Tracing the Impact of Bank Liquidity Shocks

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Abstract

While bank lending may fall in response to shocks to their liquidity, to what extent are such shocks transmitted to borrowing firms? Tracing such transmission mechanisms has proven difficult in the past due to a lack of micro data linking banks to borrowing firms and identification concerns. This paper uses differential liquidity shocks arising from unanticipated nuclear tests in Pakistan in 1998, and a dataset linking over $18,000$ firms to all 145 banks to understand the full transmission mechanism. We isolate the causal impact of the bank lending channel by showing that for the *same* firm borrowing from two different banks, its loan from the bank experiencing a 1% larger decline in liquidity drops by an additional 0.6%. The liquidity shock also leads to large declines in the probability of continued lending to old clients, and extending credit to new ones. *However*, we find that firms differ in their ability to compensate the bank lending channel shock. Larger firms, while also facing a bank lending channel, are able to offset the adverse effect by borrowing more from more liquid banks. Smaller firms on the other hand are entiely unable to hedge out the bank lending channels. Consequently, a negative bank liquidity shock increases the probability of financial distress for smaller firms, while no such effect exists for large firms. Therefore while bank liquidity shocks may not have a notable impact on overall lending as large borowers are able to compensate these shocks, they have substantial distributional consequences due to a large adverse and persistent impact on smaller firms.

To what extent do liquidity shocks have real consequences on an economy? Economists have long been interested in understanding whether the ability of banks to act as financial intermediaries is affected by shocks to their liquidity supply, with some arguing such supply shocks are behind the Great Depression, the US and Japanese recessions of the 1990s and the more recent Asian crises.[1] While separating supply from demand remains a challenge, a number of recent papers (Gertler and Gilchrist, 1994; Kashyap et. al. 1993, 1994; Kashyap and Stein 2000) provide compelling evidence for the "bank lending channel" i.e. banks lend less when faced with shocks to their deposit base. However, even if such a channel exists, it may not have any significant real consequences if firms borrowing from affected banks can compensate through alternative sources of funding. One has to therefore trace the impact of the liquidity shock to the level of the borrowing firms in order to provide a better sense of its real consequences. Unfortunately a lack of an economy wide data linking banks to firms in an environment with a significant liquidity shock has limited our understanding of this issue.

This paper attempts to do so by exploiting a natural experiment that induces differential liquidity shocks across banks in an emerging economy and using a loan-level panel dataset that comprises the universe of corporate lending in the economy, linking every borrowing firm to each lender. We find that a one percent drop in bank liquidity leads to over 0.6 percent drop in its lending. Comparing lending differences across banks for the same firm allows us to better isolate the supply side channel. While this identifies the existence of a large bank lending channel, examining overall firm borrowing shows that large borrowers are able to compensate for this shock by borrowing from more liquid banks. Consequently the bank lending channel has little net effect on these firms. In contrast, smaller borrowers are entirely unable to compensate and their overall borrowing drops one for one with the bank lending effect. Not only is this impact on smaller borrowers persistent but it leads to increased financial distress in terms of higher default rates on their loans. This presents a more nuanced understanding of the real impact of liquidity shocks: Since larger borrowers comprise the vast majority of lending in most emerging economies, liquidity shocks have little real consequences in terms of average borrowing. However, these shocks have very large *distributional* consequences as they adversely effect the large majority of (smaller) borrowers.

[1] See for example, Bernanke (1983), Bernanke and Lown (1991), Hoshi and Kashyap (2000), Woo (2003), Agenor, Aizenman, and Hoffmaister (2000).

Our paper therefore contributes to the literature by not only tracing the impact of an initial liquidity shock down to the form level, but by identifying that firms vary systematically in their ability to hedge bank-level shocks and that, despite having small real effects on aggregate lending, liquidity shocks can have substantial distributional consequences. Our distributional results highlight the limitations of bank intermediation in emerging financial markets - at times of liquidity crunches, banks cut back lending to precisely those (smaller) clients that need it the most. Moreover, the methodology utilized in the paper addresses the empirical challenges of identifying the impact of supply side shocks separately from contemporaneous demand side shocks.

The data we employ represents the universe of corporate lending in an emerging financial market, Pakistan, and matches a firm to all its creditors. This allows us to examine both the bank lending and firm borrowing channels. It links more than $18,000$ firms to banks over a four year period and provides quarterly information on the amount, type, and status of all outstanding loans. In addition to the level of detail and coverage available, the setting offers a unique opportunity to study liquidity shocks due to a natural experiment - a relatively large and exogenous deposit base shock that varied across banks. The shock was induced by unexpected nuclear tests conducted by Pakistan in 1998 in almost immediate response to similar tests by India. The subsequent international financial sanctions and the government's decision to only allow withdrawals from dollar-denominated deposits (almost half of all deposits at the time) in local currency at a disadvantaged exchange rate, led to sharp drops in deposits for banks with greater foreign currency deposits.

The bank lending channel is hard to identify, even in the presence of such exogenous liquidity shocks, because shocks to the supply of bank liquidity are typically accompanied by shocks to the demand for liquidity. For example, liquidity supply in the form of bank deposits may decline in bad times when firms also have lower demand for bank credit. Alternatively, liquidity supply might fall more for "bad banks" known to have more risky loan portfolios. We are able to provide cleaner estimates by focusing on firms that were borrowing from multiple banks at the time of the nuclear tests. This allows us to use firm fixed effects in first-differenced data and test whether the *same* firm borrowing from two different banks experiences a greater loan decline from its bank that has a relatively larger liquidity crunch (as compared to its other bank/s). This methodology controls for unobserved firm-level demand shocks that affect firms contemporaneously. Consequently, unlike previous studies, we need not rely on potentially strong identification assumptions that the unobserved demand shocks are uncorrelated with supply shocks.

Our analysis shows the presence of a large bank lending channel. For a firm borrowing from two different banks at the time of the nuclear tests, its borrowing from the bank experiencing a 1% larger liquidity decline, drops by an extra 0.6%. Our strategy controls for unobserved firm-level *changes* in the demand of credit. Examining the bank lending channel effect over time shows that the effect is sudden and persistent.

We also examine remaining identification concerns in the FE estimate. For example, what if firms finance different types of projects through different banks and that this choice is correlated with the shocks experienced by banks. In this case firm fixed effects may not account for the firm's loan level credit demand change. Since we have information on loan types, we can show that this concern is unlikely by using firm interacted with loan type fixed effects. Similarly, one may worry that if more quality sensitive banks face greater shocks, they may cut back lending relatively more to lower quality firms than other banks i.e. it is not that they are unable to lend to the firm (due to the liquidity shock), but are unwilling to do so relative to the other banks (due to the firm productivity shock). We address this by showing our result is robust to pre-shock quality differences across banks, and by showing the quality of borrowers actually falls relatively more for the banks facing greater liquidity shocks i.e. they do not display greater quality consciousness.

The bank lending channel also has a large impact on a bank's extensive margin, i.e. its decision to lend to new clients and to continue lending to existing clients. A 1% fall in bank liquidity reduces the probability of lending to new clients by 12 basis points and the probability of continuing lending to existing clients by 21 basis points. Interestingly, the bank lending channel identified in this paper works predominantly through its impact on the quantity of loan supply. We find no evidence that the bank liquidity shocks also impact the price (i.e. interest rate) of loans.

Given the strong bank lending channel, we investigate further if a firm borrowing channel also exists. Are firms able to compensate the drop in loans from their bank facing a liquidity drop by borrowing more from another bank that has better liquidity? Note that in order to examine this we can no longer use our firm fixed effects strategy since each firm has only one observation - its overall borrowing from all banks. However, our particular context offers a unique solution. While the shock is not unusual in terms of magnitude compared to shocks experienced by other economies, especially emerging markets, what makes it particularly advantageous for estimation purposes is that it varies across banks in a way that makes the relative supply shock to a bank *negatively* correlated with its liquidity demand shock. This implies that while OLS estimates are biased, they are very useful since they provide *underestimates* of the supply shock impact unlike the over-estimates that one typically worries about in the literature.

What is important is that we can not only explain why the particular shock may have resulted in a negative correlation between supply and demand shocks across banks, but we can present direct evidence that this is indeed the case.

The negative correlation between supply and demand shocks is generated by the nature of the supply shock. As explained before, the liquidity shock arose due to the loss of confidence from a partial default on dollar deposit accounts. The extent of the ensuing run was greater for banks with larger dollar-deposit accounts. While banks with more dollar deposits experienced larger declines in their deposit base, they were in fact likely to be lending to better quality and more resilient firms, i.e. those that were likely to face relatively lower demand shocks. We empirically verify this by showing that banks that experienced greater liquidity supply shocks indeed had better clients in terms of their pre-shock loan profitability and performance.

Moreover, if such a negative correlation exists we would predict that OLS estimates of the bank-lending channel would be biased downwards. We can check this by comparing OLS estimates for the sample of firms that borrow from multiple bank to our unbiased FE estimates for the *same* sample of firms. Doing so reveals that the OLS estimate is indeed an under-estimate (by almost a half) of the supply side effect.

Examining overall firm borrowing using this strategy reveals that the ability of a firm to hedge the bank-lending channel depends on whether it was a large borrower prior to the shock. The top three deciles firms in terms of pre-shock borrowing, fully compensate for the bank-level liquidity shock by borrowing more from more liquid banks, particularly those that the firm may have (also) been borrowing from before. However, the remaining smaller borrowers (bottom 70%) are completely unable to hedge the initial supply shocks to their banks.

Finally, we consider the impact of the bank supply shock on firm financial distress. We find that, consistent with the aggregate borrowing results, only smaller borrowers are likely to end up in default. The effect on such firms is large: A one percent decline in the supply of bank liquidity leads to an increase in the incidence of default of its borrowing firms by 16.4 basis points. Large borrowers show no such increase in default rates as they are able to hedge against bank specific liquidity shocks. Given our identification strategy described earlier, we argue that the higher default rates are a causal (and conservative) impact of the reduction in bank liquidity.

Since the large borrowers comprise 94% of aggregate lending in our data, bank lending channel has no net effect in dollar terms. However, in terms of number of firms, the smaller borrowers comprise 70% of all private firms in the country. This combined with the result that the bank lending channel also affects the likelihood of lending to new clients suggest that while the overall (short term) economic costs of the lending channel might be limited, there are significant distributional consequences and associated costs.

The question of how banks might transmit liquidity shocks into real shocks has been theoretically examined by papers such as Bernanke and Blinder (1988), Bernanke and Gertler (1989), Holmstrom and Tirole (1997), and Stein (1998). They show that liquidity shocks can be transmitted to firms due to market imperfections at the bank and firm level leading to a failure of the Modigliani Miller hypothesis. While this theoretical work has been accompanied by a large empirical literature, this literature has mostly focused on the first question - the bank lending channel - and has had to rely on relatively strong assumptions to separately identify the supply shock from contemporaneous demand shocks. Our paper adds to this literature on both accounts. First, our micro level data linking firms to banks allows us to answer questions regarding the ability of firms to mitigate the bank lending channel and how this varies by type of firm. Moreover, this data enables us to measure the ultimate impact of bank liquidity shocks on firm outcomes such as its financial distress. Second, the empirical strategy described above provides a more robust identification of the supply side shock.

Earlier papers such as Bernanke and Blinder (1992), Bernanke (1983), and Bernanke and James (1991) use time-series correlation between changes in liquidity and changes in loans (or output) to argue that changes in liquidity have real consequences. However, a limitation is that these results can also be attributed to omitted variables such as economy wide productivity shocks that impact both changes in the supply and demand of credit at the same time.

This led to work that uses cross-sectional variation across banks and firms to answer the same question instead of relying on aggregate time-series data. Papers such as Gertler and Gilchrist (1994), Kashyap, Lamont, and Stein (1994), Kashyap, Stein and Wilcox (1993), and Kashyap and Stein (2000) use variation in liquidity supply changes across banks and firms to account for economy wide productivity shocks. These papers show that liquidity changes across banks and firms are correlated with outcomes such as loan supply or firm output. However, a concern remains that cross-sectional variation in changes in loans or output of firms may be driven by omitted firm or bank specific demand shocks.

Other papers attempt to find sources of exogenous variation in the supply of bank liquidity. Peek and Rosengren (1997) show that the decline in the Japanese stock market was associated with reduced lending by Japanese banks in the U.S. through bank capital requirement constraints. In a later paper (2002), they show that the financial difficulties at the bank level were responsible for the decline in number of FDI projects taken up by Japanese firms in the U.S. More recently, Paravisini (2005) instruments for additional bank liquidity under a small business credit expansion program in Argentina by using pre-specified formulas for credit eligibility across banks. While these papers make further headway, there approach relies on the validity of the exogeneity assumptions and instrumentation strategies. Moreover, since the shocks in these papers affect a subset of banks and firms in the economy, they are limited in the extent to which the distributional impact of the shock can be traced.

In what follows, section I describes the data and the institutional background. Section II presents our empirical methodology. Sections III, IV and V provide results concerning bank lending and firm borrowing channels, and whether these channels have any impact on firm outcomes. Section VI concludes.

I Institutional Background and Data

A. The 1998 Liquidity Crunch

The unanticipated nuclear tests by India on the 11th of May 1998 led to retaliatory nuclear tests by Pakistan on the 28th of May. These events led to a large and sudden liquidity shock for banks in Pakistan. The extent of this shock varied across banks depending on their exposure to dollar denominated deposit accounts. We outline the sequence of events that led to these changes.

Dollar Deposit Accounts

By the early 1990s Pakistan had a relatively liberalized banking sector with significant private and foreign bank participation. An important element of the reforms in the early nineties was the introduction of the foreign currency deposit scheme[2] that allowed opening of foreign currency (mostly dollar) deposit accounts in Pakistan. The scheme was aimed at stopping the flight of dollars oversees by allowing citizens to hold such currencies within Pakistan.

An important feature of the dollar accounts was that local banks accepting dollar deposits *could not* keep the dollars but had to surrender them to the central bank in return for rupees at the prevalent exchange rate. When a depositor demanded his dollars (with interest) back, the bank obtained dollars from the central bank in exchange for rupees at the *initial* exchange rate. All exchange rate risk between the time of deposit and the time of withdrawal was borne by the central bank. The State Bank of Pakistan's (SBP) official notification (SBP notification #54, June 7, 1992) states:

> [foreign currency deposits are] required to be surrendered to the State Bank. In return the State Bank gives to the institution surrendering the foreign exchange, equivalent Pakistan Rupees at the rate prevailing on the date of surrender. The concerned institutions are entitled to receive back from the State Bank the amount of foreign exchange surrendered at the same rate at which it was surrendered to the State Bank. In other words, the State Bank assumes the exchange fluctuation risk.

The central bank did not provide this exchange rate insurance for free. It charged banks a 3% annual fee for the insurance. However, given general beliefs regarding depreciation of the local currency and the government turning a blind eye to the source of the foreign currency, these accounts became quite popular. By May 1998, in a span of six years, dollar deposits had grown to 43.5% of total deposits in Pakistan.

Although comprising almost half of total deposits, banks differed substantially in the extent to which they were able to attract those with dollars to deposit. The percentage of deposits denominated in dollars ranged from 0% to 98% across banks, with a standard deviation of 27%. The cross-bank variation in dollar deposits was clearly not exogenous. It depended on a host of factors such as the customer base of a bank, its marketing strategy, and its perceived outlook,

[2] See State Bank of Pakistan Foreign Exchange Circular # 36, 1991.

with better and more proactive banks achieving greater success in attracting such accounts. We shall both verify and exploit this feature later in section II.

"Freeze" on Dollar Deposit Accounts

When India and Pakistan tested nuclear devices in May 1998, the international community moved swiftly to impose primarily military and financial sanctions on both countries. These sanctions included a suspension of all bilateral and multilateral financial assistance available to Pakistan for exchange rate support.

In anticipation of the balance of payment problems which were certain to arise, the Prime Minister of Pakistan, along with the announcement of the nuclear tests on May 28th, declared that the foreign currency accounts would be "frozen". This meant that dollar deposit holders could only withdraw their money in rupees at a disadvantaged exchange rate i.e. not the exchange rate at the time of deposit but the lower official exchange rate at the time of withdrawal. The "freeze" amounted to a partial default on dollar deposits by the government.

The loss of confidence as a result of this partial default turned out to have a serious impact on the banking sector. Dollar deposit holders withdrew their money from banks despite only being able to do so in rupees at disadvantaged exchange rates. Figure I traces the aggregate dollar deposits over time and shows the sudden and precipitous withdrawal from dollar accounts after the nuclear tests with these deposits falling by a half within a year of the freeze.

A large part of this liquidity exited the Pakistani banking system (it was often converted back into dollars through the black market and invested abroad). Since this deposit run was experienced by banks with greater dollar deposit accounts, the liquidity shock varied substantially across banks, with several (non-dollar deposit reliant) banks continuing to experience the same deposit growth as before the shock. This is important for our empirical identification as it allows us to exploit cross-bank variation in changes to their deposit base. In other words, while the aggregate liquidity shock as a result of nuclear testing was negative,[3] our identification does not come from the aggregate shock, but from the cross-sectional redistribution of liquidity across banks induced by the nuclear tests.

Figure II illustrates this change in liquidity for the forty two commercial banks in Pakistan that issued demandable deposits in both local and foreign currency. The upper panel of Figure

[3] The average annual growth in deposit liquidity was 17.2% before the nuclear tests. The corresponding annual growth for the post-shock period fell to 5.0%.

II plots the overall change in liquidity for these banks from December '97 to December '99 against their pre-nuclear test reliance on dollar deposits. The lower panel gives the same plot but each observation is plotted proportional to its bank size in December 1997. Both panels show a negative relationship between dollar deposit exposure and changes in bank liquidity.[4] We shall exploit this feature in our estimation strategy detailed in section II.

We should point out through that while this liquidity shock was somewhat unique in terms of the nature of the differential shock it induced across banks, neither the magnitude of the shock nor the Pakistani financial system should be considered unusual so as to raise generalizability concerns for our results.

While the shock was relatively large with a overall liquidity growth slowing to 5% compared to an average of 17%, such fluctuations are not unusual, with the Pakistani economy experienced such low deposit growth at least on 4 separate occasions since in the previous two decades. Moreover, these shocks are not atypical in other economies either.

Similarly, the banking sector in Pakistan is fairly liberal and open to all private (foreign and domestic) banks. Private, Foreign and Government banks constitute roughly equal shares of domestic lending. Moreover, financial reforms in the early 90s saw the issuance of new and uniform prudential regulations to bring supervision guidelines in-line with international banking practices (Basel accord), and autonomy granted to the State Bank of Pakistan (SBP) to independently regulate all banks. All banks have access to the same centralized credit information bureau (CIB) at the SBP that provides borrower details by tracking loan-level information such as outstanding loans and default etc. While the country follows Islamic banking principals, the system is functionally similar to financial systems around the world, with deposit and lending rates determined by the market and no restrictions on raising deposits or lending.

B. Data

The primary data in this paper comes from the central information bureau (CIB) of the central bank of Pakistan which supervises and regulates all banking activity in the country. The data

[4] Since foreign currency deposit banks never actually held any dollars (with the state-bank bearing all exchange rate risk) these liquidity changes are not just accounting/book changes induced by exchange rate fluctuations, but reflect actual changes in the banks' liabilities.

has quarterly loan-level information on the entire universe of corporate bank loans outstanding in Pakistan between July 1996 and March 2000. It follows the history of each loan with information on the amount and type of loan outstanding, default amounts and duration. In addition, it also has information on the name, location and board of directors of the borrowing firm and its bank. We combine this data with annual balance sheet information on banks.

In terms of data quality, our personal examination of the collection and compilation procedures, as well as consistency checks on the data suggest that it is of very good quality. CIB was part of a large effort by the central bank to setup a reliable information sharing resource that all banks could access. Perhaps the most credible signal of data quality is the fact that all local and foreign banks refer to information in CIB on a daily basis to verify the credit history of prospective borrowers. For example, we checked with one of the largest and most profitable private banks in Pakistan and found that they use CIB information about prospective borrowers explicitly in their internal credit scoring models. We also ran several internal consistency tests on the data such as aggregation checks, and found the data to be of excellent quality. As a random check, we also confirmed the authenticity of the data from a bank branch by comparing it to the portfolio of that branch's loan officer.

Although the original data includes 145 financial intermediaries, for most of our analysis we will restrict our sample to the 42 commercial banks that were allowed to open demandable deposits (including dollar deposits). The remaining financial intermediaries had private or institutional sources of funding and are excluded because we do not have information on their changes in liquidity. The sample restriction however should not be a big concern for two reasons. First, the excluded financial intermediaries only make up 22% of overall lending at the time of nuclear tests. Second, since the excluded institutions were not taking dollar or rupee deposits, they were not seriously affected by the nuclear tests. Therefore, assuming that they only experienced the average change in liquidity in the economy, including them in our sample makes no qualitative difference to the results of this paper. Moreover, we will include all these financial intermediaries when we examine aggregate firm outcomes such as overall firm borrowing and default rates.

We use the above data to analyze the impact of credit crunch resulting from the nuclear tests of May 1998. Our starting point is the set of all performing loans at the time of nuclear tests, and we follow these loans and all new ones given out subsequently. This allows us to study how the liquidity crunch impacted both existing loans and disbursement of new loans. For most of the analysis we keep equal pre and post treatment windows and so limit our data to July 1996 and March 2000. This gives us a sample of $61,497$ firms spanning over 15 quarters. The cross-sectional unit of observation in the data is a *loan* defined as a bank-firm pair. Since a firm can borrow from more than one bank, there are a total of $71,969$ loans in the sample. In all, the sample contains 393,579 loan-quarter observations. A number of our tests will be based on loans that exist both before and after the nuclear tests. This subsample consists of 22,176 loans from 18,725 firms. Moreover, for the greater part of the analysis we will be conservative and collapse our quarterly time dimension into equal duration single "pre" and single "post" nuclear test periods by taking time-series averages of loans.[5] This time-collapsing of data has the advantage that our standard errors are robust to concerns of autocorrelation (see Bertrand, Duflo and Mullainathan (2004)).

Table I presents basic summary statistics for the loan, firm and bank level variables used in our analysis. The loan level summary statistics are presented for collapsed data and at the firm level. All loans in our sample are loans to private firms in the economy. There are some large government owned firms in sectors such as utilities, airline, and defense in our original data set. However, we exclude loans to such firms as loans to government firms are implicitly backed by government guarantees and thus may confound our analysis. In any event, including the few government owned firms does not change our results.

II Empirical Methodology

The theoretical basis for how a bank liquidity crunch might affect the supply of loans to firms has been well documented. Papers such as Bernanke and Blinder (1988), Holmstrom and Tirole (1997), and Stein (1998) provide leading explanations of this effect. These papers differ in their details but share the same basic idea.

First, when banks face a shortage in the supply of liquidity from their deposit holders, they are unable to fully compensate for the deficit through alternative sources such as bonds, equity and private debt markets. The inability to access alternative sources is driven by market

[5] The time-series averages are taken after converting all values to real 1995 rupees. Moreover, we exclude the quarter of the nuclear tests from these calculations. Thus pre average covers July 1996 through March 1998 while post average covers July 1998 through March 2000.

imperfections such as informational asymmetries and agency costs. Hence the MM-hypothesis fails at the bank level and banks are forced to cut back lending to their client firms. This happens even if there are no changes in the firms' credit worthiness. Such a reduction in bank loan supply which is unrelated to changes in the firm's demand for loans, is referred to as the bank lending channel.

Second, the market imperfections that prevent banks from raising new liquidity may also prevent the firms affected by a reduction in their loan supply from accessing new sources of financing. This second failure of MM at the firm level means that the bank lending channel also translates into a firm borrowing channel by reducing the aggregate credit available to firms. The reductions in overall borrowing might in turn affect firm outcomes such as productivity and propensity to default. Such arguments have routinely been given to explain large economic collapses ranging from the Great Depression to the recent Asian crises.

The above explanations have not gone unchallenged. Critics such as Romer and Romer (1990) argue that the inability of banks and firms to raise new financing as assumed by the above explanations is not an accurate depiction of the real world. These papers argue that shocks to the supply of bank liquidity have no important real consequences for the economy.

Although there has been a large empirical literature aimed at discriminating between the two competing explanations, the literature has generally been limited to examining only the first part - the bank lending channel - and has struggled with identifying and quantifying the causal impact of an adverse liquidity shock to banks and eventually to borrowing firms. In this section we first highlight this basic identification problem and then outline our approach for addressing it.

A. Estimating the Bank Lending Channel: The traditional identification problem

The following simple framework outlines the main econometric problem. Consider a two period model where banks provide financing to firms each period. For simplicity, we assume that a bank can only lend to one firm while firms can borrow from multiple banks.[6] Let i and j index banks and firms respectively. In period t, bank i and firm j negotiate a loan of size L_{ij}^t. In order

[6]We want to emphasize here that our purpose is not to build a fully specified model of bank intermediation. We shall deliberately only focus on those features that highlight the fundamental econometric issues.

to finance this loan bank i has to raise financing through two sources, (i) demandable deposits D_i^t, and (ii) alternate forms of financing (equity, bonds etc.) denoted by B_i^t. Since the loan L_{ij}^t is the only asset available to the bank, the following accounting identity must hold for bank i lending to firm j at time t:

$$D_i^t + B_i^t \equiv L_{ij}^t \tag{1}$$

In the spirit of the theoretical literature on the subject such as Stein (1998), we need two important ingredients in our model: (i) banks are constrained in the amount of liquidity they can raise through deposits, and (ii) raising additional liquidity through external non-deposit funds (i.e. B_i^t) is costly due to market imperfections. For simplicity these elements are introduced as follows. A bank can raise deposits costlessly but only up to a maximum amount $\overline{D}_i^t$. Raising additional financing (B_i^t) is costly with the marginal cost linear in B_i^t and given by $(\alpha_B * B_i^t)$ where $\alpha_B > 0$. The cost function for additional financing implies that the overall credit supply function for a bank (i.e. $D_i^t + B_i^t$) is linear in the cost of funds.

The total amount $(D_i^t + B_i^t)$ raised by a bank is lent to its firm in the form of a loan L_{ij}^t. The marginal return on this loan L_{ij}^t is also linear and is given by $(\overline{r}_j - \alpha_L L_{ij}^t)$. This functional form captures decreasing marginal returns as the size of the loan increases. Given the linear supply and demand curves, the equilibrium amounts of B_i^t and L_{ij}^t are given by the intersection of these curves in each period.

At the end of time t, the economy (i.e. banks and firms) receives two types of shocks. The first, a "credit supply" shock, determines the level of deposits available to each bank in period $t+1$. In particular, the supply of deposits for bank i in $t+1$ is given by $\overline{D}_i^{t+1} = \overline{D}_i^t + \overline{\delta} + \delta_i$, where $\overline{\delta}$ and δ_i are economy wide and bank-specific shocks respectively. The second shock is a "credit demand" shock that firm j experiences in the form of a shock to its productivity. In particular, the marginal return on its loan L_{ij}^{t+1} next period is now given by: $\overline{r}_j - \alpha_L L_{ij}^{t+1} + \overline{\eta} + \eta_j$. The productivity shock $(\overline{\eta} + \eta_j)$ reflects an economy wide and a firm-specific component respectively.

Given the linear set up of our model, equilibrium each period is determined by jointly solving the FOC[7] and accounting identity (1) for L_{ij} and B_i. Solutions for the two periods (assuming away corner solutions) can then be combined into a single first-differenced equation:

[7] The FOC is $\alpha_B B_i^t = \overline{r} - \alpha_L L_{ij}^t$ in period t, and $\alpha_B B_i^{t+1} = \overline{r} + \overline{\eta} + \eta_j - \alpha_L L_{ij}^{t+1}$ in period $t+1$.

$$\Delta L_{ij} = \frac{\alpha_B}{(\alpha_L + \alpha_B)}(\overline{\delta} + \delta_i) + \frac{1}{(\alpha_L + \alpha_B)}(\overline{\eta} + \eta_j) \tag{2}$$

Equation (2) although derived from an admittedly simple model, highlights some important issues. First, it shows the importance of costly external financing. Without this assumption (i.e. $\alpha_B = 0$), banks would be in a Modigliani-Miller world and shocks to deposits or "liquidity shock" (δ) would have no impact on equilibrium loan amounts. Second, and more importantly for this section, equation (2) highlights the identification problem in estimating the causal impact of a liquidity shock on loans. To see this, let us first re-write (2) as:

$$\Delta L_{ij} = \frac{1}{(\alpha_L + \alpha_B)}(\alpha_B * \overline{\delta} + \overline{\eta}) + \frac{\alpha_B}{(\alpha_L + \alpha_B)}\delta_i + \frac{1}{(\alpha_L + \alpha_B)}\eta_j \tag{3}$$

The first term on the RHS of (3) is just a constant reflecting economy wide shocks. Thus first-differencing takes out *all* secular time trends in the economy through the constant term. Let β_0 $(= \frac{1}{(\alpha_L+\alpha_B)}[\alpha_B * \overline{\delta} + \overline{\eta}])$ denote this constant. The second term on the RHS contains the main coefficient of interest. Let $\beta_1 = \frac{\alpha_B}{(\alpha_L+\alpha_B)}$, then β_1 captures the "lending channel" for each incremental unit of deposits lost. The OLS regression typically run to estimate (3) is:

$$\Delta L_{ij} = \beta_0 + \beta_1 * \Delta D_i + \eta_j + \varepsilon_{ij} \tag{4}$$

where $\Delta D_i = \delta_i$ represents the bank-specific change in deposits. However, the estimate $\hat{\beta}_1^{OLS}$ in (4) will be biased if $Corr(\delta_i, \eta_j) \neq 0$. This isolates the fundamental problem: In general δ_i and η_j are very likely to be *positively* correlated. For example, "liquidity shocks" such as bank runs are more likely to occur in banks that receive some bad news about the quality or productivity of the firms they lend to or alternatively, lower quality banks are both more likely to have weaker depositors and firms that are more sensitive to shocks. Given a positive correlation between δ_i and η_j, equation (4) will lead to an *over-estimate* of β_1 as $\hat{\beta}_1^{OLS} = \beta_1 + \frac{Cov(\delta_i,\eta_j)}{Var(\delta_i)}$.

B. An Unbiased Estimate of β_1: Firm Fixed Effects

An unbiased estimate of β_1 can be obtained by putting in firm fixed effects in equation (4) and comparing changes in loans across banks for the *same* firm. Firm fixed effects absorb the variation driven by changes in the demand of liquidity at the firm level and thus isolate the supply side. Note that since the specification is in a first-difference form the firm fixed-effects absorb all firm-specific *changes* between the pre and post-shock period. This estimation strategy implies that we have to restrict ourselves to firms that borrow from multiple banks at the time of nuclear tests. There are more than $1,800$ such firms in our sample. Empirically, the new strategy translates into running the following Fixed-Effects regression:

$$\Delta L_{ij} = \beta_j + \beta_1 * \Delta D_i + \varepsilon_{ij} \tag{5}$$

where β_j are firm fixed effects. The β_j subsume all firm specific fixed shocks η_j that were the source of bias for $\hat{\beta}_1^{OLS}$ earlier. $\hat{\beta}_1^{FE}$ in (5) is therefore an unbiased estimate of β_1, but comes at a slight cost that the sample has to be limited to firms that borrowed from multiple banks at the time of nuclear tests.[8] Note that comparing the OLS and FE estimates (in the same sample), would allow us to also infer the correlation between demand and supply shocks. If we find that $\hat{\beta} > (<) \hat{\beta}_1^{FE}$ this shows that $Corr(\delta_i, \eta_j) > (<)\ 0$ i.e. supply and demand shocks are positively (negatively) correlated. While this is not needed in obtaining unbiased estimates of the bank lending channel, as we show below it will be very useful in estimating the firm borrowing channels.

Although the firm fixed approach addresses a number of concerns in the empirical literature, there may be some residual concerns that we briefly discuss. In particular, one may question the FE approach if one believes that loan demand varies across banks even for the same firm. For example, one bank may specialize in providing short term loans while another might specialize in providing longer term loans. Thus when a macro shock hits, a firm's demand might be differentially impacted across the two banks. Note however that this alone is not sufficient to question the FE approach. In order to invalidate the FE identification strategy, one would not only need differential demand across banks for the same firm, but also that this differential demand is positively correlated with the liquidity shock experienced by a bank. Thus one needs quite specialized scenarios to invalidate the FE results. In any event, we will address this

[8] This argument is slightly more subtle. Once we model the fact that a bank lends to multiple firms, equation (3) has to be modified to include idiosyncratic demand shocks experienced by these other "$-j$" firms. The firm fixed effect will only take out firm j's demand shock and the other "$-j$" firms' demand shock components that comove with j's demand shock. However, since these remaining components are, by construction, orthogonal to j's demand shock, β_1, is identified. Put another way, from the perspective of firm j, all one requires is that its bank experiences a *net* (of other firm's demands) liquidity supply shock that is orthogonal to firm j's credit demand.

concern directly since we know the type of loan a firm takes from a bank. Specifically, we will show our results remain robust to using firm-loan type interacted fixed effects.

One may also be concerned that banks differ in how they react to changes in borrower productivity. In other words, in specification (3), what if the firm productivity shock interacts with a bank characteristic that represents the bank's differential willingness to continue lending in the face of a demand shock. In this case the firm fixed effect will not fully account for unobserved credit demand shocks. Furthermore, provided this bank characteristic is correlated with the liquidity shock, this will bias our fixed effect estimates. We will address such concerns later both by explicitly showing our results are robust to using likely bank characteristics as controls, and by examining how portfolio quality changes in response to the shock. Note that this differential response explanation would predict that the banks facing liquidity shocks (which have, as we show later, higher pre-shock portfolio/client quality) would be more unwilling to lend to firms and therefore see relatively greater improvements in quality (as they cut back more on the marginal clients than non-shocked banks). Our results in fact will show that the opposite is true.

Finally, there can also be a related concern that a firm may strategically choose to withdraw borrowing from a more affected bank in anticipation of future relationship problems. We shall also address such concerns in detail in the results section.

C. Estimating the Firm Borrowing Channel: An OLS Approach

While using firm fixed effects provides unbiased estimates for the bank lending channel, this strategy can no longer be utilized when we consider firm level outcomes, such as overall firm borrowing or measures of firm distress since by definition such outcomes will only have one observation per-firm. Specifically, we estimate:

$$\Delta\overline{L}_j = \beta_0 + \beta_1 * \Delta\overline{D}_j + \eta_j \tag{6}$$

where $\Delta\overline{L}_j$ is firm j's change in overall borrowing (aggregated over all banks) and $\Delta\overline{D}_j$ is the average liquidity shock faced by firm j's pre-shock banks. The concern as before is that $\Delta\overline{D}_j$ is correlated with η_j and so OLS will be biased. While finding instrumental variables offers one potential approach, if we could sign the potential bias in OLS, that could offer an alternate strategy. Specifically, if we can show that the liquidity shock and the unobserved demand shock are *negatively* correlated, OLS, while biased, will be very instructive since it will offer an under-estimate of the liquidity shock impact.

In general liquidity supply and demand shocks are positively correlated and are also likely to be so in our case when comparing changes over time i.e. the nuclear shock while resulting in overall liquidity falls was also likely to see firms facing reduced business opportunities and a fall in credit demand. However, we have good reason to suspect as outlined before in section I, that in the *cross-section*, the correlation between a bank's liquidity supply and it's client firms' demand shocks is in fact negative.

Recall from section I that the cross-bank variation in liquidity shocks is generated by the banks' differential exposure to dollar deposits. Banks that were more exposed to dollar deposits experienced larger declines in their deposit base. However, as we will show, the same banks are also more likely to have better loan portfolios in terms of profitability and default rates. If more profitable firms are better able to adapt to the overall macro shock resulting from nuclear tests, then these firms would experience smaller declines in their loan demand compared to less profitable firms. This would be not be the case if such initially better performing firms are exporters and if the nuclear tests also included substantial trade sanctions. However, the sanctions imposed by countries and multi-lateral institutions primarily curtailed financial assistance and suspended loans to the government of India and Pakistan. Trade restrictions were primarily on military sales (which is unlikely to affect our results since government loans are excluded from our analysis). Moreover, at the time of its nuclear tests in May 1998, several restrictions to Pakistan were already in place in connection with the Pressler and Symington Amendments (triggered by Pakistan's possession of a nuclear explosive and the receipt of uranium enrichment equipment). In fact a US International Trade Commission report (USITC, 1999) concluded that the impact of the sanctions would be minimal in India and Pakistan, with trade diversion from the US to countries in Asia and Europe. Finally, if anything exporters stood to gain through the increased depreciation in light of the financial crises induced by the shocks.

Consequently, while more dollar reliant banks experience greater reduction in their supply of liquidity the above suggests that they would face relatively larger (i.e. smaller absolute declines in) demand for liquidity. This provides the negative correlation between δ_i and η_j. In this case the OLS estimate, while biased, would still be useful as it provides a conservative estimate (an underestimate) of the true lending channel coefficient. A nice feature of our data is that not only can we test whether more dollar reliant banks were lending to more profitable firms, but we can also show that OLS indeed provides an underestimate by comparing the OLS coefficient with the unbiased FE coefficient mentioned earlier.

Table III first presents shows the negative correlation between dollar reliance and deposit growth seen in Figures IIa-b, and then presents evidence that dollar reliant had higher pre-nuclear test profitability of loan portfolios. Columns (1) and (2) of Table III regress change in bank liquidity on percentage dollar deposits before nuclear tests and show that more dollar reliant banks experienced larger declines in deposit growth. Column (1) runs an unweighted regression while column (2) weighs each observation by the size of its bank prior to nuclear tests. The weighted regression is economically more meaningful and shows that a 1% increase in the percentage of dollar deposits held by a bank prior to nuclear tests, leads to a 0.55% decline in bank liquidity. The R-sq is also high at 32%.

Columns (3) through (6) of Table III, show that more dollar reliant banks had significantly lower average default rates on their loans (columns (3) and (4)), and significantly higher overall return on assets (columns (5) and (6)). Similar results are obtained if we replace percentage dollar deposits with actual deposit change on the RHS (i.e. banks that experienced larger declines in deposits were more profitable and had lower defaults). Thus more dollar reliant banks had better quality loan portfolios. The rationale for this correlation is that since dollar deposits were very lucrative because of the government subsidized exchange rate insurance program, competition implied that banks that were of better quality and provided better services were more likely to attract dollar deposits. The evidence in Table III therefore supports the case that supply and demand shocks might be negatively correlated.[9]

In the results section we will also provide further direct evidence, as discussed above, by comparing the OLS estimate of the bank-lending channel in the *same sample* of firms for which we run the FE estimate. If, as we will find, the FE estimate is higher than the OLS estimate this

[9] One could argue here that although banks with more dollar deposits were of better quality, they might systematically lend to those firms whose liquidity demand "co-moves" with the bank's supply of liquidity (see Kashyap, Rajan and Stein (2002) for the full theoretical argument). If this were true then more dollar reliant banks would also experience larger liquidity demand shocks. While the argument is valid in general, it is unlikely to apply in our context because of the exchange rate insurance provided by the central bank. The insurance implied that banks did not have an incentive to try to hedge exchange rate fluctuation when making lending decisions.

shows that $Corr(\delta_i, \eta_j) < 0$ and therefore $Corr(\Delta\overline{D}_i, \eta_j) < 0$ i.e. the OLS estimates of firm-level outcomes will be under-estimates.[10] We should note that the assumption we are implicitly making here is the same selection that applies to multiple-bank firms (for which we can estimate the bank lending channel by using firm fixed effects) also holds for single-bank firms i.e. banks with better multiple-relationship firms (as compared to such firms for other banks) also have better single-relationship firms. This is not only plausible but examining the equivalent of Columns (3)-(6) in Table III but restricting to loans only to single-relationship firms shows the same pattern - banks with greater liquidity shocks do have better single-relationship firms.

III Results: Broad Non-parametric patterns

Before presenting the regression results we illustrate the broad findings in this paper through a few simple graphs. The subsequent regressions will show that the same patterns hold when we apply more rigorous specifications.

Figure IIIa illustrates the bank-lending channel by comparing lending to firms borrowing from banks hit with a negative liquidity shock to lending to firms borrowing from banks that experience a positive liquidity shock. We restrict our analysis to the set of firms that are borrowing at the time of the nuclear shock.[11] Banks are classified into two types - positive and negative liquidity shock based on whether bank deposits increase or decrease as a result of the nuclear shock. At each quarter we then sum all the loans to these firms that are made by the positive and negative liquidity banks. The figure then plots the time series for this aggregate lending. To ease comparability we normalize amounts so that the logarithm of lending for both positive and negative liquidity banks is forced to be 0 at the time of the shock i.e. the time series illustrates the log-ratio of total loans in a given quarter relative to the quarter of the liquidity shock. The y-axis values can then be readily interpreted as growth rates relative to the nuclear shock quarter.

Figure IIIa starkly illustrates the bank-lending channel. Subsequent to the shock, loans to

[10] While our argument is in terms of the bank-specific liquidity shock, δ_i, and a firm's demand shock, η_j, equation (6) aggregates the bank-specific liquidity shocks across all of firm j's banks. However, it is easy to show that provided $Corr(\delta_i, \eta_j) < 0 \vee i \Longrightarrow Corr(\Delta\overline{D}_i, \eta_j) < 0$ since $\Delta\overline{D}_i$ is just a weighted average of the δ_i's.

[11] We do not include loans to firms that start borrowing from a bank after the shock or stopped borrowing before the shock. Such firms are not included as the purpose of this simple illustration is to trace what happens to loans at the time of the shock. In the regression analysis we will consider such firms explicitly.

firms borrowing from the negative liquidity banks falls relative to loans to firms borrowing from the positive liquidity banks. Note that by comparing these two types of loans at each point in time (rather then a given loan over time) we ensure our results are not driven by overall time-trends in the data but are only due to the cross-sectional variation in bank liquidity induced by the nuclear shock. Moreover, prior to the shock, these two series are very comparable, suggesting that the effect is indeed due to the liquidity shock and not any differences across banks that may be correlated with the liquidity shock. The figure also makes clear that our empirical estimates are a "double-difference" estimate i.e. the bank-lending channel is the difference between lending by the positively and negatively affected banks *less* the difference between the same two types of banks before the shock. We should caution though that the comparison between the two time-series in Figure IIIa is at best a rough and simplistic measure of the bank-lending channel as compared to our subsequent regression results. For example, it does not force comparisons *within* firms (i.e. do the equivalent of the firm fixed effects strategy outlined above) nor does it differentiate between the magnitude of the liquidity shocks - only whether they are positive or negative. We choose to present this graph since it illustrates the bank lending channel very simply and clearly. The regression analysis will confirm that these simple patterns indeed hold when we impose more demanding specifications. Figures III b-c consider large (the top three deciles by borrowing size prior to the shock) and smaller borrowers separately and show the bank ending channel holds for both.

Figures IVa-b then examine the firm borrowing channel by asking what happens to a firm's overall borrowing after the shock. Specifically are firms' that were borrowing from banks with a negative liquidity shock able to overcome the drop in lending from these banks by borrowing more from positive liquidity banks? We consider large and the remaining smaller borrowers separately, since institutional evidence suggests that the former may benefit from differential access to credit. If large borrowers indeed have such differential access, we would expect them to be able to better hedge the liquidity shock. Figure IIIa groups large borrowers into two classes - those that were borrowing from banks whose average liquidity shock was negative versus those whose banks experienced a positive liquidity shock. The two lines then represent overall lending to these two groups of firms for every quarter (from all banks the firm is borrowing from then). As in Figure IIIa, the amounts are normalized to be 0 at the time of the shock. Figure IVb does the same but for the smaller borrowers.

The figures show that while large borrowers are better able to overcome their banks' liquidity shocks, smaller borrowers cannot. Figure IVa shows that both types of large borrowers - those that had negative liquidity banks at the time of the shock and those with positive liquidity ones - display similar overall borrowing trends - the difference between the two lines is not statistically significant. In sharp contrast, Figure IVb shows that after the shock, while both types of smaller borrowers - those that had negative liquidity banks and those with positive liquidity ones - show overall drops in lending, the drop is much sharper for the former i.e. smaller borrowers are unable to recover from their banks' liquidity shocks by borrowing from other banks. A potential concern here could be that Figure IVa is just picking up the fact that there is no bank-lending channel for large borrowers. However, as we saw in Figure IIIb this is no the case. Thus large borrowers do experience a drop in lending from their banks which face a negative liquidity shock but they are able to compensate for this shock by borrowing from other (more liquid) banks.

Finally Figures Va-b. examine whether these borrowing channels affect a firm's overall financial situation i.e. are firms that were borrowing from negatively affected banks at the time of the shock more likely to go into default. Note that for large borrowers this is unlikely since, as Figure IVa illustrated, they are able to compensate the initial shock. However, even the smaller borrowers may not experience any financial distress if they are able to borrow from informal sources or utilize internal funds. Figures Va-b examines trends in default rates for both type of firms. By construction, default rates are 0 prior to the shock (we exclude loans that were in default before). As before Figure Va plots average default rates for the two types of large borrowers - those that had negative liquidity banks at the time of the shock and those with positive liquidity banks. The results show by at least partially compensating for the liquidity shock, large borrowers with negative liquidity banks show no greater default rates. In fact if anything, they seem to have somewhat lower default rates, hinting at the negative selection we had mentioned earlier i.e. worst hit banks had better borrowers to begin with. In contrast, Figure Vb shows that smaller borrowers whose banks experience a negative liquidity shock, are indeed significantly more likely to default. The initial liquidity shock to these firms therefore has real affects on such firms' financial health. Note though that the effect on default shows up several quarters after the shock suggesting that these firms are able to use internal/informal means to compensate for their borrowing loss for at least the first few quarters but that such internal/informal resources are limited.

Figures III-V have illustrated all our main findings. Note that these figures also reveal that the affects are persistent over time. The next sections will now show that these broad patterns are extremely robust and hold up to cleaner empirical specifications and a variety of robustness tests.

IV Results: The Bank Lending Channel

Taking the empirical methodology to data, we start with the collapsed loan level data described in section I, with one pre and one post nuclear test observation for each loan. For expositional convenience, we divide our analysis of the bank lending channel into two parts, an "intensive margin" referring to a reduction in the amount of lending to firms borrowing at the time of the liquidity shock, and an "extensive margin" referring to complete denial of credit to existing borrowers and to new borrowers.

A. The Intensive Margin

There are 22,176 loans to 18,725 firms that are borrowing at the time of the nuclear tests. Before presenting the regression results we illustrate our "difference-in-difference" empirical strategy in its simplest form - the equivalent of Figure IIIa. Our simplest estimate of the bank-lending channel is to compare how lending changed before and after the shock for banks that experienced a negative liquidity shock as compared to banks that saw their deposit base continue to grow. Table III does this by computing the average lending before and after the (nuclear) shock for the two types of banks - those that experienced a fall in liquidity and those that experienced a gain. Comparing the two numbers before the shock (first row) show that there is little difference in average lending between the two banks. This lends further validation to our empirical strategy since it shows that the two types of banks were unlikely to differ (at least in terms of lending behavior) prior to the shock. As such one can infer that any difference between the two *after* the shock, is on account of the liquidity shock and not due to any inherent differences across these banks. The second row in the Table shows how each bank types' lending changes after the liquidity shock. While banks which experience positive changes in liquidity increase their average lending, banks faced with negative liquidity shocks show a drop in average lending.

Our estimate of the impact of the liquidity shock is then the difference in average lending between these two bank types after the shock less any difference between them before the shock. We therefore find that negatively shocked banks experienced 20.3% lower loan growth rates as compared to the banks that experienced normal deposit increases. Put another way, absent the liquidity shock, the negative liquidity shock banks should have lent 10% more but instead they lent 10.3% less. Column (1) in the Table presents exactly the same comparison but in a regression framework.

One concern with the simple comparison of means and Column (1) is that it doesn't take into account that the two bank types may be lending to different types of firms. The concern is that if firms' credit demand was affected differentially by the shock, then part of the difference after the shock could also be capturing the impact of such demand shocks. Column (2) of Table 3 corrects for this by only comparing loans across the same firms i.e. it considers only firms that borrow from both a positive and negative liquidity shock bank and computes the difference between how the firm's loan changes between its positive and negative liquidity bank. Figure VI illustrates the result in Column (2) graphically where instead of collapsing the time series we plot the difference between positive and negative over each quarter by only comparing *within* firms. The result shows that before the shock the loan for a given firm across two different banks was not different prior to the shock, but starts diverging right after the shock as the firm's borrowing decreases from the negatively shocked bank and increases from the bank whose liquidity continues to grow. The symmetry in the figure is a direct result of using firm fixed effects.

While Column (2) in Table III improves identification through the use of firm fixed effects, it still does not make use of the full information in the data since banks are classified as either positive or negative liquidity i.e. the magnitude of the liquidity shock is not made use of. Table IV presents our preferred specification and estimates (4) by first-differencing the data. We regress change in log loan amount as a result of nuclear tests on the change in log bank liquidity.[12] Since the liquidity shock comes at the bank level, changes in loans from the same

[12] Recall that the data is time-averaged to construct average lending prior to the shock and average lending subsequent to the shock. Post-shock averages for firms that stop borrowing from a bank are constructed over the quarters when they have stopped borrowing as well by assuming 0 (rather than missing) borrowing in those quarters. Similarly, if a firm goes in default it is considered as borrowing an amount 0 as well. The latter is justified since a defaulting firm is not longer actively borrowing from the bank. Neverthless, excluding such firms

bank may be correlated all our loan level regressions have errors clustered at the bank level.

Column (1) in Table IV has the preferred FE estimation strategy in equation (5) that provides an unbiased estimate of the bank lending channel coefficient. The FE strategy implies that we have to limit ourselves to the set of firms that borrowed from at least two different banks in the pre-nuclear tests period There are 1,864 such firms with a total of 5,382 loans. The results shows evidence for a large bank lending channel: A 1% decline in bank liquidity leads to 0.6% decline in a firm's loan supply from the bank. Columns (2) shows that this result is robust to further bank and loan-level controls and column (3) to including loan-type interacted with firm fixed effects.

Does using firm fixed effects make a difference? Recall that our previous discussion had suggested that OLS would provide biased estimates since it was likely that (cross-sectionally) liquidity supply and demand shocks were negatively correlated. Column (4) estimates an OLS specification for the same restricted sample of multiple-bank firms as in Column (1). The result shows that OLS indeed provides an underestimate (the lending channel coefficient drops from 0.60 to 0.35) and therefore, as suspected, liquidity supply and demand shocks are negatively correlated across banks.

The above specifications are all run on multiple-bank firms. To what extent does this sample restriction make a difference? While we cannot provide unbiased estimates of the latter type (since we cannot use firm fixed effects) a comparison of the OLS (underestimates) would be instructive. Column (5) estimates an OLS specification in the full sample of firms and shows, that if anything the bank-lending channel is even stronger in the full data which includes single relationship firms. This suggests that there may be differences in the bank-lending channel across different types of firms.

Finally, Column (6) estimates an OLS specification in the full sample and separately estimates whether the bank liquidity shock varies across different types of firms. Interestingly, we find that smaller borrowers face a significantly larger bank-lending channel than the larger borrowers. However, none of the other firms characteristics, such as whether a firm belongs to a business conglomerate, has political connections or multiple banking relations matters much. Note though that these estimates are all likely to be biased downwards as we discussed previously.

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does not affect our results qualitatively although the magnitudes of the coefficient estimates decrease slightly.

A-1. Robustness to alternative explanations

Although firm fixed effects subsume most firm specific variables such as changes in a firm's aggregate loan demand and other firm level attributes, there may be some remaining concerns that we address here.

First, one may wonder if the lending channel coefficient is driven by any systematic bank level differences. For example there may be a concern that the change in lending due to nuclear tests is simply a continuation of an old trend in the banks' liquidity positions. Similarly, perhaps the estimate is picking up differences across foreign and local banks as foreign banks may be more likely to deal in dollar deposits.

A particular example of this concern arises if banks differ in how they react to changes in borrower productivity. Note that since our results are in first differences at the loan-level, we are not concerned with level differences across banks in their willingness to lend to lower quality clients. Instead the concern is that a bank's *marginal* response to quality changes (due to firm productivity shocks) may be different: Thus more quality sensitive banks may cut back more lending to the same firm (that is hit with a productivity shock) as compared to another bank. Moreover, if the former banks is more likely to have experienced a liquidity shock then our FE estimates are biased upwards. We know from Table III that banks with better portfolio/clients (as proxied by ROA and default rates) in fact did experience a larger liquidity shock. So is this empirical concern valid? In other words do banks' display such differential quality responsiveness and is it really correlated with the liquidity shock? First, note that it is a bit unusual to posit that banks in a competitive market display such differential responses to firm productivity. Nevertheless, assuming that locally segmented markets etc. would allow this, we can directly test for this explanation by including various bank characteristics that may proxy for such differential lending sensitivity, as controls.

Therefore, column (2) includes several bank level controls such as pre nuclear test return on assets of a bank, pre-nuclear test deposit growth of a bank, log of bank size, pre-nuclear test capitalization ratio and fraction of portfolio in default, and dummies for foreign and government banks.[13] We use pre-shock bank measures rather than post-shock or changes since the latter would partly be outcomes of the liquidity shock and therefore confound our analysis. Bank

[13] Pre-98 ROA, bank size, and capitalization rate are averages over fiscal years 1996 and 1997 (fiscal years end in december). Pre-98 deposit growth is calculated as growth in deposits from dec 1996 to dec 1997.

ROA, portfolio in default and capitalization ratios in particular are likely to capture a banks' sensitivity to client quality. The results indicate that the lending channel coefficient is robust to all these bank level controls.

While this is unlikely, one may still worry that the above pre-shock measures are not appropriate because they do not correlate well with bank lending quality sensitivity after the shock or are not good proxies for this (unobserved) quality sensitivity even before the shock. We can address this remaining concern more directly by examining changes in the quality of the bank's portfolio after the shock. If the differentially sensitivity criticism is valid then the banks facing liquidity shocks should be relatively more unwilling to lend to firms experiencing productivity shocks and therefore, their portfolio quality should in fact increase more after the shock. In Table VII we will directly examine changes in firm default rate and in fact show that opposite is true - banks with greater liquidity shocks in fact see their client firms default rates increase. Thus it could not be that these banks are becoming more quality conscious then other banks.

Second, what if firms borrow different "types" of loans from different banks, and loan types are affected differentially by shocks such as the nuclear tests? In this case firm FE will not account for all demand side fluctuations correlated with bank liquidity shocks. For example, our FE estimates will be biased if firms systematically took shorter term loans from banks more hit by the liquidity crunch, and these types of loans saw a larger reduction in demand in the aftermath of nuclear tests. However, we can address such concerns since we have information on the type of loan.[14] We do so by interacting the firm fixed effects with loan type to ensure comparison of the *same* loan type and for the *same* firm across banks (this gives us 2,731 fixed effects for the 1,864 firms in the sample of firms with multiple pre-shock banks). The result in column (3) shows no significant change in the lending channel coefficient. It is also worth noting here that since most of the firms belong to traditional sectors such as textile and consumer goods, there are not many "specialized" loans that firms can take in the first place.

Finally, a related concern might be that our FE results represent a "strategic" withdrawal by firms from hard hit banks. For example, a firm may voluntarily cut back lending from a bank facing liquidity problems and switch to more liquid banks for fear that the liquidity constrained bank might become insolvent in the future. This is unlikely since banks hit by the

[14] Loan type is classified as: (i) short term (under 6 months) working capital loans, (ii) longer term fixed loans, and (iii) non-funded loans such as guarantees and letters of credit.

liquidity crunch were historically more profitable (as seen in Table III) and, while they did see profitability decline post-shock, they still remained as profitable as the banks which got positive liquidity shocks. In fact, no bank declared insolvency after the nuclear tests. Moreover, it is worth noting that this is more of an interpretational concern i.e. even if the loan decline is due to such strategic reasons, as long as it is induced through the initial supply-side shock i.e. firms choose to borrow less from the banks that were hit by a larger liquidity shock (that is exogenous to the firms' demand), one can interpret it as a bank lending channel.[15]

B. The Extensive Margin

We now investigate if liquidity crunch also impacts the extensive margin of banks by forcing them to either stop lending to firms altogether or reducing the intake of new firms. As before we start with our preferred firm FEs specification. Since this only provides estimates for large borrowers, we then also provide OLS (underestimates) for the impact on smaller borrowers.

We begin by testing if the "exit rate" of firms is higher in banks harder hit by the liquidity crunch. To do so, we start with the set of all performing loans just before the nuclear tests (there are 26,730 such loans). Then for each loan, we create a variable $EXIT$ which is 1 if the loan is not renewed at some point during the first post-nuclear test year. In other words, $EXIT$ is 1 for a loan if the firm exits the particular banking relationship in the first post test year.[16] Using this variable, we run the following regression in the multiple-bank firm sample to test if firms borrowing from more liquidity crunched banks were more likely to exit from the relationship:

$$EXIT_{ij} = \beta_j + \beta_1 * \Delta D_i + \varepsilon_{ij} \tag{7}$$

β_1 is the coefficient of interest. In the case of the full sample of firms we omit the firm fixed effects from the above specification.[17]

[15] One version that would not be consistent with a bank lending channel is if this strategic withdrawal of borrowers from the hard hit banks was not due to liquidity concerns but a new "dislike" of banks that were considered "foreign" espceially in the wake of an event that triggerred international sanctions. While it is not obvious profit-maximizers would respond to such concerns, especially as we will later show these liquidity drops can have real costs, our results are robust to including measures such as whether a bank is foreign owned etc.

[16] We will examine exit rates separately for each quarter following the shock later on in the paper. At this stage we focus on exit during the first year to capture the immediate impact of the liquidty shocks.

[17] Using a non-linear probit model gives the same results as our linear specification. We prefer to use the linear model since the results are then comparable with the Firm FEs specification where we cannot use a probit model.

Column (1) in Table V runs the firm FEs specification and shows that differential exit of firms is higher for firms lending from more credit-crunched banks. A 1% reduction in bank liquidity leads to a 21 basis points increase in the probability of exit for a loan (that is about a 1% increase in probability since the mean exit rate for loans was 20.7% during this period). Column (2) shows that the result remains robust to the same bank level controls as in Column (2) in Table IV. Column (3) runs the same specification using OLS in the full sample.

To estimate whether smaller borrowers experience the same (or larger) impact, we run the OLS specification on the full sample. The results in Column (4) shows there is no significant difference in exit rates in response to the liquidity shock between large and smaller borrowers.

Similar to exit, we also check if the uptake of new loans (or "entry") after the nuclear tests is systematically different across banks facing differential supply shocks. To run this test, we start with all loans given out in the first post nuclear test year. There are 35,921 such loans. We then create a new variable $ENTRY$, which is 1 if the loan did not exist in the pre-nuclear test period and 0 otherwise. Using $ENTRY$ as the LHS variable, we rerun equation (7).

Column (5) runs the preferred specification that includes firm fixed effects and shows that liquidity crunch significantly impacts a bank's ability to issue new loans. A 1% reduction in bank liquidity reduces its probability of making a new loan by 12 basis point (the mean entry rate in the data was 38.5%). Column (6) shows that the effect remains with bank level controls.

Columns (7)-8) run OLS in the full sample and show that smaller borrowers are more likely to enter, and differentially so for banks with greater liquidity though despite the large magnitude this is marginally significant.

Another way to understand the magnitude of the exit and entry results is to note that the standard deviation of bank liquidity shock from Table II is 30%. Thus for every one standard deviation decline in liquidity, exit rate for large borrowers goes up by 30% and entry rates go down by 9.3%.

In summary, the results in Tables IV and V show that shocks to a bank's supply of liquidity have large impacts on the lending behavior of banks on both the intensive and extensive margins. The results therefore indicate that the MM hypothesis breaks down at bank level, and shocks to the banking sector are transmitted to the loan-level through changes in the banks' lending patterns.

C. Do Liquidity shocks impact the price of loans?

We saw earlier that the presence of a large bank lending channel forces banks to restrict the availability of loans when faced with a negative shock to their supply of deposits. We can test if besides quantity, bank liquidity shocks also affect the price of loans (i.e. the interest rate charged). The loan level CIB data set does not contain information on the interest rate charged. However, another data source from the central bank records the average interest rate for loans of different sizes charged by a given bank branch at a point in time. This data can be used to proxy for the interest rate charged on a given loan using loan size and location information.

Using this data we compute the change in interest rates from December 1997 to December 1999 for each loan and regress this variable on change in log of bank liquidity as before.[18] Table VI presents the results and shows no statistically significant differential effect i.e. a firm does not experience higher interest rate changes from its bank that experienced a greater liquidity fall. Column (1) presents a firms fixed effects specification, Column (2) pushes this further by introducing loan-type interacted with firm fixed effects (so not just comparing interest rates across the same firm borrowing from two banks but across the same firm borrowing the same type of loan across two different banks). Column (3) presents the OLS (and potentially biased) results in the full sample of firms. While the coefficient magnitude rises, so do the standard errors. So while the bank lending channel affects the quantity of loan supply, it does not affect the average price charged by banks.

There could be a number of explanations for this result. For example, even if a bank raises its interest rate on loans that it continues to make in the face of a liquidity shortage, this may not increase the average bank interest rate if the marginal loan now denied by the bank used to have a high interest rate. If a bank is more likely to cut lending to relatively lower quality firms, then the marginal loan declined by the bank will have higher interest rate prior to nuclear tests. Another explanation for our result could be that the bank does not want to raise interest rates because of inter-bank loan competition, or because of the fear of increasing moral hazard concerns. However, note that if anything the magnitude of the coefficient on change in liquidity is positive, suggesting that even if there is a price effect it is in the opposite direction of what one would expect: Instead of negatively shocked banks raising their interest rates, we

[18] Out of the forty two commercial banks used in our analysis, interest rate information is available for thirty nine of these banks.

find that they are more likely to drop them (though this is not really statistically significant). We should caution though that it could simply be that our average interest rate information is too aggregated to capture differences in interest rates at the loan-level across firms, although this is unlikely since a general examination of lending suggests there is not much variation in interest rates even at the loan level.

Our interest rate results are similar in spirit to the result in Peterson and Rajan (1994) who find that closer ties between the firm and its creditor increases the availability of credit but does not lower the price of credit. This suggests that quantity rather than price is the more relevant margin in firm-bank relationships. Note that these results also address a potential concern that the bank lending channel we estimated before may be capturing an initial differential cost of capital difference i.e. If banks had lower costs of capital on account of holding foreign currency accounts, then one may worry that their lending drop after the liquidity shock is not a result of the supply shock but a price correction (i.e. the removal of the cheaper source of capital). However, if this were the case then one would expect to see such banks raise the interest rates on their loans and our results if anything, show he opposite. Such negatively affected banks actually drop their interest rates although this result is hardly economically or statistically significant.

V Results: Firm Level Impact

A. Can Firms Hedge Bank Specific Liquidity Shocks?

We have seen that shocks to the supply of a bank's liquidity translate into a drop in its client firms' loans. As section II highlighted, this reflects the inability of the bank to access external financing when faced with a credit crunch. However, even if market imperfections at the bank level force them to cut back their lending, this may not have an impact on the borrowing firms if they can compensate by borrowing from elsewhere. For example, if firms could switch to new banks and form borrowing relationships with relative ease, then the loan level impact of liquidity crunch identified earlier will be mitigated. This is particularly pertinent given our context - while many banks suffered declines in liquidity, others actually experienced significant increases.

To test for the extent of substitution to more liquid banks, one needs detailed data linking firms to all possible financial institutions that they can borrow from. This data requirement has so far made it difficult to answer the substitution question. However, we can address it since our dataset includes all loans that a firm has taken from any of the 145 bank and non-bank financial intermediaries in the country.

Recall that in the analysis so far, we restricted our attention to commercial banks that used demandable deposits as their source of liquidity. However, when looking at the question of substitutability across banks, one ought to consider *all* possible financial intermediaries in the economy. For this reason we now include all of the 145 financial intermediaries in our analysis, and construct the aggregate loan amount borrowed by each firm from all of these intermediaries before and after the nuclear tests.

We then compute the aggregate liquidity shock faced by each firm by constructing a loan-size weighted average of the change in deposits for each of the commercial banks that the firm borrowed from before the nuclear tests. Since the deposit data is available only for commercial banks, we assume non-commercial banks experience the economy wide change in liquidity. Since the non-commercial banks only make up 22% of the market share this particular assumption is not crucial for our results. For example, assuming instead that non-commercial banks experience no change in liquidity does not affect our results. We use OLS to estimate specification (6):

If there is no substitution then β_1 in (6) should be the same as that in (4) i.e. the same as the bank-lending channel effect. At the other extreme, if there is full substitution all firms will have equal access to lenders regardless of whom they borrowed from initially. A given bank's liquidity crunch will therefore have no impact on its firm's aggregate borrowing and β_1 will be zero since all firms will only respond to the aggregate liquidity shock (captured by β_0). More generally, the greater the substitution, the closer β_1 will be to zero. Recall from the methodology section that OLS estimates, while biased, are meaningful since we can sign the direction of the bias - specifically, that it provides an underestimate of the true effect. Also given evidence on the bank lending channel that large and smaller borrowers are treated differentially, we will estimate separate effects for these two types of firms.

Column (1) in Table VII shows that on average firms are unable to compensate for the bank-lending channel by increasing borrowing from more liquid banks. Column (2) shows that this result remains robust to the inclusion of firm and bank level controls.

Column (3) separates this effect for large and smaller borrowers and shows that while large borrowers almost fully offset their bank's liquidity shock, in stark contrast, the significant interaction term shows that smaller borrowers are entirely unable to hedge the initial liquidity shock faced by their banks. For a one percent decline in their initial banks liquidity, total borrowing for these firms drops by 0.76%, essentially the same result as the bank lending channel. Thus smaller borrowers are unable to avoid the adverse liquidity shock by going to other lenders in the market.[19] Figure VII presents a more non-parametric picture of this size heterogeneity. We compute the same effect separately for each firm borrowing size decile - Figure VII plots the coefficient estimate for each of the size deciles. and shows how it declines for each firm decile (except the smallest decile which appears to also be completely hedged). In particular, the top three deciles show almost no effect and justify why we include them in our "large" borrower category.

We should point out that we remain agnostic as to why borrower size matters. While our interpretation based on institutional evidence is that such larger firms have differential access to credit. one may expect such firms also to be different on a variety of influence margins. Specifically a firm's number of creditors, conglomerate membership (see Khwaja and Mian 2005b), political affiliations, location are also like to be different for such large borrowers. We measure a firm's political connectedness with a variable that equals one if any of the directors of the firm participated in a national election. Politically connected firms might be in a better position to protect themselves from liquidity shocks due to their influence.[20] However, column (3) shows that the size does matter more than these factors and in spite of these controls, we find that small borrowers are unable to hedge while larger ones, even if they have only single-banking relationships and are not politically connected or members of business conglomerates, generally face little overall borrowing losses. As an aside, note that the coefficients on a firm's political status, and conglomerate membership are all positive and significant and their interactions with the liquidity shock suggests that they are relatively better able to hedge but these interactions are only marginally statistically significant.

So how are large borrowers able to compensate the bank lending channel? Which banks are they able to borrow from to compensate? Are these their liquidity rich old banks or new ones

[19] We still cluster observations at the bank level in Table VI. However since observations across banks are aggregated at the firm level, for multiple-relationship firms we use the largest lender of a firm as the unit of clustering. Similarly, for multiple relationship firms, "bank controls" are constructed by value-weighing bank data for each of the banks a firm borrows from.

[20] See Khwaja and Mian (2005a) for details on the construction of the political connectedness.

or both? Table VII takes a closer look at these questions by separately examining firm's overall borrowing after the shock from its existing banks and new banks. Column (1) first looks at overall borrowing post-shock from the banks a firm was borrowing from prior to the shock. For every percent decrease in their banks' liquidity large borrowers face a 0.15% drop in their aggregate borrowing. We should note that this is not mechanical in that there is substantial variation across borrowers in terms of the average liquidity shocks faced by their banks (there is also significant variation across banks liquidity shocks within the same firm as well). Column (2) then looks at aggregate borrowing changes from banks a firm was not borrowing from before the shock. These changes are measure relative to the firm's total borrowing before the shock. The result shows that large borrowers also partly hedge by being able to borrow more from new banks i.e. the negative coefficient implies that if a large firm's existing banks suffered an average negative liquidity shock, the firm is able to borrow more from new banks. The coefficients in Column (2) is not directly comparable to that in column (1) since it measures the sensitivity of borrowing from new banks to the *old* banks average liquidity shock. Further checks reveal that these new banks are more likely to be the ones that experienced a positive liquidity shock. Column (3) repeats the same regression as in table VI Column (3) to provide an idea of how much of the hedging large borrowers obtain is from pre-existing banks. Recall that the OLS estimate for the bank lending channel for large borrowers was around 0.46 %. This suggests that large borrowers compensate upto two-thirds of their loan loss by going to (more) liquid pre-existing banks and the remaining third by borrowing from (liquid) banks from whom they did not have a relationship before.

B. Firm Financial Outcomes

Our results have shown that although all firms experience a relatively greater fall in loans from their banks facing a greater liquidity crunch, large borrowers are able to partially compensate for this by borrowing more from more liquid banks. This suggests that while large borrowers are unlikely to experience a change in their observed outcomes such as default propensity, smaller borrowers might be more adversely affected if their bank happens to have a negative liquidity shock. However, even smaller borrowers may not be adversely affected if they can compensate for the lower aggregate external borrowing, by tapping into internal cash reserves or other forms of informal financing such as trade credit and family loans. If these internal and informal means of financing are sufficient, then a reduction in aggregate external financing will have no impact on a firm's real outcomes.

While we do not have firm level output data, we do have default rates on a firm's loans. To the extent that such default captures a firm's financial distress, we can examine whether the liquidity shock also translates into a real impact at the firm level. We run regression specification (6) with a firm's default rate as the LHS variable. Since cross-default clauses make it unlikely a firm can default on one bank but not the other, and the data shows that this is indeed the case, the data is aggregated at the firm level.

Column (1) in Table IX shows that firms that on average experience a reduction in their banks' liquidity, experience higher default rates. In particular, a 1% reduction in liquidity of a bank increases the probability of default of its firm by about 13.7 basis points (on a mean post nuclear test default rate of 6.9 percentage points, this is a 2% increase in probability). Recall that our identification strategy suggests that the increase in default rate of firms more exposed to a liquidity crunch cannot be attributed to unobserved negative productivity shocks experienced by such firms and that, if anything, this bias leads to an underestimate. In the absence of a liquidity shock to their banks, these firms are unlikely to have had differentially higher default rates. Thus not only does a liquidity crunch reduce overall lending to firms, but it also makes it more likely for the affected firms to enter financial distress. This is particularly important since it suggests that firms cannot compensate their loss of formal credit through informal channels such as drawing on internal capital or borrowing from sister/family firms.

If higher default rates for firms borrowing from more credit-crunched banks is due to reduced loans to the firms, we should see the same relationship between change in default rates and change in a firm's loans. In general, change in loan supply is endogenous to changes in a firm's demand conditions. A potential instrument for change in a firm's loan supply is the firm's bank's liquidity.[21] Column (2) instruments the change in a firm's loans by the change in its bank's liquidity and shows an even larger effect on a firm's default rate of a reduction in its loan supply.

Recall that Table VII showed that larger borrowers experienced little/no reduction in aggregate borrowing due to their ability to hedge the bank specific shocks while smaller borrowers

[21] The first stage for this instrument is given in Table IV. To the extent that bank's experiencing greater liquidity shocks only affect their client firm's financial condition through the amount lent, the exclusion restriction for the instrument is also likely to be satisfied.

were unable to do so. If default rates increase due to the credit constraints faced by firms, one would expect the impact on default rates to be higher for smaller borrowers. This is confirmed in column (3). The results show that large borrowers experience no increase in their default rates when borrowing from liquidity constrained banks. However, in sharp contrast, smaller borrowers are affected adversely by the shock and are significantly more likely to go into financial distress. A 1% decrease in their banks' liquidity leads to a 16.4 basis points increase in their probability of default. Column (4) shows that this result is not affected if we allow for heterogeneity across other firms attributes and is robust to bank and firm level controls. Note that we cannot run IV in columns (3) and (4) because as Table VII showed, the first stage does not hold for large borrowers. These results suggest that the liquidity shock have real financial consequences that vary starkly across large and smaller borrowers - the former remain protected from the shock while the latter face its full brunt.

VI Concluding Remarks

Our study traces how liquidity supply shocks to the banking sector are transmitted to the economy. We find that while there is a large bank lending channel, this does not always translate into losses in overall firms borrowing. While smaller borrowers are unable to hedge against their bank's liquidity shocks and experience both a fall in aggregate borrowing and a greater likelihood of financial distress, large borrowers are able to hedge against bank level shocks and do not experience any financial distress. This suggests that there are important frictions in forming new banking relationships for smaller borrowers. Moreover, given the persistence of our results, such frictions do not seem to be readily overcome.

Note that Figures III-V showed that all our effects are persistent i.e. the bank-lending, firm-borrowing and financial distress results hold even several quarters after the nuclear shock. In terms of the bank-lending channel one may wonder why if the adversely affected banks indeed had better clients and therefore presumably better quality, are they not able to eventually raise more deposits and increase lending to their old clients. However, note that large borrowers are quickly able to compensate for their loan fall by borrowing from more liquid banks. Even if their initial (adversely hit) bank does raise its liquidity over time, these firms are unlikely to switch back as long as they are some switching costs. Thus the bank-lending channel is likely to persist for large borrowers over time. However, what about smaller borrowers? Since they are unable to cover their lending drop, wouldn't they borrow more from their initial bank once it recovers it's liquidity loss? All else being equal we would expect this but note that these firms do not remain unaffected. In particular, we know they are more likely to experience financial distress due to the initial shock. Thus even if the adversely affected bank does eventually raise liquidity, it may not want to increase loans to its old smaller borrowers given that they are now of lower (financial) quality. Instead the bank may prefer to choose to lend to other or new clients that remained protected from the shock. So the effects may persist in the long-run for smaller borrowers as well.

Our results therefore suggest that while liquidity shocks may not have large affects on overall lending (as large borrowers constitute the bulk of lending) they can have significant and long-lasting distributional consequences since smaller borrowers are more likely to be affected by these shocks. While this insurance due to borrowing size may be specific to the particular environment we study, the general point is that it is likely that firms differ in the extent to which they can hedge against this shock. This differential ability may be systematically related to a firm attribute such as its size, pre-existing banking relationships strength, credit history and linkages etc. Either way, a liquidity shock will then not just have level affects but also change the distribution of firms in the economy. These distributional changes will last not just because of the persistence of the initial affect but also as they get reinforced through a series of liquidity shocks that often affect economies.

As an illustration, we can use our micro-level estimates and benchmarks from the Pakistani economy to provide a sense of the magnitude of these effects. Consider an economy experiencing an aggregate drop in liquidity of 1%. How much will this liquidity shock cause aggregate lending to drop relative to what it should have been? Our results suggest that such shocks will only affect aggregate lending to smaller borrowers. In terms of impact on overall lending the affect will therefore be small since such borrowers only constitute around 6% of economy-wide lending. These firms will face drops in lending both due to a decreased level of borrowing (the intensive margin) and greater exit and less entry of such firms (the extensive margin). Using our estimates we impute that a 1% drop in liquidity leads to a 0.1% drop in aggregate lending in the economy ($= 0.06 * (1.03 + 0.20 + 0.47)$ - the terms are respectively the intensive margin, increased exit, and reduced entry effects for smaller borrowers). However, in terms of number of firms, smaller borrowers compose 70% of all firms' in the economy. Thus the liquidity impact, while not large in overall magnitude, affects over two-thirds of the firms in the economy not only by drastically reducing their borrowing but by also affecting the viability by raising the likelihood that these firms experience financial distress.

References

[1] Agenor, P. R.; Aizenman, J.; Hoffmaister, 2000. The Credit Crunch in East Asia: What can Bank Excess Liquid Assets Tell us? National Bureau of Economic Research, Inc., NBER Working Papers: 7951 2000

[2] Bernanke, B.S., and C. Lown, 1991. “The Credit Crunch.” Brookings Papers on Economic Activity 2: 205-239.

[3] Ben S. Bernanke 1983, Non monetary Effects of the Financial Crisis in the Propagation of the Great Depression. The American Economic Review, Vol. 73, No. 3. (Jun., 1983), pp. 257-276.

[4] Bernanke, B. and A. Blinder, 1988. "Credit, Money, and Aggregate Demand." American Economic Review 78(2): 435-439.

[5] Bernanke, B. and A. Blinder, 1992. "The Federal Funds Rate and the Channels of Monetary Transmission." American Economic Review 82(4): 901-921.

[6] Bernanke, B. and M. Gertler, 1989. "Agency Costs, Net Worth, and Business Fluctuations." American Economic Review 79(1): 14-31.

[7] Bernanke, Ben and Harold James, 1991. “The Gold Standard, Deflation and Financial Crises in the Great Depression: An International Comparison,” in R. Glenn Hubbard, ed., Financial Markets and Financial Crises, Chicago: University of Chicago Press, pp. 33–68.

[8] Bertrand, M.; E. Duflo, and S. Mullainathan, 2004. How much should we trust differences-in-differences estimates? Quarterly Journal of Economics, Vol. 119, Issue 1.

[9] Gertler, M. and S. Gilchrist, 1994. "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms", Quarterly journal of Economics, Vol. CIX, May.

[10] Holmstrom, Bengt; and Jean Tirole, 1997. “Financial Intermediation, loanable funds, and the real sector”. *Quarterly Journal of Economics*: 665-691.

[11] Hoshi, Takeo, and Anil Kashyap, 2000. ’The Japanese Banking Crisis: Where Did it Come From and How Will it End." In NBER Macroeconomics Annual 1999, edited by Ben S. Bemanke and Julio Rotemberg, pp. 129-201. Boston: MIT Press.

[12] Kashyap, A. and J. Stein, 2000. "What do One Million Observations on Banks Have to Say About the Transmission of Monetary Policy." American Economic Review 90(3): 407-428.

[13] Kashyap, A., O. Lamont and J. Stein, 1994. "Credit Conditions and the Cyclical Behavior of Inventories." The Quarterly Journal of Economics 109(3): 565-592.

[14] Kashyap, A., R. Rajan, and J. Stein, 2002. Banks as Liquidity Providers: An Explanation for the Co-Existence of Lending and Deposit-Taking. Journal of Finance, Vol. LVII, No. 5.

[15] Kashyap, A., J. Stein and D. Wilcox, 1993. "Monetary Policy and Credit Conditions: Evidence from the Composition of External Finance." American Economic Review 83(1): 78-98.

[16] Khwaja, A. and A. Mian, 2005a. "Do Lenders Favor Politically Connected Firms? Rent Provision in an Emerging Financial Market", Quarterly Journal of Economics, Vol. 120, Issue 4, November 2005.

[17] Khwaja, A., A. Mian and A. Qamar 2005b Identifying Business Networks in Emerging Economies. Working Paper

[18] Paravisini, D (2005). "Constrained Banks, Constrained Borrowers. The Effects of Bank Liquidity on the Availability of Credit." mimeo, MIT.

[19] Peek, J. and E. Rosengren, 1997. "The International Transmission of Financial Shock." American Economic Review 87(4): 495-505.

[20] Peek, J. and E. Rosengren, 2002. "Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States." American Economic Review 90(1): 30-45.

[21] Petersen, M. and R. Rajan, 1994. "The Benefits of Lending Relationships: Evidence from Small Business Data." The Journal of Finance 49(1): 3-37.

[22] Romer, C.D. and Romer, D.H., 1990. New Evidence on the Monetary Transmission Mechanism. Brookings Papers on Economic Activity, 149-213.

[23] Stein, J., 1998. "An Adverse Selection Model of Bank Asset and Liability Management with Implications for the Transmission of Monetary Policy." RAND Journal of Economics 29(3): 466-86.

[24] US International Trade Commission. "Overview and Analysis of the Economic Impact of U.S. Economic Sanctions with Respect to India and Pakistan". Investigation No. 332-406, Publication 3236, September 1999.

[25] Woo, David, 2003. In Search of "Capital Crunch": Supply Factors behind the Credit Slowdown in Japan. Journal of Money, Credit, and Banking v35, n6 (Part 1 Dec. 2003): 1019-38

TABLE I
SUMMARY STATISTICS

Panel A : Loan-level Variables (22,176 loans)				
Variable	Mean	S.D.		
Pre-nuclear Test Total Lending ('000)	16,479	60,768		
Change in Log Lending	-0.0028	1.23		
Post-nuclear Test Default Rate	6.8%	26.1%		
Pre-nuclear Test Interest Rate (%)	15.9%	2.7%		
Loan Type	*Fixed*	*Working Capital*	*Letter of Credit*	*Other*
Percent of total lending	32.5%	56.1%	4.2%	7.2%
Panel B: Borrower/Firm Attributes (18,725 firms)				
Politically Connected	*No*	*Yes*		
Percent of total lending (of total firms)	54% (76%)	46% (24%)		
Size	*Small*	*Large*		
Percent of total lending (of total firms)	6.4% (70%)	94% (30%)		
Location (City Size)	*Small*	*Medium*	*Large*	*Unclassified*
Percent of total lending (of total firms)	6% (14%)	13% (18%)	80% (62%)	6% (2%)
Single Relationship	*Yes*	*No*		
Percent of total lending (of total firms)	34% (90%)	66% (10%)		
Business Group Size	*Non-conglomerate*	*Conglomerate*		
Percent of total lending (of total firms)	36% (85%)	64% (15%)		
Panel C : Bank Level Variables (42 banks)				
Variable	Mean	S.D.		
Bank Assets Dec '97	33886.3	63884.7		
Average ROA ('96 & '97)	0.013	0.027		
Capitalization Rate ('96 & '97)	0.082	0.054		
Percentage of Dollar Deposits (Dec '97)	0.60	0.27		
Average Default Rate (('96 & '97)	0.086	0.13		
Growth in Deposits (Dec '97 to Dec '99)	0.046	0.30		
Bank Type	*Private*	*Foreign*	*Government*	
Percent of total lending	33.8%	36.8%	29.4%	

A "loan" is defined as a Bank-Firm pair, i.e. multiple loans of a firm from the same bank are aggregated up. The loan level data comprises all performing loans given out by the forty two commercial banks at the time of nuclear test that continued to be serviced. The pre and post data is averaged over June 1996 to March 1998, and June 1998 to December 1999 respectively. Note that since we only include performing pre-nuclear loans, default rate just prior to nuclear tests is zero by construction. Average Loan Interest Rate in Panel C is available for 39 banks only. Politically Connected = dummy for whether firm has a politician on its board; Other firm level attributes defined in Appendix I; While we report summary statistics for firm location in terms of city size as defined in Appendix I, in the subsequent regressions firm location controls are introduced as separate dummies for each city.

TABLE II
BANK LEVEL CORRELATIONS WITH PRE-TEST DOLLAR DEPOSIT EXPOSURE

Dependent Variable	Average Annual Growth in Bank Deposits (Dec '99 - Dec '97)		Average Pre-Nuclear Test Default Rate		Average Pre-Nuclear Test Bank ROA	
	(1)	(2)	(3)	(4)	(5)	(6)
Percentage of Deposits in Dollars in Dec '97	-0.17	-0.30	-0.27	-0.31	0.044	0.061
	(0.08)	(0.06)	(0.06)	(0.06)	(0.014)	(0.016)
Constant	0.12	0.17	0.25	0.28	-0.013	-0.022
	(0.05)	(0.03)	(0.04)	(0.04)	(0.009)	(0.009)
Bank-Size Weighted			No	Yes	No	Yes
Observations	42	42	42	42	42	42
R-squared	0.09	0.4	0.33	0.38	0.2	0.26

The regressions are run on the forty two commercial banks that were allowed to open dollar deposits and hence were direclty affected by the "dollar freeze" as a result of the nuclear tests in May 1998. Average Pre-nuclear test default rate is the loan-size weighted default rate of loans from a given bank over July 1996 to March 1998. The bank level default rate is defined here as a fraction between 0 to 1. Average pre-nulcear-test ROA is the average ROA of a bank over fiscal years 1996 and 1997 (years end in december). Robust standard errors in parentheses.

TABLE III

IDENTIFYING THE BANK LENDING CHANNEL

Difference-in-Difference

	Positive Liquidity Shock (10,988 loans)	**Negative Liquidity Shock** (11,188 loans)	**Difference** (22,176 loans)
Test	7.654	7.641	0.013
	(0.078)	(0.212)	(0.223)
Test	7.754	7.537	0.216
	(0.075)	(0.285)	(0.292)
(Post - Pre)	0.1	-0.103	**0.203**
	(0.029)	(0.096)	**(0.100)**

Dependent Variable	Δ Log Loan OLS (1)	FE (2)
Positive Liquidity Shock	0.203	0.211
	(0.100)	(0.050)
Constant	-0.103	--
	(0.096)	
Firm FE		Yes
Observations	22,176	5,382
R-squared	0.01	0.44

Standard errors are clustered at the bank level (42 banks)

TABLE IV
BANK LENDING CHANNEL COEFFICIENT - INTENSIVE MARGIN

Dependent Variable	Δ Log Loan Size						
	FE (1)	FE (2)	FE (3)	OLS (4)	OLS (5)		OLS (6)
Δ Log Bank Liquidity	0.60	0.63	0.64	0.46	0.64	**Δ Log Bank Liquidity**	0.33
	(0.09)	(0.10)	(0.11)	(0.14)	(0.17)		(0.17)
Lag Δ Log Bank Liquidity		0.15				**Small Firms**	0.24
		(0.10)					(0.04)
Pre-Shock Avg Bank ROA		0.99				**Δ Log Bank Liquidity ***	0.54
		(1.73)				**Small Firms**	(0.16)
Log Bank Size		0.02				**Conglomerate Firm?**	0.08
		(0.03)					(0.04)
Pre-Shock Bank		-1.16				**Δ Log Bank Liquidity ***	-0.19
Capitalization		(0.97)				**Conglomerate Firm**	(0.14)
Pre-Shock Bank Default		-0.869				**Political Firm?**	0.08
Rate		(0.36)					(0.03)
Gov. Bank Dummy		0.13				**Δ Log Bank Liquidity ***	0.01
		(0.06)				**Political Firm**	(0.14)
Foreign Bank Dummy		0.01				**Multiple Relationship Firms**	0.03
		(0.06)					(0.04)
						Δ Log Bank Liquidity *	0.18
						Multiple Relationship Firms	(0.16)
Fixed Effects	Firm	Firm	Firm * Loan-Type				
Constant	--	--	--	-0.06	-0.04	**Constant**	-0.23
				(0.04)	(0.04)		(0.04)
No of Obs	5,382	5,382	5,382	5,382	22,176	**No of Obs**	22,176
R-sq	0.44	0.44	0.6	0.01	0.02	**R-sq**	0.03

All quarterly data for a given loan is collapsed over pre and post nuclear test period. The nuclear test occurred in the 2nd Quarter of 1998, so all observation from Quarter 3 1996 to Quarter 1 1998 for a given loan are time-averaged into one. Similarly, all observation from 3rd Quarter 1998 to 4th Quarter 1999 are time-averaged into one. Standard Errors in parantheses are clustered at the bank level (42 banks in total). Data is restricted to banks that: (i) take retail (commercial) deposits (78% of all formal formal financing), (ii) loans that were not in default in the first quarter of 1998 (i.e. just before the nuclear tests), and (iii) that appear both before and after the nuclear tests.

TABLE V

BANK LENDING CHANNEL COEFFICIENT - EXTENSIVE MARGINS

Dependent Variable	Exit?				Entry?			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Log Bank Liquidity	-0.21	-0.19	-0.25	-0.20	0.12	0.15	0.34	0.12
	(0.05)	(0.05)	(0.03)	(0.05)	(0.05)	(0.04)	(0.21)	(0.05)
Small				0.152				0.288
				(0.018)				(0.02)
Small * Δ Log Bank Liquidity				0				0.344
				(0.077)				(0.21)
Constant	--	--	0.32	0.25	--	--	0.35	0.23
			(0.01)	(0.01)			(0.02)	(0.02)
Firm Fixed Effects	Yes	Yes			Yes	Yes		
Bank Controls		Yes				Yes		
No of Obs	6,517	6,517	26,730	26,730	8,516	8,516	35,921	35,921
R-sq	0.48	0.49	0.02	0.03	0.54	0.55	0.03	0.06

The data in columns (1) through (3) includes all loans that were outstanding (and not in default) at the time of the nuclear tests. For a given loan, "exit" is classified as 1 if the loan is not renewed and the firm exits its banking relationship by the first post-shock year. The data in columns (4) through (6) includes all loans given out during and after the nuclear tests quarter (2nd quarter of 1998). For a given loan, "entry" is classified as 1 if the loan entered for the first time in the first post-shock year. Bank level controls include lag change in bank liquidity, pre-shock bank ROA, pre-shock log bank size, and pre-shock bank capitalization, while firm level controls include dummies for each of the 134 cities/towns the firm is located in and 21 industry dummies. Standard Errors in parantheses are clustered at the bank level (42 banks in total).

TABLE VI
LIQUIDITY IMPACT ON INTEREST RATES

Dependent Variable	Δ Interest Rate		
	(1)	(2)	(3)
	FE	FE	OLS
Δ Log Bank Liquidity	0.28	0.33	1.53
	(0.16)	(0.21)	(1.02)
Fixed Effects	Firm	Firm * Loan-Type	
Constant	--	--	-1.59
			(0.34)
No of Obs	5,161	5,161	21,769
R-sq	0.43	0.57	0.02

All quarterly data for a given loan is collapsed over pre and post nuclear test period. The nuclear test occurred in the 2nd Quarter of 1998, so all observation from Quarter 3 1996 to Quarter 1 1998 for a given loan are time-averaged into one. Similarly, all observation from 3rd Quarter 1998 to 4th Quarter 1999 are time-averaged into one. Standard Errors in parantheses are clusterd at the bank level (42 banks in total). Data is restricted to banks that: (i) take retail (commercial) deposits (78% of all formal formal financing), (ii) loans that were not in default in the first quarter of 1998 (i.e. just before the nuclear tests), and (iii) that appear both before and after the nuclear tests.

TABLE VII
FIRM BORROWING CHANNEL COEFFICIENT

Dependent Variable	Δ Log Aggregate Loan Size			
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Δ Log Bank Liquidity	0.65	0.55	0.04	0.27
	(0.04)	(0.05)	(0.09)	(0.11)
Small Firms			0.18	0.28
			(0.02)	(0.02)
Δ Log Bank Liquidity * Small Firms			0.80	0.60
			(0.10)	(0.11)
Conglomerate Firm?				0.10
				(0.03)
Δ Log Bank Liquidity * Conglomerate Firm				-0.31
				(0.14)
Political Firm?				0.15
				(0.02)
Δ Log Bank Liquidity * Political Firm				-0.25
				(0.12)
Multiple Relationship Firms				0.17
				(0.03)
Δ Log Bank Liquidity * Multiple Relationship Firms				-0.10
				(0.15)
Bank and Firm Controls		Yes		
Constant	0.04	--	-0.08	-0.21
	(0.01)		(0.02)	(0.02)
No of Obs	18,647	18,647	18,647	18,647
R-sq	0.02	0.04	0.03	0.03

All bank loans at a point in time (from any of the 145 banks) for a given firm are summed to compute the aggregate firm level loan size. Quarterly data for a given firm is then collapsed over pre and post nuclear test period. The nuclear test occurred in the 2nd Quarter of 1998, so all observation from Quarter 3 1996 to Quarter 1 1998 for a given firm are time-averaged into one. Similarly, all observation from 3rd Quarter 1998 to 4th Quarter 1999 are time-averaged into one. Data is restricted to (i) firms that were not in default in the first quarter of 1998 (i.e. just before the nuclear tests), and (ii) that appear both before and after the nuclear tests. Bank level controls include lag change in bank liquidity, pre-shock bank ROA, pre-shock log bank size, and pre-shock bank capitalization, while firm level controls include dummies for each of the 134 cities/towns the firm is located in and 21 industry dummies. Standard Errors in parantheses are clustered at the bank level, i.e. the largest lender for a firm.

TABLE VIII
FIRM BORROWING CHANNEL COEFFICIENT

Dependent Variable	Δ Log Aggregate Loan Size Aggregating Loans Post Test Using Only		
	Existing Banks OLS (1)	New Banks OLS (2)	Existing and New OLS (3)
Δ Log Bank Liquidity	0.15	-0.40	0.04
	(0.09)	(0.08)	(0.09)
Small Firms	0.24	-0.23	0.18
	(0.02)	(0.02)	(0.02)
Δ Log Bank Liquidity * Small Firms	0.68	0.53	0.80
	(0.10)	(0.08)	(0.10)
Constant	-0.19	-2.55	-0.08
	(0.02)	(0.02)	(0.02)
No of Obs	18,647	18,647	18,647
R-sq	0.03	0.01	0.03

TABLE IX

FIRM BORROWING CHANNEL IMPACT ON FIRM FINANCIAL DISTRESS

Dependent Variable	Δ Firm Default Rate				
	OLS	IV	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)
Δ Log Bank Liquidity	-13.71		2.01	-1.25	-2.83
	(7.44)		(3.47)	(3.21)	(3.62)
Δ Log Firm Loan		-45.46			
		(12.45)			
Small Firms			3.61	2.33	1.30
			(1.18)	(0.97)	(0.94)
Δ Log Bank Liquidity * Small Firms			-18.54	-14.82	-13.02
			(4.97)	(4.02)	(3.99)
Conglomerate Firm?					-2.65
					(0.69)
Δ Log Bank Liquidity * Conglomerate Firm					4.99
					(3.65)
Political Firm?					-1.18
					(0.59)
Δ Log Bank Liquidity * Political Firm					-2.32
					(1.45)
Multiple Relationship Firms					-1.71
					(0.97)
Multiple Relationship Firms					1.49
					(3.04)
Bank and Firm Controls				Yes	Yes
Constant	8.30	5.14	5.41	--	--
	(1.35)	(0.75)	(0.77)		
No of Obs	18,647	18,647	18,647	18,647	18,647
R-sq	0.01		0.05	0.04	0.06

All bank loans at a point in time (from any of the 145 banks) for a given firm are aggregated at the firm level to compute firm default rate, loan size etc. Quarterly data for a given firm is then collapsed over pre and post nuclear test period. The nuclear test occurred in the 2nd Quarter of 1998, so all observation from Quarter 3 1996 to Quarter 1 1998 for a given firm are time-averaged into one. Similarly, all observation from 3rd Quarter 1998 to 4th Quarter 1999 are time-averaged into one. Data is restricted to (i) firms that were not in default in the first quarter of 1998 (i.e. just before the nuclear tests), and (ii) that appear both before and after the nuclear tests. Bank level controls include lag change in bank liquidity, pre-shock bank ROA, pre-shock log bank size, and pre-shock bank capitalization, while firm level controls include dummies for each of the 134 cities/towns the firm is located in and 21 industry dummies. Standard Errors in parantheses are clustered at the bank level, i.e. the largest lender for a firm.

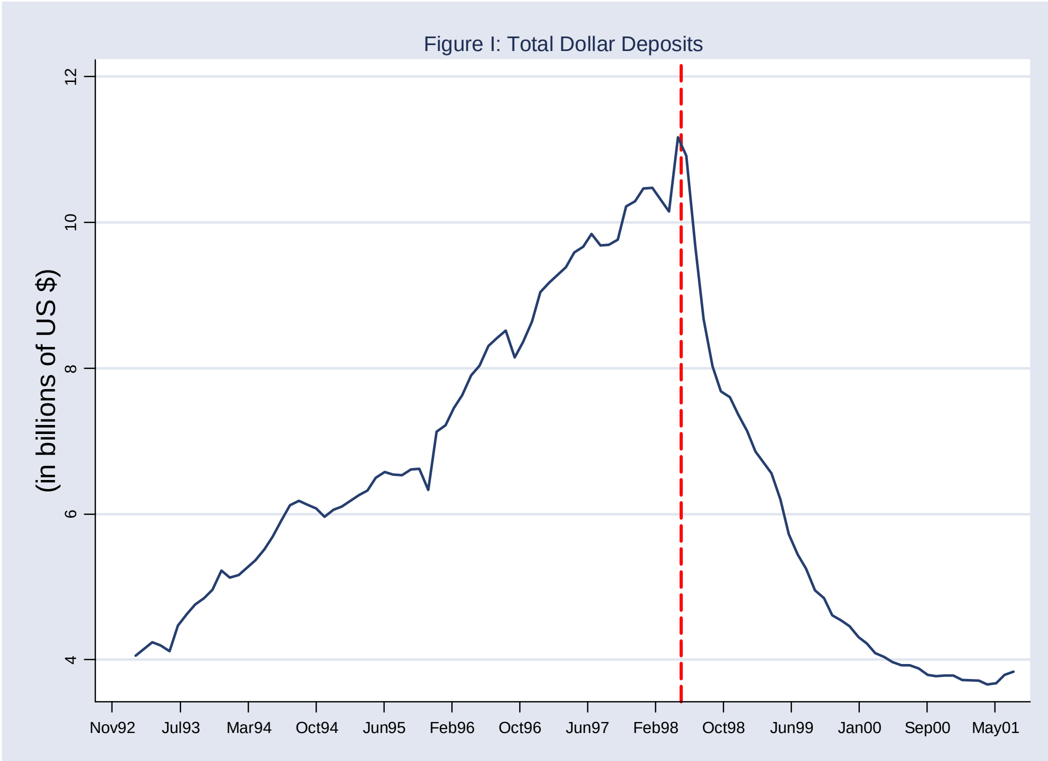
Figure I: Total Dollar Deposits
(in billions of US $)
12
10
8
6
4
Nov92
Jul93
Mar94
Oct94
Jun95
Feb96
Oct96
Jun97
Feb98
Oct98
Jun99
Jan00
Sep00
May01

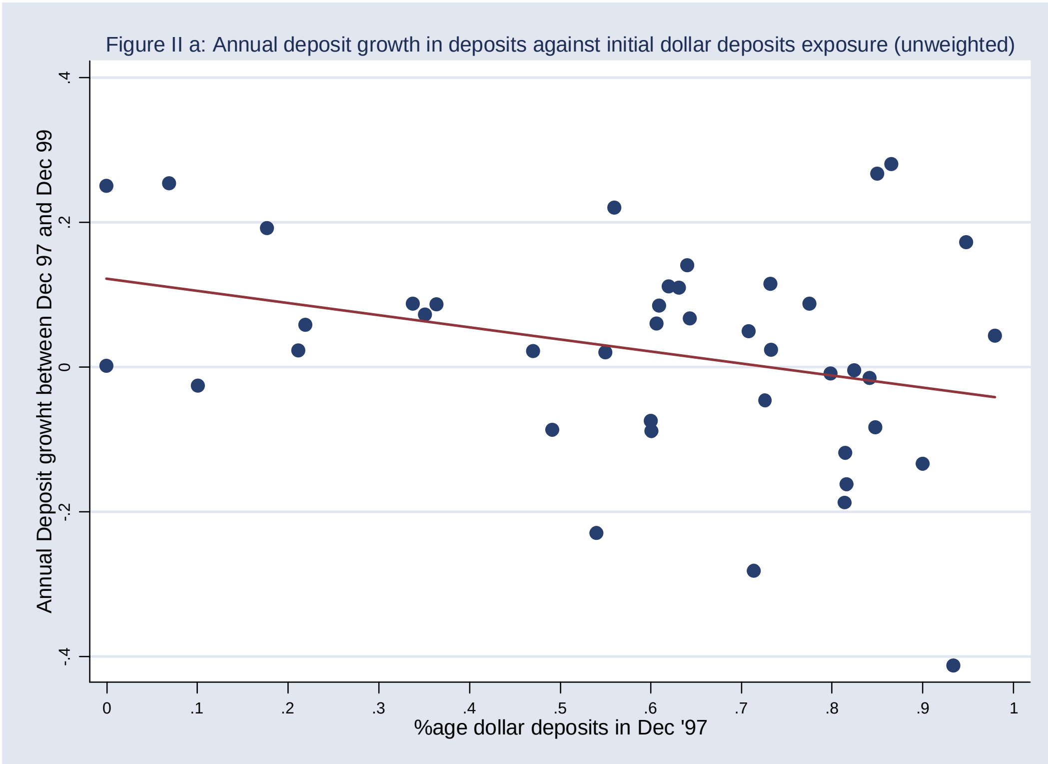
Figure II a: Annual deposit growth in deposits against initial dollar deposits exposure (unweighted)
Annual Deposit growht between Dec 97 and Dec 99
-.4
-.2
0
.2
.4
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
%age dollar deposits in Dec '97

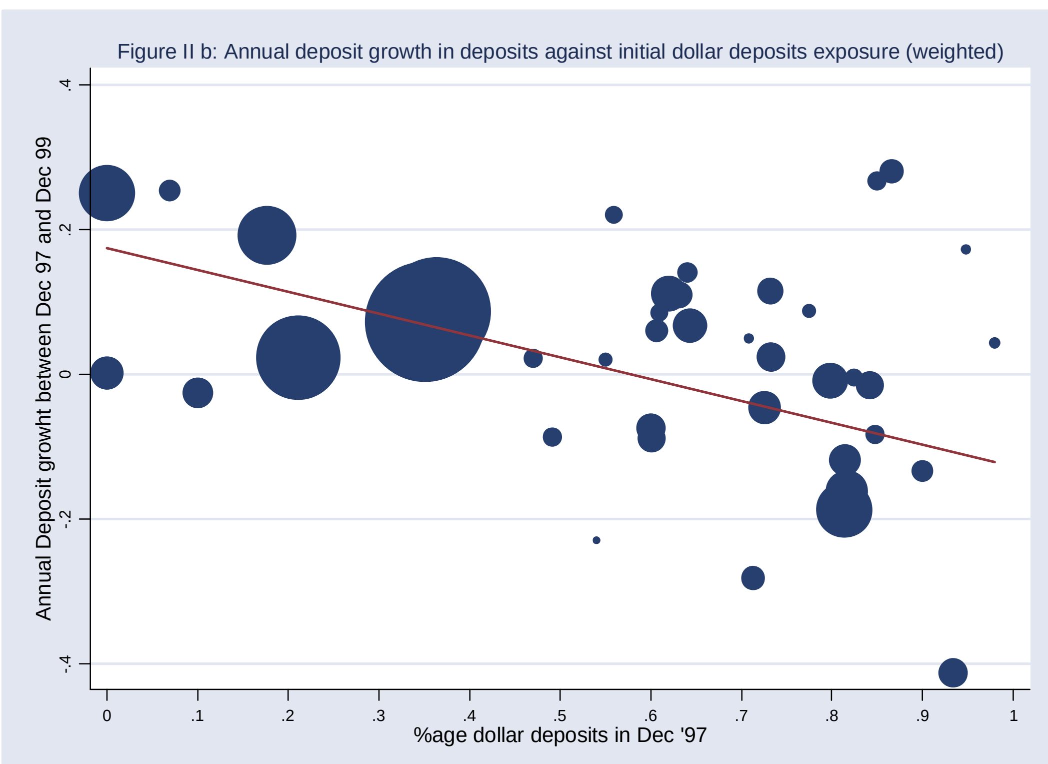
Figure II b: Annual deposit growth in deposits against initial dollar deposits exposure (weighted)
Annual Deposit growht between Dec 97 and Dec 99
-.4
-.2
0
.2
.4
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
%age dollar deposits in Dec '97

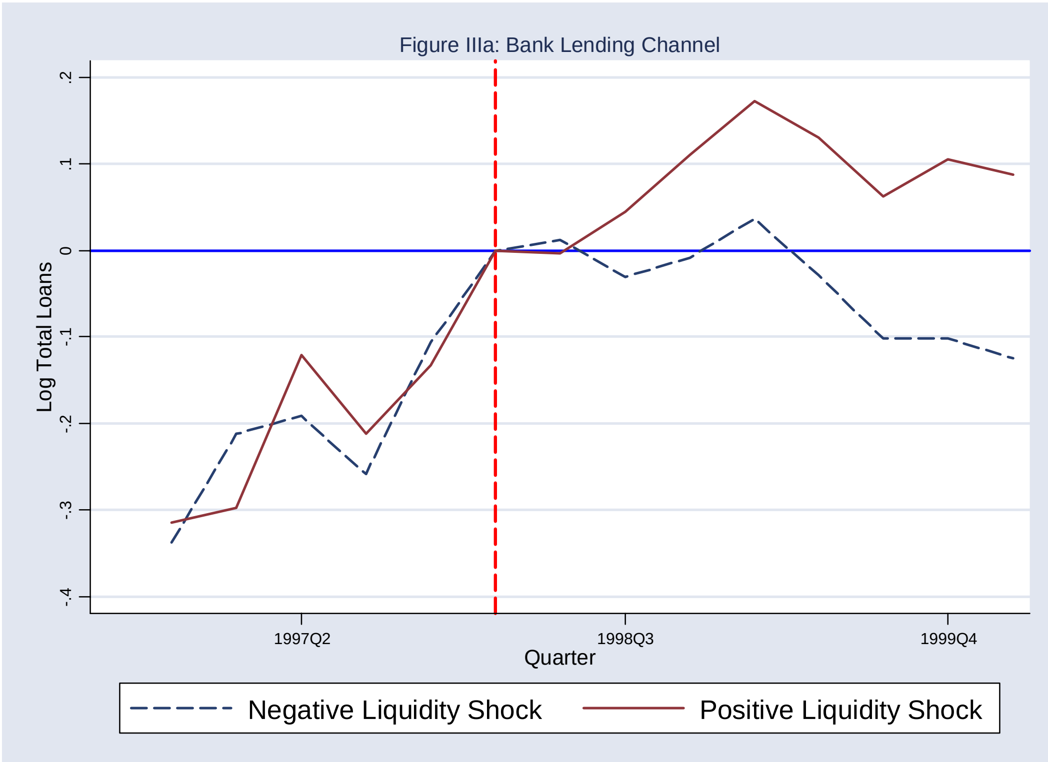
Figure IIIa: Bank Lending Channel
Log Total Loans
.2
.1
0
-.1
-.2
-.3
-.4
1997Q2
1998Q3
1999Q4
Quarter
Negative Liquidity Shock
Positive Liquidity Shock

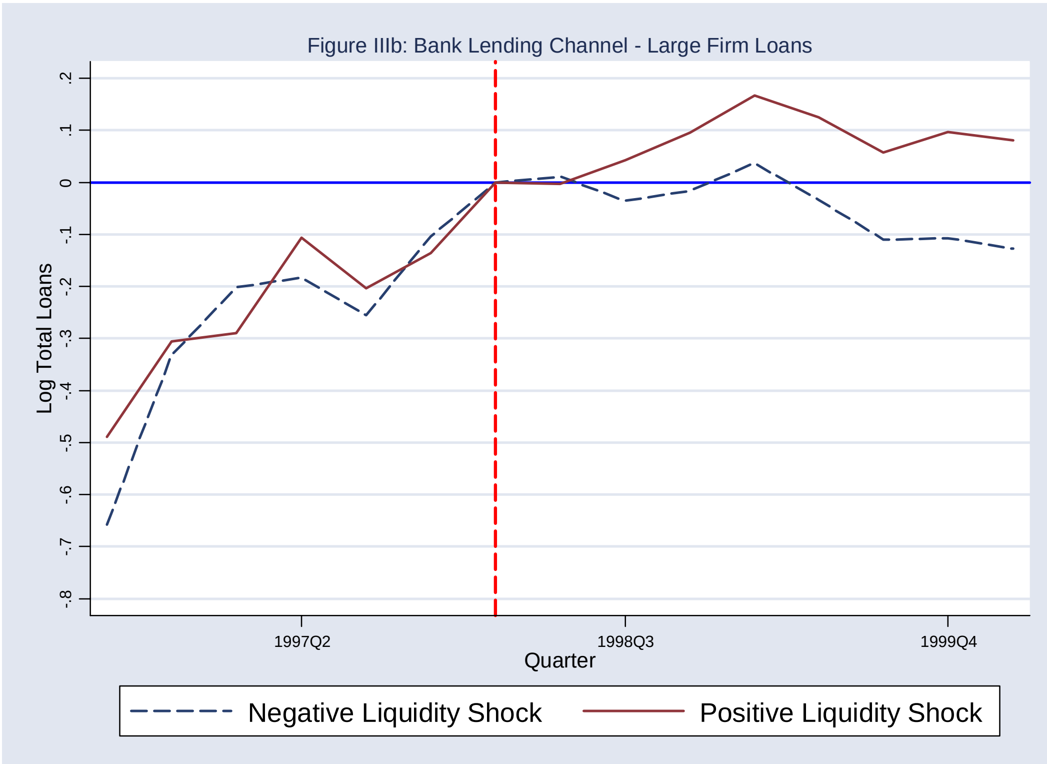
Figure IIIb: Bank Lending Channel - Large Firm Loans
Log Total Loans
.2
.1
0
-.1
-.2
-.3
-.4
-.5
-.6
-.7
-.8
1997Q2
1998Q3
1999Q4
Quarter
Negative Liquidity Shock
Positive Liquidity Shock

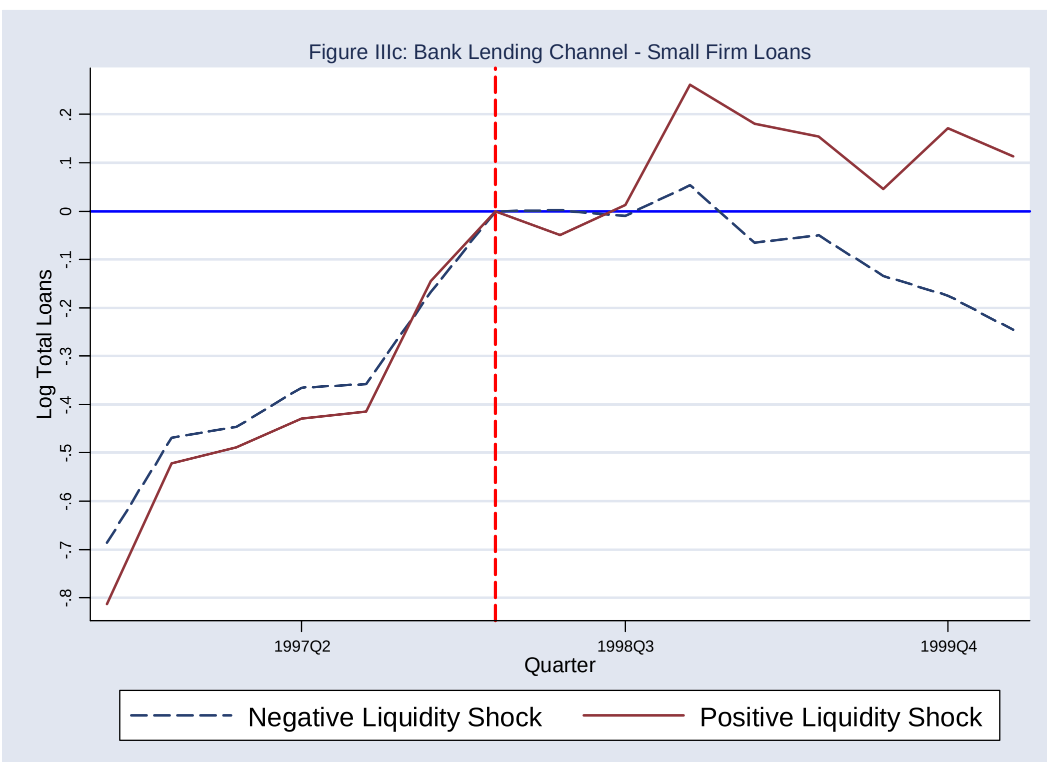
Figure IIIc: Bank Lending Channel - Small Firm Loans
Log Total Loans
.2
.1
0
-.1
-.2
-.3
-.4
-.5
-.6
-.7
-.8
1997Q2
1998Q3
1999Q4
Quarter
Negative Liquidity Shock
Positive Liquidity Shock

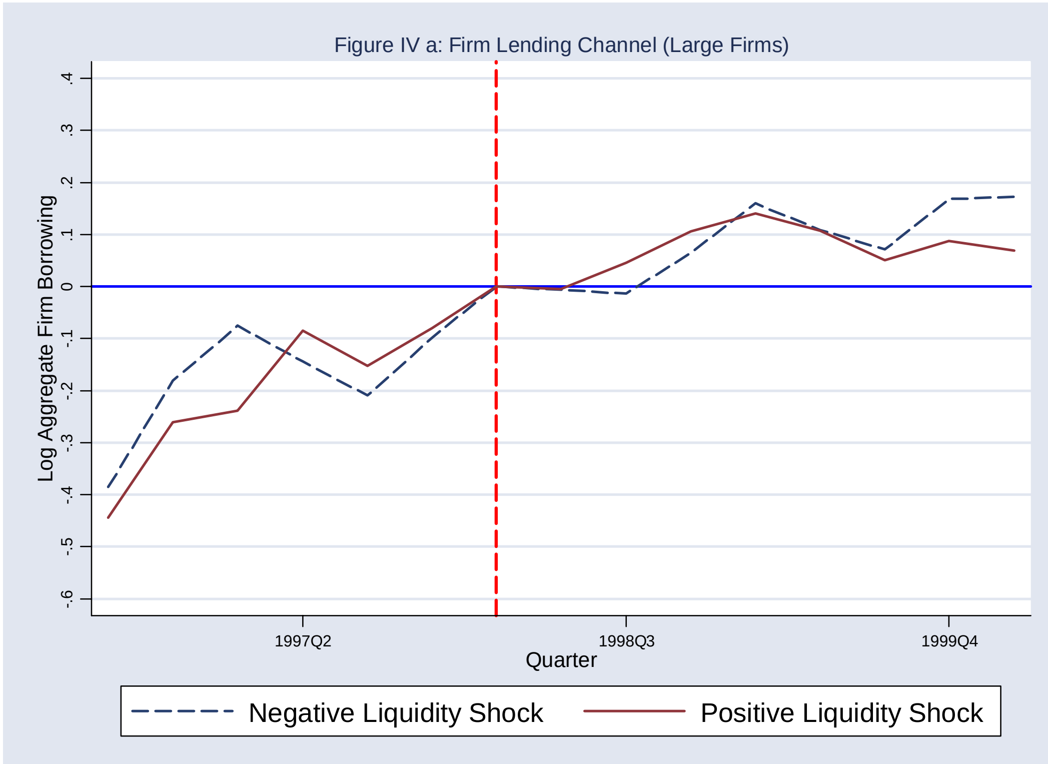
Figure IV a: Firm Lending Channel (Large Firms)
Log Aggregate Firm Borrowing
-.6
-.5
-.4
-.3
-.2
-.1
0
.1
.2
.3
.4
1997Q2
1998Q3
1999Q4
Quarter
Negative Liquidity Shock
Positive Liquidity Shock

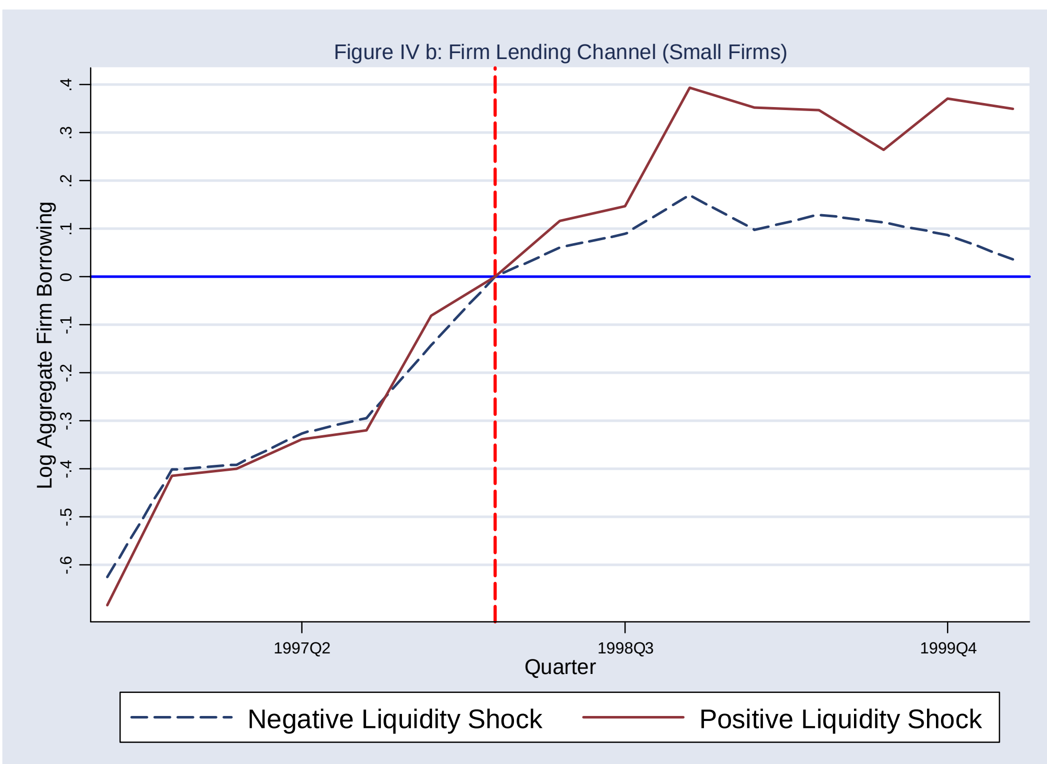
Figure IV b: Firm Lending Channel (Small Firms)
Log Aggregate Firm Borrowing
-.6
-.5
-.4
-.3
-.2
-.1
0
.1
.2
.3
.4
1997Q2
1998Q3
1999Q4
Quarter
Negative Liquidity Shock
Positive Liquidity Shock

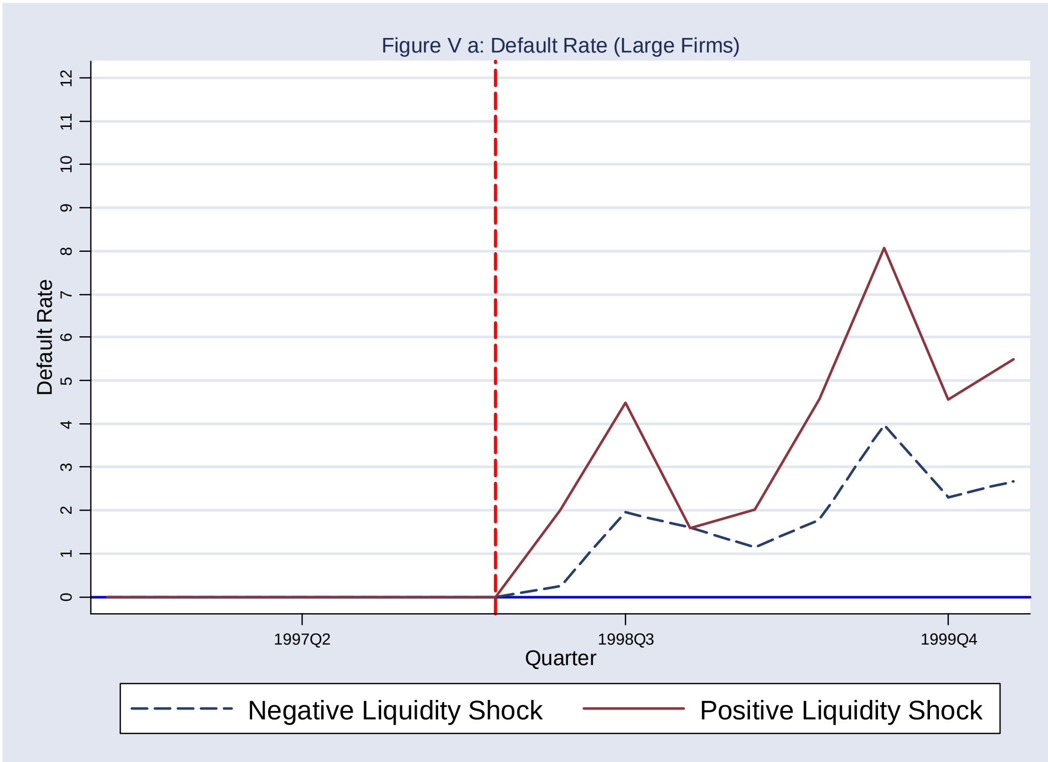
Figure V a: Default Rate (Large Firms)
Default Rate
0
1
2
3
4
5
6
7
8
9
10
11
12
1997Q2
1998Q3
1999Q4
Quarter
Negative Liquidity Shock
Positive Liquidity Shock

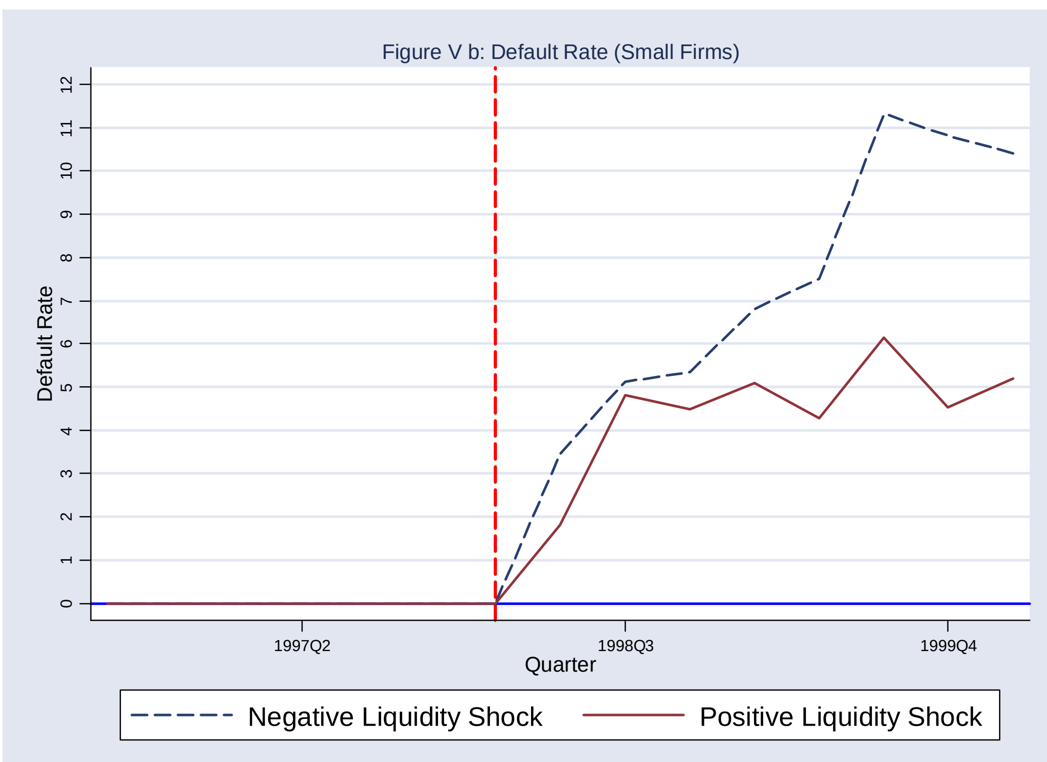
Figure V b: Default Rate (Small Firms)
Default Rate
0
1
2
3
4
5
6
7
8
9
10
11
12
1997Q2
1998Q3
1999Q4
Quarter
Negative Liquidity Shock
Positive Liquidity Shock

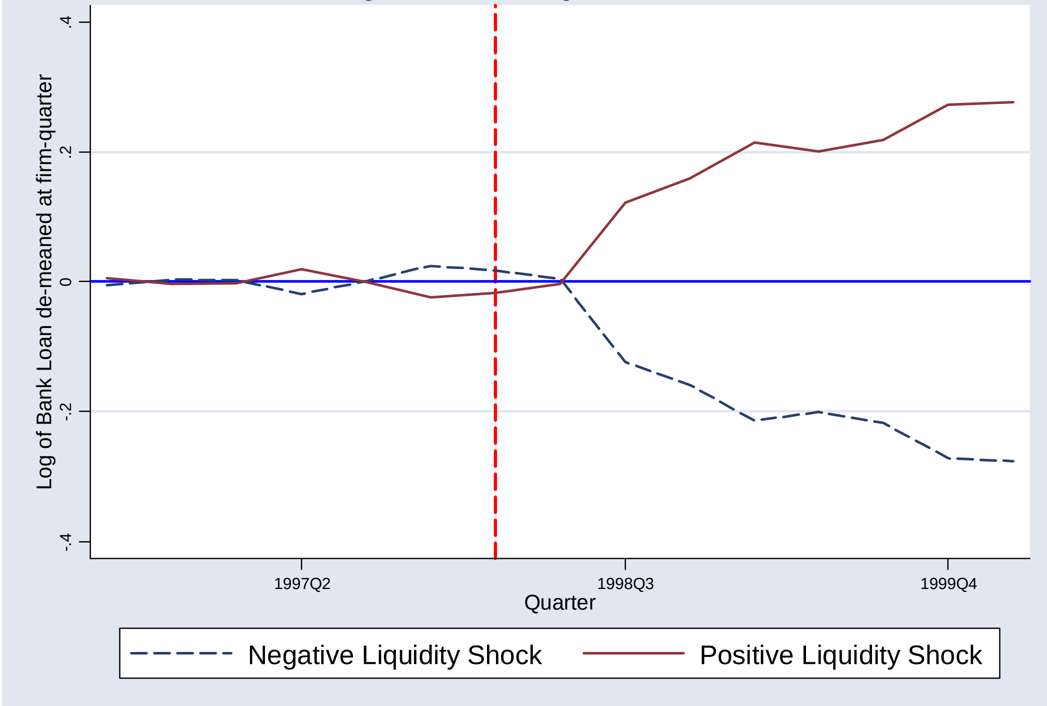

Figure VI: Bank Lending Channel with firm FE

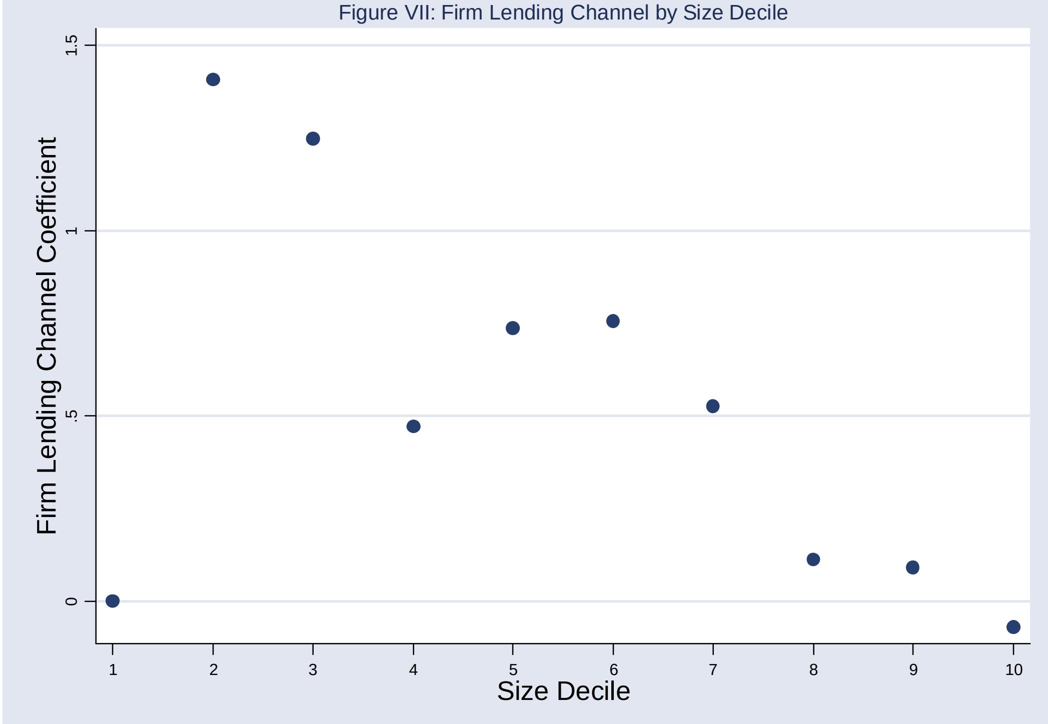

Figure VII: Firm Lending Channel by Size Decile