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How much do bank shocks affect investment? Evidence from matched bank-firm loan data

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

Mary Amiti
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Staff Report No. 604
March 2013

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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 the investment decisions of firms. We do this by developing a new methodology to separate firms' 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, which creates a role for granular shocks, as in Gabaix (2011). As a result, idiosyncratic bank shocks—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.

Key words: credit constraints, investment

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1 Introduction

Do bank shocks matter for investment rates, and if so, how much? Since the principal reason firms borrow is to finance capital expenditures, this question stands at the center of debates on the importance of financial shocks for real economic activity. The dearth of empirical work on this issue reflects the difficulty of linking credit supply shocks to firm investment decisions. For example, while several studies have offered compelling bank-level evidence that bank shocks matter for loan supply and certain types of foreign investment (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 central question of how important bank loan supply shocks are in determining the overall investment rates of their borrowers or aggregate investment more generally. Our study answers this question by providing the first estimate of how much financial institution shocks matter for overall firm-level and aggregate investment rates and establishes that creditor shocks are an important determinant of both.

We develop a new methodology that enables us to provide the first direct estimates of borrower credit and lender supply shocks using a comprehensive, matched lender-borrower data set covering all loans received from all sources by every listed Japanese firm over the period 1990 to 2010. The data contain the values of total short and long-term lending from hundreds of financial institutions to thousands of listed firms: 272,302 loans in total. A key feature of our methodology is that we do not need to rely on proxy variables that are correlated with borrower and lender shocks. Thus, we are able to 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 by movements in credit demand from the financial institutions' borrowers. Moreover, we can show that they capture the impact of idiosyncratic events such as bankruptcies, capital injections, and other factors that affect one or more institutions. We then exploit the heterogeneity in the sources of firm financing in

order 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 shocks seem much less important, suggesting that much of the fluctuation in aggregate lending and investment comes from three sources: shocks common to all firm-bank pairs, time-varying industry shocks, and idiosyncratic loan supply 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, which presumably are more constrained in their external finance options, and bank-dependent bor-

rowers 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 firms or industries that depend more on external finance or lending contract more during banking crises (e.g., Kashyap, Lamont, and Stein (1994), Dell'Ariccia, Detragiache, and Rajan (2008), Kalemli-Ozcan, Kamil, and Villegas-Sanchez (2010), and Chava and Purnanandam (2011)) do not link the contracting sectors or firms to the affected banks. Braun and Larrain (2005) have argued that the sectors more dependent on external finance 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 proxy variables for bank health 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), Jimenez et al. (2011), Santos (2012) and Chodorow-Reich (2013) provide bank-level or matched bank-firm level evidence that deteriorations in bank health or increases in the cost of raising capital cause banks to contract lending, raise rates, and/or have impacts on *foreign* markets or employment, but none of these papers address whether credit shocks affect the overall investment rates of borrowers from these institutions. Thus, the question of how much these shocks matter for investment, and therefore GDP, remains unanswered.

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 that lending supply

matters 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 holding companies.

2.1 Estimating Firm and Bank Shocks

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

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 $D^B_{bt} \equiv \left(\ln \sum_f L_{fbt} - \ln \sum_f L_{fbt-1}\right)$. 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.,

$$D^B_{bt} \approx \sum_f \phi_{fbt} \Delta \ln L_{fbt}, \tag{2}$$

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

$$D^B_{bt} = \beta_{bt} + \sum_f \phi_{fbt}\alpha_{ft} + \sum_f \phi_{fbt}\epsilon_{fbt}. \tag{3}$$

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.[1] 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 $D^B_{bt} = \gamma z_{bt} + \sum_f \phi_{fbt}\alpha_{ft} + \sum_f \phi_{fbt}\epsilon_{fbt}$. 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:

$$D^B_{bt} = \beta_{bt} + \sum_f \phi_{fbt}\alpha_{ft}. \tag{4}$$

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

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

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

where

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

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_{bt}'s that match this moment in the data. In particular, we choose our parameters to satisfy the following 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:

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

and

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

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; $\left(\bar{A}_t + \bar{B}_t \right)$ 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 $\boldsymbol{1_B}$ and $\boldsymbol{1_F}$ are $B \times 1$ and $F \times 1$ vectors of 1's; $\boldsymbol{N_t}$

is a vector containing the median firm shock in the industry containing the firm; $\boldsymbol{\Theta_t}$ and $\boldsymbol{\Phi_t}$ are matrices that contain as elements the weights of each loan to every borrower, i.e.,

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

$\boldsymbol{\tilde{A}_t}$ is a vector composed of each firm shock in year t less the median firm shock in that firm's industry in year t; and $\boldsymbol{\tilde{B}_t}$ is a vector composed of each bank shock in year t less the median bank shock in year t.[2]

The key feature of equation 9 is that one can decompose each bank's loan growth into four elements. The first term 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 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 toward 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 as the "idiosyncratic firm shock" because it captures changes in a bank's lending that might arise because the bank's particular clients received higher or lower loan amounts after controlling for what was happening in their sectors, their other lenders, and the economy as a whole.

Finally, the last term captures the idiosyncratic loan supply shock because it measures changes in bank loan supply that are independent of anything related to the firms, industries, or common shocks hitting the economy. The elements of $\boldsymbol{\tilde{B}_t}$, the $\tilde{\beta}_{bt}$, are what we refer to as the "idiosyncratic bank shocks." Each element contains the bank b's supply shock in year t less the supply shock of the median bank. Thus, if all banks except bank b suffered a negative

[2]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.

10 percent shock while bank b had no shock, that would be isomorphic in our framework to bank b experiencing a 10 percent positive shock and all other banks experiencing no shock. Since the supply shocks are already purged of all factors affecting their borrowers, our measure of idiosyncratic bank shocks reflects what is happening at each bank *relative* to the typical bank.

Our next task is to assess 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 $t-1$, w_{ft}^F be the average share of firm f in total borrowing in years t and $t-1$, and define $\boldsymbol{W_{Bt}} \equiv \left[w_{1t}^B, \cdots, w_{Bt}^B\right]$. We can now use equation 9 to obtain

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

Equation 10 provides an extremely useful means of decomposing aggregate loan movements into their constituent parts. The first term captures the impact of common shocks on aggregate lending by measuring what happens to the lending of the typical bank-firm pair.[3] The second term represents the granular industry shock because it captures the interaction between industry shocks and the size of the industries. The size of this term will depend on the degree of aggregation used and the variance of shocks within an industry. The third term is the "granular firm shock" because it measures the importance of idiosyncratic borrower

[3] As we explain in Appendix A, our methodology does not let us separate how much of the common shock was due to firm credit vs. lender supply effects. We can only identify the sum of the two effects.

shocks on aggregate lending. Again, this term will be small if borrower demand shocks are small or if the loan share of every borrower tends to be small. Finally, we refer to the last term as the "granular bank shock" because it is a weighted average of all the idiosyncratic financial institution shocks.

The importance of granular *credit* supply shocks is likely to be particularly important for aggregate lending fluctuations if lending markets are concentrated. The reason stems from the fact that the magnitude of granular credit supply shocks depends on two factors: the variance of idiosyncratic bank shocks ($\tilde{\boldsymbol{B}}_{\boldsymbol{t}}$) and the existence of large financial institutions (i.e. some of the elements of $\boldsymbol{W}_{\boldsymbol{Bt}}$ are not small). 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 due to the law of large numbers. However, as we will see in the next section, financial institutions are indeed quite large compared to the the aggregate loan market and have loan shocks that are idiosyncratic. These facts explain why we find in our econometric section that granular bank shocks matter enormously for aggregate fluctuations.

3 Data Description

3.1 Data Construction

Our data come from four sources. First, we use matched bank-firm loan data from Nikkei NEEDS FinancialQUEST for the period 1990 to 2010. Nikkei reports all short-term and long-term loans from each financial institution for every company on any Japanese stock exchange, which we sum to obtain total loans. Our definition of a 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 because we wanted to focus our results on the impact of credit supply shocks arising from private institutions on aggregate lending. Our loan measure is the total borrowing from a given financial institution in a year, comprising all loans received from each financial institution for 870 to 1,633 firms per year. Our data cover all industries, including manufacturing, mining, agriculture, and services. We exclude only the firms in the financial and insurance industries to avoid endogeneity concerns. We divide the industries using the JSIC 2-digit codes, comprising 78 industries.

In general, the Japanese fiscal year runs from April in year t to March in year $t+1$. More than 80 percent of the firms report annual loan data for the fiscal year ending in March, and the rest of the firms report loans ending in one of the other months. For most of our analysis, we will include only firms that report for the year ending in March so that a year is defined over the same time period for all of our firms.[4] We will refer to years ending in March 31 as a "fiscal year" and denote such years by the prefix "FY" to distinguish them from calendar years. Because nine months of any fiscal year occur in the previous calendar year, one should remember that a fiscal year tends to refer to information that is lagged by one year relative to a calendar year. For example, Hokkaido Takushoku Bank, which failed in November 1997, fails in FY1998 because the 1998 fiscal year closes in March 1998.

One difficulty working with these data was sorting through all the mergers and restructurings in our data. Whenever a financial institution ceases to exist, either because of a bankruptcy or failure, firms will cease reporting that financial institution as a source of loans. We investigated every financial institution in order to see if there was any report in the media of a bankruptcy or merger. If we could not find any report, we assumed that the zero loan data were accurate, but if we could find evidence of a failure or a merger, we recorded the date. Since firms sometimes reported loans coming from a restructured financial institution as coming from the prior institution, we recoded these loans as coming from the restructured institution if they occurred after the restructuring. In order to compute the

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

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 sufficient observations to estimate the bank shocks, we keep only bank-year pairs that have a minimum of five loans in t and t-1. This procedure dropped 0.6 percent 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 later period resulting from the wave of mergers in the 2000s.

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

Finally, we draw on two sources of aggregate information on economy-wide borrowings and investment-to-capital ratios. The flow of funds data from the Bank of Japan website provide data on the stock of lending to private nonfinancial corporations from private financial institutions.[5] The economy-wide investment-to-capital ratio data are measured in 2000 yen for fiscal years 1990 to 2010 from the National Accounts, Economic and Social Research

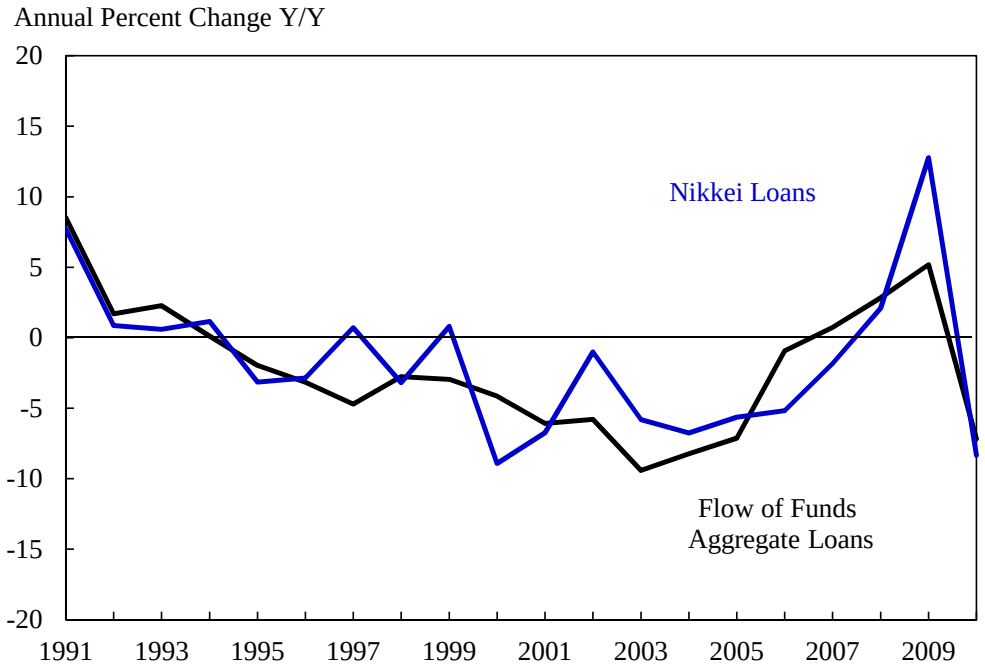
[5]The borrowing data are from the Bank of Japan website. The series number is FF'FOF_FFYS411L240.

Institute, Cabinet Office. The summary statistics are reported in Appendix B.

3.2 Data Preview

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

Figure 1: Flow of Funds and Nikkei Debt



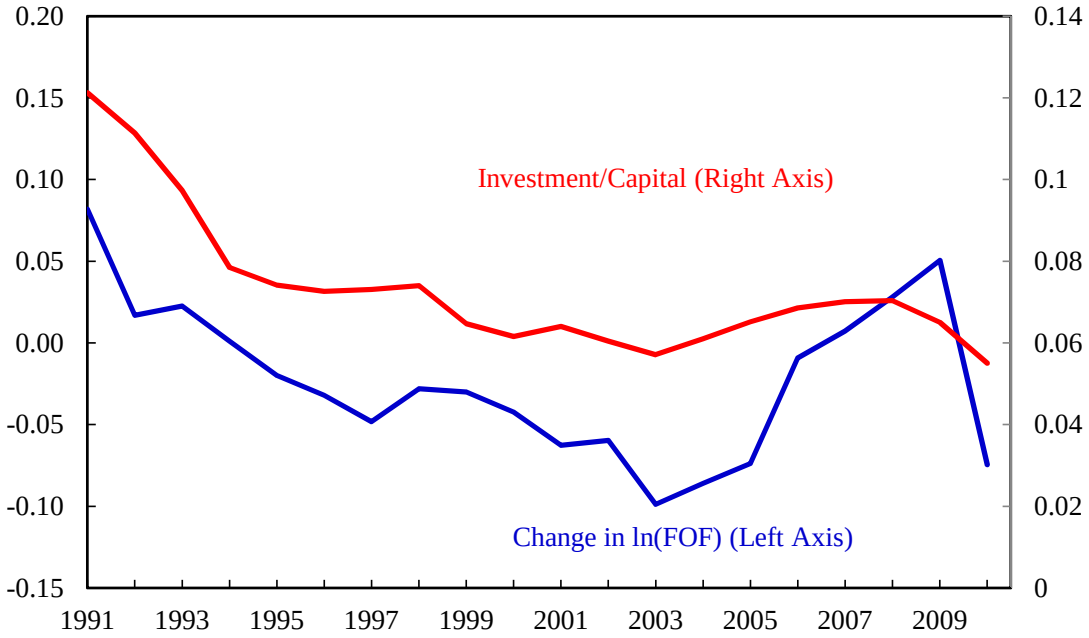
Note: Years are fiscal years, which roughly correspond to the calendar year plus one.

Figure 1 plots the annual percent change in loans to nonfinancial enterprises using the flow of funds lending data and the annual percent change in aggregate loans to nonfinancial enterprises from the Nikkei firm-level database. As can be seen from this graph, aggregate

corporate loans 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 lending became negative and remained so for a decade.

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

Figure 2: Flow of Funds and Aggregate Investment

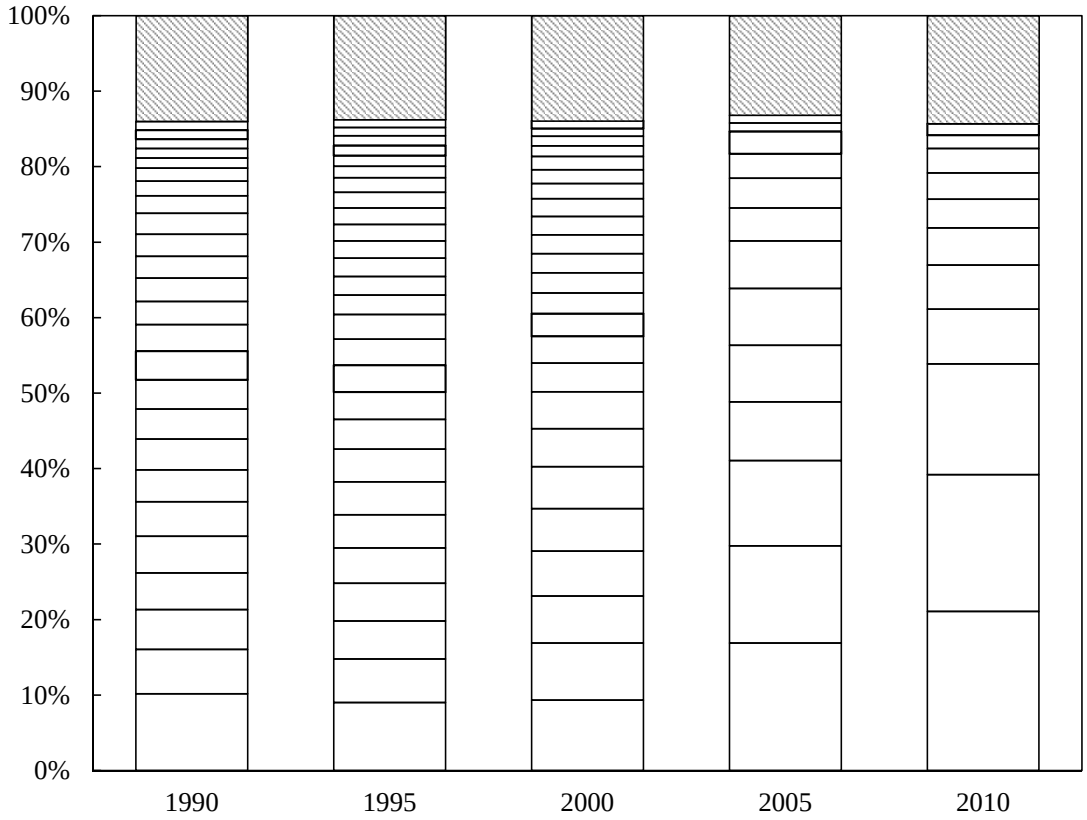


Note: Years are fiscal years which roughly correspond to the calendar year plus one.

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

by financial institution. For each year, we depict individual loan shares of every institution with a loan share exceeding one percent of aggregate lending to listed companies, and group those with a market share of less than one percent into the shaded region.

Figure 3: Bank Concentration

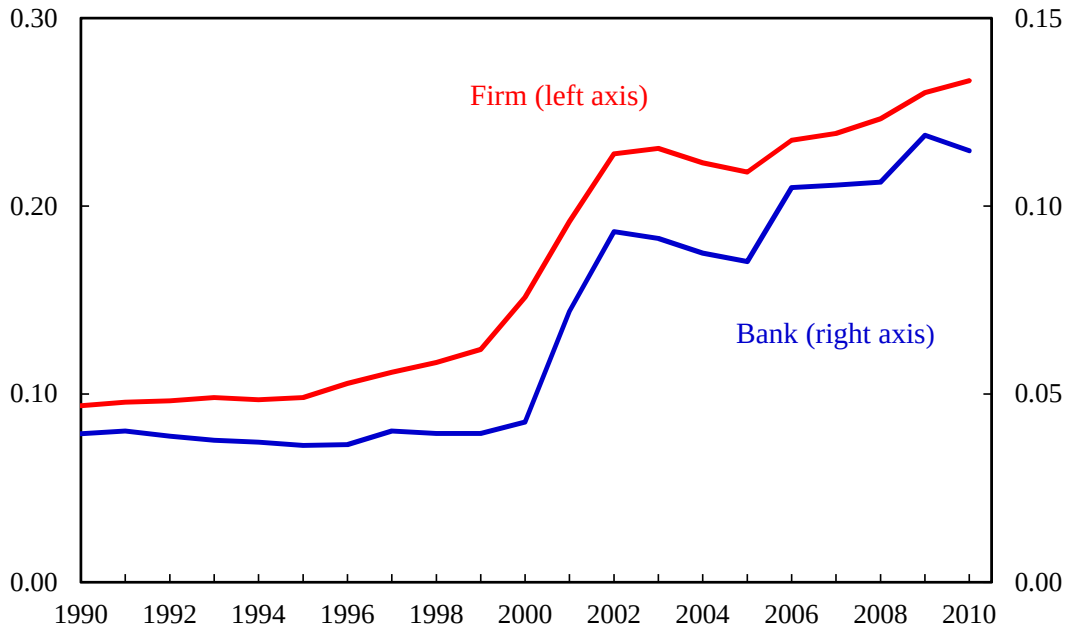


Note: Years are fiscal years, which roughly correspond to the calendar year plus one.

As the figure shows, there was a remarkable increase in concentration in Japanese finance between FY2000 and FY2010. This merger wave was driven by deregulating laws related to the formation of holding companies in 1997 and, as Sakuragawa and Watanabe (2009) argue, the 2002 "Takenaka Plan," which forced more disclosure of nonperforming loans (resulting in mergers of weak institutions). One indicator of the impact of these changes in policy is the movement in the share of corporate lending by the three largest institutions. In FY1990, the three largest Japanese banks accounted for 23 percent of aggregate lending, but this number rose to 54 percent in FY2010, with the largest financial institution, Mitsubishi UFJ Financial Group (MUFG), accounting for 21 percent of all Japanese lending.

The enormous concentration in lending in what at the time was the world's second largest economy provides the basic motivation for our suggestion that idiosyncratic bank shocks might have macroeconomic implications. If financial institutions are large relative to the size of the economy, idiosyncratic shocks to particular institutions could move macro aggregates if firms have difficulty substituting between different sources of finance.

Figure 4: Herfindahl Indexes



Notes: The Herfindahl indexes 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.

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 in 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 index $\left(= \frac{1}{F_t} \sum_f \sum_b \left(L_{fbt} / \sum_b L_{fbt}\right)^2\right)$, 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 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 that 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 period (0.07). 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 are roughly comparable with Germany (0.07) and France (0.05).

Concentration in U.S. banking is remarkably similar as well. The Federal Reserve Board reports data on the assets of bank holding companies in the U.S.[6] Most major lenders are bank holding companies, which jointly accounted for 79 percent of all assets held by commercial banks, thrifts, and credit unions in the U.S. in 2010.[7] The Federal Reserve data indicate that the three largest institutions in the U.S.—Bank of America, JP Morgan, and Citigroup—held 49 percent of all banking assets. This number is remarkably close to the 54 percent number in our Japanese sample. Moreover, the Herfindahl index for asset holdings by these institutions is 0.10, 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 in other countries. Rather, the high degree of financial market concentration appears to be a feature of many developed countries.

[6]The bank asset numbers come from the Bank Holding Company Performance Reports, which are available on the National Information Center website:
(http://www.ffiec.gov/nicpubweb/content/BHCPRRPT/BHCPR_Peer.htm).

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

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, which, 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.

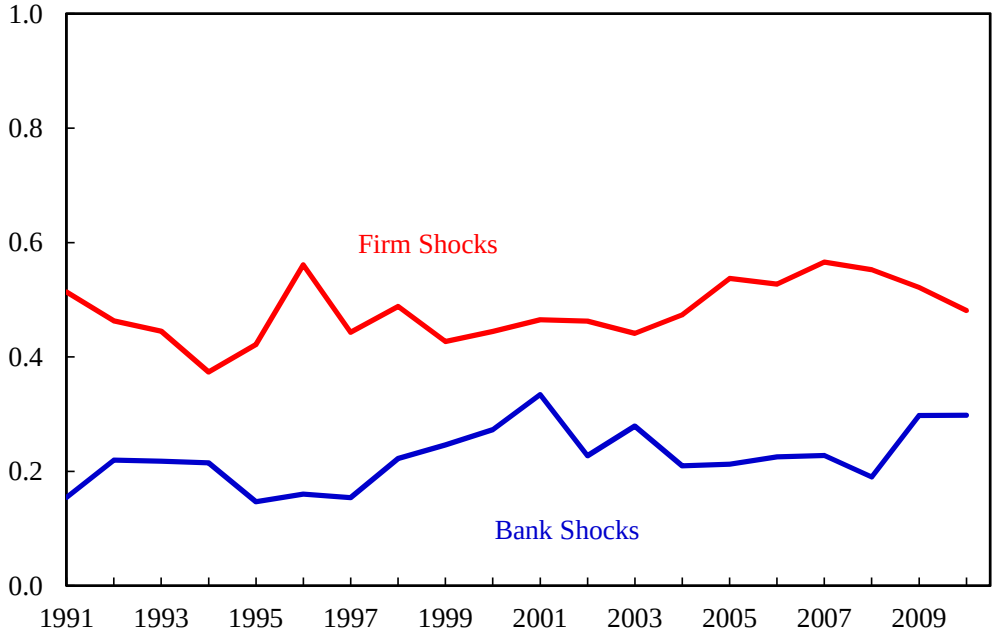
4 Results

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 and supply changes tends to be around 0.5 log units per year. This suggests that heterogeneity in firms' credit shocks 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 idiosyncratic 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 20 percentage points in a given year. This has the potential to have substantial impacts on firms if it is difficult for them to substitute financing from one bank to another.

A second interesting feature of these idiosyncratic bank shocks is the years in which there

Figure 5: Standard Deviations of Bank and Firm Shocks



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

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, and 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 FY2009-10 (calendar years 2008-09) were the years of a global financial crisis. It appears that the variance of idiosyncratic bank shocks is 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 in FY1995-97 (CY1996-98) when Japan had resolved the nonperforming loan problem of its home mortgage companies (*jusen*), and its economy was growing at an average 1.8 percent rate per year. Similarly, the standard deviation in idiosyncratic loan shocks in FY2009 was about 30 to 100 percent larger than 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.

4.2 Testing the Identifying Assumptions

We now turn to running a few tests of our estimated bank shocks to make sure that our methodology generates sensible results. We do this by first checking our identifying assumptions and then verifying that our results are consistent with the proxy variable approach that dominates the literature.

Our approach imposes the moment condition that the weighted average of the errors in equation 1 is zero, *i.e.,* $\sum_b \theta_{fbt}\epsilon_{fbt} = 0$ and $\sum_f \phi_{fbt}\epsilon_{fbt} = 0$. Fortunately, it is straightforward to test this restriction. In order to do this we can estimate equation 1 using fixed effects and denote the parameters from this unconstrained estimation as α^U_{ft} and β^U_{bt}. We next seek to test whether $\alpha^U_{ft} - \hat{\alpha}_{ft} = 0$ and $\beta^U_{bt} - \hat{\beta}_{bt} = 0$, where the $\hat{\alpha}_{ft}$'s and $\hat{\beta}_{bt}$'s are estimated using the method described in the previous section. We test this by estimating

$$\Delta \ln L_{fbt} - \hat{\alpha}_{ft} - \hat{\beta}_{bt} = \hat{\hat{\alpha}}_{ft} + \hat{\hat{\beta}}_{bt} + \epsilon_{fbt} \tag{11}$$

and using an F-test to see if we can reject the hypothesis that all of the estimated $\hat{\hat{\alpha}}_{ft}$'s and $\hat{\hat{\beta}}_{bt}$'s are zero, and therefore validate our assumption underlying the moment condition.

One difficulty of doing this is that the large number of fixed effects makes it computationally impossible to run using Stata. We therefore broke the sample into two time periods, 1991-2000 and 2001-2010, and tested each period separately.[8] The corresponding F-statistics were 0.079 with (12903, 126112) degrees of freedom and 0.24 with (15838, 80806) degrees of freedom. In both cases we could not reject the hypothesis that all of the fixed effects were the same as those obtained using the methodology outlined in the previous section.

A second concern stems from the possibility that there may be some important interaction

[8]Equation 11 can only be estimated on observations where the firm borrowed in both periods from the same bank. We therefore had to estimate our $\hat{\alpha}_{ft}$'s and $\hat{\beta}_{bt}$'s on this restricted data set in order to perform the test. Nevertheless, we still had hundreds of thousands of observations in our regressions.

effects between bank and firm health that we ignore, and this might bias our coefficients. For example, Peek and Rosengren (2005) find that weak banks not only lend less but lend relatively less to healthier firms. Similarly, Jimenez et al. (2011) find that weaker banks lend relatively more to weaker firms when overnight interest rates fall. This is easiest to consider in the context of Peek and Rosengren (2005) because we can merge their data with ours. Our principal concern is not whether interaction effects exist, but rather whether these effects would bias our estimated bank and firm shocks. Once again we can nest a variant of the specification used in Peek and Rosengren (2005) in order to test whether the introduction of the interaction term $H_{bt}H_{ft}$, which is comprised of a measure of the health of the bank and the health of the firm, would affect the point estimates of our bank and firm shocks.[9] We then estimated the following specification

$$\Delta \ln L_{fbt} - \hat{\alpha}_{ft} - \hat{\beta}_{bt} = \hat{\hat{\alpha}}_{ft} + \hat{\hat{\beta}}_{bt} + H_{ft}H_{bt} + \epsilon_{fbt} \tag{12}$$

and tested whether we could reject the hypothesis that all of the estimated $\hat{\hat{\alpha}}_{ft}$'s and $\hat{\hat{\beta}}_{bt}$'s are zero. Once again, we could not reject this hypothesis.[10]

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 $\tilde{\beta}_{bt}$ 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 in studies examining the behavior of Japanese banks is the risk-based capital ratio (*c.f.* Peek and Rosengren (1997, 2000, 2005) and Amiti and Weinstein (2011)). These authors argue that, in the aftermath of the bursting of the Japanese land and

[9]We used the same measures of bank and firm health as in Peek and Rosengren (2005): the product of the lagged value of the firm's ratio of operating income to assets interacted with a dummy that equals one if the bank's reported risk-based capital ratio is less than two percentage points above the required level. These data were available for the period 1993 to 1999.

[10]The F-statistic was 0.70 with (8815, 73148) degrees of freedom. We therefore could not reject the hypothesis that all of the $\hat{\hat{\alpha}}_{ft}$'s and $\hat{\hat{\beta}}_{bt}$'s are zero at all conventional levels of significance.

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

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

4.3 Bank Shocks and Firm-Level Investment

In this section, we assess whether these shocks matter for investment. Prior work in this area has not had a firm-specific, time-varying measure of credit constraints and therefore has focused on whether the cash flow sensitivity of investment for some classes of firms differs from that of others. As we have argued earlier, a major advantage of our approach is that we have estimates of time-varying firm credit and bank loan supply changes. Moreover, equation 8 provides us with a way of decomposing each firm's loan growth into idiosyncratic

Table 1: Validation of Bank Shocks

Dependent Variable: Bank Shock$_{b,t}$	(1)	(2)	(3)
Risk-Based Capital Ratio$_{b,t}$	0.015***		
	(0.004)		
Capital Injection$_{b,t}$		0.103***	
		(0.021)	
Δ ln(Market-to-Book Value$_{b,t-1}$)			0.092***
			(0.027)
Year Fixed Effects	Yes	Yes	Yes
Observations	658	400	843
R^2	0.042	0.032	0.019
Adjusted R^2	0.032	0.025	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 multiplied by the number of shares outstanding and divided by the book value of its equity. We take the 12-month log difference of this variable. We drop the top and bottom one percentiles for bank shocks and log differences of market-to-book value. These data were taken from Nikkei and from the Pacific Basin Capital Markets database. Robust standard errors in parentheses. ***p<0.01, **p<0.05,*p<0.1.

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 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. To put it concretely, we use equation 7 to define the aggregate bank loan shock hitting a particular firm as

$$BankShock_{ft} = \sum_b \theta_{fbt}\tilde{\beta}_{bt}. \tag{13}$$

Since we know that firm credit shocks, $\tilde{\alpha}_{ft}$, and the bank loan supply shocks, $\tilde{\beta}_{bt}$, are orthogonal by construction, $BankShock_{ft}$ must also be orthogonal to investment demand shocks

hitting the firm.

Table 2 presents our findings. In the first column of Table 2, we estimate a standard I/K regression on cash flow and the market-to-book value in which we also control for firm fixed effects and year fixed effects to sweep out any factors related to our sample of firms or correlations between firm-level investment and any common time-varying shock to the investment rate. Not surprisingly, we find the standard result that there is an association between investment and a firm's cash flow and market-to-book value. In Column 2, we add in our industry shock variable to see if the variation in investment-to-capital ratios of a given firm is also associated with the typical change in firm-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 at the industry level.

The most interesting results, however, are those reported in Columns 3, 4, and 5 of Table 2, where we add our firm and bank shock variables to the specification. Since our firms are all listed nonfinancial firms 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 from banks to finance its investment relative to a firm that finances investment through other means. In other words, a given bank shock is likely to have a much larger impact on the investment rate of a firm that finances 80 percent of its capital through bank loans than on a firm that finances only 1 percent of its capital from loans. Therefore, in addition to including the firm and bank shocks in the specification, we also include their interaction with a firm's mean loan-to-asset ratio over the sample period.[11] Column 3 of Table 2 shows that the coefficient on the bank shock entering alone is negative and significant while that on the interaction term is positive and significant, indicating that

[11] 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$_{f,t-1}$	0.048***	0.047***	0.047***	0.047***	0.048***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Market-to-Book Value$_{f,t-1}$	0.011***	0.011***	0.011***	0.011***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Bank Shock$_{f,t}$			-0.162***	-0.166***	-0.114***
			(0.044)	(0.047)	(0.043)
(Bank Shock$_{f,t}$)*(Mean Loan-to-Asset Ratio$_f$)			0.754***	0.757***	0.836***
			(0.193)	(0.193)	(0.191)
(Bank Shock$_{f,t}$)*(Mean Bond-to-Asset Ratio$_f$)				0.079	
				(0.420)	
Firm Shock$_{f,t}$					0.018***
					(0.006)
(Firm Shock$_{f,t}$)*(Mean Loan-to-Asset Ratio$_f$)					0.272***
					(0.043)
Industry Shock$_{f,t}$		0.072***	0.073***	0.073***	0.080***
		(0.018)	(0.018)	(0.018)	(0.018)
Fixed Effects					
Year	yes	yes	yes	yes	yes
Firm	yes	yes	yes	yes	yes
Observations	21,687	21,687	21,687	21,687	21,687
R^2	0.307	0.308	0.308	0.308	0.323
Adjusted R^2	0.240	0.241	0.242	0.242	0.257

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. We drop the top and bottom one percentiles of each variable .

loan-dependent firms' investments are affected by bank shocks. Interestingly, we find that negative bank shocks exert a positive impact on the investment of firms that are almost 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.[12]

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

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

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 susceptible 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 bond interaction term means that the firm's loan share is the critical determinant of a bank shock on a firm's investment. While access to the bond market might serve to lower the importance of loans as a source of finance, conditional on a given loan share of financing, we obtain equally strong estimates of the impact of loan supply shocks on firms with and without high levels of bond finance.

Adding firm-level shocks in the next column hardly affects the coefficients on the bank shocks, reflecting the fact that the firm-level shocks are orthogonal to the bank shocks by construction. The positive coefficient on the firm shock interacted with the mean loan-to-asset ratio implies 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 include only the bank shock terms and the industry effects to see if the exclusion of all potentially endogenous variables affects the results. We find that the coefficients are hardly affected, which underscores the orthogonality of our bank shock variable. Similarly, one might wonder if our results are driven only by crisis years. We therefore reran our regressions excluding the major banking crisis years (FY1991, FY1993, FY1998, and FY2009) to see if

Table 3: Firm-Level Investment Robustness

Dependent Variable: Investment$_{f,t}$/Capital$_{f,t-1}$	(1) Full Sample	(2) Crisis Years Excluded	(3) 1991-2000	(4) 2001-2010
Cash Flow$_{f,t}$/Capital$_{f,t-1}$		0.044***	0.163***	0.043***
		(0.007)	(0.016)	(0.008)
Market-to-Book Value$_{f,t-1}$		0.013***	0.010***	0.014***
		(0.002)	(0.003)	(0.003)
Bank Shock$_{f,t}$	-0.155***	-0.132***	-0.095	-0.064
	(0.044)	(0.050)	(0.072)	(0.061)
(Bank Shock$_{f,t}$)*(Mean Loan-to-Asset Ratio$_f$)	0.705***	0.881***	1.095***	0.543**
	(0.193)	(0.206)	(0.290)	(0.259)
Firm Shock$_{f,t}$		0.026***	0.015	0.023***
		(0.007)	(0.011)	(0.008)
(Firm Shock$_{f,t}$)*(Mean Loan-to-Asset Ratio$_f$)		0.216***	0.325***	0.221***
		(0.047)	(0.090)	(0.046)
Industry Shock$_{f,t}$	0.083***	0.097***	0.118***	0.058***
	(0.018)	(0.021)	(0.029)	(0.022)
Fixed Effects				
Year	yes	yes	yes	yes
Firm	yes	yes	yes	yes
Observations	21,687	17,817	9,505	12,182
R^2	0.291	0.321	0.387	0.377
Adjusted R^2	0.223	0.240	0.278	0.270

Notes: Robust standard errors in parentheses. ***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 results are robust to dropping these years.[13] The results reported in Column 2 indicate that the point estimates are hardly affected. 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

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

between the early years, when bank failures were frequent, and the later years. We find that bank shocks are significant determinants of investment in both periods, but that the point estimates are lower (although not significantly 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 anyone has shown that credit supply shocks affect firm-level investment in general and not just when there are extreme events.

A potential concern about our approach is that in a log change specification we cannot include data on financial institutions that stop lending entirely in a particular year, which might bias the coefficients on bank shocks in the firm investment equation. A simple way of addressing this concern is to express all loan changes as percent changes instead of log changes. In this case equation 1 becomes:

$$\frac{\Delta L_{fbt}}{L_{fbt-1}} = \alpha_{ft} + \beta_{bt} + \epsilon_{fbt} \tag{14}$$

The algebra for deriving the bank and firm shocks using this approach is shown in Appendix C. While we prefer working with log changes because they tend to dampen outliers in cases where loans in period $t-1$ are small and symmetrically drop new entry and exit, we rederive all of our theory in terms of percent changes to check the robustness of our results when we do not make any approximations and do not drop any firms that cease borrowing or any banks that cease lending. The results are so similar to those in Table 2 that we relegate them to a table in Appendix C and simply note that the translog structure and the exclusion of disappearing institutions does not qualitatively affect our results.

The findings in the baseline specification in Column 5 of Table 2 imply a positive relationship between bank shocks and investment for firms with loan-to-asset ratios above 0.14 (around 60 percent of firms in our sample). Meanwhile, for firms below the 0.14 threshold there is either no relationship or, if anything, a negative relationship between bank shocks and investment. These results therefore tend to bridge the gap between studies using matched bank-firm data and extreme events that find a strong relationship between bank shocks and

real economic activity (e.g., Klein, Peek, and Rosengren (2002), Khwaja and Mian (2008), Gan (2007), Amiti and Weinstein (2011), Chodorow-Reich (2013)) and those that suggest firms can circumvent these shocks by accessing bond and other markets (e.g., Adrian, Colla, and Shin (2012)). Our results intuitively indicate that bank shocks matter for firms that are heavily dependent on loans, but not so much for firms that are not dependent on loans.

4.4 Bank Shocks and Aggregate Lending and Investment

As already noted, the lending data in our sample of firms account for only around 17 percent of total lending in Japan in an average year. However, our methodology allows us to identify a pure bank 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 aggregate 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 is an identity.

However, this need not be the case if we replace the dependent variable with economy-wide aggregate loan growth from the flow of funds data. In this case, we can write the relationship between aggregate lending and lending to listed companies as,

$$\Delta L_t^{FOF} = \boldsymbol{W_{Bt} D_{Bt}} + \epsilon_t$$

or

$$\Delta L_t^{FOF} = \delta + \gamma_1 \left(\bar{A}_t + \bar{B}_t\right) + \gamma_2 \boldsymbol{W_{Bt} \Phi_t N_t} + \gamma_3 \boldsymbol{W_{Bt} \Phi_t \tilde{A}_t} + \gamma_4 \boldsymbol{W_{Bt} \tilde{B}_t} + \epsilon_t. \qquad (15)$$

If we estimate equation 15, we will only obtain coefficients of one on each term if each of the terms we measured using the Nikkei data equaled the terms for the whole economy and the error term is uncorrelated with any of the explanatory variables. Measurement

error or economy-wide variables that moved more or less than the corresponding variables in the Nikkei data could cause the coefficients to differ from one. Moreover, to the extent that one thought that economy-wide lending behavior and loans to listed companies were uncorrelated, one might expect to see a low R^2 from estimating equation 15. 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.

In other words, we can interpret the coefficients on each of these terms as the contribution of each variable to the flow of funds lending growth, while the error term corresponds to deviations in aggregate loan growth from loan growth for listed companies. Our interest is not in causality, 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 only be well explained if we include the granular term encompassing the idiosyncratic bank shocks. Interestingly, while common, industry, and granular bank shocks have coefficients close to one in Column 5, the granular firm shock is attenuated, perhaps because while we have all of the large banks in our sample, we do not have large unlisted firms, and hence there is more measurement error in the granular firm shock variable.

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

Table 4: Flow of Funds

Dependent Variable: Δ ln(Flow of Funds$_t$)						
	(1)	(2)	(3)	(4)	(5)	(6)
Common Shock$_t$	0.460*	0.485*	0.379	1.365***	1.261***	1.323***
	(0.235)	(0.258)	(0.270)	(0.183)	(0.173)	(0.182)
Industry Shock$_t$		0.836**	0.550	1.722***	1.467***	0.584***
		(0.373)	(0.431)	(0.315)	(0.286)	(0.114)
Firm Shock$_t$			0.361*		0.303**	0.225**
			(0.175)		(0.132)	(0.098)
Bank Shock$_t$				1.341***	1.319***	1.135***
				(0.250)	(0.229)	(0.197)
Constant	-0.017	-0.016*	-0.017*	-0.001	-0.002	-0.000
	(0.010)	(0.009)	(0.009)	(0.006)	(0.006)	(0.117)
Standardized Variable	No	No	No	No	No	Yes
Observations	20	20	20	20	20	20
R^2	0.233	0.343	0.391	0.751	0.785	0.785
Adjusted R^2	0.190	0.265	0.277	0.705	0.728	0.728

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

lending pairs. In other words, the data do not reject the hypothesis that the common, industry, and granular bank shocks identified in the Nikkei data are the same as those we would find in economy-wide data.

However, our main interest is in understanding the importance of the granular bank shock term. One metric of its importance is to consider how much of the variance it explains. Comparing 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 about 40 percent of the variance in aggregate lending. The fact that the granular bank shock term is highly significant and moves the R^2 of the regression substantially strongly suggests that the idiosyncratic lending decisions of large financial institutions have a large impact

on aggregate lending. In 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 also highly sensitive to idiosyncratic bank shocks. 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, 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 to a firm's investment demand will be captured in our common shock term; therefore, the granular bank shocks cannot be caused by these common shocks. The question is whether and how much granular bank shocks matter for aggregate investment.

As in the previous table, the granular bank shock term enters strongly significant and raises the R^2 of the regression from 0.24 to 0.64, 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

Table 5: Aggregate Investment

Dependent Variable: Investment$_t$/Capital$_{t-1}$						
	(1)	(2)	(3)	(4)	(5)	(6)
Common Shock$_t$	0.164*	0.162*	0.157*	0.478***	0.480***	1.386***
	(0.084)	(0.084)	(0.085)	(0.120)	(0.127)	(0.368)
Industry Shock$_t$		-0.091	-0.102	0.228	0.234	0.256
		(0.222)	(0.226)	(0.201)	(0.222)	(0.243)
Firm Shock$_t$			0.014		-0.007	-0.015
			(0.090)		(0.070)	(0.144)
Bank Shock$_t$				0.482***	0.483***	1.142***
				(0.132)	(0.138)	(0.326)
Constant	0.075***	0.075***	0.075***	0.081***	0.081***	-0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.152)
Standardized Variables	No	No	No	No	No	Yes
Observations	20	20	20	20	20	20
R^2	0.225	0.235	0.236	0.635	0.635	0.635
Adjusted R^2	0.182	0.145	0.092	0.566	0.538	0.538

Notes: Robust standard errors in parentheses. ***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.

investment-to-capital ratio by one standard deviation—about as much as common shocks.

The importance of this result can be considered in comparison with those in Table 2. In that table, we learned that bank shocks matter for a firm's investment relative to the investment of other firms but that does not necessarily imply that these bank shocks mattered overall. The results in Table 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. Since the granular bank shocks are constructed from idiosyncratic bank shocks that are orthogonal to firm credit shocks, they are macro variables that not determined by aggregate investment demand fluctuations. The fact that they matter so much for investment suggests that the strong, causal, link between

loan supply and firm-level investment that we identified in Tables 2 and 3, matters at the aggregate level as well.

5 Conclusion

Although prior work using matched bank-firm data had shown that credit shocks could affect lending and some forms of real activity, those studies did not examine the impacts of these shocks on the overall investment rates of firms or 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 for understanding GDP fluctuations.

Our paper contributes to this literature by providing the first evidence that shocks to the supply of credit affect firm investment rates. We find that even after controlling for firm credit shocks, loan supply shocks are a significant determinant of firm-level investment of loan-dependent firms. This result is particularly surprising because our sample is comprised of listed companies that have, by definition, access to equity markets. 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 are an important determinant of investment and real economic activity.

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Appendix A: 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 satisfy equations 4 and 7, $\beta_{bt} + k_t$ 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 so we will impose that $\alpha_{1t} = 0$ (or equivalently $k_t = \alpha_{1t}$).

All shocks are defined as relative to this shock. Without loss of generality, we can rewrite equation 7 as

$$\begin{aligned} D_{ft}^F &\equiv \alpha_{ft} + \sum_b \theta_{fbt} \left(\beta_{bt} - \beta_{1t}\right) + \beta_{1t} \\ &= \alpha_{ft} + \sum_{b \neq 1} \theta_{fbt} \left(\beta_{bt} - \beta_{1t}\right) + \beta_{1t}. \end{aligned} \tag{16}$$

Similarly, we can rewrite equation 4 as

$$D_{bt}^B = \beta_{bt} + \sum_{f \neq 1} \phi_{fbt} \alpha_{ft}. \tag{17}$$

Finally, for firm 1, we have

$$D_{1t}^F = \sum_{b \neq 1} \theta_{1bt} \left(\beta_{bt} - \beta_{1t}\right) + \beta_{1t} \tag{18}$$

or

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

and for bank 1, we have

$$D_{1t}^B = \beta_{1t} + \sum_{f \neq 1} \phi_{f1t} \alpha_{ft}. \tag{20}$$

If we substitute equation 19 into equation 16, we obtain

$$D^F_{ft} - D^F_{1t} = (\alpha_{ft} - \alpha_{1t}) + \sum_{b \neq 1} (\theta_{fbt} - \theta_{1bt})(\beta_{bt} - \beta_{1t}) = \alpha_{ft} + \sum_{b \neq 1} \hat{\theta}_{fbt} \hat{\beta}_{bt}, \tag{21}$$

where $\hat{\theta}_{fbt} = (\theta_{fbt} - \theta_{1bt})$, and $\hat{\beta}_{bt} = (\beta_{bt} - \beta_{1t})$. Substituting equation 20 into equation 17 gives us

$$D^B_{bt} - D^B_{1t} = (\beta_{bt} - \beta_{1t}) + \sum_{f \neq 1} (\phi_{fbt} - \phi_{f1t}) \alpha_{ft} = \hat{\beta}_{bt} + \sum_{f \neq 1} \hat{\phi}_{fbt} \alpha_{ft}, \tag{22}$$

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

For every year, equations 21 and 22 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:

$$\hat{\boldsymbol{A}}_{\boldsymbol{t}} \equiv \begin{pmatrix} \alpha_{2t} \\ \vdots \\ \alpha_{Ft} \end{pmatrix}, \hat{\boldsymbol{B}}_{\boldsymbol{t}} \equiv \begin{pmatrix} \hat{\beta}_{2t} \\ \vdots \\ \hat{\beta}_{Bt} \end{pmatrix}, \hat{\boldsymbol{D}}_{\boldsymbol{Ft}} \equiv \begin{pmatrix} D^F_{2t} - D^F_{1t} \\ \vdots \\ D^F_{Ft} - D^F_{1t} \end{pmatrix}, \hat{\boldsymbol{D}}_{\boldsymbol{Bt}} \equiv \begin{pmatrix} D^B_{2t} - D^B_{1t} \\ \vdots \\ D^B_{Bt} - D^B_{1t} \end{pmatrix} \tag{23}$$

$$\hat{\boldsymbol{\Theta}}_{\boldsymbol{t}} \equiv \begin{pmatrix} \hat{\theta}_{22t} & \dots & \hat{\theta}_{2Bt} \\ \vdots & \ddots & \vdots \\ \hat{\theta}_{F2t} & \dots & \hat{\theta}_{FBt} \end{pmatrix}, \hat{\boldsymbol{\Phi}}_{\boldsymbol{t}} \equiv \begin{pmatrix} \hat{\phi}_{22t} & \dots & \hat{\phi}_{F2t} \\ \vdots & \ddots & \vdots \\ \hat{\phi}_{2Bt} & \dots & \hat{\phi}_{FBt} \end{pmatrix} \tag{24}$$

We now can rewrite equation 21 as

$$\hat{\boldsymbol{A}}_{\boldsymbol{t}} = \hat{\boldsymbol{D}}_{\boldsymbol{Ft}} - \hat{\boldsymbol{\Theta}}_{\boldsymbol{t}} \hat{\boldsymbol{B}}_{\boldsymbol{t}} \tag{25}$$

and equation 22 as

$$\hat{\boldsymbol{B}}_{\boldsymbol{t}} = \hat{\boldsymbol{D}}_{\boldsymbol{Bt}} - \hat{\boldsymbol{\Phi}}_{\boldsymbol{t}} \hat{\boldsymbol{A}}_{\boldsymbol{t}}. \tag{26}$$

If we use this fact and insert equation 25 into equation 26, we know that any solution to equations 7 and 26 must satisfy

$$\hat{\boldsymbol{B}}_{\boldsymbol{t}} = \hat{\boldsymbol{D}}_{\boldsymbol{Bt}} - \hat{\boldsymbol{\Phi}}_{\boldsymbol{t}} \left[\hat{\boldsymbol{D}}_{\boldsymbol{Ft}} - \hat{\boldsymbol{\Theta}}_{\boldsymbol{t}} \hat{\boldsymbol{B}}_{\boldsymbol{t}} \right]. \tag{27}$$

This equation can be rewritten as

$$\left(\boldsymbol{I}_{\boldsymbol{B-1}} - \hat{\boldsymbol{\Phi}}_{\boldsymbol{t}} \hat{\boldsymbol{\Theta}}_{\boldsymbol{t}} \right) \hat{\boldsymbol{B}}_{\boldsymbol{t}} = \hat{\boldsymbol{D}}_{\boldsymbol{Bt}} - \hat{\boldsymbol{\Phi}}_{\boldsymbol{t}} \hat{\boldsymbol{D}}_{\boldsymbol{Ft}}, \tag{28}$$

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

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

and

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

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

$$\begin{aligned} \beta_{1t} &= D_{1t}^{F} - \sum_{b \neq 1} \theta_{1bt} \left(\beta_{bt} - \beta_{1t} \right) && (31) \\ &= D_{1t}^{B} - \sum_{f \neq 1} \phi_{f1t} \alpha_{ft}. && (32) \end{aligned}$$

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

$$\boldsymbol{A}_{\boldsymbol{t}} \equiv \begin{pmatrix} \alpha_{1t} \\ \vdots \\ \alpha_{Ft} \end{pmatrix}, \boldsymbol{B}_{\boldsymbol{t}} \equiv \begin{pmatrix} \beta_{1t} \\ \vdots \\ \beta_{Bt} \end{pmatrix}. \tag{33}$$

It will also be useful to define

$$\boldsymbol{D}_{\boldsymbol{Ft}} \equiv \begin{pmatrix} D^F_{1t} \\ \vdots \\ D^F_{Ft} \end{pmatrix}, \boldsymbol{D}_{\boldsymbol{Bt}} \equiv \begin{pmatrix} D^B_{1t} \\ \vdots \\ D^B_{bt} \end{pmatrix}, \boldsymbol{\Theta}_{\boldsymbol{t}} \equiv \begin{pmatrix} \theta_{11t} & \dots & \theta_{1Bt} \\ \vdots & \ddots & \vdots \\ \theta_{F1t} & \dots & \theta_{FBt} \end{pmatrix}, \boldsymbol{\Phi}_{\boldsymbol{t}} \equiv \begin{pmatrix} \phi_{11t} & \dots & \phi_{F1t} \\ \vdots & \ddots & \vdots \\ \phi_{1Bt} & \dots & \phi_{FBt} \end{pmatrix}. \tag{34}$$

We can rewrite the system of equations given

$$\begin{aligned} \boldsymbol{D}_{\boldsymbol{Ft}} &= \boldsymbol{A}_{\boldsymbol{t}} + \boldsymbol{\Theta}_{\boldsymbol{t}} \boldsymbol{B}_{\boldsymbol{t}} \\ &= \dot{\boldsymbol{A}}_{\boldsymbol{t}} + \bar{A}_t \mathbf{1}_{\boldsymbol{F}} + \boldsymbol{\Theta}_{\boldsymbol{t}} \dot{\boldsymbol{B}}_{\boldsymbol{t}} + \bar{B}_t \boldsymbol{\Theta}_{\boldsymbol{t}} \mathbf{1}_{\boldsymbol{B}} && (35) \\ &= \dot{\boldsymbol{A}}_{\boldsymbol{t}} + \boldsymbol{\Theta}_{\boldsymbol{t}} \dot{\boldsymbol{B}}_{\boldsymbol{t}} + \left(\bar{A}_t + \bar{B}_t\right) \mathbf{1}_{\boldsymbol{F}}, && (36) \end{aligned}$$

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

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

$$\begin{aligned} \boldsymbol{D}_{\boldsymbol{Bt}} &= \dot{\boldsymbol{B}}_{\boldsymbol{t}} + \boldsymbol{\Phi}_{\boldsymbol{t}} \dot{\boldsymbol{A}}_{\boldsymbol{t}} + \left(\bar{B}_t \mathbf{1}_{\boldsymbol{B}} + \boldsymbol{\Phi}_{\boldsymbol{t}} \bar{A}_t \mathbf{1}_{\boldsymbol{F}}\right) \\ &= \dot{\boldsymbol{B}}_{\boldsymbol{t}} + \boldsymbol{\Phi}_{\boldsymbol{t}} \dot{\boldsymbol{A}}_{\boldsymbol{t}} + \left(\bar{A}_t + \bar{B}_t\right) \mathbf{1}_{\boldsymbol{B}}. && (37) \end{aligned}$$

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 the industry the firm is in. Similarly, we define the idiosyncratic 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

$$\boldsymbol{D}_{\boldsymbol{F}\boldsymbol{t}} = \tilde{\boldsymbol{A}}_{\boldsymbol{t}} + \boldsymbol{N}_{\boldsymbol{t}} + \boldsymbol{\Theta}_{\boldsymbol{t}}\tilde{\boldsymbol{B}}_{\boldsymbol{t}} + \left(\bar{A}_t + \bar{B}_t\right)\mathbf{1}_{\boldsymbol{F}}, \tag{38}$$

and

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

Appendix B: Summary Statistics

By Year	Mean	Median	SD	Minimum	Maximum
Δ ln(Flow of Funds$_t$)	-0.023	-0.029	0.048	-0.099	0.082
Investment$_t$/Capital$_{t-1}$	0.073	0.069	0.017	0.055	0.121
Common Shock$_t$	-0.013	-0.005	0.050	-0.175	0.057
By Bank					
Bank Shock$_{b,t}$	-0.003	0.000	0.173	-0.714	0.645
Capital Injection$_{b,t}$	0.097	0.000	0.296	0.000	1.000
Risk-Based Capital Ratio$_{b,t}$	8.803	9.120	1.760	2.820	13.610
Δ ln(Market-to-Book Value$_{b,t-1}$)	-0.100	-0.107	0.224	-0.684	0.572
By Firm					
Investment$_{f,t}$/Capital$_{f,t-1}$	0.118	0.081	0.167	-0.398	1.745
Cash-Flow$_{f,t}$/Capital$_{f,t-1}$	0.335	0.209	0.718	-1.569	15.410
Market-to-Book Value$_{f,t}$	1.698	1.297	1.377	0.234	10.367
Bank Shock$_{f,t}$	-0.010	-0.011	0.052	-0.156	0.178
Firm Shock$_{f,t}$	0.006	0.000	0.324	-1.453	1.470
Industry Shock$_{f,t}$	0.001	0.002	0.073	-0.959	1.187
Mean Loan to Asset Ratio$_f$	0.196	0.174	0.123	0.001	0.748
Mean Bond to Asset Ratio$_t$	0.048	0.029	0.057	0.000	0.359

Appendix C: Derivation of Equations 4 and 7 using Percentage Changes

The growth in lending from institution b to firm f is given in percentage terms can be written as

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

$$L_{bt} = \sum_f L_{fbt}, \quad L_{ft} = \sum_b L_{fbt},$$

and we can write the aggregate bank loan growth in terms of the growth rates of loans to individual firms:

$$D'_{bt} = \frac{L_{bt} - L_{bt-1}}{L_{bt-1}} = \frac{\sum_f L_{fbt} - \sum_f L_{fbt-1}}{\sum_f L_{fbt-1}} = \sum_f \left(\frac{L_{fbt} - L_{fbt-1}}{L_{fbt-1}} \right) \frac{L_{fbt-1}}{\sum_f L_{fbt-1}}. \tag{2'}$$

Substituting equation $1'$ into equation $2'$ gives

$$D'_{bt} = \sum_f (\alpha_{ft} + \beta_{bt} + \varepsilon_{fbt}) \phi'_{fbt},$$

where

$$\phi'_{fbt} \equiv \frac{L_{fbt-1}}{\sum_f L_{fbt-1}} \quad \text{and} \quad \sum_f \phi'_{fbt} = 1,$$

which we expand and simplify to

$$D'_{bt} = \beta_{bt} + \sum_f \phi'_{fbt} \alpha_{ft} + \sum_f \phi'_{fbt} \varepsilon_{fbt}. \tag{3'}$$

We use the moment condition that $E\left[\sum_f \phi'_{fbt} \varepsilon_{fbt}\right] = 0$ to simplify and obtain

$$D'_{bt} = \beta_{bt} + \sum_f \phi'_{fbt} \alpha_{ft}. \tag{4'}$$

Similarly for firm borrowing, we have

$$D'_{ft} = \frac{L_{ft} - L_{ft-1}}{L_{ft-1}} = \frac{\sum_b L_{fbt} - \sum_b L_{fbt-1}}{\sum_b L_{fbt-1}} = \sum_b \left(\frac{L_{fbt} - L_{fbt-1}}{L_{fbt-1}} \right) \frac{L_{fbt-1}}{\sum_b L_{fbt-1}} \tag{5'}$$

and can substitute to obtain

$$D'_{ft} = \sum_b (\alpha_{ft} + \beta_{bt} + \varepsilon_{fbt}) \theta'_{fbt},$$

where

$$\theta'_{fbt} \equiv \frac{L_{fbt-1}}{\sum_b L_{fbt-1}} \quad \text{and} \quad \sum_b \theta'_{fbt} = 1,$$

which we expand and simplify to

$$D'_{ft} = \alpha_{ft} + \sum_f \theta'_{fbt} \beta_{bt} + \sum_b \theta'_{fbt} \varepsilon_{fbt}. \tag{6'}$$

We use the moment condition that $E\left[\sum_b \theta'_{fbt} \varepsilon_{fbt}\right] = 0$ to simplify and obtain

$$D'_{ft} = \alpha_{ft} + \sum_f \theta'_{fbt} \beta_{bt}. \tag{7'}$$

Equations $4'$ and $7'$ are analogous to equations 4 and 7 with the only difference being the definition of the weights. Hence, all of the remaining algebra is identical. The results of estimating our investment equation using this procedure are presented below in Table C1.

Table C1: Firm-Level Investment (percentage change specification)

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***	0.050***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Market-to-Book Value$_{f,t-1}$	0.012***	0.012***	0.012***	0.012***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Bank Shock$_{f,t}$			-0.163***	-0.154***	-0.145***
			(0.040)	(0.043)	(0.040)
(Bank Shock$_{f,t}$)*(Mean Loan-to-Asset Ratio$_f$)			0.666***	0.660***	0.774***
			(0.184)	(0.184)	(0.183)
(Bank Shock$_{f,t}$)*(Mean Bond-to-Asset Ratio$_f$)				-0.192	
				(0.346)	
Firm Shock$_{f,t}$					0.012**
					(0.005)
(Firm Shock$_{f,t}$)*(Mean Loan-to-Asset Ratio$_f$)					0.196***
					(0.033)
Industry Shock$_{f,t}$		0.069***	0.069***	0.069***	0.068***
		(0.017)	(0.017)	(0.017)	(0.017)
Fixed Effects					
Year	yes	yes	yes	yes	yes
Firm	yes	yes	yes	yes	yes
Observations	22,605	22,605	22,605	22,605	22,605
R^2	0.307	0.308	0.308	0.308	0.319
Adjusted R^2	0.242	0.243	0.243	0.243	0.255

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. We drop the top and bottom one percentiles of each variable .