bank b received a capital injection in year t. Risk-Based Capital Ratio$_{b,t}$ is the combined Tier 1 and Tier 2 risk-based capital according to the Basel II agreement. $\Delta \ln$(Market-to-Book Value$_{b,t-1}$) is the lagged year-on-year log change in the market-to-book value, computed as the average of the monthly share price multiplied by the number of shares outstanding and divided by the book value of each firm's equity. By firm: Investment$_{f,t}$/Capital$_{f,t-1}$ is the sum of each firm's year-on-year change in tangible fixed assets plus depreciation divided by that firm's tangible fixed assets in year $t-1$. Cash Flow$_{f,t}$/Capital$_{f,t-1}$ is firm f's ordinary income plus depreciation divided by tangible fixed assets in year $t-1$. Market-to-Book Value$_{f,t}$ is the market value of each firm divided by its shareholder equity. Bank Shock$_{f,t}$ is a weighted sum of the idiosyncratic bank shocks for all banks from which firm f was receiving a loan in year $t-1$. Firm Shock$_{f,t}$ is the idiosyncratic shock for each firm in each year. Industry Shock$_{f,t}$ is the industry level shock for the industry of which firm f is a member. Mean Loan-to-Asset Ratio$_f$ is firm f's mean ratio of total loans to total assets over the sample period. Mean Bond-to-Asset Ratio$_f$ is firm f's mean ratio of total bonds to total assets.