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The Effect of Banking Crisis on Bank-Dependent Borrowers[1]

by

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Abstract

We provide causal evidence that adverse capital shocks to banks affect their borrowers' performance negatively. We use an exogenous shock to the U.S. banking system during the Russian crisis of Fall 1998 to separate the effect of borrowers' demand of credit from the supply of credit by the banks. Firms that primarily relied on banks for capital suffered larger valuation losses during this period and subsequently experienced a higher decline in their capital expenditure and profitability as compared to firms that had access to the public-debt market. Consistent with an adverse shock to the supply of credit, crisis-affected banks decreased the quantity of their lending and increased loan interest rates in the post-crisis period significantly more than the unaffected banks. Our results suggest that the global integration of the financial sector can contribute to the propagation of financial shocks from one economy to another through the banking channel.

Keywords : Banking Crisis, Russian Default, Bank Loans, Credit Crunch.

JEL classification codes: G21, G32, D82

1. Introduction

The current subprime mortgage crisis and the associated losses to the U.S. banking system reemphasize the need to understand the impact of shocks to providers of capital on their borrowers. If a firm can easily access external capital markets or switch from one source of private capital to another, then its performance should be insensitive to the shocks experienced by its capital providers. Adverse selection and moral hazard frictions, however, can limit even a profitable and growing firm's ability to raise external capital or to substitute between private sources of capital (Holmstrom and Tirole, 1997).[1]

With such frictions in the economy, shocks that affect banks' ability to supply capital might result in suboptimal investment and working-capital management decisions for firms that extensively depend on them. Therefore, a firm's performance should be sensitive to unanticipated shocks experienced by the suppliers of its capital *over and above* the firm-specific demand-side characteristics such as profitability and growth opportunities.[2] Establishing this link between a borrower's performance and its bank's health has important implications for corporate finance and monetary policies, and in this paper we attempt to provide evidence in support of this link using shocks to the U.S. banking system during the Russian crisis as a natural experiment [see Kho, Lee, and Stulz, 2000 for further discussions about the crisis].

Empirical studies that attempt to establish this relationship face a fundamental identification challenge of separating the effect of firm-specific demand-side shocks (such as profitability and growth opportunity) from the supply-side shock. If deterioration in a bank's

[1]See Diamond, 1984; Ramkrishnan and Thakor, 1984; Leland and Pyle, 1977; Boyd and Prescott, 1986; Rajan 1992; Bernanke and Blinder, 1988; and a large literature surveyed in Gorton and Winton, 2002; and James and Smith, 2000.

[2]It is important to note that the information and/or agency friction should affect both banks and borrowers to produce this outcome. If these frictions only affect firms, then banks can raise enough money from the external market to fund their borrower's positive NPV project. However, due to frictions faced at the level of banks (Stein, 1998), a deterioration in bank-health can affect the supply of bank loans through at least three related channels: (i) there can be a direct reduction in loanable internal funds available with them; (ii) poor bank health may limit their ability to raise external capital; and (iii) due to their lower risk-appetite (e.g., due to capital adequacy constraints), banks may be inclined to change their asset mix in favor of safer securities rather than risky commercial and industrial (C&I) loans.

health is itself caused by its borrowers' poor performance, then researchers face an uphill task in establishing the causation in the other direction (Fama, 1980; King and Plosser, 1984).[3] In addition, if common economic shocks affect the performance of both the banking sector and the real economy, then the task of separating the effect of firm-specific factors from bank-specific shocks becomes more difficult.

We use shocks to the U.S. banking system during the Russian crisis of Fall 1998 to isolate the effect of supply-side frictions on firm performance. The crisis started with an announcement of the Russian government's intention to default on their sovereign debt obligations on August 17, 1998 (Kho, Lee, and Stulz, 2000). Subsequently, related events such as the announcement of the suspension of ruble trading on August 28, 1998, and massive flight of capital from Brazil on September 3, 1998 resulted in a severe financial crisis in the United States during mid-August and early September of 1998. Many U.S. banks had substantial exposure to these two countries, exposing them to significant losses and liquidity constraints during this short period.[4] This resulted in a significant loss of equity capital for several U.S. banks, which in turn adversely affected their ability to make loans. Since the decisions of the Russian government to default on their debt obligations and to suspend the currency convertibility were exogenous to the U.S. economy, we argue that this shock resulted in an exogenous inward shift in the supply of bank loans. This, in turn, allows us to trace a causal link from bank health to borrowers' performance.

First, we exploit the variation generated by this shock across firms that have access to the public-debt market and firms that do not have such access and, therefore, depend solely on their banks for debt. In particular, we make use of the fact that during our crisis period

[3]For example, prior to the failure of Continental Illinois Bank, some of its key borrowers such as International Harvesters and Nucorp Energy had experienced financial distress. Dahiya, Saunders, and Srinivasan (2003) show that there is a significant negative wealth effect for the shareholders of the lead bank when borrowers of the bank experience distress. Their evidence is consistent with the notion that borrowers' health causes deterioration in the bank's health.

[4]Gatev, Strahan, and Schuermann (2004) show that bank stocks performed very poorly during this period, losing over 10% of market capitalization in such a short window. Accounting-based measures also indicate that the banking sector's financial health was under tremendous pressure in late August and early September resulting in a credit crunch for the bank-dependent borrowers [see FDIC's quarterly report for 1998Q3 and 1998Q4].

(i.e., from August 14, 1998 to September 3, 1998), the public-debt market was functioning at reasonably normal levels, whereas banks were severely affected by the events in Russia and Brazil.[5] Thus, by comparing the stock market performance of bank-dependent and rated firms, we hope to isolate the effect of supply shock on firm value.

We find that bank-dependent firms experienced significantly larger valuation loss as compared to their rated counterparts during the crisis period. Other results show that bank-dependent firms cut their capital expenditure significantly more than the rated firms in the quarters immediately following the crisis as compared to the earlier quarters. In addition, their operating profits dropped considerably more in the post-crisis quarters as compared to the corresponding decline for the rated firms. We also investigate the effect of injection of liquidity into the banking sector by the Federal Reserve Bank in the immediate aftermath of the crisis and find that bank-dependent firms recovered a part of their initial valuation loss after these policy interventions.

In our tests we control for several proxies of firm risk, growth opportunities, and other firm characteristics that might influence the stock's return during the crisis period. To further rule out the possibility that our results are driven by large observable differences in the characteristics of rated and bank-dependent firms, we conduct a matched sample analysis. We carefully match rated and bank-dependent firms along the dimensions of firm size, default risk, stock market liquidity, and growth opportunities. We find that bank-dependent firms lose significantly higher equity value than their rated counterparts during the crisis period even on this subsample.

We conduct several tests within the set of bank-dependent firms to further understand the role of supply-side friction on their performance. In these tests we exploit the heterogeneity in their main bank's exposure to the Russian crisis. We first construct a matched sample of bank-dependent firms and their banks using multiple data sources. Using banks' quarterly

[5] During our crisis period (i.e., from August 14, 1998 to September 3, 1998), public-debt markets seemed to be functioning at relatively normal levels as is evident by the modest levels of paper-bill spread - a broadly used measure of the overall liquidity situation in the economy (see Fig, 1). It was only later in October 1998 that liquidity dried up from the public-debt market as well (see Gatev, Strahan, and Schuermann, 2004; Gatev and Strahan, 2006).

call report data and their annual statements, we measure the nature and extent of exposure of these banks to the crisis. We find considerable heterogeneity in the bank's exposure to the crisis, ranging from very high exposure for banks like Citicorp, Bank of America, and Chase Manhattan to little to negligible exposure for banks such as Banc One Corporation, and Wells Fargo. We compare the stock market performance of the borrowers of the affected banks with those of the unaffected banks and find that the affected banks' borrowers experienced significantly higher valuation loss as compared to the unaffected banks' borrowers. This result is especially powerful since it is free from any selection bias concerns that might influence comparison of rated and unrated firms. This result provides more direct evidence on the international propagation of shocks in the real sectors through linkages in the banking sector.

Our next test is also performed within the sample of bank-dependent firms, where we exploit the variation in their ability to obtain funds in a time of credit crunch. When information asymmetry between the lenders and the borrowers leads to credit rationing, borrowers with higher collateral can obtain funds more easily [e.g., see Bester's (1985) extension of Stiglitz and Weiss (1981)]. Collateral also can serve as a mitigating device for moral hazard problems (Tirole, 2006). Motivated by these theoretical models, we use a firm's *unpledged collateral*, i.e., collateral available for future borrowing, as a measure of its ability to negate the adverse consequences of the credit crunch. We find significant evidence that bank-dependent firms with higher unpledged assets perform better.

Our final test directly investigates the lending behavior of banks around the crisis period. We structure our empirical tests in the framework of an equilibrium model of demand and supply of bank credit. With a downward sloping demand curve and an upward sloping supply curve for bank credit, an adverse shock to the bank's capital should result in an inward shift in the supply curve. The supply shock-induced credit crunch, therefore, should result in a decrease in the equilibrium quantity of credit and increase in its price. We find that, as compared to the pre-crisis period, in the post-crisis period, the crisis-affected banks decreased their lending volume and increased loan spreads as compared to the unaffected banks. This evidence is consistent with an inward shift in the loan-supply curve for the bank-dependent borrowers after the Russian crisis.

Our study is related to various strands of literature in banking, corporate finance, and monetary policy. It is closely related to a large literature that studies the effect of bank-borrower relationship and the effect of the bank's health on borrower performance (see important contributions from Slovin, Sushka, and Polonchek, 1993; Kang and Stulz, 2000; Ongena, Smith, and Michalsen, 2003; Khwaja and Mian, 2008; and Parvisini, 2007). Our paper is also related to Peek and Rosengren (2000), Ashcraft (2005), and Garmaise and Moskowitz (2006), who study the real effects of deterioration in bank health or credit market competition. The key contribution of our paper is to exploit a shock that originated in a different geographical region and use it to isolate the supply-side effect. In the process, we are able to trace the *valuation implications* of bank-dependence at the time of crisis. Equally important, our paper provides evidence that as financial markets become integrated, shocks can propagate from one economy to the other through linkages in the banking sector. This has important implications for the monetary policy interventions in light of the increasing integration of the global financial markets.

At a broader level, we contribute to the empirical literature on the special role of banks in mitigating value relevant frictions in the economy (see James, 1987; Puri, 1996; Houston and James, 1996; Hadlock and James, 2002; Dahiya, Puri, and Saunders, 2003; and a large literature surveyed in Gorton and Winton, 2003). Our study is also related to the monetary economics literature on the role of credit channel in the transmission of monetary policy shocks to the real economy (Bernanke, 1983; Bernanke and Blinder, 1992; Kashyap, Stein, and Wilcox, 1993; Gertler and Gilchrist, 1994; and Kashyap and Stein, 2000). Finally, we contribute to the broader debate on the role of debt market in easing access to funds as well as the effect of financial constraints on corporate financial policies (Fazzari, Hubbard and Petersen, 1988; Whited, 1992; Kaplan and Zingales, 1997; Sufi, 2009; and Lemmon and Roberts, 2007).

Our results also have implications for the effect of the current subprime mortgage crisis on the real sector. Within the U.S., bank-dependent borrowers of banks that have been more adversely affected by the subprime mortgage crisis are predicted to be more severely affected by the crisis. In addition, countries with tighter linkages of their banking system with the U.S. banking system are predicted to be affected more severely by the crisis. These topics have been left for future research.

The rest of the paper is organized as follows. In Section 2, we describe the banking crisis of Fall 1998 and our identification strategy in more detail. Section 3 describes the data. Section 4 presents the empirical results and Section 5 concludes the paper.

2. Russian crisis and identification strategy

In the Fall of 1998, several important events took place in the international financial markets. On August 17, 1998, the Russian currency was devalued and the government announced its intention to default on sovereign debt obligations. On August 28, ruble convertibility was suspended. In related events, on September 3, 1998, there was a significant outflow of capital from Brazil. LTCM's losses became public news on September 2, 1998. All these events caused significant losses to the U.S. banks during late August and early September of 1998 as evidenced by a sharp decline in banks' stock prices over this period.

There were many reasons for banks' losses including (a) direct exposure to the Russian government bonds, (b) exposure to the Russian private borrowers, (b) losses in the derivatives market, (c) losses on brokerage credit to LTCM, and (e) increased counter-party risks in the U.S. banking system. Gatev et al. (2004) show that an equally weighted bank price index fell by about 11% during this two-week period. They also show a dramatic increase in the stock return volatility, a measure of banks' overall risk, over this time period. Fissel et al. (2006) find that default spreads on bank subordinated debt increased significantly during this period.

Accounting-based measures of bank performance confirm the deterioration in bank health obtained from the forward-looking market-based measures. FDIC's quarterly report for 1998Q3 shows that during the crisis quarter, banks made remarkably higher charge-offs and incurred significant losses on account of their overseas operations. Banks lost a significant amount of their capital in this period (Gorton and Winton, 2003). Such a large loss in their capitalization along with a dramatic increase in their risks directly compromised the banks' ability to supply funds to their borrowers. The possibility of a credit crunch induced by this adverse shock to the bank capital forms the basis of our analysis in this paper.

To directly analyze the effect of this crisis on the supply of bank loans, we obtain data on loan issuance from the Loan Pricing Corporation's Dealscan database.[6] We collect all loans on a monthly basis from this database and classify firms as bank-dependent or not based on their access to the public-debt market. We focus on the six-month period before (i.e., from February 1998 to July 1998) and after (i.e., from August 1998 to January 1999) the crisis for our analysis.[7] Next, we compute the period-by-period growth in supply of loans by simply estimating the growth in number and amount of loans for a given period as compared to the previous six-month period. As shown in Fig. 2, there is a remarkable drop (21–28%) in both the number and amount of loans issued after the crisis as compared to the pre-crisis period. The decline in the issuance of new loans is more pronounced in the subsample of bank-dependent firms.

When we analyze the commercial paper (CP) rate (see Fig. 1), a proxy for liquidity shock for the overall economy, we do not find any abnormal patterns during the event window, i.e., in the event window of August 14, 1998 to September 4, 1998. Unreported analyses also show that the yields on corporate debt and outstanding volume of Commercial Papers for non-financial firms in this period remained broadly in line with the earlier periods. Thus, this period presents a unique setting where banks suffered huge losses, but the liquidity in the public-debt market remained at the normal levels. We exploit this feature of the economy to investigate the effect of bank health on their borrowers' performance.

[6] It is worth noting that unlike the call-report data that provides quarterly information on loans disbursed to the borrowers that may be related to prior commitments, the Dealscan database allows us to capture the incremental decisions of bank managers by focusing on sanctions of new loans around this period.

[7] Results are similar for other reasonable windows, such as three months or nine months, around the crisis period.

2.1. Identification strategy

Our interest is in estimating the effect of adverse shocks to the capital of the suppliers of credit on their borrowers' performance. To motivate our empirical design, we consider a model of the following general form:

$$Y_{it} = \alpha + \beta f(demandshock)_{it} + \gamma g(supplyshock)_{it} + \epsilon_{it}.$$

Y_{it} is a measure of firm i's performance such as its value at time t. $f(demandshock)$ denotes firm-specific factors such as shocks to its profitability and growth rates that are likely to have an influence on Y_{it}. $g(supplyshock)$ measures shocks experienced by the supplier of the firm's capital and our goal is to estimate γ, the coefficient on this variable. The main difficulty in this estimation exercise lies in clearly isolating the effect of a supply shock from correlated demand shocks. Poor economic conditions often lead to an overall decline in the banking sector's financial health as well as a deterioration in the corporate sector's investment opportunity set at the same time. Additionally, the estimate can be biased due to the reverse causality since poor performance of the corporate sector can in itself *cause* a deterioration in the performance of the banking sector.

Our identification strategy is aimed at exploiting an exogenous perturbation of the supply-shock function for U.S. banks during the Russian crisis. Since the crisis was reasonably exogenous to the U.S. borrowers' demand shocks, it perturbed the supply of credit disproportionately more for the bank-dependent firms as compared to their rated counterparts. This exogenous shock to the supply-side function allows us to estimate the causal effect of banks' ability to supply funds on their borrowers' performance. In the base case, we estimate the following cross-sectional regression model to estimate the effect of this shock on firm value:

$$r_i = \beta_0 + \beta_1 bankdep_i + \sum_{k=1}^{k=K} \phi_k X_i + \epsilon_i.$$

where r_i is the market model adjusted stock return of firm i during the crisis period.[8] We first compare bank-dependent firms with their rated counterparts to exploit the disproportionate effect of this crisis on the banking sector as compared to the public-debt market. Second, within the set of bank-dependent firms, we compare the performance of firms that rely heavily on banks affected by the Russian crisis with firms that do not. The second test allows us to exploit the variation generated by the intensity of shocks experienced by different banks during the Russian crisis. X_i^k is a set of control variables discussed below.

2.2. Alternative hypotheses

We are mainly concerned with four alternative channels that might differentially affect the value of rated and bank-dependent firms at the time of crisis. They are: (i) firm size, (ii) default risk, (iii) growth opportunities, and (iv) stock market liquidity. There are several reasons to expect a relation between firm size and stock returns during the crisis period. As compared to large firms, small firms are more likely to have higher operating risks. They are also more likely to face asymmetric information problems and they are less likely to have access to alternative sources of funds. All these factors can have an impact on the firm's valuation during the crisis period, which is independent of the bank channel that we are primarily interested in. Since bank-dependent firms are much smaller than the rated firms, we need to separate the effect of firm size from the access-to-capital effect that we intend to capture.

The second alternative channel is the firm's default-risk. Firms with high risk of default are likely to be more sensitive to economic downturns than their low default-risk counterparts. The increased possibility of bankruptcy as well as the higher incidence of indirect bankruptcy costs can result in larger downward revision in the valuation of high default-risk stocks. In addition, high default-risk stocks may suffer large valuation loss due to the increased risk-

[8]We use the standard event-study methodology to compute the market model adjusted return (Kothari and Warner, 2005). For every sample firm, first we estimate the market-model beta using 250 trading days, ending 50 trading days prior to the crisis period. Based on these beta estimates, we compute the market-model adjusted returns for the event window for all firms.

aversion during the crisis period. Investors may shift their capital from riskier to safer assets purely out of increased risk-aversion concerns during a period of crisis. This *flight-to-quality* consideration has been one of the most widely discussed implications of the Russian crisis in the popular press. We want to separate the effect of *flight-to-quality* due to *poor credit quality* of firms from the *poor access to capital*.

We follow recent models developed in the credit risk literature to obtain meaningful proxies of default risk. There are two popular models of credit risk used in the literature. One is based on a reduced-form statistical approach, popularly known as the hazard-rate model; whereas the other is based on a structural modeling of a firm's equity as a call option on the firm value. The hazard-rate model (see Shumway, 2001; Chava and Jarrow, 2004) uses a maximum-likelihood approach to estimate a firm's default likelihood conditional on a set of observable characteristics. These papers show that a firm's size, past stock return, stock return volatility, and leverage are the most important determinants of its default risk. The structural approach solves for the distance-to-default and effectively measures how many standard deviations away a firm's value is from the default threshold. We compute the distance-to-default measure based on Merton-model and use it as a proxy for default risk (see Bharath and Shumway, 2008; Chava and Purnanandam, 2008). In addition, motivated by the hazard model literature, we also use firm size, past stock return, leverage, and return volatility as controls for default risk. The distance-to-default estimate is obviously correlated with these covariates, but it might contain additional information since it is a non-linear combination of these variables.[9]

The third alternative channel is the firm's growth opportunity set. Growth opportunities affect the demand of capital and firms' subsequent investments and cash flows. If firms with different growth opportunities respond differently to the crisis and if there are significant differences in the bank-dependent and rated firm's growth rates, then we need to account for this channel. We use market-to-book ratio and industry fixed effects as proxies for growth opportunities.

[9] Our results are robust to using either the distance-to-default measure or the set of other covariates alone.

Finally, we control for the firm's liquidity in the stock market. The stock market liquidity, i.e., the ease with which a firm's stock can be bought and sold in the market, can have an impact on a firm's stock return during the crisis period. A large quantity of stock sold during the crisis period can result in a relatively larger price drop for illiquid stocks as compared to their liquid counterparts. If bank-dependent firms have higher price impact of trades than their rated counterparts, then some of the drop in their stock value can be explained by this trading channel rather than the lack of access to capital. For example, if there is a higher likelihood of adverse selection in trades of bank-dependent firms, then they might have higher price impact of trade (Kyle, 1985). We measure stock market liquidity by the proportional bid-ask spread computed using daily stock price data over the past three months.

3. Data, sample construction and descriptive statistics

We obtain accounting and return data from Compustat (active and research) and CRSP tapes, respectively. We start with all firms in the intersection of these two databases having information on stock returns for the crisis period and sales and total assets for the prior fiscal year. We remove financial firms (SIC codes between 6000 and 6999) and utilities (SIC codes between 4910 and 4940). To remove the effect of bid-ask bounce from our analysis, we also exclude firms with less than a $1 stock price as of the end of the prior fiscal year. To prevent outliers from affecting our results, we winsorize data at 1% and 99% in all our analyses.

We remove firms with exposure to the crisis-affected regions. We do so to prevent any demand-side considerations from affecting our results. From the Compustat Geographical Segments file, we obtain data on all geographic segments of the firms for the prior fiscal year. If a firm reports operations in Russia or Brazil, we remove it from our sample. Instead of reporting country-level segments, many firms club their operations in various countries into a bigger geographical area such as Europe or South America. To make sure that our results are not driven by demand-side considerations, we adopt a conservative screening criteria and remove all firms that report any business activity in Russia, Brazil, Europe, Eurasia, Eastern

Europe, or South America.

In line with the earlier papers such as Kashyap, Lamont, and Stein (1994), we use the absence of public-debt rating as the proxy for bank-dependence. We drop junk-rated firms from the sample since we are interested in comparing bank-dependent firms with firms that have better access to capital in the public-debt market. In a time of crisis of this magnitude, investment-grade rated firms are likely to have better access to alternative sources of capital in both the public-debt market and the commercial-paper market. Not surprisingly, none of the junk-rated firms have access to the commercial-paper market as compared to approximately 50% for the investment-grade rated firms that do. As we explain later, eventually we compare the bank-dependent firms with rated firms with similar default risk, which minimizes any concern about our results being driven by differences in credit risk of these two groups of firms.

A firm without debt will always be classified as a bank-dependent firm in this classification scheme, since such firms do not have public-debt ratings. These firms may be either completely rationed by the debt market due to informational frictions (Stiglitz and Weiss, 1981) or they may have chosen not to rely on debt financing even though they could have accessed the public-debt market. Thus, for these firms it is not clear if the lack of a public-debt rating can be taken as a meaningful proxy for bank dependence. To avoid any potential misclassification errors, we remove from our sample firms with zero debt in the prior fiscal year. This leaves us with a sample of 2,665 bank-dependent and 304 rated firms for our base case analysis.

All accounting and market variables used in the study are obtained as of May 1998. The accounting data is lagged so that the information is available to the market during the event period. Table 1 provides descriptive statistics for the sample. The average rated firm has annual sales of $2.8 billion, which is more than six times larger than the average bank-dependent firm. There are other remarkable differences across the two groups, notably in terms of their default risk, equity return volatility, leverage, profitability, and bid-ask spread. The average bank-dependent firm is significantly riskier than the rated firm based on the default risk measure. Bank-dependent firms also have higher effective bid-ask spreads than the rated firms.

Overall, we find that there are considerable differences in the size, default risk, and stock market liquidity of rated and bank-dependent firms. Since these characteristics by themselves can explain the return differential between the two groups, we need to properly account for them in our analysis. One approach is to use a linear regression model that controls for these effects. The advantage of this approach is that we can make use of the entire sample and our inference will not suffer from the external validity considerations. However, given the large differences, especially in the firm size in the two groups, a matched sample approach is also appealing. In such an approach, we have the advantage of finding rated and bank-dependent firms in the common-support zone, i,e., in a range of broadly comparable size, default risk, and liquidity position. In Fig. 3, we plot the distribution of firm size for the rated and unrated firms. As shown in Table 1, the rated firms' size distribution is shifted considerably to the right of the bank-dependent firms. However, the upper tail of the bank-dependent firms' distribution has reasonable overlap with the lower tail of the rated firms. In our matching technique, we effectively exploit the variation across rated and bank-dependent firms in the overlap zone.

4. Results

We first provide regression results based on the entire sample of rated and bank-dependent firms, followed by a matched sample analysis. In later sections, we exploit the variation within the subsample of bank-dependent firms.

4.1. Full sample analysis

Table 1 presents the distribution of returns across rated and bank-dependent firms during the crisis period. In the 16-day crisis period that started one trading day before the Russian debt default and ended one trading day after the onset of the Brazilian crisis, the median (mean) bank-dependent firm earned -9.23% (-10.31%) market-model adjusted return as compared to -2.02%(-2.74%) for the rated firms. The differences in both the mean and median returns are statistically significant at the 1% level.

In Table 2, we provide the regression result for the base model. All models include industry fixed effects based on Fama-French industry classification. Model 1 shows that bank-dependent firms earned -3.61% lower return than firms with access to the public-debt market after controlling for firm size, leverage, and market-to-book ratio. It also shows that larger firms and firms with lower leverage earned better returns. We include several additional variables in Model 2 motivated by alternative hypotheses discussed earlier. In order to avoid a skewness problem with distance-to-default measure of risk, we first rank all firms into percentiles based on their default likelihood. We use the percentile ranking as the covariate in the regression model. We include the average bid-ask spread, calculated over the past three months, to account for the liquidity differences. In addition, motivated by the hazard rate estimates of default-likelihood, we include the prior year's stock return, return volatility, and firms' profitability as measured by its EBIDTA-to-sales ratio in the model. The estimate on *bankdep* drops marginally to -3.10% in this specification, which remains significant at the 1% statistical level.

Other estimates show that stocks with high default risk, high equity return volatility, and high past returns experienced a larger value drop during this period. In this regression, we find a positive coefficient on the bid-ask spread, indicating that illiquid stocks performed better. We investigate this further and find that the relationship between spread and returns is negative at the univariate level. This relationship reverses in the multivariate regression after we control for the firm size. One potential explanation of this finding is that large institutional investors are more likely to sell their holdings of liquid stocks during the period of crisis to generate immediate cash flows. This, in turn, causes greater decline in the equity prices of liquid stocks during periods of crisis (Pasquariello, 2007).

In Model 3, we include the interaction of market-to-book ratio with the bank-dependent indicator variable. We do so to investigate the effect of supply shock across firms with varying intensity of growth opportunities. We conjecture that the valuation effect is likely to be higher for those bank-dependent firms that are likely to forego positive NPV projects due to the lack of funds. These are more likely to be growth firms. The results from Model 3 confirm this intuition. Within the set of bank-dependent firms, firms with high market-to-book (mtb) ratio earn considerably lower returns. In this specification, the coefficient on market-to-book ratio becomes positive and significant. Together, these results indicate that the growth firms with access to the public-debt market performed well during the crisis period. In contrast, bank-dependent growth firms lost considerable market value. In unreported tests, we also include the interaction of *bankdep* with other explanatory variables of the model. We find that the negative coefficient on the interaction of *bankdep* and *mtb* remains robust to the inclusion of these other interaction terms in the model.

4.1.1. Returns during a random period

Our estimation exercise is based on one shock experienced during Fall 1998. To benchmark our results against any random period, we undertake a bootstrapping exercise. Our goal is to re-estimate the regression model of Table 2 for several randomly generated samples of 16 contiguous days of stock returns in exactly the same manner as we do for the crisis period. This allows us to compare the crisis-period return with an empirically generated distribution of returns from the random periods. This approach is analogous to a portfolio-based approach of stock returns where we consider bank-dependent firms as a portfolio of stocks with some unique characteristics and compare this portfolio's return during the Russian crisis with its return during other *normal* periods. This test also allows us to compute the statistical significance of our results after accounting for any non-normality in the data. Finally, it allows us to comment on the economic magnitude of our results as compared to a random period.

We perform the bootstrapping exercise for 100 randomly generated 16-day period returns drawn between January 1985 and December 1998. For every random period, we obtain the accounting variables from the Compustat tapes for the prior fiscal years. We then estimate the Model 1 of Table 2 and collect the coefficient estimate on the *bankdep* variable. The empirical distribution of these estimates is provided in Panel B of Table 2. In the median period, the estimate on the bank-dependent indicator variable is an insignificant -0.17% as compared to our crisis period estimate of -3.61%. There is a slight negative skewness in the empirical distribution; other than that, the distribution is fairly evenly distributed on both sides of the mean. Our crisis-period estimate of -3.61% falls below the first percentile estimate of -2.52%. These estimates provide confidence in the economic and statistical significance of our results.

We extend this exercise by generating a bootstrapped sample solely from the periods of low market returns. This exercise allows us to rule out the possibility that bank-dependent firms always perform worse than their rated counterparts during periods with large negative market returns. We find 21 non-overlapping periods with lower than -5% market returns in 16 contiguous trading days during 1985–1997. We repeat the regression estimation for these samples and present the distribution of estimated coefficients on the *bankdep* variable in Panel B of Table 2.[10] The results show that the abnormally low return of bank-dependent firms during the Fall of 1998 is not an artifact of low returns of these firms during any market downturn. In fact, the estimated coefficient of -3.61% for our estimation period is lower than the coefficient that we find for each of the 21 periods considered in the bootstrapped exercise. Overall, these results establish that bank-dependent firms were more adversely affected than their rated counterparts during the Russian crisis of 1998.

4.1.2. Other measures of financial constraints

It is an extremely challenging task to find a good proxy of financial constraint. Since the Russian crisis had a disproportionately larger impact on the banking sector, we focus on lack of access to the public-debt market as the key proxy for financial constraint in this paper. We consider two alternative measures in the robustness exercise. We first consider a firm's

[10]Since there are only 21 coefficients for this exercise, the percentile values are coarser. For example, the value corresponding to the bottom one percentile equals the minimum value of estimated coefficients across all periods.

age as an alternative measure of financial constraint since older firms are likely to have better credit history allowing them to overcome informational frictions in raising external capital. They also have a longer history of access to the public equity markets, which can further alleviate financial constraints (see Holod and Peek, 2006). We compute a firm's age based on the date of its listing on a public stock exchange. We regress crisis-period equity returns on this measure and provide the results in Models 1 and 2 of Panel A, Table 3. We find that younger firms have significantly lower returns than older firms during this period, consistent with our main argument that firms that are more likely to face frictions in raising external capital at the time of crisis experience more negative returns.

Our second measure is not a direct measure of financial constraint per se, but a measure of the firm's dependence on external financing based on Rajan and Zingales (1998). We hypothesize that firms that rely more on external capital are more likely to suffer from unanticipated shocks to the banking sector. For every firm, we compute a measure of external financing dependence by computing the difference between total investments (Compustat data item 311) and cash flow from operations (item 308) scaled by cash flow from operations. To minimize the outlier problems, we construct this measure at the industry level based on four-digit SIC codes. We compute the median ratio for every industry in a year and then take the median across all years from 1987 to 1997 as the measure of external dependence. We re-estimate the regression model using this *exdep* measure as a proxy for the likely adverse effect of the Russian crisis. Since the key explanatory variable is industry specific, we do not include industry fixed effects in these models. All standard errors, however, are clustered at the industry level. Results are provided in Models 3 and 4 of Panel A, Table 3. We find that firms that are more dependent on external financing have significantly higher valuation losses.

A useful extension of our analysis will be to compare the effect of this crisis on firms with and without access to the public equity market. Since our exercise only includes publicly traded firms, we are unable to conduct this analysis in the paper. Some recent papers have made considerable progress on this dimension by analyzing the effect of liquidity shocks on publicly traded versus private banks (Holod and Peek, 2006; Ashcraft and Bleakley, 2006). Our proxy based on a firm's age since its listing is in the spirit of these papers.

4.1.3. Effect on investments and profitability

We focus on stock returns during the crisis period as the key outcome variable since it allows us to sharply detect the unanticipated effect of the crisis on firm value. The market-based analysis is also relatively immune to the effect of subsequent policy interventions by the Fed in response to the crisis itself. As a complement to the stock return-based analysis, we study the effect of the crisis on the firm's real outcomes as well. We do so by estimating the following firm fixed effect regression model:

$$Y_{iq} = \alpha_i + \beta bankdep_i + \gamma after_q + \theta bankdep_i * after_q + \epsilon_{iq}.$$

Y_{iq} measures real outcome such as investments and profitability of firm i in quarter q; α_i denotes firm fixed effects; $bankdep_i$ is an indicator variable for bank-dependence; $after_q$ equals zero for quarters before 1998Q3, and one otherwise. Since *bankdep* is a time-invariant variable for a firm in our sample, it is subsumed by the firm fixed effect in the regression model. We identify the effect of the crisis on firms' real outcome by the coefficient on the interaction term. It measures the changes in real outcome for bank-dependent firms around the crisis quarters as compared to changes experienced by their rated counterparts over the same time period. We estimate this model using data from six quarters before the crisis and six quarters after it, i.e., from 1997Q1 to 1999Q4.[11]

We consider two measures of performance: (i) capital expenditure scaled by lagged asset (quarterly investments calculated from Compustat data item 90 scaled by lagged value of item 44), and (ii) operating income to total asset ratio (item 8 scaled by lagged value of item 44). Results are provided in Panel B of Table 3. In Model 1 we find that bank-dependent firms cut their investments significantly after the crisis as compared to their

[11]Results are robust to alternative windows around the crisis period.

rated counterparts. The coefficient on the interaction of *bankdep* and *after* is about 22% of the median level of quarterly investments by the sample firms. Therefore, the decrease in investments by bank-dependent firms is strong in economic terms as well. In Model 2, we show that bank-dependent firms experienced significant decline in their operating profits. The estimated decrease in profitability is about 67% of the sample median. These results show the detrimental effect of the crisis on bank-dependent firms' real outcomes, consistent with the negative equity returns experienced by these firms during the crisis period.

4.1.4. Liquidity injection by the Fed

Subsequent to the Russian crisis and the collapse of LTCM, the Federal Reserve Bank held two important meetings in Fall 1998. In these meetings several measures were undertaken by the Fed to provide liquidity support to the banking sector. The same theoretical argument that predicts a negative effect of poor bank-health on bank-dependent borrowers also implies that these firms should perform better when the banking system receives unexpected positive shocks from the policy makers.

On September 29, 1998, the Federal Reserve Bank cut the Fed Funds rate by 25 basis points. This action was somewhat expected by the market. Subsequently on October 15, in a largely unanticipated move the Fed Funds rate was decreased by 25 basis points. The discount lending rate was also cut by the same magnitude in the October meeting. Since the Fed rarely altered the discount lending rate during that period, we expect to find a larger effect of the October 15 FOMC actions as compared to the September 29 meeting.

We regress the market-model adjusted return around a two-day window surrounding these meetings on the bank-dependence dummy and other control variables. Results are provided in Table 4. We find that bank-dependent firms earned 0.65%–0.97% higher returns than firms with access to the public-debt market around the September meeting (Models 1 and 2), which is significant in one of the two specifications. Around the October meeting, bank-dependent firms earned about 1.10% higher returns, which is economically large and statistically significant for both specifications (Models 3 and 4). These findings lend further support to our argument, in a reverse direction, that the market value of bank-dependent firms significantly depends on the financial health of the banking sector and its ability to supply loans to borrowers.

4.2. Matched sample analysis

Given the disparity in some observable characteristics of rated and bank-dependent firms, we now conduct a matched sample analysis. We find pairs of bank-dependent and rated firms that are identical along every meaningful dimension except for the access to the public-debt market. The dimensions along which we match are motivated by competing hypotheses outlined earlier.

4.2.1. Propensity score matching

We use a propensity score method for the matching exercise (Rosenbaum and Rubin, 1983). In the first step, a probit model is estimated with the presence of public-debt rating as the binary dependent variable. We model this choice as a function of the firm's size, market-to-book ratio, leverage, past stock return, stock market liquidity, profitability, and default risk. In addition, we add Fama-French industry dummies to control for industry-specific factors.

Model 1 (*pre-match*) of Table 5 presents the estimation results. The propensity of obtaining a credit rating is positively correlated with firm size, leverage, and profitability; and negatively correlated with equity return volatility and past stock returns. We obtain a pseudo *R-square* of 70%, which indicates a reasonable fit of the model.[12] After estimating the probit model, we obtain the probability of getting rated (i.e., the propensity score) for every firm in the sample. In the final step, for every bank-dependent firm we find a rated firm with the closest propensity score. We ensure that the rated firm's propensity score is within +/-2.5% of the bank-dependent firm's score.[13] This technique uses the nearest

[12] It is worth noting that this estimation exercise is not intended for making any causal inferences about a firm's choice of obtaining a credit rating. Our limited goal is to project relevant firm characteristics on the bank-dependence choice and use the resulting likelihood score as the matching dimension.

[13] Our results are robust to changing this band to +/-5% or other comparable range.

neighborhood caliper matching approach of Cochran and Rubin (1973). We face a trade-off in terms of finding a unique rated firm as a match for every bank-dependent firm and the sample size. This, in turn, presents a trade-off between bias and efficiency in our analysis. To maximize the number of firms in our sample, we allow a rated firm to serve as a match for up to three bank-dependent firms.[14] In a setting like ours, where we have many more subjects in the treatment group as compared to the control group, it is advisable to have one control firm serve as a match for multiple treatment firms (see Dahejia and Wahba, 2002; Smith and Todd, 2005).

The matching exercise yields a sample of 235 bank-dependent firms that could get matched with a rated firm, resulting in a sample size of 470 firms. Since one rated firm can serve as a match for multiple bank-dependent firms, we ensure that all standard errors are clustered at the firm level in analysis involving the matched sample.

Before computing the difference-in-difference estimate on the matched sample, we analyze the efficacy of our matching technique. We estimate the probit model of obtaining a rating on the matched sample and present the results in Model 2 (*post-match*) of Table 5. None of the variables is significant in this estimation, indicating that after the match firms are equally balanced between rated and bank-dependent groups along these dimensions. The model's R-squared, not surprisingly, drops to 4.5% on the matched sample.

In Fig. 3, we plot the distribution of two key characteristics of the firms before and after the matching exercise. As explained earlier, there is a large difference in the distribution of firm size before the matching. After the matching, however, the distributions of rated and unrated firms are almost identical. A quick glance at the figure reveals that the post-matched sample consists of reasonably large firms in both groups. The second plot is for the firm's default risk as measured by its distance-to-default. The bank-dependent firms have higher default risk as compared to the rated firms before the match. After the match, the distribution is almost identical. In a nutshell, the matched sample is equally balanced on the observable dimensions that might influence stock returns during this period.

[14] Our results are robust with two or four repetitions.

4.2.2. Results

The matched sample results are provided in Table 6. The bank-dependent firms earned an average return of -6.61% as compared to -2.67% for the rated firms during the crisis period. The difference of -3.94% is significant at the 1% level. We find similar patterns for the median as well as the entire distribution of returns (unreported).

We also conduct a bootstrapping test similar to the test on the entire sample. For each bootstrapping period, we create a matched sample of bank-dependent and rated firms using the propensity score matching in exactly the same manner as in our main exercise. Then, we compare the returns of the two groups and report their empirical distribution in Panel B of Table 6. There is a positive but insignificant difference of ten basis points between these two groups in the average random period. The empirical distribution reveals that there is only a 1% chance of getting a return difference of -4.09% or lower for the bank-dependent firms as compared to their matched rated counterparts. The crisis period return difference of -3.94% is very close to this number. Similar to the full sample study, we also generate random samples from the periods of very low market returns only. Based on the empirically generated distribution from these periods, we find that the crisis period return difference falls between the first and the fifth percentiles of the distribution (see Panel B of Table 6).

4.2.3. Other matching criteria

As a robustness check, we adopt a dimension-by-dimension matching approach as opposed to the propensity score-based method. For every bank-dependent firm, we find all rated firms in the same industry within +/-25% of the bank-dependent firm's size. From all rated firms in this band, we pick the closest firm in terms of distance-to-default. As before, we allow a rated firm to serve as a match for up to three bank-dependent firms. The advantage of this approach is that it ensures as precise a match as possible on the dimension of firm size. Results are provided in Model 4 of Panel A of Table 6. Bank-dependent firms significantly underperformed their rated counterparts by 3.61% during the crisis period on this subsample.

4.3. Evidence from variations within bank-dependent borrowers

We now exploit the variation across bank-dependent firms' ability to raise external capital. This test allows us to meaningfully relate the frictions in raising external capital to firm value. In addition, since we draw inferences based on the bank-dependent subsample only, this analysis does not suffer from any biases created by observable or unobservable differences across rated and unrated firms.

We investigate if other sources of funds or financial flexibility mitigate the negative effect of bank dependence during the time of crisis. A bank-dependent firm can weaken its dependence on banks by maintaining higher financial flexibility through free borrowing capacity. We proxy a firm's free borrowing capacity by the extent of unpledged tangible assets available at the time of the crisis. In a lending market with adverse selection problems, collateral can serve as a mechanism to alleviate the lemons problem (see Bester, 1985; Besanko and Thakor, 1987). We hypothesize that a bank-dependent firm with a higher fraction of *unpledged* assets should suffer less. These firms should be able to raise funds relatively easily by offering their collateral at the time of crisis.

Dealscan database allows us to investigate this hypothesis since it provides information on whether a bank loan is secured or not. By definition, bank-dependent borrowers have only borrowed from banks. Therefore, by observing their past borrowing in this data set, we are able to construct a reasonable estimate of the total secured loans.[15] We obtain all bank loans outstanding at the time of the crisis and gather information on whether they are secured or not. Our sample size decreases to 630 bank-dependent firms for this analysis due to three main reasons: (a) since Dealscan database only provides the names of the borrowers, we need to hand-match this data set with the Compustat-CRSP data set using firm names, leading to a loss of many observations, (b) many loan facilities do not have information on whether the loan is secured or not, and (c) we consider only those firms that have bank loans outstanding as of August 1998.

[15] This assumes that firms have negligible secured borrowing from non-banking private institutions. For firms that borrow from these sources and provide their assets as collateral, our proxy will be noisy.

Given these data limitations, we need to interpret the results of this section with some caution. These results are based on a sample of bank-dependent firms that are relatively larger and have lower default risk than the average bank-dependent firm in our entire sample. In addition, the collateral availability and firm leverage are likely to be determined endogenously. Due to these selection issues, the coefficients on other explanatory variables in this model are not directly comparable to other models of the paper.

We create three proxies of available collateral: (a) the fraction of past loans that are unsecured, (b) one minus the ratio of dollar amount of secured loans to total dollar amount of loans, and (c) one minus the ratio of dollar amount of secured loans to the firm's total tangible assets (Compustat item number 8). Regression results are provided in Table 7. We find that bank-dependent firms with higher free collateral perform significantly better, suggesting that higher financial flexibility weakens the effect of bank-dependence on firm valuation during the time of crisis.

4.4. Evidence from variations across the banks

We now investigate whether borrowers of banks that are severely affected by the Russian crisis perform worse than borrowers of unaffected banks. This allows us to directly comment on the effect of banks' losses in the international market on their domestic borrowers' performance. We estimate the following model on the sub-sample of bank-dependent firms[16]:

$$r_i \;=\; \beta_0 + \beta_1 affbank_i + \sum_{k=1}^{k=K} \phi_k X_i + \epsilon_i.$$

where $affbank_i$ measures the exposure of firm i's bank to the Russian crisis. This measure is independent of the bank's activities in the U.S. domestic market and, therefore, exogenous to the demand-side considerations.

To estimate this model, we first need to classify banks into affected and unaffected cat-

[16] We also estimate a specification where we use the rated firms in the sample as well. We estimate the model with *bankdep*, *affbank*, and their interaction term as the key right-hand-side variables. All our results are robust. We focus on this model since it alleviates omitted-variable and selection-bias concerns.

egories based on their exposure to the Russian crisis. We use quarterly call reports filed by every FDIC-insured commercial bank to get this information. We augment this data source with information contained in the footnotes to the banks' annual statements. The latter data are provided by Kho, Lee, and Stulz (2000), who read the financial statements of 78 large banks covered in Datastream data set.

4.4.1. Identification of the bank's exposure

We first gather information on the identity of the firm's main banks from the Dealscan data set and then obtain data on the extent of their exposure to the Russian crisis using the call reports and annual statements. From Dealscan we collect all loans made to the borrowing firms that are outstanding at the time of the crisis. We restrict our attention to loans made by 78 large banks covered in the Datastream data set. The choice of these banks is driven by the study of Kho, Lee, and Stulz (2000), which is one of the sources

of information about the banks' exposure to the crisis. Since we need to manually match the identity of banks in the Dealscan data set with the identity of banks in the call report data set, it becomes easier from the data-collection viewpoint to focus on this sample.[17] This list contains all the large U.S. banks and for all practical purposes imposes no restriction on our sample. If a firm has multiple banking relationships, we keep the bank with the maximum loan amount as the firm's main bank.[18]

We collect information on banks' financial condition as of the third quarter of 1998 from call reports. Though banks do not report the extent of their business activity on a country-by-country basis in this data set, they do report losses suffered in foreign markets as a whole. We construct the first measure of exposure based on quarterly charge-offs during 1998Q3 on loans and leases made to foreign borrowers including foreign individuals, corporations,

[17]We hand-match the identity of banks from the Dealscan database with the call report database. We ensure that we obtain proper matches for banks that have merged since then, i.e., we ensure that we match borrowers with their banks as of August 1998.

[18]We have experimented with other definitions such as the average exposure of all banks of the borrower. Our results are similar.

banks, and governments. This measure does not directly capture the losses on foreign debt and equity securities, which motivates the use of our second proxy. We consider investments in foreign securities, both debt and equity, held as of 1998Q1 as the second proxy of a bank's exposure to the crisis. We lag the security holding data by two quarters to ensure that the measurement of the explanatory variable is not contaminated by the crisis event itself.

These two measures have their own advantages and shortcomings. While the foreign securities-based measure captures the extent of exposure across both debt and equity securities, it does not measure the quality of these investments. On the other hand, the charge-off-based measure is closer in spirit to the adverse capital shocks faced by the banks, but it misses the extent of losses on foreign securities. We find that both measures classify banks into affected and unaffected groups in roughly the same manner. The rank correlation between the two measures is about 70%; therefore, it is not surprising that our results remain similar based on either of the two proxies. In our empirical tests we divide both these measures by the lagged asset value of the bank to construct a scaled measure of exposure.

We complement this data by classifying banks into affected and unaffected groups based on Kho, Lee, and Stulz (2000). If a bank is classified as having exposure to the Russian or LTCM crises in their study, we classify that bank as an affected bank. We set the indicator variable $affbank_i$ to one for affected banks, and zero otherwise. This measure has a high correlation (over 80%) with the measures based on the call report data.

In Fig. 4 we plot the quarterly trend in the U.S. banks' losses on account of their foreign operations. We present two plots: one based on the quarterly charge-off data that we use for our subsequent analysis and the other based on the extent of non-performing foreign loans. Non-performing foreign loans are constructed by dividing the foreign loans and leases that are past due for over 90 days by the total assets. A clear pattern emerges from these plots. Banks experienced significant increase in losses due to their international operations around 1998Q3. The quarterly charge-off ratio in 1998Q3 is significantly higher than the preceding quarters. We find that the charge-offs increased by about 200% in this quarter as compared to the average charge-offs over the preceding four quarters. The pattern in non-performing assets is equally clear. Since we are considering 90-day overdue loans for the definition of non-performing assets (NPAs), this ratio shows a remarkable jump in 1998Q4. The foreign non-performing asset ratio in 1998Q4 is about 80% higher than the average value of this ratio measured over the preceding five quarters. Though our subsequent tests are based on cross-sectional variation in losses across banks, the time-series pattern in losses revealed by these figures provides confidence in our identification strategy.[19]

There are about 400 bank-dependent firms for which we could obtain the identity of their main banks and the banks' exposure to the crisis. Citicorp, Bank of America, Bankers Trust Corporation, Chase Manhattan Corporation, and Bank Boston Corporation rank among the top exposure banks. We find a large concentration of charge-offs within these banks. Some of the banks that had little to no exposure to the crisis include Keycorp, US Bancorp, Banc One Corporation, Wells Fargo, and National City Bank.

4.4.2. Regression results

Regression results are provided in Panel A of Table 8. All standard errors are clustered at the bank level. In our first test, we use charge-offs during 1998Q3 (scaled by lagged assets) as the measure of the bank's exposure to the crisis. We find a significant negative coefficient on charge-offs, indicating that borrowers of the crisis-affected banks lost significantly higher value than their counterparts that borrowed from unaffected banks. Based on the estimated coefficient, we find that a one-standard-deviation increase in the bank's charge-offs resulted in a decrease of about 1.4% in market returns of their borrowers. In Model 2, we use the cumulative charge-offs during 1998Q3 and 1998Q4 as the measure of banks' exposure and find similar results. Model 3 uses the foreign securities-based measure and confirms the findings. Finally, in Model 4 we use an indicator variable based on Kho, Lee, and Stulz (2000) as the proxy for exposure to the crisis.[20] We find that the crisis-affected banks' borrowers earned

[19] Since we focus on exploiting cross-sectional variations in banks' exposure to the crisis, we do not closely investigate the lead-lag relationship between charge-offs and NPAs in this paper.

[20] We do so to ensure that we do not miss any bank that reports its exposure in the annual statements, but had little exposure as of the data-reporting date.

3.54% lower returns than the unaffected banks' borrowers after controlling for the effect of firm size, default risk, and growth opportunities.

It is hard to argue that the borrowers of the affected banks are systematically different from the unaffected banks on unobservable dimensions in such a manner that they earn lower returns during the crisis period due to those unobservable differences. These results suggest that firms face value-relevant frictions in raising external capital. Further, the evidence also supports the view that the global integration of financial markets can cause shocks to propagate from one economy to another through the banking channel.

To ensure that our results are not driven by large outliers, we perform additional statistical tests. We use DFITS (see Welsch and Kuh, 1977) statistics to identify the influential observations (see Ashcraft, 2006). We first fit an OLS model using all available data points and then classify an observation as an outlier if the DFITS statistic exceeds the threshold of $2 * \sqrt(k/n)$, where k is the number of independent variables including the intercept and n denotes the sample size. We re-estimate all four models after excluding the outliers and present the results in Panel B of Table 8. We find that all results remain robust to the outlier correction. In other words, our estimation results are not driven by a few influential observations, instead they represent a general tendency in the data that borrowers of crisis-affected banks lost higher market value than their counterparts that banked with unaffected financial institutions.

4.4.3. Evidence from shift in loan supply curve

In our final test, we directly investigate the lending behavior of banks around the crisis period. A shock to the supply of credit should lead to an inward shift in the supply curve, and the resulting credit crunch should result in a decrease in the equilibrium quantity of credit and an increase in its price. It is an extremely challenging task to empirically test these implications of credit crunch because we are unable to observe the entire demand and supply curve. The issue is further complicated due to the possibility of credit rationing (Stiglitz and Weiss, 1981) as well as the possibility of changes in the composition of borrowers before and after the crisis. With these limitations in mind, we proceed with a difference-in-difference approach. We compare the changes in the quantity and the price of bank credit around the Russian crisis for crisis-affected banks as compared to the unaffected banks. The double-difference technique allows us to remove the effect of any time trend in bank credit.

To estimate this effect, we first obtain all bank loans from the Dealscan database in a two-year period surrounding the Russian crisis. We conduct the analysis both at loan level and at the bank level. In general, we estimate the following model with the loan-level data:

$$Y_{it} = \alpha_i + \beta postcrisis_{it} + \gamma affected_i + \theta postcrisis_{it} * affected_i + \kappa macrovar_{it} + \epsilon_{it}.$$

Y_{it} is either the loan spread, our proxy for the price of bank credit, or the loan amount given by bank i at time t. $postcrisis_{it}$ equals one for observations after August 1998, and zero otherwise. $affected_i$ is a dummy variable that equals one for loans from banks affected by the crisis, and zero otherwise. We use a composite measure of a bank's exposure to the crisis using information in both call reports and the Kho, Lee, and Stulz (2000) study. We classify a bank as affected by the crisis if it is classified as crisis-affected by KLS or if it falls in the top 10% of quarterly charge-off distribution.[21] We are interested in estimating θ that measures the change in loan spread or loan amount for crisis-affected banks as compared to the unaffected ones. To account for any observable or unobservable bank-specific time-invariant factors, we estimate this model with bank fixed effects. Thus, $affected_i$ gets subsumed by the fixed effects in the model. We include two macroeconomic variables, credit-spread and term-spread, as additional control variables.

Results are provided in Table 9. In Model 1, we estimate the loan spread model. We obtain a positive and significant coefficient on the $postcrisis * affected$ interaction term. After the Russian crisis, crisis-affected banks increased their loan spread by almost 24%. Model 2 shows that the amount of loans from the crisis-affected banks also decreased disproportionately more than the unaffected banks. Since Model 2 is estimated at the loan-level

[21] All banks that fall in the top 10% are also classified as crisis-affected by the KLS measure. Thus, the second measure becomes a redundant conditioning variable for this part of the analysis.

data, it does not directly estimate the overall decline in bank lending by the affected banks. To do so, we aggregate the loan-level data at the bank level per week. We then estimate the same model with total lending at the bank-week level as the dependent variable. In this estimation, presented in Model 3, the coefficient on the interaction term directly measures the decline in weekly lending volume of the crisis-affected banks as compared to unaffected ones. We find that the total lending volume declined significantly for the crisis-affected banks.

Overall, these results point toward an inward shift in the supply of bank credit for the crisis-affected banks. Taken together with the earlier results, we show that the Russian crisis of 1998 resulted in a credit crunch for bank-dependent borrowers, especially those that relied on banks affected by the crisis. This, in turn, was reflected in a disproportionately larger valuation loss for bank-dependent firms, especially for those that were dependent on the crisis-affected banks.

5. Discussion and conclusion

The Russian crisis of Fall 1998 resulted in a significant loss of equity capital for the U.S. banks. The crisis originated with the Russian government's decision to default on their obligations, and therefore, the crisis was triggered by an event that was reasonably exogenous to the investment opportunity set of the U.S. domestic firms. This natural experiment allows us to investigate the effect of adverse shocks to banks' equity capital on their borrowers' performance in a setting that is not contaminated by the borrowers' demand-side considerations. Our results strongly support the hypothesis that bank-dependent firms face adverse valuation consequences when the banking sector's financial health deteriorates. Bank-dependent firms lost disproportionately higher market value and suffered larger declines in capital investments and profitability following the crisis as compared to firms with access to the public-debt market. Among bank-dependent firms, the drop in valuation was higher for firms with lower financial flexibility and those that relied on banks with larger exposure to the crisis. Consistent with an inward shift in the loan supply curve, the crisis-affected banks decreased the quantity of loans and increased their price in the post-crisis period. Overall, we provide causal evidence that firms face value-relevant frictions in raising external capital.

Our results have important implications for literature in banking, corporate finance, and macroeconomics. We highlight the role of banks in providing capital and the role of the corporate bond market in the economy. In the past, then Fed chairman Alan Greenspan has noted the importance of corporate bond markets during the time of banking crises in emerging markets. As quoted from *The Economist* (November, 17 2005)

> .....Financial crises have a cruel way of revealing what an economy lacks. When many emerging markets suffered a sudden outflow of capital in the late 1990s, one painful lesson was that their financial systems had relied too heavily on bank lending and paid too little attention to developing other forms of finance. *The lack of a spare tyre*, said Alan Greenspan, chairman of America's Federal Reserve, in 1999, is of no concern if you do not get a flat. East Asia had no spare tyres. If a functioning capital market had existed, remarked Mr. Greenspan, the East Asian crisis might have been less severe. Developing deep and liquid corporate-bond markets, in particular, could make emerging economies less vulnerable....

Our results support this *spare tyre* view by demonstrating that corporate bond markets can have a positive impact even in developed economies such as the U.S. At a broader level, our results provide evidence in support of the presence of supply-side frictions in raising external financing, an assumption frequently made in various theoretical models of corporate finance and macroeconomics. Finally, our results suggest that the global integration of the financial sector can contribute to the propagation of shocks from one economy to another through the banking channel. These findings have implications for the ongoing subprime mortgage crisis as well as future policy designs by monetary and banking authorities.

Appendix A. Variable definitions

bankdep is a proxy for bank dependence of the firm. It is a dummy variable that takes the value of one for firms with a S&P long-term credit rating, and zero for firms without the credit rating.

log(sales) is the natural logarithm of sales of the firm measured in millions of U.S. dollars.

lever measures leverage and is the ratio of total debt from the balance sheet to total assets.

market-to-book(mtb) is the ratio of the market value of assets to total assets, where the numerator is defined as the sum of market equity, total debt, and preferred stock liquidation value less deferred taxes and investment tax credits.

exdep is computed as the difference between total investments (Compustat item 311) and cash flow from operations (item 308) scaled by cash flow from operations. We compute this variable at the industry level by taking the median number for each four-digit SIC industry code on a yearly basis.

def$_g$ is a measure of the default risk of the firm. It is the percentile ranking of the firm's default risk based on its distance to default (constructed as in Bharath and Shumway, 2008). We first compute the distance-to-default as

$$\frac{log(E + F/F) + (r_{it-1} - \sigma_V^2/2)T}{\sigma_V\sqrt{T}}$$

, where E is the market value of equity, F is the face value of debt, σ_V is the asset volatility, r_{it-1} is the firms stock return over the previous year, and T is the time horizon that is set to one year. We convert it to expected default frequency to obtain the firm's default risk.

sigma$_{equity}$ is the equity volatility of the firm over the past one year.

pastret is the past one-year stock return.

ebitda/sales is the ratio of EBITDA to the sales of the firm.

bidask is a proxy for the stock market liquidity of the firm and computed as the mean of the proportional bid-ask spread over the past three months of daily stock data.

termspread is the difference in the yields on a ten-year treasury bond and a one-year treasury bond taken from the Fed's H.15 release.

creditspread is the spread in the yields between a BAA-rated bond and a AAA-rated bond taken from the Fed's H.15 release.

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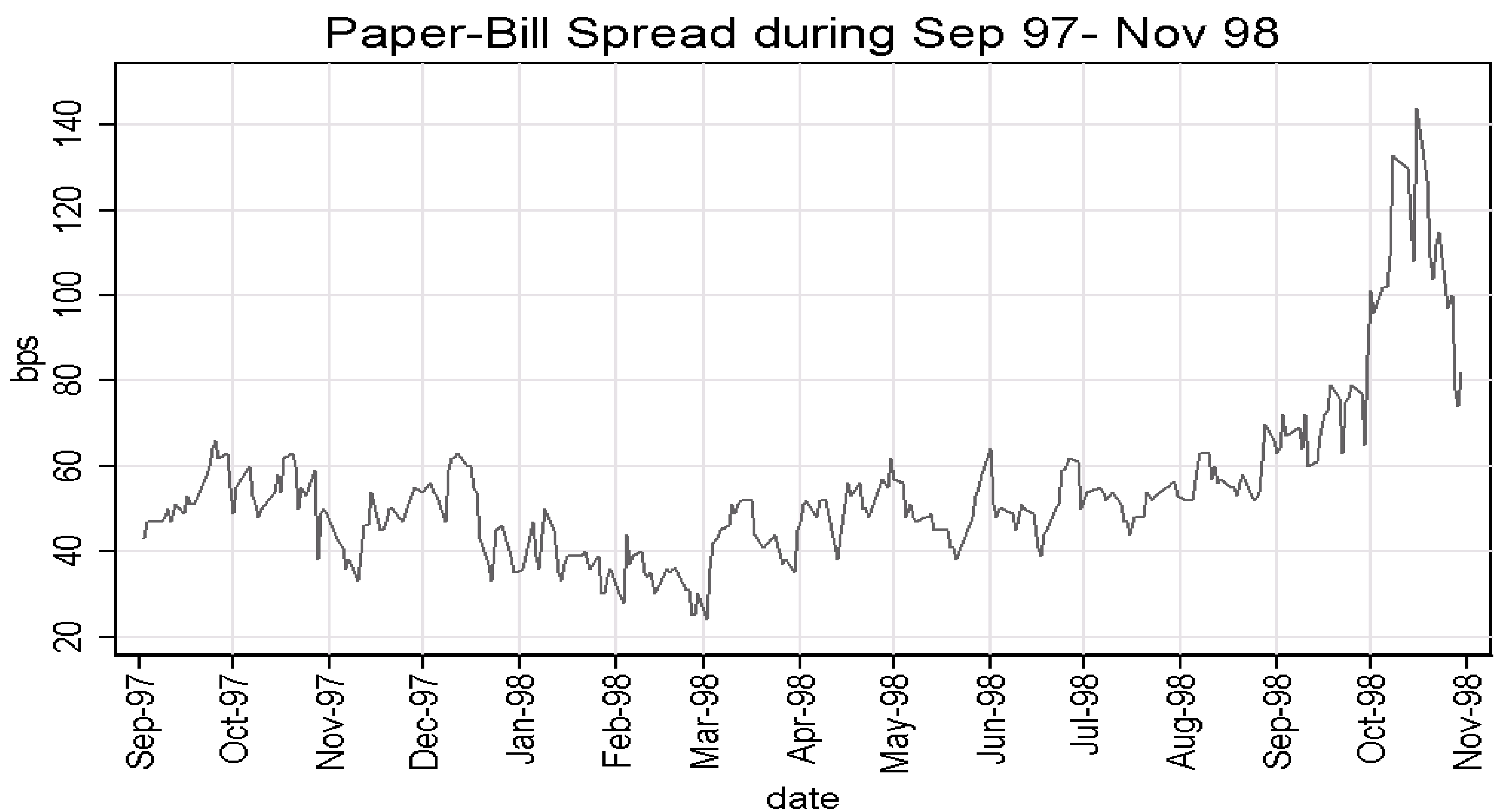


Figure 1: **Paper-Bill spread during** 1997 – 1998

This figure plots the spread between commercial paper and treasury bill rates from September 1997 to November 1998.

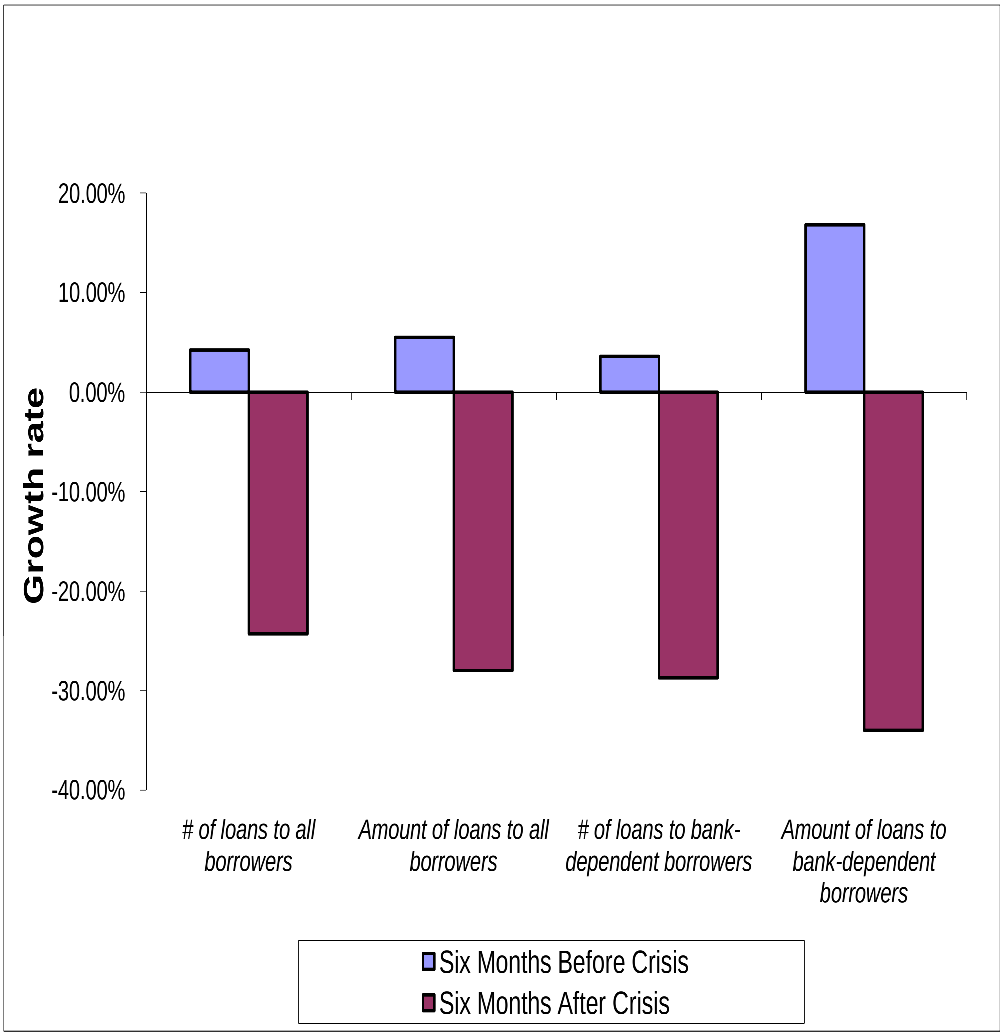


Figure 2: **Growth in bank loans**

This figure plots the growth rates in number and amount of loans around the Russian crisis period. We obtain data from the Dealscan database for all loans made during six months before the crisis (i.e., from February 1998 to July 1998) and six months after the crisis (i.e., during August 1998 to January 1999). We plot the growth in number and amount of loans during these two periods as compared to previous six months. Thus, pre-crisis numbers are compared with loan data from August 1997 to January 1998 and the post-crisis numbers are compared with the pre-crisis numbers. We provide the growth rates for all firms as well as the subset of bank-dependent firms, i.e., firms without access to the public-debt market.

Figure 3: Distribution of key characteristics: Before and after matching

The plots give the kernel density functions of the key characteristics of the firms before and after matching. More details on the matching are provided in section 4.2.1 of the paper. Distribution for the entire sample (before matching) is presented in the first column and distribution for the matched sample is presented in the second column. The first row plots log(Sales) and the second row plots distance-to-default constructed as in Bharath and Shumway (2008).

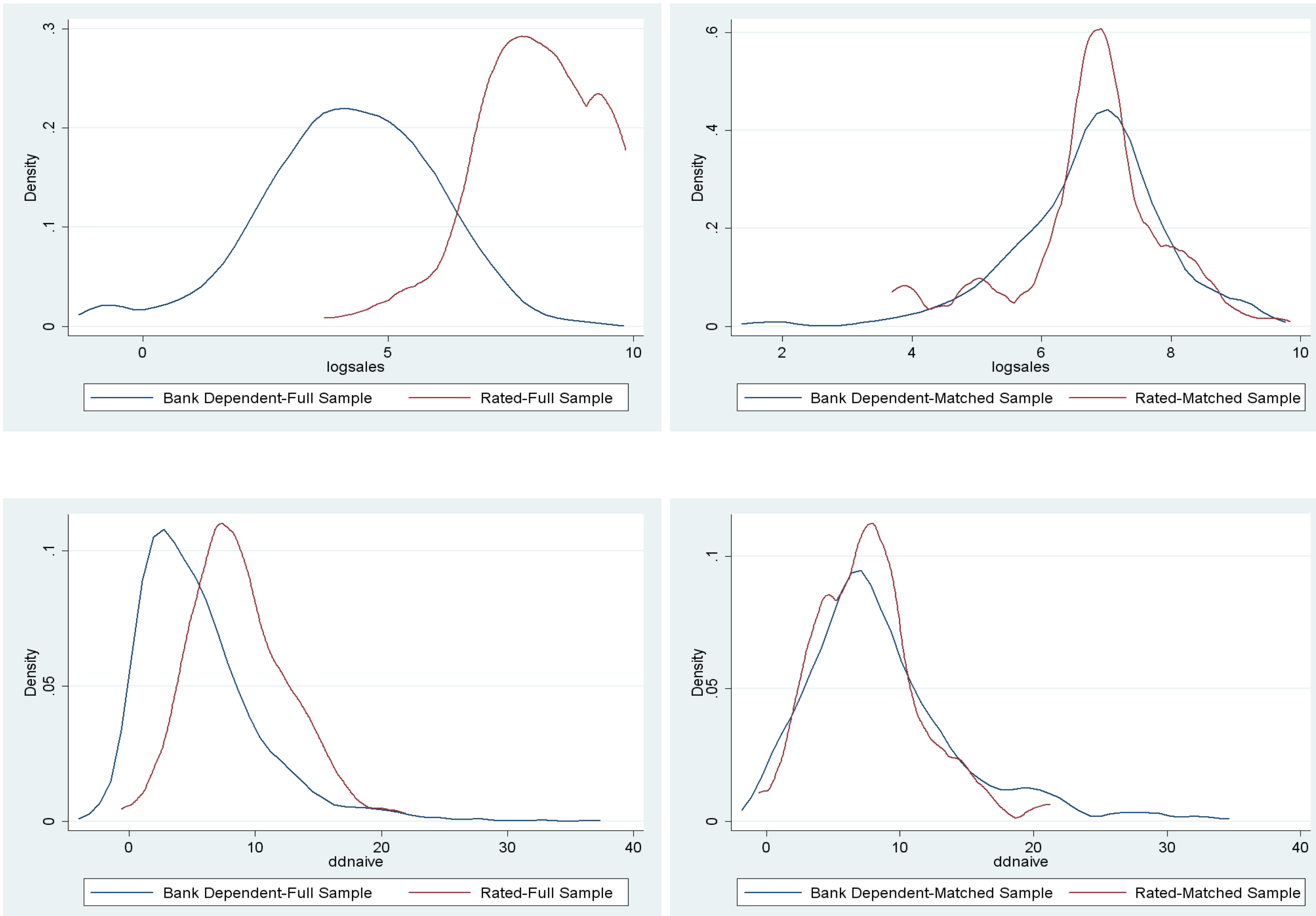
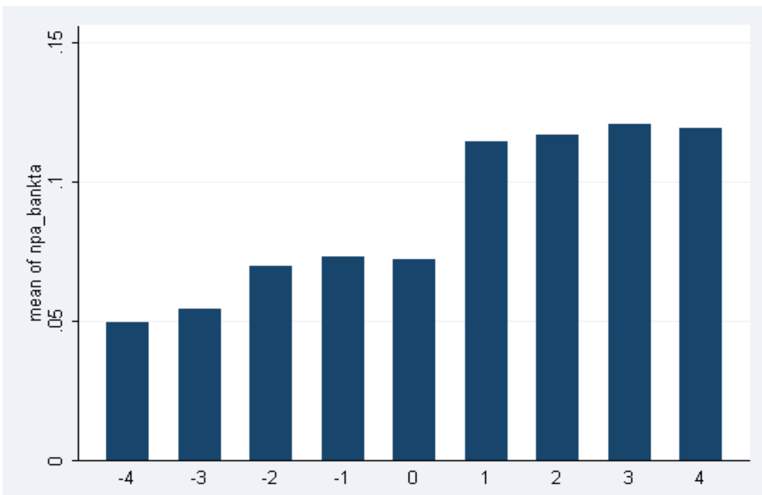


Figure 4: Trend in banks' NPA and charge-offs

The plots give the quarterly trend in U.S. banks' non-performing assets (assets past due 90 days) and charge-offs on their foreign loan portfolios around the Russian crisis. Quarter zero corresponds to 1998Q3. We plot the ratio of non-performing assets to banks' total assets in percentage terms in the first figure. The second figure plots the ratio of quarterly charge-offs to lagged value of banks' total assets in percentage terms.



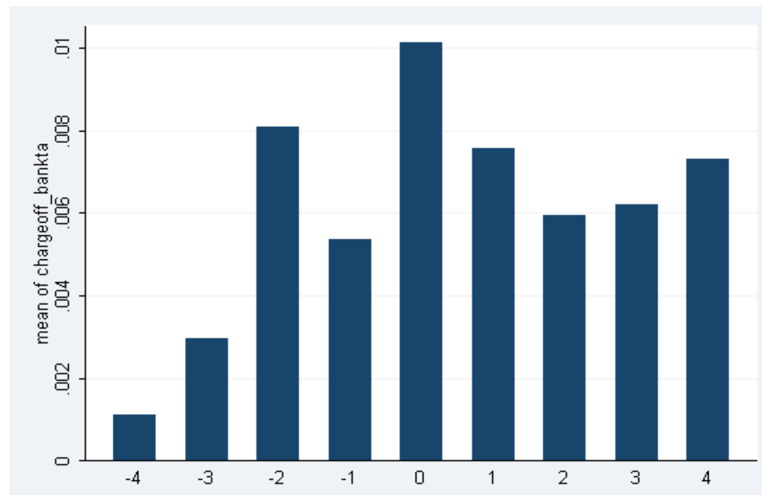


Table 1: Descriptive statistics

This table reports summary statistics of key variables used in the analysis based on the entire sample of non-financial firms in the intersection of CRSP-Compustat databases with non-missing observations on the required data, having non-zero leverage and with no direct business exposure to the crisis affected regions. All firm-level information is lagged by at least six months and is extracted as of May-1998. Presence or absence of long-term credit rating is taken as a proxy for bank-dependence. The summary statistics for the rated and bank-dependent firms are given in Panels A and B respectively. *sales* is the sales of the firm measured in millions of U.S. dollars. *lever* is the ratio of total debt (sum of long-term debt and short-term debt) to the total assets of the firm. *mtb* is the ratio of the market value of assets to total assets, where the numerator is defined as the sum of market equity, total debt, and preferred stock liquidation value less deferred taxes and investment tax credits. def_g is the percentile raking of the firm based on its expected default frequency. sigma$_{equity}$ is the equity volatility of the firm measured over the past one year. *pastret* is the past one year stock return of the firm. *ebitda/sales* is the ratio of EBITDA to the sales of the firm. *bidask* is the average bid-ask spread of the firm over the past three months using daily stock data. *CAR* is the firm's market-model adjusted stock return from 14-Aug-1998 to 4-Sep-1998.

	mean	25^{th} pctl	Median	75^{th} pctl	Std. dev.
Panel A: Rated firms (N=304)					
sales	2839.98	716.90	1243.49	3147.11	3782.97
lever	0.29	0.19	0.29	0.37	0.15
mtb	2.01	1.29	1.66	2.30	1.15
def$_g$	0.32	0.15	0.28	0.47	0.22
sigma$_{equity}$	0.34	0.28	0.32	0.36	0.10
pastret	0.13	-0.02	0.16	0.31	0.31
ebitda/sales	0.20	0.11	0.17	0.26	0.14
bidask	1.54	0.85	1.10	1.77	1.30
CAR (%)	-2.74	-8.22	-2.02	3.81	10.41
Panel B: Bank-dependent firms (N=2665)					
sales	430.83	27.24	101.38	391.04	1017.75
lever	0.23	0.06	0.19	0.34	0.20
mtb	2.16	1.22	1.65	2.48	1.51
def$_g$	0.49	0.25	0.50	0.75	0.29
sigma$_{equity}$	0.63	0.40	0.56	0.78	0.32
pastret	0.02	-0.27	0.05	0.34	0.53
ebitda/sales	-0.34	0.02	0.09	0.16	2.24
bidask	3.56	1.39	2.47	4.42	3.40
CAR (%)	-10.31	-19.84	-9.23	-0.09	16.25

Table 2: Impact of Russian crisis on bank-dependent borrowers: Full sample

Panel A of this table presents regression results relating the firm's stock return around the Russian crisis to its characteristics. The dependent variable is the market model adjusted stock return from 14-Aug-1998 to 4-Sep-1998. Variable definitions appear in Appendix A. The empirical distribution of the coefficient on *bankdep* using the same regression as in Panel A, but based on a bootstrapping exercise of 100 random samples is presented in Panel B. The panel also presents empirical distribution based on samples drawn exclusively from periods of large negative market movements. Industry fixed effects using Fama-French 48 industry codes are included in all regressions. Robust t-statistics are reported in brackets. Adjusted R^2 and the number of observations are reported in the last two rows. This estimation is based on the entire sample of non-financial firms in the intersection of CRSP-Compustat databases with non-missing observations on the required data, having non-zero leverage and with no direct business exposure to the crisis-affected regions.

Panel A: Regression results from the crisis period

	Model 1		Model 2		Model 3	
	Estimate	t-val	Estimate	t-val	Estimate	t-val
$bankdep$	-0.0361	(-3.79)	-0.0310	(-3.17)	-0.0021	(-0.15)
$log(sales)$	0.0164	(8.12)	0.0166	(6.58)	0.0160	(6.33)
mtb	0.0012	(0.47)	0.0022	(0.84)	0.0154	(3.50)
$lever$	-0.0495	(-2.88)	-0.0247	(-1.00)	-0.0238	(-0.97)
def_g			-0.0488	(-2.00)	-0.0490	(-2.01)
$bidask$			0.0053	(4.37)	0.0051	(4.25)
$pastret$			-0.0625	(-6.99)	-0.0630	(-7.05)
$sigma_{equity}$			-0.0453	(-2.27)	-0.0464	(-2.33)
$ebitda/sales$			-0.0004	(-0.19)	-0.0005	(-0.24)
$bankdep * mtb$					-0.0142	(-2.94)
R^2	0.082		0.122		0.123	
N	2,969		2,956		2,956	
Fixed effects	FF Industry		FF Industry		FF Industry	

Panel B: Regression results from bootstrapped sample

Variable	mean	p1	p5	p25	p50	p75	p90	p99
Random-period	-0.0021	-0.0252	-0.0178	-0.0069	-0.0017	0.0030	0.0084	0.0219
Down-market	-0.0044	-0.0187	-0.0133	-0.0101	-0.0039	-0.0017	0.0050	0.0096

Table 3: Other measures of financial constraints & firm performance

Panel A of this table presents regression results relating the firm's stock return around the Russian crisis to two alternative measures of financial constraints. The dependent variable is the market model adjusted stock return from 14-Aug-1998 to 4-Sep-1998. *listage* measures the firm's age since its listing on a stock exchange. *exdep* measures the extent of dependence on external financing and is computed at the industry level. Variable definitions appear in Appendix A. Robust t-statistics are reported in brackets. Adjusted R^2 and the number of observations are reported in the last two rows. In Models 3 and 4, all standard errors are clustered at the FF-industry level. Panel B presents the firm fixed effect regression results for the effect of crisis on firm's investment and profitability. The dependent variables are: quarterly investments scaled by lagged assets in Model 1, and quarterly operating income to total asset ratio in Model 2. $after$ is an indicator variable that takes a value of zero for quarters before 1998Q3, and one otherwise. Robust standard errors are presented in the brackets. These estimations are based on the entire sample of non-financial firms in the intersection of CRSP-Compustat databases with non-missing observations on the required data, having non-zero leverage and with no direct business exposure to the crisis affected regions.

Panel A: Other measures of financial constraints

	Model 1		Model 2		Model 3		Model 4	
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
$listage$	0.0006	(2.73)	0.0005	(2.12)				
$exdep$					-0.0268	(-2.37)	-0.0292	(-2.64)
$logsales$	0.0176	(9.98)	0.0177	(7.77)	0.0164	(11.40)	0.0155	(4.64)
mtb	0.0020	(0.85)	0.0030	(1.14)	0.0035	(1.71)	0.0040	(1.91)
$lever$	-0.0477	(-2.77)	-0.0254	(-1.03)	-0.0566	(-2.68)	-0.0239	(-0.91)
def_g			-0.0441	(-1.79)			-0.0571	(-2.54)
$bidask$			0.0048	(3.91)			0.0048	(4.66)
$pastret$			-0.0627	(-6.99)			-0.0674	(-7.18)
$sigma_{equity}$			-0.0462	(-2.28)			-0.0476	(-2.69)
$ebitda/sales$			-0.0007	(-0.35)			-0.0007	(-0.23)
R^2	0.079		0.120		0.049		0.096	
N	2,917		2,904		2,917		2,904	
Fixed effects	FF Industry		FF Industry		None		None	

Panel B: Other measures of firm performance

	Model 1:Capex		Model 2:Profitability	
	Estimate	t-val	Estimate	t-val
$after$	-0.0011	(-2.80)	-0.0012	(-1.87)
$bankdep * after$	-0.0026	(-5.56)	-0.0056	(-6.33)
R^2	0.527		0.619	
N	32,748		33,516	
Fixed effects	Firm		Firm	

Table 4: Liquidity injection by the Federal Reserve Bank

This table presents regression results relating the firms' stock return around the periods of liquidity injection by the Federal Reserve Bank to bank dependence. The dependent variable is the market-model adjusted stock return around the Federal Funds rate change announcements on September 29, 1998 (Models 1 and 2), and October 15, 1998 (Models 3 and 4). The event window is (0,+1) days, where day zero corresponds to the rate announcement date. Variable definitions appear in Appendix A. Industry fixed effects using Fama-French 48 industry codes are included in all regressions. Robust t-statistics are reported in brackets. Adjusted R^2 and the number of observations are reported in the last two rows. This estimation is based on the entire sample of non-financial firms in the intersection of CRSP-Compustat databases with non-missing observations on the required data, having non-zero leverage and with no direct business exposure to the crisis affected regions.

	Model 1:Sep 29, 1998		Model 2:Sep 29, 1998		Model 3:Oct 15, 1998		Model 4:Oct 15, 1998	
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
$bankdep$	0.0097	(2.19)	0.0065	(1.44)	0.0100	(1.90)	0.0110	(2.03)
$logsales$	0.0009	(1.00)	-0.0010	(-0.87)	0.0036	(3.32)	0.0021	(1.54)
mtb	-0.0003	(-0.30)	0.0000	(0.03)	-0.0011	(-0.81)	-0.0022	(-1.46)
$lever$	-0.0114	(-1.41)	-0.0133	(-1.15)	0.0042	(0.42)	0.0164	(1.16)
def_g			0.0048	(0.44)			-0.0127	(-0.88)
$bidask$			0.0003	(0.61)			-0.0013	(-2.03)
$pastret$			-0.0007	(-0.18)			-0.0093	(-1.90)
$sigma_{equity}$			-0.0167	(-1.91)			-0.0017	(-0.16)
$ebitda/sales$			0.0011	(1.10)			-0.0004	(-0.40)
R^2	0.015		0.019		0.022		0.026	
N	2,878		2,865		2,854		2,841	

Table 5: Matching estimation results

The following table presents the results of a probit regression with access to the public-debt market as the dependent variable. In *Pre-match* model, the entire sample of firms in the intersection of CRSP-Compustat databases with non-missing observations on the required data, having non-zero leverage and with no direct business exposure to the crisis-affected regions is used and in *Post-match* model, only those bank-dependent firms that can be matched to the rated firms based on the propensity score from the *Pre-Match* model are used. Robust t-statistics are reported in brackets. Pseudo R^2 and the number of observations are reported in the last two rows.

	Pre-match		Post-match	
	Estimate	t-val	Estimate	t-val
$log(sales)$	1.0363	(13.00)	-0.0770	(-0.97)
mtb	0.0058	(0.08)	-0.0421	(-0.63)
$lever$	0.9326	(2.34)	0.1635	(0.42)
$sigma_{equity}$	-2.5941	(-3.86)	-0.7068	(-1.08)
$ebitda/sales$	4.3155	(5.37)	0.9066	(1.39)
$bidask$	-0.0657	(-0.59)	-0.1127	(-0.84)
$pastret$	-0.4812	(-2.55)	-0.1866	(-0.84)
def_g	-0.9152	(-1.07)	0.5628	(0.66)
R^2	0.701		0.045	
N	2942		470	
Fixed effects	FF Industry		FF Industry	

Table 6: Evidence from matched sample

This estimation is based on the matched samples of rated and bank-dependent firms where matching has been done either based on the propensity score method or on the basis of firm size. Column 1 of Panel A provides the mean abnormal returns of bank-dependent and rated firms during Aug 14, 1998 to Sep 4, 1998, i.e., during the crisis-period. In the second and third columns, the returns are measured over several random samples of 16 contiguous days during Jan 1985 to Dec 1998. We report average returns across all random periods in these columns. In the second column, *Down market*, we draw random samples from periods of low market returns. In the third column, *Random Period*, random samples are drawn without conditioning on market return. In these three models, the construction of treatment (treat=1 for bank-dependent firms) and control (treat=0 for rated firms) groups is based on the propensity score matching method. The fourth column labeled *Size Match* provides the crisis-period return for bank-dependent and rated firms for a matched sample based on firm size within the same industry. For all four models, the mean return for the treatment and control groups and the difference between the returns of these two groups are presented in the first three rows. The fourth row contains the t-statistic for the difference in the mean returns for the treatment and control groups. In Panel B, we provide the empirical distribution of CAR for the treatment and control group from the bootstrapping exercises.

Panel A: CAR for treatment and control groups

	Crisis-period	Down-market	Random period	Size match
$CAR_{treat=0}$	-0.0267	-0.0214	-0.0016	-0.0481
$CAR_{treat=1}$	-0.0661	-0.0217	-0.0005	-0.0842
$CAR_{treat=1} - CAR_{treat=0}$	-0.0394	-0.0003	0.0010	-0.0361
t-stat for ΔCAR	-2.52	-0.36	0.58	-2.18
N	470	–	–	253

Panel B: CAR for treatment and control groups from bootstrapped samples

Variable	mean	p1	p5	p25	p50	p75	p90	p99
Random-period	0.0010	-0.0409	-0.0280	-0.0078	-0.0005	0.0083	0.0283	0.0469
Down-market	-0.0003	-0.0488	-0.0152	-0.0133	-0.0060	0.0023	0.0454	0.0520

Table 7: Impact of collateral availability

This table analyzes the impact of financial flexibility (as measured by collateral availability) on the stock market reaction during the Russian crisis. Firms' market-model adjusted stock return from 14-Aug-1998 to 4-Sep-1998 is the dependent variable. *loansec* is (1-number of firm's loans that are secured divided by total number of firms' outstanding loans in the dealscan database). *amtsec* is (1-the amount of firm's loans that are secured divided by total amount of firms' outstanding loans). *sectan* is (1-the amount of firm's loans that are secured divided by the firms' tangible assets (as proxied by the net plant, property and equipment)). Robust t-statistics are reported in brackets. Adjusted R^2 and the number of observations are reported in the last two rows. The sample is restricted to bank-dependent firms with coverage on Dealscan database and with non-missing observations on security of their loans.

	Model 1		Model 2		Model 3	
	Estimate	t-val	Estimate	t-val	Estimate	t-val
loansec	0.0306	(2.00)				
amtsec			0.0333	(2.22)		
sectan					0.0026	(2.27)
$log(sales)$	0.0079	(1.24)	0.0077	(1.21)	0.0086	(1.39)
mtb	0.0092	(1.24)	0.0091	(1.23)	0.0087	(1.17)
lever	-0.0432	(-0.85)	-0.0429	(-0.84)	-0.0311	(-0.60)
def_g	0.0115	(0.22)	0.0121	(0.23)	-0.0008	(-0.02)
bidask	0.0029	(1.21)	0.0029	(1.22)	0.0026	(1.10)
pastret	-0.0511	(-2.62)	-0.0510	(-2.62)	-0.0530	(-2.74)
$sigma_{equity}$	-0.0597	(-1.26)	-0.0588	(-1.24)	-0.0612	(-1.30)
$ebitda/sales$	0.0337	(1.05)	0.0327	(1.02)	0.0332	(1.04)
R^2	0.148		0.149		0.152	
N	630		630		628	
Fixed effects	FF Industry		FF Industry		FF Industry	

Table 8: Evidence from matched sample of banks and borrowers

This table provides regression results from a matched sample of banks and borrowers. The sample is restricted to banks and borrowers that we are able to match across CRSP, Compustat, call report data, and Dealscan. The dependent variable is the market-model adjusted stock return from 14-Aug-1998 to 4-Sep-1998. $chargeoff$ measures the quarterly charge-off scaled by lagged asset value of the firm's main bank during 1998Q3. $chargeoff2q$ is charge-off scaled by lagged assets computed over 1998Q3 and 1998Q4. $foreignsec$ measures investments in foreign securities by the firm's main bank scaled by total assets. This variable is constructed as of 1998Q1. KLS is a dummy that takes the value of one for the banks that are classified as exposed to Russia by Kho, Lee, and Stulz (2000), and zero otherwise. Other variable definitions are given in Appendix A. All models include industry fixed effects using Fama-French industry classifications. Robust t-statistics adjusted for clustering at the bank level are reported in brackets. Adjusted R^2 and the number of observations are reported in the last two rows. In Panel B, we restrict the sample to firms that are not classified as outliers based on the influence statistics computed using DFITS (see Welsch and Kuh, 1977).

Panel A: Entire sample

	Model 1		Model 2		Model 3		Model 4	
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
$log(sales)$	0.0315	(6.03)	0.0334	(6.00)	0.0306	(6.60)	0.0308	(5.97)
mtb	0.0041	(0.59)	0.0032	(0.46)	0.0033	(0.46)	0.0068	(0.92)
$lever$	-0.0591	(-0.94)	-0.0539	(-0.82)	-0.0398	(-0.61)	-0.0495	(-0.72)
$charegoff$	-0.8934	(-3.10)						
$charegoff2q$			-0.6984	(-3.01)				
$foreignsec$					-1.1101	(-2.15)		
KLS							-0.0354	(-1.95)
R^2	0.206		0.213		0.211		0.201	
N	406		391		406		402	

Panel B: Outlier corrected sample

	Model 1		Model 2		Model 3		Model 4	
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
$log(sales)$	0.0208	(5.71)	0.0241	(6.21)	0.0224	(6.37)	0.0205	(5.88)
mtb	0.0030	(0.47)	0.0063	(0.93)	0.0059	(0.88)	0.0089	(1.47)
$lever$	-0.1105	(-2.19)	-0.0923	(-1.43)	-0.0756	(-1.20)	-0.0925	(-1.71)
$chargeoff$	-0.7456	(-3.39)						
$chargeoff2q$			-0.6198	(-2.99)				
$foreignsec$					-1.0866	(-2.89)		
KLS							-0.0260	(-1.94)
R^2	0.189		0.212		0.208		0.199	
N	377		365		378		375	

Table 9: Impact of Russian crisis on lending by affected banks

In this table we analyze the impact of the Russian crisis on the lending by affected banks. The sample is restricted to banks and borrowers that we are able to match across CRSP, Compustat, call report data, and Dealscan. A bank is classified as $affected$ if it is classified as exposed to the crisis by Kho, Lee, Stulz (2000). $post$ is a dummy variable that takes the value of one if the loan is originated after Aug 1, 1998, zero otherwise. In Model 1, the dependent variable is the natural log of all-in-drawn loan spread measured as the spread over LIBOR as of the loan origination date. In Model 2, the dependent variable is the natural log of the loan amount measured in millions of US dollars. Model 1 and Model 2 are estimated at loan level, with each observation representing a loan given by the bank. The sample is restricted to loans given by the banks within two years before and after the Russian crisis (Aug 1998). In Model 3, the dependent variable is the log of loan amount, aggregated at the bank level for each week of the sample period. All three models include bank fixed effects. Robust t-statistics are reported in brackets. Adjusted R^2 and the number of observations are reported in the last two rows.

	log(Loan spread)		log(Loan amount)		log(Bank lending)	
	Estimate	t-val	Estimate	t-val	Estimate	t-val
$post * affected$	0.2424	(4.13)	-0.2488	(-2.80)	-0.3336	(-2.26)
$postcrisis$	0.0093	(0.17)	0.1041	(1.15)	0.1361	(0.99)
$termspread$	-0.0633	(-0.94)	0.1854	(1.79)	0.4490	(2.82)
$creditspread$	0.7041	(4.46)	0.0964	(0.37)	0.6798	(1.64)
R^2	0.173		0.101		0.184	
N	3,887		3,887		1,585	
Fixed effects	Bank		Bank		Bank	