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PII: S1058-3300(16)30074-X
DOI: doi: 10.1016/j.rfe.2017.03.006
Reference: REVFIN 404

To appear in: *Review of Financial Economics*

Received date: 20 July 2016
Revised date: 16 March 2017
Accepted date: 27 March 2017

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Wan-Chien Chiu[1], Chih-Wei Wang [2*], and Juan Ignacio Peña[3]

Abstract

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JEL classification: G01; G18; G32

Keywords: Bank loans; Supply shock; Debt financing; Default risk; Public debt markets

[1] Department of Quantitative Finance, National Tsing Hua University, Taiwan; e-mail wanchien418@gmail.com.

[2] Department of Finance, National Sun Yat-sen University, 70. Lianhai Rd., Kaohsiung, 804 Taiwan; e-mail chwang@mail.nsysu.edu.tw.

*Corresponding author; Phone: +886 922157576

[3] Department of Business Administration, Universidad Carlos III de Madrid, Calle Madrid 126, 28903 Getafe, Madrid, Spain; e-mail ypenya@eco.uc3m.es.

Acknowledgements

We thank participants at the 4th International Conference on Financial Engineering & Banking Society, in Guildford, UK, at the XXI Finance Forum (2013) annual meeting of the Spanish Finance Association) in Segovia, Spain, at the 4th Conference on Credit Analysis and Risk Management, in Basel, for useful comments. Chih-Wei acknowledges financial funding from MOST 105-2410-H-110-015. This research is partially supported by the College of Management, National Sun Yat-sen University, Taiwan under grant CMNSYSU-SRS-2016-04.

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We examine whether the source of debt financing is important for assessments of firms' default risk. This study reveals that during the 2007–2010 financial crisis, firms that depend mainly on financing from banks suffer higher increases in default risk than do firms with no such dependence. Conversely, firms that rely solely on financing from public debt markets do not experience significant increases in default risk. These findings suggest that the bank supply shock theory explains the transmission of financial shocks to the real economy. Finally, firms that depend on bank financing cannot offset the adverse impacts of bank lending shocks by substituting bank loans with publicly traded debt.

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1. Introduction

Debt financing literature indicates that the source of debts has impacts on firms' economic situations, investments (Chava and Purnanandam 2011), and capital structure (Faulkender and Petersen 2006). With a somewhat different approach, we focus on the link between the source of debts and firms' default risk, which explains the manifestation of financial shocks as reduced real investments.[1] Understanding what drives default risk during credit crunches thus is important for efforts to stabilize the real economy. Our evidence suggests that the debt financing source strongly influences firms' default risk during the 2007–2010 financial crisis.

How does the debt financing source affect the default risk of firms? *Credit supply shock theory* asserts that firms raising funds mainly from credit markets face challenges, because the crisis affects all credit channels (Gorton 2010). *Bank supply shock theory* further states that, in response to shocks in banking systems, banks choose not to renew loans and refrain from issuing new loans. The impaired bank financing channel then generates stronger adverse impacts on firms that rely more on financing from these banks (Ivashina and Scharfstein 2010). Furthermore, bank-dependent firms with access to public debt markets seemingly substitute their bank loans with publicly traded debts, which could mitigate the adverse impact due to bank lending shocks. We find strong evidence in support of the bank supply shock theory, in that the default risk of firms that depend on bank debt increases significantly more than the default risk of similar firms without such dependence. However, we cannot affirm credit supply shock theory, because we find that the default risk of firms that rely solely on public debts does not change significantly. Nor do substitution benefits arise; bank-dependent firms, regardless of their ability to access public debt markets, experience similar increases in their default risk.

The empirical findings reflect an appropriate selection of all listed non-financial firms in the U.S. market from 2006 to 2010, which produces a sample of 3,169 unique firms and 113,409 firm-month observations. We measure default risk with an indicator of the distance-to-default and analyze its time-series changes over the crisis period (relative to its

[1] For theoretical arguments, see Gilchrist, Sim, and Zakrajšek (2014); for empirical evidence, see Gilchrist and Zakrajšek (2012).

level during the pre-crisis period).[2] Furthermore, we adopt a difference-in-differences methodology, such that we compare the cross-sectional heterogeneity of time-series changes in default risk across firms that rely on different debt financing sources but that exhibit similar risk characteristics before the 2007–2010 crisis. This robust method reduces the concern that some unobservable risk factors may drive the results. In addition, we focus on results during the early stage of the financial crisis. Because this period is less affected by the demand-side effect, we provide more plausible results related to the supply shock effect.[3]

Default risk increases more for firms that rely on banks for financing than for other types of credit-dependent or non–credit-dependent firms. This evidence is not consistent with the notion that an overall credit crunch is the main channel of transmission for the effects of the financial crisis from the financial sector to the real economy, but it does support the bank supply shock theory. Risky firms are more exposed to supply shocks (Lemmon and Roberts 2010), so if default risk increases more for firms with low credit quality than for high credit quality firms, the supply shock effect receives further support—as we show with this article.

We further examine whether the ability to substitute bank debts with public debts is beneficial for reducing the bank-dependent firms' default risk during crises. For this test, we select only bank-dependent firms; then compare the distance-to-default of borrowers that can access public debt markets versus the distance-to-default of borrowers that are unable to do so. Our empirical evidence indicates that the substitution effect is less likely, because we find no economically or statistically important differences.

[2] The distance-to-default is a well-known, market-based, forward-looking default risk measure grounded in Merton's (1974) work.

[3] Prior research views the first-year period as well suited to distinguishing among competing explanations (supply-side and demand-side effects). Firms' default probabilities should be less affected by demand-side effects in the early stage of a crisis period, whereas in subsequent periods, this distinction may be more difficult to address, because of the heightened overall uncertainty (Duchin, Ozbas, and Sensoy 2010).

In our baseline analysis, we classify bank-dependent firms according to their repeated borrowing history from the same lead bank, as obtained from the DealScan LPC database. For robustness, we also consider another identification strategy in which we use the ratio of a firm's bank debts to its total assets before the crisis. Newly identified bank-dependent firms continue to experience a significantly greater increase in their default risk. We also perform a battery of robustness tests to reduce concerns related to the bank loan database, matching method, debt maturity structure, or whether firm value and asset volatility drive increased default risk. The results provide further support for bank supply shock theory.

We accordingly make several contributions to prior literature. First, the extent to which distress in the financial sector spills over to default risk in the real economy has remained largely unclear (see Chiu, Peña, and Wang 2015). Despite an abundance of studies of the 2007–2010 crisis, ours is one of a handful to link shocks in the financial system to corporate default risks empirically. Furthermore, we extend bank supply shock theory, often tested in emerging markets (e.g., Khwaja and Mian 2008; Schnabl 2012), by focusing on the U.S. market and considering not just firms that borrow from banks but all non-financial firms. Moreover, we complement substitution effect literature by *directly* examining whether accessing public debt markets helps bank-dependent firms mitigate their default risks during weak economic times; previous studies focus on select factors, such as firms' net investments, net debt issuances, or equity valuation losses (Chava and Purnanandam 2011; Lemmon and Roberts 2010). Finally, our study evidence regarding the substitution effect on the default risk of firms complements Santos and Winton's (2008) assertion that altered risk for bank-dependent firms during recessions is not significantly different from the changes in this risk for firms with access to public bond markets. We provide new evidence in support of this prediction.

The remainder of this paper is organized as follows: Section 2 describes the data, default risk measure, and identification strategy. Section 3 contains the main empirical results. In

Sections 4 and 5 we offer additional robustness tests to support the main findings. We conclude in Section 6 with a summary of the results and some further research suggestions.

2. Data, default risk measure, and identification strategy

2.1. Sample construction

We examine all publicly listed, non-financial firms in the U.S. market from 2006 to 2010, according to a set of data sample selection rules. First, we include only leveraged firms, which have obligations to pay for debt and thus could default. We remove firms with zero debt in the second quarter of 2006 (before the crisis). Second, we exclude financial firms (standard industrial classification [SIC] codes 6000-6999), utility companies (SIC codes 4910 and 4940), and firms in the public sector (SIC codes 9000-9999). Third, we choose firms with available daily equity prices and quarterly balance sheet information in the Center for Research in Security Prices (CRSP) and Compustat databases. We lag all accounting information by three months, to reflect reporting delays, and substitute missing accounting data with the most recent prior observations. Thus we can obtain available information on firm risk characteristics, which we use to build a matched sample. The final sample consists of 3,169 unique firms and 113,409 firm-month observations.

2.2. Default risk measure

We measure default risk at the firm level by computing a firm's distance-to-default (DTD). This measure is widely considered an indicator of default risk for non-financial corporations (Bharath and Shumway 2008). We compute it in line with the well-known Moody's KMV approach:

$$DTD \equiv \frac{\log(V/B) + \left(\mu - \sigma_V^2/2\right)T}{\sigma_V \sqrt{T}}, \quad (1)$$

where V is the firm's total asset value, B is a firm's face value of debt, σ_V is the volatility of the firm's asset return, μ is an estimate of the expected long-term return of a firm's asset return, and T is the maturity of a firm's debt. The Online Appendix contains the details of the estimation procedure. We calculate the DTD at a monthly frequency, implementing a one-year rolling window and updating it month by month.

2.3. Identification of debt financing dependence

The main purpose of this article is to examine whether firms' debt financing source is associated with firms' default risk. To test this relationship, we identify firms on the basis of their dependence on bank or public debts.[4]

Bank supply shock theory suggests that bank-dependent firms are expected to experience greater default risk in times of crisis than other similar firms with no bank dependence. To test this theory, we identify *strong* bank-dependent firms as those that borrow two or more loans from the same lead bank in the five years before the end of the second quarter of 2006, following Kahle and Stulz (2013).[5] We define a firm as having *weak* bank dependence if it borrows from banks but does not qualify as having strong bank dependence. The bank loan data came from the DealScan Loan Pricing Corporation (LPC) database. We merge DealScan and Compustat using the Compustat–LPC link file provided by Michael Roberts (Chava and Roberts 2008).

We use credit ratings to identify a firm's ability to access public debt markets (e.g., Chava and Purnanandam 2011). A firm exhibits *public debt dependence* if it had credit

[4] A firm's debts mostly consist of bank loans and public debt (see Rauh and Sufi 2010), so we mainly consider these two types when classifying a firm's debt financing dependence.

[5] We also account for mergers and acquisitions when identifying loans granted from an identical lead arranger. Consider an example to illustrate this point: Banc One Corp merged with JPMorgan Chase & Co. in 2004. If a firm had Banc One Corp as a lead bank before 2004 and JPMorgan Chase & Co. as a lead bank between 2004 and 2006Q2, we assign JPMorgan Chase & Co. as its lead bank.

ratings at the end of June 2006. The rating information came from Compustat's S&P long-term ratings. We identify a firm with neither strong nor weak bank dependence but with credit ratings as public debt-dependent (PDD).

We further discriminate between bank-dependent firms with ratings and those with no ratings. Therefore, the strong (weak) bank-dependent firms consist of two subgroups: SBs (WBs) that only have access to bank loans and SBPDs (WBPDs) that have access to both bank loans and public debt market. By comparing the default risk across the pairs of groups defined this way, we can test whether accessible public debt markets reduce the adverse impact of bank lending constraints (i.e., substitution effect).

Finally, we define credit-dependent firms (CDFs) as those classified as strong bank-, weak bank-, or public debt–dependent. Then the remaining firms are denoted not credit-dependent firms (NCDFs). Firms in the NCDF group do not rely on funding from banks before the crisis and are unrated. Therefore, we assume they obtain their financing through internal funds or equity markets, or possibly to a lesser extent from public debt markets or bank loans. By comparing the default risk of CDFs with the default risk of NCDFs, we test the credit supply shock theory, which predicts that firms that depend on debt financing experience greater default risk than similar firms that rely less on debt financing.

3. Empirical results

We present the results in four sections, focusing on (1) descriptive statistics for the default risk indicator, (2) results related to the effect of debt financing on the default risk, (3) results related to the substitution effect, and (4) analyses conducted after the Lehman bankruptcy.

3.1. Descriptive statistics for distance-to-default

We divide the sample period into five phases: pre-crisis (2006Q3–2007Q2), first-year crisis (2007Q3–2008Q2), pre-Lehman (2008Q3), post-Lehman (2008Q4–2009Q1), and last-year crisis (2009Q2–2010Q1).[6] Table 1 contains basic DTD statistics and the results of the preliminary tests over the five periods and two main groups (NCDFs and CDFs), as well as across the five CDF-based subgroups (SPBDs, SBs, WBPDs, WBs, and PDDs). We conduct our tests on a panel in which the risk measures are computed for each firm and over the five periods. We aggregate our firm–month sample into a firm–period sample by averaging all monthly DTDs for each period.

For the first-year crisis, we observe a significant decrease in the DTD (i.e., increased default risk) compared with the pre-crisis period across all groups, except for PDD (see *Diff 2-1*). Therefore, all NCDFs and most CDFs (except for rated firms without bank dependence) come close to defaulting. Moreover, SBs experience the largest DTD decrease of 1.91, followed by SBPDs with 1.66; the decrease for PDDs is obviously smaller, at only 0.29. We also compute the percentage change in DTD, which shows that the decrease is slightly greater for CDFs than for NCDFs (16.5% versus 14.4%). Notably, differences across CDF subgroups are more marked, from 22.8% for unrated firms that depend strongly on bank financing (SBs) to 5.2% for PDDs.[7]

[Insert Table 1 Here]

[6] The first phase (pre-crisis) includes one year before the beginning of the subprime crisis (usually dated around July 2007). The second phase (first-year crisis) covers several extreme economic events, such as the starting period of the subprime crisis and the Bear Stearns bankruptcy. The third phase (pre-Lehman) contains the events surrounding Lehman Brothers' bankruptcy (September 15, 2008). The fourth phase (post-Lehman) covers two quarters after this bankruptcy. The fifth phase (last-year crisis) is the final acute stage of the crisis. By this time, panic had largely subsided, the stock market had rebounded from its lowest level, and credit spreads had declined from their peaks. Kahle and Stulz (2013) use the same periods to study the supply shock theory.

[7] We build a theoretical model to illustrate that a financial crisis decreases a firm's distance to default and therefore increases its default risk. The model detail is provided in the Online Appendix.

Preliminary evidence during the first year of the crisis seems supportive of impaired access to banking financing. The data do not provide clear support for theories based on an overall credit crunch though, because rated firms without banking connections do not come closer to default during this period. Furthermore, the DTD dynamics of SPBDs and SBs are fairly similar, indicating that public debt market accessibility is not helpful for mitigating the adverse impacts of financial shocks on firms with strong bank dependence, in terms of reducing default risk. Therefore, our univariate analysis does not support the substitution hypothesis.

If we compare changes in the DTD from the pre-crisis to the last-year crisis period, we observe a strong decrease in DTD across the board, ranging from 56% (SBPDs) to 41% (PDDs), all statistically significant. Again, the CDF group experiences a slightly larger decrease (52%) than the NCDF group (49%) does, though more marked differences also appear across CDF subgroups.

3.2. Main results

The univariate result is subject to the heterogeneity of default risks across firms, which could relate to factors other than the impact of debt financing sources. To control for these factors, we build the matched sample, in which pairs of matched firms are similar in their observable risk characteristics. A firm's choice of debt financing source could be determined endogenously with its default risk during crises, so we build the matched sample using "pre-crisis" data about firm characteristics, to reduce this concern. Furthermore, in our difference-in-differences methodology, we compare *changes* in the DTD during the crisis period with those in the pre-crisis period across groups, to rule out the possibility that our findings may be driven by fundamental firm differences, not by variation in debt financing sources. This empirical methodology thus provides more reliable evidence for testing our central argument that the supply shock theory explains the effect of debt financing sources on firms' default risk. We next present the procedure for constructing the matched sample.

3.2.1. Constructing the matched sample

We use the propensity score matching method proposed by Rosenbaum and Rubin (1983) to obtain similar groups of treatment (i.e., CDFs or subgroup of CDFs) and control (i.e., NCDFs) subjects, by matching these firms' observable risk characteristics. The propensity score is the probability of belonging to the treatment group, given a vector of the following observed variables:[8] (1) *size*, or the logarithm of the book value of assets; (2) *leverage*, or the ratio of debt to assets; (3) *volatility*, or the annualized standard deviation of daily equity returns for a year; (4) *past-ret*, or the annual stock return over the previous year; (5) *cash/asset*, or the ratio of cash to assets; (6) *NI/asset*, or the ratio of net income to assets; and (7) *industry effect* (Fama–French 38 industry dummies). These variables are motivated by the hazard model literature and are among the most important determinants of default risks (e.g., Campbell, Hilscher, and Szilagyi 2008).[9]

We obtain all accounting and market variables as of the last quarter of accounting information or one-year equity market information before June 2006. To prevent outliers

[8] This propensity score is estimated from a probit regression. If we take firms with the same propensity score and divide them into two groups, the groups should be approximately balanced on the variables used to predict the propensity score. We chose the improved caliper matching method, in which the control group is matched to a treated case on the basis of a set tolerance level for the maximum propensity score distance (caliper), to avoid the risk of bad matches.

[9] We control for firm size because larger firms are more diversified, which reduces operating risks, and so they face lower default risk than smaller firms do. We include leverage because the higher the debt (high leverage), the higher the chances of default. Volatility implies the probability that a firm's asset value is below the default boundary; thus, the higher the volatility, the greater the uncertainty, and therefore the higher the default probability. Low past equity returns relate to increases in default risk. We include the ratio of cash to assets because this variable reflects a firm's ability to pay its financial debt obligations. We consider profitability (proxy of the ratio of net income to assets), because a profitable firm should be less likely to default. Finally, we allow for industry effects by means of dummy variables.

from affecting our results, we winsorize the data in all analyses at 1% and 99%. Table 2 presents the summary statistics of the control variables. As this table shows, four variables signal notable differences between NCDFs (Panel A) and CDFs (Panel B) or any subset of CDFs (Panel C). On average, the CDFs are larger, have more leverage, exhibit lower volatility, and have a lower cash-to-assets ratio than NCDFs across the mean and quantiles.

[Insert Table 2 Here]

Table 3 presents the estimation results of the full sample in Panel A and of the matched sample in Panel B. Model 1 in Panel A shows that differences in CDFs (compared to NCDFs) are positively associated with firm size, leverage, and the net income-to-assets ratio but negatively associated with equity return volatility and the cash-to-assets ratio. The signs of the coefficient estimates of the control variables are as expected. By construction, the magnitude of a firm's external debt financing relates positively to leverage but negatively to the need for internal funds (cash); large firms require more operating funds, likely resort to external sources, and usually have lower equity return volatility.

[Insert Table 3 Here]

We also implement alternative probit regressions by substituting one of the CDF subgroups (SBPDs, SBs, WBPDs, WBs, and PDDs) for the entire CDF group, one by one; we report the estimation results in Models 2–6 of Panel A of Table 3. The signs of the coefficients are consistent with Model 1, though the magnitudes are not necessarily the same. The values of the pseudo-*R*-square are larger for subgroups with ratings (between 36% and 61%) but smaller for those without ratings (between 12% and 36%), indicating that these firm characteristics can distinguish CDFs from NCDFs, especially CDFs with ratings. After matching, the estimated coefficients are no longer significant, and the pseudo-*R*-square values drop to 5.2% or lower across all specifications of the probit regressions (Panel B, Table 3).

This evidence confirms that our matched sample is equally balanced in terms of the observable dimensions that might influence the default occurrence before the crisis.[10]

3.2.2. Difference-in-differences estimations

We use a difference-in-differences method, in which we compare *changes* in the DTD with respect to a reference period (pre-crisis period here) across groups and over time, rather than the *levels* of the variable across the treatment and control groups. We thus control for potential differences in the levels of the DTD in the treatment and control groups due to their fundamental differences.[11] We define the Dif-in-Dif$(g,k)_t$ measure for groups g and k in period t as follows:

$$\text{Dif-in-Dif}\left(g,k\right)_t = \frac{\sum_{i=1}^{I}\left(X_t^{i,g} - X_{\text{pre-crisis}}^{i,g}\right)}{I} - \frac{\sum_{j=1}^{J}\left(X_t^{j,k} - X_{\text{pre-crisis}}^{j,k}\right)}{J}, \quad (2)$$

where $X_t^{i,g}$ is the average DTD for firm i in group g, which contains I firms, in period t = 1,2,3,4 (such that t = 1 corresponds to the first-year crisis, t = 2 is the pre-Lehman period, t = 3 indicates the post-Lehman period, and t = 4 is the last year of the crisis); and $X_t^{j,k}$ is the average DTD for firm j in group k, which contains J firms. The Dif-in-Dif$(g,k)_t$ term refers to the difference in the average value of the time-series change of the DTD between groups g and k in period t. We use the one-sided Wilcoxon rank-sum test to assess the statistical significance of the Dif-in-Dif estimators.[12]

[10] We also plot the marginal distributions of four key firm characteristics, before and after mapping, across CDFs and NCDFs. After mapping, the distributions are similar for both groups. The details are available in the Online Appendix.

[11] Recent studies that use the difference-in-differences method claim that this method is preferable to a multivariate regression approach, because using regressions makes it difficult to avoid endogeneity problems (e.g., Chava and Purnanandam 2011; Kahle and Stulz 2013).

[12] This test is a non-parametric alternative to the standard two-sample t-test and is more appropriate than the standard test, because the distribution of changes in the DTD is not a normal distribution.

3.2.3. Matched sample results

As discussed previously, credit or banking supply shock theory may explain how the debt financing source can affect default risk in times of crisis. In this section, we examine these theories using the matched sample. In particular, we analyze outcomes in the first-year crisis period, because the default risk during this period is less likely to be affected by demand shock, which provides more plausible evidence about the supply shock effect, if any exists.[13]

Table 4 presents the Dif-in-Dif estimation results, obtained with a treatment group of CDFs or CDF-based subgroups and a control group of NCDFs. By construction, a negative Dif-in-Dif implies that the default risk of CDFs (or any subgroup of CDFs) is larger than that of NCDFs in a given period. Surprisingly, after controlling for firm-specific risk variables, the Dif-in-Dif estimator exhibits a positive (but insignificant) sign for the group of CDFs (Model 1). This finding indicates that firms that raise funds from credit markets experience slightly lower default risk than firms that mainly finance their operations with internal funds or equity, which is not consistent with credit supply theory.[14]

[13] In addition, default risk at an early stage of the crisis offers a recession predictor, so understanding which factors (e.g., debt financing in our case) determine default risk at this stage provides more useful implications to policy makers who wish to limit recessions.

[14] The issuance of additional equity when other financing sources are scarce likely affects the firm's default risk, because it can replace debt with equity. Our sample only includes publicly traded firms, which all have access to equity markets. To account for how equity finance affects our conclusions, we examine time-series changes in net equity issuance (i.e., aggregate equity issuance minus aggregate equity repurchase divided by lagged assets) across groups, based on our matched sample. The results (available on request) show no material differences between NCDFs and any subgroup of CDFs in terms of time-series changes (crisis period versus pre-crisis) in the net equity issuance, except for a few cases in the last-year crisis period. Therefore, equity financing does not seem relevant for our study, which took place before Lehman's bankruptcy. Further research should investigate the impact of the variation of external equity dependence on default probabilities.

Notably, we find remarkably different results when we look more deeply at the subsamples of CDFs. The Dif-in-Dif estimator is negative and only significant for firms with strong bank dependence (Model 2). The estimator also indicates a negative sign for firms with weak bank dependence, but it is not significant (Model 3). Furthermore, the estimator is positive in the case of PDDs (Model 4). This evidence is inconsistent with the idea that an overall credit crunch is the main channel of transmission of the effects of the financial crisis from the financial sector to the real economy; in contrast, it offers support for the bank supply shock theory, because we find that strong bank-dependent firms suffer significantly more default risks than other firms do during the first-year crisis period.

We also examine subgroups involved in the strongly (weakly) bank-dependent group. The focal estimator exhibit consistently negative, significant signs for both SBPDs (Model 5) and SBs (Model 6) at the 5% level. With strong bank dependence, even firms with access to public credit markets are susceptible to fluctuations in the supply of capital. This result seems to suggest that a substitution effect does not exist.

These results can be implemented by comparing the means of the treatment and control groups. We conduct similar Dif-in-Dif analyses according to the median value across all model specifications (under "Median"). The result is systematically consistent with the previous findings. Overall then, we find that bank-dependent firms suffer more default risks than other firms do after controlling for firm-specific variables and the omitted variables bias. In this sense, our results offer further support for the bank supply shock effect.[15]

[Insert Table 4 Here]

[15] We acknowledge a limitation of our empirical approach; we cannot entirely rule out demand-side effects, because we perform cross-sectional analyses across firms but do not use a within-firm estimator, so that we cannot examine changes in lending by different banks to the same firm. This identification strategy controls for changes in a firm's lending opportunities (e.g., Khwaja and Mian 2008). We examine the default risk at the firm level, not at the loan level, so a within-firm approach is not suitable for our research.

3.3. Supply shock effect, conditional on credit quality

Prior literature suggests that low-credit quality firms are more exposed to supply shocks and suffer larger negative impacts due to their exposure (e.g., Lemmon and Roberts 2010). Therefore, to find support for the supply shock effect, we should observe that default risk increases more for low-credit quality firms than for high-credit quality firms.

On these grounds, we split the sample into two subsamples: low credit quality and high credit quality, on the basis of the median value of the DTD distribution for each group. The group with low DTD exhibits low credit quality, and the group with high DTD signals high credit quality. We present the Dif-in-Dif results separately for these two subsamples in Table 5. Along with the strongly bank-dependent group (Model 1), we find that the Dif-in-Dif measure maintains its negative sign for both groups but is significant only for low-credit quality firms, in terms of both means and medians. The finding suggests that high-credit quality firms are less affected by the supply shock effect, even if they have strong bank dependence. There is no significant difference in the increase in default risk between weakly bank-dependent firms and NCDFs, irrespective of their credit quality (Model 2). For PDDs (Model 3), the Dif-in-Dif measure is positive, irrespective of credit quality, but more significant in the high-credit quality group.

Therefore, riskier firms exhibit different responses to the credit contraction, relative to less risky firms. Specifically, they experience a sharper decline in the DTD relative to their less risky counterparts. The result also indicates that the negative effect is concentrated among strongly bank-dependent firms with low credit quality. For rated firms of high quality that are not dependent on bank financing though, the effect is weak. Thus, the results offer stronger evidence to support the bank supply shock theory.

[Insert Table 5 Here]

3.4. Substitution effect

The preceding results provide some evidence contrary to the substitution effect, which asserts that a firm's ability to switch financing resources between banks and public debt markets reduces the negative effects of bank lending shocks. In this section, we use a more robust methodology to test this effect by comparing the default risk on a matched sample of two groups, both of which rely on bank loans, though only one has access to public debt markets. Thus we can draw inferences from the bank-dependent subsamples only, and the analysis should be more accurate than our previous analysis, which could be subject to bias arising from observable or unobservable differences across firms.

For our difference-in-differences methodology, we use SBPDs as the treated unit, relative to the control unit of SBs, to form the matched sample. In line with the baseline analysis, we test the substitution effect in the first-year crisis period. Table 6 presents the results for strongly and weakly bank-dependent firms in Panels A and B, respectively. The matched analysis shows no evidence of economically or statistically important differences in bank-dependent firms, regardless of their capabilities to access public debt markets (Model 1). Thus, our results do not support the substitution effect.

Intuitively, riskier firms have more difficulty replacing their public debts with bank loans. Diamond (1991) also suggests that very low-rated borrowers suffer restricted access to public debt markets. These arguments imply that the substitution benefit should be stronger for high-credit quality firms than for low ones. We test separately for these two types of firms, but even within the high-credit quality group, there is no evidence of a substitution effect (Model 3). Thus, the ability to access public debt markets has a limited role in offsetting funding shocks in the early period of crises, as far as default risk is concerned.

[Insert Table 6 Here]

3.5. After Lehman's bankruptcy

In this section, we turn our attention to the supply shock theory in the years following Lehman Brothers' bankruptcy. This period corresponds with the Great Recession, in which demand-side factors had great impacts on default risk; it is difficult to disentangle the supply shock effect from demand shock effects. We provide this analysis merely to understand whether the role of bank dependence still exacerbates default risks, as it does in the early stages of the crisis. Note that we do not intend to claim that the result is entirely explained by the supply shock effect.

In Panel A of Table 7, we observe that in the post-Lehman stage (two quarters after Lehman's bankruptcy), the Dif-in-Dif estimators for the CDF group and a majority of the CDF subgroups are negatively significant at the 5% level, except for WBs at the 10% level and PDDs with no significant sign. For the last year of the crisis, the Dif-in-Dif estimator for the CDF group is negatively significant at the 5% level. Across CDF subgroups, we observe that the Dif-in-Dif estimators are negatively significant for most of bank-dependent groups but positive and nonsignificant for the PDDs. Panel B indicates no evidence of economically or statistically important differences in strongly bank-dependent firms, regardless of their capabilities to access public debt markets. For weakly bank-dependent firms, we even find that firms that can access public debt markets experience greater default risk, though with a marginal effect. Overall, the bank supply shock theory thus seems more supported by the data after Lehman's bankruptcy; the public debt markets continue in their limited role in reducing default risk, even after Lehman's bankruptcy.

[Insert Table 7 Here]

4. Additional tests: Capital IQ-based sample analysis

We identify a firm's dependence on bank debts using historical records of repeated borrowing from the same lead bank. To gauge whether this identification strategy reflects the debt structures, as expected, we turn to Capital IQ (an affiliate of S&P) and obtain firm-level debt structure variable information to build a Capital-based sample. Missing values in this database reduce the sample to 2,759 unique firms, or 87% (= 2759/3169) of the firms in the main analysis.[16]

We compute four ratios: bank debt-to-total assets, public debt-to-total assets, bank debt-to-total debt, and public debt-to-total debt. The numerator of these ratios is either *bank debt* (i.e., sum of term loans and revolving credit) or *public debt* (i.e., sum of senior bonds and notes, subordinated bonds and notes, and commercial paper). The first two ratios are divided by total assets; the latter two are divided by total debts. Table 8 presents the descriptive statistics for all four ratios in 2006 across NCDFs (Panel A), CDFs (Panel B), and subsets of CDFs (Panel C). The CDFs present larger values for the bank debt-to-total assets ratio and the public debt-to-total assets ratio, compared with NCDFs (Columns 1 and 2). That is, CDFs appear to depend more on credit than the NCDFs do.[17]

For the bank debt-to-total assets ratio (Column 1), on average, the SB group has the highest value, followed by SPBDs, WBs, WBPDs, NCDFs, and finally PDDs. This result generally fits the expected debt structures across groups. As for the public debt-to-total assets ratio (Column 2), rated firms have larger ratios than unrated firms do, as expected. The SBPD group indicates the lowest ratio, compared with other rated firms (WBPDs and PDDs), which is also consistent with our expectation. The finding regarding the bank debt-to-total debt ratio

[16] To build the Capital IQ-based sample, we apply the following rules: (1) We merge the main analysis sample with the Capital IQ database and remove firm–years for which the difference between total debt reported in Compustat and the sum of debt types reported in Capital IQ exceeds 10% of total debt (see Colla, Ippolito, and Li 2013); (2) when the bank debt-to-total debt ratio or public debt-to-total debt ratio is larger 100%, it is replaced with 100%; (3) we remove observations in which the sum of bank and public debts is greater than total debt; (4) when bank and public debt data are both missing, we replace them with zeros; and (5) if the bank debt-to-total debt ratio is missing but the public debt-to-total debt is not missing, or vice versa, we replace the missing value with the difference between 100% and the non-missing value.

[17] We should emphasize that the NCDFs identified herein are those that did not rely on bank loans in the five years before 2006 and that had no ratings, but not firms that did not have any debts.

(Column 3) also lends support to the identification strategy. For example, among unrated firms, the ratio is highest for SBs, the second highest for WBs, and then for NCDFs; among rated firms, the highest ratio is for SBPDs, followed by WBPDs, and then PDDs.

[Insert Table 8 Here]

The identified firms generally fit the classified debt structures. Nevertheless, we run additional tests to determine whether the increase in default risk is explained by bank supply shock effects at the early stage of crisis. With our Capital IQ-based sample, we identify bank dependence according to the bank debt-to-total assets ratio, then again apply difference-in-differences, for which the treatment subject is the group that contains firms whose bank debt-to-total assets ratio ranks among the top 50%, 25%, 20%, or 10% of firms in 2006, and the control subject is the group that contains the rest of the firms.

Table 9 reports the Dif-in-Dif test results. The measure (at the median) is negatively significant at the 5% level across the top 25%, 20%, and 10% of firms, consistent with the bank supply shock theory. The measure is not significant for the top 50% of firms. However, we should address that the debt variables in the Capital IQ database come from balance sheets, such that they indicate a firm's historical dependence on debt. Our main identification strategy that relies on more recent information to assess the magnitude of bank dependence should receive more credit. Therefore, this Capital IQ-based analysis provides further evidence supporting the bank supply shock theory.

[Insert Table 9 Here]

5. Robustness tests

This section contains the results of a battery of robustness tests, designed to reduce concerns that might arise related to the bank loan database, the matching method, the debt maturity structure, and whether firm value and asset volatility actually drive increased default risk.

5.1. Alternative setting for propensity score matching

In the baseline analysis, we implement matching without replacement, but a disadvantage of this technique is that the sample size can be very small, which may cause losses of statistical power and generalization. We use several alternative matched samples, which we build with replacement with a maximum of two, three, and four treated firms to one control firm. The results of these supplemental analyses are consistent with our main results (Tables R1–R3, Online Appendix). Furthermore, in our baseline analysis, the difference between the propensity scores of the treated and control units is set to be within the caliper at ±2.5%. When we change the caliper to ±5% or ±10%, the results remain consistent (Tables R4 and R5, Online Appendix).

5.2. Alternative control group

In the baseline matched sample analysis, we include NCDFs as control units. This result might be biased though, because we do not account for other unobservable variables that may increase the default risk for bank-dependent firms (SBPDs and SBs) and decrease the default risk for PDDs. To address this concern, we use the whole sample (excluding treated firms) as the control group. The results are consistent with the main analysis (Table R6, Online Appendix).

5.3. DealScan LPC bias

DealScan LPC only reports bank loan deals for large firms; small firms might be bank dependent but insufficiently represented in our sample. To address this concern, we exclude small firms from the NCDF group (i.e., those lower than the median of firm sizes in the NCDF group). The result still favors the bank supply shock effects in the first-year crisis period (see Table R7, Online Appendix).

5.4. Excluding speculative-grade firms

During crises, speculative-grade firms have difficulty accessing alternative sources of capital in public debt markets. The results indicating a limited role of public debt markets in offsetting adverse outcomes during financial crises might stem from the inclusion of speculative-grade firms in our sample. We show that even in the high-credit quality group, there is no evidence supporting a substitution effect. To improve the robustness of this finding, we use ratings to identify a firm's credit quality. We discard any firms with speculative-grade ratings (lower than S&P's BBB) and reexamine the tests with this new matched sample. The results remain similar, in additional support for our conjectures about public debt markets during a financial crisis (Table R8, Online Appendix).

5.5. Controlling for the structure of debt maturity

Bank-dependent firms tend to have more short-maturity debts than non–bank-dependent firms do. The argument for the bank credit supply channel may be not credible, because the results may be driven by the debt maturity structure rather than bank dependence. To address this issue, we reexamine our baseline model with an additional control for the debt maturity structure. Following prior literature, we consider the percentage of total debt that matures in less than three years, as a proxy for short-term debts (e.g., Datta, Iskandar-Datta, and Raman 2005; Billett, King, and Mauer 2007; Brockman, Martin, and Unlu 2010). The newly matched sample controls for debt maturity structure, in addition to the firm-level control variables in the main analysis. Next, we apply our baseline difference-in-differences methodology (Table 4) to this newly matched sample (after controlling for the debt maturity structure) and present the results in Table 10. These results are qualitatively similar to our main findings and provide further evidence of the bank credit supply theory.[18]

[18]No perfect debt maturity proxy exists. We consider many other proxies for the debt maturity structure, such as (1) the ratio of short-term debts (maturing within 1 year) over total debt; (2) the ratio of short-term debts to total

[Insert Table 10 Here]

5.6. Firm value, asset volatility, and book value of debt

We check how much of the change in the distance to default comes from the firm value, the book value of debt, and the firm volatility. Firm value represents the firm's market value of total assets; firm volatility is its asset return volatility. Both variables are implied parameters based on the KMV model in Section 2.2. We obtain the book value of debt by adding the short-term and long-term debts (i.e., Compustat items *DLCQ* + *DLTTQ*).

Returning to our benchmark model (Table 4, the difference-in-differences method on the matched sample), we replace the distance-to-default indicator with firm value, book value of debt, or asset volatility.[19] We focus on the strongly bank-dependent group and report the results in Table 11. Columns 1, 2, and 3 present results in the first-year crisis period, the pre-Lehman period, and the post-Lehman period, respectively.

The Dif-in-Dif measures under firm value (Panel A) exhibit a significantly negative sign; strong bank-dependent firms come closer to default, because they suffer from a significant reduction of firm value during crisis periods. The results for the book value of debt (Panel B) show mostly non-significant and negative signs, indicating that the percentage change in debt is indifferent between strong bank-dependent firms and otherwise similar firms. Thus, strong bank-dependent firms do not come closer to default due to their increased debt level. The asset volatility results (Panel C) display consistently positive signs that are significant in the pre- and post-Lehman periods; strong bank-dependent firms come closer to default because their asset returns are more volatile.

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assets; (3) the ratio of debts within 2 years to total debt; (4) the ratio of debts within 4 years to total debt; and (5) the ratio of debts within 5 years to total debt. Using these alternative proxies, the results are systematically consistent with our main findings when we did not control for the debt maturity structure. These results are available on request.

[19] The firm value and book value of debt are not comparable between small and large firms. Therefore, we use firm asset returns (i.e., percentage change of firm value in any crisis period relative to the pre-crisis period) and the percentage change in the book value of debt in our difference-in-differences methodology.

[Insert Table 11 Here]

The reduction of firm value and increased asset volatility thus are key driving forces for the decreased distance-to-default, whereas debt level is relatively irrelevant. Therefore, our evidence offers further support for bank credit supply theory.

6. Concluding remarks

This article examines the extent to which the source of debt financing (banks or public debt markets) affects the default risk of firms in the U.S. market from 2006 to 2010. In the initial crisis stage (2007–2009), firms with close links to bank financing suffer significantly higher increases in default risks than similar firms that do not depend on bank financing, in support of the bank supply shock theory. When firms rely solely on financing from public debt markets, they do not experience significant increases in default risk. This evidence is inconsistent with the notion that an overall credit crunch is the main channel of transmission of the effects from the financial crisis to the real economy. Finally, our results indicate that bank-dependent firms, with or without an ability to replace bank loans with public debts, experience similar increased default risk in early periods of the crisis. Public debt markets thus have a limited role in offsetting funding shocks, as far as default risk is concerned.

Our work provides useful information for policy makers interested in understanding the extent to which impairments in the bank lending channel contribute to an increase in the probability of bankruptcies, thus deepening recessions. Monetary policy can work through an impact on interest rates in the bond market or on the supply of intermediated loans. Our key result suggests that regulators should assign greater importance to fixing the bank lending channel in a timely manner when a financial crisis materializes.

Looking forward, an interesting question worth exploring is why the ability to enter into public debt markets is not helpful for reducing default risk. Custódio, Ferreira, and Laureano (2013) show that the decrease in debt maturity (increase in liquidity risk) took place mainly in public debt markets, not in private debt markets. This result may provide a possible insight to help explain our findings, but much more detailed analysis is needed; we plan to address this point with further research.

Appendix

Basic model: Do financial crises decrease a firm's distance to default?

We lay out a basic model illustrating the changes in the DTD during financial crises by relying on Merton's (1974) basic framework. We define firm value at time t as $V(t)$. By definition, $V(t) = E(t) + D(t)$, where $E(t)$ and $D(t)$ are equity market value and debt market value at time t, respectively. To clarify the analysis, we consider only three time periods: t, $t + 1$, and $t + 2$. We define the default barrier as $F(t)$, which is the face value of the debt of at time t. This debt matures at time $t + 1$. Given asset return volatility $\sigma_V(t)$, the DTD can be computed at time t as

$$\mathrm{DTD}(t) = \frac{E_t\big(V(t+1) - F(t)\big)}{\sigma_V(t) E_t\big(V(t+1)\big)}. \tag{A1}$$

where $E_t(V(t + 1))$ is the expected asset value at time $t + 1$, when debt matures, as seen at time t. We assume that $E_t(V(t + 1)) = V(t)(1 + R)$, where R is the expected asset growth rate. If $E_t(V(t + 1)) < F(t)$, we set $\mathrm{DTD}(t) = 0$. To clarify the exposition and without loss of generality,[20] we assume $R = 0$; if so, Equation (1) simplifies to

$$\mathrm{DTD}(t) = \frac{1}{\sigma_V(t)} \times \frac{V(t) - F(t)}{V(t)}. \tag{A2}$$

Suppose a financial crisis occurs at $t + 1$ and a partial impairment in the banking channel materializes. Banks do not give new loans but refinance a proportion k of the existing debt until period $t + 2$ ($0 \le k \le 1$), so the firm only has to pay back $(1 - k)F(t)$ at $t + 1$ and keeps $kF(t)$ in its books until $t + 2$. We assume that $V(t + 1) > (1 - k)F(t)$ (otherwise, the firm defaults); if so, then

$$V(t + 1) = V(t) - (1 - k)\mathrm{F}(t). \tag{A3}$$

We define the DTD at $t + 1$ similarly, as

[20] The results of this section are essentially the same if we allow for $R \neq 0$.

$$\mathrm{DTD}(t+1)=\frac{V(t+1)-kF(t)}{\sigma_V(t+1)V(t+1)} \tag{A4}$$

Substituting Equation (3) into (4) yields

$$\mathrm{DTD}(t+1)=\frac{1}{\sigma_V(t+1)}\times\frac{V(t)-F(t)}{\left(V(t)-(1-k)F(t)\right)}. \tag{A5}$$

The factor multiplying the inverse of the volatility in Equation (A5) is greater than or equal to that in Equation (A2) and less than or equal to one. Therefore, if asset volatility does not change from t to $t + 1$, we should observe DTD(t) ≤ DTD(t + 1). Given that the numerators in Equations (A2) and (A5) are the same, DTD(t + 1) will be lower than DTD(t) if

$$\sigma_V(t+1)>\sigma_V(t)\frac{V(t)}{V(t)-(1-k)F(t)}. \tag{A6}$$

If full refinancing takes place, this condition simplifies to

$$\sigma_V(t+1)>\sigma_V(t). \tag{A7}$$

In other words, to observe a decrease in the DTD in the crisis period (in comparison with the pre-crisis period), asset volatilities in the crisis period should be higher than those in the pre-crisis period and the increase should be dependent on the degree of refinancing. The higher the refinanced proportion k, the lower the difference between asset volatilities should be, to ensure that DTD(t + 1) is lower than DTD(t). The extent to which the price volatility of real assets increases during a financial crisis is an open empirical question. There is abundant evidence of increases in the volatility of stock prices during financial crises, but the volatility of equity prices may change (e.g., as a consequence of changes in leverage), though real asset volatility remains unchanged.

References

Billett, M.T., King T.-H.D., Mauer D.C. 2007. Growth opportunities and the choice of leverage, debt maturity, and covenants. *Journal of Finance* **62**(2), 697–730.

Bharath S.T., Shumway T. 2008. Forecasting default with the Merton distance-to-default model. *Review of Financial Studies* **21**(3): 1339–1369.

Brockman, P., Martin, X., Unlu, E., 2010. Executive compensation and the maturity structure of corporate debt. *Journal of Finance* **65**(3): 1123–1161.

Campbell J.Y., Hilscher J., Szilagyi J. 2008. In search of distress risk. *Journal of Finance* **63**(6): 2899–2939.

Chava S, Purnanandam A. 2011. The effect of banking crisis on bank-dependent borrowers. *Journal of Financial Economics* **99**(1): 116–135.

Chava S, Roberts M R. 2008. How does financing impact investment? The role of debt covenants. *Journal of Finance* **63**(5): 2085–2121.

Chiu W.-C., Peña J.I., Wang C.-W. 2015. Industry characteristics and financial risk contagion. *Journal of Banking & Finance* **50**: 411–427.

Colla P., Ippolito F., Li K. 2013. Debt specialization. *Journal of Finance* **68**(5): 2117–2141.

Custódio C., Ferreira M.A., Laureano L. 2013. Why are US firms using more short-term debt?. *Journal of Financial Economics* **108**(1):182–212.

Datta, S., Iskandar−Datta, M., Raman, K., 2005. Managerial stock ownership and the maturity structure of corporate debt. *Journal of Finance* **60**(5): 2333–50.

Diamond D.W. 1991. Debt maturity structure and liquidity risk. *Quarterly Journal of Economics* **106**(3): 709–737.

Duchin R., Ozbas O., Sensoy B.A. 2010. Costly external finance, corporate investment, and the subprime mortgage credit crisis. *Journal of Financial Economics* **97**(3): 418–435.

Faulkender M., Petersen M.A. 2006. Does the source of capital affect capital structure?. *Review of financial studies* **19**(1): 45–79.

Gilchrist S, Sim J.W., Zakrajšek E. 2014. Uncertainty, financial frictions, and investment dynamics. No. w20038, National Bureau of Economic Research.

Gilchrist S, Zakrajšek E. 2012. Credit spreads and business cycle fluctuations. *American Economic Review* **102**(4): 1692–1720.

Gorton, G.B. 2010. *Slapped by the invisible hand: The panic of 2007*. Oxford: Oxford University Press.

Ivashina V, Scharfstein D. 2010. Bank lending during the financial crisis of 2008. *Journal of Financial Economics* **97**(3): 319–338.

Kahle K.M., Stulz R.M. 2013. Access to capital, investment, and the financial crisis. *Journal of Financial Economics* **110**(2): 280–299.

Khwaja A.I., Mian A. 2008. Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review* **98**(4): 1413–1442.

Lemmon M., Roberts M.R. 2010. The response of corporate financing and investment to changes in the supply of credit. *Journal of Financial and Quantitative Analysis* **45**(3): 555–587.

Merton R.C. 1974. On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance* **29**(2): 449–470.

Rauh J.D, Sufi A. 2010. Capital structure and debt structure. *Review of Financial Studies* **23**(12): 4242–4280.

Rosenbaum P.R., Rubin D.B. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* **70**(1): 41–55.

Schnabl P. 2012. The international transmission of bank liquidity shocks: Evidence from an emerging market. *Journal of Finance* **67**(3): 897–932.

Santos J. A.C., Winton A. 2008. Bank loans, bonds, and information monopolies across the business cycle. *The Journal of Finance* **63**(3): 1315–1359.

Table 1

DTD descriptive statistics.

Category	NCDFs	CDFs	SBPDs	SBs	WBPDs	WBs	PDDs

1. Pre-crisis (2006Q3–2007Q2)	7.777	8.222	9.120	8.399	7.820	8.362	5.650
2. First year (2007Q3–2008Q2)	6.653	6.866	7.459	6.482	6.312	7.203	5.356
3. Pre-Lehman (2008Q3)	4.253	4.600	4.939	4.389	4.239	4.754	3.798
4. Post-Lehman (2008Q4–2009Q1)	1.986	1.782	1.817	1.864	1.324	2.010	1.347
5. Last year (2009Q2–2010Q1)	3.913	3.910	4.003	3.870	3.667	4.113	3.310
Diff 2−1	−1.124 ***	−1.356 ***	−1.661 ***	−1.917 ***	−1.508 ***	−1.159 ***	−0.294
p−Value	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.313)
%Diff 2−1	−14.45	−16.50	−18.21	−22.82	−19.29	−13.86	−5.21
Diff 5−1	−3.864 ***	−4.312 ***	−5.117 ***	−4.528 ***	−4.153 ***	−4.249 ***	−2.341 ***
p-Value	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
% Diff 5−1	−49.68	−52.45	−56.10	−53.91	−53.10	−50.81	−41.42

Note: This table presents descriptive statistics on DTD measures before and during the crisis for the subgroups of firms formed in the second quarter of 2006, involving 3,169 unique firms. The sample consists of 113,409 firm–month observations from the third quarter of 2006 through the first quarter of 2010. The sample of firms is separated into six subgroups, denoted as (i) NCDFs (not clearly credit dependent firms), (ii) SBPDs (strongly bank dependent and public debt dependent firms), (iii) SBs (strongly bank dependent but not public debt dependent firms), (iv) WBPDs (weakly bank dependent and public debt dependent firms), (v) WBs (weakly bank dependent but not public debt dependent firms), (vi) PDDs (public debt dependent but not bank dependent firms). By construction, CDFs (clearly credit-dependent firms) include subgroups 2 to 6. The detailed identification strategy is demonstrated in Section 2.3.. The *p*-values are reported by means of the Wilcoxon one-way sample *t*-test. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Table 2

Control variables: Descriptive statistics.

		Size	Leverage	Volatility	Past−Ret	Cash/Asset	NI/Asset
Panel A: NCDFs (N=1069)							
	Mean	4.88	0.19	0.55	0.15	0.30	−0.03
	25th pctl	3.52	0.02	0.38	−0.22	0.09	−0.06
	Median	4.63	0.12	0.50	0.05	0.22	0.00
	75th pctl	5.95	0.29	0.67	0.37	0.47	0.02
	Std. dev.	1.77	0.21	0.24	0.54	0.25	0.08
Panel B: CDFs (N=2100)							
	Mean	6.93	0.27	0.38	0.18	0.12	0.01
	25th pctl	5.71	0.13	0.26	−0.11	0.02	0.00
	Median	6.86	0.24	0.35	0.11	0.07	0.01
	75th pctl	8.11	0.37	0.45	0.36	0.16	0.02
	Std. dev.	1.89	0.20	0.17	0.46	0.14	0.04
Panel C: Subsets of the CDFs							
Group 1: SBPDs	Mean	8.17	0.32	0.31	0.15	0.08	0.01
(N=572)	25th pctl	7.21	0.19	0.22	−0.09	0.02	0.00
	Median	8.01	0.28	0.29	0.09	0.05	0.01
	75th pctl	9.09	0.41	0.37	0.29	0.11	0.03
	Std. dev.	1.38	0.19	0.13	0.38	0.09	0.03
Group 2: SBs	Mean	6.27	0.23	0.38	0.18	0.08	0.01
(N=301)	25th pctl	5.71	0.10	0.28	−0.12	0.02	0.00
	Median	6.33	0.20	0.36	0.11	0.04	0.01
	75th pctl	6.93	0.32	0.44	0.37	0.10	0.02
	Std. dev.	1.01	0.17	0.13	0.44	0.09	0.03
Group 3: WBPDs	Mean	7.70	0.33	0.35	0.19	0.11	0.00
(N=281)	25th pctl	6.77	0.18	0.26	−0.10	0.03	0.00
	Median	7.51	0.30	0.33	0.11	0.07	0.01
	75th pctl	8.55	0.44	0.42	0.35	0.17	0.02
	Std. dev.	1.38	0.20	0.15	0.47	0.12	0.05
Group 4: WBs	Mean	5.39	0.20	0.47	0.18	0.17	0.00
(N=730)	25th pctl	4.47	0.04	0.33	−0.17	0.03	−0.01
	Median	5.40	0.16	0.42	0.08	0.10	0.01
	75th pctl	6.39	0.29	0.55	0.39	0.24	0.02
	Std. dev.	1.37	0.19	0.20	0.54	0.19	0.05
Group 5: PDDs	Mean	8.77	0.29	0.33	0.27	0.12	0.02
(N=216)	25th pctl	7.59	0.17	0.24	0.01	0.05	0.01
	Median	8.77	0.27	0.32	0.19	0.09	0.02
	75th pctl	9.95	0.38	0.38	0.47	0.16	0.03
	Std. dev.	1.60	0.17	0.11	0.42	0.11	0.03

Note: This table reports summary statistics of the control variables used in the matching method. The sample contains leveraged non-financial firms in the U.S. market, found in the intersection of the CRSP and Compustat databases without missing observations for the required data. We consider firm characteristics that have been previously documented as determinants of default risks, including (i) Size, (ii) Leverage, (iii) Volatility, (iv) past one year's stock return (Past-ret), (v) the ratio of cash to assets (Cash/Asset), and (vi) the ratio of net income to assets (NI/Asset). The Size, Leverage, Cash/Asset, and NI/Asset variables are computed on the basis of the information available for 2006Q2. The variables Volatility and Past-Ret are obtained by using the data of daily equity returns from 2005Q3 to 2006Q2. The sample of firms is separated into six subgroups: (i) NCDFs, (ii) SBPDs, (iii) SBs, (iv) WBPDs, (v) WBs, and (vi) PDDs, where CDFs (credit-dependent firms) include subgroups 2 to 6. The detailed identification strategy is demonstrated in Table 1 as well as in Section 2.3. In Panels A and B, we report the results for NCDFs and CDFs, respectively. We also provide results across the subgroups of CDFs in Panel C.

Table 3
Matching estimation results.

	CDFs	SBPDs	SBs	WBPDs	WBs	PDDs
Model	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Estimation results on the full sample						
Size	0.264 ***	0.544 ***	0.159 ***	0.472 ***	0.063 **	0.547 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.012)	(0.001)
Leverage	0.621 ***	1.862 ***	0.004	1.777 ***	0.104	1.403 ***
	(0.001)	(0.001)	(0.988)	(0.001)	(0.552)	(0.001)
Volatility	−0.575 ***	−1.138 ***	−1.598 ***	−0.658 *	−0.520 ***	−0.220
	(0.001)	(0.004)	(0.001)	(0.090)	(0.005)	(0.677)
Past−Ret	0.032	0.194	0.076	0.064	0.015	0.214
	(0.559)	(0.133)	(0.485)	(0.594)	(0.810)	(0.156)
Cash/Asset	−2.000 ***	−3.873 ***	−4.476 ***	−1.824 ***	−1.562 ***	−1.576 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NI/Asset	1.306 **	2.148	3.848 ***	−0.113	1.607 ***	2.653
	(0.014)	(0.128)	(0.006)	(0.922)	(0.005)	(0.147)
constant	−0.195	−2.574 **	0.752	−2.587 **	−4.188	−3.732 ***
	(0.779)	(0.050)	(0.446)	(0.029)	(0.974)	(0.010)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo−R^2	0.295	0.614	0.361	0.461	0.121	0.560
# Observations	3169	1641	1370	1350	1799	1285
Panel B: Estimation results on the matched sample						
Size	−0.012	0.024	−0.007	−0.041	−0.012	−0.085
	(0.652)	(0.685)	(0.891)	(0.531)	(0.692)	(0.309)
Leverage	0.244	−0.233	−0.076	−0.035	−0.049	−0.987 *
	(0.205)	(0.610)	(0.843)	(0.930)	(0.820)	(0.094)
Volatility	0.044	0.876	−0.066	0.272	0.132	0.452
	(0.841)	(0.161)	(0.892)	(0.640)	(0.574)	(0.617)
Past−Ret	0.003	0.003	0.030	−0.134	−0.048	−0.041
	(0.969)	(0.989)	(0.848)	(0.470)	(0.528)	(0.860)
Cash/Asset	0.166	0.686	−0.020	0.288	−0.103	−0.443
	(0.425)	(0.367)	(0.978)	(0.630)	(0.633)	(0.574)
NI/Asset	0.484	−0.508	0.980	−0.594	0.535	1.715
	(0.489)	(0.817)	(0.638)	(0.735)	(0.479)	(0.553)
constant	−4.873	−0.341	0.103	0.288	0.028	6.003
	(0.981)	(0.565)	(0.813)	(0.651)	(0.911)	(0.985)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo−R^2	0.012	0.038	0.012	0.041	0.008	0.052
# Observations	1246	326	418	346	1094	230

Note: The following table presents the results of a probit regression with the CDF group (or any subgroup of CDFs) as the dependent variable. The sample of firms is separated into six subgroups: (i) NCDFs, (ii) SBPDs, (iii) SBs, (iv) WBPDs, (v) WBs, and (vi) PDDs, where CDFs (clearly credit-dependent firms) include subgroups 2 to 6. The detailed identification strategy is demonstrated in Table 1 as well as in Section 3.2. In Panel A, we use the full sample of firms in the intersection of the CRSP and Compustat databases with non-missing observations for the required data and with non-zero leverage. In Panel B, we use PSM methods to find two matched groups with similar scope in seven dimensions (Size, Leverage, Volatility, Past-Ret, Cash/Asset, NI/Asset, and Fama–French 38 industry classification (FF industry)), selected because of their importance in determining firms' default risks. The *p*-values are reported in brackets. The pseudo-R^2 values and the numbers of observations are reported in the last two rows. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Table 4
Matched sample analysis in the first-year crisis period.

	CDFs		Strong bank dependence		Weak bank dependence		PDDs	
Model	(1)		(2)		(3)		(4)	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Treated firms	−0.824	−0.806	−1.755	−1.647	−0.962	−1.015	−0.49	−0.302
Control firms	−0.851	−0.860	−0.950	−0.938	−0.892	−0.836	−0.649	−0.475
Dif-in-Dif	0.027	0.055	−0.805 **	−0.708 **	−0.069	−0.179	0.159	0.172
	(0.407)	(0.345)	(0.024)	(0.028)	(0.206)	(0.163)	(0.437)	(0.289)
# Observations	1059	1059	486	486	999	999	206	206
	SBPDs		SBs		WBPDs		WBs	
Model	(5)		(6)		(7)		(8)	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Treated firms	−1.453	−1.683	−1.836	−1.580	−1.270	−1.261	−0.888	−0.994
Control firms	−0.665	−0.783	−0.864	−0.812	−0.747	−0.836	−0.920	−0.860
Dif-in-Dif	−0.789 **	−0.900 **	−0.972 **	−0.768 **	−0.523	−0.426	0.031	−0.134
	(0.022)	(0.031)	(0.026)	(0.019)	(0.130)	(0.345)	(0.387)	(0.359)
# Observations	294	294	370	370	305	305	921	921

Note: This table shows the results of matched sample analysis on default risk indicators. The matched sample is constructed by implementing the propensity score matching method. In matching, treated firms could be CDFs, the strongly bank dependent group (that contains SBPDs and SBs), or the weakly bank dependent group (that contains WBPDs and WBs), or any CDF subgroup (SBPDs, SBs, WBPDs, WBs, or PDDs). Control group is the subset of NCDFs selected as the closest match to the treated firms on the basis of the following set of firm characteristics: size, leverage, volatility of equity returns, past one-year return, the ratio of cash to assets, the ratio of net income to assets, and an industry indicator variable (Fama–French 38 industry classification). The numbers for treated firms and control firms are time-series changes in the DTD in the first year relative to the pre-crisis period. The Dif-in-Dif value denotes the cross-sectional difference between time-series changes in the DTD of the treatment and control groups in terms of the mean or the median. The p-values are obtained by means of the Wilcoxon one-way sample t-test. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Table 5

Role of credit quality on the supply shock effect.

	Strong bank dependence		Weak bank dependence		PDDs	
Model	(1)		(2)		(3)	
Panel A: Low-credit quality (low-DTD) firms						
	Mean	Median	Mean	Median	Mean	Median
Treated firms	−0.829	−1.079	−0.346	−0.522	0.303	0.040
Control firms	−0.075	−0.331	−0.288	−0.493	−0.554	−0.569
Dif-in-Dif	−0.754 **	−0.749 **	−0.057	−0.029	0.858 *	0.608
	(0.019)	(0.039)	(0.369)	(0.417)	(0.097)	(0.284)
# Observations	271	271	573	573	110	110
Panel B: High-credit quality (high-DTD) firms						
	Mean	Median	Mean	Median	Mean	Median
Treated firms	−2.345	−1.873	−1.329	−1.637	−0.256	−0.270
Control firms	−1.918	−1.731	−1.743	−1.720	−1.878	−1.506
Dif-in-Dif	−0.427	−0.142	0.414	0.083	1.622 **	1.236 **
	(0.321)	(0.256)	(0.329)	(0.424)	(0.027)	(0.029)
# Observations	187	187	432	432	70	70

Note: This table presents the matched sample analysis in the first-year crisis period conditional on pre-crisis credit quality. We split the sample into two subsamples based on the median value of the DTD for each CDF subgroup marginal DTD distribution. The group for firms with a low DTD is considered low credit quality (Panel A) and the group with a high DTD is viewed as high credit quality (Panel B). The treatment subject is the strongly bank-dependent group, the weakly bank-dependent group, or public debt-dependent but not bank-dependent group. The control subject is the NCDFs. The numbers for the treated firms and control firms are time-series changes in the DTD in the first year relative to the pre-crisis period. The Dif-in-Dif value denotes the cross-sectional difference between time-series changes in the DTD of the treatment and control groups in terms of the mean or the median. The *p*-values are obtained by means of the Wilcoxon one-way sample *t*-test. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Table 6
Tests of the substitution effect.

Model	All firms (1)		Low credit−quality (Low DTD) (2)		High credit−quality (High DTD) (3)	
Panel A: SBPDs versus SBs						
	Mean	Median	Mean	Median	Mean	Median
Treated firms: SBPDs	−2.102	−2.043	−0.878	−1.125	−2.696	−2.104
Control firms: SBs	−1.857	−1.637	−1.076	−1.462	−2.865	−2.666
Dif-in-Dif	−0.245	−2.191	0.198	0.337	0.169	0.562
	(0.252)	(0.148)	(0.453)	(0.333)	0.350	(0.239)
# Observations.	234	234	131	131	97	97
Panel B: WBPDs versus WBs						
	Mean	Median	Mean	Median	Mean	Median
Treated firms: WBPDs	−1.510	−1.416	−1.095	−1.160	−2.073	−2.745
Control firms: WBs	−1.337	−1.634	−0.482	−0.671	−1.796	−2.026
Dif-in-Dif	−0.173	0.217	−0.613	−0.488	−0.277	−0.719
	(0.495)	(0.348)	(0.241)	(0.321)	(0.321)	(0.187)
# Observations.	234	234	115	115	101	101

Note: The table provides the results of testing the substitution effect, which assert that a firm's ability to switch financing resources between banks and public debt markets helps reduce the effect of financial crises on its default risks. Thus, we specifically choose two groups of firms; both have bank dependence but only one can obtain financing from the public debt market. That is, we use Dif-in-Dif pair of SBPDs and SBs in Panel A and for the pair of WBPDs and WBs in Panel B. We also perform the test on high-credit quality firms and low-credit quality firms, respectively in Models 2 and 3. The values for treated firms and control firms are the time-series changes in the DTD in the first year relative to the pre-crisis period. The Dif-in-Dif values denote the cross-sectional difference between time-series changes in the DTD of the treatment and control groups, in terms of the mean or the median. The *p*-values are obtained by means of the Wilcoxon one-way sample t-test. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Table 7

Matched sample analysis after Lehman's bankruptcy.

Panel A: Dif-in-Dif results with NCDFs as the control group

Treated firms	CDFs	SBPDs	SBs	WBPDs	WBs	PDDs
Model	(1)	(2)	(3)	(4)	(5)	(6)
Post-Lehman (2008Q4–2009Q1)						
Treated firms	−6.318	−6.79	−6.669	−6.624	−6.223	−4.987
Control firms	−5.616	−5.032	−5.705	−4.889	−5.69	−4.544
Dif-in-Dif	−0.702 **	−1.758 ***	−0.965 **	−1.735 ***	−0.533 *	−0.443
	(0.012)	(0.001)	(0.030)	(0.001)	(0.081)	(0.205)
# Observations	889	259	323	257	779	177
Last year (2009Q2–2010Q1)						
Treated firms	−4.516	−4.935	−4.818	−4.35	−4.367	−2.719
Control firms	−3.915	−3.326	−4.081	−3.358	−4.078	−2.762
Dif-in-Dif	−0.601 **	−1.608 ***	−0.737 *	−0.992 ***	−0.289	0.043
	(0.020)	(0.001)	(0.081)	(0.006)	(0.123)	(0.500)
# Observations	833	240	307	239	729	170

Panel B: Substitution effect

	SBPDs vs. SBs	WBPDs vs. WBs
	(1)	(2)
Dif-in-Dif (post-Lehman)	0.01	−0.471 *
	(0.401)	(0.061)
# Observations	224	194
Dif-in-Dif (last year)	−0.217	−0.706 *
	(0.262)	(0.056)
# Observations	217	190

Note: The table presents the results of matched sample analysis after Lehman's bankruptcy. The analysis includes two periods: the post-Lehman period (2008Q to 2009Q1) and the last year (2009Q2 to 2010Q1). Panel A reports the results across treatment groups for various degrees of credit dependence. Panel B reports the results on testing the substitution effect. The values for treated firms and control firms are the time-series changes in the DTD in the first year relative to the pre-crisis period. The Dif-in-Dif denotes the cross-sectional difference between the time-series changes (relative to the pre-crisis period) in the DTD of the treatment and control groups in terms of the mean. The *p*-values are obtained by means of the Wilcoxon one-way sample *t*-test. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Table 8

Descriptive statistics of bank debts and public debts in year 2006.

		(Bank debt-to-total assets) (1)	(Public debt-to-total assets) (2)	(Bank debt-to-total debt) (3)	(Public debt-to-total debt) (4)
Panel A: NCDFs (N=895)					
	Mean	8.28	9.44	42.54	54.25
	25th pctl	0.00	0.01	0.00	3.67
	Median	1.81	1.00	28.00	58.90
	75th pctl	12.05	10.12	93.69	100.00
Panel B: CDFs (N=1864)					
	Mean	10.29	11.77	38.35	48.21
	25th pctl	0.09	0.39	0.49	5.42
	Median	4.38	5.91	24.02	43.09
	75th pctl	15.83	18.05	74.80	95.68
Panel C: Subsets of the CDFs					
Group 1: SBPDs	Mean	11.01	13.81	29.96	47.41
(N=537)	25th pctl	0.29	1.95	1.20	9.67
	Median	4.15	9.97	17.35	42.25
	75th pctl	16.69	20.60	51.85	87.61
Group 2: SBs	Mean	12.00	9.28	53.96	40.31
(N=270)	25th pctl	1.53	0.12	10.38	1.96
	Median	7.70	2.39	58.86	24.95
	75th pctl	18.03	13.78	96.85	84.50
Group 3: WBPDs	Mean	8.85	17.08	26.33	55.90
(N=254)	25th pctl	0.05	3.91	0.09	20.49
	Median	2.37	12.83	11.56	57.40
	75th pctl	11.64	23.22	46.67	97.01
Group 4: WBs	Mean	10.20	8.27	46.57	48.39
(N=646)	25th pctl	0.00	0.02	0.00	1.72
	Median	4.15	1.45	42.00	41.86
	75th pctl	15.39	11.37	96.41	100.00
Group 5: PDDs	Mean	7.34	15.05	25.83	51.34
(N=157)	25th pctl	0.44	1.52	3.44	13.35
	Median	2.50	8.67	13.30	54.29
	75th pctl	10.04	19.05	40.07	92.62

Note: This table presents summary statistics of the proportion of bank debts and public debts to total debts or total assets. The sample uses debt structure variables in the Capital IQ database. We merge the main analysis sample with debt structure variables in the Capital IQ database for 2006. The sample involves 2,759 unique firms. We compute four ratios: (i) the bank debt-to-total assets ratio, (ii) the public debt-to-total assets ratio, (iii) the bank debt-to-total debt ratio, and (iv) the public debt-to-total debt ratio. The numerator of these ratios is either bank debt—the sum of term loans and revolving credit—or public debt—the sum of senior bonds and notes, subordinated bonds and notes, and commercial paper. The former two ratios are divided by total assets, while the latter two are divided by total debt. The sample of firms is separated into six subgroups, denoted as (i) NCDFs (not clearly credit dependent firms), (ii) SBPDs (strongly bank dependent and public debt dependent firms), (iii) SBs (strongly bank dependent but not public debt dependent firms), (iv) WBPDs (weakly bank dependent and public debt dependent firms), (v) WBs (weakly bank dependent but not public debt dependent firms), (vi) PDDs (public debt dependent but not bank dependent firms). By construction, CDFs (clearly credit-dependent firms) include subgroups 2 to 6. The detailed identification strategy is demonstrated in Section 2.3.

Table 9

Capital IQ-based sample analysis.

Bank debt-to-total assets	Top 50%		Top 25%		Top 20%		Top10%	
	(1)		(2)		(3)		(4)	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Treated firms	−1.169	−1.247	−1.302	−1.264	−1.323	−1.363	−1.339	−1.438
Control firms	−1.316	−1.299	−1.073	−0.940	−1.103	−1.030	−1.100	−0.998
Dif-in-Dif	0.147	0.052	−0.230 *	−0.324 **	−0.220 **	−0.333 **	−0.239 *	−0.440 **
	(0.205)	(0.369)	(0.058)	(0.047)	(0.044)	(0.050)	(0.082)	(0.028)
# Observations.	1513	1513	1081	1081	928	928	507	507

Note: This table reports the matched sample analysis results in the first-year crisis period using the Capital IQ-based sample. The treatment group contains firms having bank debt-to-total assets in the top 50%, 25%, 20%, or 10% of firms in 2006 and the control group contains the remainders of the treatment subject. The results are presented in Models 1 to 4 in this order. The numbers for treated firms and control firms are the time-series changes in the DTD in the first year relative to the pre-crisis period. The Dif-in-Dif denotes the cross-sectional difference between time-series changes in the DTD of the treatment and control groups in terms of the mean or the median. The *p*-values are obtained by means of the Wilcoxon one-way sample *t*-test. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Table 10

Matched sample analysis in the first−year crisis period: controlling for the maturity structure of debt.

	CDFs		Strong bank dependence		Weak bank dependence		PDDs	
Model	(1)		(2)		(3)		(4)	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Treated firms	−0.975	−0.965	−1.649	−1.698	−1.018	−1.073	−0.342	−0.522
Control firms	−0.844	−0.850	−0.847	−0.926	−0.926	−0.874	−0.544	−0.312
Dif-in-Dif	−0.131	−0.115	−0.801 **	−0.7728 ***	−0.092	−0.199	0.202	−0.210
	(0.296)	(0.161)	(0.016)	(0.008)	(0.311)	(0.149)	(0.342)	(0.399)
# Observations	798	798	336	336	777	777	135	135
	SBPDs		SBs		WBPDs		WBs	
Model	(5)		(6)		(7)		(8)	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Treated firms	−2.190	−2.006	−1.581	−1.538	−1.295	−1.397	−0.834	−0.881
Control firms	−0.809	−0.940	−0.921	−0.967	−0.909	−1.030	−0.712	−0.812
Dif-in-Dif	−1.381 ***	−1.066 **	−0.660 **	−0.571 **	−0.386	−0.367	−0.122	−0.069
	(0.003)	(0.031)	(0.042)	(0.033)	(0.266)	(0.141)	(0.282)	(0.426)
# Observations	179	179	281	281	193	193	721	721

Note: This table shows the results of matched sample analysis on default risk indicators. The matched sample is constructed after controlling for debt maturity structure (i.e., the ratio of debts maturing within 3 years to total debt) and the same set of variables as we use in the baseline analysis. The numbers for treated firms and control firms are time-series changes in the DTD in the first year relative to the pre-crisis period. The Dif-in-Dif value denotes the cross-sectional difference between time-series changes in the DTD of the treatment and control groups in terms of the mean or the median. The p-values are obtained by means of the Wilcoxon one-way sample t-test. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Table 11

Matched sample analysis for strong bank-dependent firms on firm value, book value of debt, and asset volatility.

	First year crisis		Pre-Lehman		Post-Lehman	
Period	(1)		(2)		(3)	
Panel A: Percentage change of firm value						
	Mean	Median	Mean	Median	Mean	Median
Dif-in-Dif	−0.080***	−0.073***	−0.067**	−0.021	−0.130***	−0.117**
	(0.007)	(0.009)	(0.029)	(0.302)	(0.000)	(0.012)
Panel B: Percentage change of book value of debt						
	Mean	Median	Mean	Median	Mean	Median
Dif-in-Dif	0.042	−0.008	−0.086	−0.066*	−0.052	−0.109
	(0.417)	(0.411)	(0.260)	(0.077)	(0.331)	(0.182)
Panel C: Time-series change of asset volatility						
	Mean	Median	Mean	Median	Mean	Median
Dif-in-Dif	0.002	0.000	0.014**	0.036**	0.057***	0.048***
	(0.264)	(0.483)	(0.015)	(0.023)	(0.001)	(0.002)

Note: This table shows the results of matched sample analysis for strong bank-dependent firms on the firm value, the book value of debt, and the asset volatility. The Dif-in-Dif value denotes the cross-sectional difference between time-series percentage changes in the firm value (Panel A), time-series percentage changes in the book value of debt (Panel B), and time-series change in the asset volatility (Panel C) of the treatment and control groups in terms of the mean or the median. Column 1, 2, and 3 present results for the first year crisis period, the pre-Lehman period, and the post-Lehman period respectively. The p-values are obtained by means of the Wilcoxon one-way sample t-test. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Highlights

(1) Firms mainly dependent on financing from banks suffer from higher increases in default risk than firms with no such dependence.

(2) Firms that rely solely on financing from public debt markets do not experience significant increases in default risk.

(3) Firms dependent on bank financing cannot offset adverse impacts of bank lending shocks by substituting bank loans with publicly traded debt.

(4) Our findings suggest that the bank supply shock theory helps explain the transmission channel of financial shocks to the real economy.