LENDING RELATIONSHIPS AND LIQUIDITY INSURANCE VALUE OF BANK CREDIT LINES: EVIDENCE FROM LOAN SPREADS

by

Tatiana Maksimenko

A dissertation submitted to the Graduate Faculty in Business in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

The City University of New York

2013

This manuscript has been read and accepted for the Graduate Faculty in Business in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

9/13/2013

Date

Prof. Linda Allen

Chair of Examining Committee

9/13/2013

Date

Prof. Joseph Weintrop

Executive Officer

Prof. Linda Allen

Prof. Theodore Joyce

Prof. Joseph Weintrop

Supervisory Committee

THE CITY UNIVERSITY OF NEW YORK

ABSTRACT

LENDING RELATIONSHIPS AND LIQUIDITY INSURANCE VALUE OF BANK CREDIT LINES: EVIDENCE FROM LOAN SPREADS

by

TATIANA MAKSIMENKO

Advisor: Professor Linda Allen

Bank lending processes and lending relationships involve two aspects, the provision of liquidity via lines of credit and the production of information via monitoring. To access the existing credit line, a borrower must be in compliance with financial covenants. When violations occur, access becomes conditional upon the bank's willingness to accommodate the customer. The bank values its reputation as an accommodating lender and views a decision regarding credit line access restrictions as a trade-off between reputational and financial capital. Since imposing restrictions on a more loyal borrower causes greater reputational damage, a bank's "willingness" to accommodate increases in the strength of the relationship with its borrower. This is the first channel through which relationships have effect. To the extent that lending also involves monitoring, relationships allow a bank to build an exploitable information advantage. This is the second channel. Most credit lines are monitored, making it difficult to isolate the effects of these two channels. I identify commercial paper backup lines of credit as loans that provide liquidity, but do not involve information production and use them to construct two measures of relationship strength that capture the extent of bank's willingness to provide liquidity (*T-intensity)* and the bank's information advantage (*I-intensity).* To make sharper inferences concerning the effect of willingness, I control for a bank's reliance on core deposits as a measure of "ability" to provide liquidity. I find that loan spreads decrease in *T-intensity* for firms without public equity. Thus, for such firms, credit lines have liquidity insurance value and it increases with relationship strength. I also find that loan spreads increase in *I-intensity* for all firms, suggesting that banks are successful at exploiting their information advantage (i.e. "holding up" borrowers). My findings imply that for relatively opaque borrowers, relationships have value even in the absence of private information production.

ACKNOWLEDGEMENTS

My deepest appreciation and gratitude goes to Professor Linda Allen, my dissertation supervisor, for the guidance and mentorship she provided to me from the start of the PhD program, through to completion of this degree. I am truly fortunate to have had the opportunity to be Professor Allen's doctoral student and will carry a lifetime memory of her patience, caring, intelligence, diligence, and erudition.

I am profoundly indebted to Professor Joseph Weintrop, my dissertation committee member and doctoral program officer, for his feedback on various aspects of this project and for being supportive and patient throughout the years.

I am very grateful to Professor Ted Joyce, my dissertation committee member, for his valuable feedback and many thought-provoking suggestions about my research.

I'd like to thank faculty and doctoral students of the Economics and Finance Department of the Baruch College, City University of New York for the contribution to my intellectual growth during my years of study. My special thanks go to my classmates and colleagues Sila Alan, Yigit Atilgan, Chih-Chieh Chiu, Stefano D'Addona, Yalan Feng, Eleni Gousgounis, Guangzhong Li, Yili Lian, Scott Murray, Nosa Omoregie, Ekkachai Saenyasiri, and Junqiang Xie. I am very grateful to Professor Armen Hovakimian, the finance program coordinator, for his mentorship and valuable advice on various aspects of conducting research.

I would not have been able to finish this dissertation without the guidance and patience of my committee members and unconditional love and support of my family. This dissertation is dedicated to my family, especially my parents, and my friends.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

1 INTRODUCTION

Modern theory of financial intermediation credits banks with the role of delegated monitors and providers of liquidity. As delegated monitors, banks mitigate adverse selection and moral hazard problems in lending by producing private borrower-specific information via screening and monitoring. As liquidity providers, banks offer credit lines to their borrowers.[1] Being relatively concentrated and having long-term horizons, which enables the intertemporal reusability of information, provides banks with greater incentives to monitor when compared to capital market investors (Diamond, 1984; Greenbaum and Thakor, 1995). Having unique institutional characteristics, such as the capacity to take deposits and access to a regulatory safety net, allows banks an advantage when providing liquidity (Berlin and Mester, 1999; Kashyap, Rajan, and Stein, 2002; Gatev and Strahan, 2006). In consideration of these two roles, there are two dimensions of the bank lending process, the production of private information and the provision of liquidity.

A rapidly growing area of research is devoted to understanding the advantages and disadvantages of bank credit lines and cash holdings as sources of corporate liquidity. Firms require liquidity to meet their contractual obligations and to undertake valuable investment projects when they arise. However, capital market frictions, such as transactions and asymmetric information costs, make capital market financing a poor liquidity source for most firms. Initially, corporate finance literature was focused on cash holdings as a source of liquidity, but, more recently, the role of lines of credit in the provision of liquidity has become a hotly debated topic. On some grounds, bank-provided liquidity is more attractive than cash holdings. Banking literature suggests that credit lines are more efficient than cash holdings as liquidity buffers (Holmstrom and Tirole, 1998) and that *bank-provided* credit lines are the cheapest source of

[1] I use the term "liquidity" in the sense of funding liquidity (the ease of borrowing funds). Early liquidity-based bank theories emphasized the provision of liquidity to depositors (Diamond and Dybvig, 1983). Later, the focus shifted to the simultaneous provision of liquidity to depositors and to borrowers (i.e., on the "dual liquidity role" of banks).

liquidity in the economy (Kashyap, Rajan, and Stein, 2002).[2] Bank-provided liquidity may also become cheaper and more available precisely when it is in higher demand due to the "re-intermediation" that occurs during crises in the capital markets (Gatev and Strahan, 2006). In addition to the advantages of credit lines proposed by the banking literature, the corporate finance literature recognizes several costs of cash holdings.[3] Given the above reasons, why do firms hold cash? The most obvious answer is that cash holdings provide unconditional access to liquidity, whereas access to a bank credit line is conditional upon borrower's performance. Despite being called loan commitments, bank credit lines represent, at best, a contingency as their contractual features give banks considerable power in restricting borrowers' access to lines, cutting line limits, increasing the price of credit, and renegotiating loan terms when borrowers' financial health deteriorates.[4] In addition, relying on bank credit lines exposes a borrower to the risk of deterioration of the bank's financial health. With the multiple advantages and disadvantages of credit lines, their liquidity insurance value (i.e., the extent to which they protect borrowers against liquidity risk) has become an active area of research.[5] Cash holdings may be costly, but their availability when they are needed is unquestioned. Credit lines are presumably cheaper and include other possible advantages, but to what extent do they provide liquidity risk protection?

Several complications arise in answering this question. First, firms' "demand for liquidity" may be driven by slightly different reasons. Failing to meet a contractual obligation due to a shortfall in cash is one thing. Having to forego a valuable investment opportunity due to the inability to obtain financing in a timely and cost-efficient manner is a different matter. Although both situations may be viewed as liquidity

---

[2] Credit lines are also provided by non-bank financial intermediaries (e.g., finance companies).

[3] For example, cash holdings introduce agency problems, typically earn less than the liabilities used to finance them, and do not offer tax shields as compared to interest payments on debt.

[4] Almost all credit lines include financial covenants and a material adverse change (MAC) clause. Some include borrowing base restrictions and performance pricing. Financial covenants specify balance sheet and operating performance ratios that the borrower must comply with. The MAC clause gives a bank the right to renege if, in the bank's opinion, a material change in the borrower's financial health has occurred. Borrowing base restrictions tie the quantity of available credit to changes in the value of pledged collateral. Performance pricing allows a bank to increase the explicit cost of credit, without even invoking renegotiation, if certain financial ratios deteriorate.

[5] Some of the studies include Sufi (2009), Demiroglu and James (2011), Barakova and Parthasarathy (2012), and Acharya, Almeida, Ippolito, and Perez (2013).

shortages, the first one is more in line with a traditional definition of liquidity risk. Demiroglu and James (2011) review a large number of recent studies and suggest that these two reasons may explain why most firms use cash reserves and credit lines simultaneously. Cash holdings are used to finance shortfalls in cash and credit lines are used as "options on liquidity." However, if, in contrast to this view, credit lines serve both purposes, then having to disentangle these two reasons and isolate credit lines' role as insurance against liquidity risk in a traditional sense becomes necessary and complicates the analysis.[6] The second complication is that measuring the impact of access to a credit line on some outcome variable (e.g., firm value, stock price, cost of credit, etc.) is confounded by the effects of a bank's private information production. Thus, one needs to isolate the effect of liquidity risk reduction that may result from having a credit line from the effects of bank's increased informedness.

The main goal of this paper is to assess the value of bank credit lines as liquidity insurance (i.e., to determine whether credit lines reduce borrowers' liquidity risk). My findings are twofold. First, I find that bank-provided access to liquidity in the form of credit lines does reduce the liquidity risk of borrowers that do not have access to equity markets. Additionally, for such firms, the value of bank-provided access to liquidity increases in their reliance on a bank for meeting their liquidity needs, controlling for the effects of information production. The second result is particularly interesting as it implies that lending relationships have value not only because of the well researched effects of information production, but also because these relationships enhance the perceived value of bank-provided liquidity insurance. I will argue that this effect is not driven by information production. My findings also imply that for a bank-borrower relationship to be valuable, it need not involve private information production; even a "transactional" relationship, in which a firm is a repeat customer of a bank, but no private information production occurs, can be valuable.

[6] Surveys offer mixed evidence as to how company managers choose between cash holdings and credit lines. Lins, Servaes, and Tufano (2010) report that fewer than a half of the 240 CFOs from 29 counties said that credit lines and cash are substitutes. Campello, Graham, Giambona, and Harvey (2009) suggest that cash and line of credit choices are made jointly, based on a survey of 794 CFOs from 31 countries.

My identification strategy involves testing a joint hypothesis: *I claim that if bank-provided liquidity insurance is valuable, its value should increase in the borrower's reliance on a bank for meeting its liquidity needs.* I test for the presence of this association, confirm it, and conclude that bank-provided liquidity insurance is valuable and increases in the extent of this reliance. I argue that this association is driven by reputational considerations and not by information production, and draw on the Boot, Greenbaum, and Thakor (1993) theory of financial and reputational capital tradeoff. A bank has the significant power to renege on its commitment to lend when a borrower violates a covenant.[7] However, it will not behave opportunistically as reneging too often will result in a loss of future business and associated loan commitment fees from this and other customers. A bank values its reputation as an accommodating lender and thinks intertemporally, weighing the damage to reputational capital against the benefit of preserving financial capital in the event of reneging. A bank may choose to honor its commitment to lend even when it expects it to result in a financial loss as this accommodation protects and/or builds its reputation. I maintain that, all else being equal, reneging on a repeat, loyal client causes greater reputational damage than reneging on a less loyal customer because (1) it results in a greater loss of future fees from this client, and (2) it sends a more negative signal to other current and prospective customers. Thus, I argue that a "borrower's reliance on a bank for meeting its liquidity needs" and the bank's "willingness" to provide liquidity (i.e., to be accommodating) are two sides of the same coin.

I examine the effect of a bank's willingness to provide liquidity using loan spread as a dependent variable and expect to find a negative association, controlling for the effects of information production and other factors.[8] [9] My choice of loan spread is somewhat arbitrary as it is not the only outcome that may

[7] I use the term "reneging" to refer to one or a combination of the following actions: restricting borrower's access to a line, cutting the line limit, renegotiating the terms of the loan, etc.

[8] Following the literature that uses Dealscan, the source of my loan data, I employ "all-in-spread-drawn" (AISD), the loan interest rate spread (over LIBOR) plus any fees in originating the loan, as a measure of borrowing costs.

[9] One possible explanation of such association is based on the standard risk-return argument. If stronger reliance is associated with a greater reduction of a firm's liquidity risk, loan spread should be lower as risk is lower. Alternatively, if a stronger reliance is associated with greater protection from liquidity risk, it should increase a firm's competitiveness and bargaining power vis-à-vis its current and potential lenders, resulting in lower loan

be affected by reduced liquidity risk and by the production of private information in lending relationships. However, the abundance of theoretical and empirical literature regarding borrowing costs makes it an interesting choice as my findings may be assessed in the context of existing empirical studies. The existing literature attributes the effects of bank-borrower relationships, positive and negative, to private information production. Since private information that the relationship bank obtains via monitoring is reusable, lending costs should go down as the lending relationship matures (as monitoring costs go down). In the meantime, the relationship bank builds an information monopoly over the borrower creating an adverse selection problem for non-lenders and switching costs for the borrower. A relationship bank can use this information advantage to "hold-up" the borrower (i.e., extract information rents). If it strategically chooses to do so, it will share lending cost savings only partially, not share them at all, or not share them at all and charge even more than it did before. Thus, stable or increasing loan rates are consistent with information rents extraction, and decreasing loan rates do not rule them out.[10] This argument is entirely information production-based as it is the private information that lowers the relationship bank's lending costs, creates the adverse selection problem for non-lenders, and eventually weakens the bargaining power of the borrower. I do not challenge the role of information production. Rather, I argue that there is an *additional* channel through which relationships can affect borrowing costs. They enhance the liquidity insurance value of credit lines and this effect, as I previously argued, is driven by reputational considerations and not by information production. I take this information-based argument and add a liquidity provision dimension to it. While the information production effect of relationships may result in higher or lower loan spreads, the liquidity provision effect should result in lower loan spreads. The overall impact of lending relationships on loan spreads is the sum of these two effects.

---

spread. While these are two slightly different explanations as to how liquidity insurance translates into lower loan spreads, it is not crucial for my analysis which one it is.

[10] The theoretical literature offers different predictions regarding the direction of loan rates. Boot and Thakor (1994) predict that the rates should decrease. Sharpe (1990) and Rajan (1992) suggest that they should increase. The empirical literature offers mixed evidence.

I build on the existing empirical specification of Bharath, Dahiya, Saunders, and Srinivasan (2011) (henceforth, Bharath et al 2011) and Schenone (2010) who regress loan spread on a measure of the bank-borrower relationship strength and control variables. This measure of relationship strength, which they call relationship intensity and I call *aggregate intensity (A-intensity)*, is a ratio of a firm's borrowing from a given bank to its total borrowing within a defined time window. [11] In the above papers, *A-intensity* is viewed as a proxy for the relationship bank's exploitable information advantage. The positive coefficient, regardless of its statistical significance, is interpreted as information rents extractions that are present, while the negative statistically significant coefficient is interpreted as that they are absent or weak. I argue that the *A-intensity* coefficient captures the net effect of information production (depending upon whether or not a bank holds-up a borrower, the loan spread may go up or down) and liquidity provision (repeated bank-borrower interactions increase the bank's reputation-driven willingness to be accommodating, so loan spread should go down). I decompose *A-intensity* into information production and liquidity provision components, which I call *I-intensity* and *T-intensity*, and use them to isolate the effects of these two aspects of relationships in my regression analysis.

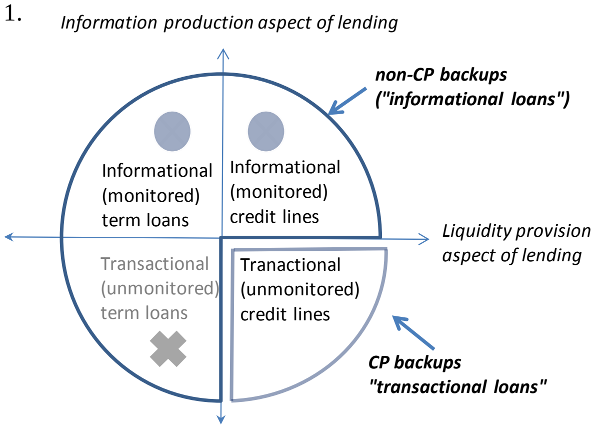
The following explains the logic behind my approach to decomposing *A-intensity*. The bank lending process has two dimensions, liquidity provisions via the issuance of credit lines and information production via monitoring. On the first dimension, there are credit lines and term loans (standard "on-the-spot" loans). On the second dimension, there are informational (monitored) and transactional (unmonitored) loans.[12] Thus, there are four categories of loans: (1) unmonitored term loans, (2) monitored

[11] My measures are based on a five-year time window and value of the loans following Bharath et al (2011). Schenone (2010) uses all prior loans (since Dealscan inception) and the number of loans.

[12] Loans that involve private information production are referred to as "relationship" loans in the literature. However, since, in this paper, I talk about the different types of relationships, I use the term "informational" loan to avoid confusion. Loans that do not involve private information production are referred to as "transactions" or "arm's length" loans in the literature. I refer to these loans as "transactional." This classification is not as unambiguous as term loans vs. credit lines, especially since the bank's monitoring effort is likely non-binary. The literature views the bank's monitoring effort as a function of bank, borrower, loan, and lending environment characteristics (i.e., as a matter of bank's strategic choice). The existence of monitored and unmonitored loans within the same bank is an accepted view (Boot and Thakor, 2000; Hauswald and Marquez, 2006; Agarwal and Hauswald, 2007). For example,

term loans, (3) monitored credit lines, and (4) unmonitored credit lines. My loan data is from the LPC Dealscan database that covers large (over $100,000) bank loans and includes loan contract terms and identifying information on lenders and borrowers at the onset of the loan. I argue that the bank's effort in monitoring the borrower depends upon the amount of "skin in the game," which is the size of a term loan and the drawn portion of a credit line, and the probability of a drawdown on the line's unused portion. The first category is presumably empty as large term loans are not likely to be unmonitored (the median loan size in my sample is $200 million). The second category consists of loans that involve only information production. The third category includes loans that involve both information production and a liquidity provision, making it difficult to isolate the liquidity provision effect. The fourth category is comprised of loans that involve only the liquidity provision. These loans, if they exist, may be instrumental in measuring the impact of the liquidity provision aspect of relationships as the overall effect of their presence is not confounded by the effect of information production. I take advantage of the availability of information on loan purpose in my data and identify commercial paper backups ("CP backups") as unmonitored credit lines and place all of the other loans in a rather heterogeneous "non-CP backups" group (Figure 1).[13] [14]

Figure 1.



in Boot and Thakor (2000), a bank offers informational loans to some and transactional loans to other borrowers, depending upon the competitiveness of the environment and the characteristics of a borrower.

[13] Most common loan purposes are corporate purposes, debt repayment, CP backup, and takeover. Table 4 presents a frequency count of loans in my sample by lending mode and loan purpose.

[14] Since monitored lines involve liquidity provisions, the non-CP backups category of loans involves not only the production of information, but also the provision of liquidity.

CP backups allow me to address the two issues mentioned earlier in this paper. First, they are insurance against liquidity risk in a traditional sense and not an option on liquidity as they may be used for one purpose only, to pay the investors if a commercial paper rollover becomes impossible. This situation arises either due to a market liquidity crunch or because the firm fails to maintain a top rating for its commercial paper, an absolute requirement to be able to borrow in this market. However, failure to maintain a prime CP rating is rarely associated with significant deterioration of credit quality. More often, it is only a minor deterioration (but sufficient to lose access to the commercial paper market) or a deterioration of short-term liquidity, which is more important for CP ratings than, for example, long-term bond ratings. Thus, by extending a CP backup line of credit, a bank provides insurance against the liquidity risk of the market and/or the borrower. Additionally, CP backups do not involve private information production. The bank knows that the takedown event will be triggered by either an unexpected market liquidity shock or a minor decline in the firm's performance that the rating agency is watching for (monitoring). Moreover, when a CP backup line is drawn, the borrower is typically required to pay the bank back within 30 days implying that the drawn portion will remain outstanding for only a short period of time during which a significant further decline of the borrower's credit quality is unlikely. For these reasons, and facing a low takedown probability in general, the bank has fewer incentives to monitor their client.[15]

To examine the impact of a borrower's reliance/dependency on a bank with respect to its liquidity needs (CP backups) and its informationally intensive borrowing (non-CP backups), I create the following measures. Each measure is based on three dimensions (firm *i*, bank *j*, and time *t*) and the firm's Dealscan-reported borrowing in the five-year period prior to *t*. I record all loans obtained by firm *i* during [*t-5; t*] and note their amounts, types (CP backup or non-CP backup), and banks' identities. *A-intensity* measures firm *i*'s overall reliance on bank *j* as a ratio of its borrowing from bank *j* to its total borrowing during [*t-5;*

[15] Assuming that credit line's purpose is related to bank's expected monitoring effort is reasonable. For example, Acharya, Almeida, Ippolito, and Perez (2013) suggest that "credit lines designated and primarily used for activities with low illiquidity-seeking risk, such as working capital management, may reflect fewer features of monitored insurance than credit lines used for activities with high illiquidity-seeking risk, such as mergers and acquisitions."

t]. *T-intensity* measures firm *i*'s reliance on bank *j* for meeting its liquidity needs as a ratio of CP backups from bank *j* to its total borrowing during [*t-5; t*]. *I-intensity* measures firm *i*'s reliance on bank *j* for its informationally intensive borrowing as a ratio of non-CP backups from bank *j* to its total borrowing during [*t-5; t*]. By construction, for each firm-bank pairing at time *t*, the sum of *I-intensity* and *T-intensity* is equal to *A-intensity* and, therefore, represents its decomposition.[16] I argue that *T-intensity* is a proxy for a bank's willingness to provide liquidity to a firm since I conjectured that a firm's greater reliance on a bank for meeting its liquidity needs (being a loyal customer) results in a more accommodating behavior of the bank. *I-intensity* is a proxy for a bank's information advantage over non-lenders. Higher values indicate a greater potential to save on lending costs, but also a greater opportunity to hold-up the borrower. As previously mentioned, the literature uses *A-intensity* as a proxy for a bank's information advantage. However, I believe that *I-intensity* is a better proxy as it excludes unmonitored loans. My approach to constructing intensity measures can be summarized as follows:

$$All\ loans = Informational\ loans\ (non-CP\ backups) + Transactional\ loans\ (CP\ backups) \qquad (1.1)$$

$$A-intensity\ = I-intensity \quad + \quad T-intensity \qquad (1.2)$$

$$\frac{All\ loans\ from\ current\ bank}{Total\ loans} = \frac{non\!-\!CP\ backups\ from\ current\ bank}{Total\ loans} + \frac{CP\ backups\ from\ current\ bank}{Total\ loans} \qquad (1.3)$$

The role of relationships in enhancing the liquidity insurance value of credit lines need not be limited to bank lending. There are other intermediaries that engage in relationship lending (Carey, Post, and Sharpe, 1998), produce private information, and value their reputation as accommodating lenders. However, bank lending is a more conducive environment for studying the role of relationships as the unique structure of bank liabilities allows me to control for banks' ability to provide liquidity and, therefore, make sharper inferences regarding their willingness to provide liquidity (measured by *T*-

[16] In my sample, the mean values of *A-intensity*, *I-intensity*, and *T-intensity* are 0.542, 0.475, and 0.067. Thus, on average, a firm's current bank has provided 54.2% of its total Dealscan-reported borrowing in the previous five years, with 47.5% in the form of non-CP backups and 6.7% in the form of CP backups.

intensity). Unlike non-bank intermediaries, banks are allowed to take retail deposits. Retail deposits and purchased liabilities (e.g., brokered CDs, repos, and federal funds) are two sources of bank short-term financing. The attraction of purchased liabilities is that the banks have significant discretion to increase or decrease their amount in response to their changing funding needs. However, purchased liabilities are highly unpredictable and their cost varies with market interest rates. Retail deposits and, more specifically, core deposits (most retail deposits fall into this category) represent a stable, cheap, and interest rate-inelastic source of financing. Core deposits are stable as depositors value liquidity services provided by their bank, do not switch banks frequently, and the majority of core deposits are FDIC-insured. Core deposit financing reduces banks' liquidity risk since core deposits do not "run" and enhance their ability to provide liquidity to borrowers in larger amounts and at a lower cost. [17] [18] There is overwhelming empirical evidence that during the recent financial crisis, banks that relied more heavily on core deposits weathered the liquidity shock to the banking system much better than banks that relied more on purchased liabilities. Banks that relied more greatly on core deposits cut their new lending by less (Ivashina and Scharfstein, 2010) and increased their precautionary liquid asset holdings by less (Cornett, McNutt, Strahan, and Tehranian, 2011). I include a ratio of a bank's core deposits to total deposits, *Bank Core Dep*, as a measure of a bank's reliance on core deposits, which proxies for the bank's ability to provide liquidity. I also include a bank's total assets, *Bank Size*, as a proxy for reputation, lending capacity, access to capital markets, and perceived risk ("too-big-to-fail"). Since size proxies for all of the above, its coefficient should be interpreted with caution.

---

[17] The regulatory safety net (deposit insurance and the central bank's lender of last resort role) makes core deposits virtually riskless to the depositors. Santos (2012) finds that insured deposits are not sensitive to the financial performance of the bank, not even during crises and recessions.

[18] Berlin and Mester (1999) argue that interest-inelasticity of core deposits shields banks from exogenous economic shocks and find that greater reliance on core deposits results in smoother loan rates. Kashyap, Rajan, and Stein (2002) argue that there are synergies in commitment lending and deposit taking. Another theoretical model that is focused on the role of core deposits is presented in Song and Thakor (2007), although it does not link deposits to the liquidity provision. In this model, a bank finds it optimal to finance informationally opaque value-adding loans with core deposits and informationally transparent transactional loans with purchased liabilities.

I examine the impact of *I-intensity*, *T-intensity*, *Bank Core Dep*, and *Bank Size* (my key explanatory variables) on *Loan Spread*, controlling for borrower, loan, and lending environment characteristics.[19] My benchmark empirical specification closely follows that of Bharath et al (2011). I expand their specification by replacing *A-intensity* with its decomposition and by including bank variables. *T-intensity* and *I-intensity* capture the strength of the two dimensions of lending relationships, provision of liquidity and production of information. *I-intensity* is a proxy for the bank's information advantage over non-lenders. The magnitude and the significance of the coefficient reflect the extent of the hold-up problem. *T-intensity,* the key variable of interest, is a proxy for the bank's willingness to provide liquidity, and I expect its coefficient to be negative. *Bank Core Dep* is a proxy for the bank's ability to provide liquidity. *Bank Size* is a proxy for a range of characteristics, as previously explained. I interpret the coefficients on bank variables as "premiums" that firms are willing to pay for these bank characteristics. My sample includes loans of public and private U.S.-based firms that were granted by the top 150 U.S. banks (ranked by Dealscan lending volume) from 1990-2008. The theory suggests that with respect to information production in relationships, the impact of the relationships should vary across the firms depending upon their life cycle stage, and that relationship bank's information advantage should have greater consequences for more opaque firms (Rajan, 1992; Boot and Thakor, 2000). With respect to the liquidity provision, I posit that a bank's willingness to provide liquidity should be more valuable to more opaque firms as they have fewer alternative sources of financing. I designate three types of firms as follows: non-Compustat (Type 1) firms are those not in Compustat or CRSP, private Compustat (Type 2) firms are those listed in Compustat, but not in CRSP, and public Compustat (Type 3) firms are those listed in both.[20] I run all of the regressions on the total sample and, in order to avoid interaction terms, on

[19] Because *I-intensity* and *T-intensity* as a pair represent a decomposition of *A-intensity*, I include either *A-intensity* or its decomposition in any given regression. Although my main interest is the decomposition coefficients, obtaining coefficients on *A-intensity* allows me to assess the effect of decomposition and to get the estimates that can be compared with Schenone's (2010) and Bharath et al.'s (2011) results.

[20] The observations corresponding to these three firm types account for 56.53%, 25.02%, and 18.45% of the total sample. The fact that having outstanding public debt requires a firm to file periodic reports with the Securities and

the firm type subsamples, loan types subsamples (CP backups vs. non-CP backups), and firm type/loan type subsamples. I use an OLS model with firm-level clustered and heteroskedasticity-corrected standard errors, firm fixed-effects, bank fixed-effects, and treatment effects models. The use of fixed-effects models is warranted by the panel structure of my data and allows me to control for unobservable firm and bank characteristics (which, if correlated with regressors, may bias OLS estimates). The treatment effects model is used to explicitly address the possible endogeneity of the loan type choice by modeling it with a separate probit-like equation. All models deliver overall consistent results and although some degree of endogeneity of loan type choice is present, controlling for it does not qualitatively change most of the OLS and fixed-effects results. My key findings are summarized below.

T-intensity (bank's willingness to provide liquidity). Loan spreads decrease in *T-intensity* in the total sample and among firms without public equity (Types 1 and 2). Thus, for such firms, bank-provided liquidity insurance is valuable, consistent with the notion that less transparent firms have limited financing options and that for them, the bank's implicit commitment to provide liquidity is valuable. My result is consistent with Barakova and Parthasarathy (2012) who find that firms without access to equity markets face larger limit cuts relative to those firms with such access, suggesting that the former are more likely to be restricted by their banks and, therefore, should benefit more from a bank's implicit commitment to lend. The "willingness discounts" apply to CP backups and non-CP backups alike.

I-intensity (bank's information advantage over non-lenders). Loan spreads increase in *I-intensity* in the total sample and in all firm type subsamples, including the firms with public equity (Type 3). This result differs from Schenone (2010) and Bharath et al (2011) who find that spreads decrease in relationship strength for firms with public equity. However, even when I use *A-intensity*, as these studies do, I still obtain a positive coefficient. The most plausible explanation for this divergence is that my sample is limited to loans from the top 150 banks, while their analysis does not impose such a restriction. If this is

Exchange Commission (SEC), which results in coverage by the Compustat database, might explain why there is a large number of Type 2 firms.

indeed the reason, it suggests that hold-up costs are a larger issue for clients of relatively large banks. I provide a detailed discussion on this divergence in the robustness checks in Section 6. It should also be noted that because my non-CP backup category includes not only term loans, but also monitored loan commitments, the impact of *I-intensity* is contaminated by the effect of the liquidity provision. Since I find that the sign of *T-intensity* is negative, my coefficients on intensities most likely underestimate the magnitude of the spread-increasing hold-up effect and the spread-decreasing access to liquidity effect. The "hold-up premiums" are paid on non-CP backups of Compustat firms (Types 2 and 3) and on CP backups and non-CP backups of non-Compustat firms (Type 1).

Bank Core Dep (bank's ability to provide liquidity). Loan spreads increase in *Bank Core Dep* in the total sample and among non-Compustat firms (Type 1), consistent with the idea that opaque firms are more likely to face restrictions in access to credit lines after violating a covenant and have a difficult time getting new loans when their bank or the entire banking system experiences liquidity shortages. This result is consistent with Demiroglu, James, and Kizilaslan (2012) who find that credit crunches are likely to have a disproportionate impact on private firms. The "ability premiums" are paid on non-CP backups.

Bank Size (bank's reputation, lending capacity, access to capital markets, and perceived risk). Loan spreads increase in *Bank Size* only among Compustat firms without public equity (Type 2). Given that these firms are larger in size and borrow more than Type 1 and Type 3 firms, but do not have access to equity markets, it appears that bank size proxies for lending capacity and access to capital markets. No effect for Type 3 firms that may enjoy certification benefits of a reputable bank suggests that size is not a good proxy for reputation. The "size premiums" are paid on CP backups and non-CP backups alike.

Impact on probability of obtaining a CP backup. In the total sample, CP backup probability increases in *Bank Size* and *Bank Core Dep*. In the subsamples, it is different. For Compustat firms with public equity (Type 3), none of the aforementioned four variables has an effect. For Compustat firms without public equity (Type 2), this probability increases in bank's willingness and ability to provide liquidity (*T-*

intensity and *Bank Core Dep*). However, it is the bank size that they pay a premium for (on CP backups and non-CP backups alike). For non-Compustat firms (Type 1), this probability increases with bank size. However, it is the bank's ability to provide liquidity (*Bank Core Dep*) that they pay a premium for (on non-CP backups).

The remainder of this paper is organized as follows. Section 2 provides the literature review. Section 3 outlines the hypotheses. Section 4 describes the data and sample selection process. Section 5 describes the methodology. Section 6 provides the estimation results. Section 7 concludes.

2 LITERATURE REVIEW

My literature review is structured as follows. *First*, I provide an overview of credit lines' contractual characteristics with the emphasis on how financial covenants affect borrowers' ability to use their lines. I review the literature on why firms demand credit lines and the theory and evidence on their value as liquidity insurance. *Second*, I overview the liquidity-based theories of banks and the benefits and the costs that arise from the banks' "dual liquidity role". I discuss the structure of bank liabilities and the role of deposit financing in mitigating banks' liquidity risk and enhancing their ability to provide liquidity to borrowers. *Third*, I review the literature on bank specialness that relies on the information production function of banks. I discuss the benefits and the costs of lending relationships as they are presented in the existing relationship lending literature. *Fourth*, I review the existing literature on the effects of lending relationships on loan rates. Additionally, I briefly review the literature on the coexistence of informationally intensive and transactional lending in one banking institution.

2.1 Contractual features of credit lines and the role of financial covenants

Credit lines, also referred to as loan commitments and revolving credit facilities, are contractual promises to lend up to a certain amount during a certain period of time. Credit lines represent a prevalent mode of bank lending to corporations.[21] The used portion of a credit line is a debt obligation that appears on the balance sheets of both parties. The unused portion remains off the balance sheets. A borrower pays a fixed spread over a riskless rate (usually the LIBOR) on a drawn portion and a commitment fee, which is a percentage of an unused portion.[22] Credit line is not a complete form of liquidity insurance because its contractual characteristics give banks substantial power to renege on their commitment to lend if the borrower's financial health deteriorates. Reneging is usually triggered by increases in borrower's credit

[21] Ergungor (2001) reports that 79% of all commercial and industrial lending is done under commitment contracts.

[22] Sufi (2009) reports that in a sample of 11,758 Dealscan-reported credit lines to more than 4,000 publicly traded firms between 1996 and 2003, the median commitment fee is 25 bps, the median interest rate on a drawn portion is 150 bps over LIBOR, and the median maturity is 3 years.

and liquidity risks, but it can also result from the bank's financial health deterioration (Demiroglu and James, 2011).The typical conditions that banks place in credit line contracts are financial covenants, material adverse change (MAC) clause, borrowing base restrictions, and performance pricing. Financial covenants are included in most credit line agreements and require maintenance of the pre-specified financial ratios on a regular basis, typically every fiscal quarter (Sansone and Taylor, 2007). The five most commonly used financial covenants are coverage (a ratio of cash flow measure to fixed charges or interest expenses), debt-to-cash flow, net worth, leverage ratio, and liquidity (often a current ratio). Roberts and Sufi (2009a) report that 97% of loans to SEC-reporting firms include at least one financial covenant and coverage and debt-to-cash flow are the most common covenants, found in 74% and 58% of credit agreements. Sufi (2009) examines credit lines of 300 randomly selected Compustat firms and also finds that coverage and debt-to-cash flow covenants have the highest prevalence occurring in 70% and 49% of credit lines that have financial covenants information (which is 72% of credit lines in his sample). Financial covenant violations are common. Nini, Smith, and Sufi (2012) find that in their sample, between 1997 and 2007, 10 to 20% of public firms were in violation of a financial covenant in any given year and 40% were in violation at least once during this period. Sufi (2009) reports that in his sample about 35% of firms had a violation during the study period. The widespread occurrence of covenant violations suggests that covenants are set fairly tightly.[23] There is also a large and growing literature on how covenant violations affect various outcomes, such as loan rates, credit availability, debt issuance, leverage, investment spending, dividend payouts, and corporate governance (Dichev and Skinner, 2002; Beneish and Press, 1993; Roberts and Sufi, 2009a; Chava and Roberts, 2008; Nini, Smith, and Sufi, 2009; Barakova and Parthasarathy, 2012). The majority of credit lines include a MAC clause, which allows a bank to renege if, *in the bank's opinion,* there was a material change in the borrower's financial condition or, to cite Shockley and Thakor (1997), to "escape its lending commitment under ambiguously defined conditions". While a MAC clause appears to be a powerful tool that provides banks with a lot of

[23] Bradley and Roberts (2004) and Demiroglu and James (2010) examine the determinants of covenant tightness.

discretion to honor their commitments, there isn't much evidence that a MAC clause is frequently invoked. Boot, Greenbaum, and Thakor (1993) argue that reputational concerns prevent banks from opportunistically invoking MAC clauses. Ergungor (2001) cites sources suggesting that courts limit banks' use of MAC clauses and often rule that their use constitutes "abuse of power and lack of good faith". In addition to financial covenants and MAC clauses, some credit lines specify a "borrowing base", which is a time-varying quantity constraint in that a firm can borrow only up to the certain percentage of the amount of its accounts receivable (Flannery and Wang, 2011). Lastly, many credit lines include performance pricing grid, which ties loan spread to the borrower's performance (typically measured by the cash flow-based ratios or credit ratings). Roberts and Sufi (2009b) report that 73% of bank loans have a pricing grid and 37% of loans have a grid based on a cash-flow based ratio. Overall, credit lines' contractual terms allow banks a significant flexibility in managing their exposure to firm-level and market-level risks, and especially to firm-level risks.

2.2 Demand for credit lines and their function as liquidity insurance

The theoretical literature on credit lines is extensive. What drives the demand, a subject of this section, is only a small part of the literature.[24] In this overview, I will first discuss alternative explanations for credit line demand. I will then focus on the liquidity insurance role of credit lines and review the rapidly growing empirical literature on this subject. The supply side is discussed in Section 2.3.

2.2.1 Alternative explanations of credit line demand

Aragwal, Chomsisengpet, and Driscoll (2011) review the literature on what drives the demand for credit lines and why firms choose credit lines over term loans. They provide the following reasons. *First*, credit lines allow firms to hedge against the deterioration of their own creditworthiness over the term of the loan (Campbell, 1978; Hawkins, 1982). A decline in credit quality may result in difficulties obtaining

[24] Ergungor (2001) provides the overview of the broad range of questions raised in this literature, such as why firms demand and banks supply credit lines, whether credit lines are put options, why they are not exercised to the limit, how they affect bank's risk exposure and interest rate, and rationing channels of monetary policy.

a new term loan, and having a partially unused credit line may solve this problem. Of course, it can be a complete solution only if the bank's promise of funds under commitment is unconditional. *Second*, credit lines may help a firm to hedge against the supply side issues and disruptions. For example, an aggregate credit shock may affect the banking industry and make it more difficult to get a new loan, as it was the case in the savings and loan crisis of the early 1990s (Morgan, 1994). Alternatively, a market-wide liquidity shock, which is especially relevant for the firms that access public debt markets (e.g., a commercial paper market), can make refinancing of the existing short-term instruments problematic either because the prices rise sharply or because the credit is simply not available, as it was the case when the commercial paper market froze following the September 2008 failure of Lehman Brothers. *Third*, credit lines may be attractive because they mitigate the agency problems in lending that make it difficult to obtain term loans from banks or access public debt and equity markets (Blackwell and Santomero, 1982; Melnik and Plaut, 1986a; Sofianos, Wachtel, and Melnik, 1990; Avery and Berger, 1991; Berger and Udell, 1992; Morgan, 1994). Some of the proposed models require credit line irrevocability for it to improve on the spot market financing (Holmstrom and Tirole, 1998), while others require that the bank is able to restrict credit line access in some states of the world. *Fourth*, firms may demand credit lines because they offer relative speed and flexibility in taking advantage of investment opportunities (Martin and Santomero, 1997). The flexibility justifies the additional costs of credit lines not paid on term loans.

These four reasons are interrelated and likely contribute to some degree in most cases, which makes it difficult to evaluate the contribution of each individual reason. [25] (In the introduction, I have discussed how using commercial paper backup lines of credit help to circumvent this problem in my analysis). For example, aggregate credit shocks from the second view often coincide with a declining firm-level credit quality from the first view. Also, some theories use liquidity shocks as a cause of agency

[25] Several studies have found that the macroeconomic developments in the market for bank loans affect the pricing and quantity of bank loans, providing support for the second view that borrowers demand credit lines to protect themselves against the declines in the aggregate supply of credit (Berger and Udell, 1992; Sofianos, Wachtel, and Melnik, 1990; Morgan, 1994; Melnik and Plaut, 1986b). Shockley and Thakor (1997) provide some support for the third view by finding that opaque firms use credit lines more heavily than they use non-bank forms of financing.

problems that loan commitments, as they argue, are designed to mitigate, thus connecting the third view with the first view. For example, in Holmstrom and Tirole (1998), a liquidity shock to the borrower leads to the moral hazard problem and, subsequently, to credit rationing. The only way to be able to borrow in this model is to buy irrevocable liquidity insurance, and credit line is one such mechanism. Boot, Thakor, and Udell (1987) also use the moral hazard problem to motivate demand for credit lines. In their model, the problem of undersupplying effort emerges as a result of a stochastic interest rate that plays a role similar to a liquidity shock in Holmstrom and Tirole (1998).

In light of this interrelatedness, it might be easier to view the first three reasons as related to the borrower's need for liquidity insurance against various firm-specific and market-wide shocks, and the fourth reason as the borrower's need for speed and flexibility in accessing the funds.

2.2.2 Empirical evidence on the liquidity insurance value of credit lines

In this section, I will overview the theoretical and empirical research on the role of credit lines as a form of liquidity insurance. Most empirical studies focus on credit lines as an alternative to cash holdings. They examine how borrower, bank, and lending environment characteristics affect a firm's choice between credit lines and cash holdings, credit line's usage, and bank's management of credit lines. My paper is related to this literature in that I assess the liquidity insurance value of credit lines *in the context of lending relationships*, which, to the best of my knowledge, the literature has not yet addressed.

Theoretical studies on the insurance value of credit lines are many. Campbell (1978) argues that credit lines protect firms against the volatile cost of the alternative sources of borrowing and volatile cash needs. Holmstrom and Tirole (1998, 2000) posit that credit lines insure firms against the possibility of future adverse shocks that may result in foregoing positive NPV projects. Boot, Thakor, and Udell (1987) argue that credit lines insure against the uncertainty of the firm's cash flows and volatility of the spot interest rates in the economy, and that firms pay a bank for this insurance service because it does not renege on its commitment. While the above papers emphasize the benefits of liquidity insurance, some argue that access to liquidity insurance may give rise to a moral hazard problem (Rothschild and Stiglitz, 1976; Holmstrom and Tirole, 1998; Avery and Berger, 1991).

More recent literature has focused on the choice between credit lines and cash holdings as the alternative sources of liquidity. Both sources have advantages and disadvantages. Cash holdings provide unconditional access to liquidity. However, they are relatively cost-inefficient as compared to the bank loans. Corporate finance literature suggests that cash holdings typically cost more than the debt used to fund them, do not offer tax shields as compared to interest payments on debt, and may pose significant agency costs. Banking literature argues that banks are the most cost-efficient providers of liquidity in the economy due to the synergies that arise from supplying liquidity to both depositors and borrowers (Kashyap, Rajan, and Stein, 2002), the access to inelastically supplied core deposits (Berlin and Mester, 1999; Gatev and Strahan, 2006; Gatev, Schuermann, and Strahan, 2007), and the existence of deposit insurance and other implicit and explicit government guarantees that further enhance the benefits of relying on deposit financing (Pennacchi, 2006; Santos, 2012). The disadvantage of credit lines is that they are not a guaranteed source of liquidity. The banks have considerable power in reneging on their commitments, usually in response to covenant violations, which happen quite often as was mentioned in the previous section. To the extent that the banks have flexibility in how to react to covenant violations, restrictions to credit line access may result from the increased risk of the borrower and/or from the deteriorating financial health of the bank. Thus, credit lines not only expose the banks to the risks of their borrowers, but also expose the borrowers to the risks of their banks. While the revocability of credit lines may lead to improved outcomes (for example, Nini, Smith and Sufi (2012) find that the actions of the creditor taken in response to covenant violation increase the firm value), the extent to which credit lines offer *liquidity insurance* remains an open question.

The fact that most firms use cash holdings and credit lines simultaneously suggests that the firm characteristics (and possibly other factors) determine the relative attractiveness of one versus the other. Two recent papers propose and test the theories that emphasize the role of firm's liquidity risk and firm's aggregate risk. Acharya, Almeida, Ippolito, and Perez (2013) introduce a model of monitored liquidity insurance in which the bank monitoring and possible line revocations are costly. The cost of monitored liquidity insurance increases in firm's liquidity risk, measured by the correlation between the firm's investment needs and cash flows. High liquidity risk firms are more likely to use cash holdings, whereas low liquidity risk firms are more likely to use credit lines. Acharya, Almeida, and Campello (2012) argue that the key determinant of how firms choose between cash and bank credit lines is their aggregate risk exposure, measured as the correlation of the firm's financing needs with those of the other firms in the economy. Because the banks price this risk, high aggregate risk firms find it optimal to use cash holdings, while low aggregate risk firms opt for credit lines.

Most empirical studies examine the liquidity insurance value of credit lines by looking at how banks manage credit lines, when firms use their lines, what determines firm's reliance on lines versus cash, the firm's financial health, the bank's financial health, and the condition of the lending environment. Regarding the frequency of credit line revocations, the evidence is mixed. Sufi (2009) argues that banks routinely use cash flow-based financial covenant violations as an excuse to restrict line access and that credit lines, therefore, represent a poor liquidity substitute for firms with low current or expected cash flows ("firms with high cash flows rely on lines of credit, while firms with low cash flows rely on cash"). In contrast, Barakova and Parthasarathy (2012) argue that banks provide relatively unconstrained access to the existing credit lines until firm-level credit risk increases considerably. Like Sufi (2009), they find the association between the cash flow-based covenant violations and access restrictions, but they argue that those are not the key determinants of restrictions. The bank's internal ratings and line utilization rates are better predictors of line access restrictions, and banks typically take no action in response to covenant violations if borrower is not high risk according to their internal scale. These findings suggest that banks aim to protect themselves from the excessive exposure to firms' credit risk but are willing to absorb their liquidity risk.

Several papers have found that the firms are able to anticipate restrictive actions of their banks and are successful at precautionary draws on their lines (which suggests that their future status was not apparent to their banks and raises some interesting questions regarding the effectiveness of bank monitoring). Kizilaslan and Manakyan (2011) find that the unexpected drawdowns predict cash flow declines, covenant violations, and rating downgrades. Jimenez, Lopez, and Saurina (2009) report that the firms that eventually default have higher line utilization rates several years before defaulting. Barakova and Parthasarathy (2012) find that firms that get a downgrade of their internal bank rating are able to anticipate future restrictions to line access and draw on their lines in advance of such restrictions.

The papers that looked at the events of the recent financial crisis generally find that the borrowers were able to access their existing lines of credit, while new lending was reduced. Demiroglu, James, and Kizilaslan (2012) find that neither public nor private firms with pre-existing lines faced reduced access to lines, although new lines were more difficult to obtain. Campello, Giambona, Graham, and Harvey (2009 and 2011) report that even small, private, and unprofitable firms were able to draw on their lines (however, they faced higher prices and difficulties obtaining new loans). Ivashina and Scharfstein (2010) and Cornett, McNutt, Strahan, and Tehranian (2011) (henceforth: Cornett et al, 2011) find that banks honored existing commitments but cut on new lending.

Several other papers looked at the credit line choice and usage. Jimenez, Saurina, and Lopez (2009) find that as the firm's financial conditions worsen, its line usage increases. The line's default status is the most important determinant of usage. Flannery and Wang (2011) show that smaller and riskier firms obtain lower borrowing cost, higher credit limit, and fewer financial covenants when they choose borrowing base lines (where the line limit is tied to the firm's inventory and receivables). Disatnik, Duchin, and Schmidt (2011) show that cash flow hedging reduces the firm's precautionary demand for cash and allows it to rely more on lines of credit. Lins, Servaes, and Tufano (2010) find that the firms use cash to insure against the shortfalls in cash, and credit lines to preserve the liquidity for investment purposes. Demiroglu and James (2011) make a similar argument in their summary of the recent literature.

Overall, the evidence on the extent to which credit lines provide liquidity insurance is mixed. The papers linking the borrowers' financial health to line access suggest that this liquidity insurance is, at best, contingent. However, there is not much agreement on the severity of access restrictions. At the same time, other studies show that line usage is higher for firms that experience profitability declines and are closer to default, that firms are able to make precautionary draws, and that financially constrained firms relied on their lines during the recent financial crisis. Thus, it remains unclear just how effective credit lines are in their liquidity provision function.

Lastly, it should be noted that, until recently, the data on line limits and draws were not available in standard databases, complicating the comparability of results. Most studies relied on hand-collected samples from SEC filings (Sufi, 2009; Disatnik, Duchin, and Schmidt, 2011; Flannery and Wang, 2011) or survey data (Lin, Servaes, and Tufano, 2010; Campello, Giambona, Graham, and Harvey, 2009 and 2011; Jimenez, Lopez, and Saurina, 2009). Capital IQ database and especially the increased availability of the Shared National Credit (SNC) regulatory database spurred a large number of papers. For example, SNC data have been used by Barakova and Parthasarathy (2012) who study how banks manage credit line usage after it has been issued, Jones, Lang, and Nigro (2005) who examine syndicate structure, Bord and Santos (2011) who examine credit line pricing, and Mian and Santos (2011) who look at firm's liquidity risk and maturity management. Capital IQ data is used in Acharya, Almeida, Ippolito, and Perez (2013).

2.3 Banks as "dual liquidity providers" and the role of deposit financing

First, I will discuss the structure of bank liabilities with an emphasis on the importance of core deposits. I will then provide an overview of liquidity-based theories of banks, the literature on the role of banks as dual liquidity providers, the liquidity risk that banks face as a result of their dual liquidity role, and the importance of core deposits in mitigating this risk and enhancing banks' ability to provide liquidity to their borrowers.

2.3.1 Composition of bank liabilities and the role of core deposits

In the traditional models of banks, their liabilities are limited to demandable retail deposits posing a risk of a run. In the real world, there is deposit insurance. Additionally, banks hold different types of liabilities, and it is not retail deposits, but other short term liabilities that are at a high risk of withdrawal. The modern banks use debentures, subordinated notes, and purchased liabilities (which include wholesale deposits and other short-term liabilities) in addition to retail deposits. Retail deposits include passbook savings accounts, checking accounts, etc. Wholesale deposits consist of large time deposits, typically in the form of brokered (negotiable) certificates of deposits (CDs). Other short-term liabilities include repos, federal funds, etc.

The regulatory reports that banks file each quarter divide total deposits (retail and wholesale deposits from the above classification) into the five categories: (1) transactions accounts (e.g., checking accounts), (2) savings accounts, (3) money market deposit accounts, (4) small time deposits (CDs with a face value less than $100,000), and (5) large time deposits. The first four categories represent retail deposits from the first classification and are collectively known as *core deposits* (Feldman and Schmidt, 2001). The fifth category, large time deposits, represents the wholesale deposits from first classification. All non-core liabilities (large time deposits and short-term and long-term non-deposit liabilities) are collectively known as managed liabilities.

Compared to managed liabilities, and especially to short-term managed liabilities, core deposits are an attractive funding source due to their stability and low cost. Withdrawal sluggishness, or stability, of core deposits is attributed to the following. First, retail depositors value liquidity services provided by their bank and may face switching costs if they want to use a different bank. Second, the majority of core deposits are FDIC-insured, especially after the recent increase of deposit insurance limit from $100,000 to

$250,000.[26] In contrast, the majority of managed liabilities are uninsured because large time deposits usually do not qualify for deposit insurance (negotiable CDs come in lot sizes of $1 million and multiples thereof) and most of the other components of managed liabilities are not deposits. Thus, modern banks' liquidity risk that arises from their liabilities is driven by unexpected withdrawals of short-term managed liabilities and not by retail deposits.[27] In addition to withdrawal sluggishness, core deposits carry lower and less volatile interest rates as compared to managed liabilities. For example, the average effective interest rate that banks paid on core deposits was 2.8% in 2007 and 1.9% in 2008, while for the managed liabilities it was 4.8% in 2007 and 3.1% in 2008 (Bech and Rice, 2009). Berlin and Mester (1999) find that market interest rate-inelasticity of core deposits shields banks from the exogenous economic shocks and show that greater reliance on core deposits is associated with smoother loan rates. Hannan and Hanweck (1988) find that uninsured depositors require higher interest rates at riskier banks, while insured depositors do not. Song and Thakor (2007) cite evidence suggesting that relative to core deposits, purchased liabilities have higher marginal cost (but lower average cost).

With stability and low cost of core deposits, why do banks use managed liabilities? Most core deposits come from the households, and the growth of aggregate deposits is naturally limited by the pace of the economic growth. This, and the fact that most deposits have relationship nature and the customers are not very eager to change their bank, makes it very difficult for a bank to use deposits for expansion. In contrast, managed liabilities are funds over which the bank has significant discretion to increase or decrease in response to changing funding needs.

Smaller banks rely more on core deposits than larger banks. For instance, Feldman and Schmidt (2001) report that in 2000, large banks (assets over $1 billion) had about 60% insured (core) deposits and

[26] In Song and Thakor (2007) theoretical model the stability of core deposits arises endogenously.

[27] Cornett et al (2011) and Santos (2012) find that uninsured liabilities did and insured deposits did not run during the recent financial crisis. It should be noted, however, that along with the benefit of reducing banks' liquidity risk deposit insurance may cause a moral hazard problem resulting from the lack of market discipline (Calomiris and Kahn, 1991; Nier and Baumann, 2006). Flannery (2001) overviews the notion of market discipline. Flannery (1998) discusses the role of market discipline in relation to regulatory supervision.

40% uninsured deposits, while small banks (assets under $1 billion) were funded with about 80% insured deposits and 20% uninsured deposits.[28] In the years before the 2007-2009 financial crisis core deposits were steadily declining (DeYoung, Hunter, and Udell, 2004; Genay, 2000). For the first time in years, in 2008 core deposits grew faster than total assets, and the growth rate of core deposits at the largest 100 banks outpaced the rate at banks outside that bank-size category (Bech and Rice, 2009). A part of the reason is that following the October 2008 collapse of Lehman Brothers, funds were fleeing the securities markets and flowing into the banking system, primarily into bank transactions deposit accounts (Cornett et al, 2011). Additionally, in October 2008 FDIC temporarily extended insurance coverage to all transactions deposits thus eliminating incentives to pull funds from any transactions accounts. Cornett et al (2011) show that in the fourth quarter of 2008 wholesale deposits fell in aggregate by almost $200 billion, while core deposits grew by about $500 billion. With these statistics, it is not surprising that the banks that were more reliant on core deposits faced less severe liquidity shortages during the crisis and found it easier to sustain their lending. Ivashina and Scharfstein (2010) find that decline in the growth rate of new lending was lower for the banks that relied more heavily on core deposits. Cornett et al (2011) find positive association between new lending and reliance on core deposits, but not total deposits, and argue that core deposits act as substitutes for liquid assets, while more volatile purchased liabilities are "flowing into banks when rates on alternative investments are low, or when economic risk is high, and flowing out of banks when rates on alternative investments are high, or economic risk is low." Thus, reliance on core deposits reduces banks' liquidity risk and enhances their ability to provide liquidity to the borrowers.

2.3.2 Banks as liquidity providers

Since in a complete and frictionless market companies and investors can achieve efficient risk allocation by interacting directly with each other (Santos, 2006), justifying the intermediary's existence requires a presence of some frictions. Early theories of banks emphasized transactions costs as a source of

---

[28] In my sample, the mean value of core deposits to total deposits ratio is 0.235 and the mean value of bank assets is $303.8 billions, based on the period of 1990-2008 and loan-bank observations. My sample is limited to loans from top 150 U.S. banks (ranked by Dealscan-reported lending volume).

frictions.[29] Modern theories suggest that frictions arise from asymmetric information. Two most prominent asymmetric information-based theories explain the existence of banks by their roles in the provision of liquidity and the production of information via monitoring. I will discuss the liquidity provision role in this section, and the information production role in Section 2.4.

There are several liquidity-based theories of banks. Early liquidity-based theories focused on the provision of liquidity to depositors (i.e., on the liability side of banks' balance sheets), whereas the information production-based theories focused on the borrowers (i.e., on the asset side of banks' balance sheets). In Bryant (1980) and Diamond and Dybvig (1983), banks add value by offering households securities (deposits) that allow for better risk sharing in the face of unpredictable idiosyncratic shocks to consumption needs over time. In these models, asymmetric information lies in shocks' unobservability and asymmetric information processing allows banks to create liquidity through their asset transformation function. Gorton and Pennacchi (1990) propose a model that hinges on the existence of informed and uninformed investors; the banks add value by creating securities that protect uninformed investors from the losses they would incur if they traded with informed investors directly. Cavalcanti, Erosa, and Temzelides (1999) argue that banks add value by creating "inside money", an instrument that can be used to trade at no cost with third parties.

Diamond and Rajan (2001a, 2001b) make a connection between bank assets and liabilities. Although they focus on provision of liquidity to depositors and not to borrowers, they note that on-balance sheet loans are illiquid. When banks experience liquidity shortages, they can sell loans or use them as a collateral. However, in times of low market liquidity such sales become more difficult. Thus, in these models liquidity risk arises from both the assets and liabilities. Diamond and Rajan (2001b) argue that the possibility of depositor runs and asset fire-sales (i.e., the banks' fragility) is precisely what allows

[29] For example, in Gurley and Shaw (1962), the role of intermediaries lies in transforming the securities issued by firms into the securities demanded by investors. The presence of transactions costs results in that having intermediaries provide services of divisibility and risk transformation is efficient.

banks to commit to perform their function, which is to provide liquidity to depositors while avoiding early liquidation of loans.

Several papers address the role of banks as providers of liquidity to the borrowers in the form of credit lines. [30] For example, Holmstrom and Tirole (1998) argue that banks are able to provide liquidity insurance against the shocks that disrupt the investments of companies by offering credit lines. However, this model does not link the liquidity provision function to bank liabilities. The subsequent research shifted focus to the simultaneous provision of liquidity to depositors and borrowers, referred to as the "dual liquidity role" of banks. The literature argues that dual liquidity role may result in valuable synergies, but it also may expose banks to significant liquidity risks. Kashyap, Rajan and Stein (2002) propose and test a theory where dual liquidity role is precisely what makes banks valuable *if* demands for liquidity from depositors and borrowers are not too highly correlated. By pooling these two classes of customers together a bank can save on the need to hold costly liquid assets (the buffer against unexpected credit line drawdowns and deposit withdrawals). As a result, banks are able to provide liquidity at a lower cost than non-bank intermediaries that do not enjoy such savings because they cannot take deposits.

This model highlights the benefits of the dual liquidity role. However, these benefits are conditional upon the low correlation of liquidity demands. If concurrent runs occur (i.e., the correlation of liquidity demands is high), a bank will experience a liquidity shock rather than the synergies. Santos (2012) provides the evidence that concurrent runs can occur when the bank's financial health is put into question. He finds that during recessions, including the recent financial crisis, the banks that suffered larger losses experienced the runs by their *uninsured* depositors and the increase in the drawdowns on the outstanding credit lines. He also finds that during good times the liquidity demands of uninsured depositors and borrowers are not strongly correlated. However, during crisis periods the correlation becomes high, suggesting that Kashyap, Rajan, and Stein's (2002) low correlation assumption may be

[30] Some of these studies were discussed in Section 2.2.1.

violated in the real world. It should also be noted that this model assumes zero risk of bank failure. It appears to be a critical assumption given the behavior of insured and uninsured deposits reported in Santos (2012). The importance of implicit government support and deposit insurance is also supported by Pennacchi (2006) who does not find deposit inflows during times of low market liquidity in the pre-FDIC period.

The evidence on the extent to which the banks enjoy the synergies of concurrent deposit taking and commitment lending is mixed. Gatev, Schuermann, and Strahan (2007) find that the volatility of bank stock returns increases in unused loan commitments (however, this effect is less pronounced for banks with high levels of transactions deposits). Gatev and Strahan (2006) show that in times of low market liquidity and high commercial paper rates "re-intermediation" occurs: investors move the funds away from the market and to the "safe heaven" of bank deposits, and borrowers, unable to rollover their commercial paper, draw on their backup lines of credit. Thus, increased drawdowns on backup lines are financed by the inflow of deposits, allowing the banks to extend new commercial paper backup lines at lower rates. At the same time, several papers that have investigated the financial crisis of 2007-2009 do not find deposit inflows and easing of credit terms for banks with higher exposure to unused credit lines. Ivashina and Scharfstein (2010) and Cornett et al (2011) report that banks with higher levels of unused credit lines experienced greater decline in lending growth, and Acharya and Mora (2012) find that such banks were offering higher interest rates during the crisis, presumably to attract more deposits.

Cornett et al (2011) use a large Call reports-based dataset to provide a comprehensive analysis of how U.S. banks managed their liquidity risk during the recent financial crisis. They argue that the most important determinants of bank liquidity risk are the (1) exposure to (off-balance sheet) unused portions of loan commitments, (2) exposure to purchased liabilities, and (3) relative size of on-balance sheet illiquid assets. They also note that the sudden increases in demand for liquidity from the borrowers are a larger and more difficult threat to manage as compared to liabilities withdrawals threat, as the former have a systemic nature (i.e., depend upon external market conditions).[31] Cornett et al (2011) find that banks with higher exposure to undrawn credit lines cut back on new lending and increased liquid asset holdings in response to the increased takedowns. Accumulation of liquid assets was particularly strong among banks that held more illiquid assets. The banks that were more reliant on stable sources of funding (core deposits and equity capital) saw greater increases in lending than the banks that relied on managed liabilities. Ivashina and Scharfstein (2010) use Dealscan data and find similar results. New lending growth fell *less* at the banks funded with core deposits and *more* at the banks exposed to unused credit lines.

In sum, the dual liquidity role of banks may result in valuable synergies but it exposes banks to the risk of en masse drawdowns on credit lines and the risk of uninsured deposit withdrawals. Stability of funding sources is crucial for the banks' ability to provide liquidity to their borrowers without having too much of their assets in the form of liquid but low-earning instruments. Equity capital and core deposits represent two stable sources of funding. Between the two, core deposits are less expensive albeit difficult to grow due to their sticky nature and limited amount on the aggregate level.

2.4 Information production aspect of bank lending

2.4.1 Banks as delegated monitors and the role of private information production

In this strand of literature, the reason for banks' existence is the information asymmetries between the borrowing firms and investors. The firms know more about their investment projects than the outside investors, which can observe this information, but only after incurring a cost. Rather than having multiple investors evaluate a firm prior to making a loan and monitoring the firm's actions once the loan

---

[31] Other factors that affect bank's liquidity risk are reliance on equity capital and institution size. Diamond and Rajan (2000) argue that equity capital lowers risk and protects depositors in times of bank distress. However, excessive equity capital can suppress liquidity creation by crowding out depositors. Berger and Bouwman (2013) find that equity capital increases small banks' survival probability at all times and for large banks only during crises. Regarding bank size, larger banks may be perceived as more safe. O'Hara and Shaw (1990) find that the Comptroller of the Currency's statement that some financial institutions are "too-big-to-fail" before Congress on September 19, 1984 had a positive wealth event for the eleven banks falling into this category. Black, Collins, Robinson, and Schweitzer (1997) find that over the years the banks mentioned in the Comptroller's announcement were indeed perceived as less risky by the market based on the changes in institutional ownership of bank stocks.

has been granted, investors may delegate these tasks to a bank through which they all provide funding to a firm. By acting as delegated monitors of investors, banks save on monitoring costs and make funding available to firms at a lower cost than direct lending (Diamond, 1984). Other papers that link the existence of banks to their screening and monitoring ability include Leland and Pyle (1977), Ramakrishnan and Thakor (1984), Fama (1985), Boyd and Prescott (1986), Allen (1990), and Winton (1995), among others.

Through its private information gathering activities, a bank effectively becomes a firm's insider. For example, Fama (1985) called a bank an "inside debt holder" due to its wide access to proprietary information. Around the time of Diamond (1984) and Fama (1985) seminal papers, the empirical literature on the uniqueness of banks started to emerge, mostly in the form of event studies. James (1987) finds that stock prices increase on the announcement of a firm obtaining new bank loan or loan renewal, and decrease on the announcement of public financing. Thus, bank's involvement appears to either increase the perceived value of a firm or uncover some positive information about a firm that was previously unknown. Lummer and McConnell (1989) find such announcement effect only for loan renewals and suggest that the value is added by established lending relationships rather than screening. However, a number of follow up papers failed to replicate this result. Other announcement effect event studies include Slovin, Sushka, and Hudson (1988), Best and Zhang (1993), and Carey, Post, and Sharpe (1998). Billett, Flannery, and Garfinkel (1995) find that loan announcement effect is driven by loans of high quality lenders, as proxied by credit rating. Slovin, Sushka, and Polonchek (1993) report that borrowers that had a relationship with Continental Illinois bank experienced negative abnormal return on the announcement of bank's insolvency and positive abnormal return on the announcement of FDIC rescue plan, suggesting that bank-borrower relationship is a valuable asset. Overall, the evidence presented in these event studies suggests that the bank involvement increases borrower's value.

2.4.2 Costs and benefits of lending relationships

The main theme of early theoretical papers mentioned in the previous section was to rationalize a role of a bank as a single entity that monitors borrowers on behalf of multiple investors. These early papers focused on one-time interactions between banks and borrowers and used very simplistic loan contract design in their analysis. In the literature that followed, the focus shifted to more realistic loan contract designs that incorporate collateral and covenants and, most importantly, to the dynamic setting. Long time horizon and repeatedness of lending allow for intertemporal information reusability (Chan, Greenbaum, and Thakor, 1986; Greenbaum and Thakor, 1995), which in turn creates greater incentives to invest in information production and leads to formation of lending relationships. Although the literature does not offer a single precise definition of a lending relationship, it is generally defined as a relationship that involves the production of borrower-specific private information over repeated interactions with a borrower (Boot, 2000). A large literature on the effects of lending relationships posits that the lending relationships can benefit the borrowers but at the same time can impose certain costs.

2.4.2.1 Benefits of lending relationships

In this section, I overview the key benefits of lending relationships that were identified in the literature. Lending relationships ensure confidentiality, promote discretion and flexibility in contracting, reduce moral hazard through better control of the borrower via covenants and inclusion of collateral requirements, allow for intertemporal smoothing of loan contract terms, and enable reputation building. The first benefit of forming a lending relationship is *confidentiality*. Campbell (1979) was the first to show that confidentiality of a relationship may facilitate information production. Bhattacharya and Chiesa (1995) and Yosha (1995) rationalize situations where the firm prefers private financing to capital market financing to protect proprietary information. In Yosha (1995), firms choose bilateral relationship financing to multilateral transactional financing to avoid disclosure of private information which might leak to competitors. Some information remains hidden if there is a cost differential between these two financing options. In Bhattacharya and Chiesa (1995), it can be in the lender's interest to share information among the borrowers, and bilateral financing might be preferred when incentive problems are severe. Lending relationships can foster *flexibility* in writing loan contracts (Boot and Thakor, 1994; von Thadden, 1995) and increase access to capital at a lower cost and/or with less collateral. In addition, banks may smooth interest rates and reschedule capital payments to help their customers overcome financial difficulties (Chemmanur and Fulghieri, 1994). A relationship with a reputable institution may also facilitate current and future funding from shareholders and outside sources (Diamond, 1991). The second benefit is increased *discretion and flexibility* in writing loan contracts. Boot and Thakor (1994) show that banks can enhance ex-ante contracting flexibility using the length of relationships. Von Thadden (1995) links contract flexibility to borrower's investment horizon and shows that a debt contract structured like a line of credit with a clause allowing a bank to deny credit mitigates borrower's myopic investment behavior that would be present in a public debt contract. Lending relationships can also increase ex-post contract flexibility because it is much easier to renegotiate with a single bank or a group of banks than with a large number of public debt holders (Berlin and Mester, 1992; Dennis and Mullineaux, 1999). Boot, Greenbaum, and Thakor (1993) argue that the possibility of renegotiation adds value to the borrower. A bank can exert control over a borrower because it has the power to adjust loan terms or to refuse future lending to the borrower that has difficulties servicing the loan. In Rajan (1992), the benefits of bank debt arise from a bank's ability to withdraw funding because such ability induces the borrower to accept positive NPV projects. In addition, a renegotiation implies discretion, and discretion involves the use of subtle, noncontractable information in decision making. Relying on such information in decision making may lead to implicit, nonenforceable contracting (e.g., a mutual commitment based on trust), which can increase the borrower's value. Implicit contracting cannot be achieved in capital markets. The third benefit of lending relationships is the use of *covenants*. The covenants can mitigate a moral hazard problem and are particularly effective in bank lending because bank debt is relatively concentrated and thus allows for renegotiation (which is presumably why bank loan covenants tend to be more stringent than public debt covenants). A bank can initially set very stringent covenants and later reset them if the new information arrival makes the initial covenants suboptimal. The outcome of the renegotiation depends on the bargaining power of the lender, and seniority of bank debt is an important factor (Diamond, 1993; Berglof and von Thadden, 1994; Gorton and Kahn, 1993). The fourth benefit of lending relationships is the use of *collateral requirements*. Collateral mitigates the adverse selection and moral hazard in lending (Chan and Thakor, 1987; Stiglitz and Weiss, 1981) because by posting collateral a borrower risks losing it if the bad state occurs. Rajan and Winton (1995) posit that collateral is effective only if its value is monitored, and the monitoring effort depends upon the distance between a bank and a borrower. The fifth benefit is that the lending relationships allow for an *intertemporal smoothing* of the loan contract terms. Petersen and Rajan (1995) show that information rents and intertemporal smoothing allow banks to provide subsidized credit to young, opaque firms that in the absence of this mechanism would not be able to get a loan simply because they are high risk in terms of adverse selection and moral hazard. Initially, these subsidies result in a loss to the bank, but they are later recouped by information rents extraction. Berlin and Mester (1999) report an additional manifestation of intertemporal transfers. They show that the interest rate-inelastic core deposit financing enables banks to smooth loan rates, which suggests complementarity between deposit financing and lending. The sixth benefit of lending relationships lies in *facilitating public debt funding* and points at the complementarity between bank loans and public debt. Hoshi, Kashyap, and Scharfstein (1993) provide the argument of simultaneous complementarity. They posit that the bank lending subjects the borrowers to monitoring, which acts as a certification device that facilitates simultaneous public debt financing. In Diamond (1991) model of sequential complementarity, a borrower may want to establish a lending relationship before it turns to capital markets because repeated borrowing from the same lender allows it to develop reputation through a history of successful debt repayments. Chemmanur and Fulghieri (1994) argue that lender reputation is central to certification role, suggesting that reputation and lending relationship value are positively correlated. In sum, lending relationships enable better information flow and more informed lending decisions and can resolve credit rationing problem for opaque borrowers.

2.4.2.2 Costs of lending relationships

The main downside of lending relationships is the hold-up costs.[32] In Sharpe (1990), a relationship bank learns valuable private information about a borrower and builds the information advantage over the non-lenders. The non-lenders, facing the adverse selection problem (Winner's curse), peg all firms that are trying to switch as lemons regardless of their true quality and offer them rates that are higher than what the average credit quality would justify. This allows the incumbent bank to overcharge its borrowers as long as the rates that it offers are lower than what they can obtain elsewhere. Thus, the borrowers become informationally captured ("held-up") by their relationship bank. While Sharpe (1990) predicts no switching between lenders, switching is allowed in other models that derive mixed strategy equilibrium (Rajan, 1992; von Thadden, 2004). In the amended version of Sharpe (1990) model, von Thadden (2004) shows that non-lenders limit the inside bank's information rents extraction by offering competitively lower rates using "optimal randomization" to borrowers that to them are observationally identical. Rajan (1992) builds on Sharpe (1990) and models agency problems between a firm and its investors that can make delegated monitoring attractive, using both the bank and arms-length financing. The model endogenizes the incumbent bank's bargaining power and predicts that the choice of financing will depend upon unobservable quality of the firm determined by the initial costly exertion of effort.

The literature also proposes the ways in which borrowers can mitigate the hold-up problem. It can be mitigated if a borrower has an option to issue public debt (Rajan, 1992; Diamond, 1991; Santos and Winton, 2008) or has relationships with multiple lenders (Houston and James, 1996). The information disadvantage of non-lenders can be alleviated by information spillovers (Hauswald and Marquez, 2003

[32] Some other potential problems are soft budget constraint, borrower's overexposure to a single bank's risk (Hubbard, Kuttner, and Palia, 2002), and a failure of a bank to meet growing credit needs and capital market access needs of a borrower (Gopalan, Udell, and Yerramilli, 2011). Soft budget constraint problem arises from the possibility of renegotiation of bank debt that may bias borrower's ex ante incentives. Granting bank debt seniority over bondholders and using collateral can alleviate this problem.

and 2006; Padilla and Pagano, 1997). The empirical evidence on the subject of hold-up costs is rather mixed. Several papers suggest that this problem exists and is significant. Santos and Winton (2008) compare loan pricing for firms without public debt market access (bank-dependent firms) and firms with such an access. They find that the firms that have issued public debt in the past pay lower loan rates, and that in recessions their loan rates rise less that the rates of the bank-dependent firms. Some papers on the number of bank relationships also find evidence of hold-up costs. Houston and James (1996) study the mix of bank and public debt for a sample of public firms and find that the firms with high growth opportunities rely less on bank debt if they have a single bank relationships, and rely more on bank debt if they have multiple bank relationships. Since the firms with high growth opportunities presumably have higher credit needs, this result suggests that the hold-up problem is a material issue. Farinha and Santos (2002) find that the firms with greater growth opportunities, less liquidity, or higher dependence on their bank are more likely to form new relationships, consistent with reducing hold-up problems. Ioannidou and Ongena (2010) show that the main reason why firms switch to a new bank is to obtain a lower loan rate (however, after some time the new lender ends up increasing it). Faulkender and Petersen (2006) find that the public firms without access to public debt markets have lower leverage than the public firms with such access, suggesting that dependence on bank financing induces credit constraints.

The above studies use very different approaches to infer the presence of hold-up costs. Arguably, the most direct way to evaluate whether the hold-up problem is present is to study the borrowing rates as a function of the lending relationship strength. My paper is closely related to this literature, discussed in the following section.

2.4.3 Lending relationships and borrowing costs

The theoretical literature offers different predictions regarding the direction of change in the borrowing rates as the lending relationship matures. Boot and Thakor (1994) posit that the borrowing rates should decrease as the relationship progresses. In their model, the borrowers pay above-market rates initially but after proving successful they pay below-market rates. In contrast, Sharpe (1990) and Greenbaum, Kanatas, and Venezia (1989) predict that the borrowing rates should increase because banks, expecting to earn information rents, initially subsidize the borrowers by offering low rates but then increase them.

The empirical studies on this subject show mixed evidence. Degryse, Kim, and Ongena (2009) provide the overview of the recent empirical works and conclude that most U.S. studies find that lending relationships are associated with lower loan rates, whereas most European studies find that the rates are higher. Some of the U.S. studies that looked at the impact of relationships on loan rates are Petersen and Rajan (1994), Berger and Udell (1995), Hao (2003), Brick and Palia (2007), Schenone (2010), and Bharath et al (2011). Between these studies, there is a great variation in the set and definition of control variables, the definition of what constitutes a lending relationship, the measure of the cost of credit, and the composition of the pool of borrowers.

The measures of lending relationship strength employed in this literature also vary. Earlier studies used loan maturity as a measure of the relationship strength. Petersen and Rajan (1994) use the National Survey of Small Business Finances (NSSBF) data and find that the loan rates are not related to the relationship length, which is consistent with information rents extractions if we assume that the lending costs *decrease* as the relationship progresses (it is generally believed that, as the monitoring costs decline over time due to the information reusability, the relationship bank's lending costs should decrease as the relationship matures). Berger and Udell (1995) also use NSSBF data and find that longer relationships are associated with *lower* loan rates for credit lines. Degryse and Van Cayseele (2000) find that the borrowing rates *increase* in the relationship length in a large sample of small Belgian firms, also consistent with information rents extraction.

Two recent studies quantify relationship strength using a measure of reliance/dependency on the relationship bank. This measure, referred to as the relationship intensity, is a ratio of borrower's loans from a given bank to all loans obtained by this borrower within a defined time window. Bharath et al (2011) use loan number- and loan value-based measures and a five-year time window. Schenone (2010) also uses number- and value-based measures, but includes all loans since the inception of the loan database. Both studies use the LPC Dealscan database that covers large (over $100,000) loans to public and private firms. Bharath et al (2011) find that the lending relationships are associated with lower loan spreads for firms with publicly traded equity. Schenone (2010) examines the sample of firms that ended up doing an IPO and finds that in the pre-IPO period loan spreads exhibit a U-shaped pattern and in the post-IPO period loan spreads decrease in the relationship strength.

Lastly, some studies use rather simple measures, such as a dummy variable that equals one if a firm borrowed from a bank during some time period preceding the current date (e.g., Gopalan, Udell, and Yerramilli, 2011).

2.5 Informational and transactional bank loans

In this short section I will briefly review the literature arguing that the banks engage in both informationally intensive and transactional lending, and that these two types of lending may coexist within one bank, although banks may choose to specialize. (My identification strategy hinges on the assumption that commercial paper backup lines of credit do not involve bank monitoring.) It is an accepted view in the recent literature that some bank loans do not involve information production. The early literature was drawing a distinction between the informationally intensive ("relationship") and transactional ("arm's-length") lending by assigning the former to banks and the latter to capital markets (investment banks and underwriters). The banks were presented as relationship lending experts that engage in screening, monitoring, and qualitative asset transformation. By contrast, capital markets were portrayed as providers of brokerage services whose expertise lies in matching buyers and sellers.[33] A number of theoretical papers describe the borrower's choice between bank and capital market financing as

[33] In the modern financial system the role of investment banks is not limited to pure brokerage. Investment banks usually underwrite their public debt issues and, therefore, temporarily absorb risk.

a choice between informational and transactional loans (Diamond, 1991; Sharpe, 1990; Rajan, 1992). While drawing this sharp distinction is convenient, especially in theory, in reality banks engage in both types of lending. Although informational lending remains a traditional core activity of commercial banks, the evolution of the banking industry in the last decades led banks to engage in transactional lending. This was a result of other institutions, such as mutual funds and pension funds, competing for deposits, and investment banks and underwriters, leveraging on financial innovation that followed rapid technological advancements, offering products that compete with bank loans.

The recent literature views banks as institutions that engage in both types of lending. In Boot and Thakor (2000), banks offer informational and transactional loans and coexist with capital markets that offer only transactional loans. Banks choose how much to invest in information production expertise and how much lending to extend either way depending on the level of interbank competition, competition from capital markets, borrower quality, and bank-specific ability to produce private information. Hauswald and Marquez (2006) develop a similar model of competition between banks that make "screened" transactional and "unscreened" informational loans but, unlike Boot and Thakor (2000), they endogenize the level of interbank competition and the bank's information production ability (as a function of distance between the bank and the borrower). In Song and Thakor (2007), banks finance their investments with deposits and with purchased liabilities and issue two types of loans, value-adding informationally opaque loans and informationally transparent transactional loans. Agarwal and Hauswald (2007) empirically investigate the determinants of informational vs. transactional loans using a sample of online and in-person small business loan applications.

3 HYPOTHESES

Bank credit lines represent a reliable source of liquidity so long as the borrower's credit and liquidity risks remain low. However, the contractual features of credit lines are such that, when these risks increase, a bank has a right to decide whether or not it will honor the commitment to lend. Financial covenants, present in virtually all credit agreements, specify certain balance sheet and operating performance ratios that the borrower must maintain at all times. Violating a covenant constitutes a technical default and provides a bank with a right to restrict the borrower's access to the undrawn portion of the line. Although financial ratios specified in financial covenants reflect both liquidity and credit risk of the borrower, the most common covenants, coverage and debt-to-cash flow, target liquidity risk more so than credit risk (Roberts and Sufi, 2009a; Sufi, 2009). That, and the fact that covenants are present in virtually all credit agreements and are frequently violated, and the banks often respond to violations by imposing line access restrictions, raises an interesting question. What is the value of credit lines as a form of liquidity insurance, given that the borrowers are likely to lose their access to liquidity precisely when they need it the most?

The answer to this question is that it depends upon the bank, more specifically upon the bank's willingness and ability to accommodate the borrower. While most studies attempt to answer the above question by looking at how often and in what manner banks respond to covenant violations and whether the borrowers are able to access their lines when they appear to need the funds, I utilize a different approach and focus on the role of bank-borrower relationships. The firms pay loan commitment fees on the undrawn funds because they view their chances of being able to access the funds in the future as sufficiently high. Thus, the bank's reputation as accommodating lender is important for its loan commitment business. I draw on the financial and reputational capital trade-off theory of Boot, Greenbaum, and Thakor (1993) and argue that when financial covenant is violated, a bank makes the access restriction decision by weighing the cost of losing reputational capital against the benefit of preserving financial capital. I hypothesize that a bank will be less likely to impose access restrictions on a loyal, reliant customer because the loss of future income from this client and the negative signal that access restriction sends to other current and prospective customers increase in the degree of customer's reliance on a bank. Thus, I argue that a bank's willingness to be accommodating increases in the strength of its relationship with a borrower. However, it must be stressed that this valuable willingness stems from the reputational considerations and not from the private information production. In essence, I argue that the repeated bank-borrower interactions can be valuable even if no information production takes place. Of course, most bank-borrower relationships involve some information production, but it is not inconsistent with the presence of the liquidity provision effect. I argue that the liquidity provision and the information production are two distinct sources of the relationship value, and it is necessary not only to distinguish between these effects, but also to control for the impact of the information production while studying the impact of the liquidity provision, and vice versa. As I will explain in this section, I control for the effect of the information production aspect of bank-borrower relationships, while the main focus is the effect of the liquidity provision aspect.

My approach to ascertaining the liquidity insurance value of bank credit lines is that if they are valuable, their value should increase in a bank's reputation-driven willingness to provide liquidity. If this association is present, it should be concluded that credit lines have the liquidity insurance value and this value increases in the bank's willingness to be accommodating.

Because most loans and lending relationships involve both the liquidity provision and the information production aspects, making it difficult to disentangle them, I take advantage of the fact that some credit lines do not involve information production. These credit lines, commercial paper backups (CP backups), represent a sufficiently large part of my sample accounting for about twelve percent of the observations. [34] I use these loans to construct a measure of a firm's reliance on a bank for meeting its liquidity needs. This measure, which I call *transactional intensity (T-intensity)*, is a ratio of firm's CP

[34] The reason why CP backups do not involve information production was discussed in the introduction.

backups from a given bank to its total borrowing within a defined time window, and it proxies for the bank's willingness to provide liquidity. I evaluate the benefits of this willingness by considering its effect on loan spreads.[35] I maintain that based on the standard risk-return argument, a bank's greater willingness to provide liquidity should translate into lower liquidity risk of the borrower and, therefore, lower loan spreads. I also maintain that the impact of this willingness should increase in a degree of the borrower's opaqueness because the literature suggests that more opaque firms are more likely to face restrictions to credit line access following a covenant violation (Barakova and Parthasarathy, 2012) and experience greater difficulties in obtaining new loans (Demiroglu, James, and Kizilaslan, 2012).[36] Accordingly, I test the following hypotheses:

Hypothesis 1 (H1): *The greater the bank's willingness to provide liquidity, the greater the liquidity insurance value of credit lines and, therefore, the lower the cost of borrowing. Put differently, higher T-intensities are associated with lower loan spreads.*

Hypothesis 2 (H2): *The more opaque the borrower, the greater the impact of the bank's willingness to provide liquidity. Put differently, loan spreads decrease more in T-intensities for more opaque firms.*

I also examine the role of information production in lending relationships by looking at its impact on the same dependent variable, loan spread. Information production takes place via monitoring the borrower and can result in increasing or decreasing loan spreads, depending on whether or not the relationship bank exploits its information advantage.[37] Monitoring costs are a component of the total lending costs, and a relationship bank passes these costs on to the borrower through the loan spread. Since the private information that a bank generates is reusable, the monitoring costs should go down as the

---

[35] Following the literature, I use "all-in-spread drawn" (AISD) as a measure of the borrowing costs. AISD measures the interest rate spread on a loan (over LIBOR) plus any fees in originating the loan.

[36] I designate three types of borrowers based on their opaqueness: non-Compustat firms, private Compustat firms, and public Compustat firms.

[37] The theory offers different predictions regarding the impact of relationships on the cost of borrowing. Boot and Thakor (1994) argue that the cost of borrowing should go down. Rajan (1992) argues that it should go up.

relationship progresses and hence the total lending costs should also go down. If a bank adjusts the loan spread accordingly, the loan spread that it charges should decrease at the relationship matures. However, the information advantage that a bank builds over the course of relationship may allow it to share the lending costs savings only partially, not share them at all, or not share them at all and charge even more than it did before. Put differently, a bank may reduce loan spreads by less than what the lending costs savings would justify, or keep them the same, or increase them. Such opportunistic behavior is possible because the bank's information advantage over non-lenders creates the adverse selection problem for the latter and, as a result, they peg all firms that attempt to switch as lemons regardless of their true quality. The relationship borrowers, facing switching costs, become "held-up" by their bank which now has the power to charge any loan spread as long as it is lower than what they can obtain from the uninformed non-lenders. This hold-up problem should be more severe for more opaque firms because the extent of the adverse selection problem facing non-lenders increases in the opaqueness of the switching firm. I hypothesize that the hold-up costs are present and more severe for more opaque firms.[38] I measure the bank's information advantage, which I call *informational intensity (I-intensity)*, as the extent of a firm's reliance on a bank for its informationally intensive borrowing. I define *I-intensity* as a ratio of firm's non-CP backups from this bank to its total borrowing within a defined time window, and test the following hypotheses:

Hypothesis 3 (H3): *The greater the bank's information advantage, the higher the cost of borrowing. Put differently, higher I-intensities are associated with higher loan spreads.*

Hypothesis 4 (H4): *The more opaque the borrower, the greater the impact of the bank's information advantage. Put differently, loan spreads increase more in I-intensities for more opaque firms.*

[38] It should be noted that, if a relationship bank does not behave opportunistically and passes the lending costs savings on to its borrowers, the spread-decreasing effect should be higher for more opaque firms because higher information asymmetries create greater potential for lending costs reduction over time. Thus, whether a relationship bank charges higher or lower spreads as the relationship matures, the magnitude of the effect will be greater for more opaque firms.

Because CP backups and non-CP backups are the mutually exclusive categories of loans, a sum of *T-intensity* and *I-intensity* is a ratio of a firm's total borrowing from a given bank to its total borrowing. I call this ratio *aggregate intensity (A-intensity)* and interpret it as a firm's overall reliance on a bank. *T-intensity* and *I-intensity* represent a decomposition of *A-intensity*. As it was discussed in the introduction, the literature interprets *A-intensity* as a measure of the bank's information advantage (Schenone, 2010); Bharath et al, 2011). However, because the numerator of *A-intensity* includes unmonitored loans, I believe that *I-intensity* is a better measure of the bank's information advantage.

The above studies implicitly assume that the effects of the lending relationships are attributable solely to the information production. In line with that view, unmonitored loans are "informationally neutral" and their inclusion in *A-intensity* as a measure of the bank's information advantage should not create a strong bias because they appear in both the numerator and denominator. The benefit of "keeping it simple" and not having to classify all loans into monitored and unmonitored probably outweighs the cost of constructing a somewhat biased measure. In contrast to the traditional view that the effects of the relationships arise from the information production alone, I maintain that the liquidity provision is another source of these effects. This conjecture requires differentiating between monitored and unmonitored loans, term loans and credit lines, and the liquidity provision and the information production aspects of relationships. The last one is especially important because, as it was mentioned earlier, these two aspects have the opposite effects on loan spreads. In sum, my conjecture implies that the overall impact of lending relationships on loan spreads is a net result of the benefits that arise from a bank's reputation-driven willingness to provide liquidity and the costs that result from the exploitation of information advantage.

In formulating Hypotheses 1 and 2, it was argued that a bank's willingness to provide liquidity to a borrower whose risk has increased is driven by the reputational considerations and that the bank is more willing to accommodate a loyal, repeat customer. To make sharper inferences concerning the effect of willingness, I control for a bank's ability to provide liquidity. The reason why credit line contracts stipulate financial covenants and other conditions that allow a bank to escape its liquidity provision commitment is that as a *dual* liquidity provider, a bank is exposed to a risk of the increased liquidity demands of the borrowers (drawdowns on the existing lines), a risk of the increased liquidity demands of the suppliers of funds, and, in the worst case scenario, the risk of the *simultaneous* increases in these liquidity demands. Financial covenants allow a bank to manage its own liquidity risk. However, the more stable the bank's funding sources, the easier it is for it to meet the liquidity demands of the borrowers and thus be more accommodating. Core deposits (which represent the majority of retail deposits) and equity capital are the most stable funding sources. Between the two, core deposits have the added benefit of being relatively cheap and interest-rate insensitive. In contrast, purchased liabilities (wholesale deposits, repos, federal funds, etc.) are the least stable funding source, albeit its popularity has been steadily increasing for more than a decade prior to the 2007-2009 financial crisis. Studies have shown that during the crisis the banks that were more reliant on core deposit financing were better able to sustain new lending in the presence of the increased drawdowns on the existing lines (Cornett et al, 2011; Ivashina and Scharfstein, 2010). I argue that a reliance on core deposit financing can be viewed as a measure of a bank's ability to provide liquidity. I define a reliance on core deposits, *Bank Core Dep*, as a ratio of core deposits to total deposits. I hypothesize that borrowers value this ability and pay higher loan spreads to more "able" banks because such banks are less likely to impose line access restrictions and more likely to issue new loans. In addition, a bank's ability to provide liquidity should be more valuable to more opaque firms because such firms are more likely to face line access restrictions (Barakova and Parthasarathy, 2012) and to be credit rationed (Demiroglu, James, and Kizilaslan, 2012). Accordingly, I test the following hypotheses:

Hypothesis 5 (H5): *The greater the bank's ability to provide liquidity, the higher the cost of borrowing. Put differently, higher core deposit ratios are associated with higher loan spreads.*

Hypothesis 6 (H6): *The more opaque the borrower, the more it values the bank's ability to provide liquidity. Put differently, loan spreads increase more in core deposit ratios for more opaque firms.*

To summarize the aforementioned six hypotheses, (1) simultaneous inclusion of *T-intensity* and *I-intensity* in my regressions allows me to separate the effects of the liquidity provision aspect of relationships (driven by reputational considerations) from the effects of the information production, and (2) simultaneous inclusion of *T-intensity* and *Bank Core Dep* allows me to separate the effects of a bank's willingness and its ability to provide liquidity.

Lastly, I consider the role of bank size. The literature suggests that bank size may proxy for a range of the bank characteristics as it is explained below.

Bank size as a proxy for information production ability and reputation. These two characteristics are interrelated because greater information production ability is likely to result in strong financial performance and, therefore, high reputation. By renewing or issuing a new loan, a bank certifies the value of a borrower. For investors, the task of identifying a good firm transforms into a task of identifying a good bank, the one with strong incentives to screen and monitor and good reputation reflected in a solid track record of quality lending. Since the information production ability and effort are not directly observable, the investors rely on some cumulative measure of long-term performance, and bank size is one such measure. First, large size likely reflects a history of successful lending. Second, it may enable scale and scope economies in the screening and monitoring process (Boot and Thakor, 2000). Byers, Fraser, and Shockley (1998) use bank size as a proxy for a monitoring ability arguing that larger banks have more specialized staff and/or better monitoring technology and thus can monitor more effectively.[39]

Bank size as a proxy for lending capacity. A bank's lending capacity is valuable to the firms with high borrowing needs. Asset size is a good proxy for lending capacity because larger asset size allows a bank

[39] Other commonly used measures of screening and monitoring ability and reputation include bank credit ratings, market share, and financial statements-based measures of past performance. Cook, Schellhorn, and Spellman (2003) use credit score, size, and loan losses as the proxies for reputation. They find that credit score and size are associated with higher loan spreads. Billett, Flannery, and Garfinkel (1995) use bank credit rating as a proxy for reputation and find that positive loan announcement effect increases in reputation. Fang (2005) finds that bond underwriters with a high market share obtain lower yields for their customers. Coleman, Esho, and Sharpe (2006) use a salary expense-based measure to proxy for the bank's monitoring effort and find that it is positively associated with loan spreads.

to absorb larger loans. [40] Also, large banks are more likely to have a network of other lenders and be more efficient in loan syndication. Gopalan, Udell, and Yerramilli (2011) show that the clients of large banks are less likely to borrow from a new lender than clients of small banks, and that when the firms borrow from a new lender they obtain larger loan amounts, suggesting that a low lending capacity is a material concern.

Bank size as a proxy for access to capital markets. Access to capital markets may be valuable to some borrowers, particularly those that require larger loans and/or access or prepare to access capital markets. Gopalan, Udell, and Yerramilli (2011) find that the firms are less likely to form new bank relationships if their banks are capable of providing underwriting services. Yasuda (2005) finds that relationship banks capable of bond underwriting are more likely to get this business from their borrowers and charge lower fees.

Bank size as a proxy for bank risk. Large banks may be perceived as less risky as a result of the government's implicit full backing of their liabilities. The eleven banks that were mentioned in the Comptroller of the Currency's "too-big-to-fail" statement experienced positive wealth effect on this announcement (O'Hara and Shaw, 1990). There is also evidence that over the years following this announcement these banks were indeed perceived as less risky based on the patterns of institutional ownership of bank stocks (Black, Colins, Robinson, and Schweitzer, 1997).

Overall, the importance of bank size should depend upon a firm's life cycle stage and, therefore, its opaqueness. The most opaque firms tend to be young and small and are not likely to benefit from a capital market access or high lending capacity. Since they do not have public securities, the reputation-driven certification effect is less relevant (Billett, Flannery, and Garfinkel, 1995), and smaller bank size may, in fact, be preferred due to a small banks' ability to process soft information (Stein, 2002). Moderately opaque firms (Type 2) tend to have larger size and higher borrowing needs but still limited

---

[40] Regulations limit bank's maximum exposure to a single borrower as a percent of bank capital.

access to capital markets. They are likely to value gaining or maintaining access to capital markets and may benefit from a bank certification effect if they have public debt or plan to issue public debt or public equity. The least opaque firms, those with public equity, have a wide range of financing options. Even though they have public securities, for them a bank certification effect may be not as dramatic because the information asymmetries are low. I test the following hypothesis:

Hypothesis 7 (H7): *It is the relatively large firms with high borrowing needs but limited access to alternative sources of financing that benefit most from the bank's large asset size. Put differently, loan spreads should increase in bank size for Type 2 firms (Compustat firms without public equity).*

4 DATA AND SAMPLE SELECTION

4.1 Data and sample

To test the Section 3 hypotheses, I construct the data set that combines information on loans (LPC Dealscan) with accounting data for borrowers (Compustat) and banks (Call reports). Dealscan database, maintained by the Loan Pricing Corporation (LPC), has detailed information on loan contract terms at the time of loan initiation for large (above $100,000) bank loans of private and public companies. This information is in part self-reported by banks and in part collected by the LPC staff from public sources and industry contacts. The data begins in early 1980s, but the coverage is thin before 1990. I use the period of 1990-2008 in my analysis. Dealscan contains detailed information on the loan contract terms (e.g., loan spread, amount, maturity, collateral offering, and covenants). The identifying information on firms and banks is limited to the company name, SIC code, and location.

What I call a "loan" in this paper corresponds to "loan facility" in Dealscan. [41] Although Dealscan covers single-bank loans, most loans are syndicated (93.7% of my sample is represented by syndicated loans). Syndicate members have varying degree of involvement with a borrower. Usually, one or two lenders assume a lead arranger role, and the rest of the members act as participants. As discussed in Dennis and Mullineaux (2000) and Sufi (2007), a lead bank structures a deal, sets loan terms and loan rate, and monitors loan terms and a borrower's condition on behalf of a syndicate. The participation of the non-leads is limited to providing their share of financing.[42] The lead banks also tend to retain a larger share of a loan than non-leads. I follow the literature in using 'Lead arranger credit', 'Lender role', and 'Bank allocation' Dealscan variables to identify lead banks. Lead arranger credit can take a 'Yes' or 'No'

---

[41] Dealscan organizes the data on the levels of loan facility and loan deal. Loan facilities are individual loans with their own contractual features (loan spread, amount, etc.). However, it is a common practice to simultaneously contract two or more loan facilities in the form of a loan deal. All facilities within a deal are governed by one loan agreement and share the same lender(s). For example, a loan deal can include one term loan and one credit line.

[42] Several studies have examined the within-syndicate moral hazard problem, which arises because the lead and the non-lead banks are asymmetrically informed (Sufi, 2007; Ivashina, 2009; Bharath et al, 2011).

value for each lender. Sufi (2007) uses this variable as a sole criterion for assigning lead status. Bharath et al (2011) use a broader definition. In addition to the Lead arranger credit criteria, they use Lender role and Bank Allocation variables to identify the roles in which a lender retains a greater than 25% share of a loan and classify those roles as the lead roles even when Lead arranger credit is a 'No'. The roles that meet these criteria are 'Agent', 'Administrative agent', 'Arranger', and 'Lead bank'. Bharath, Dahiya, Saunders, and Srinivasan (2007) use even broader definition of a lead bank by classifying all roles other than 'Participant' as the lead roles. My definition of what constitutes a lead role is closest to theirs; I include all lender roles except for 'Participant', 'Lead participant', and 'Secondary investor'.[43] My final sample includes 26 different lender roles; 45.74% of my sample observations meet the lead bank criteria of Sufi (2007) and 49.46% meet the criteria of Bharath et al (2011).

I start with gathering all data on loans to the U.S.-based firms, excluding the firms in the financial services industry (SIC codes between 6000 and 6999), where at least one lead bank (per my definition) is classified as the 'U.S. bank' by Dealscan.[44] From this set of loans, I identify 1,189 U.S. banks that acted as a lead lender at least one time. Most of these banks have a very limited presence in Dealscan. For instance, 661 banks acted as a lead on less than six loans, and 280 banks acted as a lead only once. I focus on the top 200 banks from this list and hand-match them to Call reports. Dealscan provides lender name, SIC code, country, city, and state on the loan initiation date.[45] I use the FDIC website and the National Information Center (NIC) database maintained by the FFIEC to find Regulatory ID matches (RSSD9001) for these 200 banks. Since the lender's geographical information in Dealscan is often missing, I discard some matches as unreliable. I am able to match 150 of 200 banks, including the twenty most active

[43] The list of 57 lender roles based on all Dealscan loans to the U.S. borrowers and the mean and median bank allocation shares for each role are presented in Appendix 2.

[44] Dealscan variable 'Institution type' takes 25 different values in the sample of all loans to the U.S.-based firms. 'U.S. bank' has the highest frequency of occurrence (50.03% of observations), followed by 'Western European Bank' (17.50%), 'Finance company' (8.46%), 'Asia-Pacific Bank' (7.68%), 'Foreign Bank' (6.58%), 'Investment bank' (3.42%), and 'Insurance company' (1.42%).

[45] Other variables that are useful for matching Dealscan lenders to the Call reports include the name and geographical information of the lender's first acquirer (on the acquisition date) and the lender's highest holder (as of the most recent date, which in my case is October 2008).

Dealscan lenders. Using the NIC database, I construct the chronology of mergers and acquisitions for these 150 banks in order to assign relationship status to each bank-borrower pairing on each date.[46]

To control for the firm's accounting information, I match Dealscan borrowers to the Annual Industrial Compustat files by company name, SIC code, and geographical information. I use the data from the most recent fiscal year end if it is more than 6 months before the loan date. If the most recent fiscal year end is less than six months before the loan date, I take the data from the fiscal year end that is prior to the most recent one. This procedure ensures that the accounting information is publicly available at the time of the loan initiation. In doing so, I follow Bharath, Dahiya, Saunders, and Srinivasan (2007) who note that the SEC requires that the accounting data should be made available within 90 days of the fiscal year, which makes this approach rather conservative. They also cite Fama and French (1992) who document that, on average, 19.8% of the firms do not comply with this SEC requirement. It should be noted that only 56.63% of the observations in my sample have the firm accounting information from Compustat because my sample includes a mix of public and private firms. Bank accounting data is present in all observations. I exclude firms' first loans on record because they cannot be classified as repeat or first time loans with a given bank. This exclusion is similar to Gopalan, Udell, and Yerramilli (2011) who create a balanced panel by including second, third, and fourth loan on record for each borrower and to Bharath et al (2011) who restrict the sample to loans where the borrower had at least one other loan in the previous five years, which effectively excludes first loans. I also exclude the observations with missing loan spread information. The observation unit in my sample is a loan-bank pairing.[47] The average number of lead banks per loan in the final sample is 1.92 (it would be 1.12 if I used a more conservative lead bank definition of Bharath et al, 2011). My final sample includes 52,381

---

[46] Because the knowledge that a bank has about its customer is likely to be transferred to the merged entity, I count the loans that a borrower took from a bank that subsequently merged as the prior loans for the merged entity.

[47] On any given day, a firm may contract multiple loans and each loan may have multiple leads. For example, if a firm contracts a loan deal that includes two loans and is syndicated by three leads, it will produce six observations in my sample. My unit of observation is a loan-bank pairing because I control for bank variables. Some studies use loan (Bharath et al, 2011) or loan deal (Gopalan, Udell, and Yerramilli, 2011) as a unit of observation.

observations that correspond to 150 banks, 6,592 firms, 19,023 loan deals, and 27,281 loans. In this sample, 6,582 observations (12.57%) correspond to CP backups.

I designate three firm types based on the borrower's transparency. I consider the availability of financial information in Compustat and in CRSP databases at the onset of the loan. The presence in Compustat indicates a public availability of financial records, which is the case for firms that have publicly traded debt and/or publicly traded equity. The presence in CRSP indicates that the firm has publicly traded equity.

(1) Non-Compustat (Type 1) firms are the borrowers not listed in Compustat or CRSP. These are the *most opaque firms* in my sample. The size of this subsample is 29,612 observations (56.53% of the total sample) and it corresponds to 145 banks, 4,512 borrowers, 10,788 loan deals, and 15,922 loans. CP backups account for 3,304 observations, or 11.16%, of this subsample.

(2) Private Compustat (Type 2) firms are the borrowers listed in Compustat, but not in CRSP. The size of this subsample is 13,107 observations (25.02% of the total sample) and it corresponds to 136 banks, 1,216 borrowers, 4,602 loan deals, and 6,157 loans. CP backups account for 2,644, or 20.17%, of this subsample.

(3) Public Compustat (Type 3) firms are the borrowers listed in both Compustat and CRSP. These are the *least opaque firms* in my sample. The size of this subsample is 9,662 observations (18.45% of the total sample) and it corresponds to 129 banks, 1,352 borrowers, 3,645 loan deals, and 5,202 loans. CP backups account for 634, or 6.56%, of this subsample.

Table 1 provides one-digit SIC code classification of the observations in the total sample and firm type subsamples. Type 2 firms have the highest concentration of manufacturing companies (SIC codes between 2000-3999) and the lowest concentration of services companies (SIC codes between 7000-8999).

Type 1 firms have the highest concentration of utilities, transportation and communications companies (SIC codes between 4000-4999). Type 3 firms have the highest concentration of services companies.

Four panels of Table 2 present the descriptive statistics for the total sample, firm type subsamples, and loan type subsamples (CP backups and non-CP backup), calculated using the loan-bank observations (Panels A and B) and loan observations (Panels C and D). Detailed variable definitions are provided in Appendix 1. Following the literature, I use the Dealscan 'all-in-spread-drawn' (AISD) variable as a measure of the borrowing cost. AISD is the coupon spread over LIBOR plus the annual fee. Other key loan characteristics include loan amount, loan maturity, collateral dummy, and the covenant index.[48] The data is winsorized at 0.25% and 99.75% on loan spread, maturity, and amount to eliminate the extreme outliers. In the total sample, the mean (median) values based on the loan-bank observations are as follows. Loan spread is 158.8 (137.5) bps, loan amount is \$0.44 (\$0.20) billions, loan maturity is 47.1 (59.0) months, bank size is \$303.8 (\$180.5) billions, and the core deposit ratio is 23.5% (19.8%). The collateral is present in 36.3% and the S&P senior debt rating is present in 56.9% of the total sample.[49] Out of the five most common covenants, a loan has, on average, 1.38 covenants. For the Compustat firms (Types 2 and 3), the mean (median) size of total assets is \$5.03 (1.43) billions. Other variables included in all of the regressions are credit line and term loan dummies, loan purpose dummies (CP backup and six other categories), term spread, default spread, and the survey measure of the toughness of lending standards. Section 5 provides a more detailed description of the variables.

[48] I follow Bharath et al (2011) in constructing this index. The covenant index assumes the value between 0 and 5 with the presence of each of five different covenants coded as one, and zero otherwise, and summed up (see Appendix 1). The original index, proposed by Bradley and Roberts (2004), assumes the value between 0 and 6 because it also includes the presence of the collateral. I control for collateral with a separate dummy (*Secured*).

[49] If collateral information is missing, I code it as zero. Among the observations with non-missing collateral information, 65% have collateral.

4.2 Aggregate, transactional, and informational intensity measures

As it was discussed in the introduction and in the hypotheses section, there are three measures of bank-borrower relationship strength that are central to my analysis: aggregate (*A*-), informational (*I*-), and transactional (*T*-) intensities. *A-intensity* measures a borrower's overall reliance on a bank. *T-intensity* measures a borrower's reliance on a bank for meeting its liquidity needs. *I-intensity* intensity measures a borrower's reliance on a bank for its informationally intensive ("monitored") borrowing. In Section 3 it was discussed why (1) *T-intensity* can be viewed as a proxy for a bank's willingness to provide liquidity in situations when it is not legally obligated to do so, and why (2) *I-intensity* can be viewed as a proxy for a bank's information advantage over non-lenders.

To disentangle the liquidity provision aspect of lending from the information production aspect, I consider four types of loans. On the liquidity provision dimension of lending there are term loans and credit lines. On the information production dimension there are informational ("monitored") and transactional ("unmonitored") loans. Out of the four resulting combinations (unmonitored term loans, monitored term loans, monitored credit lines, and unmonitored credit lines), the first category is presumably empty as large term loans (the median loan size in my sample is $0.20 billions) are not likely to be unmonitored. The second category consists of loans that involve only information production. The third category includes loans that involve both the information production and the liquidity provision, making it difficult to isolate the liquidity provision effect. The fourth category is comprised of loans that involve only the liquidity provision. I use the fourth category to isolate the effect of liquidity provision in lending relationships. I identify commercial paper backups ("CP backups") as unmonitored credit lines and classify all of the other loans (monitored term loans and monitored credit lines) as "non-CP backups".[50]

[50] In the introduction it was discussed why commercial paper backups do not involve information production. CP backups account for 12.57% of my total sample and 11.16%, 20.17%, and 6.56% of the Type 1, Type 2, and Type 3 firm subsamples, respectively (see Table 3). More than 97% of CP backups come in the form of '364-Day Facility' (76.3%) or 'Revolver/Line >= 1 Yr.' (21.4%) (see Table 4).

For a loan received by firm *i* at time *t*, I search the previous loans (over the five-year period) of firm *i* in Dealscan and compare the identities of the leads on the current loan with those of the leads on the previous loans, accounting for the chronology of bank mergers and acquisitions. For each (firm *i*, bank *j*) pairing at time *t*, I compare the value of prior loans on which bank *j* was among the leads to the total value of firm *i*'s loans during *[t-5; t).* I also note if the loan is a CP backup or a non-CP backup.

Aggregate intensity (A-intensity) for (firm *i*, bank *j*, time *t*) is defined as a ratio of a value of all loans to firm *i* on which bank *j* was a lead during *[t-5; t)*, to a value of all loans to firm *i* during *[t-5; t).*

$$\textit{A-intensity } i\ j\ t = \frac{\$\,Value\ of\ \textbf{all loans}\ to\ firm\ i\ during\ [t-5;t)\ on\ which\ bank\ j\ was\ a\ lead}{\$\,Value\ of\ \textbf{all loans}\ to\ firm\ i\ during\ [t-5;t)} \tag{4.1}$$

Transactional intensity (T-intensity) for (firm *i*, bank *j*, time *t*) is defined as a ratio of a value of all CP backups to firm *i* on which bank *j* was among the leads during *[t-5; t)*, to a value of all loans to firm *i* during *[t-5; t).*

$$\textit{T-intensity } i\ j\ t = \frac{\$\,Value\ of\ \textbf{CP backups}\ to\ firm\ i\ during\ [t-5;t)\ on\ which\ bank\ j\ was\ a\ lead}{\$\,Value\ of\ \textbf{all loans}\ to\ firm\ i\ during\ [t-5;t)} \tag{4.2}$$

Informational intensity (I-intensity) for (firm *i*, bank *j*, time *t*) is defined as a ratio of a value of all non-CP backups to firm *i* on which bank *j* was among the leads during *[t-5; t)*, to a value of all loans to firm *i* during *[t-5; t).*

$$\textit{I-intensity } i\ j\ t = \frac{\$\,Value\ of\ \textbf{non-CP backups}\ to\ firm\ i\ during\ [t-5;t)\ on\ which\ bank\ j\ was\ a\ lead}{\$\,Value\ of\ \textbf{all loans}\ to\ firm\ i\ during\ [t-5;t)} \tag{4.3}$$

I also define a measure of a firm's reliance on CP backups in its loan mix, irrespective of the identities of the banks. I call this measure *CPB Reliance* and define it as a ratio of a value of all CP backups to firm *i* during *[t-5; t)*, to a value of all loans to firm *i* during *[t-5; t).*

$$\textit{CPB Reliance } i\ t = \frac{\$\,Value\ of\ \textbf{CP backups}\ to\ firm\ i\ during\ [t-5;t)}{\$\,Value\ of\ \textbf{all loans}\ to\ firm\ i\ during\ [t-5;t)} \tag{4.4}$$

Because by construction *A-intensity* equals to the sum of *I-intensity* and *T-intensity*, I refer to them as a “decomposition” of *A-intensity*. I also construct variations of the above four measures using different time windows (three-year window and since Dealscan inception) and a number of loans instead of a value of loans. Table 5 provides summary statistics for these measures. All intensity measures used in the reported regression results throughout this paper are based on the five-year window and the loan values. The results are robust to a choice of time window and to using a number instead of a value of loans.[51]

In Table 5, the mean value of *A-intensity* is 0.542 in the total sample and 0.555, 0.523, and 0.526 in the firm type subsamples. On average, Type 1 firms exhibit a higher overall reliance on their banks than other firms. The mean value of *I-intensity* is 0.475 in the total sample and 0.495, 0.415 and 0.496 in the subsamples. Type 2 firms have the lowest *I-intensity*. The mean value of *T-intensity* is 0.067 in the total sample and 0.060, 0.109, and 0.030 in the subsamples. Type 3 firms have the lowest *T-intensity*, followed by Type 2 and Type 1 firms. Panel A of Table 6 reports the results of a t-test of differences in means between the subsamples. Evidently, a decomposition of *A-intensity* uncovers some interesting patterns. Based on the *A-intensity* we would conclude that Type 1 firms rely more on their banks than Type 2 and Type 3 firms, which are statistically speaking similar (0.555 vs. 0.523 and 0.526), consistent with the notion that more opaque firms are more reliant/dependent on their banks. However, despite the difference in the *A-intensity*, Type 1 and Type 3 firms have statistically speaking similar *I-intensity* (0.495 and 0.496), while Type 2 firms’ *I-intensity* is much lower (0.415). Thus, Type 2 firms are on average less reliant on their banks for informationally intensive borrowing. It is the higher *T-intensity* of Type 1 firms (0.060 vs. 0.030 for Type 3 firms) that boosts their *A-intensity*. Type 2 firms have the highest *A-intensity* (0.109 vs. 0.030 for Type 3 and 0.060 for Type 1 firms), which makes up for their low *I-intensity*, and as a result the *A-intensities* for Type 2 and Type 3 firms are not statistically different from each other. In

[51] Schenone (2010) employs similarly constructed intensity measures using all loans since Dealscan inception. She reports that the number- and value-based intensities produce qualitatively similar results.

sum, when compared to other firm types, Type 2 firms are less reliant on their banks for informationally intensive borrowing and more reliant on their banks for meeting their liquidity needs. Type 1 and Type 3 firms are similar in their reliance for informationally intensive borrowing (although the former have higher *T-intensity*). This similarity is present despite the fact that Type 1 (non-Compustat) and Type 3 (Compustat with public equity) firms have very different opaqueness levels. This observation highlights the importance of decomposing the *A-intensity*. Panel B of Table 6 presents the pairwise correlations of the intensities. *I-intensity* and *T-intensity* are negatively correlated in the total sample and in the subsamples. The negative correlation is weakest for Type 3 firms.

5 METHODOLOGY

I estimate the impact of *A-intensity* and its decomposition (*T-intensity* and *I-intensity*), bank's reliance on core deposits (*Bank Core Dep*), and bank size (*Bank Size)* on loan spreads, controlling for other factors. I use three estimation models in my analysis: OLS model, fixed-effects (FE) model (firm fixed-effects and bank fixed-effects), and treatment effects (TE) model (estimated using two-step and maximum likelihood procedures). I run the regressions on the total sample, firm type subsamples, loan type subsamples, and firm type /loan type subsamples. My total sample is an unbalanced panel where the unit of observation is the loan-bank pairing, (loan *k*, bank *j*).[52] Total sample includes 52,381 observations and corresponds to 6,592 different firms and 27,281 different loans, with the average of 4.14 loans and 7.95 observations per firm, and 1.92 banks per loan. I use the regression model of the following form: [53]

$$Loan\ Spread_{\,k\,j} = f\,(Intensities_{\,i\,j\,t}\,,\ X_{\,firm\ i\ t}\,,\ X_{\,bank\ j\,t}\,,\ X_{\,loan\,k}\,,\ X_{\,environment\ t}\,) \tag{5.1}$$

- Dependent variable: *Loan Spread* is a Dealscan variable AISD ("all-in-spread-drawn"), the coupon spread over LIBOR on the drawn amount plus the annual fee in basis points.

- Intensity measures ("*Intensities"*): *A-intensity* measures a firm's overall reliance on a bank. *T-intensity* measures a firm's reliance on a bank for meeting its liquidity needs, which proxies for a bank's willingness to provide liquidity. *I-intensity* measures a firm's reliance on a bank for informationally intensive borrowing, which proxies for a bank's information advantage over non-lenders. *A-intensity* is equal to the sum of *I-intensity* and *T-intensity;* I refer to them as a "decomposition" of *A-intensity*. In the regressions, I include either *A-intensity* or its decomposition.

---

[52] In (firm *i*, bank *j*, time *t*, loan *k*), each loan has a unique match of time and firm but can have more than one bank.

[53] My empirical specification closely follows the baseline specification in Bharath et al (2011). I expand their specification by decomposing *A-intensity* into *I-intensity* and *T-intensity* and including bank variables (core deposit ratio and bank size). My findings are robust to the inclusion of the bank equity to assets ratio, which is not statistically significant in nearly all specifications (the results are available upon request).

- Firm characteristics ("X_{firm}"): *Firm Size* is the log of borrower's total assets measured in \$ billions. *Asset Tangib.* is a ratio of Net PPE and total assets. *Leverage* is a ratio of long-term debt and total assets. *Profitability* is a ratio of EBITDA and total assets. *Type 2 Firm* and *Type 3 Firm* are the binary variables that equal 1 if a borrower is classified as a private Compustat firm and a public Compustat firm, respectively. *Rated Bank Debt* is a binary variable that equals 1 if a borrower had the S&P senior debt rating at the onset of the loan, and 0 if it was not rated of if the rating information was not available. *Prev. Deal Amount* is the log of a borrower's most recent loan deal measured in \$ billions.[54]

- Bank characteristics ("X_{bank}"): *Bank Size* is the log of bank's total assets measured in \$ billions. *Bank Core Dep* is a ratio of bank's core deposits (transactions accounts, non-transaction savings deposits, and total time deposits less than \$100,000) and total deposits, and it proxies for a bank's ability to provide liquidity. *Bank Core Dep SD* is a standard deviation of *Bank Core Dep.*

- Loan characteristics ("X_{loan}"): *CP Backup* is a binary variable that equals 1 if a loan is a CP backup. *Loan Amount* is the log of a loan size in \$ billions. *Loan Maturity* is the log of the length in months between the loan activation date and maturity date. *Secured* is a binary variable that equals 1 if a loan is secured and 0 if it is not secured of if information is missing. *Covenant index* is the index based on the presence of five different covenants coded as 1 and 0 and summed up (see Appendix 1). *Credit Line* and *Term Loan* are the binary variables for credit lines and term loans, respectively. The omitted category includes loans that could not be classified as either of the two. Finally, loan purpose dummies account for the separate variable status of CP backups. [55]

---

[54] Because a large part of my sample does not have the firm accounting information, I include the previous loan deal amount as a proxy for the firm size following Gopalan, Udell, and Yerramilli (2011). Following the literature (Santos and Winton, 2008; Bharath et al, 2011) I use the log form of this and some other variables to address the excessive skewness.

[55] I include dummies for the following purposes: Corporate purposes, Debt repayment, Working capital, and Takeover (the full list is provided in Table 3). Together with CP backup, these four stated purposes account for about 85% of the observations in my sample. The omitted category includes all of the other purposes.

- Other controls ("$X_{environment}$"): *Lend. Standards* is a survey-based measure; higher values correspond to more stringent lending standards and, therefore, lower credit availability.[56] *Default Spread* is a difference between the yields on Moody's seasoned corporate bonds with Baa rating and 10-year U.S. government bond. *Term Spread* is a difference between the yields on 10-year and one-year U.S. government bonds. Industry dummies (based on the borrower's one-digit SIC code) and calendar year dummies are also included.

5.1 OLS model

OLS estimation is performed using standard errors adjusted for heteroskedasticity and firm-level clustering, a standard approach for panel data where within-cluster errors are likely to be correlated. A shortcoming of the OLS estimator is that its consistency requires that errors are uncorrelated with the regressors. In the presence of the endogenous regressor this assumption is violated and leads to the inconsistency of the OLS estimates for the endogenous regressor and, in the linear model, for all of the other regressors that it is correlated with.[57] Because the residual captures the effect of all mismeasured and omitted variables, a regressor that is correlated with the residual ends up proxying for those mismeasured and omitted variables. Thus, the coefficient on the endogenous regressor cannot be interpreted as a marginal effect of that regressor because it will also capture the effect of the unobservables. In my case, the borrower's choice of loan type raises endogeneity concerns because loan spread and the loan type choice could be driven by some common unobserved factor(s). For example, it could be the firm's unobserved credit quality, as suggested by Bharath et al (2011), or its corporate

---

[56] Since 1990, Federal Reserve Board has been publishing a quarterly *Senior Loan Officer Opinion Survey on Bank Lending Practices*. The respondents, senior loan officers from approximately 60 U.S. domestic banks and 24 U.S. branches and agencies of foreign banks, anonymously answer a range of questions about the changes in business environment and lending practices that occurred during a three-month period prior to the survey date. According to the FRB website, "questions cover changes in the standards and terms of the banks' lending and the state of business and household demand for loans." Each quarterly survey has a set of standard questions as well as questions on one or two other topics of current interest. One of the standard questions is whether their bank tightened the standards for the C&I loans in the three months prior to the survey date. The respondents must specify whether their bank's credit standards were tightened, eased, or remained unchanged. See Appendix 1 for further details.

[57] Strictly speaking, the endogeneity of a regressor is not identical to a non-zero correlation with an error term (Greene, 2000), but it is a convenient way to think about it.

government structure, as suggested by Schenone (2010). A Durbin-Wu-Hausman (DWH) test of endogeneity implemented in the next section confirms that the CP backup choice is endogenous in the total sample and this endogeneity is driven by Type 1 and Type 2 firms.

The most obvious way to address the endogeneity problem is to include controls for unobservable variables as the additional regressors. In practice, such variables are often not available. Using my example, it would require finding a proxy for unobservable credit quality. A standard approach to addressing the endogeneity and resulting inconsistency and bias of the OLS estimator is to use instrumental variable (IV) and selection models. Under certain assumptions, these models may yield consistent estimates in the presence of the endogeneity. I discuss these models in Section 5.3.

5.2 Fixed effects (FE) models

The structure of the panel data allows for alternative way to (partially) address the endogeneity by implementing a fixed-effects (FE) model.[58] Unlike IV and selection models, this approach addresses the "missingness" of unobservables without a focus on a particular variable suspected to be endogenous. Consider the individual-specific effects model for a scalar dependent variable Y_{it} regressed on variables X_{it} , where α_i represents the individual-specific effects and ε_i is the idiosyncratic error:

$$Y_{it} = \alpha_i \mid X'_{it}\, \beta + \varepsilon_{it} \qquad (5.2)$$

FE model permits that individual-specific effects α_i are correlated with the regressors X_{it} and, therefore, allows for a limited form of endogeneity. The error term is viewed as $\upsilon_{it} = \alpha_i + \varepsilon_{it}$ and its time-invariant component α_i is allowed to be correlated with the regressors. The idiosyncratic component of

58 According to Wooldridge (2002), "The availability of panel data allows us to consistently estimate treatment effects without assuming ignorability of treatment and without an instrumental variable, provided the treatment varies over time and is uncorrelated with time-varying unobservables that affect the response." (Wooldridge, 2002, p.637) Ignorability of treatment means that receiving treatment and treatment effect are unrelated conditional upon observable covariates (Wooldridge, 2002, p.607).

the error term ε_{it} is assumed to be uncorrelated with the regressors.[59] For example, if we assume that unobserved creditworthiness simultaneously affects loan spreads and the CP backup choice, using this model would require an assumption that the CP backup choice is correlated only with the time-invariant component of the borrower's unobserved creditworthiness. To avoid the incidental parameters problem that arises from the joint estimation of $\alpha_{I, \ldots}\ \alpha_{N}$ and β coefficients, β coefficients are consistently estimated by applying OLS to the mean-differenced original model (this approach effectively eliminates α_i). The OLS estimator of the mean-differenced original model, called a within estimator, is consistent for the FE model if its assumptions are met.

Although the panel structure of the data allows for consistent estimation of the endogenous regressors using a within estimator, this estimator has low efficiency. When within variation of a regressor is low, the coefficient will be estimated imprecisely (in the extreme case, the coefficients on the time invariant regressors are not identified because within variation is not present). Unbalanced panels present an additional complication in that the one-observation groups do not contribute to the estimator because they do not have within variation. I will discuss this issue in detail in Section 6. Nevertheless, it is useful to estimate these models if only as a robustness check for the signs and magnitudes of the OLS coefficients, keeping in mind that a significant loss of efficiency and exclusion of the one-observation groups from estimation are expected.

5.3 Instrumental variables (IV) and treatment effects (TE) models

I formally address the endogeneity of the loan type choice (CP backup vs. non-CP backup) by using instrumental variables in the framework of treatment effects (TE) model. Treatment effects model is one of the models within a broad class of selection models that were developed to address unique challenges posed by the presence of a binary endogenous regressor. IV and TE models are closely related when TE model is estimated with the inclusion of instruments, the variables that are correlated with the

[59] Unlike fixed-effects models, random-effects models assume that α_i is random (i.e., that regressors are not correlated with error term).

endogenous regressor but are not correlated with the outcome variable (other than through the endogenous regressor). However, these models rely on different assumptions. TE model utilizes the binary nature of the endogenous regressor and relies on the strong distributional assumption about the error terms. Technically, identification in TE model does not require the use of instruments (exclusion restrictions), but not including them implies heavy reliance on the untestable assumption about the joint distribution of the error terms. If this assumption holds, TE model is more efficient than IV model, but it is sensitive to the failure of this assumption, which is why good instruments should be included when they are available. IV model does not rely on any distributional assumptions, but its estimation requires instruments. The following two sections provide a more formal discussion of these models. Although I use TE model to estimate equation (5.1), the DWH test for endogeneity and the tests for the instruments' relevance and validity are performed in the IV model framework. For the convenience of discussion, I include a short overview of IV model in the following section.

5.3.1 Instrumental variables (IV) model

Consider the IV model with a scalar dependent variable Y_{1i} that depends on m endogenous regressors Y_{2i} and K_1 exogenous regressors X_{1i}. This model is called a structural equation:

$$Y_{1i} = Y'_{2i}\,\beta'_2 + X'_{1i}\,\beta'_1 + u_i \quad where\ i = 1, \dots N \tag{5.3}$$

The error term u_i is uncorrelated with X_{1i} (exogenous regressors) and correlated with Y_{2i} (endogenous regressors), leading to inconsistency of the OLS estimates for betas. Obtaining a consistent estimator requires the presence of at least m instrumental variables X_2 for the endogenous regressors Y_2 that satisfy the requirement of zero correlation with the error term, referred to as the orthogonality condition: $E(u_i|X_{2i}) = 0$. The instruments X_2 must also be correlated with the endogenous variables Y_2 so that they explain some of the variation in Y_2 and thus provide identification. Reduced form model (first stage model) takes the following form:

$$Y_{2ji} = X'_{1i}\pi'_{1j} + X'_{2i}\pi'_{2j} + \upsilon_{ji} \quad where\ j = 1, \dots, m \tag{5.4}$$

Equation (5.4) is a regression of endogenous variables on all exogenous variables in the system, which includes all exogenous variables from the structural equation (X_1) and all instrumental variables (X_2). Since exogenous variables X_1 can be viewed as perfect instruments for themselves, the orthogonality assumption is equivalent to $E(u_i Z_i) = 0$, where Z is the "full" vector of instruments, $[X_1\ X_2]$. The last expression generates a moment condition from which the IV model estimators are derived. When the number of instruments is less than the number of endogenous regressors (underidentified case), no consistent estimator exists. When it is equal to (just-identified case) or higher than (overidentified case) the number of endogenous variables, the consistent estimators exist. The most commonly used estimators are the IV estimator (for the just-identified case) and the 2SLS and GMM estimators (for the overidentified case). 2SLS is the most efficient estimator if the errors in (5.3) are homoscedastic, and it is consistent and follows large-sample normal distribution if the assumptions regarding the instruments are met. However, 2SLS is not unbiased in small samples, and the bias may be substantial (Baum, 2006).

To obtain consistent estimates of the IV model, the instruments must be *valid* and *relevant*. Instrument *validity* means satisfying the orthogonality assumption of $E(u_i | X_{2i}) = 0$. It is not possible to test this assumption directly because it is a correlation with an unobservable. The indirect test for the overidentified case has been proposed, known as a Hansen's (or Sargan-Hansen) test of overidentifying restrictions. The limitations of this test prompted the literature to emphasize the importance of a good argument in support of the instrument's validity. I conduct validity test for my instruments in the next section and conclude that one of my proposed instruments meets the validity criteria. Instrument *relevance* means that the instrument must account for significant variation of the endogenous variable after controlling for the effect of the structural equation's exogenous regressors. For unique parameter estimates to exist (i.e., for the model to be identified), even a weak correlation can be sufficient. However, for large-sample approximations to be useful, much higher correlations are usually needed. The instruments that are sufficiently correlated with the endogenous variable to ensure identification but are not sufficiently correlated to use large-sample approximations in finite samples are called weak instruments. Weak instruments can lead to low precision of estimation (large standard errors and small t-statistics) and to the small sample bias because, despite their asymptotic consistency, IV estimators are not centered on β in small samples. Small sample bias has also been shown to increase with the number of instruments (Hahn and Hausman, 2002). Overidentifying restrictions ("extra" instruments) are desirable in the large samples because they produce more efficient estimates, whereas in the small samples it is not necessarily true if instruments are weak.[60] I perform a number of weak instrument tests and conclude that at least one of my instruments meets the relevance criteria. I use the IV framework to test for endogeneity and for instrument validity and relevance but do not report IV estimation results for equation (5) because TE model is considered to be a better fit when endogenous regressor is binary.

5.3.2 Treatment effects (TE) model

TE model was developed after the Heckman's original model (Heckman, 1979), which focused on the incidental truncation of a (continuous) dependent variable. This situation arises when some of the observations are excluded from the data for self-selection reasons (Heckman developed this model to estimate the average wage of women using the data in which housewives were excluded by self-selection). Thus, Heckman's model addresses the sample selection problem, a situation when observations that should be part of the analysis "self-select" out of the sample. Maddala (1983) provided the extension of the sample selection perspective to the evaluation of treatment effectiveness (TE). Here, the binary endogenous variable is explicitly included in the model. It indicates if the "treatment" was received, and we observe the outcomes for treated and untreated subjects alike. TE model can be estimated with two-step or maximum likelihood (ML) procedure. ML procedure generates more efficient estimates but they may become biased and inconsistent if the model is misspecified (Cameron, Trivedi,

[60] There is no test for what constitutes a "large enough" sample. For example, Bound, Jaeger, and Baker (1995) show that in the setting of Angrist and Krueger (1991) large sample properties of the 2SLS estimator can be expected to not fully apply despite the sample size of 300,000-500,000 observations (Wooldridge, 2002, p.104).

2009, p.186). Two-step procedure generates consistent estimates, but standard errors cannot be corrected for heteroskedasticity and clustering, which can be achieved with ML procedure.

TE model is closely related to IV model and is designed for the special case when endogenous regressor is binary.[61] Compared to IV model, TE model adds more structure by changing the first stage model (5.4) to be a latent-variable model similar to probit. Thus, TE model explicitly accounts for the binary nature of the endogenous regressor. Let Y_2* be the latent variable that determines whether a single binary endogenous regressor Y_2 is equal to 1 or 0. Equations (5.3) and (5.4) can be rewritten as (5.5):

$$Y_{1i} = \beta_2 \ Y_{2i} + X'_{1i} \beta'_1 + u_i \quad where\ i = 1, \dots N \tag{5.5}$$

$$Y^*_{2i} = X'_{1i} \pi'_{1j} + X'_{2i} \pi'_{2j} + \upsilon_i$$

$$Y^*_{2i} = \begin{cases} 1\ if\ Y^*_{2i} > 0 \\ 0\ otherwise \end{cases}$$

TE model assumes that the errors (u_i, υ_i) follow bivariate normal distribution with Var(u_i) = σ^2, Var(υ_i) =1, and Corr(u_i, υ_i) = $\rho\sigma^2$. The binary endogenous regressor Y_2 is viewed as a treatment indicator: when it equals 1 we receive treatment, and when it equals 0 we do not receive it. When the error correlation ρ equals zero, the error terms are independent and there is no endogeneity problem (this is equivalent to $\lambda = \rho\sigma$ being equal to zero). Therefore, estimating TE model also provides a test for the residuals' correlation. As it was mentioned earlier, simultaneous estimation of the above two equations can be done using the ML approach. The intuition behind simultaneous estimation is that we model the correlation between the "treatment" and the error term directly, which eliminates omitted variable bias.

[61] Although the binary nature of the endogenous regressor does not affect the reasonableness of the orthogonality assumption, in some cases complications may arise and the models explicitly designed for binary endogenous variables should be used in favor of IV model. Heckman (1997) examined the use of the IV approach to estimate the treatment effects and concluded that the standard argument justifying the use of instruments fails when responses to treatment vary from person to person, unless person-specific responses to treatment do not influence the decision to participate. This condition requires a strong assumption that person's gains from participation (which cannot be predicted from variables in outcome equations) have no influence on their decision to participate.

In the next section I will discuss the results of estimating equation (5.1) using the methods outlined above, along with the tests of endogeneity, instrument validity, and instrument relevance.

6 ESTIMATION RESULTS

6.1 OLS and fixed-effects (FE) models estimation results

Table 7 presents OLS and FE estimation results of equation (5.1) for the total sample (Panel A), firm type subsamples (Panels B-D), loan type subsamples (Panel E), and firm type / loan type subsamples (Panels F-G) using *A-intensity* and its decomposition, *I-intensity* and *T-intensity*. The dependent variable in all models is *Loan Spread*. The key explanatory variables are *T-intensity, I-intensity*, and *Bank Core Dep*, which proxy for a bank's information advantage over non-lenders, willingness to provide liquidity, and ability to provide liquidity, respectively. The six hypotheses, outlined in Section 3, connect these three variables with the dependent variable, *Loan Spread*. Two other variables to which I pay close attention are *A-intensity* and *Bank Size*. *A-intensity* measures a firm's overall reliance on a bank. Although *A-intensity* is used as a proxy for a bank's information advantage in Schenone (2010) and Bharath et al (2011), I use *I-intensity* for this purpose. I run each regression with *A-intensity* and with *T-intensity* and *I-intensity* to assess the effect of decomposition and to obtain the estimates that are comparable with the above studies. *Bank Size* is a proxy for a variety of bank characteristics, as it was discussed in Section 3.

Panel A of Table 7 reports the results for the total sample using *A-intensity*. In the baseline OLS specification, the *A-intensity* coefficient is 6.44***. The coefficient size implies that a one-standard deviation increase in *A-intensity* (which is 0.441 in Table 5) increases loan spread by 2.84 bps. Including interaction terms of *A-intensity* and firm type dummies increases the *A-intensity* coefficient to 7.58***, and it drops to 5.33*** in the bank FE model and to 2.04** in the firm FE model without interaction terms. When interaction terms are included, the firm FE coefficient becomes insignificant (1.50^{NS}). Low magnitude and insignificance of *A-intensity* in firm FE model is likely attributable to the FE estimation procedure. First, FE estimates are in general less efficient than OLS because FE procedure uses only *within-firm* variation (i.e., ignores cross-sectional firm variation). The loss of efficiency is reflected in the R-square, which is 0.523 in column 1 (OLS) and 0.250 in column 5 (firm FE). Second, the firms with only one observation in the sample do not contribute to the computation of the estimate because they have no "within" variation. As a result, FE estimates exclude the impact of one-observation firms. In my case, 21.1% of the firms in the total sample (and 24.7%, 15.5%, and 20.4% in the firm type subsamples) have only one observation. Thus, the firm FE coefficient on *A-intensity* eliminates the impact of 21.1% of firms. Comparing OLS and FE subsample results (Panel C) shows that a drop in the *A-intensity* coefficient is pronounced most for Type 1 and least for Type 2 firms, consistent with the different proportions of "non-contributing" firms in these subsamples. Why do some firms in my sample have only one or just a few observations? [62] [63] There could be many reasons, from going out of business to data censoring. However, it is likely that one of the main reasons is that my sample is limited to the loans of the top 150 U.S. banks. As I have mentioned in the data section, there are 1,189 U.S. banks in Dealscan that assumed a lead role at least once during my study period, but only a fraction of these banks is included in my analysis. The one-observation firms in my sample could be borrowing from those smaller banks that I exclude. If there is some systematic difference between the firms that rely on large and small banks, this could explain the coefficient size change. A simple descriptive analysis of the one-observation firms shows that they are smaller and borrow lower amounts as compared to the multiple-observation firms. Almost 70% of the one-observation firms are Type 1 (vs. 56% for the other firms), only 14% have the S&P senior debt rating (vs. 58% for the other firms), and their average loan size is \$0.10 billion (vs. \$0.47 billion for the other firms). For the one-observation firms that have Compustat data, the average (median) total assets are \$0.51 (\$0.13) billions, as compared to \$5.11 (\$1.49) billions for the multiple-observation Compustat firms. Overall, while some of the loss in the magnitude and significance of the *A-intensity* coefficient could be a result of controlling for time-invariant firm unobservables, e.g., unobservable credit quality, corporate governance structure, or managerial talent, it is more likely to be

[62] Some of the one-observation firms in the subsamples could be a result of switching between the subsamples as time goes by. For example, a firm is reclassified from being Type 1 to Type 3 after the IPO.

[63] When a reason for the "missingness" of data in the unbalanced panel is not correlated with the idiosyncratic error in (5.2), the resulting exclusion of some units from the estimation is not a problem. However, if the attrition is correlated with the time-variant unobservable characteristics, it results in sample selection problem and the within estimator will be biased (Wooldridge, 2006).

caused by the exclusion of the smallest firms. Firm FE estimates apply only to the top 75 to 85% percent of the sample firms in terms of their size/transparency. With that in mind, I put more emphasis on the OLS estimates in the discussion that follows.

Panel B uses *A-intensity* decomposition. *Loan Spread* increases in *I-intensity* and decreases in *T-intensity* in all specifications, and the OLS coefficients are economically and statistically significant at 11.71*** and -37.04***, respectively. One-standard deviation increase in *I-intensity* (which is 0.438 in Table 5) increases *Loan Spread* by 5.13 bps, and one-standard deviation increase in *T-intensity* (which is 0.194 in Table 5) decreases *Loan Spread* by 7.19 bps. Firm FE estimates are also highly significant, albeit lower in magnitudes (3.66*** and -9.55***). [64]

Regarding the bank variables, in Panels A and B, *Loan Spread* increases in *Bank Core Dep* in OLS models and firm FE models, and in *Bank Size* in firm FE models. The effect of *Bank Size* is consistent with the conjecture in Section 3 that bank size is more valuable for relatively large firms with limited sources of financing. Bank variables are not significant in bank FE models, where their coefficients are obtained from the *within-bank* variation, suggesting that loan spreads charged by *that* bank do not change as it grows in size or becomes more reliant on core deposits. However, firm FE results suggest that when *that* relatively large firm borrows from a larger or more "able" bank, it pays higher loan spreads.

To get a clearer picture of the differences between the firm types, I run regressions on the firm type subsamples (Panels C and D). All models are the same as in Panels A and B, except I exclude firm type indicators. For Type 2 and Type 3 firms, I estimate the models with and without Compustat controls.

[64] One interesting result in Panels A and B is that OLS coefficients on Type 1 and Type 2 firm dummies are negative and statistically significant. However, in the firm FE models the Type 2 firm dummy coefficient becomes insignificant, while the Type 3 firm dummy coefficient remains significant and increases in magnitude. Thus, after we account for firm unobservables and exclude relatively small firms, the difference in loan spread that is attributable to firm type is "erased" between Type 1 and Type 2 firms, but Type 3 firm status still matters and is associated with lowers spreads.

Their exclusion allows for a more direct comparison with Type 1 subsample results, whereas their inclusion allows for assessing the impact of not being able to include them for Type 1 firms. In Panel E, I analyze the loan type subsamples, and in Panels F and G, I look at the firm type/loan type subsamples (here, I report only OLS estimates.) For compactness of presentation, I extract five key variables of interest for OLS and firm FE models from Panels A-D and present them in Figure 2.[65]

Figure 2. OLS and firm FE results from Table 7, panels A-D.

	Total sample		**Type 1 firms**		**Type 2 firms**				**Type 3 firms**			
Compustat controls	excluded		excluded		excluded		included		excluded		included	
	OLS	Firm FE	OLS	Firm FE	OLS	Firm FE	OLS	Firm FE	OLS	Firm FE	OLS	Firm FE
Aggregate intensity												
A-intensity	6.44***	2.04**	6.75***	1.30	1.76	1.23	2.44	1.31	8.34***	3.40	6.82**	2.86
Bank Size	0.16	1.39***	0.06	1.33***	1.80**	1.92***	1.64**	1.80***	-1.65	-0.12	0.20	0.21
Bank Core Dep	7.12*	7.92**	15.88***	10.01**	3.30	4.64	2.01	3.99	-5.36	6.73	4.65	6.42
R-sq. adj.	0.523	0.25	0.508	0.229	0.572	0.326	0.612	0.349	0.469	0.253	0.514	0.281
Decomposed intensity												
I-intensity	11.71***	3.66***	12.80***	2.97**	5.89**	2.97	5.95***	3.21*	10.06***	3.66*	7.77***	3.27
T-intensity	-37.04***	-9.55***	-48.11***	-11.39**	-17.39***	-6.10*	-13.76***	-6.63**	-28.11**	-1.63	-12.90	-5.09
Bank Size	0.33	1.46***	0.18	1.39***	1.95**	2.01***	1.73**	1.89***	-1.47	-0.10	0.27	0.24
Bank Core Dep	7.22*	7.98**	15.67***	9.94**	3.37	4.72	2.02	4.07	-5.27	6.78	4.63	6.50
R-sq. adj.	0.523	0.250	0.515	0.230	0.574	0.326	0.614	0.350	0.470	0.253	0.514	0.281

The OLS coefficient on *A-intensity* is positive and significant in the Type 1 and Type 3 subsamples (6.75*** and 8.34***), and low and insignificant in the Type 2 subsample (1.76 ^{NS}). Without seeing the results of *A-intensity* decomposition, these coefficients would be somewhat puzzling if we interpreted *A-intensity* as a measure of a bank's information advantage (Schenone, 2010; Bharath et al, 2011), as they would suggest that the hold-up problem is most severe among the most transparent firms (Type 3), which is counterintuitive. Using *A-intensity* decomposition shows that it is most severe for the least transparent firms (Type 1), although the difference between Type 1 and Type 3 firms is not very large. In addition, based on *A-intensity* we would conclude that information rents extractions are not

[65] To stay focused on the differences between the firm types, I do not go into the detailed explanation of the results in Panels E-F of Table 7. The highlight is that the effect of intensities and bank variables on loan spreads is generally stronger for non-CP backups than for CP backups, and that none of these variables has an impact on CP backups of firms with public equity (Type 3).

relevant for Type 2 firms. However, the coefficient on *I-intensity,* which I argue is a better measure of bank's information advantage than *A-intensity,* suggests otherwise. The fact that it is lower for Type 2 firms than for Type 3 firms, even though the former are less transparent, could be because non-lenders believe that Type 2 firms are more likely to have "legitimate" reasons to form new bank relationships because their current bank does not meet their borrowing needs or is unable to provide access to capital markets. The coefficient on *T-intensity* is negative and significant in the total sample and in the subsamples and has the same order of magnitude between the subsamples as *I-intensity*. The main impact of controlling for Compustat variables is that *T-intensity* becomes insignificant for Type 3 firms. Overall, *A-intensity* decomposition suggests that *Loan Spread* increases in a bank's information advantage (*I-intensity*) for all firms and decreases in a bank's willingness to provide liquidity (*T-intensity*) for firms without public equity (Types 1 and 2). The overall effect of relationships on loan spreads is a net effect of a spread-increasing bank's information advantage and spread-decreasing bank's willingness (for Type 1 and Type 2 firms). For example, for Type 1 firms one-standard deviation increase in *I-intensity* (which is 0.443 in Table 5) increases loan spread by 5.67 bps, and one-standard deviation increase in *T-intensity* (which is 0.186 in Table 5) decreases loan spread by 8.95 bps.

Regarding the bank variables, the results are similar whether *A-intensity* or its decomposition is used. *Loan Spread* increases in *Bank Core Dep* only among Type 1 firms (15.88***) hence the significance of *Bank Core Dep* in the total sample is driven by Type 1 firms. For these firms, one-standard deviation increase in *Bank Core Dep* (which is 0.147 in Table 2) increases loan spread by 2.33 bps. This suggests that, consistent with Hypothesis 6, the opaque firms pay more to the banks with a greater ability to provide liquidity because such firms are more likely to face line access restrictions and credit rationing. This conjecture is also supported by the means and medians of *Lend. Standards* variable (Panel A of Table 2). Compared to Type 2 and Type 3 firms, Type 1 firms obtain their loans in times of higher credit availability, and there is no obvious reason why it would be driven by loan demand.

Loan Spread increases in *Bank Size* only among Type 2 firms and among relatively large Type 1 firms (because firm FE estimate is significant and OLS estimate is not), consistent with Hypothesis 7. Since Type 3 firms have public equity and may benefit from the bank's reputation through certification effect, and yet for them *Bank Size* is not significant, it appears that bank size may be a better proxy for lending capacity and access to capital markets than for reputation, at least in my sample. In sum, Type 1 firms pay a premium for a bank's ability and Type 2 firms pay a premium for bank size. The OLS and FE results of this section can be summarized as follows:

- Consistent with Hypotheses 1 and 2, loan spreads decrease in a bank's willingness to provide liquidity (*T-intensity*) in the total sample, and especially among the firms without public equity (Types 1 and 2).
- Consistent with Hypotheses 3 and 4, loan spreads increase in a bank's information advantage (*I-intensity*) in the total sample and for all firm types, including the firms with public equity (Type 3).
- Consistent with Hypotheses 5 and 6, loan spreads increase in a bank's ability to provide liquidity (*Bank Core Dep*) in the total sample and among Type 1 firms.
- Consistent with Hypothesis 7, loan spreads increase in *Bank Size* among the relatively large firms without public equity (Type 2). Bank size may be a better proxy for lending capacity and access to capital markets than for reputation.

6.2 Treatment Effects (TE) model estimation results

While OLS accounts for the factors that are not explicitly included in the regression through the residual, it does not account for the endogeneity of regressors. In my analysis, it can become a material concern if the borrower's loan spread (*Loan Spread*) and the loan being a CP backup as opposed to a non-CP backup (*CP Backup*) are determined by some unobservable characteristics of the borrower and the bank. If these unobservables both make it more likely that the borrower obtains a CP backup and that it pays a lower loan spread, the magnitude of the effect that *CP Backup* has on *Loan Spread* in equation (5.1) will be overestimated by OLS. In addition, in linear models the endogeneity of a regressor distorts not only its own coefficient, but also the coefficients of other regressors that it is correlated with. Since *CP Backup* is highly correlated with *T-intensity*, the key variable of interest in my analysis that measures a borrower's reliance on a bank for meeting its liquidity needs and proxies for a bank's willingness to provide liquidity, the endogeneity of the CP backup choice can lead to a distortion of the *T-intensity* coefficient.

Treatment effects (TE) model, which was briefly discussed in Section 5.3, is used to address the endogeneity of a binary regressor. While the instrumental variables (IV) model can also be used, TE model is specifically designed for the case when the endogenous variable is binary and hence is more suitable for my analysis. TE model involves estimation of two equations, first-stage and second-stage. In the first-stage equation, the dependent variable is a binary endogenous regressor. In the second-stage equation, the dependent variable and the regressors are the same as in OLS. These two equations are estimated either sequentially (two-step procedure) or simultaneously (maximum likelihood (ML) procedure). For short, I will refer to these methods as TE-2step and TE-ML. It should be noted that, unlike IV model, TE model does not require an instrument (however, when a good instrument is available it should be included). Also, unlike IV model, TE model does not require that the regressors in the first-stage equation be the instruments and the exogenous variables from OLS, not less and not more. In TE model, first-stage equation can include any variables that are believed to affect the binary outcome.

TE-2step procedure estimates first-stage equation to determine the probability that the endogenous binary variable is equal to 1 and then adjusts the sample moments of the second-stage regression to generate unbiased estimates (Campa and Kedia, 2002; Fang, 2005). The shortcoming of TE-2step is that is does not permit to correct the second-stage regression's standard errors for heteroskedasticity (Ross, 2010). TE-ML procedure proposed by Maddala (1983) is very similar to TE-2step but it estimates both equations simultaneously and allows for the standard errors' correction. It is also more efficient than TE-2step when model assumptions are met, but it is not consistent, and sometimes fails to converge. To get a good sense of the results' robustness to the choice of procedure and standard errors, I use TE-2step (with default errors) and TE-ML (with default and corrected errors), which I refer to as TE-2step/default, TE-ML/default, and TE-ML/corrected.

I propose three instruments, (1) the average level of short-term debt in borrower's industry (*ST Debt Ind)*, (2) the borrower's prior reliance on CP backups, as defined in (4.4) (*CPB Reliance)*, and (3) the "paper-bill spread", the measure of tightness of the commercial paper market (*CP Spread*). The theory suggests that good instruments must meet the validity and relevance criteria (see Section 5.3.1). Instrument is valid if it explains some variation of (i.e., is correlated with) the endogenous regressor, but does not affect the outcome variable in any way other than through the endogenous regressor. In my case, the instrument should affect the borrower's propensity to get a CP backup, but should not directly affect the loan spread. I conduct the Hansen-J test for instrument validity and conclude that the first two instruments meet the validity criteria. Instrument is relevant if the correlation between the instrument and the endogenous variable is sufficiently high, controlling for the effects of other second-stage regressors. Weak correlation may result in a low precision of estimation and small sample bias (even in the seemingly large samples; see footnote 60). I use various tests of instrument relevance, namely the Anderson canonical correlations test, the redundancy test of Hall and Peixe (2000), the Shea's partial R-squares, and the instruments' joint significance tests of Bound, Jaeger, and Baker (1995), Staiger and Stock (1997), and Stock and Yogo (2005), and conclude that only *CPB Reliance*, the second instrument, is relevant. I use *CPB Reliance* in all TE model specifications. Panels A and B of Table 8 show the tests' results. Detailed description of the instruments, the tests, and the tests' results discussion are provided in Appendix 3.

Correcting for endogeneity is necessary only if it is present, and there are different ways to test for its presence. One approach is to conduct a Darbin-Wu-Hausman (DWH) endogeneity test in the IV model framework. Another one is to examine the coefficient on parameter λ of TE-2step models, which is the extra term added to the second-stage regression to adjust its sample moments. Yet another way, in TE-ML models, is to examine the sign and significance of ρ, the correlation between the error terms of the first-stage and second-stage regressions. The DWH test suggests that *CP Backup* is endogenous in the total sample and in the Type 1 and Type 2 subsamples, but not in the Type 3 subsample (the test is discussed in Appendix 3 and the test results are reported in Panel C of Table 8). Parameter ρ in all TE-ML model specifications suggests that endogeneity is present in the total sample and in all three subsamples. Parameter λ in some TE-2step model specifications (namely, when I use decomposed intensity and include Compustat controls) suggests that in the Type 2 and Type 3 subsamples endogeneity is not present. Overall, it appears that endogeneity is present in the total sample and Type 1 subsample, and that it may be weaker in the Type 2 and Type 3 subsamples, especially in the Type 3 subsample.

Table 9 reports side by side estimation results for TE model and OLS and firm FE models. (OLS and firm FE results were reported in Table 7, but I repeat them for the ease of comparison.) In the first-stage equation of the TE model, the dependent variable is *CP backup*, and the explanatory variables are the instrument (*CPB Reliance*), the firm and bank characteristics that were used in OLS, the intensity measures, and the calendar year dummies.[66] The loan characteristics are not included because they should not affect the loan type choice. In the second-stage equation, all variables are the same as in OLS.

Table 9 includes six panels, A through F. All panels contain sets of six columns that correspond to the following combinations of models and standard errors: (1) OLS/corrected, (2) OLS/default, (3) TE-ML/corrected, (4) TE-ML/default, (5) TE-2step/default, and (6) firm FE/corrected. Comparing the results between these six approaches shows the impact of the estimation method (OLS, TE-ML, TE-2step, or firm FE) and of not correcting errors in cases where correction is possible (OLS and TE-ML).[67] The first six columns of each panel use *A-intensity*, and the next six columns use its decomposition, *T-intensity* and *I-intensity*. Panels A and B correspond to the total sample and the Type 1 subsample, both without Compustat controls. Panels C and D, and E and F, correspond to the Type 2 and Type 3 subsamples,

[66] The results are robust to the exclusion of intensities and to the inclusion of industry dummies and lending environment characteristics (lending standards, default spread, and term spread) in the first-stage equation.

[67] In TE-2step approach, standard errors cannot be corrected. In firm FE approach, standard errors are naturally clustered on the firm level and the Stata procedure adjusts them for heteroskedasticity by default.

without and with Compustat controls. In the Type 3 subsample, the ML procedure did not perform well in some specifications. In columns 3 and 8 of Panel E and in column 3 of Panel F, standard errors could not be computed due to the “non-symmetric of highly singular” variance matrix. In columns 8 and 9 of Panel F, the ML procedure failed to converge and was stopped after 15 iterations. Although standard errors are reported, the results should be interpreted with caution. The abovementioned columns are highlighted.

The contents of Table 9 are somewhat difficult to navigate. For convenience of presentation, I extract the coefficients of the five key regressors and present them in Figure 3 (total sample and Type 1 subsample), Figure 4 (Type 2 subsample), and Figure 5 (Type 3 subsample). Before discussing the results, the following should be noted about TE-2step and TE-ML. First, in all models, as compared to the TE-ML coefficients, the TE-2step coefficients on *I-intensity* and *T-intensity* are closer in magnitudes to OLS results. Thus, TE-ML finds more bias in OLS results than does TE-2step. Second, TE-2step/default and TE-ML/default for most part are in agreement about the coefficients’ statistical significance.[68] Thus, it is the absence of standard errors correction and not the difference in methods (ML vs. two-step) that is responsible for the difference in the significance levels of the TE-2step/default and the TE-ML/corrected coefficients. In terms of significance, the TE-ML/corrected coefficients are probably more reliable than the TE-2step/default coefficients.

[68] The three cases where they do not agree correspond to the second-stage coefficients and decomposed intensity. (1) In the total sample, TE-2step suggests high significance of *Bank Core Dep* (0.21***), while TE-ML suggests no significance (0.21). (2) In the Type 2 subsample, without Compustat controls, TE-2step suggests high significance of *T-intensity* (-11.74***), while TE-ML suggests no significance (-2.01). (3) In the Type 1 subsample, TE-2step suggests no significance of *T-intensity* (-0.10), while TE-ML suggests high significance (-0.17**).

Figure 3. Key estimates extracted from Table 9, Panels A and B TE, OLS, and firm FE results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Model	**OLS**		**TE-ML**		**TE-2step**	**Firm FE**	**OLS**		**TE-ML**		**TE-2step**	**Firm FE**
Std. errors	**correct**	**deflt**	**correct**	**deflt**	**deflt**	**correct**	**correct**	**deflt**	**correct**	**deflt**	**deflt**	**correct**

Total sample, without Compustat controls

Stage 2 regression, dependent variable is ***Loan Spread***												N Obs. = 45770
A-intensity	6.44***	***	7.45***	***	7.26***	2.04**						
I-intensity							11.71***	***	9.81***	***	11.02***	3.66***
T-intensity							-37.04***	***	-13.09***	***	-28.49***	-9.55***
Bank Size	0.16		0.19		0.17	1.39***	0.33		0.26		0.30	1.46***
Bank Core Dep	7.12*	**	7.92*	**	7.70**	7.92**	7.22*	**	7.85*	**	7.43**	7.98**
R-sq.	0.524					0.250	0.524					0.251
Stage 1 regression, dependent variable is ***CP Backup***												
A-intensity			-0.01		-0.02							
I-intensity									-0.03		-0.03	
T-intensity									-0.01		0.02	
Bank Size			0.03**	***	0.04***				0.03**	***	0.03***	
Bank Core Dep			0.21***	***	0.21***				0.21***		0.21***	
rho			0.429		0.348				0.377		0.138	
Prob(rho=0)			0.000						0.000			
lambda			34.55***	***	27.90***				30.19***	***	10.87***	
Pseudo R-sq.			0.345		0.345				0.345		0.345	

Type 1 firm subsample, without Compustat controls

Stage 2 regression, dependent variable is ***Loan Spread***												N obs. = 25301
A-intensity	6.75***	***	7.72***	***	7.60***	1.30						
I-intensity							12.80***	***	10.77***	***	12.06***	2.97**
T-intensity							-48.11***	***	-21.08***	***	-38.22***	-11.39**
Bank Size	0.06		0.05		0.05	1.33***	0.18		0.12		0.16	1.39***
Bank Core Dep	15.88***	***	15.57***	***	15.52***	10.01**	15.67***	***	15.48***	***	15.57***	9.94**
R-sq.	0.509					0.229	0.516					0.230
Stage 1 regression, dependent variable is ***CP Backup***												
A-intensity			-0.04		-0.04							
I-intensity									-0.03		-0.02	
T-intensity									-0.17	**	-0.10	
Bank Size			0.02	**	0.03**				0.03*	**	0.03**	
Bank Core Dep			0.11		0.10				0.11		0.10	
rho			0.486		0.415				0.425		0.159	
Prob(rho=0)			0.000						0.000			
lambda			40.95***	***	34.80***				35.47***	***	13.03***	
Pseudo R-sq.			0.342		0.342				0.342		0.342	

The following summarizes Figure 3:

- In the total sample and among Type 1 firms, TE results are not qualitatively different from OLS results. However, it should be stressed that Compustat controls were not included.
- Second-stage TE estimates of intensities have lower absolute values than OLS estimates, especially for *T-intensity*. For bank variables, TE and OLS results are very similar.
- Probability of CP backup increases in *Bank Size* and *Bank Core Dep* in the total sample, and in *Bank Size* in the Type 1 subsample. Intensities do not matter.
- Overall, the main effect of correcting for endogeneity is that *T-intensity* becomes lower in magnitude. However, it remains large and significant.

Figure 4. Key estimates extracted from Table 9, Panels C and D — TE, OLS, and firm FE results

Type 2 firm subsample, <u>without</u> Compustat controls.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Model	**OLS**		TE-ML		**TE-2step**	**Firm FE**	**OLS**		TE-ML		**TE-2step**	**Firm FE**
Std. errors	**correct**	**deflt**	correct	**deflt**	**deflt**	**correct**	**correct**	**deflt**	correct	**deflt**	**deflt**	**correct**
Stage 2 regression, dependent variable is ***Loan Spread***												N obs. = 11800
A-intensity	1.76		3.16	**	2.77*	1.23						
I-intensity							5.89**	***	4.17*	**	5.26***	2.97
T-intensity							-17.39***	***	-2.01		-11.74***	-6.10*
Bank Size	1.80**	***	1.80**	***	1.79***	1.92***	1.95**	***	1.84**	***	1.91***	2.01***
Bank Core Dep	3.30		5.91		5.15	4.64	3.37		5.75		4.24	4.72
R-sq.	0.573					0.326	0.576					0.326
Stage 1 regression, dependent variable is ***CP Backup***												
A-intensity			0.06		0.06							
I-intensity									0.00		0.01	
T-intensity									0.22*	***	0.20**	
Bank Size			0.03	*	0.03**				0.03	*	0.03**	
Bank Core Dep			0.44***	***	0.44***				0.43***	***	0.43***	
rho			0.335		0.243				0.314		0.118	
Prob(rho=0)			0.000						0.000			
lambda			22.32***	***	16.10***				20.86***	***	7.74***	
Pseudo R-sq.			0.310		0.310				0.310		0.310	

Type 2 firm subsample, <u>with</u> Compustat controls.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Stage 2 regression, dependent variable is ***Loan Spread***												N obs. = 11799
A-intensity	2.44	*	3.88*	***	2.81**	1.31						
I-intensity							5.95***	***	9.47***	***	6.21***	3.21*
T-intensity							-13.76***	***	-51.34***	***	-16.59***	-6.63**
Bank Size	1.64**	***	1.41*	***	1.58***	1.80***	1.73**	***	2.70***	***	1.80***	1.89***
Bank Core Dep	2.01		4.31		2.59	3.99	2.02		-4.68		1.56	4.07
R-sq.	0.614					0.349	0.615					0.350
Stage 1 regression, dependent variable is ***CP Backup***												
A-intensity			0.08	*	0.08**							
I-intensity									-0.07	*	0.02	
T-intensity									0.70***	***	0.24***	
Bank Size			0.01		0.01				-0.00		0.01	
Bank Core Dep			0.42***	***	0.42***				0.29**	**	0.41***	
rho			0.353		0.093				-0.894		-0.075	
Prob(rho=0)			0.000						0.000			
lambda			22.40***	***	5.84***				-63.18***	***	$\boxed{-4.65}$	
Pseudo R-sq.			0.356		0.356				0.355		0.355	

The following summarizes Figure 4:

- For Type 2 firms, it matters if Compustat controls are included. If they are not included, TE estimates have smaller absolute values than OLS estimates (ρ>0). If they are included, TE estimates have larger absolute values than OLS estimates (ρ<0).[69] For bank variables, TE and OLS estimates are similar.
- Probability of CP backup increases in *Bank Core Dep* and *T-intensity*.
- Overall, the main effect of correcting for endogeneity is that the magnitudes of *I-intensity* and *T-intensity* are larger than in OLS, if we rely on results with Compustat controls. Without Compustat controls, the effect of *I-intensity* is still there but *T-intensity* becomes insignificant.

---

[69] TE-2step model with decomposed intensity suggests no endogeneity (λ is -4.65^{NS}), while TE-ML model suggests that endogeneity is present (at -0.894, ρ is large and significant).

Figure 5. Key estimates extracted from Table 9, Panels E and F — TE, OLS, and firm FE results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Model	**OLS**		TE-ML		**TE-2step**	**Firm FE**	**OLS**		TE-ML		**TE-2step**	**Firm FE**
Std. errors	**correct**	**deflt**	correct	**deflt**	**deflt**	**correct**	**correct**	**deflt**	correct	**deflt**	**deflt**	**correct**

Type 3 firm subsample, <u>without</u> Compustat controls.

Stage 2 regression, dependent variable is ***Loan Spread*** — N Obs. = 8669

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A-intensity	8.34***	***	8.39	***	8.39***	3.40						
I-intensity							10.06***	***	8.91	***	9.10***	3.66*
T-intensity							-28.11**	***	-2.76		-6.99	-1.63
Bank Size	-1.65	**	-1.49	**	-1.50**	-0.12	-1.47	*	-1.45	*	-1.45*	-0.10
Bank Core Dep	-5.36		-5.64		-5.65	6.73	-5.27		-5.60		-5.55	6.78
R-sq.	0.472					0.253	0.473					0.253

Stage 1 regression, dependent variable is ***CP Backup***

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A-intensity			-0.04		-0.05							
I-intensity									-0.03		-0.05	
T-intensity									-0.07		-0.04	
Bank Size			0.03		0.04				0.03		0.04	
Bank Core Dep			0.17		0.16				0.17		0.16	
rho			0.298		0.292				0.274		0.229	
Prob(rho=0)			0.000						0.000			
lambda			24.05***	***	23.56***				22.08***	***	18.45***	
Pseudo R-sq.			0.380		0.380				0.380		0.380	

S.E.'s are NA (column 3) — S.E.'s are NA (column 9)

Type 3 firm subsample, <u>with</u> Compustat controls.

Stage 2 regression, dependent variable is ***Loan Spread*** — N Obs. = 8636

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A-intensity	6.82**	***	7.11	***	6.95***	2.86						
I-intensity							7.77***	***	7.22**	***	7.63***	3.27
T-intensity							-12.90	*	4.66		-8.42	-5.09
Bank Size	0.20		0.14		0.17	0.21	0.27		0.15		0.24	0.24
Bank Core Dep	4.65		3.94		4.33	6.42	4.63		3.96		4.46	6.50
R-sq.	0.517					0.281	0.517					0.281

Stage 1 regression, dependent variable is ***CP Backup***

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A-intensity			0.05		0.02							
I-intensity									0.07		0.03	
T-intensity									-0.05		-0.05	
Bank Size			-0.02		-0.01				-0.02		-0.01	
Bank Core Dep			0.18		0.16				0.18		0.16	
rho			0.256		0.121				0.249		0.064	
Prob(rho=0)			0.000						0.003			
lambda			19.80	***	9.35***				19.28***	***	$\boxed{4.96}$	
Pseudo R-sq.			0.454		0.454				0.454		0.454	

S.E.'s are N/A (column 3) — ML did not converge (columns 9 and 11)

The following summarizes Figure 5:

- For Type 3 firms, correcting for endogeneity, with or without Compustat controls, (1) does not "kill" the magnitude and significance of *I-intensity* and (2) "kills" *T-intensity* (even when default errors are used).
- It should be noted that, even though DWH endogeneity test suggests no endogeneity in the Type 3 subsample, parameters ρ and λ suggest otherwise in some specifications. [70]
- Probability of CP backup is not affected by bank variables or intensities.
- Overall, the main effect of correcting for endogeneity is that *T-intensity* becomes insignificant.

[70] Similar to Type 2 firm results in Figure 4, TE-2step model with decomposed intensity suggests no endogeneity (λ is -4.96), while the corresponding TE-ML model suggests that it is present (at 0.249, ρ is large and significant).

To summarize the above results, endogeneity correction did not affect the coefficients on *I-intensity*, *Bank Core Dep*, and *Bank Size*. There were some changes in magnitudes, but no dramatic changes in significance. In the Type 2 and Type 3 subsamples, where it is possible to compare the results with and without Compustat controls, adding Compustat controls did not cause any dramatic changes either.

As expected, since *T-intensity* and *CP Backup* are correlated, endogeneity correction affected the *T-intensity* coefficients. In the Type 2 subsample, inclusion of Compustat controls is critical. Without them, endogeneity correction "kills" the *T-intensity* coefficient's magnitude and significance. With them, the *T-intensity* coefficient's magnitude increases and its significance remains high. Because controlling for Compustat variables when they are available is preferred, I conclude that for Type 2 firms, *T-intensity* has even stronger effect than what OLS results suggest. In the Type 3 subsample, endogeneity correction "kills" the *T-intensity* coefficient, with or without Compustat controls. (TE-ML results should be interpreted with caution because the ML procedure did not converge, while TE-2step results are reliable.)

Given the different effect that inclusion of Compustat controls had in the Type 2 and Type 3 subsamples, how would the Type 1 subsample results be affected if financial variables were available? Would their inclusion "kill" the *T-intensity* coefficient as it did in the Type 3 subsample, or would it strengthen it as in the Type 2 subsample? I believe that it would be strengthened because for Type 1 firms, similar to Type 2 firms, in the absence of Compustat variables controlling for endogeneity did not "kill" *T-intensity* as it did for Type 3 firms. Same reasoning applies to the total sample.

In what follows, I summarize the entire Section 6, including the OLS, FE, and TE results. Since there are two dimensions that I am considering, the four explanatory variables and the three types of borrowers, I first summarize the results by explanatory variable and then by type of borrower. After that, I provide a short summary of the paper's key findings.

For short, I will refer to a bank's willingness to provide liquidity (*T-intensity*) simply as "willingness" and to a bank's ability to provide liquidity (*Bank Core Dep*) simply as "ability". When loan spread increases in bank's ability and size, I will refer to it as "ability premium" and "size premium". When spread decreases in bank's willingness, I will refer to it as "willingness discount". When spread increases in bank's information advantage (*I-intensity*), I will refer to it as "hold-up premium".

Summary of results by explanatory variable:

***T-intensity* (bank's willingness to provide liquidity).** Loan spreads decrease in *T-intensity* in the total sample and among the firms without public equity (Types 1 and 2). This willingness discount applies to CP backups and non-CP backups alike. [71] The firms with public equity (Type 3) do not enjoy this discount. Whether the willingness discount is higher for Type 1 or Type 2 firms is not clear since Compustat controls are not available for the former. Although their inclusion would likely increase the willingness discount, it is not clear by how much. Without them, the willingness discount is higher for Type 1 firms. These results support Hypotheses 1 and 2: the willingness discount is present in the total sample and increases in a firm's opaqueness because opaque firms are more likely to face line access restrictions (Barakova and Parthasarathy, 2012) and to have difficulty getting new loans (Demiroglu, James, and Kizilaslan, 2012).

***I-intensity* (bank's information advantage over non-lenders).** Loan spreads increase in *I-intensity* in the total sample and all subsamples. This suggests that the hold-up premiums are paid by all firms, including the ones with public equity (Type 3). They are paid on non-CP backups by Compustat firms (Types 2 and 3) and on CP backups and non-CP backups by non-Compustat firms (Type 1). The hold-up premiums are highest for Type 1, followed by Type 3 and Type 2 firms, based on the estimates without Compustat controls. Including them brings Type 2 and Type 3 firms closer to each other in terms of the

[71] See Panels E, F, and G of Table 7 for this and further references as to how the identified effects apply to the loan spreads of CP backups and non-CP backups.

hold-up premiums that they pay. These findings strongly support Hypotheses 3 and 4. However, finding the hold-up premiums for the firms with public equity (Type 3) contradicts the results of Schenone (2010) and Bharath et al (2011). This divergence is discussed in the robustness checks in the next section.

***Bank Core Dep* (bank's ability to provide liquidity).** Loan spreads increase in *Bank Core Dep* in the total sample and among Type 1 firms. Thus, non-Compustat firms (Type 1) are the only category that pays the ability premium, and it is paid on non-CP backups. This finding supports Hypotheses 5 and 6 and is consistent with Ivashina and Scharfstein (2010) and Cornett et al (2011) who find that a reliance on core deposits helped banks to sustain new lending during the recent financial crisis, and Barakova and Parthasarathy (2012) and Demiroglu, James, and Kizilaslan (2012) who find that opaque firms are more likely to face line access restriction and to be credit rationed.

***Bank Size* (bank's reputation, lending capacity, capital market access, and perceived risk).** Loan spreads increase in *Bank Size* only among Type 2 firms. Type 2 firms are characterized by large size, large loan amounts, and no access to equity markets (only Type 3 firms have it).[72] This suggests that Type 2 firms pay the size premium for a bank's lending capacity, access to capital markets, and possibly reputation (to benefit from the certification effect in the event they issue public securities). Type 3 firms may benefit from the certification effect on the existing securities. However, they do not pay the size premium, suggesting that the bank size is a better proxy for lending capacity and capital market access than for reputation.

With respect to the probability of obtaining a CP backup, based on the first-stage results reported in Figures 3-5 and in Table 9, it increases in *Bank Size* and *Bank Core Dep* in the total sample and is not affected by intensities. The subsample results show very different patterns. For Type 1 firms, this

[72] The median loan amount is $0.20 billion for Type 2 firms, as compared to $0.11 and $0.10 for Type 1 and Type 3 firms, respectively. The median total assets of Type 2 firms are $1.54 billion, as compared to $0.47 for Type 3 firms (Table 2, Panel A).

probability increases only in *Bank Size*. For Type 2 firms, it increases in *Bank Core Dep* and in *T-intensity*. For Type 3 firms, bank characteristics and intensities do not matter.

Summary of results by borrower type:

- Type 1 (non-Compustat) firms enjoy the willingness discounts and pay the hold-up premiums and ability premiums (but not size premiums). They are more likely to get a CP backup from a larger bank.
- Type 2 (Compustat without public equity) firms enjoy the willingness discounts and pay the hold-up premiums and the size premiums (but not the ability premiums). They are more likely to get a CP backup from a more "able" and "willing" bank.
- Type 3 (Compustat with public equity) firms pay the hold-up premiums. A bank's size, willingness, and ability do not matter.
- In the total sample, the effects are the same as in the Type 1 subsample, except CP backup probability increases not only in bank size, but also in its ability.

Summary of key findings:

- The firms without public equity (Types 1 and 2) enjoy the willingness discounts (i.e., loan spreads decrease in bank's relationship-driven implicit commitment to provide liquidity). In contrast, the firms with public equity (Type 3) do not benefit from it, presumably because they have alternative sources of financing. For them, the relationship-enhanced access to bank-provided liquidity makes no difference.
- All firms, even the ones with public equity (Type 3), pay the hold-up premiums.
- Although a bank's willingness, ability, and size make no difference for the firms with public equity (Type 3), they pay the hold-up premiums.
- The most opaque firms (Type 1) pay the ability premiums and enjoy the willingness discounts. Thus, for such firms, relationships are especially important because they help mitigate the ability premiums which arise because such firms are more likely to face line access restrictions and credit rationing.

- For the large firms with high borrowing needs (Type 2) a bank's willingness and ability increase their propensity to obtain a CP backup, yet they do not pay the ability premiums and even enjoy the willingness discounts. In contrast, a bank size does not influence their loan type choice but they pay the size premiums, suggesting that they see some value in bank size that is unrelated to the provision of liquidity. It could be, for example, a large bank's higher lending capacity or its ability to underwrite securities.

Figure 6 presents a compact summary of my findings with respect to directions and magnitudes of the effects of the four key explanatory variables. The three numbers next to each arrow are the (1) OLS coefficient from the models without Compustat controls, (2) standard deviation of the explanatory variable, and (3) change in loan spread resulting from a one-standard deviation change in the explanatory variable. For example, the OLS coefficient on *T-intensity* in the total sample is -37.04*** (Figure 3), the standard deviation of *T-intensity* is 0.194 (Table 5), and the effect of one standard deviation change in *T-intensity* on *Loan Spread* is, therefore, 7.19 bps. (It should be noted that even though *T-intensity* and *I-intensity* are referred to as a decomposition of *A-intensity*, the sum of their effects reported in Figure 6 is not equal to the effect of *A-intensity.)*

Figure 6. Summary of findings

	Dependent variable is *Loan Spread*				**Dependent variable is *CP Backup***			
	Total Sample	Type 1 Firms	Type 2 Firms	Type 3 Firms	Total Sample	Type 1 Firms	Type 2 Firms	Type 3 Firms
A-intensity	↑ 6.44*** 0.441 +2.84 bps	↑ 6.75*** 0.444 +3.00 bps	--- 1.76 ^{NS} 0.429 +0.76 bps	↑ 8.34*** 0.445 +3.71 bps	---	---	---	---
T-intensity	↓ -37.04*** 0.194 -7.19 bps	↓ -48.11*** 0.186 -8.95 bps	↓ -17.39*** 0.239 -4.16 bps	---	---	---	↑	---
I-intensity	↑ 11.71*** 0.438 +5.13 bps	↑ 12.80*** 0.443 +5.67 bps	↑ 5.89** 0.416 +2.45 bps	↑ 10.06*** 0.442 +4.45 bps	---	---	---	---
Bank Core Dep	↑ 7.22* 0.149 +1.08 bps	↑ 15.67*** 0.147 +2.30 bps	---	---	↑	---	↑	---
Bank Size	---	---	↑ 1.95** 1.39 +2.71 bps	---	↑	↑	---	---

6.3 Robustness checks

6.3.1 Robustness of the *T-intensity* coefficient

It is possible that *T-intensity* measure may be picking up the existence of prior CP backups and not the effect of a bank's willingness to provide liquidity. Only commercial paper issuers obtain CP backups, and such firms are very low risk because exceptional creditworthiness is a requirement to be able to get financing in the commercial paper market. If *T-intensity* captures the effect of a borrower being a commercial paper issuer, the coefficient could be reflecting, for example, a greater transparency of the borrower. I re-estimate the regressions presented in Table 7 adding the dummy variable that equals to 1 if borrower obtained a CP backup loan in the previous five years. I find that the coefficient on *T-intensity* decreases in absolute value but remains statistically and economically significant.

6.3.2 Related studies

Schenone (2010) and Bharath et al (2011) are two recent studies that use Dealscan data to look at the effect of a borrower's reliance/dependency on a bank on loan spreads. Both papers use a measure of relationship strength that is very similar to *A-intensity* and interpret it as a bank's information advantage. Schenone's (2010) measure is based on the number of loans using all borrowers' loans since Dealscan inception to date t. In Bharath et al (2011), the measure is based on the value of loans and the five-year time window prior to time t. These studies do not control for bank's financial variables. Schenone (2010) does not discuss how she defines a lead bank, but the observations in her sample are loan-banks (she controls for Dealscan bank variables, e.g. lender's their share of the loan). Bharath et al (2011) use a more restrictive definition of a lead bank than this paper's, as it was discussed in Section 4 (if I used their definition, I would have 1.12 lead banks per loan, not 1.92 as it is in my data). Also, if a loan has two or more lead banks, they calculate *A-intensity* for each lead bank and assign the highest value to the loan. They call this maximum *A-intensity*-based loan-level measure *REL(value).*

Schenone (2010) studies the pre-IPO and post-IPO loans of firms that went public during 1998-2003 (based on information in the SDC database) and had at least one loan in Dealscan before and after the IPO. Her sample includes only 250 firms. She finds that in the subsample of pre-IPO loans the relationship between loan spread and *A-intensity* is non-linear (U-shaped pattern). At first, the banks decrease loan spreads from the initial levels, but as the relationship progresses they eventually revert and begin to charge higher spreads. In the subsample of post-IPO loans, loan spreads decrease in *A-intensity*. With respect to the pre-IPO loans, it is difficult to tell if our findings are consistent because I do not conduct the kind of analysis that would allow me to confirm or reject the U-pattern. More importantly, Schenone's (2010) pre-IPO subsample of loans is limited to only 97 borrowers, the firms that ended up going public in less than five years after the loan and had at least two pre-IPO loans. Such firms, and their loans, may be systematically different from the firms and loans in my Type 1 and Type 2 subsamples. The "soon-to-be-public" borrowers may be "bigger and better" than the average firm without public equity. With respect to the post-IPO loans, there is no such systematic difference between the loans in her post-IPO subsample and the loans in my Type 3 subsample (although the sample sizes are very different). She finds that for the post-IPO loans spreads decrease in *A-intensity*, while I find the opposite in my Type 3 subsample.

Bharath et al (2011) study a large sample of post-IPO loans (the analogue of my Type 3 subsample) and find that loan spreads decrease in *REL(value)*. Since my empirical specification closely follows theirs and because they also use a large sample, I focus on their paper, not Schenone (2010), in analyzing the source of results' divergence. I attempt to recreate their baseline OLS results (Table 4 in their paper), where the coefficient on *REL(value)* is -10.15***. The most comparable result in my paper is the 6.75*** coefficient on *A-intensity* in the Type 3 firm subsample (Panel C of Table 7).

What are the differences in our data? The most important difference is that my sample is limited to loans from the top 150 U.S. banks. I had to limit the number of banks because I had to manually match them to Call reports and create the histories of mergers and acquisitions. Bharath et al (2011) and

Schenone (2010) adjust for M&A activity, but they do not match the lenders to Call reports. Thus, the sample in Bharath et al (2011) include a large number of loans from relatively small banks that are not a part of my sample. As it was mentioned in Section 4, there is a total 1,189 U.S. banks that assumed a lead role (per my definition) during 1990-2008, and I include only the top 150 banks.

Some other differences are also present. Their definition of a lead bank is more restrictive and the loan level intensity measure, *REL(value)*, is defined as the highest among the lead bank-specific *A-intensities* for a given loan that has multiple leads. Together, these two reasons should make their intensity measures higher than mine for the loans that we both include. Second, their study period is 1986-2003, while mine is 1990-2008. Thus, their data does not include the five pre-crisis years during which there could be a shift in the role and extent of bank-borrower relationships. Third, they do not control for bank variables.

Using the data in my sample, I eliminate the differences between our samples to the extent that I can. I take only post-IPO loans (Type 3 firms), exclude bank variables (*Bank Size* and *Bank Core Dep*), and convert my loan-bank level dataset into a loan-level dataset by calculating *REL(value)* for each loan using their method of taking the maximum of bank-specific *A-intensities* and assigning it to the loan. Of course, since my definition of a lead bank is broader, our values of *REL(value)* for the same loan can be different. However, it is likely a minor issue as their definition of a lead is more restrictive and they, therefore, are likely to include the relatively large syndicate members as lead banks. Such banks are more likely to be a part of my sample and to have a higher *A-intensity* than the other syndicate members that I count as lead banks and Bharath et al (2011) do not. I also limit the data to 1990-2003 and include the exact same control variables as they do, except I do not make the adjustment for real 2000 dollars and include a single indicator of the S&P senior debt rating's presence (*Rated Bank Debt*) as opposed to using multiple dummies for different values of this rating. The resulting data sample that I use to compare our results includes 1260 loans, while their sample includes 13,158 loans. Clearly, the top 150 bank requirement that I impose eliminates a lot of Dealscan loans from the analysis. [73]

Running the OLS regression on a sample of 1260 loans, I obtain the coefficient of 0.55^{NS} on *REL(value)*. When I decompose *REL(value)* into *I-intensity* and *T-intensity* I get the coefficients of 7.15^{NS} and -53.57**. To assess the impact of defining *REL(value)* as the highest of *A-intensities*, I calculate mean-based (as opposed to maximum-based) *REL(value).* The coefficient on the mean-based *REL(value)* is 3.80^{NS}, and for the corresponding *I-intensity* and *T-intensity* they are 10.91^{NS} and -0.91**. Maximum-based or mean-based, the coefficient on *REL(value)* is not significant, although the mean-based coefficient is larger in size and thus closer to the 6.75*** coefficient in my original results for Type 3 firms. Therefore, the results' divergence is somewhat affected by using the maximums of loans' *A-intensities*, as opposed to including all individual *A-intensities*. However, my coefficients (0.55^{NS} and 3.80^{NS}) are still quite far from their coefficient of -10.15*** for maximum-based *REL(value)*.

It does not appear that the difference is driven by the borrowers. The firms in my sample of 1260 loans and in their sample of 13,158 loans are quite similar. [74] Thus, it is likely that the results' difference is attributable to the absence of small banks in my sample. It appears, therefore, that relatively large and active banks impose greater hold-up costs on their borrowers.

---

[73] I have 5,202 loans in my Type 3 subsample, less than a half of 13,158 loans in Bharath et al (2011), even though I have extra five years of data (2003-2008). The difference is the loans from non-Top 150 banks.

[74] Their firms have the following means (medians): total assets of \$2.94 (\$0.36) billions, loan size of \$0.19 (\$0.05) billions, loan spread of 216.53 (212.50) bps, and 27% have a bank debt rating. My firms in the sample of 1260 loans have the following means (medians): total assets of \$.44 (\$0.57) billions, loan size of \$0.19 (\$0.10) billions, loan spread of 216.95 (200.00) bps, and 46.7% have a bank debt rating.

7 CONCLUSION

Using a sample of loans to public and private borrowers of top 150 U.S. banks, I find that bank credit lines have the liquidity insurance value for the firms without public equity. This value increases in a firm's reliance on a bank for meeting its liquidity needs. Greater reliance on a bank translates into a greater bank's willingness to be accommodating and hence greater liquidity insurance value of credit lines. The underlying mechanism of this effect is the bank's reputational considerations. To be able to access the existing credit line, a borrower must be in compliance with financial covenants. When violations occur (and the evidence suggests that it happens often), credit line access becomes conditional upon a bank's willingness to accommodate the borrower. A bank wants to lower its liquidity and credit risks but at the same time values its reputation as accommodating lender and, therefore, views the access restriction decision as a trade-off between reputational and financial capital. A bank's willingness to accommodate the borrower increases in the strength of the bank-borrower relationship because imposing restrictions on a loyal customer causes greater reputational damage.

I find that loan spreads of all firms, including the firms that have access to equity markets, increase in their reliance on a bank for informationally intensive borrowing. Thus, the banks exploit their information advantage and hold-up their borrowers. Two other findings concern the bank characteristics. Bank size is considered valuable by the large firms with high borrowing needs, but no access to equity markets. Such firms pay higher loan spreads to larger banks, presumably because they value large banks' lending capacity and ability to provide access to capital markets. Small and opaque firms pay higher loan spreads to the banks with more stable sources of financing (i.e., more reliant on core deposit financing), presumably because these firms are more likely to face credit line access restrictions and credit rationing and, therefore, see value in a bank's ability to provide liquidity. The most transparent firms do not pay higher spreads for these bank characteristics.

My results suggest that lending relationships affect loan spreads not only due to the information production, but also because the reputational considerations make banks more accommodating in providing access to liquidity when they have a relationship with their borrower. For the borrowers with limited alternative sources of financing this makes a difference. Additionally, my findings imply that for such firms, relationships are valuable even in the absence of information production.

APPENDIX 1 . Variable definitions

VARIABLE NAME	*Description*	*Source*
Loan		
Loan Spread	AISD ("all-in-spread-drawn"), basis points.	LPC
CP Backup	Dummy =1 if loan is a CP backup (based on the 'Primary purpose' field in Dealscan).	LPC
Loan Amount	Loan amount, $ billions.	LPC
Loan Maturity	Loan maturity, months.	LPC
Secured	Dummy = 1 if loan is secured, 0 if not secured or if information is N/A.	LPC
Covenant Index	Covenant index assumes the value between 0 and 5 with the presence of each of five different covenants coded as 1 and 0 otherwise and summed up (Asset sweep, Debt sweep, Equity sweep, Dividend restriction, and having two or more financial covenants) (Bharath et al (2011). Original index, proposed by Bradley and Roberts (2004),includes the presence of collateral and thus assumes the value between 0 and 6. I control for collateral with *Secured* .	LPC
Credit Line	Dummy = 1 if lending mode ('facility type' field in Dealscan) is 'Demand Loan', 'Revolver/Line < 1 Yr.', 'Revolver/Line >= 1 Yr.', or 'Revolver/Term Loan'.	LPC
Term Loan	Dummy = 1 if lending mode ('facility type' field in Dealscan) is a 'Term Loan' or any of the eight values between 'Term Loan A' and 'Term Loan H'.	LPC
Deal Amount	Deal amount (sum of the amounts of all loan within a deal), $ billions.	LPC
Firm		
Type 2 Firm	Dummy =1 if borrower appears in Compustat but not in CRSP at the onset of the loan.	CCM
Type 3 Firm	Dummy =1 if borrower appears in both Compustat and CRSP at the onset of the loan.	CCM
Firm Size	Borrower's total assets (= AT/1,000), $ billions.	CCM
Asset Tangib.	Borrower's asset tangibility, defined as net PPE to total assets (= PPENT/AT).	CCM
Leverage	Borrower's leverage ratio, defined as long term debt to total assets (= DLTT/AT).	CCM
Profitability	Borrower's profitability, defined as EBITDA to total assets (= EBITDA/AT).	CCM
Rated Bank Debt	Dummy = 1 if borrower has S&P senior debt rating at the onset of the loan. Missing values and 'NR' rating are coded as zero.	LPC
Prev. Deal Amount	The amount of the borrower's previous loan deal, $ billions.	LPC
ST Debt	Borrower's short term debt divided by total debt. Short term debt is defined as notes payable (NP), which is equal to debt in current liabilities (DLC) minus long term debt due in 1 year (DD1). Total debt is defined as debt in current liabilities (DLC) plus total long term debt (DLTT). (=(DLC-DD1)/(DLC+DLTT).	CCM
Bank		
Bank Size	Bank's total assets (= Rcfd2170/1,000,000), $ billions.	CR
Bank Core Dep	Bank's core deposits divided by total deposits. Core deposits are defined as B4the sum of transactions accounts (Rcon2215), non-transactions savings deposits (Rcon6810 + Rcon0352), and total time deposits less than $100,000 (Rcon6648). Total deposits are transactions accounts (Rcon2215) plus non-transactions accounts (Rcon2385).	CR
Bank Core Dep SD	Standard deviation of *Bank Core Dep* based on the last six end-of-quarter values.	CR
Lending environment		
Default Spread	Difference between the yields on Moody's seasoned corporate bonds with Baa rating and 10-year U.S. government bonds.	FRED
Term Spread	Difference between the yields on 10-year and 1-year U.S. government bonds.	FRED
Lend. Standards	Measure of lending standards' toughness based on the quarterly survery of loan officers conducted by the FRB. Higher values correspond to more stringent lending standards and, therefore, lower credit availability. <u>Calculation:</u> The survey respondents specify whether their bank's credit standards tightened, eased, or remained unchanged during the three-month period prior to survey date. *Lend. Standards* is a net number of respondents that reported tightening, as a percent of total number of respondents. For example, if out of 84 respondents 24 reported tightening, three reported easing, and the remaining 57 reported no change, *Lend. Standards* is equal to 0.25 (=(24-3)/84).	FRB
Proposed instruments		
#1 :ST Debt Ind	Industry average of *ST Debt* based on the one-digit SIC code of borrower's industry.	
#2 : CPB Reliance	For a given borrower at time t, using a five-year time window, reliance on CP backups is defined as ($ value of all CP backups in [t-5; t)/ $ value of all loans in [t-5; t)).	LPC
#3 : CP Spread	"Paper-bill spread" (Gatev and Strahan (2006)), a measure of commercial paper market tightness, defined as the difference between the three-month commercial paper rate for highly rated (AA) nonfinancial borrowers and the three-month T-bill rate.	FRED

SOURCES: CRSP/Compustat merged (CCM), Call reports (CR), FRED database of the St. Louise Fed (FRED), Federal Reserve Board (FRB).

APPENDIX 2 . List of lender roles based on all Dealscan loans to U.S. borrowers

This table presents the list of all lender roles based on the sample of all Dealscan loans to U.S. borrowers in my version of the database, ordered by the frequency of occurence. Mean and median bank allocation shares are provided for each role where 'Lead Arranger Credit ' variable takes value of 'Yes' and 'No'.

	Lender role			Lead arranger credit = 'No'			Lead arranger credit = 'Yes'		
					Bank allocation share			Bank allocation share	
		N obs - total	% of total	N obs	mean	median	N obs	mean	median
1	Participant	294,162	53.9%	294,063	8.5	5.2	99	39.02	27.62
2	Admin agent	65,923	12.1%	2,673	41.5	28.0	63,250	29.68	20.75
3	Co-agent	37,311	6.8%	36,762	8.5	5.9	549	32.96	31.76
4	Documentation agent	34,018	6.2%	33,231	12.4	10.2	787	23.22	20.00
5	Syndications agent	33,292	6.1%	22,111	14.1	11.8	11,181	16.85	12.49
6	Agent	30,984	5.7%	5,170	57.0	100.0	25,814	75.51	100.00
7	Managing agent	15,541	2.8%	15,491	5.9	5.0	50	32.10	29.20
8	Arranger	14,023	2.6%	3,628	11.2	6.3	10,395	53.84	50.00
9	Lead manager	5,531	1.0%	5,257	6.7	3.5	274	48.03	50.00
10	Senior managing agent	5,114	0.9%	5,113	5.7	5.3	1	6.67	6.67
11	Co-manager	3,121	0.6%	3,111	7.3	3.6	10	20.75	28.00
12	Co-arranger	1,966	0.4%	1,908	8.2	6.1	58	6.08	5.10
13	Manager	1,683	0.3%	1,670	5.7	3.8	13		
14	Lender	576	0.1%	569	12.7	8.0	7	55.00	55.00
15	Co-lead manager	448	0.1%	446	7.9	4.0	2		
16	Mandated arranger	304	0.1%	32	12.4	15.1	272	21.03	18.10
17	Bookrunner	225	0.0%	8			217	18.49	13.00
18	Co-syndications agent	202	0.0%	196	11.0	9.6	6		
19	Lead bank	198	0.0%	50	29.3	15.0	148	85.87	100.00
20	Lead arranger	152	0.0%	44	9.5	6.2	108	14.67	6.67
21	Collateral agent	145	0.0%	134	28.1	22.5	11	15.71	10.00
22	Senior lead manager	134	0.0%	134	4.2	3.7			
23	Senior manager	65	0.0%	65	6.5	5.8			
24	Sole lender	49	0.0%	9	100.0	100.0	40	99.46	100.00
25	Adviser	35	0.0%	35	1.3	-			
26	Senior co-lead manager	30	0.0%	30	6.1	5.0			
27	Dealer	20	0.0%	19			1		
28	Senior co-manager	19	0.0%	19	21.7	21.7			
29	Coordinating arranger	17	0.0%				17	21.88	14.00
30	Paying agent	14	0.0%	14	6.3	6.3			
31	Secondary investor	13	0.0%	11	8.4	2.7	2	100.00	100.00
32	Joint lead manager	10	0.0%	10	22.7	20.0			
33	Packager	10	0.0%	10	18.4	20.0			
34	Facility agent	8	0.0%	8	3.4	3.4			
35	Funding bank	7	0.0%	7	30.0	30.0			
36	Issuing agent	6	0.0%	6	33.3	33.3			
37	PRC agent	5	0.0%	5					
38	Security agent	5	0.0%	5					
39	Debt provider	4	0.0%	4	13.3	13.3			
40	Senior co-arranger	4	0.0%	4					
41	Technical	4	0.0%	4					
42	Undisclosed	4	0.0%	4	3.5	3.5			
43	Co-lead arranger	3	0.0%				3		
44	Financial adviser	3	0.0%	1			2		
45	Fronting bank	3	0.0%	3	16.7	16.7			
46	Joint arranger	3	0.0%	3					
47	Reference agent	3	0.0%	3	4.4	5.0			
48	Accepting bank	2	0.0%				2		
49	Co-lender	2	0.0%	2					
50	Custodian	2	0.0%	2					
51	L/C issuer	2	0.0%	2	22.2	22.2			
52	Co-underwriter	1	0.0%	1	18.0	18.0			
53	Coordinator	1	0.0%	1					
54	L/C issuing bank	1	0.0%	1					
55	Lead participant	1	0.0%				1	50.00	50.00
56	Purchaser	1	0.0%	1	4.5	4.5			
57	Sub-underwriter	1	0.0%	1					
	Total	545,411							

APPENDIX 3

Tests for validity and relevance of the proposed instrumental variables and the Darbin-Wu-Hausman test for the endogeneity of the loan type choice

A-3.1 Instrumental variables

I consider three instruments for the loan type choice, *CP Backup*. The first proposed instrument is the average level of short term debt in borrower's industry, *ST Debt Ind*. Short term debt level for each firm is calculated as short term debt excluding the current portion of long-term debt, divided by total debt (see Appendix 1). *ST Debt Ind* is calculated for the calendar year of the loan using all Compustat firms that belong to borrower's one-digit SIC code. The nature of business operations dictates the optimal levels of short term financing, and there is substantial variation in the reliance on short term debt between different industries. Reliance on short debt may be associated with greater liquidity needs of such firms and they may be more likely to prefer loans with the liquidity provision aspect. Also, firms from the industries with high levels of short term debt may be more reliant on commercial paper, and CP backups are required to receive commercial paper rating (which is, in turn, required for placing the paper with investors). Correlation between *CP Backup* and *ST Debt Ind* is -0.0409 in the total sample and remains negative in the subsamples. This correlation is quite low but not low enough to dismiss the instrument before conducting the formal tests for relevance and strenght.[75]

The second instrument, *CPB Reliance*, is firm's prior reliance on CP backups defined in (4.4). This variable measures the proportion of CP backups in total loans obtained in the previous five years. The intuition is that firms that had a higher proportion of CP backups in their total bank borrowing in the past are more likely to get another CP backup in the future. Unlike project financing, commercial paper programs have a revolving nature, and even though CP backup is not the only form of securing backup liquidity, it is the most common form (Samson and Bachmann, 1990). Correlation between *CP Backup* and *CPB Reliance* is 0.466 in the total sample and remains positive in the subsamples.

The third instrument, *CP Spread,* is a difference between the rate on commercial paper to high-grade borrowers and the T-bill rate, and is referred to as "paper-bill spread". Covitz and Downing (2002) argue that yields on short term commercial paper reflect both liquidity and default risk.[76] Gatev and Strahan (2006) show that short term changes in paper-bill spread reflect changes in availability of market liquidity rather than short-lived changes in default risk. I use *CP Spread,* calculated as a difference between the three-month commercial paper rate for highly rated (AA) nonfinancial borrowers and the three-month T-bill rate, as a measure of commercial paper market tightness. Correlation between *CP Backup* and *CP Spread* in the total sample is -0.0684 and remains negative in the subsamples. The mechanism underlying this negative association could be that when market liquidity drops and

---

[75] Cameron and Trivedi (2009, p.189) use an example where 0.0374 correlation between the instrument and the endogenous regressor is described as "low" but "not so low as to immediately flag a problem of weak instruments".

[76] As opposed to yields on long-term bonds that reflect only default risk.

paper-bill spread widens, the volume of newly issued commercial paper declines, and so does the number of newly issued CP backup lines (while the drawdowns on the existing lines increase).

A-3.2 Instrument validity test

Instrument validity cannot be tested in the just-identified case. In the overidentified model it is possible to test the validity of the *excess* instruments. The test, originally proposed by Sargan (1952) and extended by Hansen (1982), is known as overidentifying restrictions (OIR) test, Hansen's test, Sargan's test, and Hansen-Sargan's test, depending on the exact setting, which includes the choice of the estimator and standard errors (Cameron and Trivedi, 2009). The null hypothesis is that of correct model specification and valid excess instruments. A rejection calls either or both of these hypotheses into question, indicating that either the excess instruments are not exogenous or they are being incorrectly excluded from the regression (Baum, 2006). Aside from the issue of model specification, rejection means that at least one of the instruments is not valid. Similarly, failure to reject does not mean that all instruments are valid; it only means that excess instruments are valid. I conduct this test using a two-step estimator and standard errors robust to heteroskedasticity and firm-level clustering. The evaluated test statistic is a Hansen J statistic. Since failure to reject the null means that only some and not necessarily all instruments are valid, I conduct this test using different combinations of proposed instruments and different model specifications. Panel A of Table 8 reports p-values for Hansen J statistic corresponding to various combinations of samples (full sample or firm type subsamples), intensity measures (aggregate or decomposed intensity) and instrumental variables (all three together or pairs). Each one of the 32 reported p-values is higher than 0.05, and six p-values that are less than 0.10 correspond to combinations of instruments that involve the third instrument, *CP Spread*. Since all p-values are above 0.05, I conclude that model is correctly specified and instruments pass the validity test, although the validity of *CP Spread* is not very strong.

A-3.3 Instrument relevance tests

There are many tests for instrument relevance (the strength of its correlation with endogenous variable), and some are more formal than others. I present an overview and the results of the five commonly used approaches to assess instrument relevance.

The first approach is the Anderson's canonical correlations test (Anderson (1984), discussed in Hall, Rudebusch, and Wilcox (1996)). This test is applicable for just-identified and overidentified cases. The idea is that when estimated equation is identified, from the numerical standpoint all canonical correlations between the matrix of structural equation regressors and the matrix of first stage regressors must be statistically different from zero. The null hypothesis in Anderson's LR test is that the smallest canonical correlation is zero. A failure to reject the null means that equation's identification status is questionable.

Canonical correlations can also be used to test instrument redundancy when there is more than one instrument (Hall and Peixe, 2000), the second approach that I use. The test statistic is LR statistic based on the canonical correlations with and without the tested instruments. The null is that specified instruments are redundant. A failure to reject the null indicates that the excess instruments do not contribute to the model identification.[77]

The third approach is that of Bound, Jaeger, and Baker (1995) who proposed using the F-test of instruments' joint significance in the first stage regression. Staiger and Stock (1997) suggested a rule of thumb that instruments are weak if F-statistic is less than 10. This rule is not a formal test because F-statistic does not follow a standard distribution. In addition, such F-test can be misleading if there is more than one endogenous regressor in the model, in which case a partial Shea's R-square should instead be used (Baum (2006), p.207). I use Shea's R-square, an informal measure of instrument weakness, as the fourth approach. Higher values indicate stronger association between the instruments and the endogenous regressor, controlling for the effect of exogenous regressors.

The fifth approach involves using two formal tests of weak instruments. These tests were proposed by Stock and Yogo (2005) and represent an improvement on the aforementioned rule of thumb for F-statistic of instruments' joint significance. Both tests use the same test statistic but, depending on the selected criteria, critical values are different. With only one endogenous regressor, the test statistic is the F-statistic for instruments' joint significance in the first stage regression s. With multiple endogenous regressors, there will be multiple first stage regressions and multiple F-statistics. In this case, the test statistic is based on the matrix analogue of F-statistic, originally proposed by Cragg and Donald (1993) who used it to test for non-identification. Stock and Yogo (2005) presume identification and interpret low values of this statistic as indication of weak instruments. The null hypothesis is that instruments are strong. The test statistic is compared to critical values; if it is higher than critical values, we reject the null and conclude that instruments are not weak. Critical values depend upon the following two criteria. The first criterion is based on the concern that weak instruments may potentially create a bias in the IV estimate. This test can be conducted only if the model has at least two excess instruments. The criterion focuses on the largest bias of two-step estimator relative to OLS estimator that researcher considers tolerable. Critical values in Stock and Yogo's tables depend upon the maximum tolerable bias, number of endogenous regressors, and number of excess instruments. The second criterion is based on the concern that in finite samples weak instruments can result in size distortions of Wald tests on the parameters. This test can be applied to just-identified and overidentified cases. The Wald test underlying this criterion is the test of the joint significance of endogenous variables in the structural equation at a level of 0.05. Critical values depend upon the tolerance for size distortion of the test, number of endogenous regressors, and number of excess instruments.

Instrument relevance test results are reported in Panel B of Table 8. P-values in the Anderson canonical correlations test are under 0.01 in all model specifications that involve instrument 2 (*CPB Reliance*), thus the null hypothesis of weak instruments can be rejected. For specifications that do not include *CPB Reliance,* p-values suggest that instruments 1 and 3 are weak. Redundancy test results are consistent with those of Anderson test: *CPB Reliance* meets the redundancy criteria in all specifications while instruments 1 and 3 show mixed results. Instrument 3 (*CP Spread*) appears to be weaker than instrument 1 (*ST Debt Ind*); when tested for redundancy in the

[77] As it was discussed earlier, low explanatory power of the instruments results in greater bias of the IV estimates (Hahn and Hausman, 2002) and worsening of the large-sample approximations to the finite-sample distributions.

model that includes all three instruments, instrument 3 fails the test in all specifications. Shea's partial R-squares are very low (less than 0.001) when only instrument 1 or instrument 3 is used in isolation, once again confirming the weakness of these instruments. F-statistics of the F-test of joint significance interpreted using the rule of thumb tell the same story. Finally, Stock and Yogo's tests provide some interesting insights about the extent of weakness of instruments 1 and 3. Using all three instruments together is not expected to produce a larger than 5% distortion of the estimates and Wald statistics despite the weakness of instruments 1 and 3 that was established in the previous tests. In the "123" model specification, only one of Cragg-Donald F-statistics is less than its critical value (the statistic is 18 and is lower than the critical value of 22.5 in the test for Wald statistic distortion). Combinations of 2 and 1, and 2 and 3 pass Stock and Yogo's tests in all specifications, confirming the relevance of *CPB Reliance*.

Overall, I conclude that instruments 1 and 3 are weak and do not use them even though Stock and Yogo's tests suggest that including these two instruments along with instrument 2 (*CPB Reliance)* would not cause a substantial bias in the estimates and Wald statistics.

A-3.4 Darbin-Wu-Hausman (DWH) endogeneity test

If a variable that is in fact exogenous is treated as endogenous, IV estimator is still consistent but less efficient than OLS estimator.[78] I test for endogeneity of loan type choice (*CP Backup*) using the Durbin-Wu-Hausman (DWH) test. The idea behind the test is to fit the regression with both OLS and IV models and to compare the resulting estimates (Baum, 2006). The difference in the estimates underlies the test statistic; small difference puts endogeneity of the tested variable into question. The null hypothesis of DWH test is that OLS is an appropriate estimation technique. Rejecting the null indicates endogeneity of the tested variable.

I conduct this test using two-step estimator and standard errors robust to heteroskedasticity and firm-level clustering. The p-values of the DWH statistic are reported in panel C of Table 8. Similar to the previous tests, I report p-values of DWH test for various combinations of samples, intensity measures and instruments. Whenever instrument 2 (*CPB Reliance)* is included, p-values are lower than 0.05, except for the Type 3 subsample and decomposed intensity. Thus, the results of endogeneity test are consistent with the previously obtained results of instrument validity and relevance. When I use a strong instrument, *CPB Reliance*, endogeneity of *CP backup* is established in the total sample and among Type 1 and Type 2 firms.

[78] To quote Woodridge (2006), "[there is] an important cost of performing IV estimation when x and u are not correlated: the asymptotic variance of the IV estimator is always larger, and sometimes much larger, than the asymptotic variance of the IV estimator" (Wooldridge (2006, p.516).

TABLE 1. Industry classification of borrowers

Table 1 provides industry classification of borrowers. Borrowers that are part of the financial services industry are not included in the sample. Calculations are based on loan-bank observations. Column 1 is for the total sample. Columns 2-4 are for the three mutually exclusive subsamples: Type 1, Type 2 and Type 3 firms.
Firm types are designated in the following way. Type 1 firms are the borrowers for which financial data is not available in Compustat and in CRSP. Type 2 firms are the borrowers for which financial data is available in Compustat, but not in CRSP. Type 3 firms are the borrowers for which financial data is available in both Compustat and CRSP.

One digit SIC code	Total sample		Type 1 firms		Type 2 firms		Type 3 firms	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
.	252	0.48%	249	0.84%	1	0.01%	2	0.02%
0	186	0.36%	126	0.43%	27	0.21%	33	0.34%
1	4,031	7.70%	2,233	7.54%	1,037	7.91%	761	7.88%
2	9,380	17.91%	5,222	17.63%	2,755	21.02%	1,403	14.52%
3	11,033	21.06%	5,050	17.05%	3,750	28.61%	2,233	23.11%
4	11,183	21.35%	7,435	25.11%	2,177	16.61%	1,571	16.26%
5	7,639	14.58%	4,197	14.17%	2,005	15.30%	1,437	14.87%
7	5,561	10.62%	3,105	10.49%	1,036	7.90%	1,420	14.70%
8	3,089	5.90%	1,968	6.65%	319	2.43%	802	8.30%
9	27	0.05%	27	0.09%		0.00%		0.00%
Total	52,381	100.00%	29,612	100.00%	13,107	100.00%	9,662	100.00%

TABLE 2 , Panel A. Summary statistics for total sample and firm type subsamples

(based on loan-bank observations)

		Total sample				Type 1 firms				Type 2 firms				Type 3 firms			
		N Obs.	mean	med.	st.dev.	N Obs.	mean	med.	st.dev.	N Obs.	mean	med.	st.dev.	N	mean	med.	st.dev.
Firm	Firm total assets ($ billions)	22769	5.03	1.43	10.50	0	.	.	.	13107	7.44	2.53	13.04	9662	1.75	0.71	3.24
	Log (Firm total assets ($ billions))	22769	0.34	0.36	1.70	0	.	.	.	13107	0.86	0.93	1.70	9662	-0.38	-0.35	1.42
	Firm asset tangibility, PPETA/TA	22715	0.35	0.30	0.24	0	.	.	.	13083	0.36	0.31	0.23	9632	0.33	0.27	0.24
	Firm leverage, LT Debt/TA	22759	0.27	0.25	0.19	0	.	.	.	13101	0.26	0.25	0.17	9658	0.29	0.27	0.22
	Firm profitability, EBITDA/TA	22708	0.15	0.14	0.09	0	.	.	.	13078	0.15	0.14	0.08	9630	0.14	0.14	0.10
	Previous deal amount ($ billions)	51980	0.55	0.23	1.04	29294	0.54	0.21	1.05	13056	0.73	0.33	1.26	9630	0.36	0.20	0.54
	Rated bank debt dummy	52381	0.569	1.000	0.495	29612	0.512	1.000	0.500	13107	0.720	1.000	0.449	9662	0.538	1.000	0.499
Bank	Bank total assets ($ billions)	52296	303.8	180.5	335.9	29571	314.3	187.9	344.9	13077	290.5	178.0	318.0	9648	289.2	174.7	330.4
	Log (Bank total assets ($ billions))	52296	4.99	5.20	1.42	29571	5.03	5.24	1.42	13077	4.97	5.18	1.39	9648	4.90	5.16	1.46
	Core deposits / Total deposits	52228	0.235	0.198	0.149	29543	0.236	0.198	0.147	13064	0.238	0.200	0.151	9621	0.224	0.191	0.150
Loan	Loan spread, AISD (bps)	52381	158.8	137.5	115.8	29612	172.4	150.0	118.8	13107	115.9	75.0	100.8	9662	175.0	150.0	111.1
	CP Backup dummy	52381	0.126	0.000	0.331	29612	0.112	0.000	0.315	13107	0.202	0.000	0.401	9662	0.066	0.000	0.248
	Loan amount ($ billions)	52381	0.44	0.20	0.64	29612	0.41	0.19	0.63	13107	0.59	0.30	0.76	9662	0.30	0.18	0.42
	Log (Loan amount ($ billions))	52381	-1.68	-1.61	1.45	29612	-1.77	-1.65	1.45	13107	-1.29	-1.20	1.42	9662	-1.93	-1.74	1.37
	Loan maturity (months)	49911	47.1	59.0	25.4	27858	48.6	60.0	26.0	12702	42.3	48.0	24.5	9351	49.2	60.0	23.6
	Log (Loan maturity (months))	49911	3.63	4.08	0.76	27858	3.66	4.09	0.76	12702	3.50	3.87	0.78	9351	3.71	4.09	0.70
	Secured dummy	52381	0.36	0.00	0.48	29612	0.34	0.00	0.47	13107	0.30	0.00	0.46	9662	0.52	1.00	0.50
	Covenants index (max value = 5)	52381	1.38	0.00	1.76	29612	1.19	0.00	1.74	13107	1.28	1.00	1.61	9662	2.09	2.00	1.81
	Credit line dummy	52381	0.56	1.00	0.50	29612	0.54	1.00	0.50	13107	0.57	1.00	0.50	9662	0.61	1.00	0.49
	Term loan dummy	52381	0.24	0.00	0.43	29612	0.27	0.00	0.44	13107	0.15	0.00	0.36	9662	0.25	0.00	0.43
	Syndicated loan dummy	52381	0.937	1.000	0.244	29612	0.944	1.000	0.231	13107	0.941	1.000	0.236	9662	0.909	1.000	0.288
	N synd. lenders (leads & non-leads)	52381	12.95	9.00	12.08	29612	12.81	8.00	12.53	13107	14.13	11.00	11.75	9662	11.77	9.00	10.91
Environment	Lending standards (FED survey)	52381	7.90	0.90	23.26	29612	7.18	0.00	22.91	13107	8.65	3.50	23.52	9662	9.08	3.50	23.91
	Default spread (bps)	50810	215.5	205.0	57.3	28576	212.1	197.0	56.8	12769	219.9	210.0	58.2	9465	219.9	212.0	56.9
	Term spread (bps)	50810	113.5	80.0	107.5	28576	109.6	78.0	106.2	12769	123.1	89.0	109.4	9465	112.0	78.0	108.0
Instruments	#1 : Firm's industry avg ST debt/Tot. debt	52075	0.133	0.138	0.043	29309	0.130	0.129	0.043	13106	0.139	0.145	0.043	9660	0.134	0.141	0.041
	#2 : Firm's reliance on CP backups	49975	0.116	0.000	0.257	28208	0.103	0.000	0.245	12566	0.190	0.000	0.310	9201	0.055	0.000	0.175
	#3 : Comm. paper-to-T-bill spread (bps)	47639	26.03	21.00	22.10	26810	26.37	22.00	21.85	12024	25.25	20.00	22.51	8805	26.08	21.00	22.26
Intensities	A-intensity	49975	0.542	0.637	0.441	28208	0.555	0.680	0.444	12566	0.523	0.579	0.429	9201	0.526	0.600	0.445
	I-intensity	49975	0.475	0.455	0.438	28208	0.495	0.500	0.443	12566	0.415	0.312	0.416	9201	0.496	0.517	0.442
	T-intensity	49975	0.067	0.000	0.194	28208	0.060	0.000	0.186	12566	0.109	0.000	0.239	9201	0.030	0.000	0.126

NOTES: All variables are defined in Appendix 1. Statistics are based on the data set where loan spread, maturity and amount and number of syndicate members were winsorized at 0.25% and 99.75%. Firm types are designated as follows. Type 1 firms are the borrowers for which financial data is not available in Compustat and in CRSP. Type 2 firms are the borrowers for which financial data is available in Compustat only. Type 3 firms are the borrowers for which finan+A42cial data is available in both Compustat and CRSP.

TABLE 2 , Panel B. Summary statistics for total sample and loan type (CP backups vs. non-CP backups) subsamples

(based on loan-bank observations)

		Total sample				Non-CP backups				CP backups			
		N Obs.	mean	med.	st.dev.	N Obs.	mean	med.	st.dev.	N Obs.	mean	med.	st.dev.
Firm	Firm total assets ($ billions)	22769	5.03	1.43	10.50	19491	3.75	1.05	8.95	3278	12.63	7.51	14.90
	Log (Firm total assets ($ billions))	22769	0.34	0.36	1.70	19491	0.07	0.05	1.63	3278	1.94	2.02	1.18
	Firm asset tangibility, PPETA/TA	22715	0.35	0.30	0.24	19437	0.34	0.28	0.24	3278	0.39	0.33	0.22
	Firm leverage, LT Debt/TA	22759	0.27	0.25	0.19	19482	0.27	0.26	0.20	3277	0.24	0.25	0.13
	Firm profitability, EBITDA/TA	22708	0.15	0.14	0.09	19443	0.14	0.14	0.09	3265	0.16	0.15	0.08
	Previous deal amount ($ billions)	51980	0.55	0.23	1.04	45415	0.48	0.20	0.95	6565	1.08	0.57	1.43
	Rated bank debt dummy	52381	0.569	1.000	0.495	45799	0.526	1.000	0.499	6582	0.869	1.000	0.338
Bank	Bank total assets ($ billions)	52296	303.8	180.5	335.9	45720	308.7	176.0	348.9	6576	269.6	226.3	223.0
	Log (Bank total assets ($ billions))	52296	4.99	5.20	1.42	45720	4.97	5.17	1.45	6576	5.12	5.42	1.18
	Core deposits / Total deposits	52228	0.235	0.198	0.149	45662	0.234	0.195	0.150	6566	0.238	0.210	0.134
Loan	Loan spread, AISD (bps)	52381	158.8	137.5	115.8	45799	174.1	150.0	115.0	6582	52.1	40.0	40.2
	CP Backup dummy	52381	0.126	0.000	0.331	45799	0.000	0.000	0.000	6582	1.000	1.000	0.000
	Loan amount ($ billions)	52381	0.44	0.20	0.64	45799	0.39	0.18	0.60	6582	0.79	0.50	0.78
	Log (Loan amount ($ billions))	52381	-1.68	-1.61	1.45	45799	-1.82	-1.70	1.44	6582	-0.68	-0.69	1.00
	Loan maturity (months)	49911	47.1	59.0	25.4	43468	51.0	60.0	24.0	6443	21.1	12.0	18.1
	Log (Loan maturity (months))	49911	3.63	4.08	0.76	43468	3.75	4.09	0.69	6443	2.80	2.48	0.64
	Secured dummy	52381	0.36	0.00	0.48	45799	0.41	0.00	0.49	6582	0.03	0.00	0.16
	Covenants index (max value = 5)	52381	1.38	0.00	1.76	45799	1.51	1.00	1.81	6582	0.44	0.00	0.82
	Credit line dummy	52381	0.56	1.00	0.50	45799	0.61	1.00	0.49	6582	0.23	0.00	0.42
	Term loan dummy	52381	0.24	0.00	0.43	45799	0.27	0.00	0.44	6582	0.00	0.00	0.04
	Syndicated loan dummy	52381	0.937	1.000	0.244	45799	0.930	1.000	0.255	6582	0.983	1.000	0.130
	N synd. lenders (leads & non-leads)	52381	12.95	9.00	12.08	45799	12.46	8.00	12.14	6582	16.33	14.50	11.03
Environment	Lending standards (FED survey)	52381	7.90	0.90	23.26	45799	6.67	0.00	22.91	6582	16.47	10.90	23.92
	Default spread (bps)	50810	215.5	205.0	57.3	44408	211.6	195.0	56.5	6402	242.5	242.0	55.5
	Term spread (bps)	50810	113.5	80.0	107.5	44408	111.0	79.0	106.3	6402	130.7	93.0	113.7
Instruments	#1 : Firm's industry avg ST debt/Tot. debt	52075	0.133	0.138	0.043	45508	0.134	0.141	0.043	6567	0.128	0.127	0.039
	#2 : Firm's reliance on CP backups	49975	0.116	0.000	0.257	43488	0.070	0.000	0.199	6487	0.426	0.391	0.363
	#3 : Comm. paper-to-T-bill spread (bps)	47639	26.03	21.00	22.10	41272	26.55	22.00	22.39	6367	22.68	17.00	19.75
Intensities	A-intensity	49975	0.542	0.637	0.441	43488	0.542	0.648	0.445	6487	0.538	0.600	0.415
	I-intensity	49975	0.475	0.455	0.438	43488	0.503	0.524	0.443	6487	0.286	0.097	0.350
	T-intensity	49975	0.067	0.000	0.194	43488	0.039	0.000	0.148	6487	0.252	0.088	0.320

NOTES: All variables are defined in Appendix 1. Statistics are based on the data set where loan spread, maturity and amount and number of syndicate members were winsorized at 0.25% and 99.75%. Firm types are designated as follows. Type 1 firms are the borrowers for which financial data is not available in Compustat and in CRSP. Type 2 firms are the borrowers for which financial data is available in Compustat only. Type 3 firms are the borrowers for which financial data is available in both Compustat and CRSP.

TABLE 2 , Panel C. Summary statistics for total sample and firm type subsamples

(based on loan observations)

		Total sample				Type 1 firms				Type 2 firms				Type 3 firms			
		N Obs.	mean	med.	st.dev.	N Obs.	mean	med.	st.dev.	N Obs.	mean	med.	st.dev.	N	mean	med.	st.dev.
Firm	Firm total assets ($ billions)	11359	3.55	0.82	8.66	0	.	.	.	6157	5.40	1.54	11.13	5202	1.35	0.47	2.85
	Log (Firm total assets ($ billions))	11359	-0.17	-0.20	1.75	0	.	.	.	6157	0.32	0.43	1.82	5202	-0.75	-0.75	1.47
	Firm asset tangibility, PPETA/TA	11334	0.34	0.28	0.24	0	.	.	.	6146	0.36	0.30	0.23	5188	0.32	0.25	0.24
	Firm leverage, LT Debt/TA	11350	0.26	0.24	0.20	0	.	.	.	6151	0.26	0.24	0.18	5199	0.27	0.24	0.23
	Firm profitability, EBITDA/TA	11320	0.14	0.14	0.10	0	.	.	.	6140	0.14	0.13	0.08	5180	0.14	0.14	0.11
	Previous deal amount ($ billions)	27026	0.40	0.15	0.85	15712	0.38	0.15	0.85	6133	0.54	0.21	1.02	5181	0.28	0.13	0.51
	Rated bank debt dummy	27281	0.472	0.000	0.499	15922	0.427	0.000	0.495	6157	0.613	1.000	0.487	5202	0.444	0.000	0.497
Bank	Bank total assets ($ billions)	27230	328.1	187.9	360.8	15895	353.9	208.7	374.2	6140	291.1	171.2	331.8	5195	293.1	161.7	344.8
	Log (Bank total assets ($ billions))	27230	5.01	5.24	1.50	15895	5.12	5.34	1.48	6140	4.90	5.14	1.48	5195	4.83	5.09	1.55
	Core deposits / Total deposits	27204	0.235	0.195	0.148	15880	0.230	0.192	0.144	6136	0.252	0.212	0.157	5188	0.228	0.193	0.149
Loan	Loan spread, AISD (bps)	27281	185.1	175.0	122.4	15922	198.9	200.0	123.3	6157	140.5	110.0	113.3	5202	195.7	175.0	117.6
	CP Backup dummy	27281	0.081	0.000	0.273	15922	0.071	0.000	0.256	6157	0.140	0.000	0.347	5202	0.044	0.000	0.205
	Loan amount ($ billions)	27281	0.29	0.13	0.49	15922	0.27	0.11	0.47	6157	0.42	0.20	0.62	5202	0.22	0.10	0.35
	Log (Loan amount ($ billions))	27281	-2.17	-2.08	1.50	15922	-2.25	-2.21	1.46	6157	-1.80	-1.61	1.56	5202	-2.38	-2.30	1.48
	Loan maturity (months)	25651	46.9	54.0	24.9	14753	48.6	59.0	25.5	5921	42.6	47.0	24.2	4977	46.9	52.0	23.5
	Log (Loan maturity (months))	25651	3.63	3.99	0.75	14753	3.67	4.08	0.75	5921	3.51	3.85	0.77	4977	3.66	3.95	0.72
	Secured dummy	27281	0.40	0.00	0.49	15922	0.37	0.00	0.48	6157	0.36	0.00	0.48	5202	0.56	1.00	0.50
	Covenants index (max value = 5)	27281	1.31	0.00	1.76	15922	1.09	0.00	1.72	6157	1.31	1.00	1.65	5202	1.97	2.00	1.82
	Credit line dummy	27281	0.57	1.00	0.50	15922	0.55	1.00	0.50	6157	0.59	1.00	0.49	5202	0.62	1.00	0.49
	Term loan dummy	27281	0.27	0.00	0.45	15922	0.31	0.00	0.46	6157	0.18	0.00	0.38	5202	0.27	0.00	0.44
	Syndicated loan dummy	27281	0.878	1.000	0.327	15922	0.895	1.000	0.306	6157	0.874	1.000	0.332	5202	0.831	1.000	0.375
	N synd. lenders (leads & non-leads)	27281	9.31	6.00	10.08	15922	9.05	6.00	10.19	6157	10.50	8.00	10.19	5202	8.70	6.00	9.49
Environment	Lending standards (FED survey)	27281	7.60	0.00	23.23	15922	6.96	0.00	23.12	6157	8.20	1.80	23.10	5202	8.85	1.80	23.65
	Default spread (bps)	26375	213.3	199.0	56.9	15349	211.6	194.0	56.6	5961	214.2	202.0	56.9	5065	217.4	209.0	57.6
	Term spread (bps)	26375	112.8	81.0	107.9	15349	110.1	78.0	108.1	5961	121.5	90.0	107.7	5065	110.5	78.0	107.0
Instruments	#1 : Firm's industry avg ST debt/Tot. debt	27051	0.136	0.142	0.043	15695	0.131	0.137	0.043	6156	0.144	0.148	0.044	5200	0.139	0.143	0.041
	#2 : Firm's reliance on CP backups	25739	0.084	0.000	0.224	15018	0.074	0.000	0.214	5820	0.146	0.000	0.280	4901	0.040	0.000	0.153
	#3 : Comm. paper-to-T-bill spread (bps)	24581	26.37	22.00	22.30	14203	26.48	22.00	22.43	5651	26.11	22.00	22.11	4727	26.37	22.00	22.16

NOTES: All variables are defined in Appendix 1. Statistics are based on the data set where loan spread, maturity and amount and number of syndicate members were winsorized at 0.25% and 99.75%. Firm types are designated as follows. Type 1 firms are the borrowers for which financial data is not available in Compustat and in CRSP. Type 2 firms are the borrowers for which financial data is available in Compustat only. Type 3 firms are the borrowers for which financial data is available in both Compustat and CRSP.

TABLE 2 , Panel D. Summary statistics for total sample and loan type (CP backups vs. non-CP backups) subsamples

(based on loan observations)

		Total sample				Non-CP backups				CP backups			
		N Obs.	mean	med.	st.dev.	N Obs.	mean	med.	st.dev.	N Obs.	mean	med.	st.dev.
Firm	Firm total assets ($ billions)	11359	3.55	0.82	8.66	10270	2.79	0.67	7.40	1089	10.70	5.73	14.49
	Log (Firm total assets ($ billions))	11359	-0.17	-0.20	1.75	10270	-0.37	-0.40	1.68	1089	1.68	1.75	1.27
	Firm asset tangibility, PPETA/TA	11334	0.34	0.28	0.24	10245	0.34	0.27	0.24	1089	0.39	0.33	0.22
	Firm leverage, LT Debt/TA	11350	0.26	0.24	0.20	10262	0.27	0.25	0.21	1088	0.24	0.24	0.14
	Firm profitability, EBITDA/TA	11320	0.14	0.14	0.10	10238	0.14	0.13	0.10	1082	0.16	0.15	0.08
	Previous deal amount ($ billions)	27026	0.40	0.15	0.85	24814	0.35	0.15	0.77	2212	0.91	0.49	1.31
	Rated bank debt dummy	27281	0.472	0.000	0.499	25065	0.441	0.000	0.497	2216	0.823	1.000	0.382
Bank	Bank total assets ($ billions)	27230	328.1	187.9	360.8	25016	331.8	181.4	370.0	2214	287.2	232.4	228.7
	Log (Bank total assets ($ billions))	27230	5.01	5.24	1.50	25016	5.00	5.20	1.52	2214	5.21	5.45	1.14
	Core deposits / Total deposits	27204	0.235	0.195	0.148	24991	0.234	0.194	0.149	2213	0.245	0.212	0.136
Loan	Loan spread, AISD (bps)	27281	185.1	175.0	122.4	25065	196.5	187.5	120.5	2216	56.48	42.50	47.83
	CP Backup dummy	27281	0.081	0.000	0.273	25065	0.000	0.000	0.000	2216	1.000	1.000	0.000
	Loan amount ($ billions)	27281	0.29	0.13	0.49	25065	0.26	0.11	0.46	2216	0.65	0.40	0.71
	Log (Loan amount ($ billions))	27281	-2.17	-2.08	1.50	25065	-2.28	-2.21	1.48	2216	-0.94	-0.92	1.05
	Loan maturity (months)	25651	46.9	54.0	24.9	23488	49.3	60.0	24.1	2163	20.7	12.0	17.9
	Log (Loan maturity (months))	25651	3.63	3.99	0.75	23488	3.71	4.09	0.71	2163	2.78	2.48	0.64
	Secured dummy	27281	0.40	0.00	0.49	25065	0.44	0.00	0.50	2216	0.03	0.00	0.17
	Covenants index (max value = 5)	27281	1.31	0.00	1.76	25065	1.39	0.00	1.80	2216	0.38	0.00	0.78
	Credit line dummy	27281	0.57	1.00	0.50	25065	0.60	1.00	0.49	2216	0.23	0.00	0.42
	Term loan dummy	27281	0.27	0.00	0.45	25065	0.30	0.00	0.46	2216	0.00	0.00	0.05
	Syndicated loan dummy	27281	0.878	1.000	0.327	25065	0.872	1.000	0.334	2216	0.949	1.000	0.220
	N synd. lenders (leads & non-leads)	27281	9.31	6.00	10.08	25065	8.99	6.00	10.04	2216	12.96	11.00	9.81
Environment	Lending standards (FED survey)	27281	7.60	0.00	23.23	25065	6.84	0.00	23.01	2216	16.23	10.90	24.02
	Default spread (bps)	26375	213.3	199.0	56.9	24231	210.9	193.0	56.4	2144	240.5	240.0	55.9
	Term spread (bps)	26375	112.8	81.0	107.9	24231	111.5	80.0	107.3	2144	126.8	89.0	112.8
Instruments	#1 : Firm's industry avg ST debt/Tot. debt	27051	0.136	0.142	0.043	24845	0.136	0.142	0.044	2206	0.130	0.129	0.040
	#2 : Firm's reliance on CP backups	25739	0.084	0.000	0.224	23572	0.053	0.000	0.178	2167	0.415	0.372	0.363
	#3 : Comm. paper-to-T-bill spread (bps)	24581	26.37	22.00	22.30	22437	26.65	22.00	22.46	2144	23.52	18.00	20.37

NOTES: All variables are defined in Appendix 1. Statistics are based on the data set where loan spread, maturity and amount and number of syndicate members were winsorized at 0.25% and 99.75%. Firm types are designated as follows. Type 1 firms are the borrowers for which financial data is not available in Compustat and in CRSP. Type 2 firms are the borrowers for which financial data is available in Compustat only. Type 3 firms are the borrowers for which financial data is available in both Compustat and CRSP.

TABLE 3. Loan stated purpose frequency table

Table 3 provides classification of loans by their stated purpose. Column 1 corresponds to the total sample. Columns 2-4 correspond to the firm type subsamples. Type 1 firms are the borrowers that are neither in Compustat nor in CRSP. Type 2 firms are the borrowers that are in Compustat, but not in CRSP. Type 3 firms are the borrowers that are in both Compustat and CRSP.

		(1)		(2)		(3)		(4)	
		Total sample		**Type 1 firms**		**Type 2 firms**		**Type 3 firms**	
	Loan stated purpose	Freq.	%	Freq.	%	Freq.	%	Freq.	%
1	Acquis. line	2,632	5.02	1,619	5.47	432	3.30	581	6.01
2	CP backup	6,582	12.57	3,304	11.16	2,644	20.17	634	6.56
3	Capital expend.	190	0.36	59	0.20	33	0.25	98	1.01
4	Corp. purposes	15,956	30.46	9,836	33.22	3,784	28.87	2,336	24.18
5	Debt Repay.	8,754	16.71	4,804	16.22	2,013	15.36	1,937	20.05
6	Debtor-in-poss.	315	0.60	216	0.73	52	0.40	47	0.49
7	ESOP	14	0.03	9	0.03	4	0.03	1	0.01
8	Equip. Purch.	63	0.12	30	0.10	8	0.06	25	0.26
9	Exit financing	84	0.16	72	0.24	6	0.05	6	0.06
10	IPO Relat. Finan.	65	0.12	63	0.21			2	0.02
11	LBO/MBO	1,836	3.51	1,184	4.00	297	2.27	355	3.67
12	Lease finance	1	0.00	1	0.00				
13	Mort. Warehse.	2	0.00	1	0.00	1	0.01		
14	Other	460	0.88	324	1.09	75	0.57	61	0.63
15	Proj. finance	98	0.19	80	0.27	10	0.08	8	0.08
16	Purch. Hardware	1	0.00					1	0.01
17	Real estate	342	0.65	301	1.02	29	0.22	12	0.12
18	Rec. Prog.	16	0.03	11	0.04	3	0.02	2	0.02
19	Recap.	1,222	2.33	1,093	3.69	80	0.61	49	0.51
20	Securities Purchase	13	0.02	4	0.01	6	0.05	3	0.03
21	Spinoff	309	0.59	253	0.85	37	0.28	19	0.20
22	Stock buyback	390	0.74	112	0.38	139	1.06	139	1.44
23	Takeover	6,422	12.26	3,334	11.26	1,605	12.25	1,483	15.35
24	TelcomBuildout	48	0.09	41	0.14			7	0.07
25	Trade finance	5	0.01	3	0.01			2	0.02
26	Work. cap.	6,561	12.53	2,858	9.65	1,849	14.11	1,854	19.19
	Total	52,381	100.00	29,612	100.00	13,107	100.00	9,662	100.00

TABLE 4. Lending modes by loan purpose frequency table

This table provides a frequency count of lending modes by loan purpose in my sample. Column 1 is a breakdown of the total sample's lending modes regardless of loan purpose. Columns 2-6 correspond to the total sample's five most common stated loan purposes as indicated in the column headers. Column 7 corresponds to all other loan purposes not included in (2)-(6).

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	All purposes (Total sample)		Corporate purposes		Debt repayment		**CP backup**		Working capital		Takeover		Other	
Lending mode	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%
364-Day Facility	8,808	16.82	1,932	3.69	230	0.44	5,020	9.58	664	1.27	645	1.23	317	0.61
Acquisition Facility	93	0.18	5	0.01	15	0.03			8	0.02	17	0.03	48	0.09
Bridge Loan	661	1.26	104	0.20	39	0.07	21	0.04	8	0.02	291	0.56	198	0.38
Delay Draw Term Loan	422	0.81	78	0.15	75	0.14			32	0.06	90	0.17	147	0.28
Demand Loan	37	0.07	18	0.03	4	0.01			9	0.02	1	0.00	5	0.01
Floating Rate Bond	1	0.00	1	0.00										
Guidance Line (Uncommitted)	12	0.02	8	0.02	2	0.00			2	0.00				
Leagues/Other	20	0.04	13	0.02					1	0.00			6	0.01
Lease	45	0.09	17	0.03	10	0.02			3	0.01	11	0.02	4	0.01
Limited Line	74	0.14	18	0.03	16	0.03			11	0.02	4	0.01	25	0.05
Multi-Option Facility	28	0.05	9	0.02	14	0.03	1	0.00	2	0.00	2	0.00		
Note	19	0.04	6	0.01	2	0.00			2	0.00	1	0.00	8	0.02
Other Loan	254	0.48	151	0.29	16	0.03	6	0.01	19	0.04	3	0.01	59	0.11
Performance Standby Letter	7	0.01	4	0.01									3	0.01
Revolver/Line < 1 Yr.	1,722	3.29	904	1.73	331	0.63	72	0.14	168	0.32	59	0.11	188	0.36
Revolver/Line >= 1 Yr.	26,900	51.35	9,262	17.68	5,475	10.45	1,411	2.69	4,504	8.60	2,759	5.27	3,489	6.66
Revolver/Term Loan	635	1.21	173	0.33	227	0.43	39	0.07	49	0.09	59	0.11	88	0.17
Standby Letter of Credit	5	0.01	3	0.01					1	0.00			1	0.00
Synthetic Lease	169	0.32	87	0.17	15	0.03			6	0.01	2	0.00	59	0.11
Term Loan	5,527	10.55	1,342	2.56	1,253	2.39	11	0.02	496	0.95	1,064	2.03	1,361	2.60
Term Loan A	2,474	4.72	627	1.20	335	0.64			185	0.35	594	1.13	733	1.40
Term Loan B	3,794	7.24	1,004	1.92	554	1.06	1	0.00	324	0.62	710	1.36	1,201	2.29
Term Loan C	518	0.99	140	0.27	106	0.20			48	0.09	92	0.18	132	0.25
Term Loan D	116	0.22	38	0.07	24	0.05			13	0.02	13	0.02	28	0.05
Term Loan E	25	0.05	9	0.02	7	0.01			5	0.01	1	0.00	3	0.01
Term Loan F	7	0.01	2	0.00	3	0.01							2	0.00
Term Loan G	3	0.01									2	0.00	1	0.00
Term Loan H	2	0.00									2	0.00		
Trade Letter of Credit	1	0.00	1	0.00										
Unadvised Guidance Line	2	0.00			1	0.00			1	0.00				
Total	52,381	100.0	15,956	30.5	8,754	16.7	6,582	12.6	6,561	12.5	6,422	12.3	8,106	15.5

TABLE 5. Descriptive statistics for intensity measures and CP backup reliance measure

Intensity measures and CP Backup reliance measure are defined in (4.1) - (4.4) of Section 4. The statistics are based on the data where loan spread, amount, maturity, and number of syndicate members were winsorized at 0.25% and 99.75%. Panel A summarizes the total sample. Panels B, C and D summarize three firm type subsamples. Type 1 firms are the borrowers that are neither in Compustat not in CRSP. Type 2 firms are the borrowers that are in Compustat, but not in CRSP. Type 3 firms are the borrowers that are in both Compustat and CRSP. I use five-year time window, value-based measures in the regressions reported throughout this paper.

	***Panel A: Total sample* N. Obs = 52,381 (100%)**				***Panel B: Type 1 firms* N. Obs = 29,612 (56.53%)**				***Panel C: Type 2 firms* N. Obs = 13,107 (25.02%)**				***Panel D: Type 3 firms* N. Obs =9,662 (18.45%)**			
	N Obs.	Mean	Median	Std.dev.	N Obs.	Mean	Median	Std.dev.	N Obs.	Mean	Median	Std.dev.	N Obs.	Mean	Median	Std.dev.
Three-year time window, value of loans-based measures:																
A-intensity	44,640	.576	.778	.451	25,333	.586	.837	.452	11,261	.562	.706	.443	8,046	.563	.761	.458
T-intensity	44,640	.078	.	.222	25,333	.069	.	.208	11,261	.128	.	.276	8,046	.037	.	.156
I-intensity	44,640	.498	.5	.453	25,333	.517	.571	.455	11,261	.433	.333	.437	8,046	.526	.612	.459
CPB Reliance	44,640	.132	.	.289	25,333	.115	.	.271	11,261	.216	.	.349	8,046	.068	.	.212
Three-year time window, number of loans-based measures:																
A-intensity	44,640	.563	.667	.447	25,333	.573	.75	.449	11,261	.547	.667	.437	8,046	.554	.667	.455
T-intensity	44,640	.078	.	.218	25,333	.068	.	.204	11,261	.129	.	.273	8,046	.038	.	.154
I-intensity	44,640	.485	.5	.447	25,333	.505	.5	.45	11,261	.418	.333	.428	8,046	.517	.5	.456
CPB Reliance	44,640	.133	.	.286	25,333	.115	.	.268	11,261	.22	.	.346	8,046	.069	.	.212
Five-year time window, value of loans-based measures:																
A-intensity	49,975	.542	.637	.441	28,208	.555	.68	.444	12,566	.523	.579	.429	9,201	.526	.6	.445
T-intensity	49,975	.067	.	.194	28,208	.06	.	.186	12,566	.109	.	.239	9,201	.03	.	.126
I-intensity	49,975	.475	.455	.438	28,208	.495	.5	.443	12,566	.415	.312	.416	9,201	.496	.517	.442
CPB Reliance	49,975	.116	.	.257	28,208	.103	.	.245	12,566	.19	.	.31	9,201	.055	.	.175
Five-year time window, number of loans-based measures:																
A-intensity	49,975	.525	.5	.436	28,208	.539	.6	.44	12,566	.504	.5	.421	9,201	.51	.5	.44
T-intensity	49,975	.067	.	.19	28,208	.059	.	.18	12,566	.11	.	.238	9,201	.03	.	.125
I-intensity	49,975	.458	.4	.431	28,208	.48	.5	.437	12,566	.394	.286	.405	9,201	.48	.5	.437
CPB Reliance	49,975	.119	.	.256	28,208	.104	.	.241	12,566	.198	.	.311	9,201	.058	.	.177
All loans since Dealscan inception, value of loans-based measures:																
A-intensity	52,381	.496	.506	.426	29,612	.513	.552	.433	13,107	.47	.452	.408	9,662	.481	.474	.426
T-intensity	52,381	.055	.	.165	29,612	.051	.	.161	13,107	.088	.	.2	9,662	.024	.	.105
I-intensity	52,381	.441	.371	.42	29,612	.462	.416	.429	13,107	.382	.273	.391	9,662	.456	.424	.422
CPB Reliance	52,381	.102	.	.224	29,612	.093	.	.219	13,107	.164	.	.266	9,662	.046	.	.146
All loans since Dealscan inception, number of loans-based measures:																
A-intensity	52,381	.47	.429	.419	29,612	.49	.5	.427	13,107	.44	.375	.398	9,662	.451	.4	.417
T-intensity	52,381	.054	.	.16	29,612	.049	.	.153	13,107	.088	.	.198	9,662	.024	.	.102
I-intensity	52,381	.416	.333	.411	29,612	.441	.333	.422	13,107	.352	.25	.376	9,662	.427	.333	.412
CPB Reliance	52,381	.103	.	.22	29,612	.092	.	.213	13,107	.167	.	.264	9,662	.048	.	.146

TABLE 6. Intensity measures and CP backup reliance measure means and correlations between firm type subsamples

Panel A presents the results of t-tests for the differences between the mean values of aggregate, informational, and transactional intensities and the CP backup reliance measure. All measures are based on five-year time window and value of loans and are defined in (4.1) - (4.4) of Section 4.
Firm types are defines as follows. Type 1 firms are the borrowers that are neither in Compustat not in CRSP. Type 2 firms are the borrowers that are in Compustat, but not in CRSP. Type 3 firms are the borrowers that are in both Compustat and CRSP.

Panel A: t-test for differences in means

	Type 1 firms Mean	Type 2 firms Mean	t-stat		Type 1 firms Mean	Type 3 firms Mean	t-stat		Type 2 firms Mean	Type 3 firms Mean	t-stat	
A-intensity	0.555	0.523	6.75	***	0.555	0.526	5.50	***	0.523	0.526	-0.41	
T-intensity	0.060	0.109	-22.25	***	0.060	0.030	14.66	***	0.109	0.030	28.89	***
I-intensity	0.495	0.415	17.24	***	0.495	0.496	-0.20		0.415	0.496	-13.89	***
CPB Reliance	0.103	0.190	-30.30	***	0.103	0.055	17.65	***	0.190	0.055	37.71	***
N obs.	28,208	12,566			28,208	9,201			12,566	9,201		

Panel B. Pairwise correlations of intensity measures and CP backup reliance measure

	A-intensity	*T-intensity*	*I-intensity*	*CPB Reliance*
Total sample (N = 49,975)				
A-intensity	1			
T-intensity	0.236	1		
I-intensity	0.903	-0.205	1	
CPB Reliance	0.023	0.786	-0.324	1
Type 1 firms (N = 28,208)				
A-intensity	1			
T-intensity	0.215	1		
I-intensity	0.912	-0.204	1	
CPB Reliance	0.019	0.795	-0.314	1
Type 2 firms (N = 12,566)				
A-intensity	1			
T-intensity	0.332	1		
I-intensity	0.840	-0.233	1	
CPB Reliance	0.050	0.762	-0.386	1
Type 3 firms (N = 9,201)				
A-intensity	1			
T-intensity	0.162	1		
I-intensity	0.960	-0.122	1	
CPB Reliance	0.004	0.786	-0.220	1

TABLE 7. OLS and fixed effects (FE) estimation using aggregate intensity measure and its decomposition.

This table provides the OLS, the firm fixed-effects and the bank fixed-effects estimation results for the following equation:

Loan Spread *= f (Intensities, Firm characteristics, Bank characteristics, Loan characteristics, Environment)*

Table 7 includes seven panels, A through G, that report results for the total sample (A and B) and for the subsamples by firm type (C and D), loan type (E), and firm type/loan type (F and G). Panel A presents total sample results using *A-intensity.* Panel B does the same using *I-intensity* and *T-intensity.* Panel C presents firm type subsample results using *A-intensity.* Panel B does the same using *I-intensity* and *T-intensity.* Panel F presents firm type/loan type subsample results using *A-intensity.* Panel B does the same using *I-intensity* and *T-intensity.* Panel E presents loan type subsample results using *A-intensity*. Panel F does the same using *I-intensity* and *T-intensity*. Firm types are designated based on borrower's presence in Compustat and in CRSP at the time of loan initiation. Type 1 firms are those not in Compustat or CRSP. Type 2 firms are those listed in Compustat, but not in CRSP. Type 3 firms are those listed in both. I consider two loan types, CP backups and non-CP backups. Panels A-D present OLS and FE estimation results. Panels E, F, and G present OLS results only.

Dependent variable, *Loan Spread,* is the spread over LIBOR on the drawn amount plus the annual fee in bps. *CP Backup* is a dummy that is equal to 1 if the loan is a CP backup. Intensity measures for firm i and bank j at time t are defined as follows. *A-intensity* is a ratio of firm i's loans on which bank j was a lead to its total borrowing during [t-5; t). *T-intensity* is a ratio of firm i's CP backups on which bank j was a lead to its total borrowing during [t-5; t). *I-intensity* is a ratio of firm i's non-CP backups on which bank j was a lead to its total borrowing during [t-5; t). *Type 2 Firm* and *Type 3 Firm* are the dummies that equal to 1 if borrower is categorized as Type 2 or Type 3 firm, respectively. The third (and omitted) category is Type 1 firms. *Prev. Deal Amount* is the log of borrower's most recent loan deal measured in \$ billion. *Rated Bank Debt* is a dummy that is equal to 1 if borrower has S&P senior debt rating. *Firm Size* is the log of borrower's total assets measured in \$ billion. *Asset Tangib* is a ratio of Net PPE and total assets. *Leverage* is a ratio of long-term debt and total assets. *Profitability* is a ratio of EBITDA and total sales. *Bank Size* is the log of bank's total assets measured in \$ billion. *Bank Core Dep* is a ratio of bank's core deposits (transactions accounts, non-transaction savings deposits, and total time deposits less than \$100,000) and total deposits. *Loan Amount* is the log of loan size in \$ billion. *Loan Maturity* is the log of the length in months between loan activation date and maturity date. *Secured* is a dummy that is equal to 1 if loan is secured and 0 if it is not secured or if information is missing. *Covenant Index* is the index based on the presence of four common loan covenants as described in Appendix 1; missing information is treated as absence of covenant. *Credit Line* is a dummy that is equal to 1 if loan is a line of credit. *Term Loan* is a dummy that is equal to 1 if loan is a term loan. *Lend. Standards* is a survey measure; higher values correspond to more stringent lending standards and lower credit availability. *Default Spread* is a difference between the yields on Moody's seasoned corporate bonds with Baa rating and 10-year U.S. government bond. *Term Spread* is a difference between the yields on 10-year and 1-year U.S. government bonds.

Standard errors of OLS are corrected for heteroskedasticity and firm-level clustering. Standard errors of firm FE and bank FE models are corrected for heteroskedasticity. In addition to the reported variables, all of the regressions include industry dummies (based on borrower's one-digit SIC code), calendar year dummies and stated loan purpose dummies.

TABLE 7 , Panel A. OLS and fixed effects (FE) results

Total sample, aggregate intensity. Dependent variable : *Loan Spread*

Model	(1) OLS	(2) OLS	(3) Bank FE	(4) Bank FE	(5) Firm FE	(6) Firm FE
A-intensity	6.44***	7.58***	5.33***	6.30***	2.04**	1.50
	(1.31)	*(1.81)*	*(1.61)*	*(2.09)*	*(0.98)*	*(1.35)*
Type 2 Firm	-25.30***	-22.50***	-24.39***	-21.91***	-5.29	-5.33
	(2.49)	*(2.95)*	*(1.90)*	*(2.26)*	*(9.66)*	*(9.65)*
Type 3 Firm	-16.61***	-17.07***	-16.44***	-16.96***	-26.82***	-28.21***
	(2.66)	*(3.16)*	*(1.60)*	*(2.38)*	*(5.73)*	*(5.88)*
*A-intensity * Type 2 Firm*		-5.37**		-4.75		0.10
		(2.73)		*(3.00)*		*(2.16)*
*A-intensity * Type 3 Firm*		0.94		1.04		2.61
		(3.40)		*(3.75)*		*(2.51)*
Bank Size	0.16	0.17	0.62	0.63	1.39***	1.40***
	(0.52)	*(0.52)*	*(2.69)*	*(2.69)*	*(0.39)*	*(0.39)*
Bank Core Dep	7.12*	7.22*	5.63	5.51	7.92**	7.94**
	(4.13)	*(4.13)*	*(8.68)*	*(8.67)*	*(3.28)*	*(3.28)*
CP Backup	-71.64***	-71.56***	-70.97***	-70.90***	-46.92***	-46.94***
	(4.42)	*(4.42)*	*(4.00)*	*(3.97)*	*(4.65)*	*(4.65)*
Loan Amount	-26.59***	-26.58***	-25.99***	-25.98***	-11.96***	-11.96***
	(0.87)	*(0.87)*	*(0.64)*	*(0.64)*	*(1.01)*	*(1.01)*
Loan Maturity	-7.68***	-7.66***	-7.13***	-7.11***	-8.51***	-8.51***
	(1.85)	*(1.85)*	*(1.80)*	*(1.80)*	*(1.72)*	*(1.72)*
Secured	66.95***	66.99***	64.97***	65.00***	30.37***	30.35***
	(2.46)	*(2.46)*	*(1.86)*	*(1.86)*	*(3.03)*	*(3.03)*
Covenant Index	2.96***	2.97***	3.30***	3.30***	3.92***	3.92***
	(0.73)	*(0.73)*	*(0.72)*	*(0.72)*	*(0.91)*	*(0.91)*
Rated Bank Debt	-1.75	-1.75	-1.99	-2.00	-0.42	-0.45
	(2.19)	*(2.19)*	*(1.82)*	*(1.82)*	*(2.85)*	*(2.85)*
Credit Line	23.68***	23.64***	22.94***	22.90***	8.73***	8.74***
	(3.10)	*(3.10)*	*(3.52)*	*(3.52)*	*(2.52)*	*(2.52)*
Term Loan	72.12***	72.06***	70.53***	70.48***	37.79***	37.79***
	(3.85)	*(3.85)*	*(3.61)*	*(3.62)*	*(3.05)*	*(3.05)*
Default Spread	0.10**	0.10**	0.11***	0.10***	0.15***	0.15***
	(0.04)	*(0.04)*	*(0.03)*	*(0.02)*	*(0.04)*	*(0.04)*
Term Spread	0.04*	0.04*	0.04***	0.04***	0.07***	0.07***
	(0.02)	*(0.02)*	*(0.01)*	*(0.01)*	*(0.02)*	*(0.02)*
Lend. Standards	0.25**	0.25**	0.22***	0.22***	0.33***	0.33***
	(0.10)	*(0.10)*	*(0.06)*	*(0.06)*	*(0.10)*	*(0.10)*
R-sq. adj.	0.523	0.523	0.495	0.495	0.250	0.250
N groups			147	147	5757	5757
Avg. obs./grp			311.4	311.4	8.0	8.0
N Obs.	45770	45770	45770	45770	45770	45770

*** Signif. at 1% level; ** at 5% level; * at 10% level.

TABLE 7 , Panel B. OLS and fixed effects (FE) results

Total sample, decomposed intensity. Dependent variable : *Loan Spread*

Model	(1) OLS	(2) OLS	(3) Bank FE	(4) Bank FE	(5) Firm FE	(6) Firm FE
I-intensity	11.71***	14.08***	10.73***	12.87***	3.66***	3.33**
	(1.41)	*(1.93)*	*(1.75)*	*(2.18)*	*(1.07)*	*(1.47)*
T-intensity	-37.04***	-52.07***	-39.12***	-53.78***	-9.55***	-12.68***
	(3.22)	*(4.46)*	*(2.15)*	*(3.89)*	*(2.73)*	*(4.36)*
Type 2 Firm	-24.56***	-24.38***	-23.63***	-23.79***	-5.36	-5.88
	(2.47)	*(2.98)*	*(1.79)*	*(2.32)*	*(9.62)*	*(9.59)*
Type 3 Firm	-17.17***	-16.61***	-17.00***	-16.52***	-26.77***	-27.61***
	(2.65)	*(3.17)*	*(1.66)*	*(2.33)*	*(5.72)*	*(5.88)*
*I-intensity * Type 2 Firm*		-7.02**		-6.04*		0.46
		(3.02)		*(3.13)*		*(2.51)*
*I-intensity * Type 3 Firm*		-3.93		-3.90		1.00
		(3.57)		*(4.09)*		*(2.64)*
*T-intensity * Type 2 Firm*		32.03***		30.89***		5.14
		(6.57)		*(5.99)*		*(5.60)*
*T-intensity * Type 3 Firm*		27.17**		28.90***		12.81
		(12.22)		*(7.30)*		*(10.82)*
Bank Size	0.33	0.29	0.26	0.24	1.46***	1.47***
	(0.52)	*(0.52)*	*(2.60)*	*(2.57)*	*(0.39)*	*(0.39)*
Bank Core Dep	7.22*	7.07*	5.13	5.41	7.98**	7.95**
	(4.12)	*(4.13)*	*(8.12)*	*(8.15)*	*(3.28)*	*(3.28)*
CP Backup	-64.79***	-64.75***	-64.16***	-64.12***	-47.29***	-47.32***
	(4.27)	*(4.26)*	*(3.50)*	*(3.53)*	*(4.65)*	*(4.65)*
Loan Amount	-25.89***	-25.77***	-25.24***	-25.12***	-11.94***	-11.93***
	(0.87)	*(0.87)*	*(0.68)*	*(0.68)*	*(1.00)*	*(1.00)*
Loan Maturity	-8.21***	-8.44***	-7.59***	-7.81***	-8.53***	-8.54***
	(1.83)	*(1.83)*	*(1.75)*	*(1.74)*	*(1.72)*	*(1.72)*
Secured	66.10***	66.01***	64.00***	63.92***	30.32***	30.31***
	(2.46)	*(2.46)*	*(1.81)*	*(1.81)*	*(3.03)*	*(3.03)*
Covenant Index	2.78***	2.88***	3.15***	3.24***	3.93***	3.93***
	(0.73)	*(0.73)*	*(0.74)*	*(0.74)*	*(0.90)*	*(0.91)*
Rated Bank Debt	-0.34	-0.25	-0.58	-0.50	-0.46	-0.49
	(2.19)	*(2.18)*	*(1.93)*	*(1.96)*	*(2.85)*	*(2.85)*
Credit Line	22.46***	22.49***	21.66***	21.71***	8.49***	8.53***
	(3.06)	*(3.05)*	*(3.38)*	*(3.32)*	*(2.52)*	*(2.52)*
Term Loan	70.13***	70.01***	68.48***	68.38***	37.51***	37.55***
	(3.82)	*(3.82)*	*(3.39)*	*(3.30)*	*(3.05)*	*(3.05)*
Default Spread	0.10**	0.10***	0.11***	0.11***	0.15***	0.15***
	(0.04)	*(0.04)*	*(0.02)*	*(0.02)*	*(0.04)*	*(0.04)*
Term Spread	0.04*	0.04*	0.04**	0.04**	0.07***	0.07***
	(0.02)	*(0.02)*	*(0.01)*	*(0.01)*	*(0.02)*	*(0.02)*
Lend. Standards	0.25**	0.24**	0.22***	0.22***	0.32***	0.32***
	(0.10)	*(0.10)*	*(0.06)*	*(0.06)*	*(0.10)*	*(0.10)*
R-sq. adj.	0.528	0.529	0.501	0.501	0.251	0.251
N groups			147	147	5757	5757
Avg. obs./grp			311.4	311.4	8.0	8.0
N Obs.	45770	45770	45770	45770	45770	45770

*** Signif. at 1% level; ** at 5% level; * at 10% level.

TABLE 7 , Panel C. — OLS and fixed effects (FE) results

Firm type subsamples, aggregate intensity. — Dependent variable : *Loan Spread*

	Type 1 firms			Type 2 firms						Type 3 firms					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Model	**OLS**	**Bank FE**	**Firm FE**	**OLS**	**Bank FE**	**Firm FE**	**OLS**	**Bank FE**	**Firm FE**	**OLS**	**Bank FE**	**Firm FE**	**OLS**	**Bank FE**	**Firm FE**
A-intensity	6.75***	5.80***	1.30	1.76	1.24	1.23	2.44	1.78	1.31	8.34***	7.14**	3.40	6.82**	6.40*	2.86
	(1.84)	*(2.09)*	*(1.31)*	*(2.13)*	*(2.46)*	*(1.65)*	*(1.99)*	*(1.99)*	*(1.58)*	*(2.83)*	*(3.37)*	*(2.08)*	*(2.71)*	*(3.49)*	*(2.02)*
Firm Size							-5.73**	-5.63***	-9.70*				-14.66***	-13.78***	-14.67***
							(2.47)	*(1.09)*	*(5.43)*				*(2.78)*	*(1.72)*	*(5.30)*
Asset Tangib.							-4.51	-5.61	-13.57				4.71	4.22	67.49*
							(7.99)	*(4.56)*	*(26.36)*				*(9.02)*	*(4.37)*	*(36.83)*
Leverage							76.04***	76.08***	39.25**				77.37***	76.38***	54.19***
							(12.58)	*(7.26)*	*(16.01)*				*(9.98)*	*(7.75)*	*(17.46)*
Profitability							-217.01***	-214.18***	-200.44**				-184.76***	-176.77***	-195.22***
							(24.56)	*(19.03)*	*(36.63)*				*(23.43)*	*(28.75)*	*(37.90)*
Bank Size	0.06	0.45	1.33***	1.80**	2.06	1.92***	1.64**	2.17	1.80***	-1.65	-1.56	-0.12	0.20	-0.00	0.21
	(0.74)	*(3.10)*	*(0.49)*	*(0.86)*	*(2.61)*	*(0.72)*	*(0.78)*	*(2.69)*	*(0.66)*	*(1.13)*	*(4.28)*	*(0.80)*	*(1.10)*	*(4.36)*	*(0.78)*
Bank Core Dep	15.88***	12.38	10.01**	3.30	0.15	4.64	2.01	-0.75	3.99	-5.36	6.27	6.73	4.65	12.53	6.42
	(5.79)	*(11.80)*	*(4.74)*	*(6.42)*	*(9.24)*	*(5.68)*	*(6.31)*	*(9.07)*	*(5.46)*	*(9.42)*	*(11.25)*	*(6.46)*	*(9.69)*	*(12.19)*	*(6.22)*
CP Backup	-75.16***	-74.32***	-46.84***	-56.79***	-54.16***	-36.39***	-53.18***	-50.94***	-35.32***	-60.80***	-61.17***	-43.87***	-47.47***	-49.50***	-40.15***
	(5.77)	*(4.63)*	*(6.98)*	*(9.39)*	*(4.95)*	*(7.79)*	*(9.09)*	*(4.64)*	*(7.66)*	*(10.59)*	*(9.03)*	*(10.37)*	*(9.88)*	*(7.29)*	*(9.91)*
Loan Amount	-27.54***	-27.10***	-9.76***	-20.85***	-20.20***	-14.33***	-13.66***	-12.98***	-12.18***	-26.98***	-25.30***	-11.53***	-15.19***	-14.56***	-9.62***
	(1.14)	*(0.91)*	*(1.26)*	*(1.70)*	*(1.05)*	*(2.34)*	*(1.99)*	*(1.19)*	*(2.27)*	*(2.18)*	*(1.66)*	*(2.13)*	*(2.23)*	*(1.34)*	*(2.13)*
Loan Maturity	-1.49	-1.33	-5.78**	-19.05***	-17.71***	-5.42*	-17.69***	-16.50***	-4.58	-15.73***	-14.73***	-13.55***	-17.05***	-16.48***	-13.01***
	(2.47)	*(2.39)*	*(2.33)*	*(3.71)*	*(2.25)*	*(3.19)*	*(3.41)*	*(2.01)*	*(3.00)*	*(4.00)*	*(3.29)*	*(3.89)*	*(3.94)*	*(3.40)*	*(3.82)*
Secured	63.87***	62.52***	23.43***	71.64***	70.51***	44.63***	62.37***	61.27***	41.54***	70.73***	67.25***	26.93***	56.98***	55.28***	23.65***
	(3.48)	*(3.04)*	*(4.90)*	*(4.49)*	*(3.00)*	*(5.04)*	*(4.50)*	*(2.76)*	*(4.95)*	*(4.59)*	*(3.31)*	*(5.57)*	*(4.47)*	*(3.39)*	*(5.49)*
Covenant Index	2.86***	2.97***	3.19**	9.68***	9.78***	6.57***	8.26***	8.49***	6.21***	1.22	2.22***	4.24***	1.71	2.42***	4.23***
	(1.00)	*(0.86)*	*(1.40)*	*(1.48)*	*(0.91)*	*(1.64)*	*(1.50)*	*(0.88)*	*(1.58)*	*(1.42)*	*(0.76)*	*(1.60)*	*(1.39)*	*(0.63)*	*(1.54)*
Rated Bank Debt	-7.36**	-7.53***	-1.11	3.62	2.99	4.06	1.30	0.93	5.70	14.69***	13.71***	6.67	12.36**	11.41***	7.17
	(2.99)	*(2.31)*	*(3.95)*	*(4.10)*	*(2.92)*	*(5.82)*	*(4.06)*	*(2.89)*	*(5.89)*	*(4.67)*	*(2.56)*	*(6.22)*	*(4.97)*	*(2.57)*	*(6.04)*
Credit Line	20.91***	19.99***	5.59*	26.39***	25.48***	5.10	20.62***	19.91***	3.29	32.14***	31.25***	11.15*	24.63***	24.43***	9.72*
	(4.03)	*(4.22)*	*(3.39)*	*(6.21)*	*(4.06)*	*(5.02)*	*(5.64)*	*(3.48)*	*(4.78)*	*(7.49)*	*(7.78)*	*(5.87)*	*(6.89)*	*(7.12)*	*(5.79)*
Term Loan	71.59***	69.54***	36.25***	64.45***	62.72***	29.64***	59.15***	57.80***	28.80***	72.17***	71.36***	35.82***	65.41***	65.02***	34.90***
	(4.84)	*(4.32)*	*(4.00)*	*(8.81)*	*(4.87)*	*(6.54)*	*(8.10)*	*(4.15)*	*(6.26)*	*(8.55)*	*(9.09)*	*(6.77)*	*(7.96)*	*(8.27)*	*(6.66)*
Default Spread	0.09*	0.10***	0.14***	0.04	0.04	0.13**	0.02	0.01	0.12*	0.13	0.14***	0.23**	0.18**	0.18***	0.23***
	(0.05)	*(0.03)*	*(0.05)*	*(0.07)*	*(0.03)*	*(0.07)*	*(0.07)*	*(0.03)*	*(0.06)*	*(0.09)*	*(0.05)*	*(0.09)*	*(0.08)*	*(0.05)*	*(0.09)*
Term Spread	0.01	0.01	0.05*	0.10***	0.10***	0.11***	0.11***	0.11***	0.11***	0.05	0.04	0.06	0.05	0.05	0.07
	(0.03)	*(0.01)*	*(0.03)*	*(0.03)*	*(0.02)*	*(0.03)*	*(0.03)*	*(0.02)*	*(0.03)*	*(0.05)*	*(0.03)*	*(0.05)*	*(0.04)*	*(0.03)*	*(0.04)*
Lend. Standards	0.26*	0.24***	0.45***	0.31*	0.30***	0.29*	0.43**	0.42***	0.36**	0.28	0.20*	0.06	0.28	0.22**	0.18
	(0.14)	*(0.09)*	*(0.15)*	*(0.17)*	*(0.10)*	*(0.16)*	*(0.17)*	*(0.10)*	*(0.16)*	*(0.22)*	*(0.11)*	*(0.25)*	*(0.22)*	*(0.10)*	*(0.24)*
R-sq. adj.	0.508	0.479	0.229	0.572	0.544	0.326	0.612	0.587	0.349	0.469	0.436	0.253	0.514	0.480	0.281
N groups		137	3846		126	1107		126	1110		119	1203		118	1205
Avg. obs./grp		184.7	6.6		93.7	10.7		93.6	10.6		72.8	7.2		73.2	7.2
N Obs.	25301	25301	25301	11800	11800	11800	11799	11799	11799	8669	8669	8669	8636	8636	8636

*** Signif. at 1% level; ** at 5% level; * at 10% level.

TABLE 7 , Panel D. OLS and fixed effects (FE) results

Firm type subsamples, decomposed intensity. Dependent variable : *Loan Spread*

	Type 1 firms			Type 2 firms						Type 3 firms					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Model	**OLS**	**Bank FE**	**Firm FE**	**OLS**	**Bank FE**	**Firm FE**	**OLS**	**Bank FE**	**Firm FE**	**OLS**	**Bank FE**	**Firm FE**	**OLS**	**Bank FE**	**Firm FE**
I-intensity	12.80***	11.84***	2.97**	5.89**	5.85**	2.97	5.95***	5.72***	3.21*	10.06***	9.06**	3.66*	7.77***	7.55**	3.27
	(1.98)	*(2.15)*	*(1.42)*	*(2.41)*	*(2.64)*	*(1.92)*	*(2.27)*	*(2.08)*	*(1.85)*	*(2.95)*	*(3.60)*	*(2.16)*	*(2.84)*	*(3.76)*	*(2.08)*
T-intensity	-48.11***	-48.85***	-11.39**	-17.39***	-19.77***	-6.10*	-13.76***	-15.97***	-6.63**	-28.11**	-32.85***	-1.63	-12.90	-17.20**	-5.09
	(4.62)	*(4.48)*	*(4.46)*	*(4.37)*	*(3.34)*	*(3.35)*	*(3.84)*	*(3.21)*	*(3.24)*	*(11.14)*	*(9.67)*	*(10.18)*	*(11.22)*	*(8.63)*	*(10.08)*
Firm Size							-5.28**	-5.12***	-9.63*				-14.27***	-13.32***	-14.77***
							(2.48)	*(1.11)*	*(5.45)*				*(2.78)*	*(1.62)*	*(5.29)*
Asset Tangib.							-4.66	-5.87	-14.43				4.99	4.60	67.36*
							(8.05)	*(4.61)*	*(26.34)*				*(8.98)*	*(4.33)*	*(36.81)*
Leverage							74.25***	73.90***	39.15**				76.72***	75.62***	54.40***
							(12.41)	*(7.26)*	*(15.91)*				*(9.91)*	*(7.68)*	*(17.48)*
Profitability							-218.13***	-215.25***	-201.22**				-184.38***	-176.03***	-195.32***
							(24.51)	*(19.22)*	*(36.57)*				*(23.43)*	*(28.46)*	*(37.95)*
Bank Size	0.18	0.01	1.39***	1.95**	1.73	2.01***	1.73**	1.88	1.89***	-1.47	-1.60	-0.10	0.27	-0.04	0.24
	(0.73)	*(2.86)*	*(0.49)*	*(0.85)*	*(2.67)*	*(0.72)*	*(0.77)*	*(2.73)*	*(0.66)*	*(1.13)*	*(4.31)*	*(0.80)*	*(1.10)*	*(4.39)*	*(0.78)*
Bank Core Dep	15.67***	12.26	9.94**	3.37	-0.63	4.72	2.02	-1.63	4.07	-5.27	6.13	6.78	4.63	12.45	6.50
	(5.82)	*(10.83)*	*(4.75)*	*(6.38)*	*(9.25)*	*(5.68)*	*(6.27)*	*(9.02)*	*(5.45)*	*(9.43)*	*(11.07)*	*(6.46)*	*(9.69)*	*(12.04)*	*(6.22)*
CP Backup	-67.33***	-66.80***	-47.35***	-54.20***	-51.43***	-36.60***	-50.93***	-48.56***	-35.57***	-55.22***	-55.23***	-44.05***	-44.60***	-46.17***	-40.43***
	(5.50)	*(4.19)*	*(6.97)*	*(9.36)*	*(4.96)*	*(7.80)*	*(9.08)*	*(4.66)*	*(7.67)*	*(10.16)*	*(8.09)*	*(10.39)*	*(9.46)*	*(6.65)*	*(9.91)*
Loan Amount	-26.64***	-26.18***	-9.73***	-20.55***	-19.82***	-14.32***	-13.73***	-13.02***	-12.17***	-26.64***	-24.89***	-11.54***	-15.25***	-14.61***	-9.64***
	(1.15)	*(1.01)*	*(1.26)*	*(1.69)*	*(1.07)*	*(2.34)*	*(1.99)*	*(1.19)*	*(2.27)*	*(2.16)*	*(1.59)*	*(2.13)*	*(2.23)*	*(1.35)*	*(2.12)*
Loan Maturity	-2.22	-1.97	-5.83**	-19.29***	-17.93***	-5.45*	-17.77***	-16.54***	-4.60	-15.98***	-14.98***	-13.55***	-17.15***	-16.59***	-13.00***
	(2.45)	*(2.34)*	*(2.33)*	*(3.72)*	*(2.26)*	*(3.18)*	*(3.41)*	*(2.00)*	*(2.99)*	*(3.99)*	*(3.29)*	*(3.89)*	*(3.94)*	*(3.40)*	*(3.82)*
Secured	62.43***	60.98***	23.39***	71.33***	70.06***	44.65***	62.25***	61.05***	41.58***	70.27***	66.74***	26.90***	56.87***	55.15***	23.60***
	(3.47)	*(2.95)*	*(4.89)*	*(4.48)*	*(2.92)*	*(5.03)*	*(4.50)*	*(2.72)*	*(4.94)*	*(4.59)*	*(3.49)*	*(5.56)*	*(4.47)*	*(3.49)*	*(5.47)*
Covenant Index	2.76***	2.91***	3.23**	9.45***	9.58***	6.55***	8.15***	8.40***	6.20***	1.04	2.03**	4.23***	1.62	2.32***	4.21***
	(1.00)	*(0.89)*	*(1.40)*	*(1.47)*	*(0.91)*	*(1.64)*	*(1.49)*	*(0.89)*	*(1.58)*	*(1.44)*	*(0.78)*	*(1.61)*	*(1.40)*	*(0.65)*	*(1.54)*
Rated Bank Debt	-5.26*	-5.46**	-1.20	4.21	3.72	4.08	1.61	1.34	5.68	15.23***	14.23***	6.63	12.49**	11.52***	7.11
	(2.98)	*(2.47)*	*(3.94)*	*(4.09)*	*(2.86)*	*(5.81)*	*(4.03)*	*(2.85)*	*(5.88)*	*(4.69)*	*(2.74)*	*(6.23)*	*(4.96)*	*(2.64)*	*(6.05)*
Credit Line	19.04***	18.10***	5.37	26.04***	25.09***	4.99	20.39***	19.64***	3.16	31.22***	30.21***	11.05*	24.27***	23.98***	9.55*
	(3.95)	*(3.90)*	*(3.38)*	*(6.20)*	*(4.05)*	*(5.02)*	*(5.64)*	*(3.47)*	*(4.77)*	*(7.46)*	*(7.58)*	*(5.88)*	*(6.87)*	*(7.02)*	*(5.80)*
Term Loan	68.71***	66.69***	36.00***	63.70***	61.84***	29.43***	58.48***	57.01***	28.55***	71.18***	70.24***	35.71***	64.95***	64.44***	34.72***
	(4.77)	*(3.91)*	*(4.00)*	*(8.79)*	*(4.85)*	*(6.54)*	*(8.10)*	*(4.13)*	*(6.26)*	*(8.53)*	*(8.85)*	*(6.79)*	*(7.95)*	*(8.12)*	*(6.67)*
Default Spread	0.10*	0.11***	0.14***	0.05	0.04	0.13**	0.03	0.02	0.12*	0.13	0.14***	0.23**	0.18**	0.18***	0.23***
	(0.05)	*(0.03)*	*(0.05)*	*(0.07)*	*(0.03)*	*(0.07)*	*(0.07)*	*(0.03)*	*(0.06)*	*(0.09)*	*(0.05)*	*(0.09)*	*(0.08)*	*(0.05)*	*(0.09)*
Term Spread	0.01	0.01	0.05	0.10***	0.10***	0.11***	0.10***	0.11***	0.10***	0.05	0.04	0.06	0.06	0.05	0.07
	(0.03)	*(0.01)*	*(0.03)*	*(0.03)*	*(0.02)*	*(0.03)*	*(0.03)*	*(0.02)*	*(0.03)*	*(0.05)*	*(0.03)*	*(0.05)*	*(0.04)*	*(0.03)*	*(0.04)*
Lend. Standards	0.26*	0.24***	0.44***	0.30*	0.29***	0.28*	0.42**	0.41***	0.35**	0.28	0.20*	0.07	0.28	0.22**	0.19
	(0.14)	*(0.09)*	*(0.15)*	*(0.18)*	*(0.10)*	*(0.16)*	*(0.17)*	*(0.10)*	*(0.16)*	*(0.22)*	*(0.11)*	*(0.25)*	*(0.22)*	*(0.10)*	*(0.24)*
R-sq. adj.	0.515	0.486	0.230	0.574	0.547	0.326	0.614	0.589	0.350	0.470	0.438	0.253	0.514	0.480	0.281
N groups		137	3846		126	1107		126	1110		119	1203		118	1205
Avg. obs./grp		184.7	6.6		93.7	10.7		93.6	10.6		72.8	7.2		73.2	7.2
N Obs.	25301	25301	25301	11800	11800	11800	11799	11799	11799	8669	8669	8669	8636	8636	8636

*** Signif. at 1% level; ** at 5% level; * at 10% level.

TABLE 7 , Panel E. OLS and fixed effects (FE) results

Loan type subsamples, aggregate and decomposed intensity. Dependent variable : *Loan Spread*

	Using Aggregate intensity						Using decomposed intensity					
	Non - CP Backups			CP Backups			Non - CP Backups			CP Backups		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Model	**OLS**	**Bank FE**	**Firm FE**	**OLS**	**Bank FE**	**Firm FE**	**OLS**	**Bank FE**	**Firm FE**	**OLS**	**Bank FE**	**Firm FE**
A-intensity	7.19***	6.13***	2.88***	-1.45	-1.82**	0.05						
	(1.44)	*(1.82)*	*(1.10)*	*(1.57)*	*(0.85)*	*(0.74)*						
I-intensity							11.25***	10.30***	3.72***	6.39***	6.03***	1.16
							(1.50)	*(1.88)*	*(1.16)*	*(2.39)*	*(1.71)*	*(1.54)*
T-intensity							-53.63***	-55.06***	-8.63**	-11.70***	-12.04***	-1.33
							(4.79)	*(3.11)*	*(4.19)*	*(2.43)*	*(1.39)*	*(1.43)*
Type 2 Firm	-27.65***	-26.60***	-8.98	-6.81***	-6.53***	12.44	-26.75***	-25.72***	-8.91	-6.78***	-6.48***	12.28
	(2.88)	*(2.07)*	*(10.00)*	*(2.51)*	*(0.98)*	*(27.16)*	*(2.85)*	*(1.95)*	*(9.95)*	*(2.47)*	*(1.10)*	*(27.49)*
Type 3 Firm	-18.06***	-17.84***	-26.75***	2.75	2.65**	-6.87	-18.73***	-18.52***	-26.74***	2.40	2.36*	-6.60
	(2.80)	*(1.63)*	*(6.04)*	*(3.78)*	*(1.07)*	*(8.73)*	*(2.78)*	*(1.65)*	*(6.03)*	*(3.66)*	*(1.19)*	*(8.68)*
Bank Size	0.30	0.49	1.39***	0.42	0.94	0.10	0.43	0.20	1.43***	0.48	0.46	0.11
	(0.56)	*(2.72)*	*(0.43)*	*(0.61)*	*(2.92)*	*(0.23)*	*(0.56)*	*(2.61)*	*(0.43)*	*(0.60)*	*(2.89)*	*(0.22)*
Bank Core Dep	9.18**	5.59	8.71**	-0.35	11.36*	0.56	9.17**	4.87	8.78**	-0.10	10.69	0.54
	(4.58)	*(8.80)*	*(3.78)*	*(3.86)*	*(6.37)*	*(2.43)*	*(4.58)*	*(8.47)*	*(3.78)*	*(3.82)*	*(6.63)*	*(2.43)*
Loan Amount	-28.05***	-27.31***	-12.41***	-8.22***	-8.22***	-4.04*	-27.18***	-26.40***	-12.39***	-7.89***	-7.89***	-4.08*
	(0.94)	*(0.65)*	*(1.09)*	*(1.31)*	*(1.15)*	*(2.16)*	*(0.93)*	*(0.71)*	*(1.09)*	*(1.31)*	*(1.13)*	*(2.17)*
Loan Maturity	-6.22***	-5.72***	-7.79***	-14.87**	-14.77***	-8.48**	-7.17***	-6.60***	-7.82***	-15.14**	-15.02***	-8.54**
	(1.92)	*(1.79)*	*(1.87)*	*(6.39)*	*(2.97)*	*(3.59)*	*(1.90)*	*(1.75)*	*(1.87)*	*(6.32)*	*(2.88)*	*(3.59)*
Secured	66.75***	64.74***	28.70***	35.78***	34.17***	26.83**	65.73***	63.63***	28.72***	33.81***	32.30***	26.72**
	(2.54)	*(1.94)*	*(3.05)*	*(8.83)*	*(3.03)*	*(12.55)*	*(2.53)*	*(1.86)*	*(3.05)*	*(8.87)*	*(3.10)*	*(12.57)*
Covenant Index	2.77***	3.13***	3.68***	9.14***	9.16***	6.62***	2.48***	2.87***	3.67***	9.27***	9.31***	6.65***
	(0.76)	*(0.74)*	*(0.96)*	*(1.80)*	*(0.41)*	*(2.21)*	*(0.76)*	*(0.76)*	*(0.96)*	*(1.73)*	*(0.39)*	*(2.21)*
Rated Bank Debt	0.33	-0.11	-0.34	-7.88**	-7.59***	-3.67	2.18	1.73	-0.41	-7.75**	-7.47***	-3.61
	(2.30)	*(1.82)*	*(3.07)*	*(3.32)*	*(1.79)*	*(3.65)*	*(2.31)*	*(1.95)*	*(3.07)*	*(3.25)*	*(1.66)*	*(3.66)*
Credit Line	26.23***	25.62***	6.65**	20.76**	20.71***	13.02**	23.86***	23.26***	6.47**	20.71**	20.64***	13.02**
	(3.45)	*(3.85)*	*(2.79)*	*(9.33)*	*(4.33)*	*(5.27)*	*(3.40)*	*(3.71)*	*(2.79)*	*(9.21)*	*(4.21)*	*(5.28)*
Term Loan	72.73***	71.18***	34.86***	58.57	60.65*	28.43**	69.74***	68.19***	34.67***	56.90	58.98*	28.41**
	(4.13)	*(3.73)*	*(3.26)*	*(45.02)*	*(31.03)*	*(12.78)*	*(4.09)*	*(3.48)*	*(3.26)*	*(44.95)*	*(31.04)*	*(12.75)*
Default Spread	0.12**	0.12***	0.16***	0.04	0.03*	0.09**	0.12**	0.12***	0.17***	0.05	0.04**	0.09**
	(0.05)	*(0.03)*	*(0.05)*	*(0.04)*	*(0.02)*	*(0.03)*	*(0.05)*	*(0.03)*	*(0.05)*	*(0.04)*	*(0.02)*	*(0.03)*
Term Spread	0.05**	0.05***	0.06***	-0.03	-0.04*	0.02	0.05*	0.05**	0.06***	-0.04	-0.04**	0.02
	(0.02)	*(0.02)*	*(0.02)*	*(0.03)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*
Lend. Standards	0.29**	0.26***	0.39***	-0.10	-0.08	-0.03	0.29**	0.26***	0.39***	-0.11	-0.09*	-0.04
	(0.11)	*(0.07)*	*(0.12)*	*(0.11)*	*(0.06)*	*(0.10)*	*(0.11)*	*(0.07)*	*(0.12)*	*(0.11)*	*(0.05)*	*(0.10)*
R-sq. adj.	0.467	0.441	0.254	0.250	0.233	0.197	0.473	0.448	0.254	0.262	0.245	0.197
N groups		147	5670		77	712		147	5670		77	712
Avg. obs./grp		269.6	7.0		79.8	8.6		269.6	7.0		79.8	8.6
N Obs.	39627	39627	39627	6143	6143	6143	39627	39627	39627	6143	6143	6143

*** Signif. at 1% level; ** at 5% level; * at 10% level.

TABLE 7 , Panel F.
Firm type / loan type subsamples, aggregate intensity.

OLS and fixed effects (FE) results
Dependent variable : *Loan Spread*

	Type 1 firms		**Type 2 firms**				**Type 3 firms**			
	Non-CP backups	CP backups	Non-CP backups	CP backups	Non-CP backups	CP backups	Non-CP backups	CP backups	Non-CP backups	CP backups
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
A-intensity	7.61***	0.31	2.48	-2.75	2.73	-1.36	8.93***	-5.05	7.48***	-3.69
	(2.01)	*(2.24)*	*(2.51)*	*(2.59)*	*(2.34)*	*(2.41)*	*(2.94)*	*(5.19)*	*(2.83)*	*(4.15)*
Firm Size					-6.45**	-6.66***			-14.92***	-13.48***
					(2.79)	*(2.45)*			*(2.89)*	*(4.86)*
Asset Tangib.					-0.17	-16.08*			3.25	11.20
					(8.85)	*(8.52)*			*(9.28)*	*(18.90)*
Leverage					75.35***	67.17***			80.31***	-3.16
					(13.89)	*(14.26)*			*(10.26)*	*(24.50)*
Profitability					-259.29***	-77.46***			-184.36***	-181.12***
					(24.97)	*(19.70)*			*(24.15)*	*(42.67)*
Bank Size	0.32	-0.78	1.79*	2.03**	1.83**	1.79**	-1.51	1.18	0.35	1.66
	(0.79)	*(0.84)*	*(0.99)*	*(0.90)*	*(0.90)*	*(0.81)*	*(1.17)*	*(2.11)*	*(1.14)*	*(1.66)*
Bank Core Dep	18.88***	-3.72	4.23	-0.98	2.60	-0.41	-5.54	19.70	5.76	18.75
	(6.36)	*(5.96)*	*(7.91)*	*(4.86)*	*(7.81)*	*(4.28)*	*(9.91)*	*(15.71)*	*(10.15)*	*(12.68)*
Loan Amount	-28.84***	-7.74***	-22.76***	-7.79***	-14.57***	-3.48	-27.80***	-14.15***	-15.86***	-1.67
	(1.21)	*(1.99)*	*(1.93)*	*(2.08)*	*(2.16)*	*(3.21)*	*(2.25)*	*(4.54)*	*(2.31)*	*(4.66)*
Loan Maturity	0.54	-16.56**	-18.37***	-13.07	-16.70***	-13.31	-15.39***	4.11	-16.96***	3.47
	(2.59)	*(7.81)*	*(3.83)*	*(12.13)*	*(3.45)*	*(11.94)*	*(4.08)*	*(15.48)*	*(4.03)*	*(14.12)*
Secured	63.61***	44.60***	71.90***	19.48*	61.56***	19.56**	70.87***	46.15***	56.86***	42.73**
	(3.55)	*(15.52)*	*(4.66)*	*(10.75)*	*(4.73)*	*(9.18)*	*(4.70)*	*(16.64)*	*(4.57)*	*(16.53)*
Covenant Index	2.56**	10.11***	9.85***	7.71***	8.53***	5.77**	1.02	7.40*	1.65	6.55
	(1.04)	*(2.84)*	*(1.55)*	*(2.72)*	*(1.59)*	*(2.45)*	*(1.46)*	*(4.00)*	*(1.42)*	*(4.15)*
Rated Bank Debt	-5.12	-9.10**	5.75	-5.49	3.53	-6.20	15.27***	-7.94	12.78**	-0.63
	(3.15)	*(3.91)*	*(4.26)*	*(7.59)*	*(4.47)*	*(6.81)*	*(4.79)*	*(8.23)*	*(5.11)*	*(7.85)*
Credit Line	24.11***	24.07**	26.45***	16.02	18.39***	17.04	32.24***	-0.35	22.99***	-2.82
	(4.51)	*(11.53)*	*(6.80)*	*(17.61)*	*(6.06)*	*(17.30)*	*(8.20)*	*(23.05)*	*(7.55)*	*(21.00)*
Term Loan	72.63***	60.52***	62.68***	0.00	55.75***	0.00	72.02***	41.86	63.64***	43.03
	(5.24)	*(23.18)*	*(9.13)*	*(0.00)*	*(8.27)*	*(0.00)*	*(9.05)*	*(47.76)*	*(8.42)*	*(40.14)*
Default Spread	0.08	0.14**	0.11	-0.11**	0.08	-0.10**	0.13	0.14	0.18**	0.14
	(0.06)	*(0.05)*	*(0.09)*	*(0.05)*	*(0.09)*	*(0.05)*	*(0.09)*	*(0.09)*	*(0.09)*	*(0.09)*
Term Spread	0.03	-0.07	0.10***	0.01	0.11***	0.03	0.05	-0.08	0.05	0.00
	(0.03)	*(0.04)*	*(0.04)*	*(0.03)*	*(0.04)*	*(0.03)*	*(0.05)*	*(0.07)*	*(0.05)*	*(0.08)*
Lend. Standards	0.33**	-0.26	0.38*	0.17	0.55***	0.19	0.30	-0.19	0.29	-0.02
	(0.15)	*(0.17)*	*(0.22)*	*(0.16)*	*(0.21)*	*(0.15)*	*(0.24)*	*(0.41)*	*(0.23)*	*(0.38)*
R-sq. adj.	0.450	0.239	0.527	0.269	0.575	0.345	0.430	0.344	0.478	0.422
N Obs.	22258	3043	9304	2496	9311	2488	8065	604	8032	604

*** Signif. at 1% level; ** at 5% level; * at 10% level.

TABLE 7 , Panel G. — OLS and fixed effects (FE) results

Firm type / loan type subsamples, decomposed intensity. — Dependent variable : *Loan Spread*

	Type 1 firms				Type 2 firms				Type 3 firms	
	Non-CP backups	CP backups	Non-CP backups	CP backups	Non-CP backups	CP backups	Non-CP backups	CP backups	Non-CP backups	CP backups
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
I-intensity	12.22***	9.26***	5.50**	5.06	5.07**	5.19	10.46***	-3.06	8.41***	-4.31
	(2.09)	*(3.54)*	*(2.69)*	*(3.95)*	*(2.52)*	*(3.53)*	*(3.01)*	*(6.19)*	*(2.91)*	*(4.94)*
T-intensity	-65.06***	-12.02***	-22.91***	-11.40***	-16.78***	-8.63***	-50.95***	-8.79	-28.16	-2.53
	(6.99)	*(3.50)*	*(6.58)*	*(3.58)*	*(5.87)*	*(3.24)*	*(18.94)*	*(6.88)*	*(18.79)*	*(6.34)*
Firm Size					-5.96**	-6.24***			-14.43***	-13.67***
					(2.81)	*(2.37)*			*(2.88)*	*(4.90)*
Asset Tangib.					-0.31	-16.35**			3.61	11.00
					(8.93)	*(8.20)*			*(9.22)*	*(18.82)*
Leverage					73.89***	63.74***			79.32***	-3.13
					(13.68)	*(13.59)*			*(10.17)*	*(24.52)*
Profitability					-259.47***	-79.59***			-183.76***	-181.75***
					(24.84)	*(20.41)*			*(24.17)*	*(43.17)*
Bank Size	0.43	-0.79	1.89*	2.19**	1.86**	1.89**	-1.31	1.23	0.43	1.65
	(0.79)	*(0.82)*	*(0.99)*	*(0.88)*	*(0.89)*	*(0.79)*	*(1.17)*	*(2.09)*	*(1.14)*	*(1.66)*
Bank Core Dep	18.45***	-3.61	4.16	-0.43	2.48	0.08	-5.02	19.58	5.95	18.79
	(6.37)	*(6.05)*	*(7.88)*	*(4.68)*	*(7.78)*	*(4.10)*	*(9.91)*	*(15.74)*	*(10.16)*	*(12.70)*
Loan Amount	-27.74***	-7.57***	-22.40***	-7.54***	-14.64***	-3.69	-27.47***	-13.74***	-15.96***	-1.62
	(1.21)	*(2.00)*	*(1.92)*	*(2.09)*	*(2.16)*	*(3.14)*	*(2.22)*	*(4.60)*	*(2.31)*	*(4.64)*
Loan Maturity	-0.67	-17.09**	-18.82***	-12.91	-16.94***	-13.04	-15.68***	3.24	-17.08***	3.71
	(2.56)	*(7.81)*	*(3.83)*	*(12.11)*	*(3.45)*	*(11.92)*	*(4.06)*	*(15.82)*	*(4.02)*	*(14.33)*
Secured	62.00***	42.24***	71.69***	17.99*	61.58***	18.28**	70.07***	45.64***	56.56***	42.86**
	(3.55)	*(15.49)*	*(4.66)*	*(10.84)*	*(4.74)*	*(9.19)*	*(4.68)*	*(16.63)*	*(4.57)*	*(16.52)*
Covenant Index	2.29**	10.52***	9.54***	7.80***	8.35***	6.08***	0.85	7.16*	1.56	6.61
	(1.04)	*(2.76)*	*(1.55)*	*(2.60)*	*(1.59)*	*(2.33)*	*(1.48)*	*(4.04)*	*(1.44)*	*(4.13)*
Rated Bank Debt	-2.59	-8.73**	6.57	-5.97	3.89	-6.45	16.21***	-7.71	13.17***	-0.60
	(3.16)	*(3.91)*	*(4.28)*	*(7.39)*	*(4.44)*	*(6.67)*	*(4.80)*	*(8.31)*	*(5.10)*	*(7.83)*
Credit Line	20.86***	24.00**	25.66***	15.56	17.89***	16.62	30.55***	0.50	22.21***	-3.07
	(4.42)	*(11.50)*	*(6.77)*	*(17.56)*	*(6.05)*	*(17.24)*	*(8.15)*	*(23.38)*	*(7.54)*	*(21.09)*
Term Loan	68.57***	58.37***	61.67***	0.00	54.97***	0.00	70.15***	43.43	62.68***	42.61
	(5.15)	*(21.23)*	*(9.10)*	*(0.00)*	*(8.28)*	*(0.00)*	*(9.04)*	*(47.87)*	*(8.44)*	*(39.94)*
Default Spread	0.09	0.16***	0.11	-0.11**	0.08	-0.10**	0.13	0.14	0.18**	0.14
	(0.06)	*(0.05)*	*(0.09)*	*(0.05)*	*(0.09)*	*(0.05)*	*(0.09)*	*(0.09)*	*(0.09)*	*(0.09)*
Term Spread	0.02	-0.06	0.10***	0.01	0.11***	0.02	0.05	-0.08	0.05	0.00
	(0.03)	*(0.04)*	*(0.04)*	*(0.03)*	*(0.04)*	*(0.03)*	*(0.05)*	*(0.07)*	*(0.05)*	*(0.08)*
Lend. Standards	0.34**	-0.27	0.37*	0.16	0.54***	0.18	0.30	-0.17	0.29	-0.02
	(0.15)	*(0.17)*	*(0.22)*	*(0.16)*	*(0.21)*	*(0.15)*	*(0.23)*	*(0.41)*	*(0.23)*	*(0.38)*
R-sq. adj.	0.458	0.254	0.529	0.280	0.576	0.353	0.432	0.344	0.479	0.421
N Obs.	22258	3043	9304	2496	9311	2488	8065	604	8032	604

*** Signif. at 1% level; ** at 5% level; * at 10% level.

TABLE 8. Econometric tests for instrument validity and relevance and Durbin-Wu-Hausman test for endogeneity.

The statistical tests are performed using two-step estimator for the IV model applied to the following equation, with standard errors corrected for heteroskedasticity and firm-level clustering:

Loan Spread = *f (Intensities, Firm characteristics, Bank characteristics, Loan characteristics, Environment)*

The endogenous variable is a loan type choice (*CP Backup*). The three evaluated instrumental variables, abbreviated as “1”, “2” and “3” are: (1) Average level of short term debt in borrower’s industry in the loan calendar year, *ST Debt Ind*, (2) Borrower’s prior reliance on CP backups, *CPB Reliance,* and (3) Paper-bill spread calculated as the difference between the rate on commercial paper to high-grade borrowers and the T-bill rate, *CP Spread.*

Panel A presents the results of Sargan-Hansen test for instrument validity. Reported numbers are p-values. Null hypothesis is that of correct model specification and valid excess instruments. P-values higher than 0.05 indicate failing to reject the null and therefore correct model specification and validity of the excess instruments.

Panel B presents the results of five different tests for instrument relevance. (1) For Anderson’s canonical correlations test reported numbers are p-values. Null hypothesis is that instruments are weak. P-values lower than 0.05 indicate rejection of the null and that instruments are strong. (2) For the redundancy test reported numbers are p-values. Null hypothesis is that the specified instrument is redundant. P-values lower than 0.05 indicate rejection of the null and that the specified instrument is not redundant. (3) For Shea’s partial R-square reported numbers are Shea’s R-squares. (4) For the F-test of instruments’ joint significance in the first stage reported numbers are the values of F-statistic. The rule of thumb suggested by Staiger and Stock (1997) is that F-statistic must be above 10, otherwise instruments are weak. (5) For Stock and Yogo’s tests for weak instruments reported numbers are values of Stock and Yogo/Craggs-Donald F-statistic. These values must be compared to the provided critical values as described in the panel.

Panel C presents the results of Durbin-Wu-Hausman (DWH) test for endogeneity of *CP Backup*. Reported numbers are p-values. Null hypothesis is that OLS is an appropriate estimation technique. P-values lower than 0.05 indicate rejection of the null and that the *CP Backup* is endogenous.

In all three panels, I conduct the tests on the total sample and firm type subsamples using different measures of lending intensity (*A-intensity* or its decomposition), different combinations of potential instruments (all three, denoted “123”, only two, denoted “12”,”13” or “23”, or just one, denoted “1”,”2” or “3”) and with or without inclusion of Compustat controls (for the subsamples of Type 2 and Type 3 firms). In the test for redundancy, abbreviation “123_1” means that redundancy of instrument 1 is being tested in the model specification that includes all three instruments. The interpretation of other abbreviations follows the same logic.

Firm types are designated based on borrower’s presence in Compustat and in CRSP at the time of loan initiation. Type 1 firms are those not in Compustat or CRSP. Type 2 firms are those listed in Compustat, but not in CRSP. Type 3 firms are those listed in both. I consider two loan types, CP backups and non-CP backups.

TABLE 8, Panel A.

Sargan-Hansen test for validity of excess instruments

Ho: correct model specification and valid excess instruments

Numbers in the table are p-values

Sample				**Intensity measure**		**Compustat controls?**	**Instruments included in the model**						
Total sample	Type 1 firms	Type 2 firms	Type 3 firms	Aggr.	Decomp.		"123"	"12"	"13"	"23"	"1"	"2"	"3"
√				√			0.348	0.226	**0.097**	0.276			
√					√		0.333	0.202	**0.088**	0.275			
	√			√			0.703	0.870	0.433	0.427			
	√				√		0.667	0.824	0.460	0.384			
		√		√			0.165	0.316	**0.052**	0.371			
		√			√		0.151	0.321	**0.053**	0.347			
		√		√		√	0.189	0.592	**0.097**	0.212			
		√			√	√	0.176	0.624	0.117	0.197			
			√	√			**0.077**	0.171	0.475	**0.065**			
			√		√		**0.077**	0.174	0.584	**0.064**			
			√	√		√	**0.097**	0.491	0.177	**0.039**			
			√		√	√	**0.099**	0.496	0.246	**0.039**			

Numbers in the column headers indicate inclusion of some combination of the following instruments in the model specification:

Number 1 designates proposed instrument #1: short term debt level in borrower's industry, *ST Debt Ind* **.**

Number 2 designates proposed instrument #2: borrower's prior reliance on CP backups, *CPB Reliance* .

Number 3 designates proposed instrument #3: average CP spread at the time of loan issuance, *CP Spread* .

Proposed instruments are defined in Appendix 3

TABLE 8, Panel B.

Instrument relevance tests

Sample				Intensity measure		Compustat controls?	Instruments included in the model															
Total sample	Type 1 firms	Type 2 firms	Type 3 firms	Aggr.	Decomp.		123	123_1	123_2	123_3	12	12_1	12_2	13	13_1	13_3	23	23_2	23_3	1	2	3
Test 1: Anderson canonical correlations test. Ho: instruments are weak. Reported numbers are p-values.																						
√				√			0				0			**0.239**			0			**0.773**	0	**0.193**
√					√		0				0			**0.342**			0			**0.849**	0	**0.302**
	√			√			0				0			0.001			0			0.003	0	**0.072**
	√				√		0				0			0.003			0			0.016	0	**0.053**
		√		√			0				0			**0.091**			0			**0.204**	0	**0.104**
		√			√		0				0			**0.125**			0			**0.267**	0	**0.112**
		√		√		√	0				0			**0.081**			0			**0.137**	0	**0.129**
		√			√	√	0				0			**0.112**			0			**0.195**	0	**0.127**
			√	√			0				0			0.000			0			0.002	0	0.039
			√		√		0				0			0.002			0			0.010	0	0.038
			√	√		√	0				0			0.000			0			0.001	0	**0.061**
			√		√	√	0				0			0.001			0			0.004	0	**0.056**
Test 2. Redundancy test of Hall and Peixe. Ho: specified instrument is redundant. Reported numbers are p-values.																						
√				√				**0.766**	0	**0.250**		**0.772**	0		**0.444**	**0.128**		0	**0.360**			
√					√			**0.737**	0	**0.252**		**0.788**	0		**0.456**	**0.201**		0	**0.364**			
	√			√				0.036	0	**0.070**		**0.148**	0		0.000	**0.115**		0	0.041			
	√				√			0.034	0	**0.071**		**0.146**	0		0.003	**0.092**		0	0.041			
		√		√				**0.210**	0	**0.105**		**0.278**	0		**0.143**	**0.110**		0	**0.100**			
		√			√			**0.216**	0	**0.108**		**0.282**	0		**0.201**	**0.118**		0	**0.103**			
		√		√		√		**0.171**	0	**0.124**		**0.218**	0		**0.099**	**0.138**		0	**0.117**			
		√			√	√		**0.175**	0	**0.125**		**0.222**	0		**0.152**	**0.135**		0	**0.118**			
			√	√				0.004	0	**0.088**		0.014	0		0.001	**0.051**		0	**0.073**			
			√		√			0.005	0	**0.084**		0.015	0		0.003	0.048		0	**0.069**			
			√	√		√		0.002	0	**0.119**		0.008	0		0.000	**0.080**		0	**0.097**			
			√		√	√		0.003	0	**0.114**		0.008	0		0.001	**0.071**		0	**0.093**			

NOTES:

Numbers in the column headers indicate inclusion of some combination of the following instruments in the model specification:

Number 1 designates proposed instrument #1: short term debt level in borrower's industry, *ST Debt Ind* **.**

Number 2 designates proposed instrument #2: borrower's prior reliance on CP backups, *CPB Reliance* .

Number 3 designates proposed instrument #3: average CP spread at the time of loan issuance, *CP Spread* .

Proposed instruments are defined in Appendix 3

Numbers that follow underscore designate the instrument that is tested for redundancy. For example, "123_1" means that redundancy of instrument 1 is tested in the model specification that includes all three instruments.

TABLE 8, Panel B - continued.

Test 3. Shea's partial R-square.

Higher values indicate stronger instruments.

Sample: Total sample	Sample: Type 1 firms	Sample: Type 2 firms	Sample: Type 3 firms	Intensity measure: Aggr.	Intensity measure: Decomp.	Compustat controls?	123	12	13	23	1	2	3
√				√			0.04	0.04	0.00	0.04	0.00	0.04	0.00
√					√		0.01	0.02	0.00	0.02	0.00	0.02	0.00
	√			√			0.04	0.04	0.00	0.04	0.00	0.04	0.00
	√				√		0.02	0.02	0.00	0.02	0.00	0.02	0.00
		√		√			0.01	0.01	0.00	0.01	0.00	0.01	0.00
		√			√		0.01	0.01	0.00	0.00	0.00	0.01	0.00
		√		√		√	0.01	0.01	0.00	0.01	0.00	0.01	0.00
		√			√	√	0.01	0.01	0.00	0.01	0.00	0.01	0.00
			√	√			0.07	0.07	0.00	0.07	0.00	0.07	0.00
			√		√		0.03	0.03	0.00	0.03	0.00	0.03	0.00
			√	√		√	0.07	0.07	0.00	0.07	0.00	0.07	0.00
			√		√	√	0.03	0.03	0.00	0.03	0.00	0.03	0.00

Test 4. F-statistic of instruments' joint significance in the first stage.

Ho: instruments are weak. Staiger & Stock rule of thumb: reject Ho if F-stat. > 10

Sample: Total sample	Sample: Type 1 firms	Sample: Type 2 firms	Sample: Type 3 firms	Intensity measure: Aggr.	Intensity measure: Decomp.	Compustat controls?	123	12	13	23	1	2	3
√				√			50.41	84.30	**0.32**	76.94	**0.01**	171.16	**0.43**
√					√		26.62	48.26	**0.23**	40.48	**0.00**	97.67	**0.27**
	√			√			27.13	43.38	**1.13**	41.85	**1.03**	88.92	**0.87**
	√				√		15.47	26.83	**0.98**	23.83	**0.68**	54.79	**1.00**
		√		√			**7.02**	11.90	**0.88**	**9.88**	**0.47**	21.87	**0.90**
		√			√		**3.67**	**5.94**	**0.76**	**4.85**	**0.36**	**9.67**	**0.85**
		√		√		√	**7.20**	11.93	**0.91**	**9.94**	**0.63**	21.38	**0.80**
		√			√	√	**3.95**	**6.30**	**0.78**	**5.13**	**0.48**	**9.85**	**0.79**
			√	√			13.72	20.71	**1.92**	19.11	**2.33**	38.36	**1.00**
			√		√		**9.22**	14.53	**1.62**	12.42	**1.74**	26.52	**1.04**
			√	√		√	13.22	20.06	**2.12**	18.17	**2.89**	36.57	**0.81**
			√		√	√	**9.10**	14.43	**1.73**	12.06	**2.13**	25.90	**0.87**

Test 5. Stock & Yogo/Cragg-Donald F-statistic.

Ho: instruments are weak. Rejection rule: reject Ho if F-statistic is above critical value.

- Stock and Yogo test 1 (bias of estimate) applies only to model "123". Critical value for tolerance of 5% bias is 13.91.
- Stock and Yogo test 2 (Wald statistic distortion) critical value for tolerance of 5% distortion is : 22.3 for "123", 19.93 for "12","13" and "23", and 16.38 for "1","2" and "3".

Sample: Total sample	Sample: Type 1 firms	Sample: Type 2 firms	Sample: Type 3 firms	Intensity measure: Aggr.	Intensity measure: Decomp.	Compustat controls?	123	12	13	23	1	2	3
√				√			545.17	943.08	**1.43**	831.74	**0.08**	1917.66	**1.69**
√					√		208.41	382.60	**1.07**	317.79	**0.04**	777.93	**1.07**
	√			√			286.92	501.02	**7.38**	440.84	**8.92**	1027.86	**3.24**
	√				√		118.62	213.57	**5.90**	181.09	**5.76**	436.62	**3.72**
		√		√			48.89	79.23	**2.39**	72.54	**1.61**	157.29	**2.64**
		√			√		**18.00**	31.19	**2.07**	26.24	**1.23**	61.22	**2.52**
		√		√		√	52.48	84.09	**2.50**	77.78	**2.20**	166.66	**2.29**
		√			√	√	**19.53**	33.31	**2.18**	28.38	**1.68**	65.13	**2.31**
			√	√			210.12	330.80	**7.98**	310.93	**9.24**	655.43	**4.23**
			√		√		85.33	137.43	**6.44**	123.93	**6.68**	268.87	**4.28**
			√	√		√	193.93	306.54	**8.84**	286.29	**11.66**	606.13	**3.49**
			√		√	√	80.92	131.02	**6.91**	116.82	**8.26**	254.97	**3.63**

NOTES:

Numbers in the column headers indicate inclusion of some combination of the following instruments in the model specification:

Number 1 designates proposed instrument #1: short term debt level in borrower's industry, *ST Debt Ind* **.**

Number 2 designates proposed instrument #2: borrower's prior reliance on CP backups, *CPB Reliance* .

Number 3 designates proposed instrument #3: average CP spread at the time of loan issuance, *CP Spread* .

Proposed instruments are defined in Appendix 3

TABLE 8 , Panel C.

Durbin-Wu-Hausman test for endogeneity of loan type choice (CP Backup dummy)

Ho: OLS is an appropriate estimation technique
Numbers in the table are p-values

Sample				Intensity measure		Compustat controls?	Instruments included in the model						
Total sample	Type 1 firms	Type 2 firms	Type 3 firms	Aggr.	Decomp.		"123"	"12"	"13"	"23"	"1"	"2"	"3"
√				√			0.000	0.000	**0.944**	0.000	**0.103**	0.000	**0.394**
√					√		0.000	0.000	**0.904**	0.000	**0.107**	0.000	**0.352**
	√			√			0.000	0.000	**0.102**	0.000	**0.204**	0.000	**0.086**
	√				√		0.000	0.000	**0.107**	0.000	**0.282**	0.000	**0.073**
		√		√			0.000	0.000	**0.938**	0.000	**0.419**	0.000	**0.161**
		√			√		0.014	0.024	**0.870**	0.007	**0.390**	0.015	**0.165**
		√		√		√	0.000	0.000	**0.727**	0.000	**0.804**	0.000	**0.095**
		√			√	√	0.030	0.047	**0.634**	0.018	**0.762**	0.040	**0.096**
			√	√			0.015	0.012	**0.094**	0.008	**0.295**	0.006	**0.097**
			√		√		**0.185**	**0.132**	**0.074**	**0.108**	**0.272**	**0.077**	**0.097**
			√	√		√	**0.160**	**0.159**	**0.230**	**0.128**	**0.646**	**0.128**	**0.050**
			√		√	√	**0.491**	**0.409**	**0.174**	**0.407**	**0.621**	**0.334**	**0.051**

Numbers in the column headers indicate inclusion of some combination of the following instruments in the model specification:
Number 1 designates proposed instrument #1: short term debt level in borrower's industry, *ST Debt Ind* **.**
Number 2 designates proposed instrument #2: borrower's prior reliance on CP backups, *CPB Reliance* .
Number 3 designates proposed instrument #3: average CP spread at the time of loan issuance, *CP Spread* .
Proposed instruments are defined in Appendix 3

TABLE 9. Treatment effects (TE), OLS and firm FE estimation results.

This table provides treatment effects model estimates of the following system of equations:

***Loan Spread** = f (Intensities, Firm characteristics, Bank characteristics, Loan characteristics, Environment) (Stage 2)*

***CP Backup**= f (Instrument, Intensities, Firm characteristics, Bank characteristics) (Stage1)*

In TE model binary choice of loan type (*CP Backup*) is treated as endogenous.

In two-step estimation, Stage 1 regression is used to estimate predicted probability of *CP Backup*, which is then used to adjust the sample moments in Stage to produce unbiased estimates. The instrument used in Stage 1 is *CPB Reliance*, a ratio of value of all CP backups to the total value of all loans obtained by a firm in the last five years. Stage 2 regression includes the same regressors as OLS models in Table 7. In maximum likelihood (ML) estimation, Stage 1 and Stage 2 equations are estimated simultaneously. For short, I refer to these two methods as TE-2step and TE-ML. TE-2step produces unbiased estimates but does not permit correcting standard errors. TE-ML permits error correction and is more efficient than TE-2step when model assumptions are met but it is not consistent, and sometimes the estimation procedure fails to converge.

Table 9 includes six panels, A through F, that report estimation results for the total sample (A) and for the subsamples by firm type (B - F). Firm types are designated based on firm's presence in Compustat and in CRSP at the time of loan initiation. Type 1 firms are those not in Compustat or CRSP. Type 2 firms are those listed in Compustat, but not in CRSP. Type 3 firms are those listed in both.

Each panel has 12 columns: six specifications using *A-intensity* and another six using its decomposition (*I-intensity and T-intensity).* Each set of six columns corresponds to the following combinations: (1) OLS/corrected standard errors (s.e.'s), (2) OLS/default s.e.'s, (3) TE-ML/corrected s.e.'s, (4) TE-ML/default s.e.'s, (5) TE-2step/default s.e.'s, and (6) firm FE/corrected s.e.'s. "Corrected" s.e.'s are corrected for heteroskedasticity and firm-level clustering. Two-step procedure does not allow for s.e.'s correction and in firm FE model errors are always corrected

Dependent variable, *Loan Spread*, is the spread over LIBOR on the drawn amount plus the annual fee in bps. *CP Backup* is a dummy that is equal to 1 if the loan is a CP backup. Intensity measures for firm i and bank j at time t are defined as follows. *A-intensity* is a ratio of firm i's loans on which bank j was a lead to its total borrowing during [t-5; t). *T-intensity* is a ratio of firm i's CP backups on which bank j was a lead to its total borrowing during [t-5; t). *I-intensity* is a ratio of firm i's non-CP backups on which bank j was a lead to its total borrowing during [t-5; t). *Type 2 Firm* and *Type 3 Firm* are the dummies that equal to 1 if borrower is categorized as Type 2 or Type 3, respectively. The third (and omitted) category is Type 1 firms. *Prev. Deal Amount* is the log of borrower's most recent loan deal measured in $ billion. *Rated Bank Debt* is a dummy that is equal to 1 if borrower has S&P senior secured debt rating. *Firm Size* is the log of borrower's total assets measured in $ billion. *Asset Tangib* is a ratio of Net PPE and total assets. *Leverage* is a ratio of long-term debt and total assets. *Profitability* is a ratio of EBITDA and total sales. *Bank Size* is the log of bank's total assets measured in $ billion. *Bank Core Dep* is a ratio of bank's core deposits (transactions accounts, non-transaction savings deposits, and total time deposits less than $100,000) and total deposits. *Loan Amount* is the log of loan size in $ billion. *Loan Maturity* is the log of the length in months between loan activation date and maturity date. *Secured* is a dummy that is equal to 1 if loan is secured and 0 if it is not secured or if information is missing. *Covenant Index* is the index based on the presence of four common loan covenants as described in Appendix 1; missing information is treated as absence of covenant. *Credit Line* is a dummy that is equal to 1 if loan is a line of credit. *Term Loan* is a dummy that is equal to 1 if loan is a term loan. *Lend. Standards* is a survey measure; higher values correspond to more stringent lending standards and lower credit availability. *Default Spread* is a difference between the yields on Moody's seasoned corporate bonds with Baa rating and 10-year U.S. government bond. *Term Spread* is a difference between the yields on 10-year and 1-year U.S. government bonds.

In addition to the above variables, OLS regressions and Stage 2 regressions of TE-ML and TE-2step models include industry dummies (based on borrower's one-digit SIC code), calendar year dummies and loan purpose dummies. Stage 1 regressions include calendar year dummies.

TABLE 9 , Panel A. Treatment effects (TE), OLS, and firm FE results

Total sample, <u>without</u> Compustat controls.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Model	**OLS**		**TE-ML**		**TE-2step**	**Firm FE**	**OLS**		**TE-ML**		**TE-2step**	**Firm FE**
Std. errors	**correct**	**deflt**	**correct**	**deflt**	**deflt**	**correct**	**correct**	**deflt**	**correct**	**deflt**	**deflt**	**correct**
Stage 2 regression, dependent variable is ***Loan Spread***												
A-intensity	6.44***	***	7.45***	***	7.26***	2.04**						
	(1.31)		*(1.32)*		*(0.90)*	*(0.98)*						
I-intensity							11.71***	***	9.81***	***	11.02***	3.66***
							(1.41)		*(1.42)*		*(0.93)*	*(1.07)*
T-intensity							-37.04***	***	-13.09***	***	-28.49***	-9.55***
							(3.22)		*(3.28)*		*(2.68)*	*(2.73)*
Type 2 Firm	-25.30***	***	-22.81***	***	-23.31***	-5.29	-24.56***	***	-22.78***	***	-23.92***	-5.36
	(2.49)		*(2.47)*		*(0.95)*	*(9.66)*	*(2.47)*		*(2.47)*		*(0.93)*	*(9.62)*
Type 3 Firm	-16.61***	***	-18.67***	***	-18.16***	-26.82***	-17.17***	***	-18.67***	***	-17.66***	-26.77***
	(2.66)		*(2.63)*		*(1.04)*	*(5.73)*	*(2.65)*		*(2.63)*		*(1.02)*	*(5.72)*
Bank Size	0.16		0.19		0.17	1.39***	0.33		0.26		0.30	1.46***
	(0.52)		*(0.52)*		*(0.34)*	*(0.39)*	*(0.52)*		*(0.52)*		*(0.33)*	*(0.39)*
Bank Core Dep	7.12*	**	7.92*	**	7.70**	7.92**	7.22*	**	7.85*	**	7.43**	7.98**
	(4.13)		*(4.10)*		*(3.41)*	*(3.28)*	*(4.12)*		*(4.09)*		*(3.35)*	*(3.28)*
CP Backup	-71.64***	***	-123.76***	***	-114.07***	-46.92***	-64.79***	***	-114.14***	***	-82.62***	-47.29***
	(4.42)		*(5.43)*		*(3.15)*	*(4.65)*	*(4.27)*		*(5.60)*		*(3.83)*	*(4.65)*
Rated Bank Debt	-1.75	*	1.87	**	1.30	-0.42	-0.34		2.10	**	0.58	-0.46
	(2.19)		*(2.18)*		*(0.93)*	*(2.85)*	*(2.19)*		*(2.18)*		*(0.92)*	*(2.85)*
Lend. Standards	0.25**	***	0.23**	***	0.24***	0.33***	0.25**	***	0.24**	***	0.26***	0.32***
	(0.10)		*(0.10)*		*(0.05)*	*(0.10)*	*(0.10)*		*(0.10)*		*(0.14)*	*(0.10)*
R-sq.	0.524					0.250	0.524					0.251
Stage 1 regression, dependent variable is ***CP Backup***												
CPB Reliance			1.97***	***	1.92***				1.91***	***	1.89***	
			(0.07)		*(0.03)*				*(0.09)*		*(0.05)*	
A-intensity			-0.01		-0.02							
			(0.03)		*(0.02)*							
I-intensity									-0.03		-0.03	
									(0.04)		*(0.03)*	
T-intensity									-0.01		0.02	
									(0.08)		*(0.05)*	
Type 2 Firm			0.13**	***	0.17***				0.13***		0.17***	
			(0.05)		*(0.02)*				*(0.05)*		*(0.02)*	
Type 3 Firm			-0.20***	***	-0.16***				-0.20***		-0.16***	
			(0.08)		*(0.03)*				*(0.08)*		*(0.03)*	
Bank Size			0.03**	***	0.04***				0.03**	***	0.03***	
			(0.01)		*(0.01)*				*(0.01)*		*(0.01)*	
Bank Core Dep			0.21***	***	0.21***				0.21***		0.21***	
			(0.08)		*(0.08)*				*(0.08)*		*(0.08)*	
Rated Bank Debt			0.40***	***	0.38***				0.40***		0.38***	
			(0.06)		*(0.02)*				*(0.06)*		*(0.02)*	
rho			0.429		0.348				0.377		0.138	
Prob(rho=0)			0.000						0.000			
lambda			34.55***	***	27.90***				30.19***	***	10.87***	
Pseudo R-sq.			0.345		0.345				0.345		0.345	
N Obs.	45770		45770		45770	45770	45770		45770		45770	

NOTES:

TE-ML and TE-2step stand for Treatment effects models estimated with maximum likelihood and two-step methods.

"Corrected" errors are clustered and heteroscedasticity corrected. *** Signif. at 1% level; ** at 5% level; * at 10% level.

The following coefficients are not reported: (1) *Prev. deal amount, Bank core dep. sd* , and year dummies in Stage 1 and Stage 2, and (2) *Loan Amount, Loan Maturity, Secured, Covenant Index, Credit Line, Term Loan, Default Spread, Term Spread* , and industry and loan purpose dummies in Stage 2.

TABLE 9 , Panel B. Treatment effects (TE), OLS, and firm FE results

Type 1 firm subsample, without Compustat controls.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Model	**OLS**		TE-ML		**TE-2step**	**Firm FE**	**OLS**		TE-ML		**TE-2step**	**Firm FE**
Std. errors	**correct**	**deflt**	correct	**deflt**	**deflt**	**correct**	**correct**	**deflt**	correct	**deflt**	**deflt**	**correct**
Stage 2 regression, dependent variable is ***Loan Spread***												
A-intensity	6.75***	***	7.72***	***	7.60***	1.30						
	(1.84)		(1.86)		(1.27)	*(1.31)*						
I-intensity							12.80***	***	10.77***	***	12.06***	2.97**
							(1.98)		(2.00)		(1.29)	*(1.42)*
T-intensity							-48.11***	***	-21.08***	***	-38.22***	-11.39**
							(4.62)		(4.90)		(3.81)	*(4.46)*
Bank Size	0.06		0.05		0.05	1.33***	0.18		0.12		0.16	1.39***
	(0.74)		(0.74)		(0.48)	*(0.49)*	(0.73)		(0.74)		(0.47)	*(0.49)*
Bank Core Dep	15.88***	***	15.57***	***	15.52***	10.01**	15.67***	***	15.48***	***	15.57***	9.94**
	(5.79)		(5.79)		(4.84)	*(4.74)*	(5.82)		(5.79)		(4.73)	*(4.75)*
CP Backup	-75.16***	***	-138.10***	***	-128.93**	-46.84***	-67.33***	***	-125.88**	***	-88.83***	-47.35***
	(5.77)		(7.10)		(4.53)	*(6.98)*	(5.50)		(7.53)		(5.47)	*(6.97)*
Rated Bank Debt	-7.36**	***	-2.74	**	-3.18**	-1.11	-5.26*	***	-2.19	*	-4.06***	-1.20
	(2.99)		(2.98)		(1.28)	*(3.95)*	(2.98)		(2.98)		(1.26)	*(3.94)*
Lend. Standards	0.26*	***	0.24*	***	0.25***	0.45***	0.26*	***	0.24*	***	0.26***	0.44***
	(0.14)		(0.14)		(0.07)	*(0.15)*	(0.14)		(0.14)		(0.07)	*(0.15)*
R-sq.	0.509					0.229	0.516					0.230
Stage 1 regression, dependent variable is ***CP Backup***												
CPB Reliance			1.99***	***	1.91***				2.00***	***	1.96***	
			(0.09)		(0.04)				(0.12)		(0.07)	
A-intensity			-0.04		-0.04							
			(0.05)		(0.03)							
I-intensity									-0.03		-0.02	
									(0.05)		(0.04)	
T-intensity									-0.17	**	-0.10	
									(0.11)		(0.08)	
Bank Size			0.02	**	0.03**				0.03*	**	0.03**	
			(0.02)		(0.01)				(0.02)		(0.01)	
Bank Core Dep			0.11		0.10				0.11		0.10	
			(0.11)		(0.11)				(0.11)		(0.11)	
Rated Bank Debt			0.39***	***	0.38***				0.39***	***	0.38***	
			(0.07)		(0.03)				(0.07)		(0.03)	
rho			0.486		0.415				0.425		0.159	
Prob(rho=0)			0.000						0.000			
lambda			40.95***	***	34.80***				35.47***	***	13.03***	
Pseudo R-sq.			0.342		0.342				0.342		0.342	
N Obs.	25301		25301		25301	25301	25301		25301		25301	25301

NOTES:

TE-ML and TE-2step stand for Treatment effects models estimated with maximum likelihood and two-step methods.

"Corrected" errors are clustered and heteroscedasticity corrected. *** Signif. at 1% level; ** at 5% level; * at 10% level.

The following coefficients are not reported: (1) *Prev. deal amount, Bank core dep. sd* , and year dummies in Stage 1 and Stage 2, and (2) *Loan Amount, Loan Maturity, Secured, Covenant Index, Credit Line, Term Loan, Default Spread, Term Spread* , and industry and loan purpose dummies in Stage 2.

TABLE 9, Panel C. Treatment effects (TE), OLS, and firm FE results

Type 2 firm subsample, <u>without</u> Compustat controls.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Model	**OLS**		**TE-ML**		**TE-2step**	**Firm FE**	**OLS**		**TE-ML**		**TE-2step**	**Firm FE**
Std. errors	**correct**	**deflt**	**correct**	**deflt**	**deflt**	**correct**	**correct**	**deflt**	**correct**	**deflt**	**deflt**	**correct**
Stage 2 regression, dependent variable is ***Loan Spread***												
A-intensity	1.76		3.16	**	2.77*	1.23						
	(2.13)		(2.14)		(1.51)	*(1.65)*						
I-intensity							5.89**	***	4.17*	**	5.26***	2.97
							(2.41)		(2.43)		(1.61)	*(1.92)*
T-intensity							-17.39***	***	-2.01		-11.74***	-6.10*
							(4.37)		(4.23)		(3.75)	*(3.35)*
Bank Size	1.80**	***	1.80**	***	1.79***	1.92***	1.95**	***	1.84**	***	1.91***	2.01***
	(0.86)		(0.86)		(0.57)	*(0.72)*	(0.85)		(0.86)		(0.56)	*(0.72)*
Bank Core Dep	3.30		5.91		5.15	4.64	3.37		5.75		4.24	4.72
	(6.42)		(6.39)		(5.58)	*(5.68)*	(6.38)		(6.36)		(5.53)	*(5.68)*
CP Backup	-56.79***	***	-90.84***	***	-81.58***	-36.39***	-54.20***	***	-87.95***	***	-66.81***	-36.60***
	(9.39)		(10.95)		(5.34)	*(7.79)*	(9.36)		(11.24)		(6.41)	*(7.80)*
Rated Bank Debt	3.62	**	6.06	***	5.37***	4.06	4.21	**	6.06	***	4.89***	4.08
	(4.10)		(4.12)		(1.73)	*(5.82)*	(4.09)		(4.11)		(1.72)	*(5.81)*
Lend. Standards	0.31*	***	0.30*	***	0.31***	0.29*	0.30*	***	0.30*	***	0.30***	0.28*
	(0.17)		(0.17)		(0.09)	*(0.16)*	(0.18)		(0.17)		(0.09)	*(0.16)*
R-sq.	0.573					0.326	0.576					0.326
Stage 1 regression, dependent variable is ***CP Backup***												
CPB Reliance			1.74***	***	1.73***				1.61***	***	1.63***	
			(0.12)		(0.05)				(0.15)		(0.08)	
A-intensity			0.06		0.06							
			(0.06)		(0.04)							
I-intensity									0.00		0.01	
									(0.07)		(0.05)	
T-intensity									0.22*	***	0.20**	
									(0.11)		(0.08)	
Bank Size			0.03	*	0.03**				0.03	*	0.03**	
			(0.02)		(0.02)				(0.02)		(0.02)	
Bank Core Dep			0.44***	***	0.44***				0.43***	***	0.43***	
			(0.15)		(0.14)				(0.15)		(0.14)	
Rated Bank Debt			0.37***	***	0.33***				0.37***	***	0.33***	
			(0.10)		(0.05)				(0.10)		(0.05)	
rho			0.335		0.243				0.314		0.118	
Prob(rho=0)			0.000						0.000			
lambda			22.32***	***	16.10***				20.86***	***	7.74***	
Pseudo R-sq.			0.310		0.310				0.310		0.310	
N Obs.	11800		11800		11800	11800	11800		11800		11800	11800

NOTES:
TE-ML and TE-2step stand for Treatment effects models estimated with maximum likelihood and two-step methods.
"Corrected" errors are clustered and heteroscedasticity corrected. *** Signif. at 1% level; ** at 5% level; * at 10% level.
The following coefficients are not reported: (1) *Prev. deal amount, Bank core dep. sd* , and year dummies in Stage 1 and Stage 2, and (2) *Loan Amount, Loan Maturity, Secured, Covenant Index, Credit Line, Term Loan, Default Spread, Term Spread* , and industry and loan purpose dummies in Stage 2.

TABLE 9 , Panel D. Treatment effects (TE), OLS, and firm FE results

Type 2 firm subsample, with Compustat controls.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Model	**OLS**		**TE-ML**		**TE-2step**	**Firm FE**	**OLS**		**TE-ML**		**TE-2step**	**Firm FE**
Std. errors	**correct**	**deflt**	**correct**	**deflt**	**deflt**	**correct**	**correct**	**deflt**	**correct**	**deflt**	**deflt**	**correct**
Stage 2 regression, dependent variable is ***Loan Spread***												
A-intensity	2.44	*	3.88*	***	2.81**	1.31						
	(1.99)		(2.03)		(1.42)	*(1.58)*						
I-intensity							5.95***	***	9.47***	***	6.21***	3.21*
							(2.27)		(2.57)		(1.51)	*(1.85)*
T-intensity							-13.76***	***	-51.34***	***	-16.59***	-6.63**
							(3.84)		(5.38)		(3.33)	*(3.24)*
Bank Size	1.64**	***	1.41*	***	1.58***	1.80***	1.73**	***	2.70***	***	1.80***	1.89***
	(0.78)		(0.78)		(0.54)	*(0.66)*	(0.77)		(0.86)		(0.54)	*(0.66)*
Bank Core Dep	2.01		4.31		2.59	3.99	2.02		-4.68		1.56	4.07
	(6.31)		(6.29)		(5.26)	*(5.46)*	(6.27)		(7.35)		(5.25)	*(5.45)*
CP Backup	-53.18***	***	-86.63***	***	-61.98***	-35.32***	-50.93***	***	51.16***	***	-43.58***	-35.57***
	(9.09)		(11.29)		(5.19)	*(7.66)*	(9.08)		(8.39)		(5.95)	*(7.67)*
Rated Bank Debt	1.30		1.24		1.30	5.70	1.61		2.05		1.66	5.68
	(4.06)		(4.04)		(1.71)	*(5.89)*	(4.03)		(4.55)		(1.71)	*(5.88)*
Lend. Standards	0.43**	***	0.42**	***	0.43***	0.36**	0.42**	***	0.31**	***	0.42***	0.35**
	(0.17)		(0.17)		(0.09)	*(0.16)*	(0.17)		(0.14)		(0.09)	*(0.16)*
Firm Size	-5.73**	***	-2.75	***	-4.98***	-9.70*	-5.28**	***	-14.64***	***	-5.80***	-9.63*
	(2.47)		(2.65)		(0.79)	*(5.43)*	(2.48)		(2.46)		(0.80)	*(5.45)*
Asset Tangib.	-4.51		-5.14	*	-4.72	-13.57	-4.66		-3.92		-4.52	-14.43
	(7.99)		(8.28)		(3.00)	*(26.36)*	(8.05)		(7.74)		(3.00)	*(26.34)*
Leverage	76.04***	***	69.61***	***	74.51***	39.25**	74.25***	***	89.89***	***	75.19***	39.15**
	(12.58)		(11.79)		(3.93)	*(16.01)*	(12.41)		(14.99)		(3.92)	*(15.91)*
Profitability	-217.01**	***	-201.47**	***	-213.10**	-200.44***	-218.13**	***	-265.16**	***	-221.42**	-201.22***
	(24.56)		(25.88)		(8.55)	*(36.63)*	(24.51)		(25.15)		(8.63)	*(36.57)*
R-sq.	0.614					0.349	0.615					0.350
Stage 1 regression, dependent variable is ***CP Backup***												
CPB Reliance			1.43***	***	1.43***				0.34***	***	1.31***	
			(0.13)		(0.05)				(0.09)		(0.08)	
A-intensity			0.08	*	0.08**							
			(0.05)		(0.04)							
I-intensity									-0.07	*	0.02	
									(0.06)		(0.05)	
T-intensity									0.70***	***	0.24***	
									(0.09)		(0.08)	
Bank Size			0.01		0.01				-0.00		0.01	
			(0.02)		(0.02)				(0.02)		(0.02)	
Bank Core Dep			0.42***	***	0.42***				0.29**	**	0.41***	
			(0.14)		(0.14)				(0.12)		(0.14)	
Rated Bank Debt			0.11	**	0.05				0.02		0.06	
			(0.12)		(0.05)				(0.09)		(0.05)	
Firm Size			0.32***	***	0.35***				0.33***	***	0.35***	
			(0.04)		(0.01)				(0.03)		(0.01)	
Asset Tangib.			0.03		-0.03				-0.02		-0.03	
			(0.16)		(0.07)				(0.13)		(0.07)	
Leverage			-0.61**	***	-0.46***				-0.54**	***	-0.46***	
			(0.29)		(0.12)				(0.25)		(0.12)	
Profitability			2.49***	***	2.64***				2.89***	***	2.65***	
			(0.50)		(0.22)				(0.42)		(0.22)	
rho			0.353		0.093				-0.894		-0.075	
Prob(rho=0)			0.000						0.000			
lambda			22.40***	***	5.84***				-63.18***	***	-4.65	
Pseudo R-sq.			0.356		0.356				0.355		0.355	
N Obs.	11799		11799		11799		11799		11799		11799	

NOTES:

TE-ML and TE-2step stand for Treatment effects models estimated with maximum likelihood and two-step methods.
"Corrected" errors are clustered and heteroscedasticity corrected. *** Signif. at 1% level; ** at 5% level; * at 10% level.
The following coefficients are not reported: (1) *Prev. deal amount, Bank core dep. sd* , and year dummies in Stage 1 and Stage 2, and (2) *Loan Amount, Loan Maturity, Secured, Covenant Index, Credit Line, Term Loan, Default Spread, Term Spread* , and industry and loan purpose dummies in Stage 2.

TABLE 9, Panel E. Treatment effects (TE), OLS, and firm FE results

Type 3 firm subsample, <u>without</u> Compustat controls.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Model	**OLS**		TE-ML		**TE-2step**	**Firm FE**	**OLS**		TE-ML		**TE-2step**	**Firm FE**
Std. errors	**correct**	**deflt**	correct	**deflt**	**deflt**	**correct**	**correct**	**deflt**	correct	**deflt**	**deflt**	**correct**
Stage 2 regression, dependent variable is ***Loan Spread***												
A-intensity	8.34***	***	8.39	***	8.39***	3.40						
	(2.83)		.		(2.04)	*(2.08)*						
I-intensity							10.06***	***	8.91	***	9.10***	3.66*
							(2.95)		.		(2.08)	*(2.16)*
T-intensity							-28.11**	***	-2.76		-6.99	-1.63
							(11.14)		(0.00)		(9.77)	*(10.18)*
Bank Size	-1.65	**	-1.49	**	-1.50**	-0.12	-1.47	*	-1.45	*	-1.45*	-0.10
	(1.13)		(0.00)		(0.75)	*(0.80)*	(1.13)		(0.00)		(0.75)	*(0.80)*
Bank Core Dep	-5.36		-5.64		-5.65	6.73	-5.27		-5.60		-5.55	6.78
	(9.42)		(0.00)		(7.77)	*(6.46)*	(9.43)		(0.00)		(7.75)	*(6.46)*
CP Backup	-60.80***	***	-96.35	***	-96.16***	-43.87***	-55.22***	***	-91.80	***	-86.14***	-44.05***
	(10.59)		(0.00)		(8.20)	*(10.37)*	(10.16)		(0.00)		(10.27)	*(10.39)*
Rated Bank Debt	14.69***	***	16.55	***	16.50***	6.67	15.23***	***	16.56	***	16.33***	6.63
	(4.67)		.		(2.15)	*(6.22)*	(4.69)		.		(2.14)	*(6.23)*
Lend. Standards	0.28	**	0.28	**	0.29**	0.06	0.28	**	0.28	**	0.28**	0.07
	(0.22)		.		(0.12)	*(0.25)*	(0.22)		.		(0.12)	*(0.25)*
R-sq.	0.472					0.253	0.473					0.253
Stage 1 regression, dependent variable is ***CP Backup***												
CPB Reliance			2.86	***	2.82***				2.87	***	2.82***	
			.		(0.11)				.		(0.16)	
A-intensity			-0.04		-0.05							
			(0.00)		(0.06)							
I-intensity									-0.03		-0.05	
									(0.00)		(0.07)	
T-intensity									-0.07		-0.04	
									(0.00)		(0.20)	
Bank Size			0.03		0.04				0.03		0.04	
			.		(0.03)				.		(0.03)	
Bank Core Dep			0.17		0.16				0.17		0.16	
			.		(0.23)				.		(0.23)	
Rated Bank Debt			0.45	***	0.41***				0.45	***	0.41***	
			.		(0.07)				.		(0.07)	
rho			0.298		0.292				0.274		0.229	
Prob(rho=0)			0.000						0.000			
lambda			24.05***	***	23.56***				22.08***	***	18.45***	
Pseudo R-sq.			0.380		0.380				0.380		0.380	
N Obs.	8669		8669		8669		8669		8669		8669	
			(S.E.'s are NA)						(S.E.'s are NA)			

NOTES:

TE-ML and TE-2step stand for Treatment effects models estimated with maximum likelihood and two-step methods.

"Corrected" errors are clustered and heteroscedasticity corrected. *** Signif. at 1% level; ** at 5% level; * at 10% level.

The following coefficients are not reported: (1) *Prev. deal amount, Bank core dep. sd* , and year dummies in Stage 1 and Stage 2, and (2) *Loan Amount, Loan Maturity, Secured, Covenant Index, Credit Line, Term Loan, Default Spread, Term Spread* , and industry and loan purpose dummies in Stage 2.

In models (3) and (8) standard errors could not be estimated due to the "nonsymmetric or highly singular" variance matrix.

TABLE 9 , Panel F. Treatment effects (TE), OLS, and firm FE results

Type 3 firm subsample, with Compustat controls.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Model	**OLS**		**TE-ML**		**TE-2step**	**Firm FE**	**OLS**		**TE-ML**		**TE-2step**	**Firm FE**
Std. errors	**correct**	**deflt**	**correct**	**deflt**	**deflt**	**correct**	**correct**	**deflt**	**correct**	**deflt**	**deflt**	**correct**
Stage 2 regression, dependent variable is ***Loan Spread***												
A-intensity	6.82**	***	7.11	***	6.95***	2.86						
	(2.71)		.		(1.96)	*(2.02)*						
I-intensity							7.77***	***	7.22**	***	7.63***	3.27
							(2.84)		(2.81)		(1.99)	*(2.08)*
T-intensity							-12.90	*	4.66		-8.42	-5.09
							(11.22)		(11.82)		(8.71)	*(10.08)*
Bank Size	0.20		0.14		0.17	0.21	0.27		0.15		0.24	0.24
	(1.10)		.		(0.72)	*(0.78)*	(1.10)		(1.09)		(0.73)	*(0.78)*
Bank Core Dep	4.65		3.94		4.33	6.42	4.63		3.96		4.46	6.50
	(9.69)		.		(7.43)	*(6.22)*	(9.69)		(9.58)		(7.42)	*(6.22)*
CP Backup	-47.47***	***	-75.61	***	-60.91***	-40.15***	-44.60***	***	-74.53***	***	-52.37***	-40.43***
	(9.88)		(0.00)		(7.99)	*(9.91)*	(9.46)		(17.83)		(9.29)	*(9.91)*
Rated Bank Debt	12.36**	***	12.90	***	12.62***	7.17	12.49**	***	12.90***	***	12.60***	7.11
	(4.97)		.		(2.20)	*(6.04)*	(4.96)		(4.89)		(2.20)	*(6.05)*
Lend. Standards	0.28	**	0.29	**	0.28**	0.18	0.28	**	0.29	**	0.28**	0.19
	(0.22)		.		(0.12)	*(0.24)*	(0.22)		(0.21)		(0.12)	*(0.24)*
Firm Size	-14.66***	***	-12.70	***	-13.76***	-14.67***	-14.27***	***	-12.71***	***	-13.88***	-14.77***
	(2.78)		(0.00)		(1.21)	*(5.30)*	(2.78)		(2.82)		(1.21)	*(5.29)*
Asset Tangib.	4.71		6.27		5.40	67.49*	4.99		6.26		5.29	67.36*
	(9.02)		.		(3.95)	*(36.83)*	(8.98)		(8.91)		(3.95)	*(36.81)*
Leverage	77.37***	***	73.21	***	75.48***	54.19***	76.72***	***	73.25***	***	75.86***	54.40***
	(9.98)		.		(4.56)	*(17.46)*	(9.91)		(9.93)		(4.56)	*(17.48)*
Profitability	-184.76***	***	-180.88	***	-182.95***	-195.22***	-184.38***	***	-180.93***	***	-183.50***	-195.32***
	(23.43)		(0.00)		(9.20)	*(37.90)*	(23.43)		(22.98)		(9.20)	*(37.95)*
R-sq.	0.517					0.281	0.517					0.281
Stage 1 regression, dependent variable is ***CP Backup***												
CPB Reliance			1.98	***	1.95***				2.04***	***	1.99***	
			.		(0.12)				(0.25)		(0.18)	
A-intensity			0.05		0.02							
			.		(0.07)							
I-intensity									0.07		0.03	
									(0.09)		(0.08)	
T-intensity									-0.05		-0.05	
									(0.26)		(0.21)	
Bank Size			-0.02		-0.01				-0.02		-0.01	
			(0.00)		(0.03)				(0.03)		(0.03)	
Bank Core Dep			0.18		0.16				0.18		0.16	
			.		(0.25)				(0.25)		(0.25)	
Rated Bank Debt			0.15	*	0.12				0.15	*	0.12	
			.		(0.08)				(0.13)		(0.08)	
Firm Size			0.51	***	0.53***				0.51***	***	0.53***	
			.		(0.03)				(0.06)		(0.03)	
Asset Tangib.			0.37	***	0.39***				0.37	***	0.39***	
			.		(0.13)				(0.24)		(0.13)	
Leverage			-0.71	***	-0.71***				-0.71**	***	-0.71***	
			(0.00)		(0.17)				(0.35)		(0.17)	
Profitability			2.80	***	2.79***				2.81***	***	2.80***	
			.		(0.37)				(0.76)		(0.37)	
rho			0.256		0.121				0.249		0.064	
Prob(rho=0)			0.000						0.003			
lambda			19.80	***	9.35***				19.28***	***	4.96	
Pseudo R-sq.			0.454		0.454				0.454		0.454	
N Obs.	8636		8636		8636		8636		8636		8636	
NOTES:			(S.E.'s are NA)						(did not converge)			

TE-ML and TE-2step stand for Treatment effects models estimated with maximum likelihood and two-step methods.
"Corrected" errors are clustered and heteroscedasticity corrected. *** Signif. at 1% level; ** at 5% level; * at 10% level.
The following coefficients are not reported: (1) *Prev. deal amount, Bank core dep. sd* , and year dummies in Stage 1 and Stage 2, and (2) *Loan Amount, Loan Maturity, Secured, Covenant Index, Credit Line, Term Loan, Default Spread, Term Spread* , and industry and loan purpose dummies in Stage 2.

In model (3) s.e.'s could not be estimated due to the "nonsymmetric or highly singular" variance matrix. In models (8) and (9) ML procedure failed to converge after 15 iterations.

REFERENCES

1. Acharya, V., Almeida, H., and Campello, M., 2012, Aggregate risk and the choice between cash and credit lines, Working paper, New York University and University of Illinois.
2. Acharya,V., Almeida, H., Ippolito, F., and Perez, A., Credit lines as monitored liquidity insurance: Theory and evidence, January 2013, Working paper.
3. Acharya, V. and Mora, N., 2011, Are banks passive liquidity backstops? Deposit rates and flows during the 2007-2009 crisis, Working paper, New York University Stern School of Business.
4. Agarwal, S., Chomsisengphet, S., and Driscoll, J., 2011, How do private firms use credit lines? *Economic Perspectives 25(2)*, 71-79.
5. Agarwal, S. and Hauswald, R., 2007, The choice between arm's-length and relationship debt: Evidence from eLoans, Working paper, Federal Reserve Bank of Chicago and American University.
6. Allen, F., 1990, The market for information and the origin of financial intermediation, *Journal of Financial Intermediation 1(1)*, 3-30.
7. Angrist, J. and Krueger, A., 1991, Does compulsory school attendance affect schooling and earnings? *Quarterly Journal of Economics 106(4),* 979-1014.
8. Avery, R. and Berger, A., 1991, Loan commitments and bank risk exposure, *Journal of Banking and Finance 15(1)*, 173-192.
9. Barakova, I. and Parthasarathy, H., 2012, How committed are bank corporate line commitments? Working paper, Office of the Comptroller of the Currency.
10. Baum, C., 2006, An introduction to modern econometrics using Stata, A Stata Press Publication, StataCorp LP.
11. Bech, M. and Rice, T., Profits and balance sheet developments at U.S. commercial banks in 2008, *Federal Reserve Bulletin*, June 2009.
12. Beneish, M. and Press, E., 1993, Costs of technical violation of accounting-based debt covenants, *The Accounting Review 68*, 233-257.
13. Berger, A. and Bouwman, C., 2013, How does capital affect bank performance during financial crises? *Journal of Financial Economics*, forthcoming.
14. Berger, A. and Udell, G., 1992, Some evidence on the empirical significance of credit rationing, *Journal of Political Economy 100(5),* 1047-1077.
15. Berger, A. and Udell, G., 1995, Relationship lending and lines of credit in small business finance, *Journal of Business 68*, 351-381.
16. Berglof, E. and vonThadden, E., 1994, Short-term versus long-term interests: Capital structure with multiple investors, *Quarterly Journal of Economics 109(4),* 1055-1084.
17. Berlin, M. and Mester, L., 1992. Debt covenants and renegotiations, *Journal of Financial Intermediation 2*, 95–133.
18. Berlin, M. and Mester, L., 1999, Deposits and lending relationships, *Review of Financial Studies 12*, 579 - 608.

19. Best, R. and Zhang, H., 1993, Alternative information sources and the information content of bank loans, *Journal of Finance 48*, 1507-1522.

20. Bharath, S., Dahiya, S., Saunders, A., and Srinivasan, A., 2007, So what do I get? The bank's view of lending relationships, *Journal of Financial Economics 85*, 368-419.

21. Bharath, S., Dahiya, S., Saunders, A., and Srinivasan, A., 2011, Lending relationships and loan contract terms, *Review of Financial Studies 24 (4),* 1141-1203.

22. Bhattacharya, S. and Chiesa, G., 1995, Proprietary information, financial intermediation and research incentives, *Journal of Financial Intermediation 4*, 328-357.

23. Billett, M., Flannery, M., and Garfinkel, J., 1995, The effect of lender identity on the borrowing firm's equity return, *Journal of Finance 50,* 699-718.

24. Black, H., Collins, M., Robinson, B., and Schweitzer, R., 1997, Changes in market perception of riskiness: the case of too-big-to-fail, *Journal of Financial Services Research 20*, 389-406.

25. Blackwell, N. and Santomero, A., 1982, Bank credit rationing and the customer relation, *Journal of Monetary Economics 9(1),* 121-129.

26. Boot, A., 2000, Relationship banking: What do we know? *Journal of Financial Intermediation 9(1),* 7-25.

27. Boot, A., Greenbaum, S., and Thakor, A., 1993, Reputation and discretion in financial contracting, *American Economic Review 83(5),* 1165-1183.

28. Boot, A. and Thakor, A., 1994, Moral hazard and secured lending in an infinitely repeated credit market game, *International Economic Review 35*, 899-920.

29. Boot, A. and Thakor, A., 2000, Can relationship banking survive competition? *Journal of Finance 55,* 679-713.

30. Boot, A., Thakor, A., and Udell, G., 1987, Competition, risk neutrality and loan commitments, *Journal of Banking and Finance 11*(3), 449-471.

31. Bord, V. and Santos, J., 2011, Banks' liquidity and cost of liquidity for corporations, Working paper, Federal Reserve Bank of New York.

32. Bound, J., Jaeger, D., and Baker, R., 1995, Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak, *Journal of the American Statistical Association 90,* 443-450.

33. Boyd, J. and Prescott, E., 1986, Financial intermediary-coalitions, *Journal of Economic Theory 38(2),* 211-232.

34. Bradley, M. and Roberts, M., 2004, The structure and pricing of corporate debt covenants, Working paper, Duke university.

35. Brick, I. and Palia, D., 2007, Evidence of jointness in the terms of relationship lending, *Journal of Financial Intermediation 16,* 452-476.

36. Bryant, J., 1980, A model of reserves, bank runs, and deposit insurance, *Journal of Banking and Finance 4,* 335-344.

37. Byers, S., Fraser, D., and Shockley, R., 1998, Lender identity and borrower returns: the evidence from foreign bank loans to U.S. corporations, *Global Finance Journal 9,* 81-94.

38. Calomiris, C., Himmelberg, C., and Wachtel, P., 1995, Commercial paper, corporate finance, and the business cycle: A microeconomic perspective, *Carnegie-Rochester Conference Series On Public Policy 42*, 203-250.

39. Calomiris, C. and Kahn, C., 1991, The role of demandable debt in structuring optimal banking arrangements, *American Economic Review 81*, 497-513.

40. Cameron, C. and Trivedi, P., 2005, Microeconometrics: methods and applications, Cambridge University Press, NY.

41. Cameron, C. and Trivedi, P., 2009, Microeconometrics using Stata, A Stata Press Publication, StataCorp LP.

42. Campa, J. and Kedia, S., 2002, Explaining the diversification discount, *Journal of Finance 57*, 1731-1762.

43. Campbell, T., 1978, A model of the market for lines of credit, *Journal of Finance 33(1),* 231-244.

44. Campbell, T., 1979, Optimal investment financing decisions and the value of confidentiality, *Journal of Financial and Quantitative Analysis 14,* 232-257.

45. Campello, M., Giambona, E., Graham, J., and Harvey, C., 2009, Liquidity management and corporate investment during a financial crisis, *Review of Financial Studies 24,* 1944-1979.

46. Campello, M., Giambona, E., Graham, J., and Harvey, C., 2011, Access to liquidity and corporate investment in Europe during the credit crisis of 2009, Working paper, University of Illinois, University of Amsterdam, and Duke University.

47. Cantillo, M. and Wright, J., 2000, How do firms choose their lenders? An empirical investigation, *Review of Financial Studies 13*, 155-189.

48. Carey, M., Post, M. and Sharpe, S., 1998, Does corporate lending by banks and financing companies differ? Evidence in private debt contracting, *Journal of Finance 53*, 845-878.

49. Cavalcanti, R., Erosa, A., and Temzelides, T., 1999, Private money and reserve management in a random-matching model, *Journal of Political Economy 107(5)*, 929-945.

50. Chan, Y., Greenbaum, S., and Thakor, A., 1986, Information reusability, competition and bank asset quality, *Journal of Banking and Finance 10(2),* 243-253.

51. Chan, Y. and Thakor, A., 1987, Collateral and competitive equilibria with moral hazard and private information, *Journal of Finance 42,* 345-363.

52. Chava, S. and Roberts, M., 2008, How does financing impact investment? The role of debt covenants, *Journal of Finance 63*, 2085-2121.

53. Chemmanur, T. and Fulghieri, P., 1994, Reputation, renegotiation and the choice between bank loans and publicly traded debt, *Review of Financial Studies 7,* 475-506.

54. Coleman, A., Esho, N., and Sharpe, I., 2006, Does bank monitoring influence loan contract terms? *Journal of Financial Services Research 30(2),* 177-198.

55. Cook, D., Schellhorn, C., and Spellman, L., 2003, Lender certification premiums, *Journal of Banking and Finance 27(8),* 1561-1579.

56. Cornett, M., McNutt, J., Strahan, P., and Tehranian, H., 2011, Liquidity risk management and credit supply in the financial crisis, *Journal of Financial Economics 101(2),* 297-312.

57. Covitz, D. and Downing, C., 2002, Insolvency or liquidity squeeze? Explaining very short-term corporate yield spreads, October 2002, FEDS Working Paper No. 2002-2045.

58. Cragg, J.G. and Donald, S.G., 1993, Testing identifiability and specification in instrumental variables models, *Econometric Theory 9*, 222-240.

59. Degryse, H., Kim, M and Ongena, S., Microeconometrics of banking: Methods, applications and results, Oxford University Press, 2009.

60. Degryse, H. and Van Cayseele, P., 2000, Relationship lending within a bank-based system: Evidence from European small business data, *Journal of Financial Intermediation 9*, 90-109.

61. Datta, S., Iskandar-Datta, M., and Patel, A., 1999, The pricing of initial public offers of corporate straight debt, *Journal of Financial Economics 51*, 435-449.

62. Demiroglu, C. and James, C., 2010, The information content of bank loan covenants, *Review of Financial Studies 23*, 3700-3737.

63. Demiroglu, C. and James, C., 2011, The use of bank lines of credit in corporate liquidity management: A review of empirical evidence, *Journal of Banking and Finance 35(4),* 775-782.

64. Demiroglu, C., James, C., and Kizilaslan, A., 2012, Bank lending standards and access to lines of credit, *Journal of Money, Credit, and Banking 44(6),* 1063-1089.

65. Dennis, S. and Mullineaux, D. J., 2000, Syndicated loans, *Journal of Financial Intermediation 9(4),* 404-426.

66. DeYoung, R., Hunter, W., and Udell, G., 2004, The past, present, and probable future for community banks, *Journal of Financial Services Research 25*, 85-133.

67. Dezso, C. and Ross, D., 2012, Are banks happy when managers go long? The information content of managers' vested option holdings for loan pricing, *Journal of Financial Economics 106(2),* 395-410.

68. Diamond, D., 1984, Financial intermediation and delegated monitoring, *Review of Economic Studies 62*, 393-414.

69. Diamond, D., 1991, Monitoring and reputation: the choice between bank loans and directly placed debt, *Journal of Political Economy 99,* 689-721.

70. Diamond, D., 1993, Seniority and maturity of debt contracts, *Journal of Financial Economics 33(3),* pp. 341-68.

71. Diamond, D. and Dybvig, P, 1983, Bank runs, deposit insurance and liquidity, *Journal of Political Economy 91*, 401-419.

72. Diamond, D. and Rajan, R., 2000, A theory of bank capital, *Journal of Finance 55*, 2431-2465.

73. Diamond, D. and Rajan, R., 2001a, Banks and liquidity, *American Economic Review 91*, 422-425.

74. Diamond, D. and Rajan, R., 2001b, Liquidity risk, liquidity creation, and financial fragility: a theory of banking, *Journal of Political Economy 109*, 287-327.

75. Dichev, I. and Skinner, D., 2002, Large sample evidence on the debt covenant hypothesis, *Journal of Accounting Research 40*, 1091-1123.

76. Disatnik, D., Duchin, R., and Schmidt, B., 2012, Cash flow hedging and liquidity choices, Working paper.

77. Ergungor, O., 2001, Theories of bank loan commitments, *Federal Reserve Bank of Cleveland Economic Review 37(3),* 2-19.

78. Fama, E., 1985, What’s different about banks? *Journal of Monetary Economics 15(1),* 29-39.

79. Fama, E. and French, K., 1992, Cross-section of expected stock returns, *Journal of Finance 47*, 427-465.

80. Fang, L., 2005, Investment bank reputation and the price and quality of underwriting services, *Journal of Finance 60*, 2729-2761.

81. Farinha, L. A. and Santos, J., 2002, Switching from single to multiple bank lending relationships: Determinants and implications, *Journal of Financial Intermediation 11*, 124-151.

82. Faulkender, M. and Petersen, M., 2006, Does the source of capital affect capital structure? *Review of Financial Studies 19(1)*, 45-79.

83. Feldman, R. and Schmidt, J., Increased use of uninsured deposits: Implications for market Discipline, *Federal Reserve Bank of Minneapolis-fedgazette,* March 2001:18-9.

84. Flannery, M., 1998, Using market information in prudential bank supervision: a review of the US empirical evidence, *Journal of Money, Credit, and Banking 30*, 273-305.

85. Flannery, M., 2001, The faces of ‘‘market discipline’’, *Journal of Financial Services Research 20*, 107-119.

86. Flannery, M. and Wang, X., 2011, Borrowing base revolvers: Liquidity for risky firms, Working paper, University of Florida.

87. Gatev, E., Schuermann, T., and Strahan, P., 2007, Managing bank liquidity risk: How deposit-loan synergies vary with market conditions, *Review of Financial Studies 22(3),* 995-1020.

88. Gachev, E. and Strahan, P., 2006, Banks' advantage in hedging liquidity risk: Theory and evidence from the commercial paper market, *Journal of Finance 61(2),* 867-892.

89. Genay, H., 2000, Recent trends in deposit and loan growth: Implications for small and large banks, *Chicago Fed Letter 160*, December 2000.

90. Gopalan, R., Udell, G., and Yerramilli, V., 2011, Why do firms form new banking relationships? *Journal of Financial and Quantitative Analysis 46(5),* 1335-1365.

91. Gorton, G. and Kahn, J., 1993, The design of bank loan contracts, collateral, and renegotiation, Working paper, National Bureau of Economic Research, NBER Working Papers: 4273 Gorton, G. and Pennacchi, G., 1990, Financial intermediaries and liquidity creation, *Journal of Finance 65(1),* 49-71.

92. Gorton, G. and Pennacchi, G., 1990, Financial intermediaries and liquidity creation, *Journal of Finance 45*, 49-71.

93. Greenbaum, S., Kanatas, G. and Venezia, I., 1989, Equilibrium loan price under the bank-client relationship, *Journal of Banking and Finance 13*, 221-235.

94. Greenbaum, S. and Thakor, A., 1995, Contemporary financial intermediation, Dryden Press, New York.

95. Greene, W., 2000, Econometric Analysis, 4th ed, Upper Saddle River, NJ: Prentice Hall.

96. Gurley, J. and Shaw, E., 1962, Money in a theory of finance, Washington, D.C.: The Brookings Institution.

97. Hahn, T., "Commercial paper," in *Instruments of the Money Market* (Seventh Edition), Timothy Q. Cook and Robert K. LaRoche, ed. Federal Reserve Bank of Richmond (1993).

98. Hahn, J. and Hausman, J., 2002, A new specification test for the validity of instrumental variables, *Econometrica 70*, 163-189.

99. Hall, A. and Peixe, F., 2000, A consistent method for the selection of relevant instruments, in Contributed papers: Econometric Society World Congress 2000.

100. Hall, A., Rudebusch, G., and Wilcox, D., 1996, Judging instrument relevance in instrumental variables estimation, *International Economic Review 37(2),* 283-298.

101. Hannan, T. and Hanweck, G., 1988, Bank insolvency risk and the market for large certificates of deposit, *Journal of Money, Credit, and Banking 20*, 203-211.

102. Hansen, L., 1982, Large sample properties of generalized method of moments estimators, *Econometrica 50(4),* 1029-1054.

103. Hao, L., 2003, Bank effects and the determinants of loan yield spreads, Mimeo, NYU.

104. Hauswald, R. and Marquez, R., 2003, Information technology and financial services competition, *Review of Financial Studies 16*, 921-48.

105. Hauswald, R. and Marquez, R., 2006, Competition and strategic information acquisition in credit markets, *Review of Financial Studies 19*, 967-1000.

106. Hawkins, G., 1982, An analysis of revolving credit agreements, *Journal of Financial Economics 10*, 59-81.

107. Heckman, J., 1979, Sample selection bias as a specification error, *Econometrica 47,* 153-161.

108. Heckman, J., 1997, Instrumental Variables: A study of implicit behavioral assumptions used in making program evaluations, *The Journal of Human Resources 32(3),* 441-462.

109. Holmstrom, B. and Tirole, J., 1998, Private and public supply of liquidity, *Journal of Political Economy 106*, 1-40.

110. Holmstrom, B. and Tirole, J., 2000, Liquidity and risk management, *Journal of Money, Credit, and Banking 32,* 295-319.

111. Hoshi, T., Kashyap, A., and Scharfstein, D., 1993, The choice between public and private debt: An analysis of post-deregulation corporate financing in Japan, Working paper, National Bureau of Economic Research, Working Papers: 4421.

112. Houston, J. and James, C., 1996, Bank information monopolies and the mix of private and public debt claims, *Journal of Finance 51*, 1863-1889.

113. Hubbard, R., Kuttner, K., and Palia, D., 2002, Are there bank effects in borrowers' costs of funds? Evidence from a matched sample of borrowers and bank, *Journal of Business 75 (4),* 559-581.

114. Ioannidou, V. and Ongena, S., 2010, “Time for a change”: Loan conditions and bank behavior when firms switch banks, *Journal of Finance 65,* 1847-1877.

115. Ivashina, V., 2009, Asymmetric information effects on loan spreads, *Journal of Financial Economics 92(2),* 300-319.

116. Ivashina, V. and Scharfstein, D., 2010, Bank lending during the financial crises of 2008, *Journal of Financial Economics 97*, 319-338.

117. James, C., 1987, Some evidence on the uniqueness of bank loans, *Journal of Financial Economics 19*, 217-235.

118. Jimenez, G., Lopez, J. and Saurina, J., 2009, Empirical analysis of corporate credit lines, *Review of Financial Studies 22,* 5069-5098.

119. Jones, J., Lang, W., and Nigro, P., 2005, Agent bank behavior in bank loan syndications, *Journal of Financial Research 28(3),* 385-402.

120. Kanatas, G., 1987, Commercial paper, bank reserve requirements, and the informational role of loan commitments, *Journal of Banking and Finance 11(3),* 425-448.

121. Kashyap, A., Rajan, R. and Stein, J., 2002, Banks as liquidity providers: An explanation for the co-existence of lending and deposit-taking, *Journal of Finance 57*, 33-74.

122. Kizilaslan, A. and Manakyan, K., 2011, Strategic credit line usage and performance, Working paper, University of Florida.

123. Leland, H. and Pyle, D., 1977, Informational asymmetries, financial structure and financial intermediation, *Journal of Finance 32*, 371-387.

124. Lins, K., Servaes, H., and Tufano, P., 2010, What drives corporate liquidity? An international survey of cash holdings and lines of credit, *Journal of Financial Economics 98,* 160-176.

125. Lummer, S. and McConnell, J., 1989, Further evidence on the bank lending process and the capital market response to bank loan agreements, *Journal of Financial Economics 15*, 31-60.

126. Maddala, G., 1983, Limited-dependent and qualitative variables in econometrics, Cambridge, MA: Cambridge University Press.

127. Martin, J. and Santomero, A., 1997, Investment opportunities and corporate demand for lines of credit, *Journal of Banking and Finance 21(10),* 1331-1350.

128. Melnik, A. and Plaut, S., 1986a, The economics of loan commitment contracts: Credit pricing and utilization, *Journal of Banking and Finance 10(2),* 267-280.

129. Melnik, A. and Plaut, S., 1986b, Loan commitment contracts, terms of lending, and credit allocation, *Journal of Finance 41(2),* 425-435.

130. Mian, A. and Santos, J., 2011, Liquidity risk, maturity management and the business cycle, Working paper.

131. Moody's Investors Service, Special comment: Migration of debt structures and revolver usage as firms approach default, December 2008.

132. Morgan, D., 1994, Bank credit commitments, credit rationing, and monetary policy, *Journal of Money, Credit, and Banking 26(1),* 87-101.

133. Nier, E. and Baumann, U., 2006, Market discipline, disclosure and moral hazard in banking, *Journal of Financial Intermediation 15*, 332-361.

134. Nini, G., Smith, D., and Sufi, A., 2009, Creditor rights and firm investment policy, *Journal of Financial Economics 92*, 400-420.

135. Nini, G., Smith, D., and Sufi, A., 2012, Creditor control rights, corporate governance, and firm value, *Review of Financial Studies 25*, 1713-1761.

136. O'Hara, M. and Shaw, W., 1990, Deposit insurance and wealth effects: the value of being ''too big to fail'', *Journal of Finance 45*, 1587-1600.

137. Ongena, S. and Smith, D., 2000, Bank relationships: A Survey, in P. Harker and S.A. Zenios (eds.), *The performance of Financial Institutions*, Cambridge University Press, London, 221-258.

138. Padilla, A. and Pagano, M., 1997, Endogenous communication among lenders and entrepreneurial incentives, *Review of Financial Studies 10*, 205-236.

139. Pennachi, G., 2006, Deposit insurance, bank regulation, and financial system risks, *Journal of Monetary Economics 53*, 1-36.

140. Petersen, M. and Rajan, R., 1994, The benefits of lending relationships: Evidence from small business data, *Journal of Finance 49*, 3-37.

141. Petersen, M. and Rajan, R., 1995, The effect of credit market competition on lending relationships, *Quarterly Journal of Economics 110*, 406-443.

142. Petersen, M. and Rajan, R., 2002, Does distance still matter? The information revolution in small business lending, *Journal of Finance 57*, 2533-2570.

143. Rajan, R., 1992, Insiders and outsiders: The relationship between relationship and arm's length debt, *Journal of Finance 47*, 1367-1400.

144. Rajan, R. and Winton, A., 1995, Covenants and collateral as incentives to monitor, *Journal of Finance 50,* 1113-1146.

145. Ramakrishnan, R. and Thakor, A., 1984, Information reliability and a theory of financial intermediation, *Review of Economic Studies 51*, 415-432.

146. Roberts, M. and Sufi, A., 2009a, Control rights and capital structure: an empirical investigation, *Journal of Finance 64*, 1657-1695.

147. Roberts, M., Sufi, A., 2009b, Renegotiation of financial contracts: evidence from private credit agreements, *Journal of Financial Economics 93*, 159-184.

148. Rogers, W., 1993, Regression standard errors in clustered samples, *Stata Technical Bulletin 13*, 19-23.

149. Ross, D., 2010, The "dominant bank effect": how high lender reputation affects the information content and terms of bank loans, *Review of Financial Studies 23(7),* 2730-2756.

150. Rothschild, M. and Stiglitz, J., 1976, Equilibrium in competitive insurance markets: An essay on the economics of imperfect information, *Quarterly Journal of Economics 90(4),* 629-649.

151. Samson, S. and Bachmann, M, 1990, Paper backup policies revisited, *Standard & Poor's Creditweek,* September 10, 1990, 23-24.

152. Sansone, A. and Taylor, A., 2007, The handbook of loan syndications and trading, McGraw-Hill.

153. Santos, J., 2006, Insuring banks against liquidity shocks: The role of deposit insurance and lending of last resort, *Journal of Economic Surveys 20(3),* 459-482.

154. Santos, J., 2011, Bank loan pricing following the subprime crisis, *Review of Financial Studies 24(6),* 1916-1943.

155. Santos, J., 2012, Combining deposit taking with credit line provision and the risk of concurrent runs by depositors and firms, Working paper.

156. Santos, J. and Winton, A., 2008, Bank loans, bonds, and informational monopolies across the business cycle, *Journal of Finance 63*, 1315-1359.

157. Sargan, J., 1958, The estimation of economic relationships using instrumental variables, *Econometrica 26,* 393-415.

158. Schenone, C., 2004, The effect of banking relationships on the firm's IPO underpricing, *Journal of Finance 59*, 2903-2958.

159. Schenone, C., 2010, Lending relationships and information rents: Do banks exploit their information advantages? *Review of Financial Studies 23(3)*, 1149-1199.

160. Sharpe, S., 1990, Asymmetric information, bank lending and implicit contracts: A stylized model of customer relationships, *Journal of Finance 45*, 1069-1087.

161. Shockley, R. and Thakor, A., 1997, Bank loan commitment contracts: Data, theory, and tests, *Journal of Money, Credit, and Banking 29(4),* 517-534.

162. Slovin, M., Sushka, M., and Hudson, C., 1988, Corporate commercial paper, note issuance facilities, and shareholder wealth, *Journal of International Money and Finance 7*, 289-302.

163. Slovin, M., Sushka, M., and Polonchek, J., 1993, The value of bank durability: Borrowers as bank stakeholders, *Journal of Finance 48 (1),* 247-266.

164. Sofianos, G., Wachtel, P., and Melnik, A., 1990, Loan commitments and monetary policy, *Journal of Banking and Finance 14(4),* 677-689.

165. Song, F. and Thakor, A., 2007, Relationship banking, fragility and the asset-liability matching problem, *Review of Financial Studies 20(6),* 2129-2177.

166. Staiger, D. and Stock, J., 1997, Instrumental variables regression with weak instruments, *Econometrica 65*, 557–86.

167. Stein, J., 2002, Information production and capital allocation: Decentralized versus hierarchical firms, *Journal of Finance 57*, 1891-1921.

168. Stiglitz, J. and Weiss, A., 1981, Credit rationing in markets with imperfect information, *American Economic Review 71*, 393-410.

169. Stock, J. and Yogo, M., 2005, Testing for weak instruments in linear IV regressions, in D.W.K. Andrews and J.H. Stock, eds., Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg, Cambridge: Cambridge University Press, 2005, pp. 80-108.

170. Sufi, A., 2007, Information asymmetry and financing arrangements: Evidence from syndicated loans, *Journal of Finance 62*, 629-668.

171. Sufi, A., 2009, Bank lines of credit in corporate finance: An empirical analysis, *Review of Financial Studies 22,* 1057-1088.

172. von Thadden, E., 1995, Long-term contracts, short-term investment, and monitoring, *Review of Economic Studies 62,* 557-575.

173. von Thadden, E., 2004, Asymmetric information, bank lending, and implicit contracts: The winner's curse, *Finance Research Letters 1*, 11-23.

174. Winton, A., 1995, Delegated monitoring and bank structure in a finite economy, *Journal of Financial Intermediation 4(2)*, 158-187.

175. Wooldridge, J., 2002, Econometric analysis of cross section and panel data, The MIT Press, Cambridge, Massachusetts.

176. Wooldridge, J., 2006, Introductory econometrics: a modern approach, 3rd. ed., New York: Thomson.

177. Yosha, O., 1995, Information disclosure costs and the choice of financing source, *Journal of Financial Intermediation 4,* 3-20.

178. Yun, H., 2009, The choice of corporate liquidity and corporate governance, *Review of Financial Studies 22(4),* 1447-75.