

Dollars Dollars Everywhere, Not a Dime to Lend:

Credit Limit Constraints on Financial Sector Absorptive Capacity

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Abstract

The events of 9/11 led to an unexpected surge of capital into Pakistan. This provides a rare opportunity to understand the micro-level causes preventing emerging economies from effectively utilizing liquidity booms. We show that despite the surge of capital, an aggregate demand boom, and sharply falling cost of capital, banks were remarkably sluggish in increasing firm credit. Consequently Pakistan became a net exporter of capital. Using quarterly loan-level data covering the entire banking sector and all borrowing firms in the economy, we show that backward looking pre-9/11 credit limit constraints imposed by banks are largely responsible for the *limited absorptive capacity* of the banking sector. Banks are unable to extend credit in sync with firm demand, particularly for smaller firms and those facing more stringent collateral requirements. Our evidence provides important clues for why emerging markets often find it difficult to attract and retain capital. We estimate the economy wide cost of this limited absorptive capacity to be 2.3% of GDP.

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While growth theories based on diminishing returns predict that capital should flow towards developing countries, economists have long been puzzled by evidence to the contrary (e.g. Lucas (1990)). Policies aimed at pushing capital into developing countries have also largely failed to achieve their desired results. In recent years, not only have developing countries continued to export domestic savings abroad, but high growth countries such as China, Korea, and India have exported even more (Gourinchas and Jeanne, 2006; Prasad, Rajan and Subramanian, 2006).

One possible explanation for international capital flows is that financial markets in developing countries lack the ability to effectively absorb and hence attract or retain capital¹. Recent work by Cabellero, Farhi and Gourinchas (2007), proposes that such *limited absorptive capacity* of the local financial sector can explain current global macro imbalances. Typically limited absorption of capital is driven by a firm's inability to pledge future cash flows as banks rely on balance sheet factors such as collateral and historical cash flows when extending credit.

However empirically identifying the importance of limited absorptive capacity remains extremely difficult. Consider the ideal experiment needed to do so. One would have to pump capital into an economy, and test whether investment and balance of payment patterns are driven by an inability of the financial sector to intermediate capital effectively. We often lack such an experimental influx of capital, and can seldom observe how capital is transmitted through the financial system.

This paper exploits the unique consequences of 9/11 for Pakistan to test how an emerging economy responds to a large and unanticipated liquidity boom. We then use a comprehensive loan-level data set, that links the entire banking sector to borrowing firms in Pakistan, to test whether the inability to effectively intermediate the liquidity inflow can be explained by the limited absorptive capacity of the banking sector due to the "backward looking" lending practices alluded to earlier.

A surprising consequence of the events following 9/11 was a large inflow of capital into Pakistan, accompanied by a positive aggregate demand shock. Pakistan's ensuing cooperation with the US ended the international financial isolation that had been in place since its nuclear

¹Other possible explanation proposed in the literature include: (a) production complementarities that lead to low-level equilibrium traps (Kremer, 1993), (b) political uncertainty (Lucas, 1990), (c) government protection against higher economic volatility (Bhagwati 1998, Rodrik 1998, Stiglitz 2000), and (d) Central Bank reserve accumulation to carry out lender of last resort responsibilities (Holmstrom and Tirole, 1998).

tests in 1998. There was also a large reversal in private capital flight as Pakistanis became increasingly uneasy with keeping their savings in the West. Consequently Pakistan became awash with liquidity and cost of capital plummeted from 7% to less than 1% within a couple of years. At the same time, aggregate demand surged as consumption and investment went up due to increased domestic wealth and reconstruction efforts in Afghanistan.

However, despite the availability of cheap credit and higher investment needs, banks were remarkably sluggish in increasing credit. While the real estate sector and stock market surged, banks continued to show remarkable reluctance to increase credit growth. Consequently Pakistan exported capital back and experienced a large increase in gross capital transfers and current account surplus.

We use our loan-level data to provide micro-evidence that the financial sector failed to absorb capital inflows, despite massive reductions in cost of capital and an increase in aggregate demand, due to pre-9/11 and backward looking borrowing limits imposed on firms by banks. These limits are based primarily on a firm's balance sheet factors, such as pledgeable assets and historical cash flows, and therefore are slow to respond to sharp changes in expectations. A novel feature of our data is that it records the "credit limit" set by a bank for each borrowing firm separately.

Given that unused lines of credit are costless in Pakistan, firms generally try to get the maximum possible credit line from a bank. They therefore serve as useful benchmarks for the balance sheet based debt capacity of a firm. If credit limits are truly backward looking, and hence rigid in the short run even in the face of large changes induced by unanticipated events like 9/11, then there are a number of testable predictions. First, *ceteris paribus*, firms with greater initial "financial slack" (*i.e.* unused credit limits) should experience larger growth in bank credit. We refer to this as the *financial slack effect*. Second, the financial slack effect should increase sharply right around 9/11 when there was an unanticipated liquidity surge in Pakistan. Third, the financial slack effect should be stronger among industries that experienced a larger (unexpected) increase in investment demand due to 9/11. Fourth, the financial slack effect should be stronger for firms that face greater rigidity in their credit limits (e.g. small firms). Finally, the financial slack effect should disappear for firms that ex-ante, for regulatory reasons, are *not* restricted by their balance sheet conditions.

We find strong support for all of the above predictions in a sample of 22,485 actively bor-

rowing firms at the time of 9/11. There is a large financial slack effect: a 1 percentage points larger pre-9/11 financial slack for a firm is associated with 0.21 percentage point higher growth in the firm's borrowing post-9/11.

A potential objection to the financial slack effect is that it may capture differences in credit demand growth across firms, instead of binding credit limits. This is a valid objection if firms with greater financial slack are those that have larger expected credit demand. If this were the case, it would be no surprise to actually see these firms grow faster ex-post. We check for this concern by estimating the financial slack effect at a quarterly frequency over the entire sample period. If financial slack effect around 9/11 was driven by *anticipated* credit demand, then we should see a similar magnitude effect in earlier periods as well. However the effect kicks in right after 9/11, not earlier.

An alternative explanation of the financial slack effect is that initial financial slack reflects an "option value" that only materializes when an unanticipated boom like 9/11 materializes. In other words, pre-9/11 financial slack is proxying for better quality firms that benefit more from 9/11 events. However, a series of tests provide evidence against this - and related - explanations.

A credible measure of firm quality is credit history. We know that firms in our sample with better credit history borrow disproportionately more after 9/11. However, including credit history as a firm quality control does not reduce the financial slack effect. We also control for firm quality using firm-director fixed effects, i.e. two firms share a fixed effect if they have a director in common. Since top management is a key determinant of firm quality, common-director fixed effect non-parametrically control for a wide range of potential firm quality attributes (e.g. political affiliation, conglomerate membership etc.). The financial slack effect remains unchanged.

Additional evidence further supports the hypothesis that the financial slack effect is driven by credit limit constraints. We find that the effect is stronger among industries receiving a larger (unexpected) post-9/11 demand shock, and also among smaller firms that are likely to face more rigid credit limit constraints.

We also conduct a falsification test based on banks lending guidelines, which are very different for exporters compared to non-exporters. Since future sales (export orders) are pledgeable with much greater ease, banks do not restrict exporters to balance sheet based credit limits. The government further facilitates the relaxation of potential credit limit constraints for exporters

through its large export-financing program operated through banks. Thus if the financial slack effect is truly driven by credit limit constraints, then one should *not* find this effect within exporting firms. Our data strongly confirms this prediction.

The limited absorptive capacity of the banking sector due to balance sheet based credit limits thus significantly retards the ability of banks to respond to the 9/11 boom. How costly is this? The costs may not be very large if firms can substitute out of the formal market by borrowing from alternative sources of funds. However, we find that this is unlikely to be the case. Using the likelihood of financial distress as a proxy for firm performance, we show that firms that faced binding credit limits were also more likely to enter into default post-9/11. Our conservative estimates of the incremental return forgone due to binding credit limits comes out to be 2.3% of GDP in present value terms.

There is a large literature aimed at estimating financial constraints at firm level². The key innovation in this paper is that it is the first to evaluate the absorptive capacity of an entire financial system in response to an unanticipated capital influx. We can thus provide a direct link for how performance within the financial sector affects macro outcomes such as the equilibrium cost of capital, domestic asset prices, and the current account. The other main difference between our work and existing literature is that the latter has mostly focused on investigating the relationship between investment and internal cashflow in order to understand financial constraints. Our paper on the other hand focuses on the role that ex-ante credit limits play in determining how firms respond to changes in the economic environment.

I The Context - Background and Aggregate Impact

A. Background

Pakistan's economy was suffering from weak growth, low investment, and balance of payment problems in the period preceding 9/11. Growth had declined to 3-4% from an average rate of 6% in the first half of 1990s, central bank reserves could only cover seven weeks of imports, and the black market exchange rate premium had risen to almost 6%. While a single factor is seldom the sole cause of macroeconomic weakness, the nuclear tests conducted by Pakistan in 1998 in

²A non-exhaustive list includes, Fazzari, Hubbard and Petersen, 1988, 2000; Poterba, 1988; Kaplan and Zingales, 1997, 2000; Blanchard, Lopez-de-Silanes and Shleifer, 1994; Lamont, 1997; Almeida, Campello and Weisbach, 2004; Rauh, 2006 and Banerjee and Duflo 2004.

response to similar tests by India, and the ensuing international financial sanctions played a large role in stagnating the economy. Denial of access to international liquidity by agencies such as the IMF put severe pressure on the Central Bank to keep interest rates high in order to stem balance of payment crises. The real lending rate rose to 9% compared to an average of 5% in the first half of 1990s. The high cost of liquidity kept the local economy distressed as firms found it difficult to borrow at higher interest rates.

B. The Events of 9/11

The events that followed 9/11 led to a sudden reversal of Pakistan's economic fortunes and the subsequent period witnessed an unprecedented economic upsurge. The net result of 9/11 on the macro economy was an unexpected surge in the supply of liquidity, a sharp drop in real interest rates, and a rise in aggregate demand. We describe these changes in more detail below.

Liquidity Surge and Interest Rate Drop

There was a large inflow of liquidity into the banking sector in the months following the events of 9/11. There were three main reasons for the inflow. First, Pakistan's willingness to help in the campaign against Afghanistan renewed the government's access to the IMF, World Bank, and other foreign liquidity providers that had been severely curtailed due to the post-1998 nuclear test sanctions. Second, a crack-down on the *hundi* or informal foreign exchange market stemmed the flow of capital flight through the black market and forced foreign remittances (Pakistan's largest "export") to be channelled through the banking system. Also the breakdown of the informal market and tightened capital controls made it more difficult to send capital abroad through the black market. Third, a perceived fear of what the US and other western economies might do to private capital held by Pakistanis abroad led a large number of investors to relocate their foreign savings back into Pakistan. Thus 9/11 acted as an exogenous shock that increased the "home bias" of Pakistani savers towards domestic assets.

Figure I(a) plots the monthly flow of remittances into Pakistan, and shows the dramatic increase in these inflows following 9/11. In a two year span between June 2001 and June 2003, remittances went up by almost 300%. A net consequence of this liquidity inflow was the dramatic rise in foreign exchange reserves shown in Figure I(b). The reserves reached an all time high of \$10 Billion by December 2002 - an increase of over \$7 Billion and almost 5 times in less than two years. The black market premium in informal currency markets (Figure

I(c)) also declined precipitously and essentially vanished within a year as the exchange rate appreciated. Commercial banks also saw a large expansion in deposits and recorded an average yearly increase of 16% from December 2001 to December 2003 - the highest sustained growth in over ten years.

The surge in liquidity supply was accompanied by a dramatic drop in interest rates. This interest rate drop reflects two forces at work. First, the Central Bank no longer felt a need to defend its currency against speculation. Second, for reasons we shall explore in great detail, the economy (e.g. the banking sector) found it difficult to quickly absorb the new liquidity flowing into Pakistan. The net result is shown in Figure I(d) that plots domestic interest rates (weighted average deposit rates) over time. The average nominal rate fell from 7% in June 2001 to less than 1% in nominal terms by December 2003. Our conceptual framework exploits this rapid drop in interest rates to generate tests for the credit limit hypothesis.

Positive Aggregate Demand Shock

The immediate period after 9/11 was likely to have been detrimental to firms due to heightened uncertainty in the region and the threat of war in neighboring Afghanistan. However, the situation rapidly changed within the first few weeks, and the overall effect of 9/11 on aggregate demand in Pakistan was positive. This was in no small part due to Pakistan's immediate cooperation with the US after 9/11 that saw the lifting of financial sanctions and provided greater economic opportunities.

Figure II(a) shows the aggregate demand increase in terms of investment and export growth both of which increased substantially, and firm default propensity, which declined. As further evidence of a positive demand shock, Figure II(b) plots the Karachi Stock Exchange price index for publicly listed firms, and shows a sharp and persistent rise in stock prices following 9/11. Thus, apart from the influx of liquidity, a second impact of 9/11 was a positive overall shift in aggregate demand.

C. Macro Impact

Given the falling cost of funds and positive demand shock one would expect an increase in overall bank lending to firms, absent any lending constraints. However, the macro evidence is extremely stark and shows little change in corporate lending despite such a large and positive net demand shock.

Figure III(a) examines the change in bank lending at the firm level as a result of 9/11. It plots the quarter by quarter firm specific growth rate of loans over time. The growth rate between quarters t and $t + 1$ is computed separately for each firm borrowing at time t , and the average of these growth rates over all firms is then plotted over time separately for small (below median borrowing size) and large firms. A firm's borrowing from all banks is aggregated up before computing the firm-specific growth rates.

The figure shows that despite the large drop in the cost of capital and the positive demand shock in the economy, there is relatively little change in overall lending to firms. While the growth rates are generally positive after 9/11, they are no larger than the pre-9/11 growth rates. Given that the cost of capital dropped significantly post-9/11, one would have expected to see an increase in loan growth. Similarly, figures III(b) and III(c) show that 9/11 did not lead to appreciably higher entry rates for new borrowers, or lower exit rates for already borrowing firms. The reluctance of banks to lend out new credit despite an abundance of liquidity can also be seen from figure III(d) that shows a sharp reduction in loan-to-deposit ratio of banks after 9/11 as banks put more of their assets in government securities.

The net effect of the inability of banks to absorb capital in the face of the liquidity surplus is shown in Figure IV. The figure shows that the economy became a net exporter of capital after 9/11 and started running current account surpluses. Thus the private in-flight of capital is partly reversed by an official capital outflow as domestic interest rates plummeted.

The muted response of bank lending to large drops in interest rate, when aggregate demand is going up, is already suggestive of borrowing constraints. This evidence cannot be rationalized in an unconstrained world without resorting to either an extremely low and implausible interest elasticity of capital, or an equally improbable steep marginal product curve. In order to provide more direct evidence on borrowing constraints, we next focus on the micro-level predictions of credit limit constraints that can then be tested in the loan level data and take advantage of the natural experiment induced by the events of 9/11.

II Conceptual Framework and Methodology

A. Basic Set Up

Consider an economy with N_f firms and N_b banks, indexed by i and j respectively. Each firm has access to a production technology (Y_i) that requires investment (K_i) up front. A firm finances this investment with internal wealth (W_i) and external debt (D_i) from banks. We introduce financial frictions in external financing by assuming a firm may choose to strategically default *ex post*.

In particular, firms can choose to hide their revenue from banks and courts at a non-monetary cost c_i per unit of capital investment ($0 \leq c_i \leq 1$). One can think of c_i as a measure of firm's "reliability" or (inverse of) the level of financial frictions a firm experiences. This setup, which is a common way of introducing financial frictions (see for example Aghion, Banerjee and Piketty, 1999), gives the convenient result that banks require internal wealth (i.e. collateral) ω_i for every dollar of capital invested.³ Firms thus differ in the degree of collateral constraints they face.

The purpose of collateral requirements is to discourage firms from hiding their revenue *ex post*. Consequently there is no strategic default in equilibrium and all firms face the same interest rate R . The equilibrium level of firm-level investment is determined by solving the first order condition subject to the collateral constraint. We parametrize firm production, Y_i , as a diminishing returns technology with,

$$Y_i = \Lambda_i \frac{K_i^{(1-\frac{1}{\gamma})}}{(1-\frac{1}{\gamma})} \tag{1}$$

where Λ_i reflects firm-specific productivity and γ represents the elasticity of capital with respect to the cost of capital. The unconstrained demand for capital, \tilde{K}_i , is given by the FOC:

$$\tilde{K}_i = \left(\frac{\Lambda_i}{R} \right)^\gamma \tag{2}$$

(2) represents the unconstrained or ideal level of investment for a firm. However, only firms with sufficient internal wealth can invest \tilde{K}_i . Other firms will be bound by their total wealth

³Solving, we get $\omega_i = \left(\frac{R-c_i}{R} \right)$, and thus the collateral requirement is decreasing in c_i , with $0 < \omega_i \leq 1$.

\bar{W}_i , implying that they can only invest capital up to $\bar{K}_i = \frac{\bar{W}_i}{\omega_i}$. Thus wealthier firms, and more “reputable” firms (i.e. firms with higher c_i) are able to borrow more.

The above discussion implies that the equilibrium amount of capital invested by firm i is given by $K_i = \text{Min}(\tilde{K}_i, \bar{K}_i)$. Since external debt is proportional to capital, we can equivalently write down the solution as $D_i = \text{Min}(\tilde{D}_i, \bar{D}_i)$, where $\tilde{D}_i = (1 - \omega_i)\tilde{K}_i$ and $\bar{D}_i = (1 - \omega_i)\bar{K}_i$. The advantage of writing the solution in terms of external debt is that \bar{D}_i has a natural economic interpretation. It represents a firm’s “debt capacity” or “credit limit” as determined by a bank after reviewing the firm’s reliability (c_i) and available collateral (\bar{W}_i).

We have deliberately kept our setup flexible, without relying too much on specific functional form assumptions. For example, the production process (1) allows for heterogeneity in firm level productivity.⁴ There is also flexibility in how financially constrained firms are, as determined by their total internal wealth \bar{W}_i and collateral constraints ω_i .

B. Comparative Statics

Our set up can now be used to analyze how an economy reacts to financial shocks. We consider two such shocks based on the consequences of 9/11 for Pakistan: an economy wide drop in the cost of capital, ϕ_t , and a firm specific productivity/demand shock, η_{it} .

Let t index time, and consider shocks hitting the economy between periods $t - 1$ and t . It will be convenient to convert all variables to log form, with lower case alphabets representing the log of respective upper case variables.⁵ The dynamics for productivity and cost of capital are given by:

$$\begin{aligned}\alpha_{i,t} &= \alpha_{i,t-1} + \eta_{it} \\ r_t &= r_{t-1} - \phi_t\end{aligned}\tag{3}$$

where η_{it} has a symmetric distribution with positive mean, and $\phi_t > 0$ is an economy wide constant. The economic shocks force firms to re-evaluate their first order conditions, including

⁴As will become clear later on, introducing fixed costs or other similar forms of convexities in the production function will also not change any of our results. Since our analysis will focus on response of firms to economic shocks, all we need is for the production function to have diminishing returns *at the margin*.

⁵ α represents the log of Λ , and r , the log of R .

demand for external financing.

(i) Case I: No External Financing Constraints

If a firm is unconstrained, then credit limits are not relevant. This will be the case when either c_i or \bar{W}_i is large. For an unconstrained firm, the change in (log of) bank debt is simply given by,

$$\Delta \tilde{d}_{it} = \gamma(\eta_{it} + \phi_t) \tag{4}$$

where $(\eta_{it} + \phi_t)$ is the “net demand” shock hitting a firm. The change in debt is proportional to the elasticity of capital, γ , and is the joint result of a movement along the marginal product curve due to the price drop ϕ_t , and a shift in the marginal product curve due to the productivity shock η_{it} .

(ii) Case II: External Financing Constraints

In contrast, the change in bank debt for firms that face borrowing constraints will not only depend on the size and direction of net demand shock $(\eta_{it} + \phi_t)$ as before, but *also* on the firm’s initial “financial slack”. We define financial slack as $s_{i,t-1} = (\bar{d}_{i,t-1} - d_{i,t-1})$, *i.e.* the (log) distance between the credit limit of a firm and its actual bank borrowing.

Specifically, to the extent that the process of setting credit limits is not fully forward looking and the growth in investment needs outstrips the growth in pledge-able assets that determine the credit limit, a firm’s borrowing will be constrained by how much financial slack it has. This is because the firm is unable to borrow beyond its credit limit and the limit does not adjust quickly enough to cater to the increased demand. This “stickiness” in the credit limit is a natural consequence of the nature of financial frictions: The ex-post enforcement concern implies that a firm’s debt capacity is a function of its existing reputation, c_i , and total wealth, \bar{W}_i . Since both these variables change slowly over time, it is reasonable to assume that credit limit will not increase as rapidly as required under a large net positive demand shock.

While we will provide direct evidence that credit limit setting is indeed backward looking and credit limits are quite sticky in section III, for the purposes of tractability we will assume here that credit limit is fixed in the short run. However, as we have discussed, the predictability

of financial slack for future borrowing holds as long as credit limits are sufficiently sticky. More formally, we obtain the following result:

Result 1: Assuming, the firm specific demand/productivity shock η_{it} is uncorrelated with initial financial slackness $s_{i,t-1}$, the change in bank debt varies positively with $s_{i,t-1}$ if and only if firms face borrowing constraints.

While the proof is relegated to the appendix, Figure I offers a simple illustration. The x-axis traces the magnitude of the net demand shock, and the y-axis represents the actual change in a firm’s bank debt. The unconstrained firm’s borrowing change, as given in equation (4), is represented by a line of slope γ passing through the origin (line A). In contrast, the change in borrowing for a constrained firm is capped by how much financial slack they have, as represented by the dashed line B for a firm with some positive slack.⁶

Figure V shows that if firms are unconstrained, they can borrow as much as they desire and in particular, financial slackness plays no role. However, a constrained firm’s borrowing will vary positively with the extent of their financial slackness. This is easiest to see for large enough demand shocks where all firms will only be able to expand borrowing to exactly as much as their own limit allows.

C. Base Empirical Specification

Given Result 1, we can run the following empirical specification to test for borrowing constraints:

$$\Delta d_{it} = \alpha + \beta_1 s_{i,t-1} + \varepsilon_{it} \tag{5}$$

where Δd_{it} is change in bank debt for firm i . If firms are not financially constrained, we should estimate a zero slope; conversely borrowing constraints imply a positive slope i.e. a positive coefficient β_1 . However, as result 1 states, this is true provided that the estimate of β_1 is unbiased or in other words, $Corr(s_{i,t-1}, \varepsilon_{it}) = 0$. Strictly speaking we just need to ensure

⁶Figure I also illustrates the case of a constrained firm that is already facing binding credit-constraints (i.e. $s_{i,t-1} = 0$). Such firms cannot take advantage of positive demand shocks at all and their response is given by curve C. The response to negative shocks for such firms is also muted since they were not borrowing as much as they would have liked in period $t - 1$.

that $Corr (s_{i,t-1}, \varepsilon_{it}) > 0$ since a negative correlation would only lower our ability to establish credit constraints (i.e. β_1 would be underestimated).

Figure VI illustrates the relationship in (5) using a simulation exercise based on the actual distribution of $s_{i,t-1}$ and plausible demand shocks. Figure VI(a) first shows that the change in firm borrowing is uncorrelated with initial slackness in the absence of financial constraints.⁷ In comparison, when firms are financially constrained, as in Figure VI(b), the bivariate relationship clusters along the 45^0 line, *i.e.* firms can only respond to positive shocks to the extent allowed by their initial credit limits. β_1 in (5) is therefore the slope of the fitted line in the simulation exercises of Figure VI. However, the magnitude of β_1 is not readily interpretable without imposing further structure on the model and the magnitude of the shocks.

While in theory one could estimate (5) in any time period, the ability to capture the underlying financial constraint on the average firm is much better in the face of large and positive demand shocks such as those implied by 9/11. In other words, if the positive demand shock is small, then despite firms facing borrowing constraints, the typical firm may still be able to borrow as much as it desires since it has enough slack. In terms of Line B in Figure V, such a firm would be moving along the (initial) 45^0 line and not hitting its limit.

Therefore our primary specification will be the cross-sectional equivalent of (5), where we collapse the firm data into two equal time-periods - a pre-period (6 quarters before the 9/11 quarter) and a post-period (6 quarters after the 9/11 quarter). Our dependent variable is the (log) change in a firm's (average) borrowing over the two periods and $s_{i,t-1}$ is the firm's financial slack right before 9/11. This time-collapsing of data has the advantage of reducing noise and also our standard errors are robust to concerns of auto-correlation (see Bertrand, Duflo and Mullainathan, 2004). Moreover, since we still have quarters before the "pre-period", we can construct and control for lagged values (*i.e.* values in the "pre-pre-periods"). Finally, while we have imposed a linear relationship in (5), we shall also estimate the relationship between a firm's change in borrowing and it's pre-shock financial slack non-parametrically.

⁷One might question how $s_{i,t-1}$ can be defined for firms that are not constrained. However, $s_{i,t-1}$ can still be defined since it is the distance between a bank's credit limit and actual borrowing. The only difference is that bank credit limit is no longer tied to a firm's internal wealth, but instead will fluctuate according to firm's credit demand *i.e.* credit limits are not sticky.

D. Further Predictions

The preceding analysis implies additional comparative statics results with respect to the size of demand shocks and the severity of credit limit constraints. These are summarized below.

Result 2: Suppose the firm specific demand/productivity shock η_{it} is uncorrelated with initial financial slackness $s_{i,t-1}$. Then the sensitivity between change in bank debt and $s_{i,t-1}$ (i.e. β_1) is greater for firms with larger demand shocks and firms with stricter borrowing constraints.

The first part of the result holds since lending differences between firms with different values of $s_{i,t-1}$ are larger if the desired growth in credit demand is higher. Conversely, if this change is small, it will only constrain the borrowing of firms that have little or no financial slack left, whereas all other firms (with differing financial slack) will not be constrained and will be able to borrow as much as they need. The second part follows from the discussion earlier that showed that β_1 goes to zero for firm without any credit limit constraints. Formal proofs are given in the appendix. We can test result 2 by modifying equation (5) to:

$$\Delta d_{it} = \alpha + \beta_1 s_{i,t-1} + \beta_2 (s_{i,t-1} * X_i) + \beta_3 X_i + \varepsilon_{it} \quad (6)$$

where X_i is a firm attribute such as the industry demand shock as a result of 9/11, or a proxy (e.g. size) for a firm's credit limit constraints.

E. Identification Concerns

The first-difference specification in (5) has the advantage that it completely absorbs firm-level unobservables such as initial productivity ($\alpha_{i,t-1}$) and financial frictions (ω_i). However identification issues arise if a firm's initial financial slack is correlated with unobserved factors, such as firm productivity shocks (η_{it}),⁸ that influence its loan growth i.e. if $Corr(s_{i,t-1}, \varepsilon_{it}) \neq 0$. The primary concern is that $Corr(s_{i,t-1}, \varepsilon_{it}) > 0$ which would bias our estimate of β_1 upwards.

First of all there are legitimate scenarios that would produce a *negative* correlation between $s_{i,t-1}$ and ε_{it} , and thus bias β_1 downwards. For example, firms that benefit more from the

⁸The other shock, ϕ_t , (cost of capital drop) is a constant for all firms and thus is uncorrelated with $s_{i,t-1}$ by definition.

improving economic environment (i.e. firms with larger η_{it}) may have a higher productivity and hence greater loan demand even prior to 9/11. This would make them more likely to have smaller pre-9/11 slack $s_{i,t-1}$. Similarly, if demand shocks are positively correlated (e.g. a firm is in a growing sector), then firm's with smaller slack will be the ones with higher future loan demand.

Our main concern therefore is to consider scenarios that would produce a positive correlation between $s_{i,t-1}$ and ε_{it} . We consider two broad categories of such concerns:

(i) Slack Positively Correlated with Future Credit Growth

Financial slack in $t-1$ may be spuriously correlated with future credit growth due to mean reversion in loan demand. For example, suppose that the average loan demand is fixed for a firm over time but there are idiosyncratic shocks to demand each period. Then firms that experience low demand in period $t-1$ will have high $s_{i,t-1}$, and are also more likely (on average) to receive a larger loan demand shock in period t . Mean reversion in loan demand therefore artificially creates a positive correlation between financial slack and loan growth. However, since we observe credit growth over a long period of time, we can directly control (and check) for mean reversion in our sample.

A related cause for spurious correlation between $s_{i,t-1}$ and subsequent credit growth is forward looking credit limits. For example, suppose firms correctly anticipate increases in future loan demand *and* convince their lenders to provide them with greater *current* financial slack. Then $s_{i,t-1}$ and η_{it} will be positively correlated. Note first that to the extent the anticipated loan demand growth is correlated with firm quality q_i , our checks below will get at this concern. However, if anticipated loan demand growth is uncorrelated with fixed firm quality q_i , then this concern is harder to deal with unless one can argue that the demand shock in question was unanticipated. The advantage of focusing on 9/11 is precisely that it provides such unanticipated variation: It is unlikely any firm could have anticipated either the event or the net demand shock it generated, especially given the sudden economic reversal it led to. We can take this a step further and “net out” anticipation effects. We do so by estimating the financial slack effect in a “placebo” period (prior to 9/11) and making the conservative assumption that the placebo period effect is entirely due to anticipation biases. Then the “true” financial slack effect is the estimated effect for the 9/11 period less the estimated effect for the placebo period.

(ii) Slack Positively Correlated with Firm Quality

Suppose there is an unobserved firm quality attribute q_i , such that firms with better quality have greater financial slack $s_{i,t-1}$. For instance, perhaps when dealing with better quality firms, banks continuously set credit limits that are substantially higher than the firm’s normal anticipated demand. Furthermore, higher quality firms may also have a greater “option value” in ensuring that they always retain financial slack. If such high q_i firms are also in a better position to take advantage of the improving economic environment due to 9/11, then q_i and η_{it} , and hence $s_{i,t-1}$ and ε_{it} , will be positively correlated.

We address these concerns in a series of robustness tests. First, we include a variety of controls for measures of firm quality, and test whether our estimate of interest (β_1) is affected. The first measure of quality is a firm’s late payment history, since it is likely that firms that have been late in their payments historically are of poorer quality.

We next use a non-parametric measure of firm quality based on a firm’s directorship. As we know the identity of the board of directors for every firm in our sample, we create “common director” groups such that two firms are linked together if they have a common director. We then put in common director fixed effects in our main specification, thereby comparing two or more firms that share a director in common, but differ in their initial financial slack. Since majority of firms in our sample are owned by the directors themselves, the identity of directors is likely to be a key determinant of firm quality. Therefore including common director fixed effects controls for all time-invariant factors, such as firm quality or business and political influence, that are common to a firm’s owner. This strategy comes close to including firm fixed effects especially when restricted to firms in common director groups of only two to three firms.

While we cannot include firm fixed effects in our first-differenced firm-level data, we could introduce firm fixed effects, if we exploit shocks over other time periods as well i.e. estimate (5) in the time-series and include firm fixed effects. While we discuss the results of doing so, we don’t emphasize this specification since it forces us to include non-9/11 periods. Recall from the discussion above that a big advantage of focusing on the 9/11 period was that the shock was plausibly unanticipated. However, non-9/11 periods are likely to have significant anticipated components and while they may address firm quality issues, they raise the concerns we detailed above arising from have anticipated credit growth effects.

Finally, several of the tests where we examine the heterogeneity of β_1 - such as heterogeneity across firms that face differing financial constraints - offer falsification tests. For example, pru-

dential regulations allow exporters to use future orders as loan collateral. Given our framework above, we would expect loan growth for such firms to not be affected by their initial financial slack. In sharp contrast, both the unobserved firm quality and anticipated loan demand would predict as large or an even stronger effect for such firms, since exporters are generally better quality firms. As we will show, our heterogeneity tests offer further support against the aforementioned identification concerns.

III Data

The banking sector in Pakistan is liberalized and fairly representative of emerging markets. Financial reforms in the early 90s brought uniform prudential regulations in-line with international banking practices (Basel accord) and autonomy was granted to the central bank, the State Bank of Pakistan (SBP), for regulation. Private banking thrived in Pakistan, and by 2000 government, local private and foreign banks made up 44.4%, 31.3% and 24.3% of lending to private sector respectively.

The loan level data for our analysis comes from the Central Information Bureau (CIB) of SBP. This data is used by the central bank to supervise and regulate all banking activity in Pakistan. It is collected at quarterly frequency and covers the universe of corporate lending in Pakistan between June 1996 and June 2003. The data follows the history of each loan with information on the amount and type of loan outstanding, default amounts and duration. It also has information on the name, location and board of directors of the borrowing firm and its bank.

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. 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.

Table I presents summary statistics for our main variables of interest in the loan-level data set. Statistics are averaged at the firm-level separately for pre and post 9/11 periods of 6 quarters each. The loan level data is first aggregated up to the firm-level and then time averages are taken after converting all values to real 1995 rupees. Our sample is restricted to firms that were not in default in the pre-9/11 period, and borrow in at least two quarters in each period. The former restriction allows us to focus on initially “active performing loans”, whereas the latter, although it does not qualitatively affect our results (it only excludes 2% of the firms), provides more precise estimates. This results in a final sample of 22,485 unique firms.

A. Financial Slack

Financial slack is the difference between a firm’s credit limit as set by its bank, and the outstanding loan amount. Credit limit, i.e. \bar{D}_i in section II’s terminology, is determined by a bank after reviewing the firm’s financial history and collateral. A useful feature of loan financing in Pakistan is that a firm can costlessly borrow up to its credit limit. This free option value of credit limits implies that firms generally try to get as large a credit limit as possible.

Thus a credit line is bounded only by a bank’s perception of a firm’s debt capacity, which is precisely what we want to measure from a theoretical perspective. We construct the distance between a firm’s credit limit and its actual borrowing prior to 9/11 (i.e. $s_{i,t-1}$) for all private firms in Pakistan. An important fact regarding the credit limit variable is that it was not collected by SBP after the first half of 2001. Hence we do not have credit limit data after 9/11. However, as the conceptual framework highlighted, it is the pre-9/11 credit limit that is critical for conducting our empirical tests.

Slack “Stickiness”

The borrowing constraints formalized in section II arise if credit limits are “sticky”, *i.e.* not fully forward looking. While estimating a positive coefficient on financial slack in specification (5) provides evidence for such stickiness, in this section we also provide direct evidence on the backward looking process of setting credit limits and the observed stickiness of such limits. Our examination is also consistent with evidence from other emerging markets, such as India (Banerjee and Duffo, 2004).

The backward looking nature of determinants of credit limit are obvious once one considers the central bank's prudential regulations that provide strict guidelines to banks in terms of how credit limits should be set. These guidelines are very conservative in terms of collateral requirements, and bind a firm's credit limit to its past cash-flows. For example, total unsecured lending for a given firm cannot exceed Rs 500,000 (about \$ 8,500). A firm's total debt cannot exceed four times its total equity, and a firm's current assets to current liability ratio cannot drop below 0.75.

While all banks must comply with these conservative regulations, banks often *voluntarily* impose even harsher collateral and financial ratio restrictions, such as historical cash-flow to debt service not dropping below a threshold. Similarly, bank manuals emphasize that collateral must have high liquidation value and preferably be very liquid. For example, the following quote comes from one of the bank's manuals,

“(the applicant must provide) liquid and readily convertible security with more than adequate margin; readily marketable collateral fully under bank's control having high value which can withstand volatile market conditions.”

Table II(a) provides direct evidence for the conservative, asset-backed and backward looking credit limit policies by providing the composition of collateral for bank loans in pre and post-9/11 periods. First, unsecured lending comprises only 1% of total lending in the banking sector. Second, the majority of lending is securitized with “hard” assets such as fixed assets, merchandise (which is also fairly liquid), and real estate. Finally, despite the large net positive demand shock due to 9/11, there is virtually no effect on the composition of collateral.

While lending rules impose strict restrictions on credit limits, one could argue that banks find enough loopholes (or fudge data) in practice to get around them. While this is possible our subsequent empirical tests serve as checks for whether banks allow credit limits are flexible or not. We can also present direct evidence that credit limits are sluggish and often do not adjust even when firms that are pushing against their limits.

Panel A in Table II(b) shows how financial slack is correlated with firm attributes. Consistent with sticky credit limits, financial slack is tighter if previous credit growth was high. Similarly, consistent with the notion that smaller firms are more credit constrained, smaller firms have tighter financial slack. However, financial slack is *not* correlated with firm attributes

that reflect firm quality or how 9/11-induced demand shocks affected them.

Panel B provides further evidence on the stickiness of credit limits, particularly for smaller firms that are more likely to face constraints. Were credit limits responsive to a firm's growth potential, one would expect that limits would change each year for most firms as they face a variety of demand shocks. Yet almost half the firms do not experience any change in their credit limit (defined as a greater than 2% nominal shift) from one year to the next, suggesting that limits are infrequently updated. This is all the more surprising since column (2) in Panel B shows that more than a third of small firms are actually facing binding limits (i.e. have no financial slack). Column (3) then shows that even for the small firms that are hitting against their credit limits, credit limits are increased in less than 30% of the cases.

Panel C checks how credit limits respond to industry demand shocks in the pre-9/11 sample where we have credit limit information. Column (1) shows that the credit limit does *not* increase relatively more for firms in industries that experienced a net positive growth over the period. This suggests the process of updating credit limits is not very responsive to a firm's future growth potential. Column (2) establishes that the firms we identified as belonging to positive growth industries indeed had higher loan growth (although muted due to the credit constraint limits). Together the two results show that, consistent with sticky credit limits, financial slack gets relatively tighter for firms with better growth opportunities and suggests that if anything, OLS estimates of the financial slack effect may be underestimates.

While unlikely, at this stage one may question whether credit limit and in turn financial slack have any real bite at all. One can conduct a simple test to establish that financial slack does indeed matter. We do so by estimating an analogous specification to (5) but at the *loan-level*. Since credit limits are separately set by a bank for each firm, financial slack is loan specific. This allows including firm fixed effects as long as we restrict to multiple-bank firms. Doing so (regression not shown) gives a significant positive coefficient (0.11) on a firm's financial slack from a given bank. In other words, a given firm is able to borrow more from the bank from which it faces greater financial slack. We should caution that this result should not be taken as evidence for the presence of borrowing constraints (since it does not address whether a firm's overall borrowing is constrained by its financial slack) but simply that financial slack does have a real (allocative) impact, even once all firm-level unobservables are taken into account. Subsequent tests will show that in fact financial slack also affects a firm's overall borrowing.

IV Results: Financial Slack and Borrowing

A. Time-series Evidence

We begin by estimating equation (5) non-parametrically in Figure VII(a). The figure categorizes firms each period into “high” slack and “low” slack based on whether they are in the top or bottom quartiles of initial financial slack respectively for that period. We use the firm’s average slack in the three previous quarters as its initial financial slack to reduce noise. Since we do not have financial slack data after 9/11, we use the average slack over the three consecutive quarters prior to 2001Q3 as our post-9/11 slack measure for each firm.⁹ We also demean a firm’s borrowing in a given quarter by netting out its average borrowing during its entire history so that cross-sectional comparisons can be made.

The result indicates that there is no discernible difference between high and low slack firms in the period prior to 9/11. However, right after 9/11, the two curves start diverging. This is consistent with the hypothesis of credit limit constraints in the face of large concurrent liquidity and demand shocks created by 9/11. The lack of divergence between the two curves prior to 9/11 further indicates that the post 9/11 divergence is not a result of any pre-existing trends.

Figure VII(b) repeats the exercise parametrically. We first run a modified version of specification (5) where we estimate a separate β_1 for each time-period. The figure then plots these coefficients (and confidence intervals). Thus each coefficient is the parametric analogue of the difference between the two curves in Figure VII(a). Financial constraints would imply a significant positive coefficient during periods when the economy experiences a net positive demand shock. The result confirms this prediction as there is a sharp upward trend in the coefficients immediately following 9/11. Moreover, the confidence intervals confirm that almost all regression coefficients prior to 9/11 are not significantly different from zero, whereas they are after 9/11.

⁹A potential concern could be whether using the three pre-9/11 quarters data as the initial slack measure for all the quarters post-9/11 could mechanically generate some of the patterns we see (divergence between low and high slack firms). However, we checked for this by conducting a falsification exercise where we assume as if the slack measure does not exist after June 2000 and extrapolate the slack measure to all quarters after June 2000. Doing so shows no evidence that the trends we see at 9/11 could be generated mechanically (i.e. we see no trend divergence at the fake break-point created at June 2000). Moreover, the cross-sectional regression results presented later (Table III(b)), use the same variable construction criteria for initial slack in all sample periods and produce similar results, suggesting that the slack extrapolation in Figures VII(a)-(b) is not an issue.

B. Primary Specification

We now turn to our primary cross-sectional specification and estimate (5) in the time-averaged data with one post-9/11 and one pre-9/11 period. Figure VIII first presents the non-parametric kernel plot of the relationship between lending growth over the 9/11 period and initial financial slack, and shows a monotonically increasing trend, suggesting the presence of borrowing constraints. The graph confirms that increases in the degree of credit constraints decrease loan growth linearly.

Table III presents the primary regression results. The dependent variable is a firm’s borrowing growth over the post and pre 9/11 periods and the variable of interest is the coefficient on a firm’s initial (pre-9/11 period) financial slack. Column (1) shows that a 1% increase in a firm’s financial slack pre-9/11 leads to a 0.21% increase in its loan growth and the result is significant at the 1% level. Column (2) shows that this effect is robust to non-parametrically allowing for differences across firm location, industry, and lead-bank fixed effects. There are a total of 134 city, 75 industry and 119 lead-bank fixed effects. While the initial financial slack measure used in Table III is averaged over the previous three quarters, our results are robust to averaging the slack measure over shorter or longer time periods.

Section II had highlighted the identification concern that the results in column (1) and (2) might be driven by mean reversion. Column (3) tests for this by controlling for a firm’s lagged loan growth prior to 9/11 and shows that while there is mean reversion (the coefficient on the lagged growth rate is negative), the coefficient of interest on financial slack does not change at all. In fact Column (4) shows that the small drop in the coefficient in column (3) is due to a reduction in sample size (lagged loan growth is missing for firms that do not have a sufficiently long history prior to 9/11). An alternate specification to check mean reversion is to control for the initial level of borrowing. Column (5) does so and shows that the coefficient on financial slack remains unchanged.

The test in column (5) can also be seen as an “over-identification” test. Since financial slack is defined as credit limit less actual borrowing, one concern could be that slack is proxying for one of its two components, *i.e.* the variation we are picking up is not in the *difference* between limit and borrowing, but in either one of the two. For example, if credit limit is similar for all firms then the variation in financial slack is really driven by differences in a firm’s initial borrowing. Alternately, we may be concerned that the slack result is really picking up variation in credit

limit across firms. Neither of the two would be consistent with our theoretical predictions, which posit that a firm’s ability to grow under financial constraints is limited by its available slack (not the level of initial borrowing or the credit limit).

Thus one way to test for such concerns is to control for either of the two components of financial slack and ensure that the slack result is robust to this. Column (5) already shows that this is indeed the case for initial (log) borrowing. Column (6) instead includes initial (log) credit limit as a control and again shows that the coefficient on financial slack is unaffected.

Finally, another somewhat mechanical concern may be that our results are confounded by strategic delay considerations i.e. banks are worried about the uncertain situation due to 9/11 (both in terms of how long the increased liquidity will last and firm investment options) and therefore delay making longer term loans. While this is unlikely given our data spans a year and a half after 9/11 and the situation cleared up pretty soon after 9/11, we nevertheless check for this concern by rerunning specification (5) using only short-term working capital loans. Column (7) shows that the coefficient on financial slack hardly changes (in fact the point estimate is larger) suggesting that such optimal delay type concerns are not important.

C. Further Robustness Checks

Section II highlighted additional identification concerns would arise if initial financial slack were positively correlated with future credit demand due to anticipated demand or unobserved firm quality. We check for these concerns below.

Expected Credit Growth

Could the results in Table III be spuriously generated by anticipated credit demand being correlated with initial financial slack? Since the economic shocks as a result of 9/11 were completely unanticipated, this is highly unlikely. Yet one way to test for this is to reconstruct the 9/11 estimation equation around a “placebo” period. If our financial slack effect is not driven by the large unanticipated shocks due to 9/11 but really due to the usual anticipated changes over time, then we should find a very similar effect around our placebo period as well. We therefore re-estimate equation (5) around the placebo cutoff date of January 2000.

Columns (1) and (2) in Table IV show that while the coefficient on financial slack is positive and significant, it is much smaller (almost one-third the size) than the coefficient in Table III. The difference between the coefficient around 9/11 and placebo shock is explicitly captured by

columns (3) and (4) that show that the 9/11 coefficient is significantly bigger. It is important to highlight that the coefficient around placebo period does not necessarily signify an expected credit growth effect because even under the credit limit hypothesis one would on average expect a positive coefficient. Rather the point of the exercise is that even if we assume that the entire pre-9/11 effect reflects the bias stemming from anticipated credit growth effects, and attribute a similar bias to the 9/11 period, there is still a substantial additional impact (0.12) of initial financial slack on loan growth around 9/11.

Firm Quality

The financial slack effect could reflect unobserved firm quality if quality is positively correlated with both initial financial slack and credit demand shocks. To the extent that prior loan demand is also a sign of firm productivity, Table IIb suggests that better quality firms in fact have *lower* financial slack at any given time. Hence, if anything, not controlling for firm quality should lead to underestimating the true effect of financial slack.

Nevertheless, Table V performs additional checks for the firm quality concern. Column (1) controls for firm quality using a firm's late payment history as a proxy for quality. Late payment history is a variable that indicates whether a firm was late in its interest payments since 1996. The coefficient on late payment in column (1) is negative, indicating that late payment is indeed correlated with lower credit growth post-9/11. Note that the coefficient on financial slack hardly changes with the inclusion of this firm quality control.

Columns (2) through (5) control for firm quality non-parametrically by including common director fixed effects. Since quality is largely a function of top management, and the majority of firms in our sample are owned by their directors, two firms that share the same director are likely to have very similar quality. Specifically, including common director fixed effects controls for all time-invariant factors, such as firm quality or business and political influence, that are common to a firm's owners. We restrict our attention to the subset of firms that have at least one other firm with whom they share management, since including firms in single management groups are completely absorbed by the director fixed effect.

Column (2) repeats our standard specification on the sub-sample of firms that share directors with other firms. This is done to check whether sample restriction alters our main effect, and it does not. Column (3) then includes common director fixed effects (total of 4,922 FEs) and shows that our coefficient of interest remains unchanged. Columns (4)-(5) take this a step

further and only consider firms that form common director groups of two to three firms. Thus the common director fixed effects absorb a lot more of the overall sub-sample variation in column (5). However, the results are even stronger, once again confirming that firm quality is not spuriously generating the coefficient on financial slack.

The results in Tables III to V together provide compelling evidence that firms are indeed credit constrained - Banks are unable to increase lending to these firms in the face of a drop in the cost of capital and a positive demand shock, due to an inability to increase credit limits as quickly. We now explore whether this result varies across different firm types, and in doing so provide further support for our identification strategy.

V Results: Heterogeneity

Result 2 in section II showed that firms facing large demand shocks and/or greater credit constraints are likely to show a larger financial slack effect. This section explores these predictions further.

A. Demand Shocks

While 9/11 was a positive demand shock on average, it affected industries differentially. For example, the cement, energy, and construction sectors received a disproportionately larger boom due to reconstruction efforts in Afghanistan. This allows us to categorize firms as facing high or low demand shocks due to 9/11, based on the demand shock experienced by their industry.

For firms that receive low demand shocks, the difference in lending between those closer to their credit limit as compared to those further away will be small, since even those closer to the limit may have enough slack to obtain their desired increase in borrowing. As such the coefficient on financial slack in specification (5) will be small. However, for firms experiencing a large demand shock, it is likely that only those firms with substantial financial slack will be able to obtain their desired financing - the coefficient on financial slack will be large.

The results in Table VI show that this is indeed the case. Columns (1)-(2) separately estimate specification (5) for firms experiencing relatively high and low demand shocks. The main effect of high demand shock industries is 0.22, whereas it is only 0.11 for low demand shock industries. Column (3) pools the two types of firms and shows that the difference between the

two is statistically significant. Column (4) ensures that the result is robust to industry, location, and lead-bank fixed effects. Finally, column (5) includes firm size decile dummies interacted with financial slack to ensure that the demand shock heterogeneity is not driven by comparisons across different firm sizes.

Note that to the extent that these industry-level shocks themselves are orthogonal to firm quality - which is likely since the shocks are due to an event that was not only unexpected but whose impact was also not foreseeable - these results offer a further robustness check on our identification: Both unobserved firm quality or anticipation effects concerns would not readily generate the result that firms that unexpectedly received greater demand shocks have a larger financial slack effect .

B. Firm Type

If loan growth responsiveness to initial financial slack is indeed reflective of credit constraints, one would expect this response to be higher for firms that face greater credit constraints. We explore this heterogeneity along two firm characteristics - size and whether a firm exports or not. A recurrent theme in the literature suggests that larger firms may be less credit constrained both because they have better reputation and more collateralizable assets to offer. Export status, while also reflective of quality, is directly suggested by an examination of collateral requirements in Pakistan. Specifically, firms are allowed to use future export orders as collateral and therefore it is likely that loans to such firms are less constrained by initial financial slack.

Size

We divide firms into two sizes based on whether their total borrowing pre-9/11 is above or below the median. The results in Column (1) of Table VII show that smaller firms tend to be more credit constrained than larger ones as the coefficient on a firm's initial financial slack is smaller for the large firms Column (2) shows that this effect is robust to non-parametrically allowing for differences across firm location, industry, and lead-bank fixed effects. In addition, by also including industry fixed effects interacted with initial financial slack (Column (3)), we ensure that the effect is not driven by comparing firms in different industries, since firm size may vary across industries. Figure IX presents the results for a finer firm size classification where we group firms into size deciles. Each point is the coefficient on initial financial slack for firms of a given decile. The figure shows a clear trend by initial borrowing size i.e. as firms's

get larger, they are less constrained in their borrowing by their initial financial slack.

Exporters

An examination of banking regulations in our context suggests that, all else equal, exporting firms face lower credit limit constraints as compared to non-exporters. Central bank prudential regulations explicitly allow banks to ignore usual collateral and financial ratio restrictions when lending to exporting firms.¹⁰ Moreover, our examination of the private credit manuals at three of the main banks shows that banks are also willing to have more relaxed lending policies for exporting firms. One important reason is that the future sales of exporters are considered sufficient collateral by banks because the export orders mostly originate from reputable international firms with verifiable information. The Export Finance Scheme (EFS), for instance, relies primarily on export orders for approving subsidized loans.

The relaxation of lending rules for exporters suggests that exporting firms will be less constrained by balance sheet variables. Exporters, by virtue of using future export orders as collateral, may therefore be able to expand as much as needed when faced with a positive demand shock. Non-exporting firms however, will remain constrained for the reasons discussed previously.

Columns (4) and (5) in Table VII show that this is indeed the case. We split our sample and estimate the primary specification (5) separately for non-exporters and exporters. Column (4) shows the same large effect on non-exporters, but Column (5) shows that exporting firms show no correlation between initial financial slack and future borrowing (both the point estimate and standard errors are small).

Column (6) shows the same result but in the pooled sample where we interact initial financial slack with a firm being a non-exporter. Column (7) shows that this effect is robust to non-parametrically allowing for differences across firm location, industry, and lead-bank fixed effects. Column (8) takes a further step to ensure that the effect is not driven by comparing firms of different sizes, since one may be concerned that exporters are larger than non-exporters. We do so by not only including dummies for each firm decile but interacting each of these with initial financial slack. The coefficient on financial slack for non-exporting firms remains large

¹⁰For example, quoting from prudential regulations, “For the purpose of this regulation, following shall be excluded / exempted from the per party limit of Rs 500,000/- on the clean facilities:

- (a) Facilities provided to finance the export of commodities eligible under Export Finance Scheme.
- (b) Financing covered by the guarantee of Pakistan Export Finance Guarantee Agency.”

and significant.

These results offer a useful falsification test for our identification strategy as well, since we would predict no (or a small) effect of initial financial slack on exporters but a large effect on non-exporters. In contrast, alternate explanations would predict the opposite or at best, no difference between the two. Recall one of our primary concerns was that the financial slack effect may be biased upwards due to unobserved firm quality. Since exporting firms are generally of better quality than non-exporters (and do have lower default rates in our data as well), if quality concerns were significant one would expect the coefficient on financial slack to be even larger for exporters. Similarly, if there were mechanical mean reversion or anticipation effects, one would expect these biases to be just as important for exporters. The fact that exporting firms show no effect therefore further substantiates our credit limit constraints explanation.

C. Bank Type

While we didn't discuss this explicitly in section II, one may ask whether the degree of credit constraints varies across different types of banks. If certain banks are more conservative/backward looking in their lending, then one would expect to see a larger financial slack effect for loans from these banks. However, if the conservatism is driven due to common factors such as prudential regulations, one would expect all banks to show such sensitivity.

Table VIII examines this by separating out loans made by government, private domestic and foreign banks. While our primary specification is still run at the firm level (firm's with multiple banks are assigned their dominant bank's type), as we will show, the results are similar in a loan level specification.

Column (1) shows that there is hardly any difference in the coefficient on financial slack across the three bank types. As we add more firm-level controls (Columns (2) and (3)), we get slightly larger coefficients on private domestic and foreign banks suggesting that if anything, they are likely to be more conservative than government banks. However, both the magnitude and statistical significance of these results is weak – the coefficients are not significant at conventional significance levels – and so we would caution against drawing such inferences. Finally, Column (4) repeats this test at the loan-level, thus exploiting cross-bank differences within the same firm (*i.e.* firm fixed effects), and finds similar results. These results suggest that specific form of constraints we have identified, arise more due to common factors such as the legal and

regulatory environment, rather variation in bank organizational structures that may make them conservative and sluggish (see Stein, 2002).

VI The “Real” Costs of Financing Constraints

The results above offer evidence for how backward-looking credit limit constraints limit the absorptive capacity of an economy. Yet what are the real costs of such constraints? How much real output did not get realized because banks in Pakistan were unable to fully pass on the positive financial shock after 9/11 to borrowing firms? Answering this question is necessarily hard, yet even a tentative back of the envelope calculation based on the micro-evidence is quite revealing.

The counter-factual to be estimated is the aggregate return on the amount of money that was not lent to firms due to credit limit constraints. First, one has to estimate the amount of this “missed lending”. Second, impute a (relative to its alternate use) rate of return.

In order to estimate missing lending, let us assume that firms with financial slack $s_{i,t-1}$ equal or greater than 1 are completely unconstrained (10.6% of all firms), i.e. they can borrow as much as they like, *given* the range of shocks experienced as a result of 9/11. While this is admittedly arbitrary, figure VIII suggests it is conservative since even firms with slack greater than 1 show increasing loan growth as slack increases.¹¹ We can then compute missing loans as follows. Consider a firm with a given $s_{i,t-1}$, and loan size, $L_{i,t-1}$. Take the estimated coefficient $\hat{\beta}_1$ to be 0.2. Since we assume that $s_{i,t-1} = 1$ reflects unconstrained growth and figure VIII shows a fairly linear relationship, the unconstrained growth of firm i would have been $(1 - s_{i,t-1}) * 0.2$. The total missing loan is then $(L_{i,t-1} * (1 - s_{i,t-1}) * 0.2)$. Since the estimated $\hat{\beta}_1$ also varies by firm size decile significantly, it is better to allow for this heterogeneity. Total missing loans (ML) are then given by the sum:¹²

$$\sum_i (L_{i,t-1} * (1 - s_{i,t-1}) * \hat{\beta}_{1j}) \quad (7)$$

¹¹As a firm becomes unconstrained, one would expect that it would show no relationship between loan growth and its initial financial slack. In terms of Figure VIII, this suggests that one way to determine whether a firm is no longer financially constrained is to see if loan growth “levels off” in the figure. This only really happens for firms with slack higher than 2 suggesting out cutoff of 1 is quite conservative.

¹²When (1-s) is negative for a firm, we set it equal to zero

for firm i in size decile j . Computing this in our sample, gives us a total of 45.4 billion rupees in missing loans.

Second, we need to impute the rate of return on this missed lending. While one could make different assumptions about this return, it is simpler to present a higher bound where the unlent amount is assumed to generate zero net returns i.e. the economy just gains the book value. The investment distortion is therefore losing future streams of income generated had the amount been lent to firms. Given the market price of a firm reflects the present value of its underlying assets, we can impute this net present value by subtracting book from market value.

Using this approach and a Market to Book ratio for Pakistan estimated at 2.96 (IFC emerging market database — EMDB), we get the net present value of the return to the missed investment would have been Rs. $45.4 \times 1.96 = 88.9$ billion rupees, or 2.3% of GDP in 2000.

We should caution that these estimates suffer from biases that could both over or underestimate the true effect. In estimating the amount of missed lending, while we were conservative in assuming that firms with slack greater than one were completely unconstrained, we assumed that firms could not compensate with informal/internal sources of capital. In the unlikely case that firms can generate their desired capital from such alternate sources at equal cost, there would be no real impact on the economy.

However, Table IX provides evidence that firm's are unable to fully compensate. Keeping the same sample of firms we have in our primary specification (non-defaultors), we ask whether firms that are constrained in the sense of facing less financial slack, are more likely to default post-9/11. Column (1) shows that this is indeed the case - Going from no slack to a slack of 1 lowers the likelihood of firm default by 0.03 percentage points. As a percent of mean default rates for these set of firms, this represents a 50% increase in default rates. Columns (2)-(3) shows the result is robust to additional controls.

Finally, columns (4)-(5) presents evidence on the relative importance of internal credit markets. We focus on firms that are in common-ownership groups (as in Table V) as ask how much the default rate effect falls once we include common director fixed effects. This offers an indirect test of the importance of internal (to the management group) credit markets. Our results suggest that at best such markets can compensate for half the loss a firm faces dues to its credit limit constraints. Since the majority of firms do not belong to management groups, this suggests that even if internal credit markets can serve to lessen the real costs of the credit

constraints identified, these costs will remain substantial.¹³

Moreover, it is likely that we are under-estimating the true costs since one would expect that the rates of return are higher for constrained firms and there may be additional costs arising from distributional consequences of financial constraints. These distributional implications arise as smaller firms face more borrowing constraints, allowing larger and possibly not as efficient firms to survive at the expense of smaller more innovative ones.

VII Conclusion

The literature increasingly suggests that liquidity supply matters: banks are unable to cushion borrowing firms against shocks to their liquidity supply - the bank lending channel is significant (Peek and Rosengren, 1997; Kashyap and Stein, 2000) - and liquidity supply shocks can therefore have large real effects (Bernanke, 1983; Peek and Rosengren, 2000). In related work on Pakistan (Khwaja and Mian, 2008), we also identify both the presence of a large bank lending channel, and find that small firms are entirely unable to compensate such bank lending shocks and face real losses.

While this literature has examined the damaging impact of *negative* liquidity shocks, how do banks and the economy respond when they benefit from a positive liquidity shock? One may hope that if banks pass on all shocks, negative and positive, to their clients, then positive liquidity shocks would prompt a borrowing and investment boom. The adverse effects of liquidity crunches could then be overcome as long as liquidity booms are to follow.

However, the results in our paper present a more troubling picture. The response to liquidity crunches and booms may be asymmetric: while banks cut back lending when faced with a liquidity crunch, they do not lend nearly as enough to firms when faced with large liquidity inflows. The events of 9/11 led to substantial capital inflows into formal financial markets in Pakistan due to reverse capital flight and increased remittances, with deposits rates falling by a half in just over a year. However, despite this sharp reduction in the cost of capital and evidence of an accompanying economic recovery, we find that banks, faced with sluggish and backward

¹³While one may question whether firm default is a good measure of real outcomes (firms may strategically default), in a related paper on Pakistan, Zia (2006a) uses real *output* data to arrive at a similar conclusion. He shows that firm-level exports decline once banks restrict credit (previously offered under an export incentive scheme) to firms. Those firms that are able to retain output, do so only because they can borrow more from other banks, rather than drawing on informal/internal capital sources.

looking credit limits, were unable to increase lending to the corporate sector. The asymmetric response is not surprising once one realizes there is an inherent difference between cutting back lending versus increasing it. The former requires little additional information regarding the firm and banks can always justify doing so in the spirit of sensible prudence. However, increasing lending requires the bank to be able to assess the future potential of a firm, secure it against relatively liquid collateral and justify the increase, a task made even harder when faced with strict prudential regulations.

Moreover, the Pakistani experience, and one that seems to be borne out in other emerging markets, suggests that apart from not being able to take advantage of the increased liquidity, there may be further unwelcome implications of *positive* financial shocks in emerging markets: sudden liquidity surges may spur excessive speculation. As banks could not lend rapidly enough, investors in Pakistan quickly turned to other markets such as equity and real-estate, where prices increased sharply. In a two year period following 9/11 not only did the stock market index increase five-fold to an all time record high, but housing prices appreciated at well over a 100% a year. Evidence that this was a speculative bubble is becoming increasingly apparent with the recent collapse of the real estate market and a noticeable cooling off in the equity markets.

Our results therefore offer a note of caution that in the absence of well-functioning financial markets, liquidity booms may be unable to undo the impact of liquidity crunches. Too much money too soon may generate limited gains for the economy with liquidity either escaping to more speculative (and less regulated) markets or to the global market.

VIII Appendix

A. Solving for collateral requirement, ω_i :

A firm finances its investment K_i with external debt D_i and internal wealth W_i , i.e. $K_i = D_i + W_i$. Given the ex-post threat of strategic default, the following I.C. condition must be satisfied for all firms.

$$Y_i - c_i K_i \leq Y_i - (K_i - W_i)R \quad (8)$$

where $R > 1$ is gross lending interest rate. Condition (8) implies that for a given investment level K_i , a firm must invest minimum internal funds given by,

$$W_i \geq \left(\frac{R - c_i}{R} \right) K_i \quad (9)$$

A firm would want to put in the minimum possible internal funds for diversification reasons. Thus (9) holds in equilibrium, and we get $\omega_i = \frac{W_i}{K_i} = \left(\frac{R - c_i}{R} \right)$. Since no firm defaults in equilibrium, R is constant across all firms.

B. Proof of Result 1:

First consider an unconstrained firm. For this firm its change in borrowing is given by: $\Delta d_{it} = \Delta \tilde{d}_{it} = \gamma(\eta_{it} + \phi_t)$. Therefore, $\frac{\partial E(\Delta d_{it})}{\partial s_{i,t-1}} = 0$. Now consider a firm that faces financial constraints. In this case the solution to the firm's borrowing change in response to a net demand shock, illustrated in Figure I, can be written down more formally as:

$$\Delta d_{it} = \left\{ \begin{array}{l} s_{i,t-1} \text{ if } (\Delta \tilde{d}_{it} \geq s_{i,t-1}) \\ \Delta \tilde{d}_{it} \text{ if } (\Delta \tilde{d}_{it} < s_{i,t-1}) \ \& \ s_{i,t-1} > 0 \\ \text{Min}\{0, \Delta \tilde{d}_{it} - (\bar{d}_{i,t-1} - \tilde{d}_{i,t-1})\} \text{ if } (\Delta \tilde{d}_{it} < 0 \ \& \ s_{i,t-1} = 0) \end{array} \right\}$$

What is of relevance to us though is that $\frac{\partial \Delta d_{it}}{\partial s_{i,t-1}} = 1$ when $\Delta \tilde{d}_{it} \geq s_{i,t-1}$, and 0 otherwise. Given a distribution for η_{it} with a CDF $F(\cdot)$ and using $\Delta \tilde{d}_{it} = \gamma(\eta_{it} + \phi_t)$ this allows us to solve for the expected value of this gradient i.e. $\frac{\partial E(\Delta d_{it})}{\partial s_{i,t-1}} = 1 - F\left(\frac{1}{\gamma}s_{i,t-1} - \phi_t\right) \geq 0$.

C. Proof of Result 2:

If firms are financially constrained, the previous proof shows that $\frac{\partial E(\Delta d_{it})}{\partial s_{i,t-1}} = 1 - F(\frac{1}{\gamma}s_{i,t-1} - \phi_t)$. Now consider two sets of firms with differing distribution of demand shocks. An easy way to parameterize firms that faced more positive demand shocks is using FOSD i.e. $F_{high}(x) \leq F_{low}(x) \forall x$. This immediately implies that $\frac{\partial E(\Delta d_{it})}{\partial s_{i,t-1}}|_{high} \geq \frac{\partial E(\Delta d_{it})}{\partial s_{i,t-1}}|_{low}$.

For the second part of the result note that, all else being equal, firms with stricter financial constraints i.e. a higher value of ω_i , will have lower credit limits \bar{D}_i and therefore lower $s_{i,t-1}$. Since $\frac{\partial^2 E(\Delta d_{it})}{\partial^2 s_{i,t-1}} \leq 0$ this in turn implies $\frac{\partial^2 E(\Delta d_{it})}{\partial \omega_i \partial s_{i,t-1}} \geq 0$.

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Figure I(a): Establishing Magnitude of Financial Inflows After 9/11

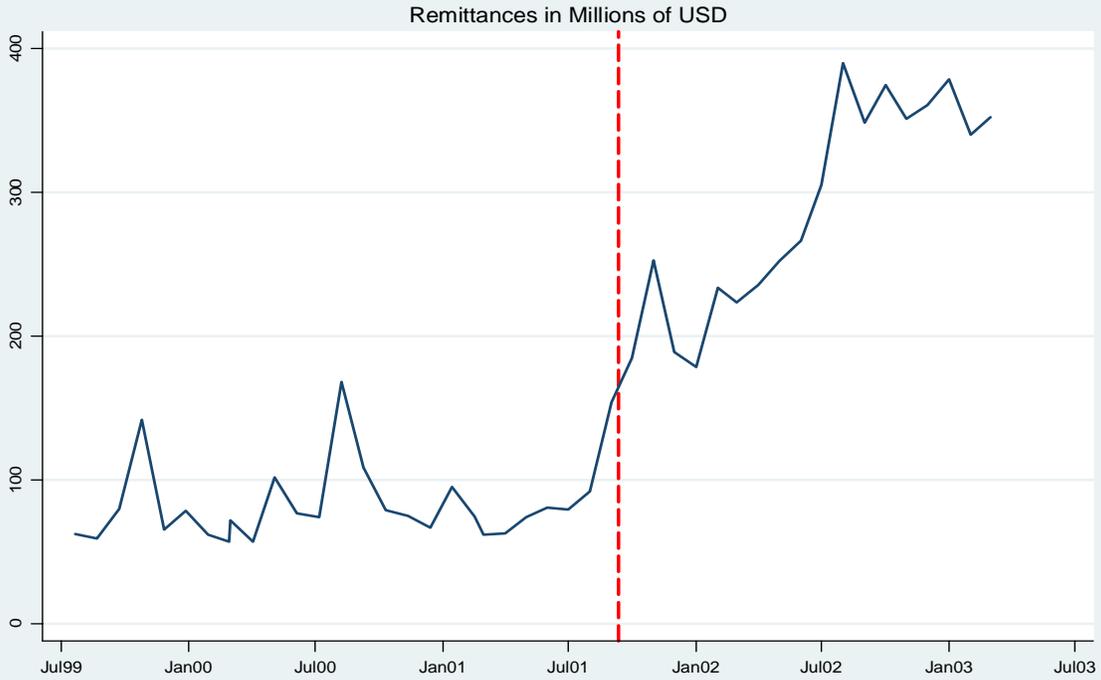
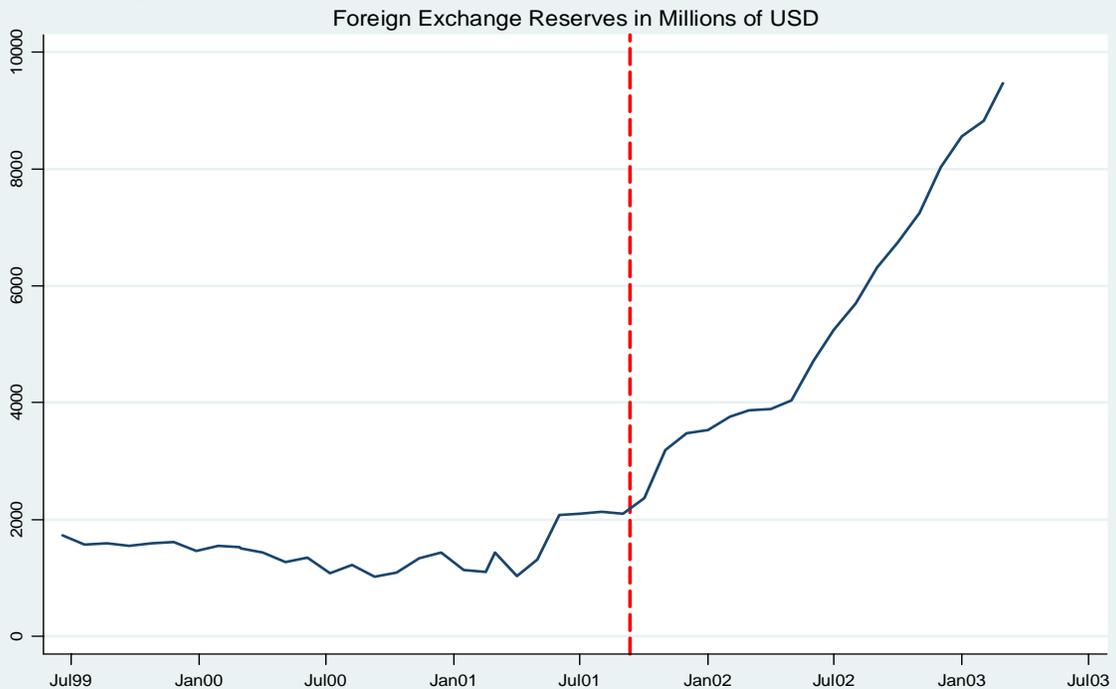


Figure I(b): Establishing Magnitude of Financial Inflows After 9/11



These Figures plot the time-series movements in remittance inflows into Pakistan, and foreign exchange reserves of the country. The vertical dashed line represents September 2001. The apparent jump in remittances right before september,2001 is a seasonal pattern.

Figure I(c): Establishing Movements in Exchange and Interest Rates After 9/11
Official Exchange and Kerb Market Rates in USD (log scale)

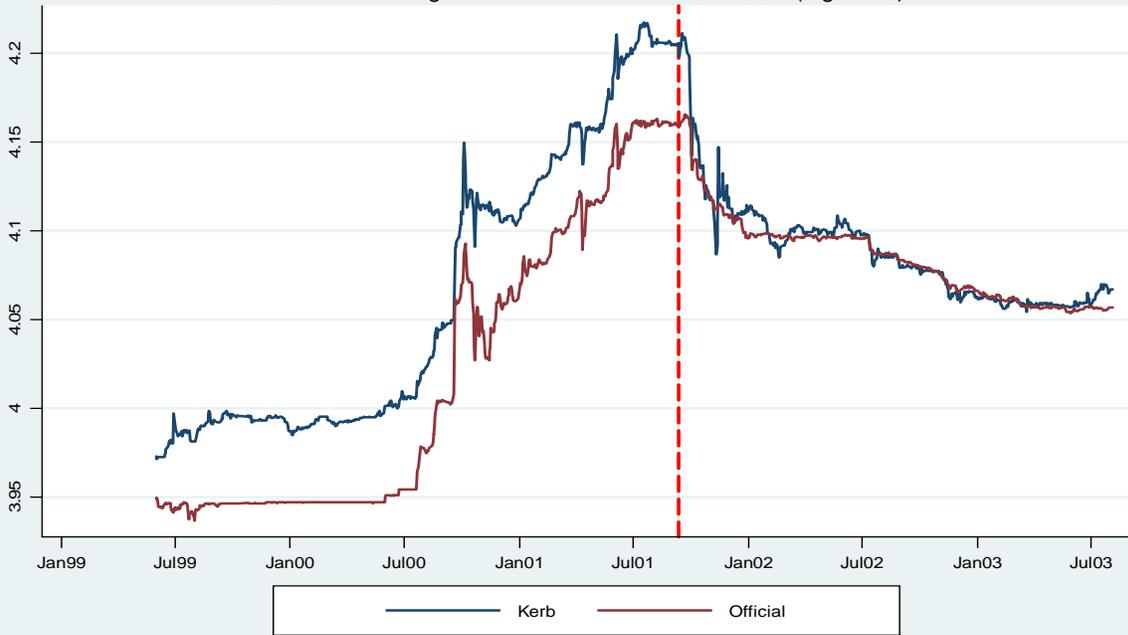
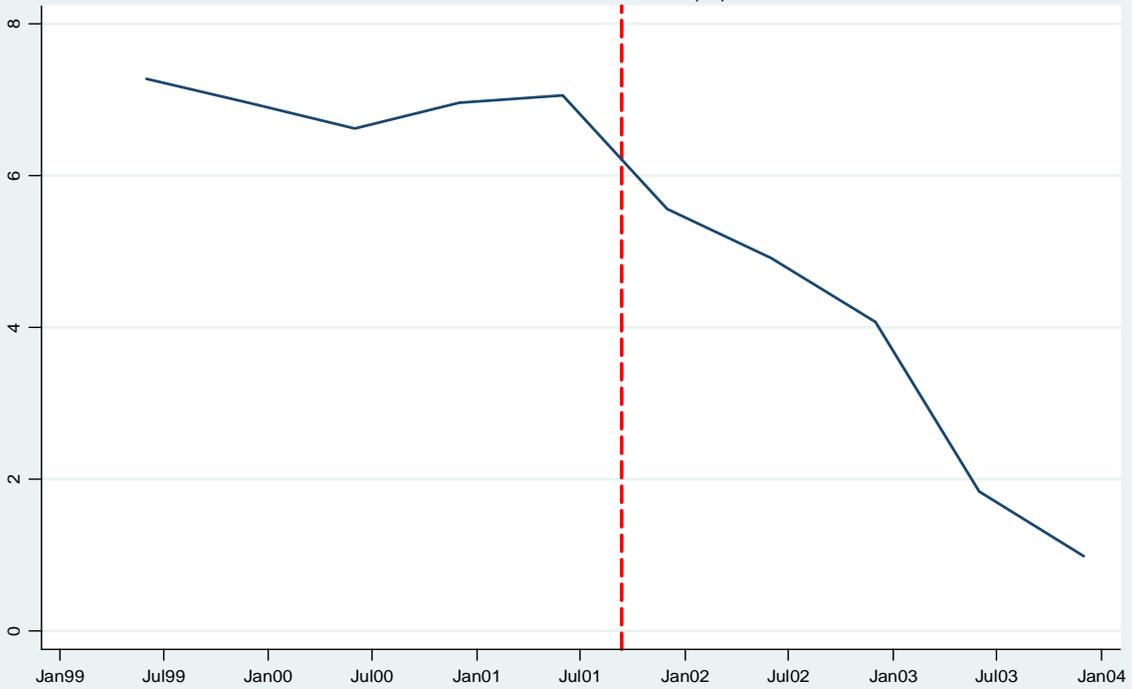


Figure I(d): Establishing Movements in Exchange and Interest Rates After 9/11
Domestic Interest Rates (%)



These Figures plot the time-series movements of exchange rates and domestic interest rates in Pakistan. The vertical dashed line represents September 2001.

Figure II(a): Establishing Positive Demand Shock After 9/11

Aggregate Demand Effect

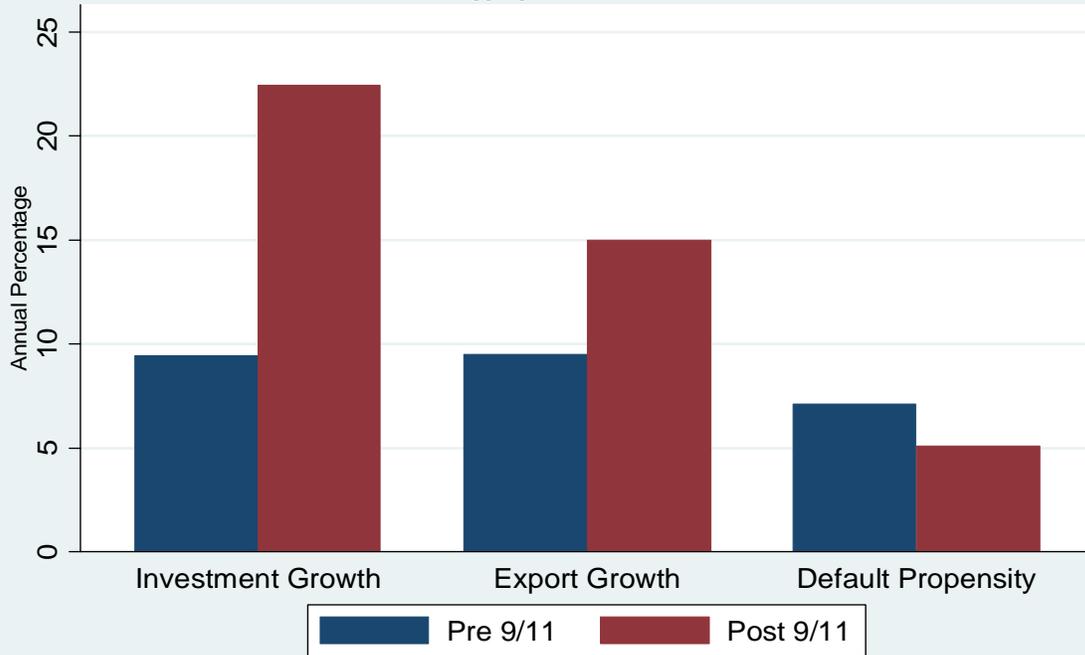


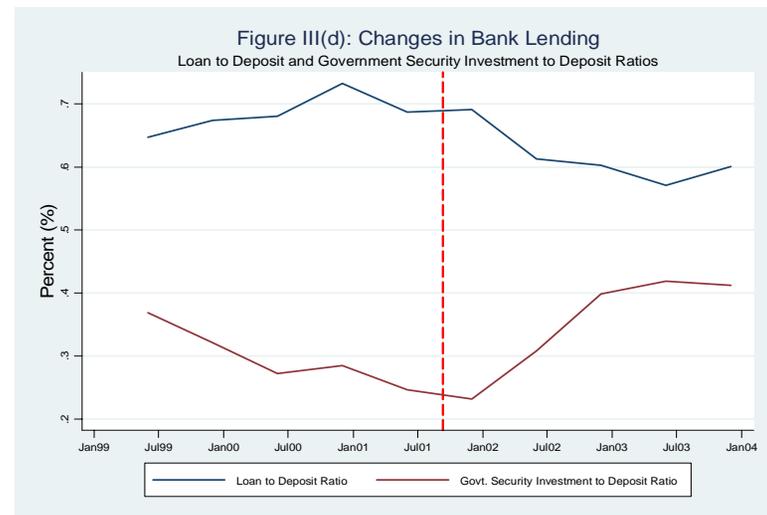
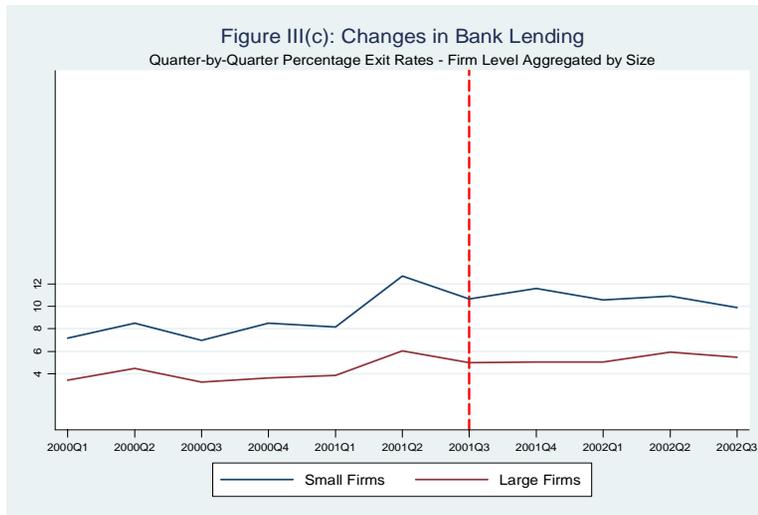
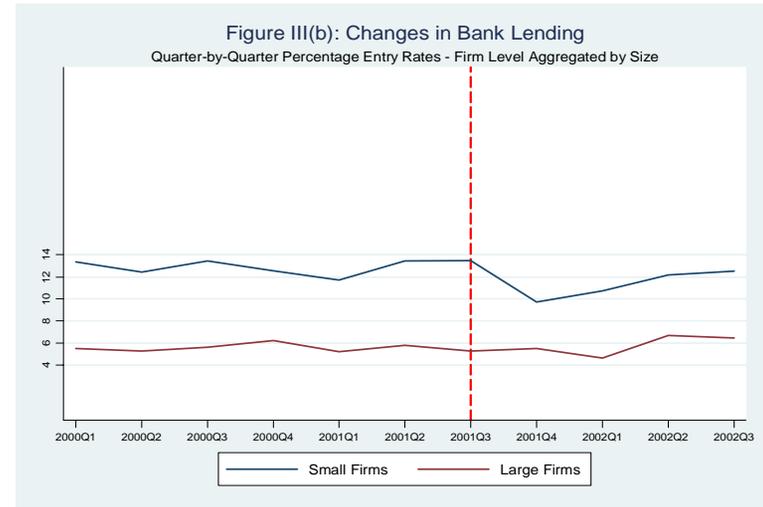
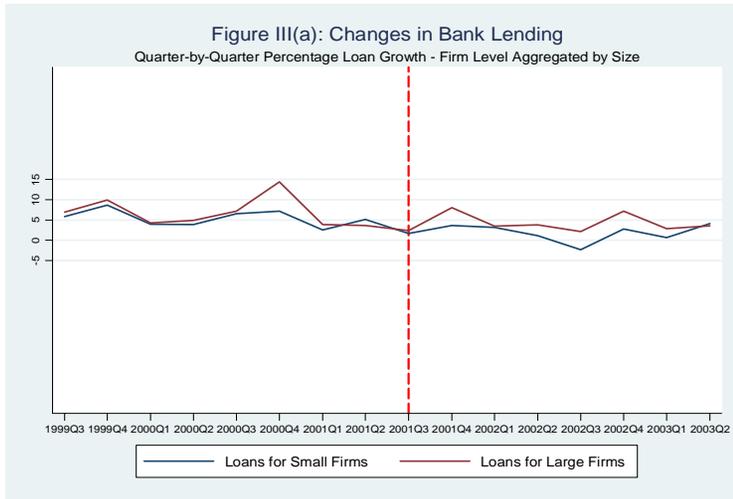
Figure II(b): Establishing Positive Demand Shock after 9/11

Karachi Stock Exchange Index Closing Levels

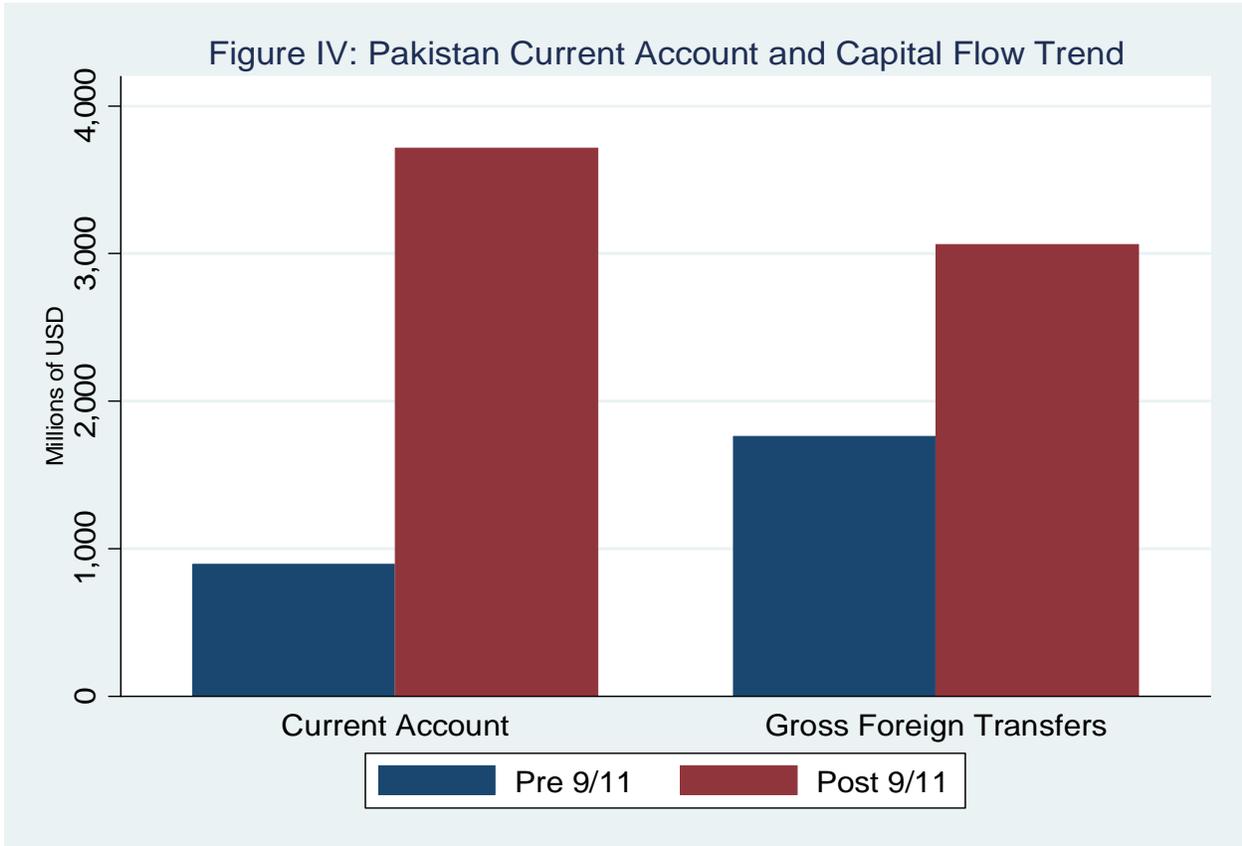


These Figures characterize changes in aggregate demand, and the Karachi Stock Exchange index after 9/11. The vertical dashed line represents September 2001.

Figures III(a)-(d): Changes in Bank Lending

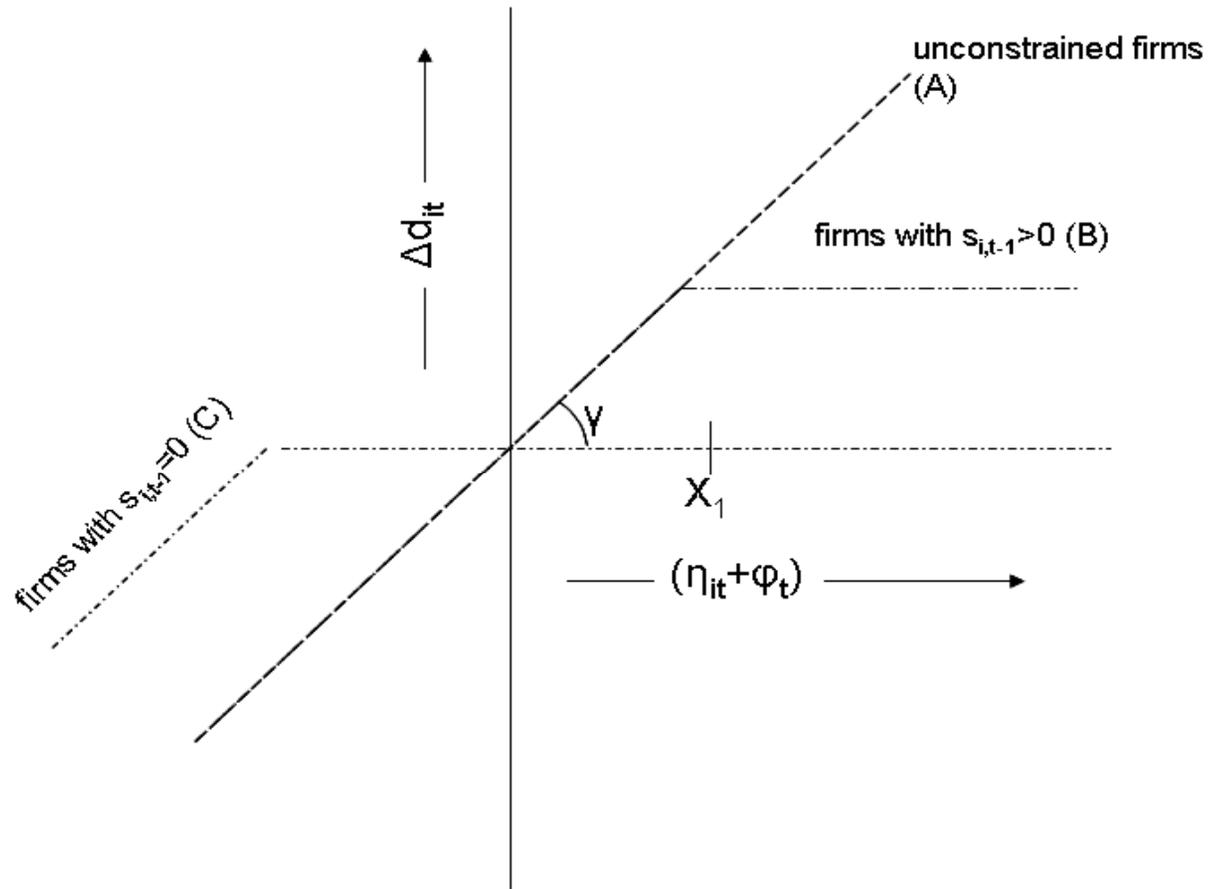


These Figures plot the time-series change in bank lending, both for the intensive margin and the extensive margin. The intensive margin for firms is defined as loan growth for existing customers, whereas the extensive margin for firms is defined as entry into and exit from bank loan relationships. The vertical dashed line represents September 2001.



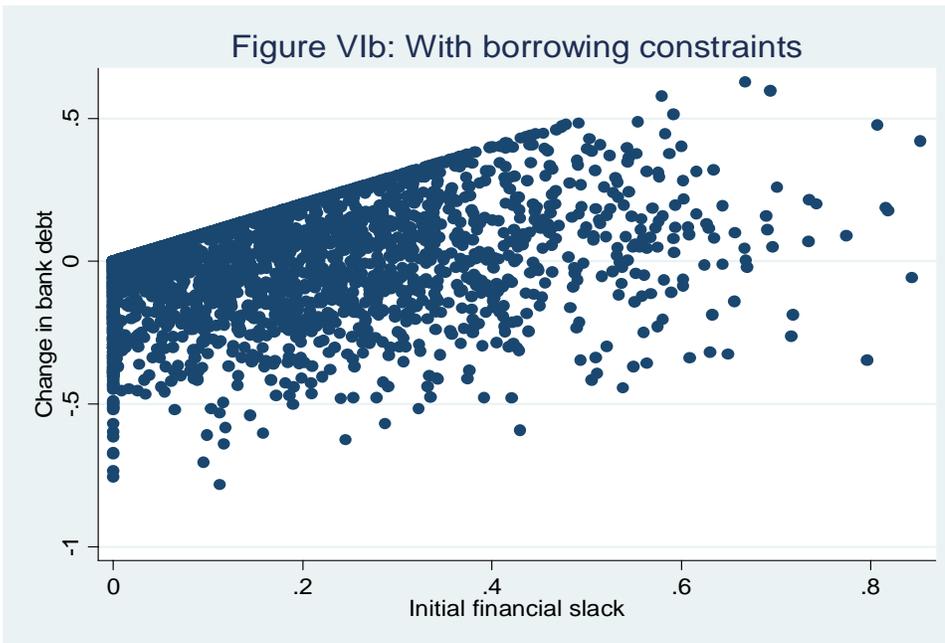
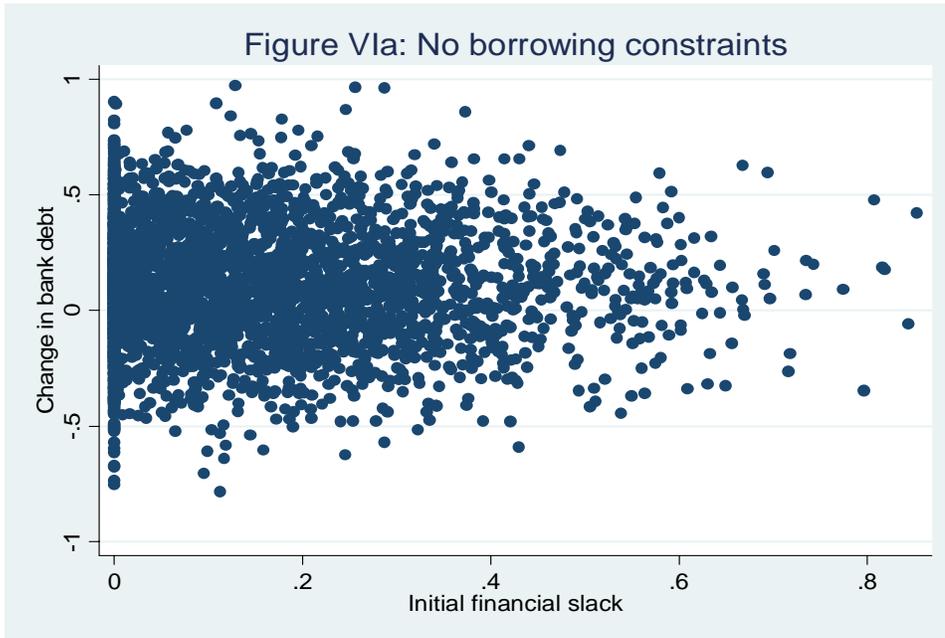
This Figure plots the Pre and Post 9/11 average yearly flows in Pakistan's Current Account and Gross Foreign Transfers.

Figure V: Relationship Between Change in Bank Debt and Credit Demand Shocks



This Figure illustrates how bank lending responds to shocks for constrained and unconstrained firms. The horizontal axis represents the magnitude of the net demand shock for a firm, and the y-axis represents the change in the firm's bank debt. Line A represents the relationship between demand shocks and change in bank debt for unconstrained firms. The path for constrained firms depends on their initial financial slack, $s(i,t-1)$. Constrained firms with zero initial financial slack will be on path C, whereas those firms with positive slack will be on path B.

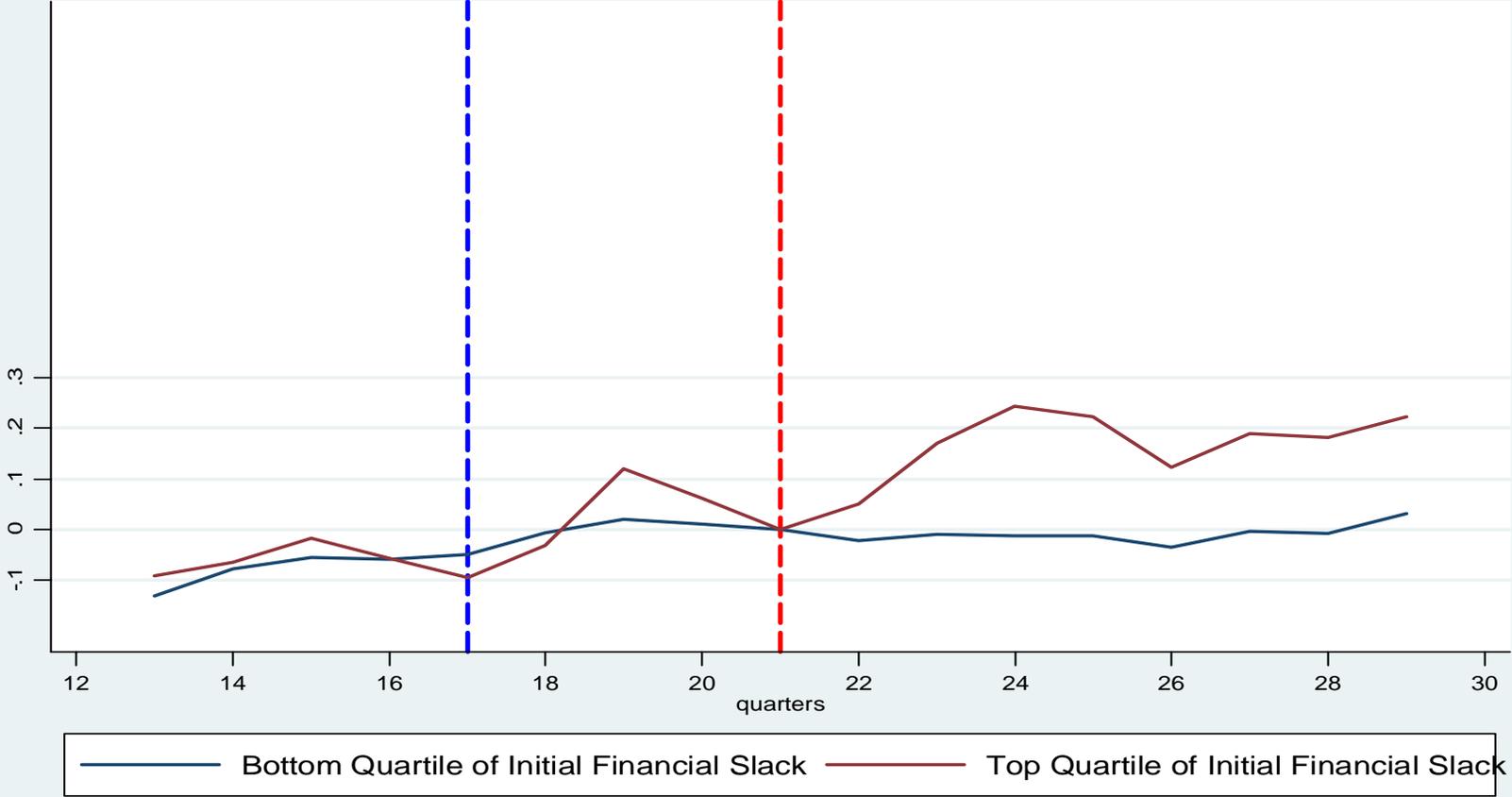
Figures VI (a)-(b): Relationship Between Change in Bank Debt and Initial Financial Slack



These Figures plot the empirical relationship between change in bank debt and initial financial slack with and without borrowing constraints, based on a simulation exercise. The simulation was conducted using the actual distribution of initial financial slack, and plausible values of demand shocks.

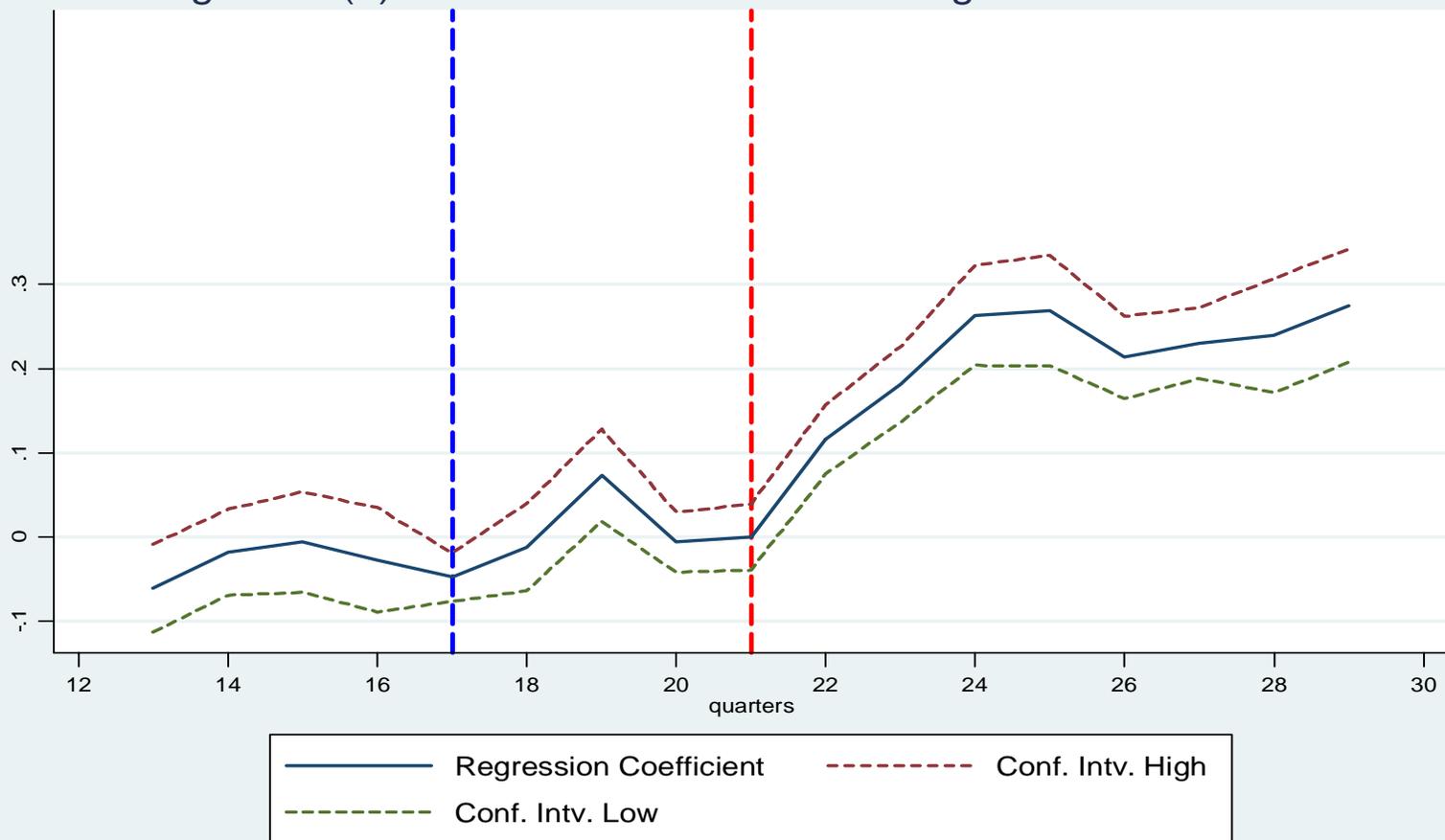
Figure VII(a): Cumulative Loan Growth Regression Coefficients

High vs. Low Slack Firms



This Figure plots the quarter-by-quarter regression coefficients for all quarter dummies from the regression of cumulative loan growth on quarter dummies, separately for top and bottom quartile firms based on initial financial slack. Cumulative loan growth is the de-meaned value of the log of loans for each firm.

Figure VII(b): Cumulative Loan Growth Regression Coefficients



This Figure plot the continuous quarter-by-quarter regression coefficients from the regression of cumulative loan growth on all quarter dummy interactions with initial financial slack. Cumulative loan growth is the de-meanned value of the log of loans for each firm. The coefficients on these interaction terms are then plotted, along with a 95% confidence interval band. The regression also include all quarter dummy interactions with firm level controls such as size, industry, location, and dominant bank.

Figure VIII: Kernel Plot of Loan Growth Against Initial Financial Slack

Kernel regression, $bw = .5$, $k = 3$

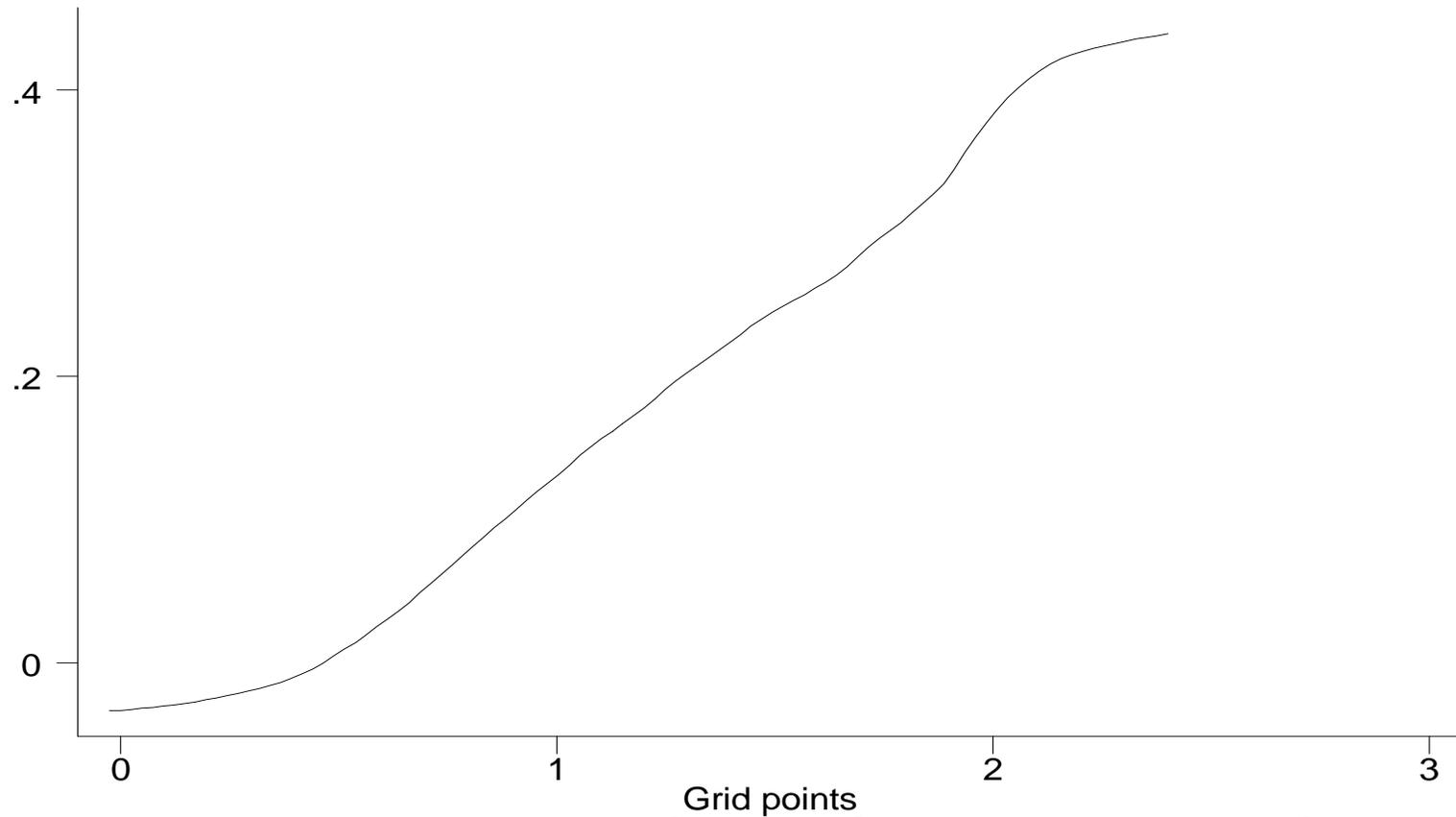
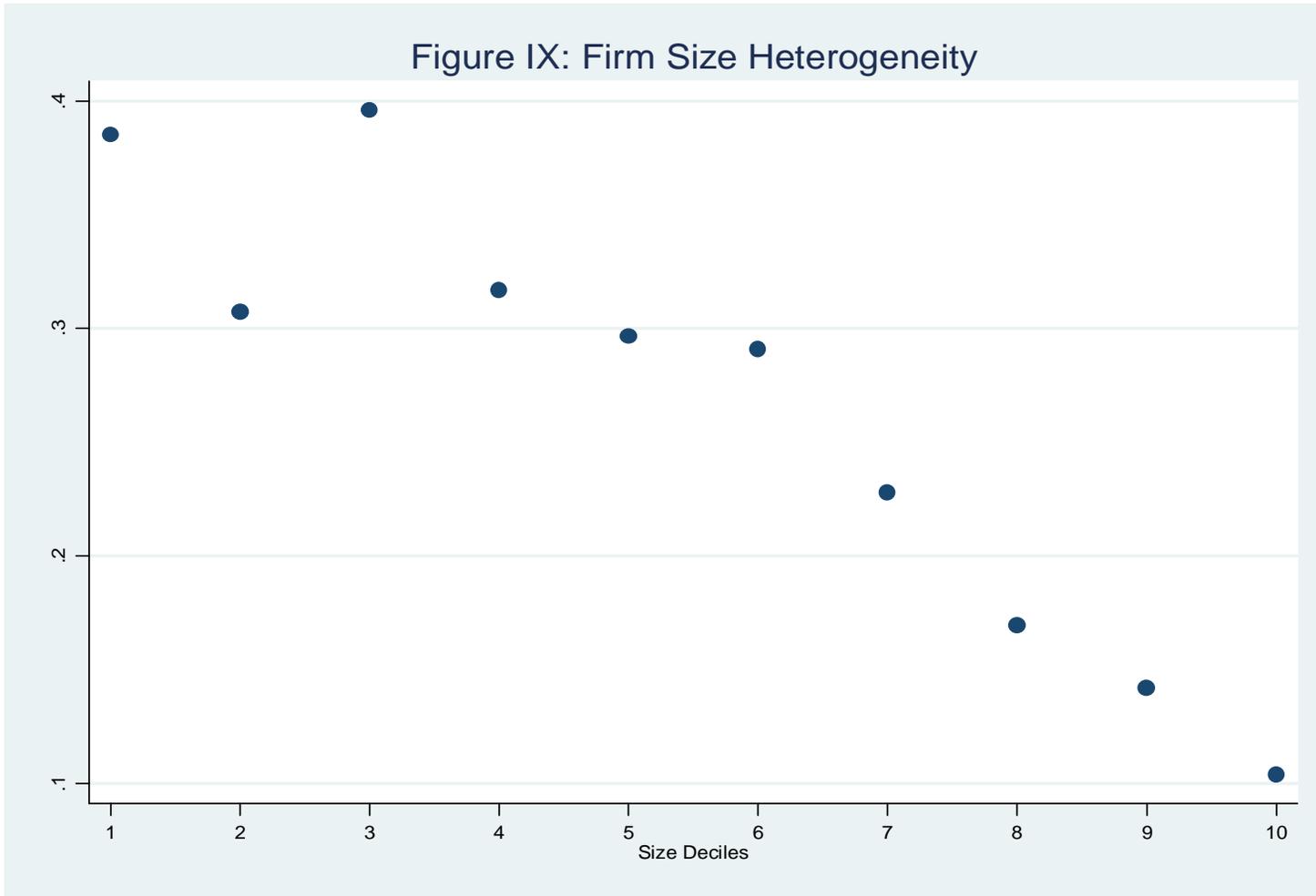


Figure VIII: Kernel Plot - Loan Growth On Initial Financial Slack

This Figure plots the non-parametric kernel regression of lending growth on initial financial slack.

Figure IX: Firm Size Heterogeneity



This Figure plots the regression coefficients on the interactions of firm size decile dummies with initial financial slack. The regression is loan growth on these interactions, and the coefficients are also presented separately in Column (1) of Table VI. All regression coefficients are statistically significant at the 5% level or better.

Table I: Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)
	Pre 9/11: 1999Q4-2001Q2			Post 9/11: 2001Q4-2003Q2		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
<i>(000's Rs.)</i>						
Loan Size	22,485	136,146	1,774,895	22,485	168,524	2,586,862
Credit Limit	22,485	186,804	2,054,935		--	--
Financial Slack	22,485	0.39	0.48		--	--
Default Rate		--	--	22,485	0.04	0.16

This table presents statistics for the loan level CIB data from September 1998 to June 2003. The data is aggregated at the firm level for two equal time periods: Pre 9/11 and Post 9/11; where Post represents all quarters after September 2001. The loan data is averaged over each period by first converting all values to real 1995 Rupees, and then taking time-series averages of loans over all quarters in each period. "Financial Slack" is the difference in logs between credit limit and actual borrowing. The default rate is not reported for the Pre 9/11 period as our starting sample is of non-defaulting firms. Credit limit and thus financial slack data is not available for the Post 9/11 period.

Table II(a): Banking Sector Loan Collateral Requirements

	(1)	(2)
	Pre 9/11: 1999Q4-2001Q2	Post 9/11: 2001Q4-2003Q2
<i>Percentage of Loan Portfolio that is:</i>		
Unsecuritized	0.96	1.03
Securitized by:	99.04	98.97
Stocks and Other Financial Instruments	4.13	5.06
Merchandise (Raw Materials and Finished Goods)	37.74	35.49
Fixed Assets including Machinery	12.70	13.04
Real Estate (Land and Buildings)	22.05	22.16
Fixed Deposits and Insurance	5.30	3.58
Other Secured Advances and Guarantees	17.13	19.64

This table characterizes the average composition of loan portfolios across the banking sector in Pakistan. The data have been obtained directly from the Central Bank, the State Bank of Pakistan.

Table II(b): Credit Limit and Financial Slack Attributes

PANEL A : CORRELATION OF FINANCIAL SLACK WITH FIRM ATTRIBUTES

(1)

	Financial Slack
<i>Lagged Loan Growth</i>	-0.307***
<i>Log Firm Size</i>	0.044***
<i>Exporting Firm</i>	0.001
<i>Late Payment in Pre-Period</i>	-0.009
<i>Hi Demand Shock Industry</i>	-0.015

PANEL B : CREDIT LIMIT STICKINESS

	(1)	(2)	(3)
% of firms for whom:	Limit Unchanged	Limit Usage Ratio Binds	Limit Increased Limit Usage Ratio Binds
<i>Small Firms</i>	46.62	35.09	28.73
<i>Large Firms</i>	17.95	26.05	59.48

PANEL C : DEMAND SHOCK VARIATION

	(1)	(2)
	Log(Credit Limit Post 2000) - Log(Credit Limit Pre 2000)	Log(Loans Post 2000) - Log(Loans Pre 2000)
<i>Hi Shock Industry (defined in 2000)</i>	0.018 (0.017)	0.046 (0.021)
<i>Constant</i>	0.067 (0.013)	-0.002 (0.013)
<i>Observations</i>	19,355	19,355

This table characterizes the financial slack and credit limit variables. Panel A presents cross sectional correlations of financial slack with various firm attributes, with significance levels indicated by the asteriks. Panels B establishes the "stickiness" of credit limits through a simple counting exercise. Panel C explores variation in credit limit and loan growth around January 2000, by high and low demand shock industries.

Table III: Does Financial Slack Predict Credit Growth?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Dep Var = Loan Growth</i>	All Firms		Firms with Non-Missing Lagged Loan Growth		All Firms		<i>Dep Var = Working Capital Loan Growth</i>
Initial Financial Slack	0.208 (0.020)	0.197 (0.016)	0.179 (0.015)	0.182 (0.017)	0.158 (0.016)	0.237 (0.021)	0.226 (0.025)
Lagged Loan Growth			-0.011 (0.014)				
Lagged Log Loan Level					-0.076 (0.008)		
Lagged Log Credit Limit						-0.074 (0.008)	
Constant	-0.061 (0.021)	0.031 (0.099)	0.103 (0.102)	0.097 (0.101)	0.563 (0.112)	0.548 (0.112)	0.167 (0.370)
Industry, City, and Bank FEs		YES	YES	YES	YES	YES	YES
Observations	22,485	22,485	15,156	15,156	22,485	22,485	16,049
R-squared	0.032	0.104	0.089	0.089	0.137	0.136	0.073

These regressions test the relationship between loan growth and credit limit constraints. The dependent variable is the first difference in log(loans) for 6 quarters before and 6 quarters after 2001Q3. "Initial Financial Slack" is the log difference between a firm's credit limit and its borrowing for 6 quarters prior to 2001Q3. "Lagged Loan Growth" is the first difference in log(loans) for 6 quarters before and 6 quarters after 2000Q1. Column (7) restricts the LHS variable to only working capital loans. "Initial Financial Slack" is the log difference between a firm's credit limit and its borrowing for 6 quarters prior to 2001Q3. Regression specifications in columns (2) to (7) also include dummies for each of the 134 cities/towns firms are located in, 75 industry dummies, and 119 dominant bank dummies, where dominant bank is where each firm has the largest share of borrowing. Standard errors in all specifications are clustered at the dominant bank level.

Table IV: Does Financial Slack Predict Credit Growth? Placebo Period

	(1)	(2)	(3)	(4)
<i>Dep Var = Loan Growth</i>	Firms around "Placebo" (Jan 00) shock		Firm around "Placebo" and "9/11" shock	
Initial Financial Slack	0.088 (0.017)	0.087 (0.017)	0.088 (0.017)	0.089 (0.018)
9/11 * Initial Financial Slack			0.123 (0.020)	0.113 (0.016)
Industry, City, and Bank FEs		YES		YES
9/11 Shock Dummy			YES	YES
Observations	19,355	19,355	41,992	41,992
R-squared	0.010	0.050	0.020	0.060

These regressions test the relationship between loan growth and credit limit constraints for a "Placebo" shock (i.e. January 2000), and in the time-series with both "Placebo" and 9/11 shocks. The dependent variable is the first difference in log(loans) for 6 quarters before and 6 quarters after 2000Q1 and 2001Q3, respectively. "Initial Financial Slack" is the log difference between a firm's credit limit and its borrowing for 6 quarters prior to 2000Q1 and 2001Q3, respectively. Regression specifications in columns (2) and (4) also include dummies for each of the 134 cities/towns firms are located in, 75 industry dummies, and 119 dominant bank dummies, where dominant bank is where each firm has the largest share of borrowing. Columns (3) and (4) also include a 9/11 shock time dummy. Standard errors in all specifications are clustered at the dominant bank level.

Table V: Robustness Checks - Firm Quality

	(1)	(2)	(3)	(4)	(5)
<i>Dep Var = Loan Growth</i>					
	All Firms	All Multi-Firm Groups		Groups of 2 or 3 Firms Only	
Initial Financial Slack	0.197 (0.015)	0.19 (0.021)	0.20 (0.024)	0.21 (0.019)	0.34 (0.041)
Late Paymen History?	-0.110 (0.018)				
Constant					
Industry, City, and Bank FEs	YES	YES	YES	YES	YES
Common Director FEs			YES (4,922 FEs)		YES (3,811 FEs)
Firm FEs					
9/11 Dummy					
Lagged Loan Growth and Interaction with 9/11 Dummy					
Observations	22,485	10,678	10,678	4,917	4,917
R-squared	0.105	0.1	0.5	0.15	0.85

These regressions conduct robustness checks of firm quality with parametric and non-parametric controls. Parametric controls include a measure of firm quality, "Late Payment in Pre-period?", which is a dummy =1 if a firm has ever been late on its repayment of loans prior to 2001Q3. Non-parametric controls include management fixed effects and firm fixed effects. Management fixed effects are constructed using firm director information: firms that share common directors are considered to be under the same management. Column (2) repeats our standard specification for firms that are part of multi-firm groups, and Column (3) then includes common director fixed effects in the specification. Columns (4) and (5) repeat this exercise but only for groups of 2 or 3 firms. All regression specifications also include dummies for each of the 134 cities/towns firms are located in, 75 industry dummies, and 119 dominant bank dummies, where dominant bank is where each firm has the largest share of borrowing. Standard errors are clustered at the dominant bank level.

Table VI: Varying Demand Shocks Across Industries

	(1)	(2)	(3)	(4)	(5)
<i>Dep Var = Loan Growth</i>	High Demand Shock	Low Demand Shock		Full Sample	
Initial Financial Slack	0.223 (0.021)	0.101 (0.022)	0.101 (0.022)	0.104 {0.019}	--
High Demand Shock * Initial Financial Slack			0.122 (0.024)	0.106 (0.020)	0.084 (0.021)
Constant	-0.07 (0.023)	0.007 (0.017)	0.007 (0.017)		
Industry, City, and Bank FEs				YES	YES
Firm Size FEs and All Interactions with Initial Financial Slack					YES
Observations	19,819	2,666	22,485	22,485	22,485
R-squared	0.037	0.007	0.033	0.104	0.111

These regressions test for heterogeneous effects across industries that were hit by varying degrees of demand shocks after 9/11. "High Demand Shock" industries primarily include cement, energy, and construction sectors, and "Low Demand Shock" industries primarily include textiles and chemicals. Columns (1) and (2) present regression results separately for high and low demand shock industries, respectively, and columns (3)-(5) repeat this exercise in a continuous specification. The dependent variable is the first difference in log(loans) for 6 quarters before and 6 quarters after 2001Q3. "Initial Financial Slack" is the log difference between a firm's credit limit and its borrowing for 6 quarters prior to 2001Q3. The specifications in columns (3)-(5) also include a "High Demand Shock" Dummy. The specifications in columns (4) and (5) also include dummies for each of the 134 cities/towns firms are located in, 75 industry dummies, and 119 dominant bank dummies, where dominant bank is where each firm has the largest share of borrowing. The specification in column (5) also includes all firm size decile dummies and their interactions with "Initial Financial Slack". Standard errors in all specifications are clustered at the dominant bank level.

Table VII: Firm Type Heterogeneity - Firm Size and Export Status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<u>Firm Size Heterogeneity</u>			<u>Exporter Heterogeneity</u>				
<i>Dep Var = Loan Growth</i>				Non- Exporting				
				Firms	Exporting Firms		Full Sample	
Initial Financial Slack	0.137 (0.015)	0.143 (0.017)	--	0.216 (0.021)	0.001 (0.033)	0.001 (0.033)	0.003 (0.034)	--
Small Firms * Initial Financial Slack	0.140 (0.035)	0.110 (0.028)	0.115 (0.027)					
Non-Exporting Firms * Initial Financial Slack						0.215 (0.039)	0.202 (0.038)	0.160 (0.032)
Constant	-0.017 (0.013)			-0.066 (0.022)	0.055 (0.029)	0.055 (0.028)		
Industry, City, and Bank FEs		YES	YES				YES	YES
All Interactions of Industry FEs with Initial Financial Slack			YES					
Firm Size Decile FEs and All Interactions with Initial Financial Slack								YES
Observations	22,485	22,485	22,485	21,529	956	22,485	22,485	22,485
R-squared	0.037	0.106	0.110	0.035	0.001	0.033	0.105	0.112

These regressions test for heterogeneous effects based on firm type -- firm size and export status. Columns (1) - (3) present firm size heterogeneity results. "Small Firms" is defined as a dummy=1 for firms below the 70th percentile in size. The specifications in Columns (1) - (3) also include a "Large Firms" Dummy. Columns (4) - (8) present firm export status heterogeneity results. Column (4) - (5) presents regression results discretely for exporting and non-exporting firms, and Columns (5)-(8) conduct the same comparison in the pooled data. The dependent variable is the first difference in log(loans) for 6 quarters before and 6 quarters after 2001Q3. "Financial Slack" is the log difference between a firm's credit limit and its borrowing for 6 quarters prior to 2001Q3. The specifications in columns (6)-(8) also include a "Non-Exporting Firm" Dummy. The specifications in columns (2) - (3) and (7) - (8) also include dummies for each of the 134 cities/towns firms are located in, 75 industry dummies, and 119 dominant bank dummies, where dominant bank is where each firm has the largest share of borrowing. The specification in column (3) also includes all interactions of industry dummies with "Initial Financial Slack". The specification in column (8) also includes all firm size decile dummies and their interactions with "Initial Financial Slack". Standard errors in all specifications are clustered at the dominant bank level.

Table VIII: Bank Type Heterogeneity

	(1)	(2)	(3)	(4)
<i>Dep Var = Loan Growth</i>	Firm Level -- All Firms			Loan Level -- Multiple-Bank Firms
Initial Financial Slack	0.208 (0.050)	0.172 (0.024)	--	0.150 (0.038)
Foreign Bank * Initial Financial Slack	-0.038 (0.059)	0.041 (0.036)	0.062 (0.043)	0.022 (0.061)
Private Bank * Initial Financial Slack	0.009 (0.053)	0.038 (0.028)	0.049 (0.033)	-0.044 (0.045)
Industry, City, and Bank FEs		YES	YES	
Firm Size Decile FEs and All Interactions with Initial Financial Slack			YES	
Firm FEs				YES
Observations	22,485	22,485	22,485	15,260
R-squared	0.033	0.104	0.104	0.549

These regressions test for heterogeneous effects based on bank ownership type. The dependent variable is the first difference in log(loans) for 6 quarters before and 6 quarters after 2001Q3. "Initial Financial Slack" is the log difference between a firm's credit limit and its borrowing for 6 quarters prior to 2001Q3. The specifications in columns (2)-(3) also include dummies for each of the 134 cities/towns firms are located in, 75 industry dummies, and 119 dominant bank dummies, where dominant bank is where each firm has the largest share of borrowing. The specifications in Column (3) also includes the interactions of all firm size decile dummies with "Initial Financial Slack". The specification in Column (4) is run at the loan-level and the data is restricted to firms that have relations with multiple banks. Standard errors in Columns (1) - (3) are clustered at the dominant bank level, where dominant bank is where each firm has the largest share of borrowing. Standard errors in Column (4) are clustered at the bank level.

Table IX: Effect of Financial Slack on Default

	(1)	(2)	(3)	(4)	(5)
<i>Dep Var = Δ Default Rate</i>				All Multi-Firm Groups	
Initial Financial Slack	-0.027 [0.005]	-0.03 [0.005]	-0.03 [0.005]	-0.029 (0.0050)	-0.019 (0.0033)
Late Paymen History?			0.049 [0.011]		
Industry, City, and Bank FEs		YES	YES	YES	YES
Common Director FEs					YES (4,922 FEs)
Observations	23,010	23,010	23,010	10,678	10,678
R-squared	0.01	0.09	0.09	0.11	0.68

These regressions study the effects of financial slack on changes in default rate, with parametric and non-parametric controls. Parametric controls include a measure of firm quality, "Late Payment in Pre-period?", which is a dummy =1 if a firm has ever been late on its repayment of loans prior to 2001Q3. Non-parametric controls include management fixed effects. Management fixed effects are constructed using firm director information: firms that share common directors are considered to be under the same management. Column (4) repeats our standard specification for firms that are part of multi-firm groups, and Column (5) then includes management fixed effects in the specification. The dependent variable is the first difference in default rate for 6 quarters before and 6 quarters after 2001Q3. "Initial Financial Slack" is the log difference between a firm's credit limit and its borrowing for 6 quarters prior to 2001Q3. All regression specifications except column (1) also include dummies for each of the 134 cities/towns firms are located in, 75 industry dummies, and 119 dominant bank dummies, where dominant bank is where each firm has the largest share of borrowing. Standard errors in all specifications are clustered at the dominant bank level.