Dollars Dollars Everywhere, Nor Any Dime to Lend: Credit Limit Constraints on Financial Sector Absorptive Capacity

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Dollars Dollars Everywhere, Nor Any Dime to Lend: Credit Limit Constraints on Financial Sector Absorptive Capacity

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We exploit an unexpected inflow of liquidity in an emerging market to study how capital is intermediated to firms. We find that backward-looking credit limit constraints imposed by banks make it difficult for firms to borrow, despite readily available bank liquidity, healthy aggregate demand, and a sharply falling cost of capital. The resulting aggregate failure to extend and retain capital in the economy suggests that agency costs that force banks to rely on sticky balance-sheet-based credit limits prevent emerging economies from effectively intermediating capital. (*JEL* E22, E44, G21)

While growth theories based on diminishing returns predict that capital should flow toward 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 2007; Prasad, Rajan, and Subramanian 2007).

One possible explanation for such international capital flows is that financial markets in developing countries lack the ability to effectively absorb and hence

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attract or retain capital.[1] Recent work by Cabellero, Farhi, and Gourinchas (2008) proposes that such *limited absorptive capacity* of the local financial sector can explain current global macro-imbalances. A common driving force behind this is firms' inability to pledge future cash flows in order to borrow 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 article exploits the unique consequences of 9/11 in Pakistan to see how an emerging economy responds to a large and unanticipated liquidity boom. We then use a comprehensive loan-level dataset that links the entire banking sector to borrowing firms in Pakistan, and 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. Pakistan's ensuing cooperation with the United States ended the international financial isolation that had been in place since its nuclear 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, there was no loss in aggregate demand, and if anything this rose as consumption and investment went up due to increased domestic wealth and reconstruction efforts in Afghanistan.

However, despite the availability of cheap credit and potentially higher investment needs, banks were remarkably sluggish in extending credit. Consequently Pakistan started to run a significant current account surplus. We use our loan-level data to provide micro-evidence that the financial sector failed to absorb capital inflows due to sticky balance-sheet-based borrowing limits imposed on firms by banks. These limits are based primarily on a firm's 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 they record the "credit limit" set by a bank for each borrowing firm separately. Since unused lines of credit are

[1] Other possible explanations 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 2000).

costless in Pakistan, firms generally try to get the maximum possible credit line from a bank. 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 be stronger for firms in industries that experienced a larger (unexpected) increase in investment demand due to 9/11. Third, the effect should be stronger for firms that face greater rigidity in their credit limits, such as smaller firms. Finally, the financial slack effect should not hold for firms that ex ante, for various reasons, are *not* restricted by their balance sheet conditions. Exporting firms satisfy this condition since export sales are readily pledgeable, making such firms relatively immune to binding credit limit concerns. We find strong support for all of the above predictions in a sample of 22,485 actively borrowing firms at the time of 9/11.

The financial slack effect that we find is large, with a 1-percentage-point-larger pre-9/11 financial slack leading to a 0.21-percentage-point-higher growth in the firm's borrowing post-9/11. However, could this result be driven by spurious correlations? While the first-difference specification accounts for level differences across firms, a remaining empirical concern is that pre-9/11 financial slack may be correlated with *changes* in credit demand after 9/11. One reason for such spurious correlation may be mean reversion. Firms with above average credit demand today, and hence lower financial slack, may mean revert to average credit demand tomorrow. This will spuriously create a positive correlation between financial slack today and subsequent credit growth. However, using lagged growth in bank credit, we show that mean reversion does not drive the financial slack effect.

Financial slack may also be spuriously correlated with subsequent credit growth due to unobserved firm quality. For example, banks may provide higher credit limits and hence more slack to better-quality firms because these firms are expected to grow faster. Moreover, such firms may also have a higher option value of unused lines of credit if they are in a better position to take advantage of an improving economic environment. As we discuss later in the article, our results that both larger firms and exporters show a smaller/no financial slack effect already suggest that this concern is less likely. Nevertheless, we also use parametric and non-parametric measures of firm quality to address concerns that pre-9/11 financial slack may be proxying for better-quality firms.

Our parametric measure of firm quality is based on the pre-9/11 default history of a firm. Firms with low pre-9/11 period default rates experience larger credit growth as a result of 9/11, justifying the use of pre-9/11 default history as a measure of firm quality. However, including the pre-9/11 default history as a firm quality control does not reduce the financial slack effect.

The non-parametric firm quality controls are based on firm-director fixed effects. Two firms share a fixed effect if they have a director in common.

Since top management is a key determinant of firm quality, the common-director fixed effect non-parametrically controls for a wide range of potential firm quality attributes (e.g., political affiliation, conglomerate membership, etc.). The financial slack effect remains the same even with the inclusion of common-director fixed effects.

Finally, if credit limit constraints are binding at the firm level, we can also test for a *loan (bank-firm pair)-level* credit allocation prediction (i.e., that a firm borrowing from multiple banks will borrow relatively more from the bank with which it has greater financial slack). An advantage of this specification is that one can fully absorb time-varying firm attributes, such as firm credit demand shocks, by including firm fixed effects. Doing so shows that financial slack influences credit allocation even when comparing changes within the same firm.

The limited absorptive capacity of the banking sector due to balance-sheet-based credit limits 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 while all firms benefit from the aggregate boom through a lower probability of distress, the drop is larger for firms with financial slack. We also present some tentative estimates that suggest that the loss of GDP due to this limited absorptive capacity may have been substantial.

There is a large literature aimed at estimating financial constraints at the firm level.[2] There is also an accompanying literature that suggests that financial constraints may additionally be caused by frictions within lending institutions.[3] While the firm-level literature has mostly focused on investment-cash-flow sensitivity in order to understand financial constraints, the potential endogeneity issues of this approach have led to some recent work that tries alternative routes to identifying financial constraints, such as using oil price changes to look at the outside-industry investment of oil companies (Lamont 1997), studying systematic relationships between cash savings and cash flow within firms (Almeida, Campello, and Weisbach 2004), exploiting non-linear funding rules in pension plans to identify the dependence of investment on internal financial resources (Rauh 2006), and exploiting a real estate price shock to distinguish between firms based on their ex ante real estate holdings (Gan 2007).

Our approach in this article is different in that we do not, nor do we believe we need to, take a stance on any particular channel of borrowing frictions since we directly observe the credit limit variable itself for all firms

2 A non-exhaustive list includes Fazzari, Hubbard, and Petersen 1988, 2000; Poterba 1988; Kaplan and Zingales 1997, 2000; and Blanchard, Lopez-de-Silanes, and Shleifer 1994.

3 See, for instance, Liberti and Mian (2009), who study loan officer incentives and bank hierarchies and identify agency problems in this setting.

in our dataset. Moreover, our approach permits directly examining the manifestation of frictions between firms and banks—credit limit constraints—that prevents banks from lending beyond "balance-sheet factors," whatever these factors may be. In this regard, our article is not about identifying a particular channel of financial constraints, but rather about studying a shock to overall liquidity in the entire economy. Specifically, rather than exploit shocks that directly depend on a firm's type (such as whether it owns real estate or not), we consider a shock to the overall supply of liquidity in an economy. Thus every firm in the economy, regardless of its type, is exposed to this shock. However, our methodology is still able to exploit time-series variation across firms by taking advantage of two unique features: (1) having data on the credit limit a firm faces for each loan; and (2) the shock considered (generated due to the events of 9/11) is entirely unexpected and therefore uncorrelated with previous trends. This allows us to compare lending to two firms—both with the same credit limit (and thus evidently the same type)—but at the time of the unanticipated shock, one of these firms is borrowing closer to its credit limit (has less "financial slack") than the other. The unanticipated nature of the shock ensures that at the time of the shock, these same two firms differ only in terms of how much credit limit they have remaining, that is, their financial slack. If credit limits were indeed backward looking and sticky, one would predict (as we find) that the firm with greater financial slack is able to borrow more after the unanticipated (positive) liquidity shock to the economy/lenders. We conduct numerous robustness checks for our results, as summarized above and explained in detail later in the article.

Since we have the universe of bank lending, we are also able to link this micro-level friction to its macro-consequences and examine the absorptive capacity of an entire financial system in response to an unanticipated capital influx. Finally, since the data are by definition representative of lenders and borrowers, we are able to shed further light on the nature of these frictions by examining whether they vary across firms and lenders.

While this article considers the impact of a positive liquidity shock, it also relates to the bank-lending channel literature that typically focuses on negative liquidity shocks to banks and traces whether these shocks affect lending (Peek and Rosengren 1997; Kashyap and Stein 2000). In particular, a related paper (Khwaja and Mian 2008, KM henceforth) finds evidence of a large bank-lending channel using similar data from an earlier time period in Pakistan, when the economy experienced a negative liquidity shock due to the 1998 nuclear tests. A comparison of results in the two papers reveals an interesting asymmetry in how the economy responds to negative versus positive liquidity shocks. KM find that when faced with negative liquidity shocks, banks cut back lending to firms. This is due to frictions banks face on their *borrowing* side (i.e., the usual "bank-lending channel") such that they are unable to borrow liquidity externally to compensate for their deposit base shock. However, this article shows that the converse is not always true, i.e., banks do not necessarily increase lending when faced with a positive liquidity shock. This is due to *firm-level* frictions banks face on their *lending* side. Thus, while banks may have sufficient liquidity available, they are constrained by how much they can increase lending due to standard frictions or agency costs at the firm level. It is not surprising, therefore, why these two types of frictions—on the borrowing and the lending side—may lead to an asymmetric response to liquidity shocks. We will discuss this in more detail in the conclusion.

This article proceeds as follows. The next section lays out the context of our study with information on background and the aggregate-level impact of the 9/11 shock on the local economy. Section 2 provides the conceptual framework and empirical methodology, and Section 3 describes the data. Section 4 presents results on financial slack and borrowing along with robustness checks, while Section 5 presents results on heterogeneity. Section 6 estimates the real costs of such financial constraints, and Section 7 concludes.

1. The Context—Background and Aggregate Impact

1.1 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 the 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 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 the 1990s. The high cost of liquidity kept the local economy distressed, as firms found it difficult to borrow at higher interest rates.

1.2 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 economy was an unexpected surge in the supply of liquidity, a sharp drop in real interest rates, and a relative rise in aggregate demand. We describe these changes in more detail below.

1.2.1 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 crackdown 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 channeled 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 U.S. 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 toward domestic assets.

Figure 1(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 1(b). The reserves reached an all-time high of $10 billion by December 2002, an increase of over $7 billion and almost five times in less than two years. The black-market premium in informal currency markets (Figure 1(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 1(d), which plots domestic interest rates (size-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.

1.2.2 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 generally positive, at least relative to what the situation had been pre-9/11. This was in no small part due to Pakistan's immediate cooperation with the U.S. after 9/11, which saw the lifting of financial sanctions and provided new economic opportunities.

Figure 2(a) shows the aggregate demand change in terms of GDP, investment, employment, and export growth, all of which increased substantially

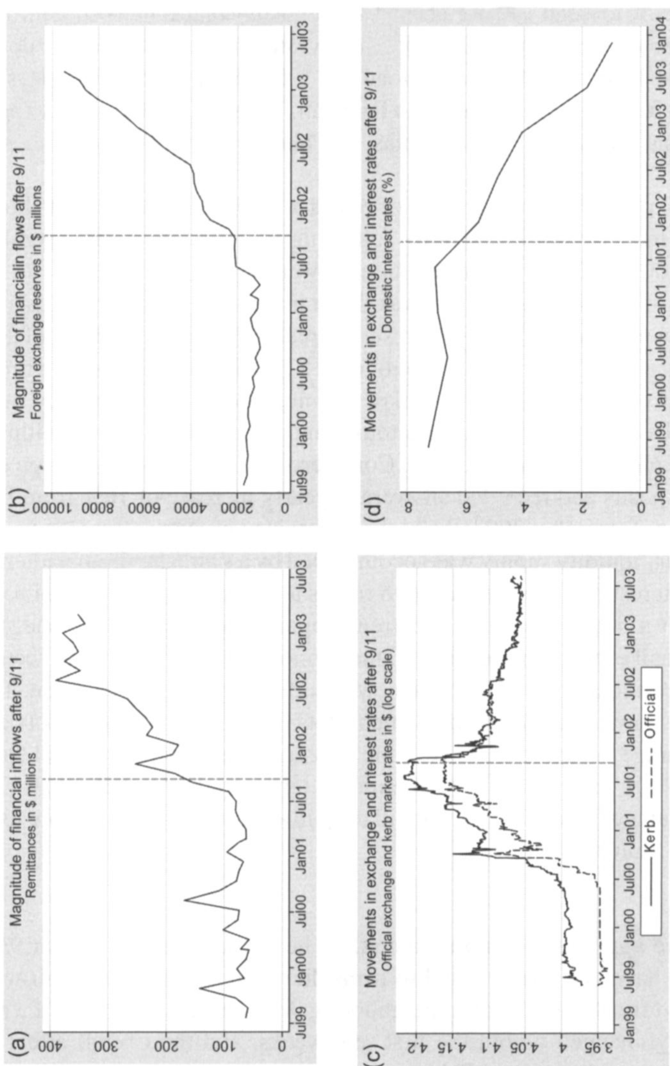

Figure 1
Magnitude of financial inflows after 9/11
Figures 1(a)–(d) plot the time-series movements in remittance inflows, foreign exchange reserves, exchange rates, and domestic interest rates in Pakistan. The vertical dashed line represents September 2001.

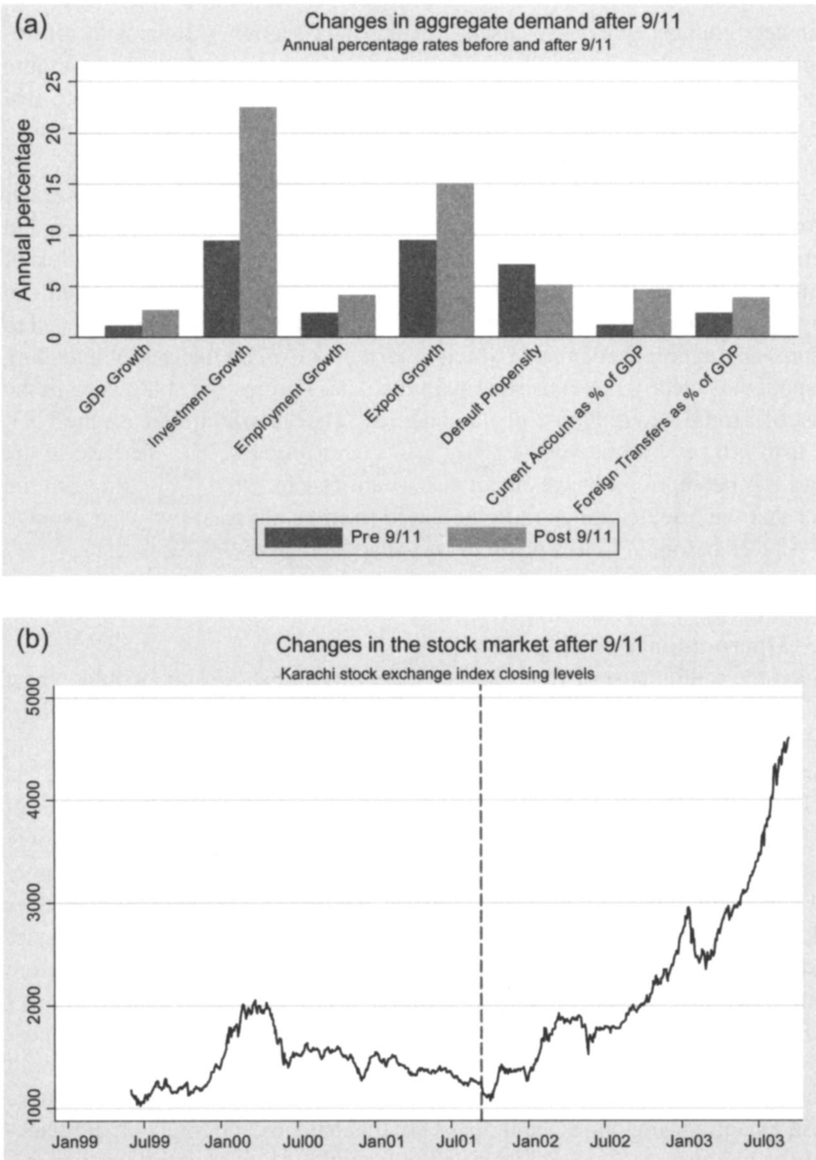

Figure 2
(a) Changes in aggregate demand after 9/11; (b) Changes in the stock market after 9/11
Figures 2(a)–(b) characterize changes in aggregate demand and the Karachi Stock Exchange index after 9/11. The vertical dashed line represents September 2001.

post-9/11, and firm default propensity, which declined. Since these variables are only available yearly, we average them over a couple of years pre- and post-9/11. The figure also shows the current account balance and gross foreign transfers change, which we discuss in the next section. Along with affirming a positive demand shock, the increases in growth rate shown in Figure 2(a) provide evidence for an increase in investment opportunities since real GDP, investment growth, employment growth, and export growth all picked up substantially after 9/11.

As further evidence of a positive demand shock, Figure 2(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, it seems that the events of 9/11 were, on net, also a positive shift in aggregate demand. At the very least, the view that these events may have led to depressing aggregate demand (which in turn may explain the lack of a lending response) is clearly not consistent with the data. Further, the sharp drop in the cost of capital, along with a positive demand shock, would increase the NPV of firm projects, at the very least of short-term projects. The increase in the market's perception of investment opportunities can also be gauged from the fact that the price-earnings ratio increased from an abysmal two-year average of −32.21 before 9/11 to a positive two-year average of 9.92 after 9/11.

1.3 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 3(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 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.

Figure 3 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. This is particularly stark since, as is typical and even more so in emerging economies, bank loans are the main avenue for external financing for the average firm. Pakistan is no exception to this, with less than 3% of firms in our sample listed on the stock market, and bank loans constituting two-thirds of the total capital structure even for listed firms.

Figure 3(a) shows that while the lending 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 3(b) and 3(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

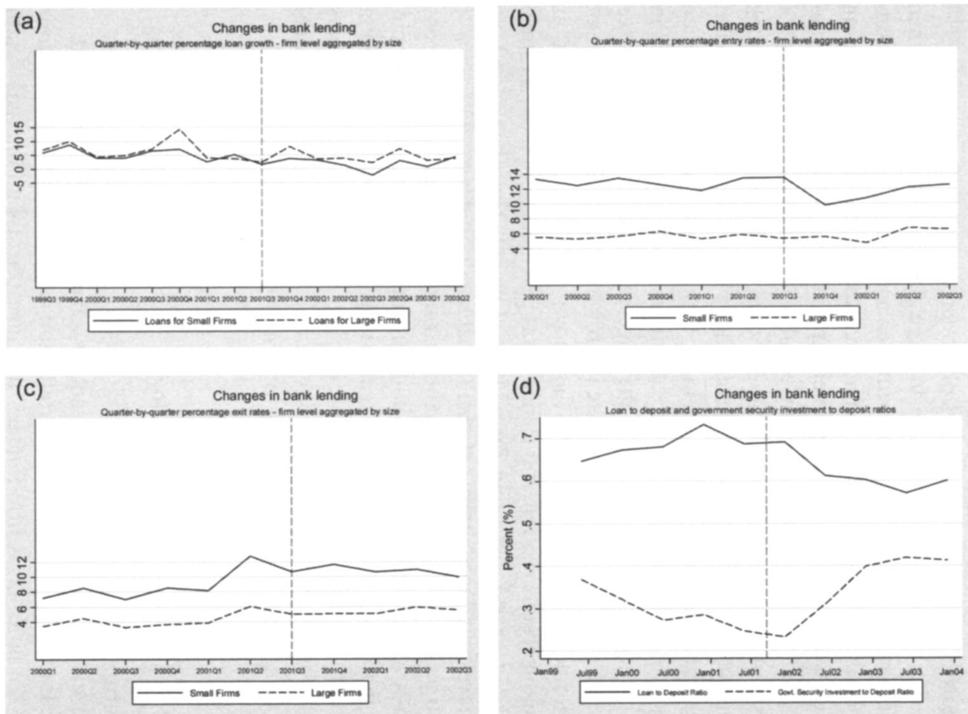

Figure 3
Changes in bank lending
Figures 3(a)–(d) plot the time-series change in bank lending, for both the intensive margin and the extensive margin. The intensive margin for firms is defined as loan growth for existing customers, whereas the extensive margin for firms is defined as entry into and exit from bank loan relationships. The vertical dashed line represents September 2001.

an abundance of liquidity can also be seen from Figure 3(d), which shows a sharp reduction in loan-to-deposit ratio of banks after 9/11 as banks put more of their increased 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 the last two bar graphs in Figure 2(a): 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 and investment opportunities are 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. Another possible explanation could be that the positive shock was perceived as being temporary; however, the evidence suggests otherwise. Specifically, if the shock was perceived to be temporary, it would have been unlikely to see the more-than-100% increase in the stock index as depicted in Figure 2(b), or the dramatic increase in the price-earnings ratio. Similarly, we should not have observed a sharp increase in growth rates of GDP, investment, employment, and exports for after 9/11, as shown in Figure 2(a). Further, as evidenced in our results section, if the shock was perceived as temporary, then firms would not have been vying for additional capital from banks and we should not have found the significant results that we do in the article.

In order to provide direct evidence on borrowing constraints, we now focus on the micro-level predictions of credit limit constraints that can then be empirically tested in the loan-level data and take advantage of the natural experiment induced by the unanticipated events of 9/11. The following section presents a theoretical framework, the purpose of which is to motivate our empirical methodology and outline the accompanying empirical predictions.

2. Conceptual Framework and Methodology

2.1 Basic setup

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 that 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 a firm's "reliability" or (the inverse of) the level of financial frictions a firm experiences. This setup, which is a common way of introducing financial frictions (e.g., Aghion, Banerjee, and Piketty 1999), gives the convenient result that banks require internal wealth (such as collateral) ω_i for every dollar of capital invested.[4] Firms thus differ in the degree of constraints on their credit limits set by banks.

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

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

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, $\widetilde{K}_i$, is given by the FOC:

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

However, only firms with sufficient internal wealth can invest $\widetilde{K}_i$. Other firms will be bound by their total wealth $\overline{W}_i$, implying that they can only invest capital up to $\overline{K}_i = \frac{\overline{W}_i}{\omega_i}$. 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 $K_i = Min(\widetilde{K}_i, \overline{K}_i)$. Since external debt is proportional to capital, we can equivalently write the solution as $D_i = Min(\widetilde{D}_i, \overline{D}_i)$, where $\widetilde{D}_i = (1-\omega_i)\widetilde{K}_i$ and $\overline{D}_i = (1-\omega_i)\overline{K}_i$. The advantage of writing the solution in terms of external debt is that $\overline{D}_i$ 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 ($\overline{W}_i$).

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.[5] There is also flexibility in how financially constrained firms are, as determined by their total internal wealth $\overline{W}_i$ and collateral constraints ω_i.

2.2 Comparative statics

This setup can be used to analyze how an economy reacts to financial shocks. We consider two such shocks based on the consequences of 9/11 for

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

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

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 lowercase alphabets representing the log of respective uppercase variables.[6] The dynamics for productivity and cost of capital are given by

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

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 demand for external financing.

2.2.1 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 $\overline{W}_i$ is large. For an unconstrained firm, the change in (log of) bank debt is simply given by

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

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}.

2.2.2 Case II: External financing constraints. In contrast, the change in bank debt for firms that face borrowing constraints will depend not only 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 $s_{i,t-1} = (\overline{d}_{i,t-1} - d_{i,t-1})$, 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 pledgeable 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, $\overline{W}_i$. Since both these variables change slowly

[6] α represents the log of A, and r, the log of R.

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 3, 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 4 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

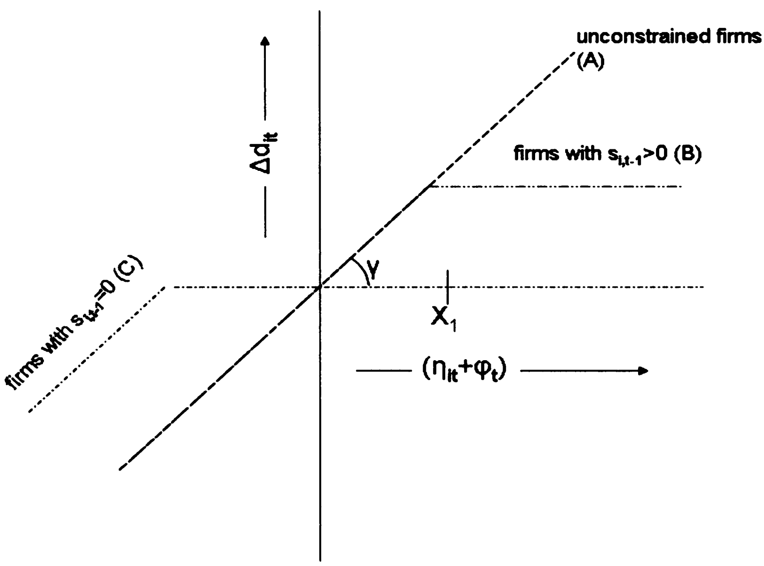

Figure 4
Relationship between change in bank debt and credit demand shocks
Figure 4 illustrates how bank lending responds to shocks for constrained and unconstrained firms. The horizontal axis represents the magnitude of the net demand shock for a firm, and the y-axis represents the change in the firm's 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 with positive slack will be on path B.

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.[7]

Figure 4 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 limit allows.

2.3 Base empirical specification

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

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

where $\triangle d_{it}$ 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.

Figures 5(a)–(b) illustrate the relationship in (5) using a simulation exercise based on the actual distribution of $s_{i,t-1}$ and plausible demand shocks. Figure 5(a) first shows that the change in firm borrowing is uncorrelated with initial slackness in the absence of financial constraints.[8] In comparison, when firms are financially constrained, as in Figure 5(b), the bivariate relationship clusters along the 45° 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 Figures 5(a)–(b). However, the magnitude of β_1 is not readily interpretable without imposing further structure on the model and the magnitude of the shocks. Moreover, as is clear from the figure, one would not expect a slope of 1 since some firms may simply not have enough of a credit demand to have the limit constraint bind.

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 4, such a firm would be moving along the (initial) 45° line and not hitting its limit.

[7] Figure 1 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 $t-1$.

[8] One 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 the bank's credit limit is no longer tied to a firm's internal wealth, but instead will fluctuate according to the firm's credit demand (i.e., credit limits are not sticky).

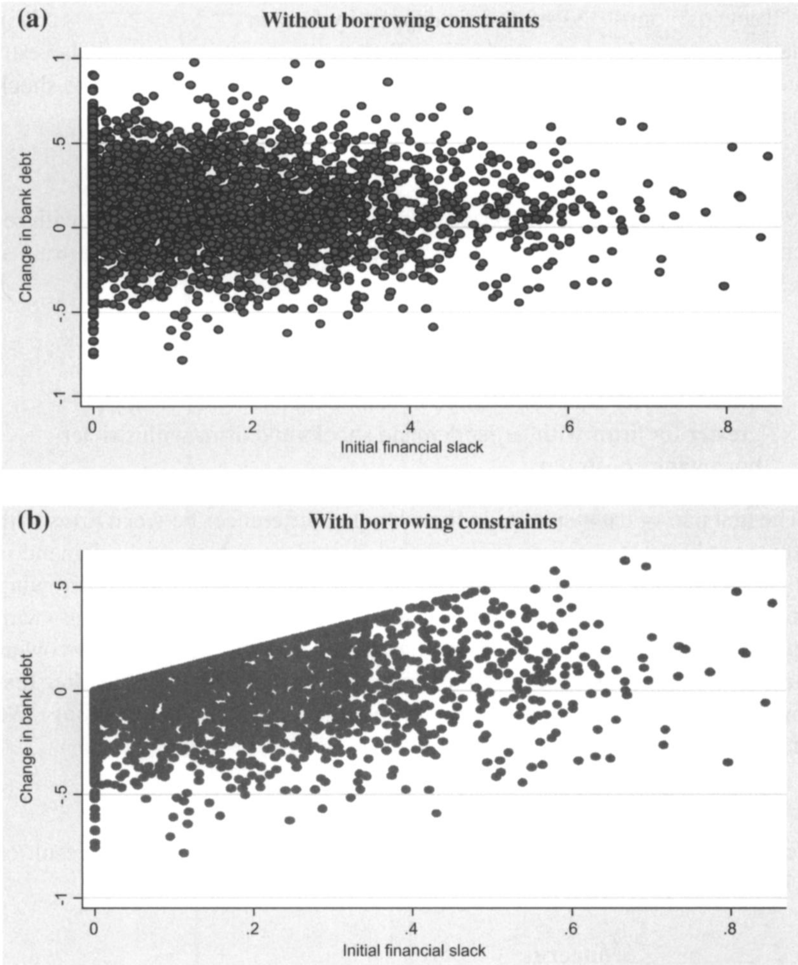

Figure 5
(a) Without borrowing constraints; (b) With borrowing constraints
Figures 5(a)–(b) plot the empirical relationship between change in bank debt and initial financial slack with and without borrowing constraints, based on a simulation exercise. The simulation was conducted using the actual distribution of initial financial slack, and plausible values of demand shocks.

Therefore, our primary specification will be the cross-sectional equivalent of (5), where we collapse the firm data into two time periods, a pre- and a post-period, respectively several quarters before and after 9/11. 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 its pre-shock financial slack non-parametrically.

2.4 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 firms without any credit limit constraints. We can test result 2 by modifying equation (5) to

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

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.

2.5 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 time-varying factors, such as firm productivity shocks (η_{it}),[9] 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 upward.

Before addressing such concerns, we should note that there are legitimate scenarios that would produce a *negative* correlation between $s_{i,t-1}$ and ε_{it}, and thus bias β_1 downward. For example, firms that benefit more from the improving economic environment (i.e., firms with larger η_{it}) may have a higher

[9] The 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.

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 firms with smaller slack will be the ones with higher future loan demand.

Now consider scenarios that would produce a positive correlation between $s_{i,t-1}$ and ε_{it}.

First, it is possible that financial slack in $t-1$ is 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 that 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. However, the 9/11 shock was large and completely unanticipated, making it unlikely that firms or banks could forecast the coming boom.

While the 9/11 shock was unanticipated, one may still be concerned that if higher-quality firms generically perform better, then such firms will have a greater "option value" in retaining financial slack. To the extent that banks also recognize this, these firms will be able to obtain greater financial slack and also borrow more during 9/11. More generally, banks may provide higher credit limits and hence more slack to better-quality firms because these firms are expected to grow faster. We address such firm quality concerns in a series of tests detailed in Section 4.2. These tests explicitly control for firm quality using parametric and non-parametric techniques. They show that the financial slack effect is robust to including direct measures of firm quality such as past performance, and to introducing common director/firm fixed effects.

3. Data

The banking sector in Pakistan is liberalized and fairly representative of emerging markets. Financial reforms in the early 1990s 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 the private sector, respectively.

The loan-level data for our analysis come from the Central Information Bureau (CIB) of SBP. These data are 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 follow the history of each loan with information on the amount and type of loan outstanding, default amounts, and duration. They also have 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 set up 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 1 presents summary statistics for our main variables of interest in the loan-level dataset, as well as bank balance-sheet data and firm balance-sheet data for publicly listed firms. The CIB statistics are averaged at the firm level separately for two pre- and one post-9/11 periods that comprise six quarters each.[10] The loan-level data are 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 at the time of the 9/11 shock, and borrowed for at least two quarters in the pre- and post-9/11 period. The former restriction allows us to focus on "active performing loans," while the latter provides more precise estimates. The two-quarter restriction excludes only 2% of firms, and does not qualitatively affect our results. The sample selection criteria give us a final sample of 22,485 firms. The bank balance-sheet data provide information on all 50 lending institutions operating in the country during the sample period. Note that the balance-sheet data are available only for publicly listed firms, which constitute just 1% of our sample. Panel C of Table 1 presents these summary statistics.

3.1 Financial slack

Financial slack is defined as the (log) difference between a firm's credit limit as set by its bank, and the outstanding loan amount. Credit limit, i.e., $\overline{D_i}$ in

10 The post-period includes an additional 7th quarter in order to exploit all the data available. The results are similar if we exclude this last quarter.

Table 1
Summary statistics

	(1) Obs	(2) Mean	(3) Std. Dev.
PANEL A: CIB DATA - FIRM LEVEL			
Loan Size *(1995 US $)*	22,485	5,018,807	76,333,226
Lagged Loan Size *(1995 US $)*	22,485	3,971,578	51,776,400
Loan Growth	22485	0.02	0.56
Lagged Loan Growth	15156	0.08	0.50
Twice Lagged Loan Growth	9731	0.10	0.71
Lagged Credit Limit *(1995 US $)*	22,485	5,449,370	59,945,595
Initial Financial Slack	22,485	0.39	0.48
PANEL B: BANK BALANCE SHEET DATA			
Deposits *(1995 US $)*	50	1,922,475,788	2,905,028,296
Lagged Deposits *(1995 US $)*	50	1,512,455,951	2,450,230,455
Advances *(1995 US $)*	50	1,090,402,567	1,529,779,463
Lagged Advances *(1995 US$)*	50	966,099,475	1,517,159,277
PANEL C: PUBLICLY LISTED FIRMS BALANCE SHEET DATA			
Publicly Listed?	239	0.01	
Fixed Assets *(1995 US $)*		21,277,110	81,386,790
Lagged Fixed Assets *(1995 US $)*		20,483,040	85,129,150
Sales *(1995 US $)*		52,220,400	138,232,900
Lagged Sales *(1995 US $)*		40,435,910	92,590,630
Investment *(1995 US $)*		6,607,926	27,490,070
Lagged Investment *(1995 US $)*		4,834,313	20,263,080

This table presents summary statistics for the loan-level CIB data, bank balance-sheet data, and firm balance-sheet data for publicly listed firms (restricted to firms that are not in default in 2000Q1–2001Q2). The CIB data are aggregated at the firm level and represent data from 1998Q3 to 2003Q2. The loan data are averaged by first converting all values to real 1995 rupees, and then taking time-series averages of loans over all quarters. The 1995 US dollar-rupee exchange rate ($1 = Rs.34.28) is used to convert to 1995 US $. Variables in the table represent values averaged over the range 2001Q4–2003Q2 (the "post-9/11" period). Lagged variables represent values averaged over the range 2000Q1–2001Q2 (the "pre-9/11" period). Twice Lagged variables represent values averaged over the range 1998Q3–1999Q4 (the "pre-pre-9/11" period). Initial Financial Slack is the difference in logs between credit limit and actual borrowing in the pre-9/11 period. Twice Lagged Default Rate is the ratio of defaulted loans to total loans pre-pre-9/11 period. Credit Limit and thus Financial Slack data are not available for the post-9/11 period.

Section 2'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. Of course, even without an explicit fee, banks likely would be cautious in how much liquidity support they commit to, and may impose some implicit costs on firms for unused lines of credit. As discussed in great detail later in this article, the empirical concern that may arise is that banks may impose different implicit costs based on firm quality, and since firm quality is not directly observable, this may introduce an omitted-variable bias. We devote a substantial portion of this article (Sections 4.2 and 5) to conducting robustness checks on such empirical concerns and find our results to be robust.

For now, the important aspect of our empirical setting is that a firm's credit line is bounded only by a bank's perception of that 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 firms in Pakistan. A limitation regarding the credit limit variable is that it was not collected by SBP after the first half of 2001 due to a format change in the data that banks had to report, in which several other reported variables were also dropped/added. 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.

3.1.1 Slack "stickiness." The borrowing constraints formalized in Section 2 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 Duflo 2004).

The backward-looking nature of determinants of credit limit is not surprising 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 2(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, Column (2) shows that despite the large net-positive demand shock due to 9/11, there is virtually no effect on the composition of collateral.

Table 2(a)
Banking sector loan collateral requirements

	(1) Pre 9/11 Period	(2) Post 9/11 Period
Percentage of Loan Portfolio that is:		
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
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 2(b)
Credit limit and financial slack attributes

PANEL A : CORRELATION OF FINANCIAL SLACK WITH FIRM ATTRIBUTES

	(1) Financial Slack
Lagged Loan Growth	−0.307***
Log Firm Size	0.044***
Exporting Firm	0.001
Twice Lagged Default Rate	0.007
High Demand Shock Industry	−0.015

PANEL B : CREDIT LIMIT STICKINESS

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

PANEL C : DEMAND SHOCK VARIATION

	(1) Log(Credit Limit Post 2000) – Log(Credit Limit Pre 2000)	(2) Log(Loans Post 2000) – Log(Loans Pre 2000)
High Demand Shock Industry	0.018	0.046
(defined in 2000)	(0.017)	(0.021)
Constant	0.067	−0.002
	(0.013)	(0.013)
Observations	19,355	19,355

This table characterizes the financial slack and credit limit variables. Panel A presents cross-sectional correlations of Initial Financial Slack with various firm attributes. Initial Financial Slack is the log difference between a firm's credit limit and its borrowing in the pre-9/11 period. Lagged Loan Growth is the first difference in log(loans) between the post-9/11 and pre-9/11 periods. Log Firm Size is the log of total loans. Exporting Firm is a dummy = 1 if a firm is an exporter. Twice Lagged Default Rate is the average default rate of each firm in the pre-pre-9/11 period, and default rate is the ratio of defaulted loans to total loans. High Demand Shock Industry is a dummy = 1 for industries including the cement, energy, and construction sectors. Significance levels are indicated by the asterisks. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. Panel B establishes the "stickiness" of credit limits through a simple counting exercise, separately for small and large firms. Panel C examines the relative change in credit limit and loan growth around January 2000 for high-demand shock industries (i.e., those that grew significantly during this period).

Panel A in Table 2(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 likely reflect firm quality, such as its past default history (twice lagged default rate), export status, or with whether the firm was in an industry that experienced substantial growth after 9/11.

Panel B in Table 2(b) provides evidence that credit limits are sluggish and often do not adjust even when firms are pushing against their limits. This is particularly true for smaller firms that are more likely to face constraints. If credit limits were responsive to a firm's growth potential, one would expect that limits would change each year for most firms, as firms 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.

Another test for the stickiness of credit limits is to check if limits respond to positive demand shocks. We can only conduct such a test in the pre-9/11 sample when we have data on credit limits. Column (1) in Panel C shows that credit limit does *not* increase relatively more for firms in industries that experienced a net positive growth over the pre-9/11 period. This suggests that the process of updating credit limits is not very responsive to a firm's future growth potential. Column (2) shows that the firms we identified as belonging to positive-growth industries indeed had somewhat higher loan growth (although likely muted due to the credit constraint limits). Thus, consistent with sticky credit limits, financial slack gets relatively tighter for firms with better growth opportunities, which would bias estimates of the financial slack effect downward.

4. Results: Financial Slack and Borrowing

4.1 Primary specification

Before presenting results from the primary cross-sectional specification, we illustrate the result graphically in the time series. Figure 6 shows how the overall borrowing varies over time between firms that had "low" and "high" slack at the time the 9/11 shock hit. The figure categorizes firms based on whether they are below or above median financial slack at the time of 9/11. We also demean a firm's borrowing in a given quarter by its borrowing in the quarter prior to 9/11. Thus, the vertical axis represents a firm's borrowing relative to 9/11.

Figure 6 not only illustrates our main finding, but also lends credence to our identification assumption. The figure shows that there is no discernible

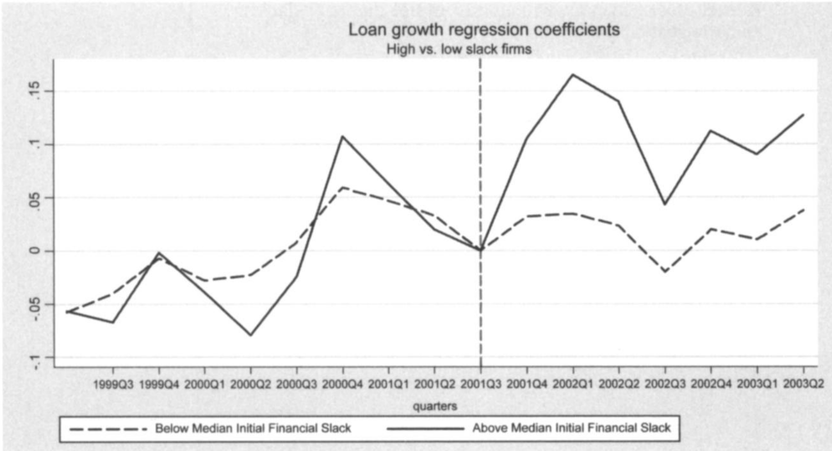

Figure 6
Loan growth regression coefficients: High- vs. low-slack firms
Figure 6 plots the quarter-by-quarter regression coefficients for all quarter dummies from the regression of loan growth on quarter dummies, separately for above- and below-median firms based on Initial Financial Slack, where Initial Financial Slack is the log difference between a firm's credit limit and its borrowing for six quarters prior to 2001Q3. The dependent variable is the log of loans, demeaned at the firm level in each quarter by that firm's borrowing in 2001Q3. Thus, the vertical axis represents growth relative to 9/11.

difference in borrowing between high- and low-slack firms prior to 9/11. However, right after 9/11, the two lines start diverging and the difference between them becomes statistically significant.[11] The financial slack effect is captured by the difference in borrowing levels between the two types of firms after 9/11. The lack of difference between the two prior to 9/11 indicates that the post-9/11 divergence is not a result of any pre-existing trends or because firms that were high-slack at the time of the 9/11 shock were systematically different from low-slack firms.

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 7 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. While the relationship is mostly linear, as one would expect, the graph does seem to flatten out at high values of financial slack.[12]

Table 3 presents the primary regression results. The dependent variable is a firm's borrowing growth over the post- and pre-9/11 periods, and the

[11] Drawing confidence intervals around both lines (not shown to avoid cluttering the figure) shows that while the confidence intervals overlap pre-9/11, they do not do so post-9/11.

[12] The initial part of the graph is also somewhat flatter, suggesting that there may be some "lumpiness" in the investment decision (i.e., firms with small amounts of slack do not (slightly) increase borrowing since the amount may be below the minimum needed to make the investment).

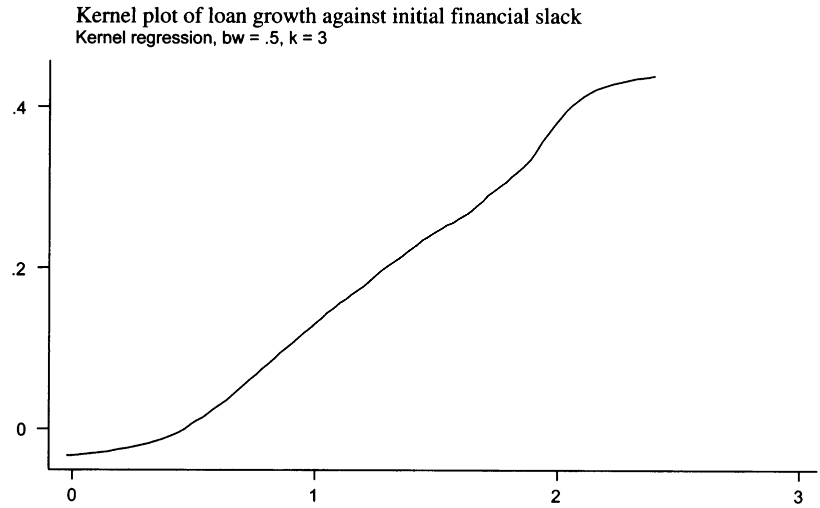

Figure 7
Kernel plot of loan growth against initial financial slack
Figure 7 plots the non-parametric kernel regression of Loan Growth on Initial Financial Slack. Loan Growth is the difference in log(loans) between the post- and pre-9/11 quarters. Initial Financial Slack is the log difference between a firm's credit limit and its borrowing for six quarters prior to 2001Q3.

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 3 is averaged over the previous three quarters, our results are robust to averaging the slack measure even if we average over somewhat shorter or longer time periods.

Section 2 highlighted the identification concern that the results in Columns (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). Columns (5) and (6) do the same by introducing an additional lag.

An alternative specification to check mean reversion is to control for the initial level of borrowing. Column (7) does so and shows that the coefficient on financial slack remains unchanged. To the extent that future loan demand is

Table 3
Does financial slack predict credit growth?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep Var = Loan Growth	All Firms		Firms with Non-Missing Lagged Loan Growth		Firms with Non-Missing Twice Lagged Loan Growth		All Firms		Dep Var = Working Capital Loan Growth
Initial Financial Slack	0.21	0.2	0.18	0.18	0.15	0.160	0.16	0.237	0.226
	(0.020)	(0.016)	(0.015)	(0.017)	(0.016)	(0.019)	(0.016)	(0.021)	(0.025)
Lagged Loan Growth			−0.011		−0.01				
			(0.014)		(0.016)				
Twice Lagged Loan Growth					−0.06				
					(0.015)				
Lagged Log Loan Level							−0.076		
							(0.008)		
								(0.008)	
Constant	−0.06								
	(0.021)								
Industry, City, and Bank FEs		YES	YES	YES	YES	YES	YES	YES	YES
Observations	22,485	22,485	15,156	15,156	9731	9731	22,485	22,485	16,049
R-squared	0.03	0.1	0.09	0.09	0.08	0.08	0.14	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) between the post-9/11 and pre-9/11 periods. Initial Financial Slack is the log difference between a firm's credit limit and its borrowing in the pre-9/11 period. Lagged Loan Growth is the first difference in log(loans) between the pre-9/11 and pre-pre-9/11 periods. Twice Lagged Loan Growth is the first difference in log(loans) between the pre-pre-9/11 period and six quarters before 1998Q2. Lagged Log Loan Level is the log of loans in the pre-9/11 period. Lagged Log Credit Limit is the log of credit limits in the pre-9/11 period. Columns (1)–(2) present results for our full sample. Columns (3)–(4) restrict the sample to firms for whom lagged loan growth data is available. Columns (5)–(6) restrict the sample to firms for whom both lagged loan growth and twice lagged loan growth data are available. Column (9) restricts the LHS variable to only working capital loans. Regression specifications in Columns (2)–(9) 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.

correlated with past growth, these tests also allay concerns that the relationship may be driven by expected loan growth concerns.[13]

An additional concern is that since financial slack is defined as credit limit less actual borrowing, financial slack could be 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. Alternatively, we may be concerned that the slack result is really picking up variation in credit limit across firms, as one may expect if the expected loan growth concerns were important, i.e., a firm that expected to grow in the future would demand greater credit limits now. 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 (7) already showed that this is indeed the case for initial (log) borrowing. Column (8) 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). For example, they may fear that the newfound liquidity is temporary and prone to flight back. Thus, they may hesitate to make longer-term loans against this potentially short-term availability of liquidity, and this concern may be more salient for low-slack firms. However, we feel this concern is unlikely given that our data span a year and a half after 9/11 and the liquidity situation cleared up pretty soon after 9/11. Moreover, the drop in interest rates was permanent and interest rates stayed low for a while. Nevertheless, even under such circumstances, banks should at least be willing to extend short-term working capital loans if firm credit limit constraints are not binding. We therefore rerun specification (5) using only short-term working capital loans. Column (9) shows that the coefficient on financial slack hardly changes (in fact, the point estimate is larger), suggesting that strategic delay/hesitancy by banks to extend credit is unlikely to explain our results.

[13] An alternative test for expected credit growth concerns is to make an extreme assumption that apart from 9/11, all changes in other time periods were entirely driven by anticipation effects. Examining Figure 1(d) shows that the largest interest-rate drop apart from 9/11 occurred during the first half of 2000. Thus, the maximum anticipation effect would likely be over this period. Estimating the financial slack effect for this period shows that it is significantly smaller—almost a third—of the financial slack effect we find after 9/11. Thus, even if we "net out" the maximum financial slack effect over any other (anticipated) period, we still find that the 9/11 slack effect is large and significant, suggesting that anticipation effects are unlikely to be a primary driver of our results.

4.2 Robustness checks—firm quality

We now check for the concern highlighted in Section 2.4 that financial slack may reflect unobserved firm quality due to such firms having greater anticipated demand or a higher option value of retaining financial slack. We should note, though, that Table 2(b) shows that financial slack at the time of 9/11 is negatively correlated with prior credit growth. Since better-quality firms are likely to have higher growth in credit demand, if anything, financial slack would be negatively correlated with firm quality, leading to an underestimate of the true financial slack effect. Nonetheless, we check directly for the concern that financial slack and firm quality may be positively corrected.

Our first check uses the default history of firms in the pre-9/11 period as a measure of firm quality. Recall that our sample was selected on firms that were not in default in the quarters immediately preceding 9/11. However, some firms may have entered default temporarily in the periods prior to this. We therefore compute the average default rate in the "pre-pre-9/11" period as a measure of firm quality and include it as a control in Column (1) of Table 4. The coefficient on this twice lagged default rate in Column (1) is negative, indicating that past default history is indeed correlated with lower credit growth post-9/11 and therefore a plausible measure of firm quality. However, the coefficient on financial slack hardly changes with the inclusion of this firm-quality control.

Table 4
Robustness checks—firm quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep Var = Loan Growth	All Firms	All Multi-Firm Groups		Groups of 2 or 3 Firms Only		Loan Level – Multiple-Bank Firms	
Initial Financial Slack	0.197	0.19	0.20	0.21	0.34	0.079	0.106
	(0.016)	(0.021)	(0.024)	(0.019)	(0.041)	(0.023)	(0.026)
Twice Lagged Default Rate	−0.238						
	(0.050)						
Constant						−0.184	
						(0.025)	
Industry, City, and Bank FEs	YES	YES	YES	YES	YES		
Common Director FEs			YES		YES		
			(4,922 FEs)		(3,811 FEs)		
Observations	22,485	10,678	10,678	4,917	4,917	15,260	15,260
R-squared	0.104	0.1	0.5	0.15	0.85	0.004	0.545

These regressions conduct robustness checks of firm quality with parametric and non-parametric controls. The dependent variable is the first difference in log(loans) between post-9/11 and pre-9/11 periods. Initial Financial Slack is the log difference between a firm's credit limit and its borrowing in the pre-9/11 period. Parametric controls include a measure of firm quality, Twice Lagged Default Rate, which is the average default rate of each firm in the pre-pre-9/11 period. Non-parametric controls include Common Director Fixed Effects. These 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. Columns (1) through (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. Columns (6) and (7) are run on *loan-level* data restricted to firms borrowing from multiple banks at the time of 9/11. Column (7) adds firm FEs. Standard errors are clustered at the dominant-bank level in specifications 1–5 and at the bank level in specifications 6–7.

We next use a non-parametric measure of firm quality based on a firm's directorship. Using 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 common director fixed effects in our main specification, thereby only comparing *within* sets of two or more firms that share a director but differ in their initial financial slack. Since the 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.

We restrict our attention to the subset of firms that have at least one other firm with whom they share management, since firms in single management groups are completely absorbed by the director fixed effect. Column (2) repeats our standard specification on this subsample and shows that the main effect remains unchanged. 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 subsample variation in Column (5). However, the results are even stronger, once again confirming that it is unlikely that firm quality is spuriously generating the coefficient on financial slack.

The regressions so far have been run at the firm level (i.e., we aggregated loan-level data for a given firm across all banking relationships). This was because the theory was based on credit limit constraints at the *firm* level. However, if credit limit constraints are binding at the firm level, then there is also a loan-level *credit allocation* prediction that we can test. In particular, suppose that credit limit is fixed at the firm level for reasons discussed in Section 2, and total credit limit for a firm is divided across two banks. The two banks are aware of each other's credit limits through the central database, thus making sure that their combined limit does not exceed a firm's aggregate debt capacity ($\overline{D}$ in Section 2). If a firm does not use its credit limits proportionately from the two banks, there will be differing financial slacks from the two banks at the time of 9/11. Therefore, in the face of a positive credit demand shock 9/11, a firm will borrow relatively more from the bank with greater financial slack. This is the *within*-firm credit allocation prediction that we test in Column (6).

A key advantage of the credit allocation prediction is that it allows one to use firm fixed effects and hence absorb any differences in firm quality and firm-specific shocks to credit demand. The result confirms the credit allocation prediction, as a firm borrows relatively more from the bank it has greater financial slack with prior to 9/11 shock. Column (6) is naturally restricted to firms with multiple banking relationships, and a unit of observation represents a loan (i.e., a firm-bank pair). While the coefficient on financial slack is smaller, this is entirely due to the sample restriction, as Column (7) shows. Column (7) repeats the test without firm fixed effects and shows that our standard effect is smaller on this subsample. The reduction in financial slack effect is due to the fact that multiple relationship firms tend to be larger in size. We explore the size heterogeneity in greater detail in the next section.

An alternative strategy to including firm fixed effects while still examining overall borrowing would be to estimate an analogous specification to (5) in the time series by utilizing other time periods apart from 9/11. While the financial slack effect remains just as large if we were to do so, we do not present the results from this specification since it necessitates exploiting changes over non-9/11 time periods as well, and this raises significant concerns that the results will be confounded by anticipation effects. An empirical strength of our study is to exploit the fact that the economy experienced a large and clearly unanticipated (positive) liquidity shock during 9/11, and our results are more compelling precisely because they only exploit this unexpected change; including other time periods would undermine this.

The results in Tables 3 and 4 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.

5. Results: Heterogeneity

Result 2 in Section 2 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.

5.1 Demand shocks

While 9/11 was a positive demand shock on average, it affected industries differentially. Specifically, the building materials, construction, energy, and petroleum sectors received a disproportionately larger boom due to reconstruction efforts in Afghanistan. In contrast, industries such as textiles and chemicals did not enjoy such a large boom. The sector-level ranking is based on changes in sector-specific GDP growth rates over this period. This heterogeneity 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

Table 5
Varying demand shocks across industries

Dep Var = Loan Growth	(1) High Demand Shock	(2) Low Demand Shock	(3) Full Sample	(4)	(5)
Initial Financial Slack	0.22	0.1	0.1	0.1	–
	(0.021)	(0.022)	(0.022)	(0.019)	
High Demand Shock * Initial Financial Slack			0.12	0.11	0.08
			(0.024)	(0.020)	(0.021)
Constant	−0.07	0.01	0.007		
	(0.023)	(0.017)	(0.017)		
Industry, City, and Bank FEs				YES	YES
Firm Size FEs and All Interactions with Initial Financial Slack					YES
R-squared	0.04	0.007	0.03	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 include cement, energy, and construction sectors, and Low Demand Shock industries include textiles and chemicals. The industry classification is based on sector-specific GDP growth numbers. Columns (1)–(2) present regression results separately for high- and low-demand shock industries, respectively, and Columns (3)–(5) repeat this exercise in a pooled specification. The dependent variable is the first difference in log(loans) between post-9/11 and pre-9/11 periods. Initial Financial Slack is the log difference between a firm's credit limit and its borrowing in the pre-9/11 period. 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.

able to obtain their desired financing; the coefficient on financial slack will be large.

The results in Table 5 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.

5.2 Firm type

If loan growth responsiveness to initial financial slack is reflective of credit constraints, one would expect this response to be higher for firms facing greater credit constraints. We explore this heterogeneity along two firm characteristics: size and whether a firm exports or not.

5.2.1 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 6 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 larger firms. Column (2) shows that this effect is robust to non-parametrically

Table 6
Firm type heterogeneity—firm size and export status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Firm Size Heterogeneity			Exporter Heterogeneity				
Dep Var = Loan Growth				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			−0.066	0.055	0.055		
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 a dummy = 1 for firms below the 70th percentile in size. The specifications in Columns (1)–(3) also include a Small Firms dummy. Columns (4)–(8) present firm export status heterogeneity results. Columns (4)–(5) present regression results separately 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) between the post-9/11 and pre-9/11 periods. Initial Financial Slack is the log difference between a firm's credit limit and its borrowing in the pre-9/11 period. 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 the 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.

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

5.2.2 Exporters. If there is a set of firms that *do not* face constraints in increasing their credit limit, then the theory implies a simple falsification test: The financial slack effect should be zero for such firms. A look at the lending guidelines of various banks, as well as prudential regulations, shows that exporting firms are a lot less likely to face binding credit limit constraints.[14]

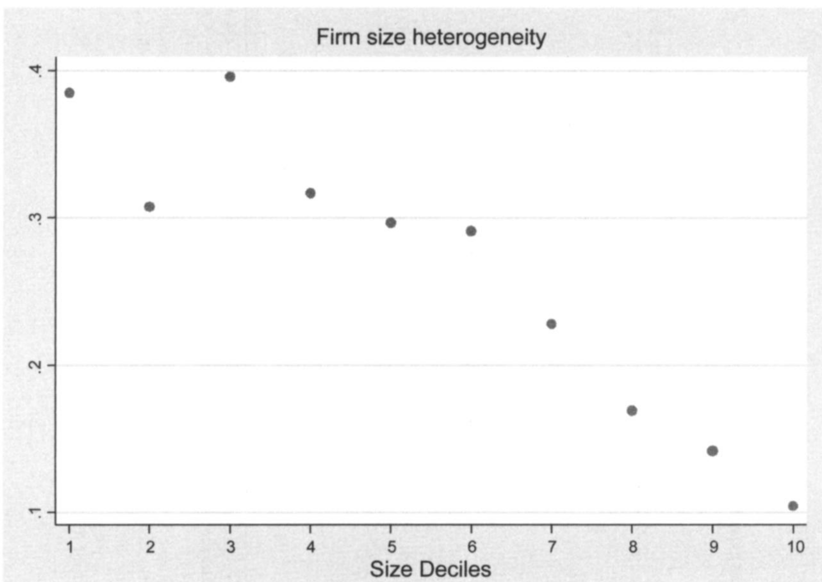

Figure 8
Firm-size heterogeneity
Figure 8 plots the regression coefficients on the interactions of Firm Size Decile dummies with Initial Financial Slack. The dependent variable on these regressions is the first difference in log(loans) post- and pre-9/11 quarters. Initial Financial Slack is the log difference between a firm's credit limit and its borrowing for 6 quarters prior to 2001Q3. All regression coefficients are statistically significat at the 5% level.

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[14] For example, quoting from prudential regulations, "For the purpose of this regulation, the 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."

The reason for this is that future export sales of exporting firms are easily pledgeable, while the same is not true for other firms. Export orders often come from reputable international firms, or are backed by foreign banks. Thus, banks are willing to lend against expected export orders from, say, Levi's, but not against future sales growth in the local market.

The relaxation of lending rules for exporters suggests that exporting firms will be less constrained by balance-sheet variables. Exporters may therefore be able to expand as much as needed when faced with a positive demand shock, regardless of their financial slack at the time of the shock. Columns (4) and (5) in Table 6 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) in Table 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 and significant.

Since 9/11 led to an appreciation of the currency, one may be concerned about the negative terms of trade effect on exporters. In fact, the removal of financial sanctions post-9/11 created a boost for exporters and the net impact on exporters was positive, as the evidence in Figure 2(a) shows. Export growth increased by more than 5 percentage points following 9/11.

Both the exporter and firm-size results offer further support for the financial slack hypothesis. While we would expect a smaller/no effect of initial financial slack on unconstrained firms under this hypothesis (Result 2), alternate explanations do not readily generate such heterogeneity. For example, if the results are driven by mean reversion or anticipation/option value effects due to unobserved firm quality, it is likely that such factors are just as important for exporters/larger firms.[15]

5.3 Bank type

Does the degree of credit limit constraints, and hence financial slack effect, vary across bank types? Table 7 separates loans made by government, private domestic, and foreign banks. Since our primary specification is run at the

15 Admittedly, the ability to detect the financial slack effect in subsamples relies on whether there is underlying variation in financial slack. Our size and export status categories are broad enough that we retain significant variation both in financial slack and loan growth, so this is not a concern.

Table 7
Bank type heterogeneity

Dep Var = Loan Growth	(1)	(2)	(3)	(4)
	Firm Level – All Firms			Loan Level – Multiple-Bank Firms
Initial Financial Slack	0.21	0.17	–	0.150
	(0.050)	(0.024)		(0.038)
Foreign Bank * Initial Financial Slack	−0.04	0.04	0.06	0.022
	(0.059)	(0.036)	(0.043)	(0.061)
Private Bank * Initial Financial Slack	0.01	0.04	0.05	−0.044
	(0.053)	(0.028)	(0.033)	(0.045)
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	0.03	0.1	0.1	0.549

These regressions test for heterogeneous effects based on bank ownership type. The dependent variable is the first difference in log(loans) between the post-9/11 and pre-9/11 periods. Initial Financial Slack is the log difference between a firm's credit limit and its borrowing in the pre-9/11 period. 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 specification 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 are restricted to firms that have relations with multiple banks. Thus, the fixed effects specification compares outcomes for the same firm across different banks. Standard errors in Columns (1)–(3) are clustered at the dominant-bank level, where the dominant bank is where each firm has the largest share of borrowing. Standard errors in Column (4) are clustered at the bank level.

firm level, we assign firms with multiple banks to their lead bank. 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. Finally, Column (4) repeats this test at the loan level, thus exploiting cross-bank differences within the same firm (i.e., using firm fixed effects), and also finds little difference across bank types.

An alternative source of variation across banks is bank liquidity as measured by their deposit growth. The bank-lending channel literature suggests that banks that face lower liquidity reduce lending more. Conversely, one may think that more-liquid banks would not be constrained in their lending. However, as we argue in the conclusion, the mechanism behind this article—constraints on the lending side—is just as likely to hold for liquid banks. Exploring specifications similar to those in Table 7 (regressions not shown) shows that the financial slack effect is the same for banks with varying liquidity. In other words, even banks that see large liquidity gains display as large of a financial slack effect.

These results suggest that the specific form of constraints we have identified arise more due to common factors such as the legal and regulatory environment, rather than variation in bank organizational structures or available liquidity, which may make them conservative and sluggish (Stein 2002).

6. The "Real" Costs of Financing Constraints

A novel feature of our article is that we can directly observe credit limits (and the associated estimate of credit constraints) for all firms in the economy. The results offer evidence for how backward-looking credit limit constraints limit the absorptive capacity of an economy. Thus, a natural question is how large is the macro-impact of our estimates? In other words, 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? While answering this question is extremely challenging and beyond the scope of this article, even a tentative back-of-the-envelope calculation based on the micro-evidence is quite revealing. The limitation of such a question is such that one needs to make certain assumptions regarding the marginal product of capital, and we outline these assumptions and acknowledge their limitations below.

To estimate the aggregate return on credit not lent to firms due to credit limit constraints, we need the amount of such "missed lending," as well as the opportunity cost of missed lending. Suppose that firms with financial slack $s_{i,t-1}$ equal to 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.[16] 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 $\widehat{\beta}_1$ to be 0.2. Since we assume that $s_{i,t-1} = 1$ reflects unconstrained growth and Figure 7 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 $\widehat{\beta}_1$ 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[17]

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

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 generation had the amount been lent to firms. Given that the market price of a firm reflects the present value of

16 As 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 7, 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 that our cutoff of 1 is quite conservative.

17 When $(1\text{-}s)$ is negative for a firm, we set it equal to zero.

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), we get that the net present value of the return to the missed investment would have been Rs 45.4*1.96=88.9 billion rupees, or 2.3% of GDP in 2000.

We should caution that these estimates are intended as illustrations. They are also likely to suffer from biases that could both over- or under-estimate 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 alternative sources at equal cost, there would be no real impact on the economy.

However, Table 8 provides evidence that firms are unable to fully compensate. Keeping the same sample of firms we have in our primary specification (non-defaulters), we ask whether firms that are constrained in the sense of facing less financial slack are relatively 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 percentage of mean default rates for this set of firms, this represents a 50% increase in default rates. Columns (2)–(3) show that the result is robust to additional controls. We should note that the likely interpretation of this result is not that a lack of financial slack induces the firm to enter bankruptcy, but that firms with financial slack are in a better position to take advantage of the new growth opportunities

Table 8
Effect of financial slack on default

	(1)	(2)	(3)	(4)	(5)
Dep Var = Δ *Default Rate*				All Multi-Firm Groups	
Initial Financial Slack	−0.028	−0.031	−0.031	−0.029	−0.019
	(0.006)	(0.005)	(0.005)	(0.005)	(0.003)
Twice Lagged Default Rate			0.197		
			(0.036)		
Industry, City, and Bank FEs		YES	YES	YES	YES
Common Director FEs					YES (4,922 FEs)
Observations	22,485	22,485	22,485	10,678	10,678
R-squared	0.01	0.08	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. The dependent variable is the first difference in default rate between the post-9/11 and pre-9/11 periods. Initial Financial Slack is the log difference between a firm's credit limit and its borrowing in the pre-9/11 period. Parametric controls include a measure of firm quality, Twice Lagged Default Rate, which is the average default rate of each firm in the pre-pre-9/11 period. Non-parametric controls include Common Director Fixed Effects. These 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 Common Director Fixed Effects in the specification. 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 the dominant bank is where each firm has the largest share of borrowing. Standard errors in all specifications are clustered at the dominant-bank level.

due to the availability of external financing. They are consequently less likely to enter financial distress going forward.

Finally, Columns (4)–(5) of Table 8 present evidence on the relative importance of internal credit markets. We focus on firms that are in common-ownership groups (as in Table 4) and 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 due 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.[18]

While we had previously shown the robustness of our results to unobserved firm-quality concerns, one may question whether the financial distress results reflect this concern. This is not the case, since the default measure being considered in Table 8 is future and not past default. If this result indeed reflected unobserved firm quality, we would have expected that initial financial slack would be correlated with past default and thus spuriously generate the results in Table 8. Our previous results show that not only is the main specification robust to introducing such past default history as a control (Column 1, Table 4), but financial slack is not even correlated with past default history (Table 2(b)). Thus, analogous regressions to those in Table 8 (not shown) show that using past (rather then future) default history show no significant effect of financial slack.

While the cost estimates are clearly tentative, they are likely to be underestimates since not only would one expect the rates of return to be higher for constrained firms, but additional costs arise due to the 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.

7. Conclusion

The results show that banks are constrained in their willingness to lend to firms due to agency and informational frictions, even when banks have ample liquidity. This offers an interesting and asymmetric contrast to the findings in the bank-lending channel literature and related work on Pakistan (Khwaja and Mian 2008, henceforth KM). KM use the same data from an earlier time period, and exploit the differential liquidity shocks that banks faced as a result

[18] While one may question whether firm default is a good measure of real outcomes (firms may strategically default), in a related paper on Pakistan, Zia (2008) 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.

of nuclear tests in 1998. The article finds the presence of a large bank-lending channel as banks cut back 60 cents in lending for every dollar drop in liquidity.

Why do banks cut back when faced with a negative liquidity shock, but do not expand on the upside as we find in this article? The answer, outlined in the introduction, comes from recognizing that there are two different frictions at play: a bank-level friction on the bank's borrowing side and a firm-level friction (as in Kiyotaki and Moore 1997) on the bank's lending side.

The bank-level friction binds when banks are hit with a negative liquidity shock, while the firm-level friction binds on the upside. Faced with a negative liquidity shock, banks are unable to borrow from external sources, and hence have to cut back on lending. In the event of a positive liquidity shock, while banks have sufficient liquidity, they are constrained by the "debt capacity" of firms. As our theoretical section outlined, such firm-borrowing limits are the natural outcome of agency issues between the bank and firms.[19] Since bank-level frictions bite on the downside and firm-level frictions bite on the upside, excessive volatility in liquidity can be especially costly for underdeveloped financial markets.

We would like to emphasize that our results do not necessarily imply that either banks or bank regulators are inefficient. As the theoretical framework illustrates, the decision by banks not to expand beyond a firm's credit limit is constrained efficient. Agency frictions force banks to establish backward-looking credit limits. Similarly, central banks may impose credit limit constraints to ensure that moral hazard does not drive banks to ignore agency concerns vis-à-vis borrowing firms. The more lax regulation for exporting firms may also be justified on the grounds that future export sales are much easier to verify and hence pledge against. However, since the fundamental constraint is driven by agency frictions, economy-wide efforts to relax such frictions, such as improvements in rule of law and transparency, should make banks less reliant on backward-looking credit-limit-based lending and increase efficiency (see Liberti and Mian 2008 for evidence).

Finally, there may be further unwelcome implications of banks' inability to pass on positive financial shocks in emerging markets. Sudden liquidity surges may spur excessive speculation, as was witnessed. As banks could not lend

[19] There is a somewhat subtle point here. The KM paper shows that while there is a substantial bank-lending channel, this channel has *no net effect* on large firms (that receive 90% of overall bank credit) because they can substitute out of the bank liquidity shock by borrowing from more-liquid banks. These firms do not face a credit limit constraint, as they only had to *replace* their borrowing loss from one bank by going to another and thus did not seek an enhancement in their aggregate credit limit. A simple example illustrates this further: Suppose the aggregate borrowing of a firm is limited to \$100 due to balance-sheet factors (such as available collateral). When one of the banks that the firm is borrowing from receives a negative liquidity shock, it cuts back lending by, say, \$10 (the lending channel in the KM paper). However, the lending channel has no net effect on the firm because it can go to another, more liquid bank and borrow the loss of \$10 (the firm substitution channel in the KM paper) since that bank willingly increases its credit limit. However, if there is a positive demand and liquidity shock (as we argue was the case after 9/11) and the firm has to borrow \$110, then the banks are not willing to lend the extra amount because the firm does not have sufficient balance-sheet assets, even though banks have sufficient liquidity (the result in this article).

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 fivefold to an all-time record high, but housing prices appreciated at well over 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. Such adverse consequences of capital surges are not unique to Pakistan: Rogoff and Reinhart (2008) show across a range of economies that run-ups in asset prices and subsequent financial crises are often precipitated by large capital inflows.

Appendix

A.1 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:

$$Y_i - c_i K_i \leq Y_i - (K_i - W_i)R, \tag{A1}$$

where $R > 1$ is gross lending interest rate. Condition (A1) implies that for a given investment level K_i, a firm must invest minimum internal funds given by

$$W_i \geq \left(\frac{R - c_i}{R}\right) K_i. \tag{A2}$$

A firm would want to put in the minimum possible internal funds for diversification reasons. Thus, (A2) 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.

A.2 Result 1

First, consider an unconstrained firm. For this firm, its change in borrowing is given by $\Delta d_{it} = \Delta\widetilde{d}_{it} = \gamma(\eta_{it} + \phi_t)$. 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 1, can be written down more formally as

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

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

A.3 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 distributions 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 $\overline{D}_i$ 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 that $\frac{\partial^2 E(\Delta d_{it})}{\partial \omega_i \partial s_{i,t-1}} \geq 0$.

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