The Effect of Banking Crisis on Bank-Dependent Borrowers

by

Sudheer Chava and Amiyatosh Purnanandam

September 2, 2008

1We are grateful to Viral Acharya, Adam Ashcraft, Kerry Back, Sreedhar Bharath, Tom George, Todd Gormley, John Graham, Charles Hadlock, Andrew Hertzberg, Shane Johnson, Steve Kaplan, Anil Kashyap, Han Kim, Dmitry Livdan, Paolo Pasquariello, Uday Rajan, Michael Roberts, Anthony Saunders, Philip Strahan, Amir Sufi, Bhaskaran Swaminathan, Sheridan Titman, Haluk Unal, Toni Whited, Andrew Winton, Luigi Zingales, and seminar participants at Michigan State University, Texas A&M University, University of Maryland, University of Minnesota, University of Texas at Austin, European Finance Association’s 2006 meetings in Zurich, FDIC, FDIC-CFR Conference, 42nd Bank Structure Conference at Federal Reserve Bank of Chicago, Federal Reserve Bank of New York, Financial Intermediation Research Society’s meetings in Shanghai, Systemic Risk Conference at Federal Reserve Bank of Atlanta, and Western Finance Association’s 2006 meetings in Keystone for helpful comments. Financial support from FDIC’s Center for Financial Research is gratefully acknowledged. All remaining errors are our own.

2Chava is from the Mays School of Business, Texas A&M University; e-mail: schava@mays.tamu.edu. Purnanandam is from Ross School of Business, University of Michigan; e-mail: amiyatos@umich.edu.
Abstract

We provide causal evidence that bank’s health affects borrower’s performance by separating the effect of demand of credit from the supply of credit using the exogenous shock to the U.S. banking system during the Russian crisis of Fall 1998. Firms that primarily relied on banks for capital suffered larger valuation losses as compared to firms that had access to the public-debt market. Within the set of bank-dependent firms, the valuation loss was higher for firms that were dependent on banks with large exposure to the crisis. Consistent with an inward shift in the loan-supply curve, in the post-crisis period, crisis-affected banks decreased the quantity of their lending and increased the price. Our findings indicate that firms do face value-relevant frictions in raising external capital. Our results also suggest that the global integration of 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.
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. But, adverse selection and moral hazard frictions can limit even a profitable and growing firm’s ability to raise external capital or to substitute between private sources of capital. Banks can mitigate these frictions by screening and monitoring the borrowers (Holmstrom and Tirole, 1997, 1998).

With such frictions in the economy, however, shocks that affect banks’ ability to supply capital might result in suboptimal investment and working-capital management decisions for firms that extensively depend on banks. 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. 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.

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 health is itself caused by its borrowers’ poor performance, then researchers face an uphill task in establishing the causation in the other direction (see, Fama (1980) and King and

1Also see Diamond, 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.

2It 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 (see 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.
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 the shocks to the U.S. banking system during the Russian crisis of Fall 1998 to isolate the effect of supply-side shocks 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. 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. 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 its debt obligations and to suspend its 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 borrower-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 the public debt market was functioning at reasonably normal levels, whereas banks were severely affected by the events in Russia and Brazil. Thus, by comparing the stock

---

3For 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.

4Gatev, 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).

5During our crisis period (i.e., from August 14, 1998 to September 3, 1998) public debt markets seemed
market performance of bank-dependent firms with a matched sample of rated firms, we hope to isolate the effect of supply-shock on firm value. In the matched sample analysis, we carefully match along the dimensions of firm size, default risk, stock market liquidity, and growth opportunities to rule out the possibility that our inference is contaminated by these observable differences across rated and unrated firms. We find that bank-dependent firms lose 3.94% more of their equity value than their rated counterparts during the crisis period.

Our second set of tests is performed within the set of bank-dependent firms. 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 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 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 experience significant valuation loss of about -4.34% as compared to the unaffected banks’ borrowers around this crisis. 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). Thus, both the key sources of financial constraint, adverse selection

---

to be functioning at relatively normal levels as is evident by the modest levels of paper-bill spread - a broadly used measure of 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, a period that we use for falsification test (see Gatev, Strahan, and Schuermann (2004) and also Gatev and Strahan (2006)).
and moral hazard frictions, can be mitigated with collateral. 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 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 is predicted to 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. Notable among them are 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) and Ashcraft (2003), who study the real effects of deterioration in bank health. 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 some value relevant frictions in the economy (see Puri, 1996, Dahiya, Saunders, and Puri, 2003, and a large literature surveyed in Gorton and Winton, 2002). 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 (Sufi, 2006, Lemmon and Roberts, 2007, Fazzari, Hubbard and Petersen, 1988, and Kaplan and Zingales, 1997).

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 & 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. At the same time, on September 2, 1998, the news about the LTCM’s losses were made public. 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 bank’s overall risk, over this time period. Fissel et al. (2004) document 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 about 25% of their capital in this period (Gorton and Winton, 2005). 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 supply of bank loans, we obtain data on loan issuance from the Loan Pricing Corporation’s Dealscan database. It’s 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, Dealscan database allows us to capture the incremental decisions of bank managers by focusing on sanctions of new loans around this period. 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. 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. Figure 2 plots

---

6Results are similar for other reasonable windows, such as 3 months or 9 months, around the crisis period.
the growth in number and amount of loans during this period. There is a remarkable drop (21-28%) in both the number and amount of loans issued after the crisis as compared to pre-crisis period. The decline in issuance of new loans is more pronounced in the sub-sample of bank-dependent firms.

When we analyze the CP rate, 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.

2.1 Identification strategy

Our interest is in estimating the effect of adverse shocks to the suppliers of capital on their borrowers’ performance. We first discuss the identification challenge faced by empirical models attempting to estimate these effects. Subsequently, we discuss our empirical strategy to deal with this issue using the Russian crisis of 1998. To motivate our empirical design, consider an empirical model of the following general form:

\[
y_{it} = \alpha + \beta f(demand_{shock})_{it} + \gamma g(supply_{shock})_{it} + \epsilon_{it}
\]

\(y_{it}\) is a measure of firm \(i\)’s performance at time \(t\). This can be value of the firm or the amount of credit obtained by the firm. \(f(demand_{shock})\) measures firm-specific factors that affect the performance measure. These measures should capture shocks to the firm’s profitability, growth opportunities and risks. We term all these firm-specific factors as the demand-side factors in the rest of the paper. \(g(supply_{shock})\) measures shocks experienced by the supplier of the firm’s capital. Our goal is to estimate \(\gamma\), the coefficient on the supply-shock variable.
The main difficulty lies in obtaining an unbiased estimate of $\gamma$, which measures the effect of the supply side shock on the firm’s performance over and above the factors that influence its demand side considerations. If one or more of these demand side factors cannot be separated from the supply shock, then the estimated coefficient can be easily misleading. In statistical terms, the classical OLS assumption that the error term is independent of the supply shock might not hold. The model mis-specification or omitted variable bias can come from common economic shocks that affect both the supply-side factors and the demand-side factors. An example of such a factor can be the poor economic condition as a whole that leads to an overall decline in the banking sector’s financial health and 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 corporate sector can in itself cause a deterioration in the performance of the banking sector.

Our identification strategy is aimed at exploiting the shift in the supply-shock function, $g(\text{supplyshock})$ during the Russian crisis. As argued in the previous section, this crisis was reasonably exogenous to the demand-side considerations of the U.S. borrowers. This perturbation of the supply-side function allows us to causally estimate the effect of banks’ ability to supply funds on the borrowers’ performance. Our key hypothesis is that the adverse effect of Russian crisis on the U.S. banking sector has a disproportionately large impact on firms that relied on banks as their main source of capital. Since change in stock value is captured by the market return on a firm’s equity, we estimate the following cross-sectional regression model to test our key hypothesis:

$$r_i = \beta_0 + \beta_1 \text{supplyshock}_i + \sum_{k=1}^{K} \phi_k X_i + \epsilon_i$$

$r_i$ is the market model adjusted stock return of firm $i$ during the crisis period. In general, $\text{supplyshock}_i$ is a measure of the extent of shock faced by firm $i$’s supplier of capital. We use the standard event-study methodology to compute the market model adjusted return (see 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.
use two levels of analysis to capture the effect of *supply shock*. First, we 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. In the second method, we exploit the variation generated by the intensity of shocks experienced by different banks during the Russian crisis. $X_{ik}$ is a set of control variables that we discuss in detail in the subsequent section.

The above model is essentially a difference-in-difference estimation technique, where we already have taken the difference in the market value of a firm’s equity across the crisis period as the dependent variable. An alternative model can be estimated using two sets of cross-sectional data, one before and one after the crisis. With these datasets, we can test our hypothesis by estimating the following model:

$$\ln(value)_{it} = \alpha + \beta_{bankdep_i} + \gamma_{after_{it}} + \theta_{bankdep_i \times after_{it}} + \sum_{k=1}^{K} \zeta_{k} X_{it} + \epsilon_{it}$$

The dependent variable $\ln(value)_{it}$, market value of equity, measures the firm’s value at time $t$, where $t \in (before, after)$. $after_{it}$ is a dummy variable that takes a value of zero for the pre-crisis date and one after that date. The estimate on interaction term, $\theta$, is the coefficient of interest in this regression. It measures the change in bank-dependent firm’s value around the crisis period as compared to the drop in the rated firm’s value. We prefer the first model specification based on stock return as the dependent variable due to three main advantages: (a) stock return is a better measure of performance if there are payouts, stock splits or stock issuances during this period, (b) stock return has better statistical properties than market value, and (c) stock return can be easily adjusted for a firm’s systematic risk, for example, by using CAPM model. In an unreported robustness test, we estimate the alternative model with firm value as the dependent variable and obtain similar results.

Our basic premise is that the origin of Russian crisis was exogenous to the performance
of U.S. domestic borrowers (with no direct exposure to the crisis affected region) and, therefore, we can trace the effect of the shock to the supply of bank capital on the borrower’s performance. To test this empirically, we use the lack of public debt rating as a proxy for bank-dependence in our first test. During the crisis period, the public debt market was operating at relatively normal levels. This gives us a source of variation across rated and bank-dependent firms at the time of crisis.

Our test will be ideal if firms are randomly assigned to rated and unrated groups, which is unlikely to be true. As we show later, there are significant differences between these two groups in terms of size, default risk, and stock market liquidity. It is likely that the decision to obtain rating is systematically related to these firm characteristics, which by themselves can affect the market valuation of firms during the crisis period. If we knew the exact functional form of the relation between these characteristics and the outcome variable, then we could directly control for them in the OLS setting. However, in the absence of strict theoretical guidelines, any assumption on the exact functional form is likely to suffer from severe specification bias.

Given these difficulties and in the absence of a randomized assignment of firms into the two groups, we proceed with a matched sample technique. The matching technique is based on the following idea. For each firm in the bank-dependent group, we find a comparable rated firm that serves as a counterfactual for the bank-dependent firm. The comparable firm is obtained on the basis of the nearest neighborhood caliper matching (Cochran and Rubin, 1973) using propensity score method (Rosenbaum and Rubin, 1983). The identifying assumption in this method is that conditional on the set of matching variables, the assignment of firms to the two groups is independent of the potential outcome (see Heckman and Vytlacil, 2008). Thus, the difference between the average stock returns across the two groups yields an unbiased and consistent estimate of the average treatment effect. Our goal is to obtain observationally equivalent set of firms in the rated and unrated group, so that we can attribute any difference between the performance of the two groups to the supply-side shock. The observational equivalence should be on those dimensions that are likely to be correlated
with a firm’s performance during the crisis period. These factors generate alternative hypotheses and thus motivate the inclusion of control variables in the regression model and the dimensions along which we match rated and bank-dependent firms.

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 of 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-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 and 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 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.8

Our third alternative channel is the firm’s growth opportunity set. Growth opportunities affect the demand of capital and firm’s 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.

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

8Our results are robust to using either the distance-to-default measure or the set of other covariates alone.
likelihood of adverse selection in trades of bank-dependent firms, then they will 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 & 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 $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. A firm reporting operations in Europe or Eurasia may have operations in Russia. 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 a 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 the 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 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. We calculate a firm's default risk by Merton-model-implied distance-to-default, which effectively is the volatility-adjusted measure of market leverage. The average bank-dependent firm is significantly riskier than the rated firm based on this measure. When we analyze the components of default risk, we find that bank-dependent firms have lower leverage but significantly higher equity return volatility. Bank-dependent firms also have higher effective bid-ask spread 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 more 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 Figure 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 firm’s 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 the 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 sub-sample of bank-dependent firms. The full sample test uses a linear regression approach and serves as a benchmark for the rest of the analysis.

4.1 Full sample analysis

Table 1 presents the distribution of returns across the rated and bank-dependent firms during the crisis period. In the 16-day crisis period that started a trading day before the Russian debt default and ended a trading day after 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 firm. 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 basic model. All models include industry fixed effects based on Fama-French industry classification. Model 1 shows that the 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 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 firm’s profitability as measured by its EBITDA-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 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 find that the relation between spread and returns is negative at the univariate level. Once we control for the firm’s size, this relation reverses in the regression.

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 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.

4.1.1 Returns during 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, in turn, allows us to compute the statistical significance of our results after accounting for any non-normality in the data. It also 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 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 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.

Given the disparity in the observable characteristics of the rated and bank-dependent firms, we now turn to the matched sample analysis. Our general approach is to find pairs of bank-dependent and rated firms, where both firms in a pair are identical along every meaningful dimension except for the access to public-debt market. The dimensions along which we match are motivated by competing hypotheses outlined above.
4.2 Matched sample analysis

4.2.1 Propensity score matching

We use the propensity score method for matching bank-dependent firms with rated firms along multiple dimensions (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 variables along which we want to match rated and bank-dependent firms. These variables are firm size, market-to-book ratio, leverage, past stock return, stock market liquidity, profitability, and distance-to-default based measure of default likelihood. In addition, we add Fama-French industry dummies to control for industry specific factors.

Model 1 (pre-match) of Table 3 presents the estimation results. The propensity of obtaining 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. It is worth noting that this estimation exercise is not intended for making any causal inferences between a firm’s choice of obtaining credit rating and its characteristics. Our limited goal is to project several of the firm characteristics on the bank-dependence choice and use the resulting likelihood score as the matching dimension.

After estimating the Probit model, we obtain the probability of getting rated for every firm in the sample. This is called the propensity score. 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. This technique uses the nearest 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

---

9Our results are robust to changing this band to +/-5% or other comparable range.
a rated firm to serve as a match for up to three bank-dependent firms.\textsuperscript{10} 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 rating on the matched sample and present the results in Model 2 (\textit{post-match}) of Table 3. None of the variables is significant in this estimation, indicating that after the match firms are equally balanced between rated and bank-dependent group along these dimensions. The model’s R-squared, not surprisingly, drops to 4.5\% on the matched sample.

In Figure 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 proxied by the distance to default of the firm. 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. As the probit model on the post-match sample suggests, we find similar patterns along other dimensions. In a nutshell, the matched sample is equally balanced on the observable dimensions that might influence stock returns during this period.

\textsuperscript{10}Our results are robust with two or four repetitions.
4.2.2 Results

After establishing the equivalence of firms in the bank-dependent and rated groups along observable dimensions, we analyze the difference in stock returns of these two groups in Table 4. The bank-dependent firms earned -6.61% mean return as compared to the average return of -2.67% for the matched sample of rated firms. 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.

We also conduct a bootstrapping test similar to the test on the entire sample. We generate 100 random samples of 16-day return between January 1985 and December 1998. For each period, we create a matched sample of bank-dependent and rated firms using 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 4. There is a positive but insignificant difference of 10 basis points between these two groups in an average random period. This can serve as a falsification test. The empirical distribution reveals that there is only a 1% chance of getting 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.

4.2.3 Returns During CP Crisis of October 1998

The CP-bill spread, a measure of overall liquidity in the economy, increased dramatically in October 1998 (see Fig 1). Unlike our event window of late August and early September, during this period firms in general - both bank-dependent and others - faced severe liquidity crisis. Though firms with access to public debt market may still have relatively better access to capital than bank-dependent firms, the difference narrowed considerably during this period. Thus, we expect the market’s differential response to narrow or perhaps completely disappear during this period, as compared to our base period, when the wedge between access to capital across firms with and without access to public debt markets was quite high.

We use this period from October 5, 1998 to October 19, 1998 as another falsification
period. We report the return on bank-dependent and rated firms during this period in Table 4. We find no statistical difference between the two groups during this period. This result shows that our main findings are less likely to be explained by any omitted variables such as a missing risk factor. In our base event window, when CP-bill spreads are not too high (as compared to historical levels) and banks experience considerable losses, we find a large and statistically significant difference in value drop for bank-dependent firms as compared to the matched rated firms. A month later when there is a systematic drop in liquidity across all firms, i.e., when all firms in a way became bank-dependent, this difference disappears. In addition, during a normal random period there is no difference between the two groups either.

4.2.4 Other matching criteria

As a robustness check, we perform an alternative matched sample analysis. We adopt a dimension-by-dimension matching 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. Among all rated firms in this band, we pick the firm that is the closest in terms of the distance-to-default measure of distress risk. 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 provided in the fourth model in Panel A of Table 4 indicate that bank-dependent firms significantly under-performed their rated counterpart during the crisis period by 3.6%.

4.3 Evidence from variations within bank-dependent borrowers

We now exploit the variation across the bank-dependent firm’s 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 sub-sample only, this analysis doesn’t 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 crisis. In a lending market with adverse selection problems (such as Stiglitz and Weiss (1981)), collateral can serve as a mechanism to alleviate the lemons problem (see Bester (1985) and Besanko and Thakor (1987)). We hypothesize that a bank-dependent firm with a higher fraction of unpledged assets should suffer less. These firms can be the first to obtain funding from banks at the time of crisis by offering their collateral. At the same time, these firms also have the potential to offer collateral to non-banking financial institutions or to other private lenders in the event of refusal of credit by their own banks.

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 dataset we are able to construct a reasonable estimate of the total secured loans.\textsuperscript{11} We obtain all bank loans outstanding at the time of crisis and 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 dataset with COMPUSTAT-CRSP dataset using firm names, leading to loss of many observations, (b) many loan facilities do not have information on whether the loan is secured, and (c) we consider only those firms that have bank loans outstanding as of August 1998.

We create three proxies of available collateral: (a) the fraction of past loans (out of all 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 in Table 5. For each specification, we find that bank-dependent firms with higher available collateral perform significantly better than the remaining bank-dependent firms (at 5% or better

\textsuperscript{11}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.
significance level). Thus, higher financial flexibility weakens the effect of bank dependence on firm valuation during the time of crisis. In every specification, we control for the firm’s distance-to-default as well as other characteristics that are likely to be associated with its default risk. We do so to minimize the concerns that unpledged collateral is simply a proxy for low credit risk.

4.4 Evidence from variations across the banks

So far in our tests, we have exploited the variation in a firm’s dependence on banks and its ability to raise capital from other sources. In our next set of tests, we exploit the variation along the bank’s dimension. We investigate whether the borrowers of banks that are severely affected by the Russian crisis perform worse than the borrowers of banks that are not affected by the crisis. This allows us to directly comment on the effect of banks’ losses in the international market on its domestic borrowers’ performance. This test has several econometric advantages as well. Rather than comparing bank-dependent firms with their rated counterparts, we can now compare borrowers of affected and unaffected banks within the set of bank-dependent firms itself. This allows our econometric tests to identify the effect of variation in the supply of capital independently of omitted variable and self-selection concerns present in studies involving the comparison of rated and unrated firms.

In particular, we estimate the following model on the sub-sample of bank-dependent firms\textsuperscript{12}:

\[ r_i = \beta_0 + \beta_1 \text{affbank}_i + \sum_{k=1}^{K} \phi_k X_i + \epsilon_i \]

In the above models, \text{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. This, we argue, allows us to identify and

\textsuperscript{12}We also estimate a specification where we use the rated firms in the sample as well and estimate the model with \textit{bankdep}, \textit{affbank}, and the 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.
hence causally estimate the valuation effect of the supply of capital.

To estimate this model, we need to first classify banks into affected and unaffected categories based on their exposure to the Russian crisis. We use two primary sources of data to obtain information on a bank’s exposure to the crisis. Our first source of data is the call reports required to be filed by every FDIC-insured commercial bank on a quarterly basis. We augment this data source with the information contained in the footnotes to the banks’ annual statements. The latter data is provided by Kho, Lee, and Stulz (2000), who read the financial statements of 78 large banks covered in the Datastream dataset.

4.4.1 Identification of the bank’s exposure

To construct these proxies, we first need to gather information on the identity of the firm’s main banks and then obtain data on the extent of exposure of these banks to the Russian crisis. We obtain information on the banking relationship from the Dealscan dataset. From this dataset, we collect all loans made to the borrowing firms in our sample which are outstanding at the time of crisis. We restrict our attention to loans made by 78 large banks covered in the Datastream dataset. 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 dataset with the identity of banks in the Call Report dataset, it becomes easier from the data collection viewpoint to focus on this sample. This list contains all the large U.S. banks and, therefore, 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.

Our first source of information is the call report data filed by all bank holding companies on a quarterly basis. We collect information on the bank’s financial condition as of the third quarter of 1998. 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 the borrowers with their banks as of August 1998.
Though banks do not report the extent of their business activity on a country-by-country basis in this dataset, they do report much useful information on their involvement in the foreign markets at an aggregate level. From the call report, we get the dollar amount of non-performing loans and leases made to foreign borrowers. This item includes loans made to foreign individuals, corporations, banks, and governments. Given the data limitation this is a reasonable measure of a bank’s losses due to their loans and investments in Russia during this time period. This measure doesn’t directly capture the losses on the foreign debt and equity securities, which motivates the use of our second proxy below.

We consider investments in foreign loans and securities - both debt and equity - held as of 1998Q3 as our second proxy for a bank’s exposure to the crisis. Foreign loans measure all commercial, bank-to-bank, and government loans extended to foreign borrowers. Foreign securities measure all the direct investments through marketable securities. This measure captures the extent of a bank’s exposure to the crisis in the international market, whereas the non-performing loan-based measure captures the quality of its exposure. These two measures have their own advantages and shortcomings. The foreign loan and securities-based measure captures the extent of exposure across both loans and securities, but it doesn’t measure the quality of these investments. The non-performing loans-based measure is closer in spirit to the adverse capital shocks faced by the banks, but this misses the 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 83%; therefore, it is not surprising that our results remain similar based on either of the two proxies.

Our second source of data is the study by Kho, Lee, and Stulz (2000). They consider the same sample of banks to analyze the effect of various international crises on the stock returns of these banks. They obtain information on whether these banks are exposed to a particular crisis or not from their annual reports. Kho, Lee, and Stulz (2000) show that the stock market distinguishes between banks with and without any exposure to a crisis country. They show that the crisis-exposed banks earned significantly lower returns than the non-exposed banks during our crisis period, especially in the event window of August 27,
1998 to September 3, 1998 (see Table 1 of their paper for details). We use their classification as our second measure of a bank’s exposure to the crisis. If a bank is classified as having exposure to the Russian 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 correlation of about 70% with the measure based on call report data.\textsuperscript{13}

\subsection*{4.4.2 Details of banks exposure & regression results}

Our sample drops to 391 bank-dependent firms for which we could obtain the identity of their main banks and their exposure to the crisis. The average (median) bank’s foreign NPA amounts to about 5 bps (0 bps) as a percentage of its total assets. The average holding of foreign loans and securities as a percentage of total assets is 1.4% (median 0.02%). As per the Kho, Lee, and Stulz (2000) measure, 7 banks are classified as having exposure to the crisis, whereas the others are not. Thus, there was considerable heterogeneity in the bank’s exposure to the international crisis in Fall 1998. Both the call-report exposure measures indicate that Citicorp, Chase Manhattan Corporation, Bankers Trust, Bank of America, and Bank of New York had considerable exposure. Each one of these banks has foreign NPA of over 5bps, with Citicorp’s NPA as high as 82 bps. These banks’ foreign loans and securities range from 2-14% as of 1998Q3. They are also classified as being exposed to the crisis as per Kho, Lee, Stulz (2000) exercise. Some of the banks that have little to no exposure to the crisis are Wells Fargo, Banc One Corporation, National City Bank, and Wachovia Corporation.

We use these three measures as proxies for $affbank$ and provide the regression results in Table 6. All standard errors are clustered at the bank level. In our first test, we use $Affected_{foreign NPA}$ as the measure of bank’s exposure. $Affected_{foreign NPA}$ is computed as the log of [one plus foreign NPA (in basis points) as a percentage of bank’s total assets]. We

\textsuperscript{13}The call report-based measures are continuous, whereas Kho, Lee, and Stulz (2000) measure is dichotomous. In our subsequent tests, we create dichotomous variables based on the call-report dataset as well. If a bank has more than average foreign NPA and foreign loans and securities, we classify it into the affected group. The correlation of 70\% is based on the indicator variable-based classification.
add one basis point to this variable to include banks with zero foreign NPA in the analysis. Model 1 presents the regression result. The coefficient on $\text{Affected}_{\text{foreignNPA}}$ is negative and significant; borrowers of crisis-affected banks experience significantly higher negative returns. We obtain similar result for the second proxy $\text{Affected}_{\text{foreignsec}}$ that is based on the holdings of foreign loans and securities (Model 2).

Finally, in Model 3, we combine information from Kho, Lee, and Stulz (2000) with the aforementioned exposure proxies.\(^{14}\) We create a dummy variable $\text{Affected}_{\text{KLS}}$ that takes the value of one if the bank is classified as exposed by Kho, Lee, and Stulz (2000) or if the bank is classified as exposed based on call-report measures. We find that the crisis-affected bank’s borrowers earn 4.34% lower returns than the unaffected bank’s borrowers after controlling for the effect of firm size, default risk, growth opportunities, and stock market liquidity. This is an economically large valuation effect. The result is statistically significant at the 1% level.

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. 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 economy to the other through the banking channel.

4.4.3 Evidence from the shift in loan-supply curve

In our final test, we directly investigate 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 demand curve and an upward sloping

\(^{14}\)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. To do this, we need to create a dichotomous measure of exposure based on the continuous call-report measures. We classify a bank with foreign NPA greater than 5bps and foreign loans and securities greater than 2% as affected banks. These cut-off points are motivated by the empirical distribution of these two measures. In particular, we find that the extent of NPAs and foreign loans and securities fall drastically, almost in a discrete fashion, at these thresholds.
supply curve for the bank credit, any shock to the supply of credit should lead to an inward shift in the supply curve. The credit crunch, therefore, 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 and thus allows us to estimate the effect of supply shock. This methodology is less likely to be affected by the changes in composition of borrowers of the banks around the crisis period.

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:

\[ Y_{it} = \alpha + \beta_{postcrisis_{it}} + \gamma_{affected_i} + \theta_{postcrisis_{it}} \cdot affected_i + \kappa_{macrovar_{it}} + \epsilon_{it} \]

\( Y_{it} \) is either the loan spread, our proxy for the price of bank credit, or the loan amount for firm \( i \) 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 the composite measure of bank’s exposure to crisis (Model 3) from the previous section. We are interested in estimating \( \theta \) 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 refine this model by including bank fixed effects on the right hand side. In this model, \( affected_i \) gets subsumed by the fixed effects so we cannot comment on the coefficient on this variable. However, it allows us to consistently estimate \( \theta \), our main variable of interest, after
accounting for any bank-specific unobserved heterogeneity. In particular, this methodology is less susceptible to biases due to unobserved quality of the borrowers of a given bank. We only present results from the fixed-effect model to save space. We include two macroeconomic variables, credit-spread and term-spread, as additional control variables.

Results are provided in Table 7. 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 19%. Model 2 shows that the amount of loan from the crisis-affected banks also decreased disproportionately more than the unaffected banks. Since Model 2 is estimated at the loan-level data, it doesn’t 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 claim that 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 the disproportionately large 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, an exogenous event caused by the Russian government’s decision to default, resulted in significant loss of equity capital and consequently, a capital crunch in the U.S banking sector, independent of the U.S. borrower’s financial health. This natural experiment allows us to investigate the effect of bank’s health on the bank-dependent firm’s value. Our results strongly support the hypothesis that bank-dependent firms face
adverse valuation consequences when banking sector’s financial health deteriorates. Among bank-dependent firms, the drop in valuation is 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 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 crisis 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 can be taken as evidence in support of costly 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 current sub-prime mortgage crisis as well as future policy designs by monetary and banking authorities.
References


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 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 US dollars.

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

**Market-to-Book** 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.

**DD** is a measure of the default risk of the firm. It is the percentile ranking of the firms based on the distance to default (constructed as in Bharath and Shumway (2008)) and is defined as

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

where \(E\) is the market value of equity, \(F\) is the face value of debt, \(\sigma_V\) is the asset volatility, and \(r_{it-1}\) is the firms stock return over the previous year, \(T\) is the time horizon that is set to one year.

**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 Fed’s H.15 release.

**creditspread** is the spread in the yields between a BAA rated bond and a AAA rated bond taken from Fed’s H.15 release.
Figure 1: Paper-Bill spread during 1997 – 98
Figure 2: Growth in Bank Loans

This figure plots the growth rates in number and amount of loans around the 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 sub-set of bank-dependent firms - firms without access to public debt-market.
Figure 3: Distribution of Key Characteristics of Bank-Dependent and Rated Firms: 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).
Table 1: Descriptive Statistics
This table reports summary statistics of key variables used in the analysis. All firm level information is lagged by at least six months and is extracted as of May-1998. COMPUSTAT is the source for all firm level balance sheet information. 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 US 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. DD is the percentile ranking of the firm based on distance to default (computed based on Bharath and Shumway (2008)). 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.

<table>
<thead>
<tr>
<th></th>
<th>Panel A: Rated Firms (N=304)</th>
<th></th>
<th>Panel B: Bank-Dependent Firms (N=2665)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>25th pctl</td>
<td>Median</td>
</tr>
<tr>
<td>sales</td>
<td>2839.98</td>
<td>716.90</td>
<td>1243.49</td>
</tr>
<tr>
<td>lever</td>
<td>0.29</td>
<td>0.19</td>
<td>0.29</td>
</tr>
<tr>
<td>mtb</td>
<td>2.01</td>
<td>1.29</td>
<td>1.66</td>
</tr>
<tr>
<td>DD</td>
<td>0.32</td>
<td>0.15</td>
<td>0.28</td>
</tr>
<tr>
<td>sigma_equity</td>
<td>0.34</td>
<td>0.28</td>
<td>0.32</td>
</tr>
<tr>
<td>pastret</td>
<td>0.13</td>
<td>-0.02</td>
<td>0.16</td>
</tr>
<tr>
<td>ebitda/sales</td>
<td>0.20</td>
<td>0.11</td>
<td>0.17</td>
</tr>
<tr>
<td>bidask</td>
<td>1.54</td>
<td>0.85</td>
<td>1.10</td>
</tr>
<tr>
<td>CAR (%)</td>
<td>-2.74</td>
<td>-8.22</td>
<td>-2.02</td>
</tr>
</tbody>
</table>
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. Industry fixed effects using Fama-french 48 industry codes are included in all regressions. Robust t-statistics computed using Huber/White/sandwich estimate of variance are reported in brackets. Adjusted $R^2$ and the number of observations are reported in the last two rows.

### Panel A: Regression results from full sample

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>$t$-val</td>
<td>Estimate</td>
</tr>
<tr>
<td><code>bankdep</code></td>
<td>-0.0361</td>
<td>(-3.79)</td>
<td>-0.0310</td>
</tr>
<tr>
<td><code>log(sales)</code></td>
<td>0.0164</td>
<td>(8.12)</td>
<td>0.0166</td>
</tr>
<tr>
<td><code>mtb</code></td>
<td>0.0012</td>
<td>(0.47)</td>
<td>0.0022</td>
</tr>
<tr>
<td><code>lever</code></td>
<td>-0.0495</td>
<td>(-2.88)</td>
<td>-0.0247</td>
</tr>
<tr>
<td><code>DD</code></td>
<td>-0.0488</td>
<td>(-2.00)</td>
<td>-0.0490</td>
</tr>
<tr>
<td><code>bidask</code></td>
<td></td>
<td></td>
<td>0.0053</td>
</tr>
<tr>
<td><code>pastret</code></td>
<td>-0.0625</td>
<td>(-6.99)</td>
<td>-0.0630</td>
</tr>
<tr>
<td><code>sigma_equity</code></td>
<td>-0.0453</td>
<td>(-2.27)</td>
<td>-0.0464</td>
</tr>
<tr>
<td><code>ebitda/sales</code></td>
<td>-0.0004</td>
<td>(-0.19)</td>
<td>-0.0005</td>
</tr>
<tr>
<td><code>bankdep * mtb</code></td>
<td></td>
<td></td>
<td>-0.0142</td>
</tr>
</tbody>
</table>

| $R^2$          | 0.082      | 0.122      | 0.123      |
| $N$            | 2969       | 2956       | 2956       |

Fixed Effects FF Industry FF Industry FF Industry

### Panel B: Regression results from bootstrapped sample

<table>
<thead>
<tr>
<th>Variable</th>
<th>mean</th>
<th>p0</th>
<th>p5</th>
<th>p10</th>
<th>p25</th>
<th>p50</th>
<th>p75</th>
<th>p90</th>
<th>p99</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>bankdep</code></td>
<td>-0.0021</td>
<td>-0.0252</td>
<td>-0.0178</td>
<td>-0.0069</td>
<td>-0.0017</td>
<td>0.0030</td>
<td>0.0084</td>
<td>0.0219</td>
<td></td>
</tr>
</tbody>
</table>
Table 3: Matching Estimation Results

The following table presents the results of a probit regression with bank dependence as the dependent variable. In Pre-Match model, the entire sample 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. More details on the matching algorithm are provided in section 4.2.1 of the paper. Robust t-statistics computed using Huber/White/sandwich estimate of variance are reported in brackets. Pseudo $R^2$ and the number of observations are reported in the last two rows.

<table>
<thead>
<tr>
<th></th>
<th>Pre-Match</th>
<th></th>
<th>Post-Match</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>$t$-val</td>
<td>Estimate</td>
<td>$t$-val</td>
</tr>
<tr>
<td>log(sales)</td>
<td>1.0363</td>
<td>(13.00)</td>
<td>-0.0770</td>
<td>(-0.97)</td>
</tr>
<tr>
<td>mtb</td>
<td>0.0058</td>
<td>(0.08)</td>
<td>-0.0421</td>
<td>(-0.63)</td>
</tr>
<tr>
<td>lever</td>
<td>0.9326</td>
<td>(2.34)</td>
<td>0.1635</td>
<td>(0.42)</td>
</tr>
<tr>
<td>sigma_{equity}</td>
<td>-2.5941</td>
<td>(-3.86)</td>
<td>-0.7068</td>
<td>(-1.08)</td>
</tr>
<tr>
<td>ebitda/sales</td>
<td>4.3155</td>
<td>(5.37)</td>
<td>0.9066</td>
<td>(1.39)</td>
</tr>
<tr>
<td>bidask</td>
<td>-0.0657</td>
<td>(-0.59)</td>
<td>-0.1127</td>
<td>(-0.84)</td>
</tr>
<tr>
<td>pastret</td>
<td>-0.4812</td>
<td>(-2.55)</td>
<td>-0.1866</td>
<td>(-0.84)</td>
</tr>
<tr>
<td>DD</td>
<td>-0.9152</td>
<td>(-1.07)</td>
<td>0.5628</td>
<td>(0.66)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.701</td>
<td></td>
<td>0.045</td>
<td></td>
</tr>
<tr>
<td>$N$</td>
<td>2942</td>
<td></td>
<td>470</td>
<td></td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>FF Industry</td>
<td>FF Industry</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 4: Impact of Russian Crisis on Bank-Dependent Borrowers: Evidence from Matched Sample

Panel A of this table provides the mean abnormal returns (measured as market model adjusted stock returns) over various time periods. In the first column, Aug-98, the abnormal returns are for the period Aug 14, 1998 to Sep 4, 1998. In the second column, CP-Period, the abnormal returns are for CP crisis period 5 Oct, 1998 to 19 Oct, 1998. In the third column random period, the returns are measured over 100 random samples of 16 contiguous days during Jan 1985 to Dec 1998. In these three models, the construction of treatment (treat=1) and control (treat=0) groups is based on the propensity score matching in Table 3 as described in detail in section 4.2.1 of the paper. In the fourth column, the returns are measured during the crisis period Aug 14, 1998 to Sep 4, 1998, but the matching criteria is based on Size within the same industry (See section 4.2.4 for more details on the matching). For all the four models, the mean return for the treatment and control groups and the difference between the returns of these two groups is 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, the CAR for the treatment and control group from a bootstrapping exercise is provided (details in Section 4.2.2)

### Panel A: CAR for treatment and control groups

<table>
<thead>
<tr>
<th></th>
<th>Aug-98</th>
<th>CP period</th>
<th>Random Period</th>
<th>Size Match</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CAR_{treat=0}$</td>
<td>-0.0267</td>
<td>-0.0195</td>
<td>-0.0016</td>
<td>-0.0481</td>
</tr>
<tr>
<td>$CAR_{treat=1}$</td>
<td>-0.0661</td>
<td>-0.0107</td>
<td>-0.0005</td>
<td>-0.0842</td>
</tr>
<tr>
<td>$CAR_{treat=1} - CAR_{treat=0}$</td>
<td>-0.0394</td>
<td>0.0091</td>
<td>0.0010</td>
<td>-0.361</td>
</tr>
<tr>
<td>t-stat for $\Delta CAR$</td>
<td>-2.52</td>
<td>0.54</td>
<td>0.58</td>
<td>-2.18</td>
</tr>
<tr>
<td>N</td>
<td>470</td>
<td>460</td>
<td>100</td>
<td>253</td>
</tr>
</tbody>
</table>

### Panel B: CAR for treatment and control groups from a bootstrapped sample

<table>
<thead>
<tr>
<th>variable</th>
<th>mean</th>
<th>p1</th>
<th>p5</th>
<th>p25</th>
<th>p50</th>
<th>p75</th>
<th>p90</th>
<th>p99</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CAR_{treat=0}$</td>
<td>-0.0016</td>
<td>-0.0555</td>
<td>-0.0364</td>
<td>-0.0166</td>
<td>-0.0034</td>
<td>0.0085</td>
<td>0.0252</td>
<td>0.1020</td>
</tr>
<tr>
<td>$CAR_{treat=1}$</td>
<td>-0.0005</td>
<td>-0.0549</td>
<td>-0.0296</td>
<td>-0.0145</td>
<td>0.0003</td>
<td>0.0097</td>
<td>0.0198</td>
<td>0.0913</td>
</tr>
<tr>
<td>$CAR_{treat=1} - CAR_{treat=0}$</td>
<td>0.0010</td>
<td>-0.0409</td>
<td>-0.0280</td>
<td>-0.0078</td>
<td>-0.0005</td>
<td>0.0083</td>
<td>0.0283</td>
<td>0.0469</td>
</tr>
</tbody>
</table>

41
Table 5: Impact of Financial Flexibility: Collateral
This table analyzes the impact of financial flexibility (as measured by collateral availability) on the stock market reaction during the Russian crisis. The sample is restricted to bank-dependent firms with coverage on Dealscan Database. Firm’s 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 firm’s outstanding loans in the dealscan database). *amtsec* is (1-the amount of firm’s loans that are secured divided by total amount of firm’s outstanding loans). *sectan* is (1-the amount of firm’s loans that are secured divided by the firm’s tangible assets (as proxied by the net plant, property and equipment)). Robust t-statistics computed using Huber/White/sandwich estimate of variance are reported in brackets. Adjusted $R^2$ and the number of observations are reported in the last two rows.

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
<th>Model 3</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>$t$-val</td>
<td>Estimate</td>
<td>$t$-val</td>
<td>Estimate</td>
<td>$t$-val</td>
</tr>
<tr>
<td>loansec</td>
<td>0.0306</td>
<td>(2.00)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>amtsec</td>
<td></td>
<td></td>
<td>0.0333</td>
<td>(2.22)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>sectan</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.0026</td>
<td>(2.27)</td>
</tr>
<tr>
<td>log(sales)</td>
<td>0.0079</td>
<td>(1.24)</td>
<td>0.0077</td>
<td>(1.21)</td>
<td>0.0086</td>
<td>(1.39)</td>
</tr>
<tr>
<td>mtb</td>
<td>0.0092</td>
<td>(1.24)</td>
<td>0.0091</td>
<td>(1.23)</td>
<td>0.0087</td>
<td>(1.17)</td>
</tr>
<tr>
<td>lever</td>
<td>-0.0432</td>
<td>(-0.85)</td>
<td>-0.0429</td>
<td>(-0.84)</td>
<td>-0.0311</td>
<td>(-0.60)</td>
</tr>
<tr>
<td>DD</td>
<td>0.0115</td>
<td>(0.22)</td>
<td>0.0121</td>
<td>(0.23)</td>
<td>-0.0008</td>
<td>(-0.02)</td>
</tr>
<tr>
<td>bidask</td>
<td>0.0029</td>
<td>(1.21)</td>
<td>0.0029</td>
<td>(1.22)</td>
<td>0.0026</td>
<td>(1.10)</td>
</tr>
<tr>
<td>pastret</td>
<td>-0.0511</td>
<td>(-2.62)</td>
<td>-0.0510</td>
<td>(-2.62)</td>
<td>-0.0530</td>
<td>(-2.74)</td>
</tr>
<tr>
<td>sigmaweight</td>
<td>-0.0597</td>
<td>(-1.26)</td>
<td>-0.0588</td>
<td>(-1.24)</td>
<td>-0.0612</td>
<td>(-1.30)</td>
</tr>
<tr>
<td>ebitda/sales</td>
<td>0.0337</td>
<td>(1.05)</td>
<td>0.0327</td>
<td>(1.02)</td>
<td>0.0332</td>
<td>(1.04)</td>
</tr>
</tbody>
</table>

$R^2$          | 0.148   |          | 0.149   |          | 0.152   |          |
$N$              | 630     |          | 630     |          | 628     |          |

Fixed Effects | FF Industry | FF Industry | FF Industry |
Table 6: Impact of Russian Crisis on Bank-Dependent Borrowers: Evidence from Matched Sample of Banks and Borrowers

In this table we provide the regression results from a matched sample of banks and borrowers. The sample is restricted to the banks and borrowers 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. Affected$_{f_{\text{oreignNPA}}}$ measures the NPA of the bank from foreign operations extracted from Sep-1998 call report data of the bank. Affected$_{f_{\text{oreignsec}}}$ measures the losses from trading in foreign securities scaled by the total assets of the bank and is extracted from Sep-1998 call report data of the bank. Affected$_{KLS}$ is a dummy that takes the value of one for the banks that are classified as exposed to Russia by Kho, Lee, Stulz (2000) or by call-report-based measures. Other variable definitions are given in Appendix A. Robust t-statistics computed using Huber/White/sandwich estimate of variance and 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.

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th></th>
<th></th>
<th>Model 2</th>
<th></th>
<th></th>
<th>Model 3</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>t-val</td>
<td>Estimate</td>
<td>t-val</td>
<td>Estimate</td>
<td>t-val</td>
<td>Estimate</td>
<td>t-val</td>
</tr>
<tr>
<td>Affected$<em>{f</em>{\text{oreignNPA}}}$</td>
<td>-0.0158</td>
<td>(-2.02)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.0434</td>
<td>(-2.66)</td>
</tr>
<tr>
<td>Affected$<em>{f</em>{\text{oreignsec}}}$</td>
<td></td>
<td></td>
<td>-0.0239</td>
<td>(-1.84)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Affected$_{KLS}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.0355</td>
<td>(5.71)</td>
</tr>
<tr>
<td>log(sales)</td>
<td>0.0352</td>
<td>(6.33)</td>
<td>0.0344</td>
<td>(5.96)</td>
<td>0.0355</td>
<td>(5.71)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>mtb</td>
<td>0.0030</td>
<td>(0.46)</td>
<td>0.0031</td>
<td>(0.47)</td>
<td>0.0062</td>
<td>(0.95)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>lever</td>
<td>-0.0296</td>
<td>(-0.46)</td>
<td>-0.0302</td>
<td>(-0.47)</td>
<td>-0.0323</td>
<td>(-0.49)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>intercept</td>
<td>-0.3700</td>
<td>(-4.24)</td>
<td>-0.3324</td>
<td>(-4.32)</td>
<td>-0.2277</td>
<td>(-5.87)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.204</td>
<td></td>
<td>0.202</td>
<td></td>
<td>0.205</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>391</td>
<td></td>
<td>391</td>
<td></td>
<td>386</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 7: 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 the banks and borrowers we are able to match across CRSP, COMPUSTAT, call report data and, Dealscan. A bank is classified as affected if the bank is classified as exposed to Russia by Kho, Lee, Stulz (2000) or by call-report-based measures. post is a dummy that takes the value of one if the loan is originated after Aug 1, 1998. 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 computed using Huber/White/sandwich estimate of variance are reported in brackets. Adjusted $R^2$ and the number of observations are reported in the last two rows.

<table>
<thead>
<tr>
<th></th>
<th>log(Loan Spread)</th>
<th>log(Loan Amount)</th>
<th>log(Bank Lending)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>t-val</td>
<td>Estimate</td>
</tr>
<tr>
<td>post * affected</td>
<td>0.1937</td>
<td>(3.56)</td>
<td>-0.2058</td>
</tr>
<tr>
<td>postcrisis</td>
<td>-0.0041</td>
<td>(-0.07)</td>
<td>0.1216</td>
</tr>
<tr>
<td>termspread</td>
<td>-0.0591</td>
<td>(-0.90)</td>
<td>0.1812</td>
</tr>
<tr>
<td>creditspread</td>
<td>0.7076</td>
<td>(4.41)</td>
<td>0.0923</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.036</td>
<td></td>
<td>0.003</td>
</tr>
<tr>
<td>$N$</td>
<td>3887</td>
<td></td>
<td>3887</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Bank</td>
<td></td>
<td>Bank</td>
</tr>
</tbody>
</table>