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 methodology to separate firm credit shocks from loan 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 as in Gabaix (2011). As a result, idiosyncratic bank shocks - i.e. movements in bank loan supply net of borrower characteristics and general credit conditions - can have large impacts on aggregate loan supply and investment. We show that these idiosyncratic bank shocks explain 40 percent of aggregate loan and investment fluctuations.

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1 Introduction

Since the work of Bernanke and Gertler (1989), a large empirical literature has developed examining how the financial accelerator and credit crunches can affect real economic activity. While there have been several studies offering compelling bank-level evidence that bank shocks matter for loan supply and certain types of foreign investment (c.f. 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 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 bridges this gap by providing the first estimate of how much financial institution shocks matter for overall firm-level and aggregate investment rates, thereby establishing that creditor shocks are an important determinant of both firm-level and aggregate investment.

This paper makes use of a comprehensive, matched lender-borrower dataset covering all loans received from all sources by every listed Japanese firm over the period 1990 to 2010. The data contains the values of total short and long-term lending from hundreds of financial institutions to thousands of listed firms: 272,302 loans in total. We use these data to develop a new methodology that enables us to provide the first direct estimates of borrower credit and lender supply shocks. A key feature of our methodology is that we do not need to rely on proxy variables that are correlated with borrower and lender shocks and therefore can identify the shocks directly from the data. These lender supply shocks measure idiosyncratic movements of loan supply at the financial institution level that cannot be explained by common credit shocks hitting all financial institutions or even movements in credit demand by the financial institutions' borrowers. Thus, we show that they capture the impact of idiosyncratic events such as bankruptcies, capital injections, and other factors that affect one or more institutions but cannot be understood as common to all institutions or even institutions with similar lending portfolios. We then exploit the heterogeneity in the sources of firm financing to identify firm-specific, time-varying loan supply shocks hitting firms to

demonstrate that firms that borrow heavily have investment rates that are very sensitive to loan supply shocks in the financial institutions that supply them with credit. Moreover, we show that these loan supply channels are not only important determinants of investment in financial crisis years, but in non-crisis years as well.

Armed with these idiosyncratic loan supply shocks estimated from micro data, we then develop a theoretically sound aggregation method that enables us to apply these estimates to national accounts data. Our approach builds on Gabaix's (2011) methodology to develop a method for estimating "granular" loan supply shocks, which measure the aggregate loan supply movements that arise from the idiosyncratic credit supply shocks of large lenders. We use these granular shocks to measure how important the idiosyncratic 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. Interestingly, firm-level credit demand shocks seem much less important, suggesting that much of the fluctuation in aggregate lending and investment reflects time-varying industry shocks coupled with idiosyncratic loan supply shocks.

Finally, we show that one can also estimate how the dramatic rise in concentration in Japanese finance, which mirrors the rise in other countries, has affected the variance of these granular loan supply shocks. One might expect that the rise in financial market concentration has produced a rise in the variance of granular loan supply shocks because the idiosyncratic loan activities of large financial institutions matter more. Surprisingly, we show that this intuition is not correct. While rising concentration is associated with a rise in the pure variance of idiosyncratic financial institution shocks, we also show that the covariance of idiosyncratic financial shocks between financial institutions has fallen dramatically over the last two decades in Japan. Since the covariance term dominates, the overall variance of granular financial shocks has fallen in Japan due to the fact that the current set of large financial institutions, while larger, tend not to covary as much with each other as earlier

financial institutions. This result counterintuitively indicates that rising financial market concentration is not associated with greater sensitivity to idiosyncratic loan shocks.

Our work is related to a number of previous studies. One important strand of literature is the set of papers (c.f. 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 asking 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.

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 to be more financially sensitive. For example, Gertler and Gilchrist (1994) found that small firms, who presumably are more constrained in their external finance options, and bank-dependent borrowers are more sensitive to monetary policy fluctuations. This 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. Similarly, results showing that industries that depend more on external finance or lending are the same industries that contract more during banking crises (e.g., Kashyap, Lamont and Stein (1994), Dell'Ariccia, Detragiache and Rajan 2008 and Chava and Purnanandam (2011)) do not link the contracting sectors or firms to the affected banks. Braun and Larrain (2005) have argued it is the sectors that are more dependent on external finance that are more cyclical, and this cyclicality may be particularly manifest during banking crises. Thus, it is difficult to know if there is a common factor that drives 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 exploited natural experiments, sometimes coupled with particular classes of borrowers, to demonstrate that credit 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), Amiti and Weinstein (2011) and Santos (2012) 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, but none of these papers address whether credit shocks affect the overall investment rates of borrowers from these institutions.

The fact that these studies have focused on either small firms or small wedges of the national economy has meant that even proponents of the possibility of lending supply mattering have often been quite circumspect. For example, although Ashcraft (2005) examined how the failure of healthy bank subsidiaries affected county level output in Texas and found a significant link, 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." Thus, a major outstanding question is whether credit crunches matter only for small firms and/or firms without access to other sources of capital, or whether it is a phenomenon with broader implications. 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 credit shocks matter for small but not large firms. Consistent with this work, we find evidence that lender supply shocks matter for loan dependent firms but not for firms that borrow little to finance their capital expenditures. However, we are also able to show that despite this heterogeneity in effect, these credit supply shocks matter in the aggregate.

Finally, our paper is also related to the work of Buch and Neugebauer (2011) who use aggregate bank loan data to construct granular bank residuals and regress them on cross-country GDP growth. However, our work differs from theirs in a number of respects. First, rather than ascribing idiosyncratic lending 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 loan supply shocks from firm credit shocks and time varying common and industry shocks. This eliminates any worry that an observed correlation between granular bank shocks and GDP arises 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 and bank credit 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 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 presents the results, and Section 5 concludes.

2 Empirical Strategy

Our econometric approach begins by specifying a fairly general empirical model that we then 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 financial institutions in our data comprise banks, insurance companies, and various components of holding companies.

2.1 Estimating Firm and Bank Shocks

We begin with some notation. 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 from institution b to firm f as

$$\Delta \ln L_{fbt} = \alpha_{ft} + \beta_{bt} + \epsilon_{fbt}, \tag{1}$$

where we can interpret α_{ft} as a firm loan credit shock , β_{bt} as a lender supply shock, and ϵ_{fbt} is an error term.

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 part of the firm credit shock, α_{ft}. Firm credit shocks can then be defined as firm-specific changes in lending that are orthogonal to what is happening at the lending institution. Thus, if all banks stop lending to a particular firm because it is seen as a poor credit risk, we will call that a firm credit shock because it reduces the amount of loans received by that firm from all banks. Similarly, the evergreening incentives observed by Peek and Rosengren (2005) in which banks systematically lent more to weaker firms would appear in α_{ft}. The lender supply shocks (β_{bt}), however, capture all factors that cause loan supply of an institution to change *irrespective* of the credit conditions of its borrowers. By construction, these shocks are orthogonal to borrower credit shocks. These might include difficulties that the lender might have in making loans due to the cost or availability of credit it faces or the increased ease it has in making loans due to a capital injection or regulatory change. Alternatively, if financially weak banks were to evergreen existing loans and therefore lend more, as in Peek and Rosengren (2005), that would appear in our setup as a positive bank loan supply shock. Thus, β_{bt} is a quite general measure of changes in loan supply due to a wide variety of causes.[1]

[1] One additional concern is that Peek and Rosengren (2005) find that troubled banks lend more to troubled

While one could estimate equation 1 using a large set of firm and bank fixed effects, in practice, this is extremely 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. Imposing these adding-up constraints is not possible without matched bank-firm data, but the availability of such data makes our task straightforward. We begin by noting that the growth in bank lending can be written as $D_{bt}^{B} \equiv \left(\ln \sum_f L_{fbt} - \ln \sum_f L_{fbt-1}\right)$. Our next task is to map changes in individual loan growth given by equation 1 into changes in aggregate bank lending. It is well-known that one can map disaggregated growth changes into aggregate growth changes extremely accurately by assuming a translog functional form. In this case, we can write aggregate bank loan growth as a Tornqvist index of the growth rates of loans to individual firms, i.e.

$$D_{bt}^{B} \approx \sum_f \phi_{fbt} \Delta \ln L_{fbt} \tag{2}$$

where

$$\phi_{fbt} \equiv \frac{1}{2}\left(\frac{L_{fbt}}{\sum_f L_{fbt}} + \frac{L_{fbt-1}}{\sum_f L_{fbt-1}}\right),$$

If we substitute equation 1 into equation 2, we obtain

firms. In our empirical setup, that would appear as a relationship between the error term and product of the explanatory variables. If we write I_{ft} as an indicator variable that is one if the loan is to firm f, and zero otherwise and I_{bt} as an indicator variable that is one if the loan is from bank b and zero otherwise, then a bias would only occur if I_{bt} were correlated with $I_{bt}I_{ft}$. Since I_{bt} and I_{ft} are uncorrelated, it is easy to show that I_{bt} must be uncorrlated with $I_{bt}I_{ft}$:

$$\begin{aligned} cov\left(I_{bt}, I_{bt}I_{ft}\right) &= E\left[I_{bt}^2 I_{ft}\right] - E\left[I_{bt}\right] E\left[I_{bt}I_{ft}\right] = E\left[I_{bt}^2\right] E\left[I_{ft}\right] - E\left[I_{bt}\right]^2 E\left[I_{ft}\right] = 0 \\ &= E\left[I_{bt}^2\right] E\left[I_{ft}\right] - E\left[I_{bt}\right]^2 E\left[I_{ft}\right] = 0 \end{aligned}$$

$$D_{bt}^{B} = \beta_{bt} + \sum_{f} \phi_{fbt}\alpha_{ft} + \sum_{f} \phi_{fbt}\epsilon_{fbt}. \tag{3}$$

Now that we have laid out our basic structure, we can consider how it compares with that of earlier studies. Much of the existing empirical literature analyzing bank channels is explicitly or implicitly based on the structure contained in equations 1 and 3.[2] Since the econometrician does not observe β_{bt} and α_{ft}, prior studies have typically resorted to finding a proxy variable, z_{bt}, which is assumed to be correlated with β_{bt} but not with α_{ft} or ϵ_{fbt} in order to estimate $\Delta \ln L_{fbt} = \gamma z_{bt} + \alpha_{ft} + \epsilon_{fbt}$ or $D_{bt}^{B} = \gamma z_{bt} + \sum_f \phi_{fbt}\alpha_{ft} + \sum_f \phi_{fbt}\epsilon_{fbt}$. 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 $\gamma \neq 0$. It is important to note, however, that this method does not allow for the identification of β_{bt}. Thus, the existing empirical papers tell us how much particular proxy variables (e.g. capital adequacy ratios, market-to-book values, government credit supply, etc.) matter for loan supply shocks, but not how much bank shocks matter in general. Clearly, in order to estimate the impact of bank loan supply shocks in general, we need to have estimates of β_{bt}.

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 using matched bank-firm data. In particular, since the expectation of a weighted average of a series of mean zero errors is also mean zero, we can impose the following moment condition on the data: $E\left[\sum_f \phi_{fbt}\epsilon_{fbt}\right] = 0$. This implies that we can choose our parameters such that in our data the following equation holds

$$D_{bt}^{B} = \beta_{bt} + \sum_{f} \phi_{fbt}\alpha_{ft}. \tag{4}$$

Our next task is to exploit the fact that not only do firm and bank shocks matter for lending, they also matter for borrowing. The key insight is that just as firm credit shocks and bank loan-supply shocks must aggregate to yield a bank's loan growth as specified in

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

equation 4, these same shocks must also aggregate to yield a *firm's* aggregate loan demand. Again, using the same translog aggregating structure, we have

$$D_{ft}^F \equiv \left(\ln \sum_b L_{fbt} - \ln \sum_b L_{fbt-1} \right) \approx \sum_b \theta_{fbt} \Delta \ln L_{fbt}, \tag{5}$$

where

$D_{ft}^F \equiv (\ln \sum_b L_{fbt} - \ln \sum_b L_{fbt-1})$

and

$$\theta_{fbt} \equiv \frac{1}{2} \left(\frac{L_{fbt}}{\sum_b L_{fbt}} + \frac{L_{fbt-1}}{\sum_b L_{fbt-1}} \right).$$

If we substitute equation 1 into equation 5, we obtain

$$D_{ft}^F = \alpha_{ft} + \sum_b \theta_{fbt} \beta_{bt} + \sum_b \theta_{fbt} \epsilon_{fbt}, \tag{6}$$

where we know that the $E\left[\sum_b \theta_{fbt} \epsilon_{fbt}\right] = 0$. We therefore will proceed by picking a set of α_{ft}'s and the β_{ft}'s that match this moment in the data. In particular, we choose our parameters to satisfy the following moment condition:

$$D_{ft}^F = \alpha_{ft} + \sum_b \theta_{fbt} \beta_{bt}. \tag{7}$$

As we show in Appendix A, it is possible to use these moment conditions to estimate the α's and β's and obtain a decomposition of each firm's aggregate borrowing and each bank's aggregate lending into four terms as in the equations below:

$$\boldsymbol{D_{Ft}} = \tilde{\boldsymbol{A}}_{\boldsymbol{t}} + \boldsymbol{N_t} + \boldsymbol{\Theta_t} \tilde{\boldsymbol{B}}_{\boldsymbol{t}} + \left(\bar{A}_t + \bar{B}_t \right) \boldsymbol{1_F} \tag{8}$$

$$\boldsymbol{D_{Bt}} = \tilde{\boldsymbol{B}}_{\boldsymbol{t}} + \boldsymbol{\Phi_t} \tilde{\boldsymbol{A}}_{\boldsymbol{t}} + \boldsymbol{\Phi_t} \boldsymbol{N_t} + \left(\bar{A}_t + \bar{B}_t \right) \boldsymbol{1_B}, \tag{9}$$

where $\boldsymbol{D_{Bt}}$ is a $B \times 1$ vector whose elements are each bank's total loan growth in year t,

$\boldsymbol{D_{Ft}}$ is a $F \times 1$ vector whose elements are each firm's total loan growth in year t, $\tilde{\boldsymbol{B}}_{\boldsymbol{t}}$ is a vector composed of each bank shock in year t less the median bank shock in in year t; $\boldsymbol{\Theta_t}$ and $\boldsymbol{\Phi_t}$ are matrices that contain as elements the weights of each loan to every borrower, i.e.

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

$\tilde{\boldsymbol{A}}_{\boldsymbol{t}}$ is a vector composed of each firm shock in year t less the median firm shock in that firm's industry in year t; $\boldsymbol{N_t}$ is a vector containing the median firm shock in the industry containing the firm; $\left(\bar{A}_t + \bar{B}_t\right)$ are the median firm and bank shocks in year t, which reflect any shocks that would affect all lending pairs identically in a year; and $\mathbf{1_B}$ and $\mathbf{1_F}$ are $B \times 1$ and $F \times 1$ vectors of 1's.[3]

The key feature of equation 9 is that one can decompose each bank's loan growth into four elements, which are easiest to understand by proceeding from right to left. The first term on the right measures changes in lending that are common to all lending pairs. We will refer to this as the "common shock" because it captures any force that would cause all lending to rise or fall (such as an interest rate change). The second term from the right is 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 towards borrowers in certain industries. We call this term the "industry shock" since it 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 from right as the "idiosyncratic firm shock" because it captures changes in a bank's lending that might arise because the bank's particular clients demanded higher or lower loan amounts after controlling for what was happening in their sectors and the economy as a whole. Finally, the first term on the left captures the idiosyncratic loan supply shock because it measures

[3]We could have defined the decompositions in equations 8 and 9 using the mean shock instead of the median. We decided to use the median because we thought it better to think of common shocks as those affecting the typical firm. Moreover, we also found that the average shock is more sensitive to extreme shocks hitting small firms and banks, and we wanted to reduce the impact of these outliers.

changes in bank loan supply that are independent of anything related to the firms, industries, or common shocks hitting the economy. We refer to this term as the "idiosyncratic bank shock".

Our next task is to understand the relative importance of idiosyncratic firm and financial institution shocks, as well as common shocks on fluctuations in aggregate lending. The problem we face is that while equation 9 decomposes log changes in bank lending into the appropriate shocks, one cannot aggregate them in such a way that aggregate lending can be exactly decomposed into bank, firm, industry, and common shocks. One solution is to again use a Tornqvist index to aggregate either the bank or firm loan changes to obtain the impact of each type of shock on aggregate output and rely on the property that it is a second order approximation of the log change.

More specifically, let w_{bt}^B be the average share of bank b in total lending in years t and $t-1$, and let w_{ft}^F be the average share of firm f in total borrowing in years t and $t-1$. Define $\boldsymbol{W_{Bt}} \equiv \left[w_{1t}^B, \cdots, w_{Bt}^B\right]$ and $\boldsymbol{W_{Ft}} \equiv \left[w_{1t}^F, \cdots, w_{Ft}^F\right]$. We can now use equation 9 to obtain

$$\boldsymbol{W_{Bt}D_{Bt}} = \boldsymbol{W_{Bt}\tilde{B}_t} + \boldsymbol{W_{Bt}\Phi_t\tilde{A}_t} + \boldsymbol{W_{Bt}\Phi_t N_t} + \left(\bar{A}_t + \bar{B}_t\right). \tag{10}$$

Equation 10 provides an extremely useful means of decomposing aggregate loan movements into their constituent parts. We will refer to the first term as the "granular bank shock" because it is a weighted average of all of the idiosyncratic financial institution shocks. As Gabaix (2011) has shown, if all institutions were sufficiently small or if their idiosyncratic shocks were sufficiently small, then one should expect this term to be small because on average these idiosyncratic shocks should cancel out. However, the fact that financial institutions are quite large means that this term can be large in the data. The second term is the "granular firm shock" because it measures the importance of idiosyncratic borrow shocks on aggregate lending. Again, this term will be small if borrower demand shocks are small or if the share of all borrowers tends to be small. The third term represents the granular industry shock because it captures the interaction between industry shocks and the size of the indus-

tries. The size of this term will depend on the degree of aggregation used and the variance of shocks within an industry. Finally, the last term captures the impact of common shocks on aggregate lending by measuring what happens to the lending of the typical bank-firm pair.

2.2 The Variance of the Granular Residual

We have already seen that Japan, like most developed countries, experienced a dramatic increase in lender concentration. This raises the question of whether this increase in concentration is likely to have also raised the volatility associated with the granular residual. On the one hand, it is possible to argue that increased financial market concentration is likely to increase loan volatility because a given shock to a larger institution will have a more substantial impact than a shock to a smaller one. On the other hand, it is often argued that large complex financial institutions are less volatile because they take advantage of economies of scale and scope to reduce the magnitude of their idiosyncratic shocks. Moreover, more sophisticated financial institutions might result in lower aggregate volatility because these institutions may pursue investment strategies that are less correlated with each other. This also could reduce the granular residual because the correlation between idiosyncratic shocks hitting large institutions might fall.

One of the difficulties in evaluating these different theories is that one must be able to isolate the amount of aggregate fluctuations driven by particular institutions. Fortunately, equation 10 provides a simple way of doing this. The first term in equation 10 is the impact of idiosyncratic financial shocks on aggregate lending. In other words, it tells us how much bank supply shocks alone contribute to aggregate loan volatility.

We now can move from understanding changes in loan supply to understanding the volatility of the granular bank shock. We can write the variance in idiosyncratic bank shocks in a moment in time as $Var\left(\boldsymbol{W_{Bt}}\tilde{\boldsymbol{B}}_{\boldsymbol{t}}\right)$. If we assume that each institution has an underlying variance of loan supply shocks, $\sigma_b^2 = Var\left(\tilde{\beta}_{bt}\right)$, then we can write

$$Var\left(\boldsymbol{W_{Bt}}\tilde{\boldsymbol{B}}_{\boldsymbol{t}}\right) \equiv \sigma_{Bt}^2 = \sum_b \left(w_{bt}^B\right)^2 \sigma_b^2 + \sum_{b \neq b'} w_{bt}^B w_{b't}^B \sigma_{bb'}, \tag{11}$$

where the first summation term tells us how much of the variance in the granular shock is due to the relative importance of the the variances of the idiosyncratic banks shocks of each of the institutions in existence in time t, and the second summation term tells how much of the variance in the granular residual is due to the covariance between the various financial institutions.

To get some intuition for this equation, it is worth noting that if the variances of all financial institution shocks are identical and independent, then we can rewrite equation 11 as

$$\sigma_{Bt}^2 = H_t \sigma^2, \tag{12}$$

where $H_t = \sum_b \left(w_{bt}^B\right)^2$ is a Herfindahl index of bank loans in time t, and σ^2 is the variance in idiosyncratic bank shocks. Equation 12 provides the math behind the intuition that a rise in bank concentration (as measured by the Herfindahl index) is likely to result in more aggregate volatility *provided the variance of all financial institutions is unchanged*. However, in order to understand whether the variance of the granular residual has risen due to these mergers, we need to also account for changes in the variances of the pre-merger and post-merger institutions. In order to do this, we first difference equation 11 to obtain

$$\Delta\sigma_{Bt}^2 = \left[\sum_b \left(w_{bt}^B\right)^2 \sigma_b^2 - \sum_b \left(w_{bt-1}^B\right)^2 \sigma_b^2\right] + \left[\sum_{b \neq b'} w_{bt}^B w_{b't}^B \sigma_{bb'} - \sum_{b \neq b'} w_{bt-1}^B w_{b't-1}^B \sigma_{bb'}\right]. \tag{13}$$

Equation 13 provides a decomposition of the variance of the granular bank shock due to changes in concentration. The first term in square brackets tells us how changing concentration affects the variance of the granular bank shock. Entry and exit of financial institutions in equation 13 is taken into account by changes in the weights multiplying the variances. If

an institution does not exist in a given time period, it will have a zero weight and therefore not matter for the variance. One can obtain some simple intuition for this term by realizing that if all institutions had the same variance, then this component would tell us how increases in the Herfindahl ratio affect systemic risk as in equation 12. Alternatively, in a world with heterogeneous financial institution risk, this term tells us the extent to which aggregate loan volatility is rising because more risky financial institutions are gaining market share. The second term in square brackets in this equation tells us how the covariance between institutions changes over time. For example if bank mergers and deregulation allows institutions to be more different from each other, then one might expect this term to be negative because shocks to one institution have a lower correlation with those at another institution.

Empirically, implementing equation 11 requires us to measure the variance of the loan supply shocks emanating from each financial institution. We define the variance of a bank shock as

$$\sigma_b^2 = \frac{1}{n_b} \sum_t \left(\tilde{\beta}_{bt}^2 - E\left[\tilde{\beta}_{bt}\right] \right)^2$$

and the covariance as

$$\sigma_{bb'} = \frac{1}{n_{bb'}} \sum_t \left(\tilde{\beta}_{bt} - E\left[\tilde{\beta}_{bt}\right] \right) \left(\tilde{\beta}_{b't} - E\left[\tilde{\beta}_{b't}\right] \right).$$

If a bank or bank-pair is present for more than one year, we can implement this by computing

$$\sigma_b^2 = \frac{1}{n_b} \sum_t \left(\tilde{\beta}_{bt} - \frac{1}{n_b} \sum_t \tilde{\beta}_{bt} \right)^2, \tag{14}$$

and

$$\sigma_{bb'} = \frac{1}{n_{bb'}} \sum_t \left(\tilde{\beta}_{bt} - \frac{1}{n_{bb'}} \sum_t \tilde{\beta}_{bt} \right) \left(\tilde{\beta}_{b't} - \frac{1}{n_{bb'}} \sum_t \tilde{\beta}_{b't} \right). \tag{15}$$

However, if a bank or bank pair is only present for one year, we impose the moment condition

that the expected value of the idiosyncratic shock is zero $E\left[\tilde{\beta}_{bt}\right] = 0$ on the data. This means that we would compute the variances and covariances as follows: σ_b^2 is $\frac{1}{n_b}\sum_t \tilde{\beta}_{bt}^2$, where n_b is the number of years that the bank is in the sample. Similarly we write the covariance, $\sigma_{bb'}$, as $\frac{1}{n_{bb'}}\sum_t \tilde{\beta}_{bt}\tilde{\beta}_{b't}$, where $n_{bb'}$ is the number of years that banks b and b' are both in the sample.

3 Data Description

3.1 Data Construction

Our data comes 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. Our measure of financial institution 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 those that are government banks or cooperatives (12 financial institutions). We dropped loans from government institutions such as the Development Bank of Japan and the Export-Import Bank of Japan. Our loan measure is the total borrowing from a given financial institution in a year, comprising all of the loans received from each financial institution for 870 to 1,633 firms per year. Our data covers all industries, including manufacturing, mining, agriculture, and services. We only exclude 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 $t+1$, with over 80 percent of the firms reporting annual loans 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 only include firms that report for the year ending in March. We will refer to years ending in March 31 of a year 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 occurs 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. For example, Hokkaido Takushoku Bank, which failed in November of 1997, will fail in FY1998 in our data because the 1997 fiscal year would have closed in March of 1997.

One of the difficulties of working with this data was sorting through all of the mergers and restructurings in our data. Whenever a financial institution ceased to exist either because of a bankruptcy or failure, firms will cease reporting that financial institution as a source of loans. We therefore investigated every case in which all firms in our sample ceased reporting loans from a particular financial institution 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 was 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 financial institution as coming from the prior institution we recoded these loans as coming from the restructured institution if they occured 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 financial institutions in our data, we did not have any gaps associated with mergers.

A related issue concerned the definition of a financial institution. In general, we erred on the side of assuming that institutions changed whenever an institution was nationalized or privatized. For example, when Long-Term Credit Bank failed in 1998 and then reopened as Shinsei Bank in 2000, we counted that as three institutions: LTCB, "Nationalized LTCB", and Shinsei Bank.

To ensure there were sufficient observations to estimate the bank shocks, we only keep bank-year pairs that have a minimum of five loans in t and t-1. This procedure dropped

0.6% of the observations. The number of financial institutions in the sample ranges from 101 to 166 depending on the year, with a smaller number of financial institutions in the latter period resulting from the wave of mergers in the 2000s.

The second source of data is from 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 market-to-book value for our analysis. 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.

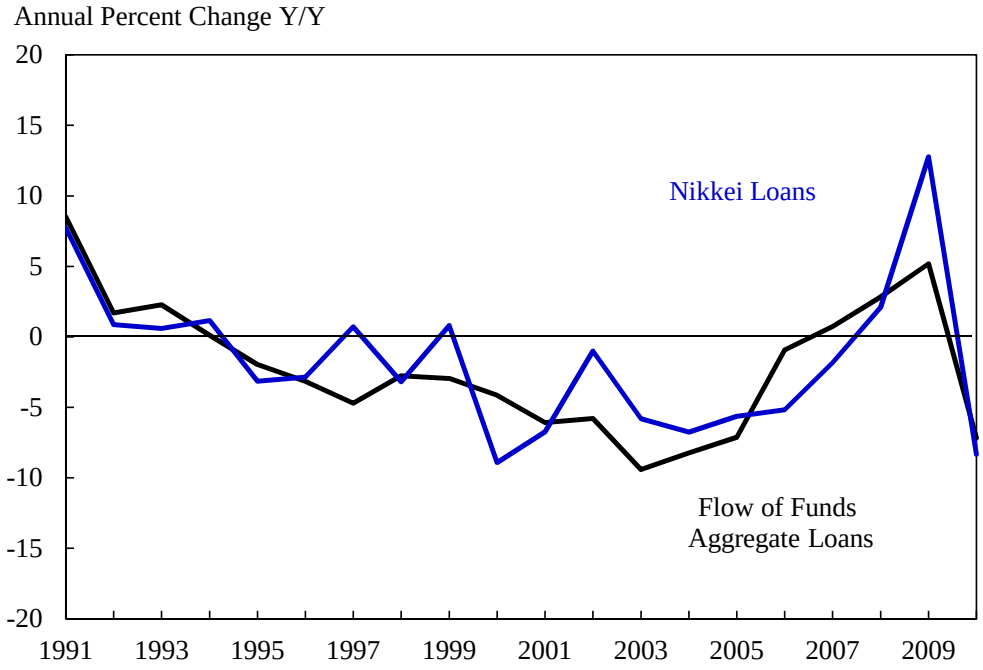
Finally, we draw on two sources of aggregate information on economy-wide borrowings and investment-to-capital ratios. The Flow of Funds data from the bank of Japan website provide data on the stock of lending to private non-financial corporations from private financial institutions.[4] The economy-wide investment-to-capital ratio data is measured in 2000 Yen for fiscal years 1990 to 2010 from National Accounts, Economic and Social Research Institute, Cabinet Office.

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 in order to demonstrate the plausibility of using information on listed companies as a means of understanding aggregate fluctuations. Even though lending to listed financial firms in the Nikkei data only accounted for 17 percent of aggregate lending in 1990 and 18 percent in 2010, the aggregate lending to listed companies from our firm-level data exhibits a similar pattern as lending in the broad economy. In Figure 1, we plot the annual percent changes in the flow of funds borrowing data with the aggregate lending data from the Nikkei database. As one can see from this graph, aggregate

[4]The borrowing data is from the Bank of Japan website. The series number is FF'FOF_FFYS411L240.

Figure 1: Flow of Funds and Nikkei Debt



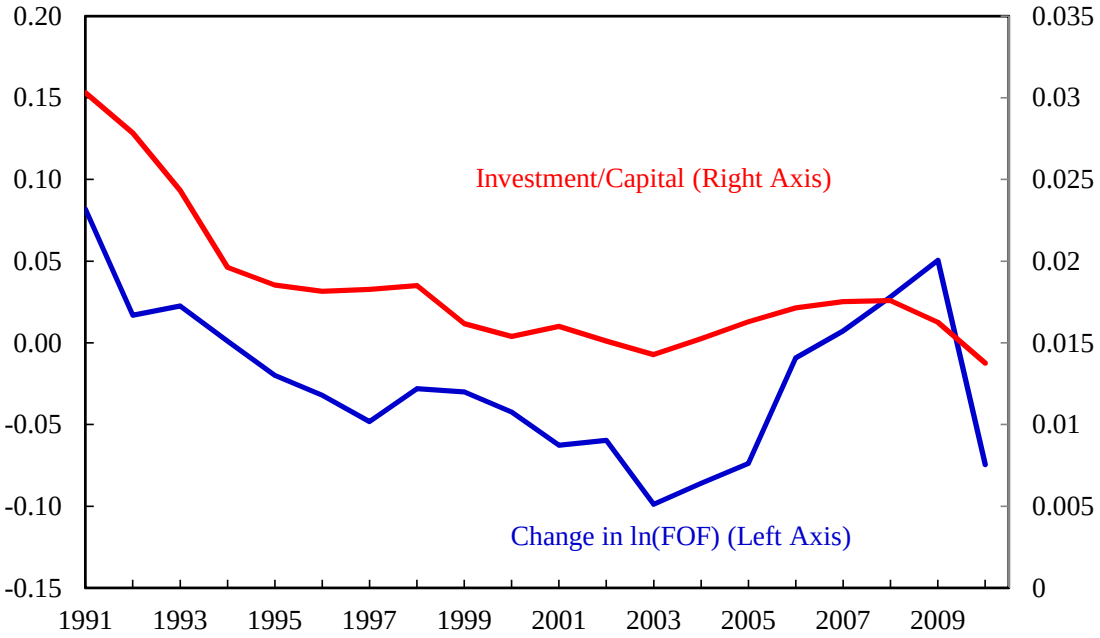
Note: Years are fiscal years which roughly correspond to the calendar year plus one.

corporate borrowing tracks 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 borrowing became negative and remained so for a decade.

Second, we show that there is a clear positive association between economy-wide non-financial corporate borrowing and economy-wide investment in the data. In Figure 2 we see that the growth rate in the stock of lending to private non-financial corporations from private financial institutions using the Flow of Funds data tracks the aggregate investment-to-capital ratio fairly closesly. The correlation between the two series is 0.72, illustrating the tight relationship between borrowing and investment.

Finally, we need to show that there is sufficient "granularity" in the financial sector so that one can plausibly argue that shocks to major financial institutions in Japan are sufficiently large so that an idiosyncratic shock at one of them, such as the failure of Long-Term Credit Bank, might actually move a macroeconomic aggregate. Figure 3, shows a breakdown of

Figure 2: Flow of Funds and Aggregate Investment



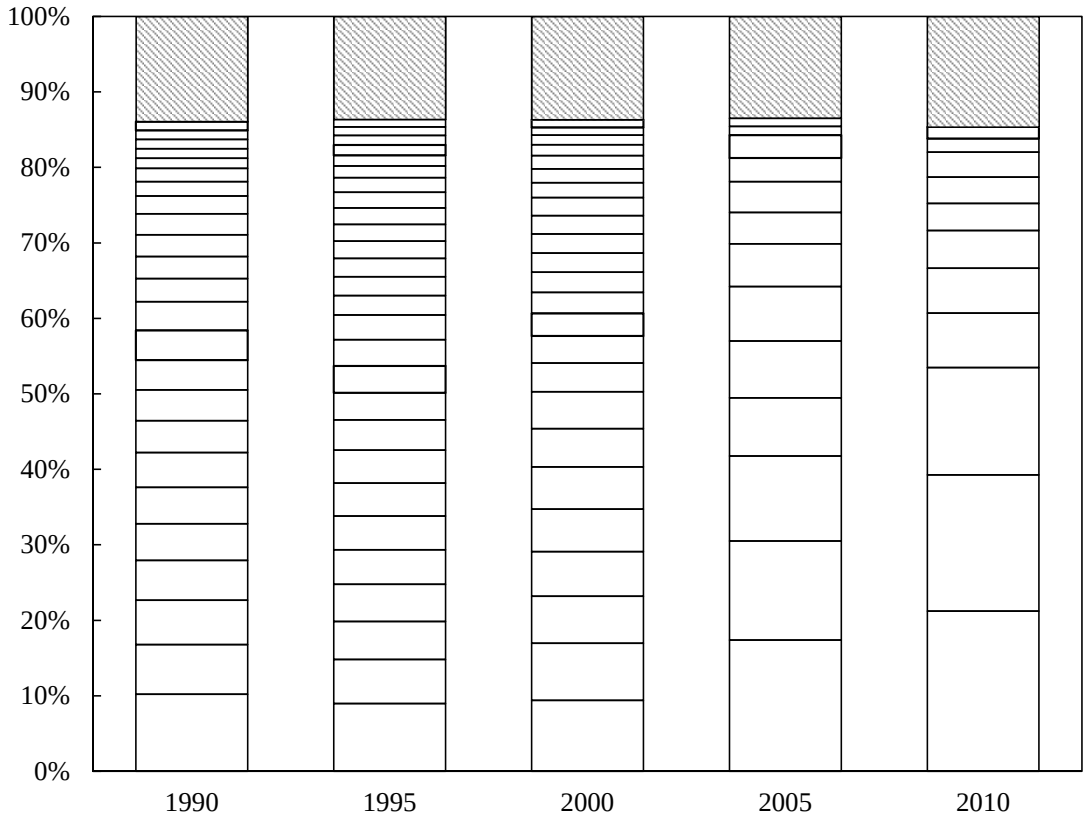
Note: Years are fiscal years which roughly correspond to the calendar year plus one.

total lending by financial institution. In each year we depict individual loan shares of every institution with a loan share exceeding 1 percent of aggregate lending to listed companies. As one can see from the figure, there was a remarkable increase in concentration in Japanese finance between FY2000 and FY2010. In FY1990, the three largest financial institutions in Japan accounted for 23 percent of aggregate lending, but this number has risen to 53 percent in FY2010, with the largest institution, MUFJG, accounting for 21 percent of all Japanese lending.

The enormous concentration in lending in what at the time was the world's second largest economy is at the center of our suggestion that idiosyncratic bank shocks might have macroeconomic implications. To the extent that one believes that an analyst armed only with macroeconomic aggregate statistics would have a hard time understanding the health of a "megabank" like SMFG, there is the possibility that idiosyncratic shocks to individual institutions might affect aggregate behavior.

The rise in Japanese concentration appears remarkable until one contemplates it in the

Figure 3: Bank Concentration

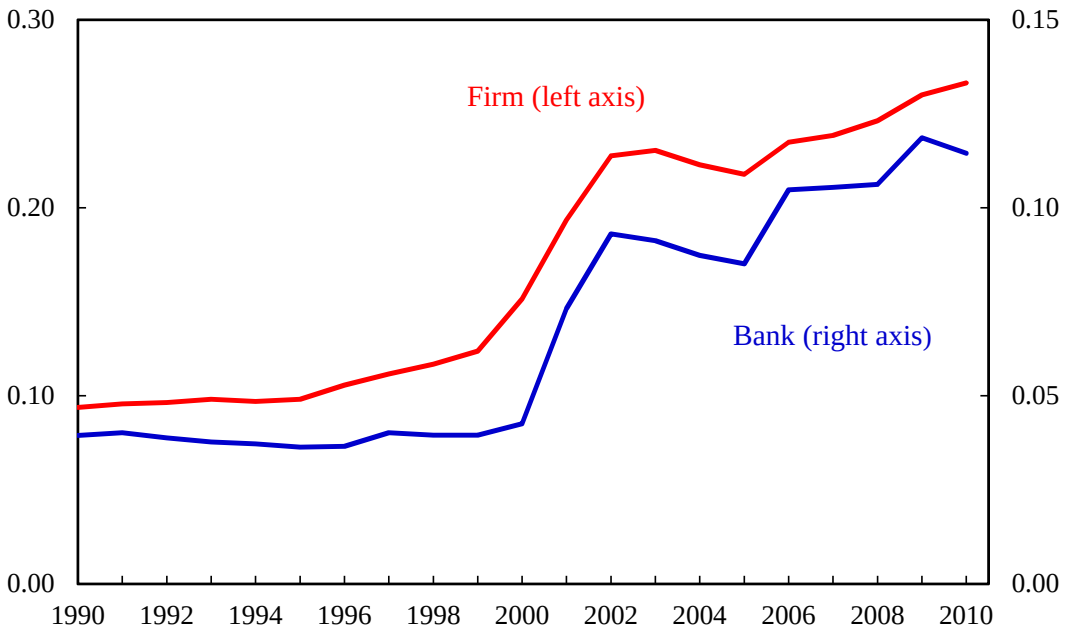


Note: Years are fiscal years which roughly correspond to the calendar year plus one.

international context. Japan's merger wave was driven by deregulating laws related to the formation of holding companies in 1997, and as Sakuragawa and Watanabe (2009) argues, the 2002 "Takenaka Plan", which forced more disclosure of non-performing loans (resulting in mergers of weak institutions). Similarly, many other countries pursued various legal changes that helped contribute to rising financial concentration.

In Figure 4 we can see the dramatic impacts of the Japanese reforms on concentration by examining movements in the Herfindahl indexes of bank lending. We compute the Herfindahl indexes two ways. The bank Herfindahl index $\left(= \sum_b \left(\sum_f L_{fbt} / \sum_{fb} L_{fbt}\right)^2\right)$ is a measure of the sum of the squared bank lending shares and indicates how concentrated the Japanese aggregate lending market is. The firm Herfindahl $\left(= \frac{1}{F_t} \sum_f \sum_b \left(L_{fbt} / \sum_b L_{fbt}\right)^2\right)$, by contrast, measures how concentrated each firm's borrowing is on average. Until around FY1999, these measures tell us that banking concentration in Japan was fairly constant, but there was a

Figure 4: Herfindahl Indices



Notes: The Herfindahl indices for banks and firms are the sums of squared shares of total lending by bank and total borrowing by firm, respectively. This is a measure of the degree to which loans are concentrated among a few banks or firms. Years are fiscal years which roughly correspond to the calendar year plus one.

remarkable increase in concentration in the immediate aftermath of the regulatory changes and financial crises in 1997 (FY1998), with both indexes almost tripling in the following years.

Although the rapid rise in Japanese banking concentration is quite striking, it is important to remember that Japan is not an outlier in this dimension. As Amel et al. (2004) show, the growth in merger activity in Japan's banking and insurance industry was quite similar to the ones in other industrial countries. Similarly, the high degree of Japanese financial market concentration is not very different from what we see in other countries. For example, Buch and Neugebauer (2011) calculate bank Herfindahl indexes for many western European countries between 1996 and 2006. The average Herfindahl for western European countries was 0.24, which is more than triple the Japanese value over this time period (0.073). Japanese Herfindahl indexes computed from our data tend to look low compared with those of the

United Kingdom (0.12) and Italy (0.11) and roughly comparable with Germany (0.072) and France (0.05).

Concentration in U.S. banking is remarkably similar as well. The Federal Reserve Bank reports data on on the assets of bank holding companies in the US.[5] Most major lenders are bank holding companies and jointly these institutions accounted for 79 percent of all assets held by commercial banks, thrifts, and credit unions in the US in 2010.[6] The Federal Reserve Bank data indicate that the largest three institutions in the US – Bank of America, JP Morgan, and Citigroup – held 49 percent of all banking assets. This number is remarkably close to the 55 percent number in our Japanese sample. Moreover the Herfindahl index for asset holdings by these institutions is 0.10, which is almost exactly equal to the Japanese number of 0.11 for FY2010. Therefore, any observed large impacts from bank shocks in Japan cannot be attributed to a more concentrated banking sector than other countries. Rather, the high degree of financial market concentration appears to be a feature of many developed countries.

The staggering degree of concentration in financial markets means that the largest bank holding companies are not small compared to the size of even the largest economies. Thus, if it is difficult for firms to easily switch their financing sources, as Hubbard, Kuttner and Palia (2002) stress is a common problem, it could be the case that idiosyncratic shocks to individual financial institutions are transmitted to firms. Similarly, the rise in concentration in corporate borrowing and financial institution lending raises questions of whether idiosyncratic movements in the lending behavior of individual institutions are likely to be generating larger aggregate shocks more recently or whether there have been offsetting forces. We turn to understanding each of these next.

[5]The bank assets 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).

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

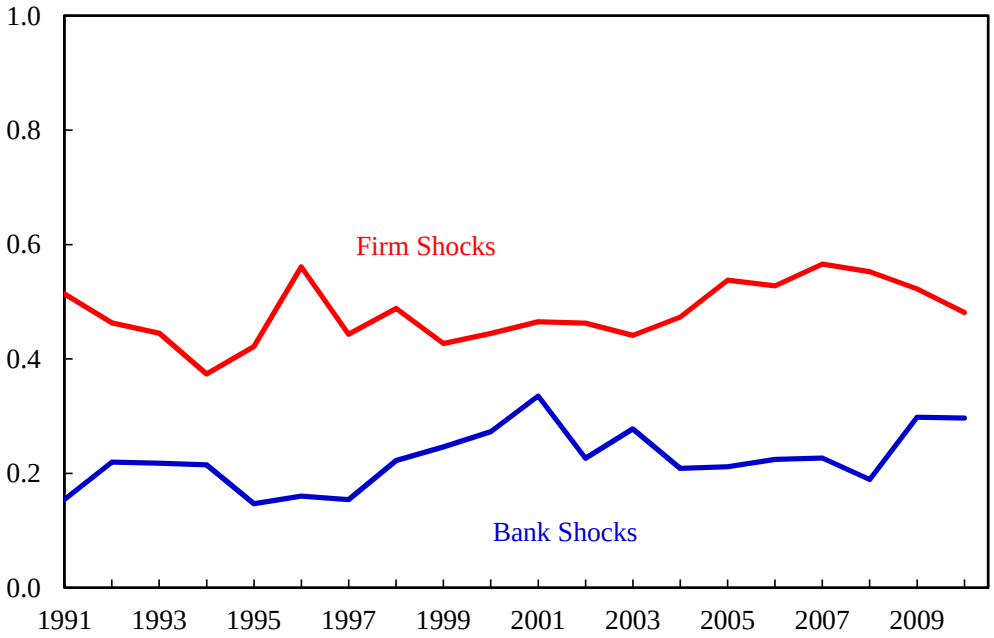
4 Results

4.1 Estimating Firm and Bank Shocks

In Figure 5 we plot the standard deviation of the estimated firm and bank idiosyncratic shocks, $\tilde{\alpha}_{ft}$ and $\tilde{\beta}_{bt}$, that form the elements of $\tilde{\boldsymbol{A}}_{\boldsymbol{t}}$ and $\tilde{\boldsymbol{B}}_{\boldsymbol{t}}$ in equations 8 and 9. The graph indicates substantial heterogeneity in the loan supply shocks of individual banks and the credit shocks experienced by firms. The standard deviation in firm credit shocks that is not explainable by industry or common demand changes tends to be around 0.5 log units per year. This suggests that heterogeneity in firms' apparent demand for funds is quite large. Bank heterogeneity in idiosyncratic loan supply is about half as large but quite substantial considering that only a few institutions account for half of all lending and therefore idiosyncatic shocks to a few institutions can move aggregate lending substantially. The median standard deviation of 0.2 means that around one-third of Japanese financial institutions saw their idiosyncratic loan supply rise or fall relative to other institutions by more than twenty percentage points in a given year. This has the potential to have substantial impacts on firms if it is difficult for firms to substitute financing from one bank to another.

A second interesting feature of these idiosyncratic bank shocks is the years in which there is maximal dispersion in the behavior of financial institutions. The six years with the largest dispersion in bank idiosyncratic shocks correspond to fiscal years 1999-2001, 2003, 2009, and 2010 (or calendar years 1998-2000, 2002, 2008, 2009). The first three years correspond to the first Japanese financial crisis, FY2003 corresponds to the year that Japan introduced the "Takenaka Plan" ending the previous policy of regulatory forbearance, and FY2009-2010 (calendar years 2008-9) were the years of a global financial crisis. It appears that the variance of idiosyncratic bank shocks are particularly large in years when the financial system is under strain. For example, the variance in loan shocks in FY2000 (CY1999) was twice as large as it was between FY1995-7 (CY1996-8) when Japan had resolved the non-performing loan problem of its home mortgage companies (*jusen*) and Japan's economy was growing at an

Figure 5: Standard Deviations of Bank and Firm Shocks



Notes: These are the standard deviations of the the firm shocks, removing the common and industry-specific compontent, and bank shocks, removing the common component, in each year. Years refer to fiscal years, which roughly correspond to the calendar year plus one.

average 1.8 percent per year rate. Similarly, the standard deviation in idiosyncratic loan shocks in FY2009 was about 30-100 percent larger as it was in any of the five previous years. These data suggest that idiosyncratic financial shocks matter most in crisis years, which is consistent with the notion that bank health is likely to matter the most when a financial crisis pushes some, but not all, banks to the brink of bankruptcy.

We know that our bank shocks must be uncorrelated with firm shocks, but we would also like some validation that they are correlated with factors that we think should cause them to rise or fall. To say this mathematically, we would like our estimates of β_{bt} to be correlated with proxy variables, z_{bt}, that we think should affect a bank's supply of credit. Fortunately, the prior literature has identified a number of such proxy variables. One of the most common variables used for this purpose for studies examining the behavior of Japanese banks is the risk-based capital ratio (c.f. Peek and Rosengren (1997, 2000, 2005); Amiti and Weinstein (2009)). These authors argue that in the aftermath of the bursting Japanese

Table 1: Validation of Bank Shocks

Dependent Variable: Bank Shock$_{b,t}$	(1)	(2)	(3)
Risk-Based Capital Ratio$_{b,t}$	0.015***		
	(0.003)		
Capital Injection$_{b,t}$		0.107***	
		(0.032)	
Δ ln(Market-to-Book Value$_{b,t-1}$)			0.092***
			(0.027)
Year Fixed Effects	Yes	Yes	Yes
Observations	658	398	843
R^2	0.042	0.034	0.019
Adjusted R^2	0.032	0.027	0.009

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 mulitplied 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. These data were taken from Nikkei and from the Pacific Basin Capital Markets data base. ***p<0.01, **p<0.05,*p<0.1.

land and stock bubble, banks with low levels of capital adequacy were forced to cut back on lending. In other words, if we denote the risk-based capital ratio of a bank by RCR_{bt}, these studies are based on the idea that $corr\left(\beta_{bt}, RCR_{bt}\right) > 0$. Similarly, Montgomery and Shimizutani (2009) have argued that the capital injections implemented between 1997 and 1999 should have caused risk-based capital to rise in some banks and therefore should be positively correlated with bank shocks. Finally, several of these studies have also argued that deteriorations in a bank's market-to-book value in a crisis, MTB_{bt-1}, should lead to lower bank lending lending, and thus $corr\left(\beta_{bt,}MTB_{bt-1}\right) > 0$.

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 loan supply shocks. Thus, our results are consistent with prior work suggesting that these measures of bank health matter. 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 lender supply shocks. Assessing these impacts is the subject of the next section.

4.2 Bank Shocks and Firm-Level Investment

A major question, however, is 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 with that of others. As we have argued earlier, a major advantage of our approach is that we have estimates of time varying firm credit and bank loan supply changes. Moreover, equation 8 provides us with a way of decomposing each firm's loan growth into firm credit shocks, idiosyncratic bank 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 loan 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. Put concretely, we use equation 8 to define the aggregate bank loan shock hitting a particular firm as

$$BankShock_{ft} = \sum_{b} \theta_{fbt}\beta_{bt}. \tag{16}$$

Since we know that firm credit shocks, α_{ft}, and the bank loan supply shocks, β_{bt}, are orthogonal by construction, this measure is also orthogonal to investment demand shocks hitting the firm.

Table 2 presents our findings. In the first column of Table 2, we run 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 investment and a firm's cash-flow and market-to-book ratio as measured by Tobin's Q. 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-credit shocks within an industry. We find a positive and significant coefficient on the industry credit 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 on the industry level.

The most interesting results, however, are those reported in Columns 3-5 of Table 2 where we add our firm and bank shock variables to the specification. Since our sample of firms are all listed companies that have access to both equity and bond markets, it makes sense to consider the impact of a firm credit or bank loan supply shock as having a different impact on a firm that borrows a lot 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 80 percent of its capital through bank loans than on a firm that only finances 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 firm's mean loan-to-asset ratio over the sample period.[7] In Column 3 of Table 2, we see that the coefficient on the bank shock entering alone is negative and significant while that on the interaction term is positive and significant, showing that loan-dependent firms' investments are affected by bank shocks.

One concern about these results is that firms that have access to forms of capital other

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

Table 2: Firm-Level Investment

Dependent Variable: Investment$_{f,t}$/Capital$_{f,t-1}$	(1)	(2)	(3)	(4)	(5)
Cash-Flow$_{f,t}$/Capital$_{f,t-1}$	0.050***	0.050***	0.050***	0.050***	0.051***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Market-to-Book Value$_{f,t-1}$	0.009***	0.009***	0.009***	0.009***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bank Shock$_{f,t}$			-0.158***	-0.170***	-0.111**
			(0.044)	(0.048)	(0.044)
(Bank Shock$_{f,t}$)*(Mean Loan to Asset Ratio$_f$)			0.730***	0.739***	0.814***
			(0.189)	(0.188)	(0.187)
(Bank Shock$_{f,t}$)*(Mean Bond to Asset Ratio$_f$)				0.252	
				(0.422)	
Firm Shock$_{f,t}$					0.019***
					(0.007)
(Firm Shock$_{f,t}$)*(Mean Loan to Asset Ratio$_f$)					0.264***
					(0.042)
Industry Shock$_{f,t}$		0.070***	0.070***	0.070***	0.078***
		(0.017)	(0.017)	(0.017)	(0.017)
Fixed Effects					
Year	yes	yes	yes	yes	yes
Firm	yes	yes	yes	yes	yes
Observations	21,678	21,678	21,678	21,678	21,678
R^2	0.310	0.310	0.311	0.311	0.326
Adjusted R^2	0.243	0.244	0.245	0.245	0.261

Notes: Bootstrapped standard errors in parentheses (1000 bootstrap replications). ***p<0.01, **p<0.05, *p<0.1. We drop the top and bottom one percentiles of each variable .

than loans may be less susceptible to credit shocks. To some extent we have already corrected for this by noting that the effect of credit shocks is most keenly felt by firms that are on average larger borrowers. However, it might also be the case that firms that also raise a lot of financing from bond markets are less susceptable to bank loan 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 interaction term means that simply knowing 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 loan supply shocks on firms with and without high levels of bond finance.

Adding firm-level shocks in the next column has little impact. The bank shock coefficients are hardly affected, which reflects the fact that the firm-level shocks are orthogonal to the bank shocks by construction. The positive coefficient on the firm shock interacted with mean loan-to-asset implies that there is a very strong association between firm credit 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 firm-level investment.

These results are robust to a number of alternative specifications. In Column 1 of Table 3, we only include the bank interaction terms and the industry effects to see if the exclusion of all potentially endogenous variables affects the results. We find that the coefficients are hardly affected, which underscores the orthogonality of our bank shock variable. Similarly, one might wonder if our results are only driven by crisis years. We therefore reran our regressions excluding the major banking crisis years (FY1991, FY1993, FY1998, FY2009) to see if the results are robust to dropping these years. The results reported in Column 2 indicate that the point estimates are hardly affected.[8] Finally, in Columns 3 and 4, we divide the sample into two halves (FY1991-FY2000 and FY2001-FY2010) to see if there is a difference between the early years when bank failures were frequent and the later years. We

[8]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 that the *jusen*, or housing finance companies began failing, and the year that the first major banks began failing. The last crisis year corresponds to the first year of the more recent financial crisis.

find that bank shocks are significant determinants of investment in both periods, but that the point estimates are lower (although not signficantly so) in the later years. Because we obtain our results for two non-overlapping subsamples, we can be confident that no single event or year is driving our results. This is the first time that anyone has shown that credit supply shocks affect firm-level investment in general and not just when there are extreme events.

Table 3: Firm-Level Investment Robustness

Dependent Variable: $\text{Investment}_{f,t}/\text{Capital}_{f,t-1}$	(1)	(2)	(3)	(4)
$\text{Cash-Flow}_{f,t}/\text{Capital}_{f,t-1}$		0.048***	0.165***	0.041***
		(0.007)	(0.018)	(0.007)
$\text{Market-to-Book Value}_{f,t-1}$		0.011***	0.008***	0.011***
		(0.002)	(0.003)	(0.003)
$\text{Bank Shock}_{f,t}$	-0.155***	-0.131***	-0.095	-0.061
	(0.044)	(0.049)	(0.079)	(0.060)
$(\text{Bank Shock}_{f,t})*(\text{Mean Loan to Asset Ratio}_{f})$	0.693***	0.880***	0.970***	0.568**
	(0.191)	(0.196)	(0.290)	(0.256)
$\text{Firm Shock}_{f,t}$		0.026***	0.014	0.024***
		(0.008)	(0.012)	(0.008)
$(\text{Firm Shock}_{f,t})*(\text{Mean Loan to Asset Ratio}_{f})$		0.210***	0.329***	0.213***
		(0.049)	(0.091)	(0.047)
$\text{Industry Shock}_{f,t}$	0.079***	0.093***	0.118***	0.054**
	(0.017)	(0.021)	(0.031)	(0.021)
Fixed Effects				
Year	yes	yes	yes	yes
Firm	yes	yes	yes	yes
Observations	21,678	17,795	9,535	12,143
R^2	0.294	0.324	0.389	0.375
Adjusted R^2	0.227	0.243	0.281	0.268

Notes: Bootstrapped standard errors in parentheses (1000 bootstrap replications). ***p<0.01, **p<0.05, *p<0.1. Column (2) drops crisis years (1991, 1993, 1998, 2009). Column (3) uses a restricted sample from 1991-2000, and Column (4) uses a sample restricted to 2001-2010. We drop the top and bottom one percentiles of all the variables.

The findings in the baseline specification in Column 5 of Table 2 imply that there is 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) whereas 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. Peek, Klein, and Rosengren (2002), Khwaja and Mian (2008), Gan (2007), Amiti and Weinstein (2011)) and those that suggest that 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 not so much for firms that are not dependent on loans. Interestingly, we find that bank shocks, if anything, exert a negative impact on the investment of firms that are largely unreliant on loans for their financing needs, which may reflect the fact that firms that don't rely much on loans for finance actually benefit relatively when credit conditions tighten.

4.3 Bank Shocks and Aggregate Lending and Investment

As we already noted, the lending data in our sample of firms only accounts for around 17 percent of total lending in Japan in an average year. However, our methodology allows us to identify a pure bank loan 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 impact is to realize that if we were to regress the left-hand side of equation 10 on each of the right-hand side terms, we would obtain coefficients of one on each term since the equation must add up.

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 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. 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 regressing economy-wide loan growth on the right-hand side terms in equation 10. Finally, even if we were to obtain coefficients of 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 loan supply might have a very small impact on aggregate lending.

To see how much these shocks matter for total loan growth, therefore, we can exploit the fact that if we regress aggregate lending on the four terms on the right-hand side of equation 10, 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 - we are decomposing aggregate loan growth into orthogonal components - but in trying to understand how important the terms we identified in equation 10 are in determining aggregate loan fluctuations.

In Table 4, we regress aggregate lending growth from the flow of funds on the various components of lending growth that we identified from the Nikkei matched bank-firm data. As one can see in the first five columns of the table, aggregate lending can be meaningfully decomposed into the factors only if we include the granular term encompassing the idiosyncratic bank shocks. Interestingly, while industry and common shocks are significantly correlated with aggregate loan growth in Columns 4-6, the granular firm terms are never significant perhaps because even the largest borrowers in our sample are small relative to the aggregate level of borrowing in Japan.

Table 4: Flow of Funds

Dependent Variable: Δ ln(Flow of Funds$_t$)						
	(1)	(2)	(3)	(4)	(5)	(6)
Common Shock$_t$	0.457	0.486	0.380	1.360***	1.256***	1.319***
	(0.338)	(0.368)	(0.395)	(0.233)	(0.229)	(0.240)
Industry Shock$_t$		0.880*	0.599	1.724***	1.469***	0.573***
		(0.455)	(0.598)	(0.377)	(0.412)	(0.161)
Firm Shock$_t$			0.351		0.304	0.226
			(0.345)		(0.230)	(0.171)
Bank Shock$_t$				1.328***	1.310***	1.124***
				(0.287)	(0.281)	(0.241)
Constant	-0.017*	-0.016*	-0.017*	-0.001	-0.002	0.000
	(0.010)	(0.009)	(0.010)	(0.007)	(0.007)	(0.132)
Standardized Variable	No	No	No	No	No	Yes
Observations	20	20	20	20	20	20
R^2	0.230	0.347	0.392	0.750	0.785	0.785
Adjusted R^2	0.187	0.270	0.278	0.704	0.727	0.727

Notes: Bootstrapped standard errors in parentheses (1000 bootstrap replications). ***p<0.01, **p<0.05, *p<0.1. All variables, including log change in the FOF, are standardized in (6) with mean 0 and standard deviation 1. The sample is for the 1991-2010 period.

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 investment is explainable by examining the factors we identified in the Nikkei sample. Moreover the coefficients on the common shock, industry shock, and granular bank shock 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 does not reject the hypothesis that the common, industry, and granular bank shocks identified in the Nikkei data are the same as those that 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 it explains by comparing Column 3 with Columns 4 and 5. If we compare Columns 3 and 5, we see that adding the granular bank shock term raises the R^2 of the regression by 0.39, indicating that idiosyncratic bank shocks account for over one third 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 understanding the idiosyncratic lending decisions of large financial institutions has a substantial impact on understanding aggregate lending. In the last column of the table 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 highly sensitive to factors that cannot be captured by factors varying at the industry, borrower, or aggregate level. In an economy composed of small financial institutions, this term would have to be zero, but the fact that it is so large implies that much of aggregate lending is explainable by the idiosyncratic 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. Our results from the previous sections have already established exogeneity of the bank shocks and firm shocks, the fact that there is a strong relationship between firm-level investment and bank shocks, and finally that aggregate lending is tightly linked to granular idiosyncratic loan shocks. Our next question is whether these granular bank shocks cause movements in aggregate investment. By construction, any common shock

Table 5: Aggregate Investment

Dependent Variable: $Investment_t/Capital_{t-1}$						
	(1)	(2)	(3)	(4)	(5)	(6)
$Common\ Shock_t$	0.041	0.040	0.040	0.120***	0.121***	1.394***
	(0.029)	(0.030)	(0.033)	(0.031)	(0.032)	(0.367)
$Industry\ Shock_t$		-0.019	-0.020	0.058	0.060	0.258
		(0.058)	(0.067)	(0.049)	(0.057)	(0.245)
$Firm\ Shock_t$			0.001		-0.003	-0.025
			(0.044)		(0.031)	(0.253)
$Bank\ Shock_t$				0.121***	0.121***	1.143***
				(0.033)	(0.034)	(0.321)
Constant	0.019***	0.019***	0.019***	0.020***	0.020***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.161)
Standardized Variables	No	No	No	No	No	Yes
Observations	20	20	20	20	20	20
R^2	0.222	0.229	0.229	0.634	0.634	0.634
Adjusted R^2	0.179	0.138	0.084	0.565	0.537	0.537

Notes: Bootstrapped standard errors in parentheses (1000 bootstrap replications). ***p<0.01, **p<0.05, *p<0.1. All variables, including aggregate investment, are standardized in (6) with mean 0 and standard deviation 1. The sample is for the 1991-2010 period.

to firm's investment demand will be captured in our common shock term, therefore the granular bank shocks are orthogonal to these common shocks. The question is whether and how much they matter for aggregate investment.

As in the previous table, we see in Table 5 that unless one includes the granular bank shock, the other elements in the decomposition of loan growth do not matter for understanding aggregate investment. Once again, the granular bank shock term enters strongly significant and raises the R^2 of the regression from 0.23 to 0.63, which indicates that these idiosyncratic bank shocks also account for 40 percent of the fluctuations in aggregate investment. In terms of economic significance, we see in Column 6, 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.

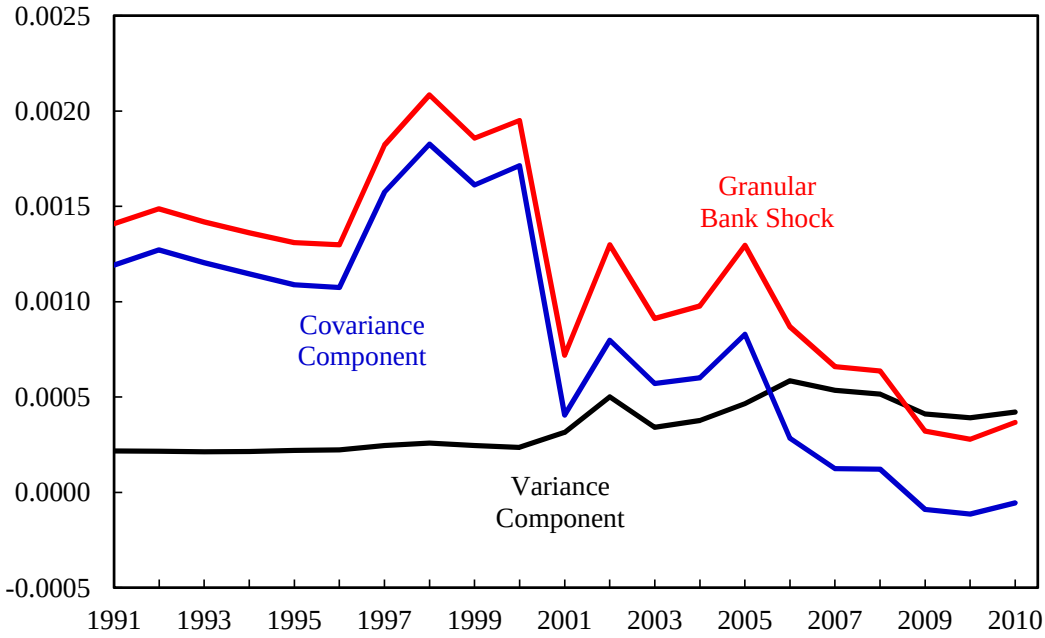
The importance of this result can be considered in comparison with those in Table 2. In that table we learned that bank shocks matter at the firm level, but we had no way of understanding whether the fact that bank shocks mattered for a firm's investment *relative to the investment of other firms* also meant that that these bank shocks mattered overall. The results in Table 5 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.

4.4 Movements in the Variance of the Granular Residual

The rapid growth in lending concentration that we saw in Figure 4 coupled with the insights from equation 12 suggests that we might expect to see that the variance of financial institution shocks rise over time. The intuition that increased concentration is likely to increase the variance of idiosyncratic shocks is based on two assumptions that can be empirically examined in the data. The first is the merger of banks does not create new institutions that have much lower variances in their idiosyncratic loan supply shocks. If the merger of institutions produces new institutions with lower variance, then equation 11 indicates that the variance of the granular bank shock will fall. Similarly, changes in the covariance between institutions can cause the variance of the granular residual to fluctuate.

Figure 6 shows the movements in the two terms determining the magnitude of the granular bank shock variance. There are three interesting features of this variance decomposition. First, as one might suspect, the rising concentration in Japanese finance has produced a substantial increase in the variance term in equation 4. Between 1991 and 2010, the increase in the variance component doubled reflecting the increasing concentration in Japanese finance that we saw in Figure 4. This increase in variance reflects the fact that as banks and insurance companies merged into large financial conglomerates, the variance of the new

Figure 6: Granular Bank Shock



Note: The granular bank shock line denotes the total variance of financial shocks from all sources. The variance component is the part from the variance terms, and the covariance component is the part due to the covariances among financial institutions. Years are fiscal years which roughly correspond to the calendar year plus one.

institutions was not sufficiently low to offset their larger market share, which meant that the variance component rose.

While the increase in the variance of the granular bank shock associated with the pure variance moves as expected, the second striking element of Figure 6 is that the variance component is extremely small compared with the covariance term at the start of the sample. In other words, prior to the formation of large financial holding companies in Japan in the late 1990's, Japan was characterized by many small financial institutions with very high covariances in their idiosyncratic shocks. This may reflect the relatively unsophisticated nature of Japanese finance in which the larger Japanese financial institutions present in 1990s pursued investment strategies that were quite similar to each other. For example, Long-Term Credit Bank, the Bank of Tokyo-Mitsubishi, and Nippon Credit Bank, which were among the largest banks in the world in the 1990s, had idiosyncratic bank shocks that were highly correlated with other large institutions. Similarly, many of the largest Japanese banks may

have also pursued similar investment strategies resulting in a high degree of correlation in their idiosyncratic shocks. Since, holding fixed the σ_b^2's, the merger of large institutions with positive covariances has a much smaller impact on the granular bank shock than the merger of institutions whose idiosyncratic bank shocks are independently distributed, the impact of all of these mergers was lessened.

Indeed, the third most striking feature of the plot is the decline in the variance caused by the massive decline in the covariance of idiosyncratic bank shocks. Although the covariance term rose substantially with the mergers occurring immediately before the financial crisis - largely due to the formation of the Bank of Tokyo-Mitsubishi from the merger of the Bank of Tokyo and Mitsubishi Bank - the nationalization of Long-Term Credit Bank and Nippon Credit Bank resulted in a collapse in the covariance term. While one might attribute this to a mechanical relationship in which the nationalized banks only existed for two years and therefore we may not have been able to accurately measure their covariance, the fact that privatized and restructured institutions that came out of these bankruptcies, Shinsei Bank and Aozora Bank, did not exhibit the same degree of covariance as the earlier institutions suggests that the downward trend is not due simply to the few years in which some large institutions were nationalized. Moreover, the continued decline in the covariance through the latter half of the sample when there were very few bank failures indicates that bankruptcies cannot be driving our results.

Perhaps what is most striking is that the variance of the granular bank shock achieves its lowest value in the late 2000's just as the world was hit by a major financial crisis. These results are complementary to those we saw in Table 2 showing that the impact of idiosyncratic shocks on firm-level investment was lower in the later period. One possible explanation is that the Takenaka Plan, announced in October of 2002, was successful in Japan in providing enough regulatory oversight to reduce the magnitude of idiosyncratic shocks hitting individual banks. Alternatively, it is possible that most of the impact of the global financial shocks in 2008 was either commonly felt by all Japanese financial institutions

or largely affected borrowers and not creditors. Regardless of the causes, the importance of the covariance term indicates the problem of inferring an increase in aggregate volatility based solely on a rise in financial concentration.

5 Conclusion

Although prior work using matched bank-firm data had shown that credit shocks could affect lending and real activity, those studies did not examine whether these shocks affected overall investment rates of firms nor the impacts on the aggregate economy. Thus, while we had compelling papers that served as a "proof of concept", it was difficult to understand how important creditor shocks were in a real economy.

Our paper contributes to this literature by providing the first evidence that shocks to lender credit supply affect borrower investment rates. Moreover, the fact that so much lending is intermediated through a few financial institutions means that idiosyncratic shocks hitting large financial institutions can move aggregate lending and investment. We show that about 40 percent of the movement in these variables can be attributed to these granular bank shocks. This means that the idiosyncratic fates of large financial institutions is an important determinant of investment and real economic activity.

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A Appendix: Derivation of Equation 9

A.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 solve this system of equations, $\beta_{bt} + k_t$ and $\alpha_{ft} - k_t$ must also be a solution. This means that we need to choose a numeraire in order to find a solution, and later we will impose that $\alpha_{1t} = 0$ (or equivalently $k_t = \alpha_{1t}$, and all shocks are defined as relative to this shock. Without loss of generality, we can rewrite equation 7 as

$$\begin{aligned} D_{ft}^F &\equiv \alpha_{ft} + \sum_b \theta_{fbt} \left(\beta_{bt} - \beta_{1t}\right) + \beta_{1t} \\ &= \alpha_{ft} + \sum_{b \neq 1} \theta_{fbt} \left(\beta_{bt} - \beta_{1t}\right) + \beta_{1t}. \end{aligned} \tag{17}$$

Similarly, we can rewrite equation 4 as

$$D_{bt}^B = \beta_{bt} + \sum_{f \neq 1} \phi_{fbt} \alpha_{ft}. \tag{18}$$

Finally, for firm 1, we have

$$D_{1t}^F = \sum_{b \neq 1} \theta_{1bt} \left(\beta_{bt} - \beta_{1t}\right) + \beta_{1t} \tag{19}$$

or

$$\beta_{1t} = D_{1t}^F - \sum_{b \neq 1} \theta_{1bt} \left(\beta_{bt} - \beta_{1t}\right), \tag{20}$$

and for bank 1, we have

$$D_{1t}^B = \beta_{1t} + \sum_{f \neq 1} \phi_{f1t} \alpha_{ft}. \tag{21}$$

If we substitute equation 20 into equation 17, we obtain

$$D^F_{ft} - D^F_{1t} = (\alpha_{ft} - \alpha_{1t}) + \sum_{b \neq 1} (\theta_{fbt} - \theta_{1bt})(\beta_{bt} - \beta_{1t}) = \alpha_{ft} + \sum_{b \neq 1} \hat{\theta}_{fbt}\hat{\beta}_{bt}, \tag{22}$$

where $\hat{\theta}_{fbt} = (\theta_{fbt} - \theta_{1bt})$, and $\hat{\beta}_{bt} = (\beta_{bt} - \beta_{1t})$. Substituting equation 21 into equation 18 gives us

$$D^B_{bt} - D^B_{1t} = (\beta_{bt} - \beta_{1t}) + \sum_{f \neq 1} (\phi_{fbt} - \phi_{f1t})\alpha_{ft} = \hat{\beta}_{bt} + \sum_{f \neq 1} \hat{\phi}_{fbt}\alpha_{ft}, \tag{23}$$

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

For every year, equations 22 and 23 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 numeraire.* To see this, we use some matrix algebra. We begin with a few definitions:

$$\hat{\boldsymbol{A}}_{\boldsymbol{t}} \equiv \begin{pmatrix} \alpha_{2t} \\ \vdots \\ \alpha_{Ft} \end{pmatrix}, \hat{\boldsymbol{B}}_{\boldsymbol{t}} \equiv \begin{pmatrix} \hat{\beta}_{2t} \\ \vdots \\ \hat{\beta}_{Bt} \end{pmatrix}, \hat{\boldsymbol{D}}_{\boldsymbol{Ft}} \equiv \begin{pmatrix} D^F_{2t} - D^F_{1t} \\ \vdots \\ D^F_{Ft} - D^F_{1t} \end{pmatrix}, \hat{\boldsymbol{D}}_{\boldsymbol{Bt}} \equiv \begin{pmatrix} D^B_{2t} - D^B_{1t} \\ \vdots \\ D^B_{Bt} - D^B_{1t} \end{pmatrix} \tag{24}$$

$$\hat{\boldsymbol{\Theta}}_{\boldsymbol{t}} \equiv \begin{pmatrix} \hat{\theta}_{22t} & \dots & \hat{\theta}_{2Bt} \\ \vdots & \ddots & \vdots \\ \hat{\theta}_{F2t} & \dots & \hat{\theta}_{FBt} \end{pmatrix}, \hat{\boldsymbol{\Phi}}_{\boldsymbol{t}} \equiv \begin{pmatrix} \hat{\phi}_{22t} & \dots & \hat{\phi}_{F2t} \\ \vdots & \ddots & \vdots \\ \hat{\phi}_{2Bt} & \dots & \hat{\phi}_{FBt} \end{pmatrix} \tag{25}$$

We now can rewrite equation 22 as

$$\hat{\boldsymbol{A}}_{\boldsymbol{t}} = \hat{\boldsymbol{D}}_{\boldsymbol{Ft}} - \hat{\boldsymbol{\Theta}}_{\boldsymbol{t}}\hat{\boldsymbol{B}}_{\boldsymbol{t}}, \tag{26}$$

and equation 23 as

$$\hat{\boldsymbol{B}}_{\boldsymbol{t}} = \hat{\boldsymbol{D}}_{\boldsymbol{Bt}} - \hat{\boldsymbol{\Phi}}_{\boldsymbol{t}}\hat{\boldsymbol{A}}_{\boldsymbol{t}}. \tag{27}$$

If we use this fact and insert equation 26 into equation 27, we know that any solution to equations 7 and 27 must satisfy

$$\hat{\boldsymbol{B}}_{\boldsymbol{t}} = \hat{\boldsymbol{D}}_{\boldsymbol{Bt}} - \hat{\boldsymbol{\Phi}}_{\boldsymbol{t}} \left[\hat{\boldsymbol{D}}_{\boldsymbol{Ft}} - \hat{\boldsymbol{\Theta}}_{\boldsymbol{t}} \hat{\boldsymbol{B}}_{\boldsymbol{t}} \right]. \tag{28}$$

This equation can be rewritten as

$$\left(\boldsymbol{I}_{\boldsymbol{B-1}} - \hat{\boldsymbol{\Phi}}_{\boldsymbol{t}} \hat{\boldsymbol{\Theta}}_{\boldsymbol{t}} \right) \hat{\boldsymbol{B}}_{\boldsymbol{t}} = \hat{\boldsymbol{D}}_{\boldsymbol{Bt}} - \hat{\boldsymbol{\Phi}}_{\boldsymbol{t}} \hat{\boldsymbol{D}}_{\boldsymbol{Ft}}, \tag{29}$$

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 $(\boldsymbol{I}_{\boldsymbol{B}} - \boldsymbol{\Phi}_{\boldsymbol{t}} \boldsymbol{\Theta}_{\boldsymbol{t}})$ to yield

$$\hat{\boldsymbol{B}}_{\boldsymbol{t}} = \left(\boldsymbol{I}_{\boldsymbol{B-1}} - \hat{\boldsymbol{\Phi}}_{\boldsymbol{t}} \hat{\boldsymbol{\Theta}}_{\boldsymbol{t}} \right)^{-1} \left(\hat{\boldsymbol{D}}_{\boldsymbol{Bt}} - \hat{\boldsymbol{\Phi}}_{\boldsymbol{t}} \hat{\boldsymbol{D}}_{\boldsymbol{Ft}} \right) \tag{30}$$

and

$$\hat{\boldsymbol{A}}_{\boldsymbol{t}} = \hat{\boldsymbol{D}}_{\boldsymbol{Ft}} - \hat{\boldsymbol{\Theta}}_{\boldsymbol{t}} \left(\boldsymbol{I}_{\boldsymbol{B-1}} - \hat{\boldsymbol{\Phi}}_{\boldsymbol{t}} \hat{\boldsymbol{\Theta}}_{\boldsymbol{t}} \right)^{-1} \left(\hat{\boldsymbol{D}}_{\boldsymbol{Bt}} - \hat{\boldsymbol{\Phi}}_{\boldsymbol{t}} \hat{\boldsymbol{D}}_{\boldsymbol{Ft}} \right). \tag{31}$$

We then can compute β_{1t} through two equivalent methods:

$$\begin{aligned} \beta_{1t} &= D^F_{1t} - \sum_{b \neq 1} \theta_{1bt} \left(\beta_{bt} - \beta_{1t} \right) && (32) \\ &= D^B_{1t} - \sum_{f \neq 1} \phi_{f1t} \alpha_{ft}. && (33) \end{aligned}$$

A.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.

We do this by developing a method to separate the common shocks from the idiosyncratic firm shocks and then proceed to isolate the industry shocks. 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 idiosyncratic firm credit shock as the difference between the

actual shocks and the median shock, i.e. $\dot{\boldsymbol{A}}_{\boldsymbol{t}} \equiv \boldsymbol{A}_{\boldsymbol{t}} - \bar{A}_t \mathbf{1}_{\boldsymbol{F}}$, and similarly the idiosyncratic financial institution loan shock as $\dot{\boldsymbol{B}}_{\boldsymbol{t}} \equiv \boldsymbol{B}_{\boldsymbol{t}} - \bar{B}_t \mathbf{1}_{\boldsymbol{B}}$, where

$$\boldsymbol{A}_{\boldsymbol{t}} \equiv \begin{pmatrix} \alpha_{1t} \\ \vdots \\ \alpha_{Ft} \end{pmatrix}, \boldsymbol{B}_{\boldsymbol{t}} \equiv \begin{pmatrix} \beta_{1t} \\ \vdots \\ \beta_{Bt} \end{pmatrix}. \tag{34}$$

It will also be useful to define

$$\boldsymbol{D}_{\boldsymbol{Ft}} \equiv \begin{pmatrix} D^F_{1t} \\ \vdots \\ D^F_{Ft} \end{pmatrix}, \boldsymbol{D}_{\boldsymbol{Bt}} \equiv \begin{pmatrix} D^B_{1t} \\ \vdots \\ D^B_{bt} \end{pmatrix}, \boldsymbol{\Theta}_{\boldsymbol{t}} \equiv \begin{pmatrix} \theta_{11t} & \dots & \theta_{1Bt} \\ \vdots & \ddots & \vdots \\ \theta_{F1t} & \dots & \theta_{FBt} \end{pmatrix}, \boldsymbol{\Phi}_{\boldsymbol{t}} \equiv \begin{pmatrix} \phi_{11t} & \dots & \phi_{F1t} \\ \vdots & \ddots & \vdots \\ \phi_{1Bt} & \dots & \phi_{FBt} \end{pmatrix}. \tag{35}$$

We can rewrite the system of equations given

$$\begin{aligned} \boldsymbol{D}_{\boldsymbol{Ft}} &= \boldsymbol{A}_{\boldsymbol{t}} + \boldsymbol{\Theta}_{\boldsymbol{t}} \boldsymbol{B}_{\boldsymbol{t}} \\ &= \dot{\boldsymbol{A}}_{\boldsymbol{t}} + \bar{A}_t \mathbf{1}_{\boldsymbol{F}} + \boldsymbol{\Theta}_{\boldsymbol{t}} \dot{\boldsymbol{B}}_{\boldsymbol{t}} + \bar{B}_t \boldsymbol{\Theta}_{\boldsymbol{t}} \mathbf{1}_{\boldsymbol{B}} \qquad (36) \\ &= \dot{\boldsymbol{A}}_{\boldsymbol{t}} + \boldsymbol{\Theta}_{\boldsymbol{t}} \dot{\boldsymbol{B}}_{\boldsymbol{t}} + \left(\bar{A}_t + \bar{B}_t\right) \mathbf{1}_{\boldsymbol{F}}, \qquad (37) \end{aligned}$$

where we move from the second line to the third by making use of the fact that the sum of 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

$$\begin{aligned} \boldsymbol{D}_{\boldsymbol{Bt}} &= \dot{\boldsymbol{B}}_{\boldsymbol{t}} + \boldsymbol{\Phi}_{\boldsymbol{t}} \dot{\boldsymbol{A}}_{\boldsymbol{t}} + \left(\bar{B}_t \mathbf{1}_{\boldsymbol{B}} + \boldsymbol{\Phi}_{\boldsymbol{t}} \bar{A}_t \mathbf{1}_{\boldsymbol{F}}\right) \\ &= \dot{\boldsymbol{B}}_{\boldsymbol{t}} + \boldsymbol{\Phi}_{\boldsymbol{t}} \dot{\boldsymbol{A}}_{\boldsymbol{t}} + \left(\bar{A}_t + \bar{B}_t\right) \mathbf{1}_{\boldsymbol{B}}. \qquad (38) \end{aligned}$$

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

$$\boldsymbol{D}_{\boldsymbol{Ft}} = \tilde{\boldsymbol{A}}_{\boldsymbol{t}} + \boldsymbol{N}_{\boldsymbol{t}} + \boldsymbol{\Theta}_{\boldsymbol{t}}\tilde{\boldsymbol{B}}_{\boldsymbol{t}} + \left(\bar{A}_t + \bar{B}_t\right)\mathbf{1}_{\boldsymbol{F}}, \tag{39}$$

and

$$\boldsymbol{D}_{\boldsymbol{Bt}} = \tilde{\boldsymbol{B}}_{\boldsymbol{t}} + \boldsymbol{\Phi}_{\boldsymbol{t}}\tilde{\boldsymbol{A}}_{\boldsymbol{t}} + \boldsymbol{\Phi}_{\boldsymbol{t}}\boldsymbol{N}_{\boldsymbol{t}} + \left(\bar{A}_t + \bar{B}_t\right)\mathbf{1}_{\boldsymbol{B}} \tag{40}$$