Bank Capital and Lending Relationships*

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Abstract

This paper investigates the mechanisms behind the matching of banks and firms in the loan market and the implications of this matching for the provision of credit. I find that bank-dependent firms borrow from well capitalized banks, while firms with access to the bond market borrow from banks with less capital. This matching improves access to credit during a crisis by pairing bank-dependent firms with stable banks. Small firms pay a premium to borrow from high capital banks, consistent with these banks offering the benefit of stability. During the financial crisis, bank-dependent borrowers faced significantly greater loan supply from their relationship banks than they would have without this matching.

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1 Introduction

Banking relationships are an important source of external finance for many firms. Over the course of lending relationships, banks gather private information on borrowers to mitigate informational frictions. An extensive literature highlights the effects of banking relationships on firms' cost of capital and non-financial outcomes.[1] An important segment of this literature shows that informational frictions make it costly for firms to switch lenders, leading to a "credit channel" that transmits shocks from banks to their borrowers.[2] While the effects of banking relationships are well understood, there is little evidence on the mechanisms behind the formation of these relationships. What drives a firm to borrow from one bank instead of another? And if there is endogenous matching in the loan market, what are the consequences for the provision of credit? These are the questions I address in this paper.

I begin by showing that bank-dependent firms borrow from well capitalized banks, while firms with access to the public debt markets borrow from banks with less equity capital. Quantitatively, I find that bank-dependent firms borrow from banks with 1.8% higher equity capital ratios than banks lending to rated firms. This difference is economically significant, equivalent to 14% of the mean and 27% of the standard deviation of bank capital. In alternative terms, my empirical matching model implies that a bank-dependent firm would be willing to travel 196 miles, or 24% of the mean firm-bank distance, to borrow from a bank with one standard deviation higher capital. This sorting is evident in nearly every year between 1987 and 2012 and is robust to the empirical approach used. My paper is the first to show this robust stylized fact on the matching of banks and firms.

[1]Early theories on this subject include Leland and Pyle (1977), Diamond (1984, 1991), Fama (1985), Sharpe (1990), and Rajan (1992). For empirical work, see James (1987), Petersen and Rajan (1994, 1995), Berger and Udell (1995), Puri (1996), Berlin and Mester (1999), Peek and Rosengren (2000), Hubbard, Kuttner, and Palia (2002), Dahiya, Puri, and Saunders (2003), Berger et al. (2005), Degryse and Ongena (2005), Bharath et al. (2007, 2011), Ivashina et al. (2009), Schenone (2010), Dass and Massa (2011), Bolton et al. (2013), and Botsch and Vanasco (2015).

[2]Theoretical work in this area includes Bernanke (1983) and Holmstrom and Tirole (1997). For empirical evidence, see Slovin, Sushka, and Polonchek (1993), Gertler and Gilchrist (1994), Kang and Stulz (2000), Khwaja and Mian (2008), Paravisini (2008), Leary (2009), Chava and Purnanandam (2011), Lin and Paravisini (2011), Schnabl (2012), Chernenko and Sunderam (2014), and Chodorow-Reich (2014).

This endogenous matching has important implications for the provision of credit. Bank health is closely related to lending activity and informational frictions prevent bank-dependent borrowers from offsetting reductions in loan supply.[3] There is broad cross-sectional variation in bank capital ratios, with well capitalized banks better able to absorb shocks. Figure 1 presents a concrete example, from the financial crisis, of the association between bank capital and lending activity following a macroeconomic shock. Two salient points on this plot are JPMorgan, which was poorly capitalized prior to the crisis and cut lending by 75% during the crisis, and Wells Fargo, which had twice as much equity capital and cut lending by 48%. This anecdotal evidence suggests it would have been easier to obtain bank credit from Wells Fargo than from JPMorgan during the crisis. The intuitive conclusion from this plot is that bank-dependent firms benefit from having relationships with better-capitalized banks, like Wells Fargo, that cut lending by less in a downturn.

Based on a counterfactual exercise from my empirical matching model, I find that during the financial crisis, bank-dependent firms faced 2.2% greater loan supply growth from their pre-crisis relationship banks than if they borrowed from the nearest bank. Relative to the reverse matching, with bank-dependent firms borrowing from poorly capitalized banks, bank-dependent firms faced 6.6% greater loan supply growth. This is beneficial in the aggregate because under these alternative matching assignments, bank-dependent firms would have been much worse off, while firms with access to the public debt markets would not have benefited substantially, as they were able to obtain credit from the bond market to partially offset reductions in bank lending. Thus, firms and banks naturally match in a way that improves access to credit in a crisis and mitigates the transmission of financial shocks to the real economy.

I arrive at these findings by taking a varied empirical approach to a dataset of syndicated loans merged with borrower and lender characteristics. First, I use reduced-form regressions

[3] Empirical evidence on the association between bank capitalization and lending activity includes Gambacorta and Mistrulli (2004), Berger and Bouwman (2009, 2013), Cornett et al. (2011), Beltratti and Stulz (2012), and Carlson, Shan, and Warusawitharana (2013).

to uncover the key correlations between firm and bank characteristics, narrow the mechanisms behind the matching of banks and firms, and explore the pricing consequences of this matching. Then, for a more robust description of the matching equilibrium, I apply the Fox (2010) semi-parametric matching model to the loan market. This model allows me to quantify trade-offs among match characteristics and to generate counterfactual matching assignments, which I use to derive quantitative implications of matching for the provision of credit. It is beneficial relative to alternative matching models (e.g. Sorensen 2007) or models of differentiated product demand (e.g. Berry, Levinsohn, and Pakes 2004) because it treats transfer payments as unobservable, avoiding the need for counterfactual pricing information and values of non-price contract terms. Chen and Song (2013) also use the Fox (2010) model to study the syndicated loan market, finding positive assortative matching by size, but they do not study the association between borrower bank-dependency and bank capital structure.

I derive several hypotheses on the matching equilibrium using mechanisms from the banking theory literature. Theories of relationship lending (Sharpe 1990; Rajan 1992), bank monitoring (Holmstrom and Tirole 1997; Coval and Thakor 2005; Allen, Carletti, and Marquez 2011; Mehran and Thakor 2011), and bank risk management (Gornall and Strebulaev 2014) lead to the prediction that bank-dependent firms should borrow from well capitalized banks. However, theories in which bank fragility induces monitoring (Calomiris and Kahn 1991) and liquidity creation (Diamond and Rajan 2001), and theories of moral hazard and risk-shifting (Jensen and Meckling 1976; Admati et al. 2013) lead to the opposite sorting, with bank-dependent firms borrowing from poorly capitalized banks. Ultimately, how firms and banks choose each other is an empirical question that I answer in this paper.

The matching of bank-dependent firms with well capitalized banks is consistent with theories of relationship lending, whereas the evidence suggests it is not driven solely by bank risk management. Bank capital factors into the matching of firms with lead arrangers, who have a monitoring role, but does not factor into the matching with participant lenders, who have financial exposure but do not have a monitoring role. I also find that small firms pay a premium to borrow from well capitalized banks, consistent with these banks offering the benefit of stability. Controlling for borrower credit risk and borrower-time unobservables, a one standard deviation increase in bank capital corresponds to a 18 basis point increase in the all-in-drawn spread paid by firms that are too small to issue index-eligible bonds. This premium is economically significant, equivalent to 10% of the average loan spread. Small firms face a trade-off between paying a premium to borrow from a stable bank or borrowing from a fragile bank at a lower interest rate.

This paper contributes to several strands of literature. It fills a gap in the extensive literature on relationship lending by shedding light on how these relationships are formed in the first place. Prior literature shows that large firms borrow from large banks and small firms borrow from small banks (Stein 2002; Hubbard, Kuttner, and Palia 2002; Cole, Goldberg, and White 2004; Berger et al. 2005), firms borrow from banks that are geographically close (Petersen and Rajan 1995, 2002), firms match with banks by export country specialization (Paravisini, Rappoport, and Schnabl 2014), firms are more likely to borrow from prior relationship lenders (Bharath et al. 2007), and small growth firms are more likely to switch banks to obtain additional credit (Ongena and Smith 2001; Gopalan, Udell, and Yerramilli 2011). My finding is an important addition to this set of facts because of its implications for the operation of the credit channel. While prior literature on the credit channel focuses on the ex post effects of bank shocks on borrowers, I show that banks and firms take these effects into account ex ante and endogenously match in a way that mitigates them. Bolton et al. (2013) show evidence of a similar mechanism, with relationship banks holding more capital to insure their borrowers, but my paper is the first to show that this mechanism affects the ex ante matching of banks and firms.

This paper also contributes to the literature relating bank capital structure to the intermediation activities of the bank.[4] My paper is the first to directly tie the bank's capital

[4] Theoretical work in this area includes Holmstrom and Tirole (1997), Diamond and Rajan (2000, 2001), Coval and Thakor (2005), Bolton and Freixas (2006), Allen, Carletti, and Marquez (2011), Mehran and Thakor (2011), and Bolton et al. (2013). Empirical work includes Hubbard, Kuttner, and Palia (2002), Gambacorta and Mistrulli (2004), Berger and Bouwman (2009, 2013), Cornett et al. (2011), Mehran and

structure to its lending clientele. Banks with more equity capital are more involved in lending to bank-dependent firms, which can be interpreted as relationship lending (similar to Bolton et al. 2013). In this vein, my work relates to the literature on optimal bank capital structure and capital regulation.[5] Although I cannot speak to the welfare implications of raising capital ratios across the board, the revealed preference of bank-dependent firms is for banks with higher capital. This suggests that equity capital is beneficial for relationship lending, which has the real benefit of reducing costs of asymmetric information.

The remainder of the paper proceeds as follows. Section 2 outlines the varying theoretical predictions on the matching of firms and banks. Section 3 describes the data and discusses measurement issues. Section 4 presents reduced-form evidence on the matching of firms and banks. Section 5 presents evidence from a semi-parametric matching model. Section 6 discusses the implications of the results and concludes.

2 Conceptual Framework

The theoretical literature on banking and lending relationships offers few predictions on how firms and banks should match, but several theories offer mechanisms that can be used to derive predictions. Interestingly, different types of theories lead to conflicting predictions on the nature of the matching equilibrium, making this an empirical question that requires resolution. In this section, I outline the theoretical predictions that motivate my empirical analysis.

Some theories predict a sorting of firms to banks that weakens the credit channel, while others predict a sorting that strengthens it. By weakening the credit channel, I mean that bank-dependent firms borrow from high capital banks, so firms that are susceptible to lending cutbacks borrow from banks that are cushioned against financial shocks. The opposite

Thakor (2011), Murfin (2012), Bolton et al. (2013), Carlson, Shan, and Warusawitharana (2013), and Roberts (2015).

[5] Berger et al. (2008), Gropp and Heider (2010), Shleifer and Vishny (2010), Admati et al. (2013), Baker and Wurgler (2013), Allen, Carletti, and Marquez (2014), Gornall and Strebulaev (2014), Thakor (2014), Acharya, Mehran, and Thakor (2015), DeAngelo and Stulz (2015).

matching pattern, with bank-dependent firms borrowing from low capital banks, strengthens the credit channel because the most susceptible firms borrow from the most susceptible banks.

Table 1 summarizes these predictions in simple two-by-two matrices for reference. Bank-dependent firms are small and informationally opaque, while rated firms are large and relatively transparent. Information asymmetry and credit risk are closely related concepts, so I group bank-dependent firms with low credit quality firms and rated firms with high credit quality terms in this table. I discuss the empirical measurement of these economic variables in Section 3.2.

Multiple lines of theoretical and empirical work can be extended to predict that the matching between firms and banks should weaken the credit channel. Sharpe (1990) and Rajan (1992) present models in which firms are unable to transfer the information generated over the course of a lending relationship. If the bank fails or becomes distressed and refuses to roll over loans, its borrowers are unable to transfer information about their quality to other banks. Firms that are revealed to be good quality over the course of a lending relationship then pay higher rates after they switch banks. Informationally opaque borrowers benefit more from lending relationships and suffer more from relationship termination, so these firms prefer to borrow from stable banks. Empirical evidence suggests that capital enhances bank stability (Cornett et al. 2011; Beltratti and Stulz 2012; Fahlenbrach, Prilmeier, and Stulz 2012; Berger and Bouwman 2013; Carlson, Shan, and Warusawitharana 2013; Demirguc-Kunt, Detragiache, and Merrouche 2013). Thus, the **relationship lending** hypothesis predicts that bank-dependent firms prefer to borrow from well capitalized banks.

Several theories of banking suggest that bank capital incentivizes the banker to screen and monitor borrowers. In these models, capital gives the bank a stake in loan performance and helps to ameliorate the moral hazard problem that arises when the bank loans out borrowed funds (Holmstrom and Tirole 1997; Coval and Thakor 2005; Allen, Carletti, and Marquez 2011; Mehran and Thakor 2011). Bank equity, as an information-sensitive claim, also induces shareholders to monitor bank management (Boot and Thakor 1993). Allen, Carletti, and Marquez (2011) directly predict that firms for which monitoring adds value should prefer to borrow from well capitalized banks. Small and informationally opaque firms benefit from the certification provided by diligent screening and monitoring, so based on theories of capital-induced monitoring, they prefer well capitalized banks. I refer to this as the **equity monitoring** hypothesis.

Boot, Greenbaum, and Thakor (1993) study when it is optimal for banks to renege on loan commitments, showing that financially strong banks are more likely to honor loan commitments. Bank-dependent firms value the bank's ability to honor its loan commitments because it is costly for them to substitute to other sources of capital. Ivashina and Scharfstein (2010) find that this is an empirically relevant concern, as borrowers of Lehman Brothers drew down their credit lines to ensure they had access to those funds. The **financial commitment hypothesis** predicts that bank-dependent firms borrow from well capitalized banks.

Another line of work focuses on the bank's risk management problem. Gornall and Strebulaev (2014) model the joint capital structure decision of the bank and its borrowers. They predict that low leverage banks lend to high leverage borrowers, while high leverage banks lend to low leverage borrowers. This **risk management** hypothesis predicts that banks with high capital lend to firms with worse credit quality.

In sum, theories of private information, bank incentives, and bank risk management, combined with empirical evidence on bank capital and stability, lead to the prediction that small, informationally opaque, and less creditworthy borrowers borrow from well capitalized banks. While the theoretical and empirical support for the sorting of bank-dependent firms to high capital banks is strong, there are alternative theories that lead to opposite predictions.

There is a line of theories suggesting that bank fragility incentivizes monitoring (Calomiris and Kahn 1991) and facilitates liquidity creation (Diamond and Rajan 2001). In these **fragility monitoring** theories, banks are funded by demand deposits and capital, and the threat of a run by depositors induces the bank to monitor and collect payments from borrowers. This mechanism predicts that informationally opaque firms, which benefit from monitoring, borrow from high leverage banks and more transparent firms borrow from low leverage banks, which have weaker incentives to monitor.

There are also conflicting theories on bank risk-taking. Admati, DeMarzo, Hellwig, and Pfleiderer (2013) argue that high leverage induces banks to engage in asset substitution (Jensen and Meckling 1976), investing in riskier assets to increase the likelihood of high shareholder and management payouts, while failing to internalize the increase in expected distress costs borne by creditors. Furlong and Keeley (1989) also predict that risk-shifting occurs in bank portfolios. Calem and Rob (1999) predict a U-shaped relation between bank capital and asset risk, with under-capitalized banks engaging in risk-shifting. These **risk-shifting** hypotheses predict that low capital banks lend to less creditworthy borrowers than high capital banks.

Under several of these hypotheses of firm-bank matching, the bank offers benefits to its borrowers that depends on its capital. The equity monitoring, relationship lending, and financial commitment hypotheses predict that bank-dependent borrowers value the monitoring and stability of future funding offered by a high capital bank. These borrowers are willing to pay a premium to borrow from a high capital bank, relative to what they would pay on a loan from a low capital bank.

Baker and Wurgler (2013) present evidence that high capital banks have a higher cost of capital than low capital banks. Bank-dependent borrowers face high switching costs, so their banks have hold-up power and can pass along their costs of capital. In light of this evidence and the benefits of bank capital predicted by the equity monitoring, relationship lending, and financial commitment hypotheses, I predict that high capital banks earn an interest rate premium, after accounting for borrower and loan characteristics.

Alternatively, under the fragility monitoring hypothesis, low capital banks offer monitoring benefits to bank-dependent borrowers and can charge a premium for this service. Consistent with this, Hubbard, Kuttner, and Palia (2002) find that low capital banks earn a loan spread premium on loans to small and opaque borrowers, although they attribute this to low capital banks having higher cost of capital.

As evidenced here, the literature on banking and lending relationships leads to conflicting predictions about the matching of firms and banks and the consequences for loan pricing. Thus, it is necessary to go to the data and test these hypotheses in the loan market.

3 Data

I construct a sample of syndicated loans matched with firm and bank characteristics to test the hypotheses outlined in the previous section. In this section, I describe the sample construction, explain how I measure the economic variables referred to in the hypotheses, and discuss the characteristics of the sample.

3.1 Sample Construction

The principal sources of data for this paper are LPC DealScan and Compustat. I merge borrower and lender characteristics from Compustat with the information on corporate loans in DealScan to construct a sample of firm-bank-loan observations from 1987 to 2012 that includes borrower and lender characteristics in the quarter of loan origination.

My starting point is the DealScan-Compustat Link from Chava and Roberts (2008).[6] This table matches loan facilities from DealScan with borrower identifiers in Compustat between 1983 and August 2012. I exclude loans originated before 1987 because DealScan coverage is sparse before then. Due to differences in financing strategies between financial and non-financial firms, I exclude loans to financial companies (SIC between 6000 and 6999) from the sample.

Accounting rules vary across countries, which impacts the interpretation of capital and other accounting ratios, with especially stark effects for banks.[7] Due to these differences, I

[6]I thank Sudheer Chava and Michael Roberts for making these data available on WRDS.

[7]To illustrate the magnitude of the differences, based on its 2011 end-of-year balance sheet, JPMorgan

restrict my analysis to banks and borrowers based in the United States.

While the Chava and Roberts (2008) link table allows me to merge the loan data with borrower characteristics, a similar table is not available for lenders. I hand-match the names of active lenders in DealScan with bank names in Compustat to create a link table for lenders. Most of the loans in DealScan are syndicated loans, with one or more lead arrangers and several participating lenders. I focus my analysis on the lead arranger(s) rather than on syndicate participants, because the lead arranger has an active role in originating the loan and monitoring the borrower, whereas participants are essentially passive investors. Some of my analysis includes these other syndicate participants, which are drawn from the same set of banks that are matched as lead arrangers. When I refer to the firm's bank or lender, unless I specify it as a participant, I mean the lead arranger(s) on the loan.

I attempt to match the Bank Compustat identifiers for all lenders with at least 50 loans or at least $10 billion in loan volume in the DealScan-Compustat sample.[8] There are several bank mergers during the sample period. When a bank exits the Compustat sample, I identify the acquiring bank using information from news articles.[9] It is important to track mergers because the acquired bank sometimes shows up in DealScan after it has become a subsidiary of the surviving bank.

The observation level in my sample is the firm-bank-loan triplet, with firm and bank characteristics observed quarterly. Each bank makes several loans per quarter, and firms often have multiple loans in a quarter or a single loan with multiple lenders. I account for the former type of repetition by clustering all regressions by bank. The latter sort of repetition does not have a significant impact, as all results are similar when the sample is restricted to firm-quarter observations with one lead bank.

had book assets of $2.26 trillion under U.S. Generally Accepted Accounting Principles (GAAP) and $4.06 trillion under International Financial Reporting Standards (IFRS).

[8] I also match all bank subsidiaries with smaller DealScan loan amounts when the name is similar to the main lending subsidiary. After matching the most active lenders to Compustat, I look for lenders with similar names in DealScan. For example, Bank One Corp. has 1,011 loans and Bank One East Lansing has 2 loans. I match both banks with Bank One Corp. in Compustat.

[9] Continuing the previous example, Bank One was acquired by JPMorgan in 2004. Bank One lending subsidiaries in DealScan are matched with Bank One until 2004Q1 and with JPMorgan from 2004Q2 onward.

This matching results in good coverage of the DealScan-Compustat sample. I am able to match Compustat identifiers for the lead arranger on 87% of the loans and 97% of the loan volume in the DealScan-Compustat sample. The primary cause of lost observations is missing data on borrowers in Compustat. After merging data on borrower characteristics in the quarter of loan origination, the sample contains 55% of the loans and 66% of the loan volume in the DealScan-Compustat sample.

My empirical analysis examines the association between borrower bank-dependency and bank capital structure. The lenders in this sample are heterogeneous in terms of non-lending activities, liability structure, and regulation. To ensure comparability among banks, I exclude banks that do not have deposits reported in Compustat or the FDIC Call Reports.[10] This restriction excludes the pure investment banks like Goldman Sachs and Lehman Brothers, but includes universal banks like JPMorgan Chase and Citigroup. I also exclude Bank of New York Mellon and State Street, as these banks are primarily custodian banks and are not focused on lending. While these restrictions do not ensure perfect comparability, it ensures similar regulatory treatment and results in only a small loss of observations. The final sample includes 50% of the loans and 60% of the loan volume in the DealScan-Compustat sample.

3.2 Measurement of Economic Variables

The hypothesis development in Section 2 refers to economic characteristics of borrowers and banks that require empirical proxies for my analysis. Appendix Table A.1 defines all the variables referenced in this paper.

I define a borrower as bank-dependent if it does not have a long-term issuer rating from Standard and Poor's. This definition has been used in prior empirical work (Kashyap, Lamont, and Stein 1994; Chava and Purnanandam 2011) and serves as a measure of both the borrower's informational opacity and access to public debt markets. The main results

[10] I merge the FDIC Call Reports by the name of the FDIC-insured national banking subsidiary. The main effect of this inclusion criterion is the retention of Citigroup, which is one of the most active lenders in DealScan but does not report deposits at the bank holding company level in Compustat.

are qualitatively similar if I use borrower size instead of non-rated status to proxy for bank-dependency. To proxy for borrower default risk, I use the naive distance-to-default from Bharath and Shumway (2008), which performs similarly to the Merton (1974) distance-to-default in predicting default but does not require numerical estimation of asset volatility and the value of assets.[11]

The theories underlying the hypothesis development do not specify the empirical measurement of bank capital, and there is little consensus in the empirical literature on this topic.[12] I use the ratio of market capitalization to quasi-market assets[13] at the bank holding company level as the measure of bank capital for several reasons.

The choice to use the market value of equity rather than the book value is well-motivated. Market capitalization provides an accurate value of the shareholders' stake in the bank and the price at which the bank could raise new capital. In contrast, book equity is an accounting ratio based on the past performance and financing activities of the bank, and depends in part on the timing of loan loss recognition and other accounting decisions. The theories motivating the hypotheses in this paper are based on the bank having a stake in its performance, the franchise value of the bank, and information sensitivity of the equity

[11] The naive distance-to-default from Bharath and Shumway (2008) is:

$$DtD = \frac{\log(\frac{E+D}{D}) - (r - 0.5\sigma_A^2)T}{\sigma_A\sqrt{T}},$$

where E is market capitalization, D is short-term debt plus half of long-term debt, r is the trailing one-year stock return, σ_A is asset volatility, defined as

$$\sigma_A = \frac{E}{E+D}\sigma_E + \frac{D}{E+D}(0.05 + 0.25\sigma_E),$$

with σ_E estimated with the standard deviation of the trailing one year of daily stock returns, and maturity $T = 1$.

[12] To demonstrate this, among the papers cited in the hypothesis development, some use market capitalization from the bank holding company (Acharya et al. 2010; Fahlenbrach, Prilmeier, and Stulz 2012), some use book equity from the bank holding company (Murfin 2012; Jayaranam and Thakor 2014), some use tangible book equity and risk-adjusted regulatory ratios from the holding company (Beltratti and Stulz 2012; Demirguc-Kunt, Detragiache, and Merrouche 2013), some use book equity ratios from the banking subsidiary (Hubbard, Kuttner, and Palia 2002; Berger and Bouwman 2013), and some use risk-adjusted regulatory ratios from the banking subsidiary (Cornett et al. 2011; Carlson, Shan, and Warusawitharana 2013).

[13] Quasi-market assets are defined as total assets minus book common equity plus market capitalization.

stake. All of these theories relate more closely to the market value than to the book value of equity. Nevertheless, Appendix Table A.24 shows that the main result is robust to using book equity instead of market equity to proxy for bank capital.

Similarly, the decision to use an equity ratio instead of a risk-adjusted capital ratio is motivated by the theories supporting my hypotheses. On one hand, the Tier 1 regulatory capital ratio, which risk-weights assets in the denominator to facilitate comparison across banks with different portfolios, is beneficial in principle as a measure of bank safety. However, the numerator of Tier 1 capital has the same shortcomings as the book equity ratio, and the denominator is only informative if the risk-weighting classification accurately captures asset risk. Tier 1 capital performed substantially worse than market equity at predicting changes in bank lending volume during the financial crisis.[14] My results do not hold when I use regulatory Tier 1 capital as the measure of bank capital, likely for the same reasons Tier 1 capital is a poor predictor of crisis performance and lending activity.

Most of the lenders in my sample are subsidiaries of large bank holding companies. I measure bank capital at the bank holding company, rather than at the banking subsidiary, for several reasons. First, the market value of equity is available for the holding company, but not for its subsidiaries. Second, the "source of strength" doctrine of the Federal Reserve induces bank holding companies to prevent their banking subsidiaries from failing, so the financial strength of the holding company directly affects the financial strength of its subsidiaries (Ashcraft 2008). Finally, Houston, James, and Marcus (1997) show that loan growth at banking subsidiaries is sensitive to the holding company's capital position and insensitive to the subsidiary's own capital, due to the operation of internal capital markets.

[14] Compare Figure 1 to Appendix Figure A.4. In a regression of the change in lending volume during the financial crisis on pre-crisis bank capital , the R^2 for market equity is 54% and the t-statistic is 4.20, while the R^2 for Tier 1 capital is 14% and the t-statistic is 1.51. Excluding Northern Trust and PNC Bank reduces the R^2 to 3% and the t-statistic to 0.62 for Tier 1 capital. Related to this point, Demirguc-Kunt, Detragiache, and Merrouche (2013) show that book equity is more predictive of crisis performance than Tier 1 capital.

3.3 Sample Characteristics

Table 2 reports summary statistics for my sample. All variables are winsorized at the 1% level to mitigate the influence of outliers. Loan characteristics are presented at the firm-bank-loan level, while firm characteristics are presented by firm-quarter and bank characteristics are presented by bank-quarter, so differing levels representation do not affect these statistics.

There are 32,141 firm-loan-bank observations and 26,833 distinct loans in the sample that considers only lead arrangers. The median loan in the sample is a $180 million revolving credit facility with 4-year maturity and a credit spread of 175 basis points. The bank retains 20% of the typical loan, for an investment of 0.14% of its book equity. Most of the loans are for general corporate purposes and working capital. About three-quarters of the loans are revolving credit facilities and about one-quarter are term loans.

There are 21,710 firm-quarter observations for the 4,712 firms in the sample. In 57% of firm-quarter observations, the firm has a long-term issuer rating from S&P, and the firm is bank-dependent in the other 43% of observations. The typical firm in the sample is large and well-established, having higher leverage and profitability than the average firm in Compustat. This is noteworthy, because many of the hypotheses on the matching of banks and firms rely on firms being informationally opaque and suffering from financial constraints. Both the literature and evidence from my sample suggest that the bank-dependent firms in the DealScan-Compustat sample are susceptible to financial frictions. Lin and Paravisini (2011) and Chodorow-Reich (2014) show that small, non-rated borrowers in the DealScan-Compustat sample were differentially affected by reductions in bank lending around the WorldCom bankruptcy in 2002 and the Lehman Brothers bankruptcy in 2008, respectively.[15]

The banks in the sample are large, with the median bank having $49 billion in assets. This is to be expected from lead arrangers in the syndicated loan market. The bank market

[15] To provide additional support, in Appendix Table A.4 I replicate the finding of Chava and Purnanandam (2011) in my sample, showing that bank-dependent borrowers suffered a valuation loss of 3% relative to rated borrowers during the Russian default crisis of 1998, which directly affected banks but only indirectly affected firms. My ability to replicate this result suggests that the non-rated firms in my sample are indeed financially constrained.

equity ratio exhibits substantial variation, with a mean of 12.85% and a standard deviation of 6.53%. Book equity ratios are typically lower and less variable, with mean and standard deviation of 7.47% and 1.96%. Table 3 lists the 33 banks with more than 50 loans in the sample. There are 59 banks included in the sample in total. As mentioned before, there are several bank mergers in the sample period. Table 3 uses the current bank names and identifiers in Compustat, which are based on the SEC filings of the surviving corporate entities.[16]

The bulk of the sample is comprised of loans from JPMorgan Chase, Bank of America, Citigroup, Wells Fargo, and Wachovia. This is unsurprising, as these are the largest commercial banks in the U.S. during my sample period. About one-third of the sample includes loans from relatively smaller banks, which provides additional variation in bank size and capital. In Appendix Table A.19, I show that the main results hold when I exclude the top five banks from the sample.

My sample accounts for a substantial portion of commercial bank lending. The average quarter in my sample contains issuance of 8.4% of the amount of commercial and industrial loan holdings at large domestically chartered commercial banks.[17] For instance, if the typical loan is refinanced annually, then my sample accounts for 34% of the commercial loan issuance by large domestic banks.

4 Reduced-Form Results

This section presents and discusses my reduced-form empirical analysis of the hypotheses presented in Section 2. First, I present reduced-form evidence on the matching of firms and

[16]For example, JPMorgan Chase in Compustat was originally Chemical Bank until 1995, then Chase Manhattan until 2000, then JPMorgan Chase from 2000 to present. Table A.9 in the Appendix details all of the bank mergers incorporated in the matching of DealScan lenders with Compustat bank holding companies.

[17]Issuance reported here only includes positions retained by the large commercial banks in my sample. For the typical syndicated loan in my sample, 44% is sold to banks and non-bank lenders outside of my sample. Commercial bank loan holdings are from the Federal Reserve Bank of St. Louis, Release H.8. The large bank statistics contain the top 25 domestically chartered commercial banks ranked by size.

banks. Next, I refine my approach and narrow down the mechanisms driving the matching equilibrium. Lastly, I show that high capital banks earn a loan spread premium when lending to small firms.

4.1 Evidence on Firm-Bank Matching

In Section 2, I used existing theories to derive several predictions on the matching of firms and banks. For the initial test of these predictions, I regress bank capital on the borrower bank-dependent indicator, distance-to-default, and control variables:

$$c_{bt} = \beta_0 + \beta_1 BankDep_{ft} + \beta_2 DtD_{ft} + \beta_3 X^B_{bt} + \beta_4 X^L_{lt} + \beta_5 X^F_{ft} + d_t + d_b + d_f + \varepsilon_{ft}. \quad (1)$$

The dependent variable c_{bt} is bank capital, which I measure with the market equity ratio (see Section 3.2). The explanatory variables of interest are $BankDep_{ft}$, which equals one if the firm does not have a long-term issuer rating from S&P, and DtD_{ft}, the borrower's naive distance-to-default (Bharath and Shumway 2008). The coefficients β_1 and β_2 test the sorting patterns predicted in Table 1 Panel A. The vectors of variables X^B_{bt}, X^L_{lt}, and X^F_{ft} contain bank, loan, and firm-specific control variables from the quarter of loan origination.

In all regressions, I include calendar quarter fixed effects to remove time trends. I control for bank size to distinguish the effects of size and capital, as larger banks tend to have lower capital ratios. I include controls for borrower characteristics (asset tangibility, profitability, cash, operating leverage, Tobin's Q, years since IPO, and industry and state dummies) and loan characteristics (maturity, type, and purpose) to mitigate the impact of omitted factors that are correlated with both the firm attributes of interest and the firm's choice of bank. Finally, some specifications include bank or firm fixed effects, which remove time-invariant factors that drive matching, but require within-bank and within-firm variation in capital, rated status, and distance-to-default.

Table 4 reports the regression estimates. The coefficient on the bank-dependency indicator is positive and statistically significant in all specifications, indicating that non-rated firms borrow from high capital banks and rated firms borrow from low capital banks. Column (1) implies that bank-dependent firms borrow from banks that have 1.78% higher capital, which is equivalent to 14% of the mean bank capital ratio and 27% of the standard deviation. Unreported, all of the control variables have insignificant coefficients except for Tobin's Q, which is positively associated with bank capital. Firms with high Tobin's Q have more growth opportunities, which are harder to evaluate than assets in place, so this is consistent with well capitalized banks alleviating informational frictions.

The relation between bank-dependency and bank capital remains highly significant after including borrower fixed effects. This is interpreted as the borrower switching from a high capital bank to a low capital bank after acquiring a credit rating, or switching from a low capital bank to a high capital bank after losing its credit rating.[18] The magnitude of the coefficient decreases by about half, due to most borrowers either having a rating or not having a rating for the entire sample period, but it is still economically significant. This shows that the possession of a credit rating is directly related to the firm's choice of bank and that the matching is not driven by time-invariant firm types.

The coefficient on bank-dependency also remains significant after the addition of bank fixed effects. The magnitude of the coefficients decreases by four-fifths, which is unsurprising, given that banks' capital ratios are highly persistent (see Appendix Figure A.1). The significance of the association between bank capital and these borrower attributes after controlling for bank fixed effects suggests that the matching of firms and banks is related to bank capital itself and not driven by time-invariant bank types.

The bank's capital ratio is unrelated to the borrower's distance-to-default. The specification with controls but without fixed effects is almost statistically significant, but the economic magnitude of the coefficient is small. This supports the hypotheses that empha-

[18] The majority of within-firm variation in the bank-dependency indicator is driven by firms acquiring a credit rating, rather than losing their rating. During the sample period, 681 firms acquired a credit rating and 300 firms lost their credit rating. There are 155 firms that obtained a credit rating and then lost it during the sample period.

size information costs and access to outside funding and detracts from the risk management hypothesis, which emphasizes credit risk.[19]

The results in Table 4 support the hypotheses that predict a weakening of the credit channel relative to a random matching, with bank-dependent firms borrowing from high capital banks and rated firms borrowing from low capital banks. The results are inconsistent with the contrasting predictions of the fragility monitoring and risk-shifting hypotheses. The finding that lender capital and borrower distance-to-default are unrelated suggests that the risk management hypothesis, which is related to credit risk, is less likely to drive the matching of banks and firms than the relationship lending, equity monitoring, and financial commitment hypotheses, which are related to information costs and access to outside credit. However, the results presented here offer no way to distinguish among these informational hypotheses.

4.2 Evidence on the Mechanism

In this section, I attempt to distinguish among the relationship lending, equity monitoring, financial commitment, and risk management hypotheses, which all predict that bank-dependent firms borrow from high capital banks. First, I use the different roles of lead arrangers and participants in syndicated loans to distinguish between informational hypotheses and hypotheses relating to risk and commitment. Second, I use the difference in the importance of commitment between revolving credit facilities and term loans as a test of whether financial commitment drives the firm-bank matching equilibrium.

4.2.1 Lead Arrangers versus Participants

My discussion and analysis thus far has focused on lead arrangers, because the lead arranger most closely represents the relationship lender in theories such as Sharpe (1990). The lead

[19] Distance-to-default proxies for the borrower's probability of default, but it also possible that banks differ in the size of their risk exposures. In Appendix Table A.10, I show that bank capital is unrelated to the percentage of assets staked on each loan, which proxies for the bank's portfolio diversification. Thus, neither the probability of default nor the quantity of loan risk is related to bank capital.

arranger initiates contact with the firm, screens its credit quality, negotiates loan terms, and monitors the borrower for covenant violations. To reduce its exposure to the borrower, the lead arranger sells stakes in the loan to passive participant lenders. My data include information on both lead arrangers and participants, which are drawn from the same pool of banks. This distinction between roles allows for more refined hypothesis testing.

The relationship lending and equity monitoring hypotheses relate to the information-gathering role of the lead arranger. These hypotheses do not apply to participant banks because they do not actively monitor the borrower. The financial commitment hypothesis relates to the willingness of lenders to honor undrawn loan commitments and applies to both lead arrangers and participants. Likewise, the risk management hypothesis is relevant for both leads and participants, as default is costly for both types of lender. Table 1 Panel B presents the matching predictions for participant lenders. The predictions are the same as those for lead arrangers, except the informational hypotheses are excluded.

Table 5 reports the results of a regression analysis in line with the previous section, including both lead and participant lenders. The regressions include an interaction of the borrower's bank-dependency indicator and distance-to-default with an indicator for whether the bank is a lead arranger, which allows firms to sort differently to lead arrangers and participants. The results show significant differences in the matching of firms to lead arrangers and participants. The coefficients on the interaction of the borrower bank-dependency indicator and the lead bank indicator are significant and similar in magnitude to the coefficients in Table 4. Bank-dependent borrowers match with well capitalized lead arrangers, while rated borrowers match with lead arrangers with less capital. In contrast, there is no association between borrower bank-dependency and the capital of participant lenders, which casts doubt on the hypotheses that apply to participants. The relation between bank capital and borrower distance-to-default is insignificant in all specifications, for both lender types, consistent with the previous results.

These findings are inconsistent with the risk management and financial commitment hypotheses of firm-bank matching. They support the relationship lending and equity monitoring hypotheses, which posit an important role for lead arrangers but not for participants. Based on the different behavior of lead arrangers and participant banks, along with the limited association between bank capital and borrower default risk, it seems likely that informational frictions, rather than credit risk or commitment to undrawn facilities, drive the matching of banks and firms.

One difference between lead arrangers and participants, which is glossed over in Table 5, is that lead arrangers retain a large share of the loan than participants. The median lead arranger allocation is 20%, while the median participant allocation is 8.56%. I find some evidence that participants with high capital receive smaller allocations, but there is no relation between participant capital and loan positions as a percentage of bank assets. Thus, the quantity dimension of bank risk-taking is consistent with neither risk management nor risk-shifting. It seems unlikely that loan allocations drive the lack of correlation between borrower attributes and participant capital.[20]

4.2.2 Revolving Credit Facilities versus Term Loans

Another useful distinction in my data is the difference between revolving credit facilities and term loans. Revolving credit facilities make up nearly three-quarters of the loans in my sample and term loans comprise most of the remainder. Revolvers can be drawn and repaid several times over the life of the loan and often serve as liquidity insurance for firms. In contrast, term loans are fully drawn at origination and can be prepaid before maturity, but cannot be redrawn after repayment. Term loans are used less for liquidity and more for capital expenditures.

Under the financial commitment hypothesis, firms with high switching costs worry that the bank will renege on its commitment to an undrawn facility, forcing them to find al-

[20]Unreported, I estimated the regressions in Table 5 using loans where the lead arranger and participants had similar allocations. This restriction reduced the sample size by 96% and the resulting coefficients were insignificant.

ternative funding, so they prefer to borrow from financially strong banks. However, this hypothesis relates only to revolving facilities and not to term loans, as term loans have no commitment element. If bank-dependent firms are more likely to borrow from high capital banks on term loans as well as revolving credit facilities, then the financial commitment story is an unlikely explanation for the matching of firms and banks.

To test this prediction, I estimate the reduced-form matching regression in equation (1), including interactions of the borrower's bank-dependency indicator and distance-to-default with an indicator for revolving credit facilities, to allow firms to sort differently to banks for revolvers and term loans.[21] Table 6 presents evidence inconsistent with the financial commitment hypothesis. Bank-dependent firms borrow from high capital banks and rated firms borrow from low capital banks for both revolving credit facilities and term loans. In fact, the negative coefficients on the interaction between the bank-dependency and revolving facility indicators implies that bank-dependent borrowers have a stronger preference for high bank capital on term loans than on revolving credit facilities.[22]

The conclusion from Table 6 is that bank-dependent firms prefer high capital banks for both revolvers and term loans. This is inconsistent with commitment to undrawn facilities as a driver of the matching equilibrium because the bank cannot renege on a term loan. The cost of relationship termination at maturity and the value of screening and monitoring are similar for both revolving credit facilities and term loans, so the evidence here is consistent with these hypotheses.

[21] In these regressions, the sample is restricted to revolving credit facilities and term loans. This leads to a small reduction in sample size due to the exclusion of letters of credit, synthetic leases, and other less common loan types.

[22] One confounding factor is that firms often take out revolvers and term loans from the same bank. This could lead to spillover effects from revolving credit facilities to term loans and vice versa. In Appendix Tables A.16 and A.17, I consider firm-bank relationships with only term loans or revolving credit facilities, respectively. Statistical power is weaker in these specifications, but the coefficients have the same sign and remain statistically significant.

4.3 Bank Effects on Loan Spreads

Both the relationship lending and equity monitoring hypotheses involve high capital banks providing valuable benefits to firms, which should allow them to earn an interest rate premium relative to low capital banks. This prediction also requires that competition among banks is imperfect, so they are able to capture some of the surplus generated by relationship lending and monitoring. To test whether high capital banks earn a premium, I estimate the following regression:

$$S_{lt} = \beta_0 + \beta_1 BankDep_{ft} * c_{bt} + \beta_2 c_{bt} + \beta_3 X^B_{bt} + \beta_4 X^L_{lt} + \beta_5 X^F_{ft} + d_t + d_f + d_{bf} + \varepsilon_{lt}. \quad (2)$$

The dependent variable is the all-in-drawn spread, which is the loan's credit spread over LIBOR plus annual fees to the lenders. The endogenous matching of firms and banks creates a correlation between bank capital and price-relevant borrower characteristics, making it challenging to identify the effect of bank capital on loan spreads. Specifically, bank-dependent borrowers are less creditworthy and pay higher interest rates than rated borrowers, and these firms are more likely to borrow from high capital banks. In the absence of a natural experiment, I control for a host of price-relevant borrower and loan characteristics to remove any correlation between bank capital and the regression residual. I also include borrower fixed effects to control for unobserved borrower characteristics that could be correlated with both loan spreads and bank capital. Due to limited information on non-price terms, such as covenants and collateral requirements, I am unable to include these terms and must assume that they are uncorrelated with bank capital.[23] The loan spread premium estimates are unbiased as long as the control variables capture all of the price-relevant terms that are also correlated with bank capital.

The most important determinant of loan spreads is the borrower's credit risk. I control

[23] Murfin (2012) finds that well capitalized banks offer looser covenants than poorly capitalized banks. Whether the magnitude of this effect is large enough to bias my estimates is an empirical question. Unfortunately, data on covenants are too sparse to include them in this analysis.

for credit risk with distance-to-default and indicator variables for each credit rating category (i.e. AAA, AA+, etc.). Other borrower controls include log assets, asset tangibility, profitability, cash, operating leverage, Tobin's Q, years since IPO, and industry and state dummies. I add indicators for whether the borrower issued bonds or stock during the life of the loan, to capture any potential bundling of lending and underwriting (Drucker and Puri 2005). I also include relationship length, the number of years since the first loan between the bank and the firm, to capture hold-up or learning effects on loan pricing. The remaining loan controls include loan amount as a percentage of borrower assets, the bank's position in the loan as a percentage of its book equity, loan maturity, and indicators for loan type and purpose. I include calendar quarter fixed effects to capture time variation in market conditions. Finally, I consider borrower, borrower-year, and borrower-year-bank-dependent fixed effects to control for unobserved time-invariant and time-specific borrower heterogeneity.

Table 7 presents estimates of the bank capital premium. Surprisingly, there is not much evidence of a premium for high capital banks when lending to bank-dependent firms. The coefficient on the interaction of bank capital and the bank-dependency indicator is positive, as expected, but it is statistically insignificant. One potential reason for the weakness of these results is that non-rated status does not perfectly capture bank-dependency. While the correlation between firm size and the possession of a credit rating is very strong, there are many large non-rated firms that may not be bank-dependent.

As an alternative way to capture bank-dependency, I use the minimum bond issue size for the Barclays/Lehman Brothers Corporate Bond Index, which Faulkender and Petersen (2006) use to instrument for rated status. The corporate bond market is characterized by infrequent institutional trading in large blocks, so a minimum issue size is necessary to create a liquid market in a firm's bonds. Following Faulkender and Petersen (2006), I use the median book leverage of firms in my sample to translate the minimum issue size into a minimum book assets cut-off.[24] There is evidence of a loan spread premium for borrowers

[24]The minimum issue sizes in the Barclays/Lehman Brothers Corporate Bond Index are $1 million from 1986 to 1988, $50 million from 1989 to 1992, $100 million from 1993 to 1998, and $150 million from 1999

that are smaller than the minimum size for inclusion in the bond index. The specifications in column (4-6), which account for unobserved borrower heterogeneity, imply that for firms below the index cut-off, a one standard deviation increase in bank capital corresponds to a loan spread premium of between 15 and 18 basis points.

The premium exhibited in Table 7 is economically significant, equivalent to between 8% and 10% of the mean all-in-drawn spread, and indicates that high capital banks provide valuable benefits to small borrowers. Under the relationship lending hypothesis, the benefits are stability and the preservation of private information, while under the equity monitoring hypothesis, the benefits are screening and certification to overcome information asymmetry. Small firms are most susceptible to financial constraints and information asymmetry, so they are most willing to pay to borrow from high capital banks.[25]

Two comments are in order. First, the results here do not demonstrate that high capital banks earn higher profits than low capital banks, as I am unable to observe their cost of capital. Baker and Wurgler (2013) present evidence that high capital banks have higher cost of capital than low capital banks. Second, the results here suggest that matching bank-dependent firms with high capital banks generates an economic surplus and that banks are able to capture some of this surplus. However, it is not possible to identify the total surplus, which depends on the relative negotiating power of banks and firms. In the next section, I take the division of surplus as unobserved and study which firm-bank matches generate the most total surplus.

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to present. The below index cut-off indicator equals one if 0.34 times the firm's book assets is less than the minimum issue size.

[25]Hubbard, Kuttner, and Palia (2002) ask the same question with respect to loan spreads and arrive at the opposite result. They explore whether the bank's cost of capital is passed along to borrowers, using an indicator for book equity below 5.5% as a trigger for increased cost of capital. The friction they propose to allow banks to pass along costs to borrowers is switching costs, which is similar to my relationship lending hypothesis. They find an economically significant premium for banks with low book equity when lending to small and non-rated borrowers, in contrast to my finding that banks with high market equity earn a premium when lending to low market-to-book borrowers. Unreported, I find that their result holds in my sample. As I discuss in Section 3.2, market equity is well motivated as a measure of bank capital, but this difference between the pricing impact of book and market equity remains a puzzle.

5 Semi-Parametric Matching Model

To account for the impact of endogenous loan spreads and non-price loan terms on the matching of banks and firms in the loan market, I turn to the semi-parametric matching estimator developed by Fox (2010). In this section, I describe the Fox (2010) model, discuss why it is a good fit for this application, and outline the estimation procedure. Then, I review the model estimates and compare them to the reduced-form results. Lastly, I use the model to generate counterfactual equilibria to demonstrate the implications of endogenous matching.

The model serves two purposes for my application. First, it allows me to quantify trade-offs among several match characteristics, whereas the reduced-form approach can only describe pairwise correlations in the data. Second, it allows me to generate counterfactual matching assignments, which I use to quantify the impact of endogenous matching on the provision of credit.

The identification problem that differentiates this setting from other selection problems is that transfer payments between the firm and the bank are difficult to value. While I was able to estimate a premium for high capital banks using data on interest rates, this estimation controlled for unobservable borrower attributes with fixed effects. It is difficult to precisely estimate the interest rate a firm would pay if it borrowed from a different bank than the one observed, for use as a model input. Additionally, it is difficult to place a value on non-price loan terms like covenants and collateral requirements.

The Fox (2010) model has substantial benefits for my application. It explicitly accounts for transfer payments, but treats them as unobservable, which is advantageous relative to other options, such as models of differentiated product demand. The model identifies which firm and bank characteristics are complements and substitutes and estimates the relative contribution of each match characteristic to the total economic surplus generated by the firm-bank match.

Fox (2010) is the first to empirically estimate a many-to-many matching game with transferable utility, applying his model to the matching of car parts suppliers and automotive assemblers.[26] Chen and Song (2013) also use the Fox (2010) model to study the syndicated loan market, finding positive assortative matching by size, but they do not study the association between the bank's capital structure and its lending clientele.

5.1 Empirical Matching Model

Fox (2010) uses the observed matching equilibrium as the outcome to be explained and posits a latent match value function that drives this outcome. The estimator is based on the equilibrium concept of pairwise stability, which means that no pair of agents find it beneficial to break their existing matches to match with each other.[27] In my context, this means that any swap of firms among banks is sub-optimal.

To illustrate how the pairwise stability estimator works, consider two loans from my sample in the second quarter of 2005: Berry Petroleum borrowed from Wells Fargo and Bio-Rad Laboratories borrowed from JPMorgan Chase. The model considers a value function based on match characteristics and compares the total value of the observed matches to the total value of the swapped matches pairing Berry Petroleum with JPMorgan Chase and Bio-Rad Laboratories with Wells Fargo. The model does not consider the possibilities of both firms borrowing from one of the banks or either firm borrowing from a lender outside the sample or exiting the loan market. Nevertheless, the inequalities derived from swapping matches are informative about the factors driving matching and lead to consistent estimates of the match value function. The necessary condition for consistency is that the likelihood of observing the equilibrium matches is higher than the likelihood of observing the counterfactual

[26] Sorensen (2007) estimates a model of many-to-one matching without transfers to study the effect of venture capitalists on the success of entrepreneurial companies. The key difference between Sorensen (2007) and Fox (2010) is that Sorensen assumes there are no transfer payments between agents.

[27] Under substitutable preferences, pairwise stability implies full stability. Substitutable preferences mean that if bank b chooses firm f from the set of firms F, then it will choose f from a subset of F that includes f. Essentially, this means that there are no complementarities among firms in the bank's portfolio, which seems reasonable here. See Hatfield and Kominers (2012) for a technical discussion of matching market equilibrium.

matches.[28] The downside of the pairwise stability estimator is that the model only uses a subset of the available moment conditions in the data.

The pairwise stability condition involves transfers, which are partially available in my data. While I observe loan spreads, I have incomplete data on covenants and collateral requirements, which are difficult to translate to value terms anyway. The use of loan spreads in the matching model is problematic because loan spreads are largely determined by the credit risk of the borrower and are affected by other relationship-specific attributes. This means that the value to Wells Fargo of Berry Petroleum paying 125 basis points is not the same as the value of Bio-Rad Laboratories paying 125 basis points. Fortunately, the Fox (2010) estimator assumes transfers are unobservable and provides a way to estimate match value without them.[29]

Consider the match between bank b and firm f. The match (b, f) provides value $V_b(b, f) + t(b, f)$ to the bank and $V_f(b, f) - t(b, f)$ to the firm, where $t(b, f)$ is the unobserved transfer from the firm to the bank, which can be negative. The total match value is given by $V(b, f) = V_b(b, f) + V_f(b, f)$. Assume that match values are additively separable, so the bank's portfolio of loans is worth $V_b = \sum_{f \in \mu(b)} V_b(b, f) + t(b, f)$. This assumption is quite reasonable in the loan market. Fox (2010) shows that summing the pairwise stability conditions for two

[28] Fox (2007) shows that the pairwise maximum score estimator is consistent when using data on a subset of choices. All that is required is the rank order property, where choice probabilities are rank ordered by the agent's deterministic choice payoffs. When one conditions on a subset of the full choice set, the choice probabilities in the subset are still rank ordered by their deterministic payoffs. This implies that the matching estimator used here provides consistent estimates of the covariates contributing to match value, even though the comparisons are restricted to pairwise swaps.

[29] I attempted to estimate a matching model with transfers, similar to Akkus, Cookson, and Hortascu (2015), but the inability to compare loan spreads for different firms as transfers to the bank prevented me from obtaining reasonable estimates. A similar, but slight different, issue drives my decision not to apply a multinomial choice model. The "Micro BLP" model of Berry, Levinsohn, and Pakes (2004) might be a good fit for this setting, but it requires price information for the non-chosen goods, which are unavailable here. Continuing the example from before, Berry Petroleum borrowed from Wells Fargo, and I do not know what its loan spread would have been if it had borrowed from JPMorgan Chase instead.

matches (b_1, f_1) and (b_2, f_2) yields a condition that does not depend on transfer information:

$$V_b(b_1, f_1) + t(b_1, f_1) \geq V_b(b_1, f_2) + t(b_2, f_2) + (V_f(b_1, f_2) - V_f(b_2, f_2)),$$
$$V_b(b_2, f_2) + t(b_2, f_2) \geq V_b(b_2, f_1) + t(b_1, f_1) + (V_f(b_2, f_1) - V_f(b_1, f_1))$$

$$\Rightarrow \quad V(b_1, f_1) + V(b_2, f_2) \geq V(b_2, f_1) + V(b_1, f_2) \tag{3}$$

where $t(b_2, f_2) + (V_f(b_1, f_2) - V_f(b_2, f_2))$ is the maximum firm f_2 would pay to bank b_1 to switch from its equilibrium match with bank b_2.

One consequence of this condition is that characteristics of the matched pair and interactions among firm and bank characteristics drive the match value function, rather than individual characteristics of firms and banks. Each firm and each bank appear on both sides of the inequality, so any individual characteristics cancel out. One way to generate interactions is to take the product of bank and firm characteristics (Chen and Song 2013; Akkus, Cookson, and Hortascu 2015), which is how I translate the theoretical predictions to the matching model. For instance, the product of the borrower's bank-dependency indicator and bank capital enters the value function as the analogue to the coefficient on borrower bank-dependency in Table 4. A positive coefficient on this product means that bank-dependency and bank capital are complements, with bank-dependent firms preferring high capital banks. A negative coefficient means that they are substitutes, with bank-dependent firms preferring low capital banks.

There are several underlying assumptions in this model. The model conditions on the observed matching assignment being the optimal one, as there is potential for multiple equilibria in a many-to-one matching market with transfers. The pairwise stability condition imposes a capacity constraint on banks, with each bank lending to the same number of firms under all counterfactuals. Economically, this means that the model only considers the bank's choice of borrowers, taking its loan market participation as given, and does not shed light on the bank's portfolio allocation problem. Additionally, the decision of banks and firms to enter the loan market is unmodeled and taken as exogenous. Likewise, bank and firm characteristics are taken as exogenous and assumed to be unaffected by the matching outcome. The exogeneity of characteristics to the matching is reasonable for banks and is plausible for firms, given that all outcomes condition on the firm receiving a loan.

Parametrizing the match value function as $V(b,f) = X'_{bf}\beta + \varepsilon_{bf}$, where X_{bf} includes match characteristics and interactions between firm and bank characteristics, the empirical objective function is a sum of indicators for whether a given pair of matches satisfies pairwise stability:

$$Q(\beta) = \sum_{t=1}^{T} \sum_{(b_1,f_1),(b_2,f_2)\in\mu_t} \mathbf{1}\left[X'_{b_1f_1}\beta + X'_{b_2f_2}\beta \geq X'_{b_1f_2}\beta + X'_{b_2f_1}\beta\right] \tag{4}$$

I take each quarter to be an independent "matching market." Within each matching market, all pairs of observed firm-bank matches are considered in the objective function. To avoid complications from many-to-many matching, I restrict the sample so that many-to-one matching holds within each quarter, with each firm only matching with one lead arranger.[30]

Optimization sets the parameters to maximize the proportion of satisfied pairwise stability inequalities. I use the differential evolution algorithm (Storn and Price 1997) to optimize the objective function.[31] Differential evolution randomizes movements across the parameter space so that the algorithm doesn't get "stuck" in the flat regions of the objective function before it reaches the global optimum.

The estimator is semi-parametric, positing a linear form assumed for the value function but leaving the structure of unobservables unmodeled. As with many maximum score estimators (Manski 1975), it is not possible to point-identify parameters. Identification is only up to arbitrary order-preserving transformations of the parameters. In empirical applications, I fix a highly significant parameter to provide scale for the other parameters.

[30]Many-to-many matching could introduce complementarities among lead arrangers that complicate interpretation of my results. Restricting to firms that obtain loans from only one bank in a given quarter reduces the sample size by 29% from 21,710 to 15,362 firm-quarter observations. This is a non-trivial decrease in sample size, but the reduced-form results from Table 4 are nearly identical in this subsample. Note that the number of observations in this table is lower than advertised here because the regressions require all of the control variables to be non-missing.

[31]I thank Rainer Storn for providing MATLAB code on his website.

Bootstrapping is inconsistent for the maximum score estimator (Delgado, Rodriguez-Poo, and Wolf 2001), so I construct confidence intervals by drawing 100 subsamples of size n_s, which I set to one-quarter of the full set of pairwise stability inequalities.[32] The maximum score converges at a $\sqrt[3]{N}$ rate, so the empirical sampling distribution is given by:

$$\tilde{\beta}_s = \left(\frac{n_s}{N}\right)^{1/3} \left(\hat{\beta}_s - \hat{\beta}\right) + \hat{\beta}, \tag{5}$$

where $\hat{\beta}$ is the full sample estimate and $\hat{\beta}_s$ is the estimate from subsample s. I take the 2.5th and 97.5th percentiles of the distribution as the 95% confidence interval. Coefficients are considered statistically significant if their confidence intervals do not contain zero.

5.2 Matching Model Estimates

The computational cost of estimating the semi-parametric matching model is substantially higher than the cost of estimating a linear regression and increases with the size of the parameter set. With this in mind, I select a set of covariates that are closely related to the hypotheses on firm-bank matching, but exclude most of the control variables from the reduced-form analysis. All firm- and bank-specific variables are demeaned each quarter, so they are interpreted as values relative to the quarterly mean.

The covariate of interest in the match value function is the interaction of the borrower bank-dependency indicator and bank capital. One confounding factor in this analysis is bank size. Large banks tend to have low capital and small banks tend to have high capital. In the reduced-form analysis, I controlled for bank size in all specifications. Here, I include the interaction of bank size and borrower size in the match value function, which differentiates the contribution of bank size from the contribution of bank capital to the match value. Based on prior evidence that geography matters for relationship-building and monitoring, I

[32] Appendix Table A.26 reports confidence intervals based on block subsampling half of the banks or half of the quarterly matching markets, which is more appropriate if there is correlation within-bank across time or within-market. The confidence intervals from block subsampling are wider but inference is unchanged, as the coefficient estimates remain statistically significant.

include the distance between the borrower's and the bank's headquarters as a covariate.[33] To account for industry specialization, I include an indicator for whether the borrower is in the bank's top three Fama-French industries by volume in a given quarter. To account for persistence in lending relationships, I include an indicator for whether there is a prior loan in the sample between the firm-bank pair. I use this variable to scale the others in the match value function. I estimate the model setting the coefficient on the prior relationship indicator equal to +1000 and -1000, and choose the specification that satisfies a larger percentage of the pairwise stability inequalities.

Table 8 reports estimates of the matching model. Unsurprisingly, setting a positive coefficient for the prior relationship indicator yields better model fit than a negative coefficient. The coefficients on the product of borrower size and bank size are positive and significant, consistent with prior evidence of positive assortative matching by size. The coefficients on the distance between borrower and bank headquarters are negative and significant, indicating that firms are more likely to borrow from banks that are headquartered nearby. Finally, the coefficients on industry specialization are positive and significant, indicating that banks specialize in lending to certain industries.

Consistent with the reduced-form results on firm-bank matching, the coefficient on the product of borrower bank-dependency and bank capital in column (1) is positive and significant. This means that bank-dependent borrowers match with high capital banks and rated borrowers match with low capital banks. This finding is robust to defining borrower bank-dependency with a continuous variable for borrower size, as the coefficient in column (2) is negative and significant, indicating that small firms borrow from well capitalized banks. Column (3) excludes the interaction of firm size and bank size, yielding a larger coefficient on the interaction of borrower bank-dependency and bank capital, consistent with these

[33]It may be more appropriate would be the distance between the borrower's headquarters and the bank's nearest major office, but I do not have information on bank office locations. However, the headquarters may be the more important location for this sample of syndicated loans. Large loan commitments are likely approved by a risk manager at the bank's headquarters, so there is less informational distance if the borrower is located close to both the loan officer and the risk manager. The results are robust to excluding geographic distance from the model.

covariates being positively correlated. Column (4) shows that the coefficient estimates are similar when the prior relationship indicator is excluded from the model.

The fit of the main model specification is very good, with over 90% of the pairwise stability inequalities satisfied by the estimated parameters. This is comparable to or better than the fit reported in other papers using the Fox (2010) model.[34] One way to test the fit of the model is to assign firms to banks according to the model parameters and check how many of the observed matches are predicted by the model parameters. These assignments will not be identical due to econometric error and the potential for multiple equilibria in a many-to-one matching market with transfers.

The bottom panel of Table 8 reports the results of this exercise. The model does substantially better than a random assignment at predicting matches, with 53% of the true matches predicted by the model parameters. The rate of prediction in column (4) is substantially lower, underscoring the importance of existing relationships in predicting the matching assignment. Overall, it is apparent that there is an important unobservable element to matching.

Interpretation of the matching model coefficients is not straightforward, beyond identifying firm and bank characteristics as complements and substitutes, as the match value is latent and the counterfactuals involve pairwise comparisons of banks and firms, rather than absolute levels of outcomes. However, it is possible to calculate the relative importance of each model covariate by comparing the change in latent match value from a standard deviation shift in the covariate with the change in latent match value from shifting other model covariates. The matching of bank-dependent firms to high capital banks is about 1% as important as the existence of a prior relationship in determining the observed matching equilibrium. This seems like a small effect, but given the importance of prior relationships in determining the firm's lender, this effect is economically important. The effects of size, geography, and specialization are larger in magnitude, but these are also well-known factors

[34]See, for examples, Fox (2010), Chen and Song (2013), Akkus, Cookson, and Hortascu (2015), and Eren (2015).

in the corporate loan market.

An alternative way to interpret the matching model coefficients is that a bank-dependent firm would be willing to travel 196 miles, or 24% of the average firm-bank distance, to borrow from a bank with one standard deviation (6.5%) higher capital. Overall, the matching model estimates are indicative of an equilibrium in which total economic surplus is enhanced by pairing bank-dependent firms with well capitalized banks. In the next section, I explore the implications of this matching for the provision of credit in a crisis.

5.3 Counterfactual Matching and Financial Crisis Loan Supply

The matching model allows me to generate counterfactual matching equilibria by altering one or more of the parameter estimates.[35] The main implication of the endogenous matching of bank-dependent firms with well capitalized banks is that bank-dependent firms are less likely to suffer constrained access to credit in a downturn. In this section, I derive quantitative implications from the financial crisis based on various counterfactual scenarios.

The outcome of interest in these counterfactuals is the growth in loan supply during the financial crisis of the banks that matched with bank-dependent firms prior to the crisis. As supply is unobservable, I measure each bank's loan supply growth using cross-sectional variation in the growth in annualized total lending volume by each bank from the pre-crisis period (October 2004 to June 2007) to the crisis period (October 2008 to June 2009), as shown in Figure 1.[36] In Appendix Table A.29, I demonstrate that cross-sectional differences in lending growth reflect differential changes in supply, rather than differential changes in demand for loans from these banks, using a Khwaja and Mian (2008) style regression in which

[35]Counterfactual matchings are generated by the following algorithm. Under the counterfactual value function, match values are calculated for every potential firm-bank match in each quarterly market. Each bank has a quota equal to the number of borrowers it lent to under the observed equilibrium. Matches are selected by sorting match values in descending order, removing banks from the market when their quotas are exhausted.

[36]I account for lending growth by Wachovia and National City, which were acquired in the crisis by Wells Fargo and PNC Bank, as follows. If the borrower received a loan from the acquired bank in the pre-crisis period and from the acquirer bank during the crisis, then I attribute the crisis lending to the acquired bank. In the small set of cases where the borrower received loans from both the acquired and the acquirer banks in the pre-crisis period, I attribute the loan to the acquirer bank.

I control for borrower demand using firm fixed effects.[37] This assumption is also supported by the observation that borrowers of poorly capitalized banks were significantly more likely to issue bonds during the financial crisis (Figure 2). Becker and Ivashina (2014) point out numerous reasons why firms are unlikely to prefer bonds to loans during a downturn in the absence of a contraction in loan supply.

An important trend prior to the financial crisis was "disintermediation," with financial intermediaries originating loans, packaging and selling them to institutional investors, rather than retaining exposure to borrowers. The removal of the connection between borrower relationships and credit exposure had real consequences, leading to the origination of poor quality loans (Keys et al. 2010). Disintermediation was a factor in the corporate loan market as well, with non-bank institutional investors accounting for 70% of the increase in syndicated loan volume between 2001 and 2007, according to Ivashina and Sun (2011). However, through the securitization boom, the standard remained in the corporate loan market that lead arrangers retain a stake in each loan package, likely due to lower institutional appetite for reduced screening incentives or the repeated nature of corporate lending. An interesting counterfactual to the observed matching equilibrium in the corporate loan market is one of "total disintermediation," with firms borrowing from the nearest bank, with no regard for its fragility, because the bank will sell the loan and its relationship with the firm ends after origination.

Table 9 contains estimates of the loan supply growth faced by bank-dependent firms during the financial crisis under various scenarios, some of which are inspired by disintermediation. The sample used here includes loan originations between 2004 and 2007Q2, to ensure the firm has an active relationship with the bank during the crisis period. I re-estimate the model with this sample to obtain the parameters that drive matching in the pre-crisis period. The coefficients are qualitatively similar to those in Table 8. To avoid double-counting, I use the most recent relationship for each firm when averaging the loan supply growth faced by

[37] This exercise is similar to Chodorow-Reich (2014) Table V.

bank-dependent firms.

Table 9 reports estimates of the effect of matching on the provision of credit during the financial crisis. The row titled Model Prediction confirms that the matching model captures the key forces driving firms' access to credit. Shutting off the interaction between bank-dependency and capital causes the firm to face 1.6% lower loan supply growth during the financial crisis. Reversing this interaction, so that bank-dependent firms borrow from poorly-capitalized banks, leads to a larger 6.6% drop in the loan supply growth available to bank-dependent firms. Shutting off the other individual parameters in the matching model does not lead to significant effects on the provision of credit. These results highlight the importance of the matching of bank-dependent firms with well capitalized banks for the provision of credit in a crisis.

The bottom rows of Table 9 consider additional counterfactual matching assignments. Suppose only some firms were able to travel to match with the optimal bank, due to heightened informational frictions. Under an assignment where the top quartile of firms by size match by the model and the remaining firms match to the nearest bank, the loan supply growth faced by bank-dependent firms is 2.4% lower than it is under the observed matching. Similarly, if all firms and banks match by distance, this loan supply growth is 2.2% lower. Finally, the simplest baseline is a random assignment of banks and firms, which results in 2.9% lower loan supply growth by the pre-crisis lenders of bank-dependent firms.

The results presented here suggest that the endogenous matching of banks and firms reduced the impact of the financial crisis on the real economy. While bank-dependent firms faced a dramatic reduction in loan supply during the financial crisis, this contraction in credit supply would have been as much as 6.6% worse under counterfactual matching assignments. It is important to note that I focus on bank-dependent firms here because non-bank-dependent firms are able to offset reductions in loan supply by issuing public debt. Thus, the endogenous matching of bank-dependent firms with well capitalized banks improves aggregate access to credit over the counterfactuals outlined here.

6 Conclusion

In this paper, I present novel evidence on the mechanisms behind the matching of firms and banks and the implications of this matching for the provision of credit. I show that bank-dependent firms borrow from well capitalized banks, while firms that can access the public debt markets borrow from banks with less capital. Firms that are most susceptible to reductions in loan supply borrow from the most resilient banks, while the borrowers of fragile banks are able to substitute into bonds when loan supply shrinks. The evidence presented here points to borrowers' informational frictions and access to outside funding as drivers of this matching, rather than the risk management policies of banks.

The matching equilibrium in the loan market has important implications for the credit channel that transmits financial shocks to the real economy. During the financial crisis, bank-dependent borrowers faced significantly higher loan supply growth under endogenous matching than they would have under alternative matching assignments. Under distance-based matching or random assignment of banks and firms, the financial crisis would have led to even larger reductions in employment and real output, as bank-dependent firms would have faced worse access to credit, while firms with access to the public debt markets would not have been significantly better off.

My findings have implications for the current debate on bank capital requirements. Although I cannot speak to the welfare implications of raising capital ratios across the board, the revealed preference of bank-dependent firms is for banks with more equity capital. Relationship lending offers real benefits by reducing costs of asymmetric information, so my results point to a real benefit of higher capital ratios.

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8 Tables

Table 1: Theoretical Predictions

This table summarizes the hypotheses described in Section 2. In the empirical tests, bank capital is defined as the market equity ratio. Bank-dependency is proxied by possession of a long-term issuer rating, while credit quality is measured by naive distance-to-default (Bharath and Shumway 2008).

Panel A: Matching Predictions - Lead Arrangers

Firm Type	Low Bank Capital	High Bank Capital
Bank-Dependent Low Quality	Fragility Monitoring Risk-shifting	Relationship Lending Equity Monitoring Financial Commitment Risk Management
Rated High Quality	Relationship Lending Equity Monitoring Financial Commitment Risk Management	Fragility Monitoring Risk-shifting

Panel B: Matching Predictions - Participants

Firm Type	Low Bank Capital	High Bank Capital
Bank-Dependent Low Quality	Risk-shifting	Financial Commitment Risk Management
Rated High Quality	Financial Commitment Risk Management	Risk-shifting

Panel C: Loan Spread Predictions

	Low Bank Capital	High Bank Capital
Spread Premium	Fragility Monitoring	Relationship Lending Equity Monitoring Financial Commitment

Table 2: Summary Statistics

This table reports summary statistics for the variables used in the analysis. The sample contains new loan originations matched with lead arrangers, with characteristics observed from the first quarterly filing after origination. Summary statistics on participant banks are included in the Appendix. See Appendix Table A.1 for variable definitions.

Panel A: Loan Variables

	Mean	StDev	25th	Med	75th	Loan-Bank Obs
Credit Spread (bps)	186	134	75.0	175	255	28,657
Maturity (Years)	3.83	2.04	2.01	4.20	5.00	30,417
Facility Amount ($MM)	454	938	50.0	181	500	32,140
Amount/Firm Assets	0.16	0.16	0.05	0.11	0.22	32,140
Bank Allocation	0.36	0.33	0.11	0.20	0.50	11,586
Bank Position/Equity (%)	0.43	0.84	0.05	0.14	0.40	11,586
Revolving Facility	0.71	0.45	0	1	1	32,141
Term Loan	0.23	0.42	0	0	0	32,141
Corporate Purposes	0.39	0.49	0	0	1	32,141
Working Capital	0.17	0.37	0	0	0	32,141
Debt Repayment	0.15	0.36	0	0	0	32,141
Takeover	0.14	0.35	0	0	0	32,141
Lead Arranger Count	1.40	0.69	1	1	2	32,141
Participant Count	2.56	2.84	0	2	4	32,141
Secured Indicator	0.72	0.45	0	1	1	4,563

Panel B: Firm Variables

	Mean	StDev	25th	Med	75th	Firm-Qtr Obs
Book Assets ($B)	5.59	21.46	0.30	1.00	3.60	21,710
Bank-Dependent Indicator	0.43	0.50	0	0	1	21,710
Bonds Indicator	0.40	0.49	0	0	1	21,710
Distance-to-Default	5.87	4.27	2.76	5.25	8.20	19,555
Market Leverage	0.32	0.23	0.13	0.29	0.47	20,776
Equity Volatility	0.47	0.25	0.29	0.41	0.58	20,246
Equity Beta	0.88	0.57	0.49	0.82	1.20	20,249
Tangibility	0.35	0.24	0.15	0.29	0.52	21,660
Profitability	0.03	0.02	0.02	0.03	0.05	20,184
Cash	0.07	0.09	0.01	0.03	0.08	21,691
Operating Leverage	0.26	0.17	0.12	0.22	0.35	18,442
Tobin's Q	1.33	0.83	0.81	1.07	1.57	20,776
Years since IPO	21.19	19.72	6.32	14.11	30.33	20,279

Panel C: Bank Variables

	Mean	StDev	25th	Med	75th	Bank-Qtr Obs
Book Assets ($B)	156	359	21.8	48.7	105	3,062
Market Equity (%)	12.9	6.53	7.76	12.4	16.9	3,062
Book Equity (%)	7.47	1.96	6.16	7.54	8.82	3,062
Tier 1 Capital (%)	9.29	1.80	7.90	8.80	10.5	2,161
Equity Market-to-Book	1.84	0.90	1.22	1.70	2.27	3,062
Equity Volatility	0.32	0.18	0.21	0.28	0.38	3,061
Equity Beta	1.07	0.44	0.78	1.04	1.31	3,061
Deposits/Assets	0.68	0.11	0.63	0.68	0.75	3,005
Sample Loans/Assets	0.05	0.04	0.02	0.04	0.07	3,062

Table 3: Most Active Banks in the Sample

This table reports the 34 banks with more than 50 loans in the sample. In the full sample, there are 61 distinct banks. Bank names are reported as in Compustat, with (Old) signifying the pre-merger incarnation of the bank. First and Last Quarter are the first and last quarters each bank appears in the sample. Observations is the number of loan observations for each bank.

Bank	First Quarter	Last Quarter	Observations
JPMorgan Chase	1987Q2	2012Q4	7,266
Bank of America	1988Q1	2012Q4	6,917
Citigroup	1998Q4	2012Q4	3,024
Wells Fargo	1987Q3	2012Q4	2,083
Wachovia	1987Q4	2008Q3	1,467
Citicorp (Old)	1987Q1	1998Q3	1,006
Bank One	1987Q4	2004Q1	1,002
BankAmerica (Old)	1987Q1	1998Q2	910
FleetBoston	1987Q2	2003Q4	828
JP Morgan (Old)	1987Q1	2000Q3	710
PNC Financial	1987Q3	2012Q2	687
SunTrust	1987Q4	2012Q4	681
Bankers Trust	1987Q1	1999Q1	626
US Bancorp	1987Q3	2012Q4	470
BankBoston	1987Q3	1999Q2	421
Key Bank	1989Q4	2012Q2	399
Chase Manhattan (Old)	1987Q1	1995Q4	359
Silicon Valley Bank	1993Q4	2012Q2	319
Comerica	1989Q3	2012Q2	286
First Chicago (Old)	1987Q2	1995Q3	279
Wells Fargo (Old)	1987Q3	1998Q2	232
National City	1987Q4	2008Q3	230
First Chicago NBD	1995Q4	1998Q2	216
Wachovia (Old)	1987Q2	2001Q2	192
Manufacturers Hanover	1987Q1	1991Q3	174
Mellon Financial (Old)	1987Q2	2002Q4	154
Continental Bank	1987Q1	1994Q2	152
Security Pacific	1987Q1	1991Q4	117
First Interstate	1987Q2	1995Q4	106
Corestates Financial	1987Q3	1997Q4	92
Fifth Third Bank	1994Q2	2012Q2	65
Regionals Financial	2001Q1	2012Q2	56
M&T Bank	1990Q4	2011Q2	53

Table 4: Reduced-Form Matching Regressions

This table reports regressions of lead arranger capital on borrower and loan characteristics. Bank Capital is defined as the market equity ratio. Bank-Dependent is an indicator equal to one if the borrower does not have a S&P long-term issuer rating. Distance-to-default is the naive distance-to-default from Bharath and Shumway (2008). Control Variables include borrower tangibility, profitability, cash, operating leverage, Tobin's Q, years since IPO, industry and state dummies, loan type and purpose dummies, and loan maturity. Calendar quarter fixed effects are included to account for time trends. *t*-statistics based on standard errors clustered by bank are reported in brackets.

Bank Capital (%)	(1)	(2)	(3)	(4)	(5)
Borrower Bank-Dependent	1.776***	0.928**	0.798***	0.415***	0.169**
	[3.15]	[2.36]	[2.70]	[3.89]	[2.24]
Borrower Distance-to-Default		-0.017	-0.033	-0.029	-0.005
		[-0.91]	[-1.66]	[-1.44]	[-0.40]
Quarter FEs	X	X	X	X	X
Bank Log(Assets)		X	X	X	X
Control Variables			X	X	X
Borrower FEs				X	
Bank FEs					X
Observations	20,504	20,504	20,504	20,504	20,504
R^2	0.59	0.65	0.67	0.81	0.84

Table 5: Reduced-Form Matching Regressions - Lead Arrangers and Participants

This table reports regressions of bank capital on borrower and loan characteristics. Each regression considers both lead arrangers and participants, with the indicator Lead Dummy equal to one if the bank is the lead arranger. The interactions Borrower Bank-Dependent*Lead and Borrower Distance-to-Default*Lead allow lead arrangers and participants to have different coefficients. Bank Capital is defined as the market equity ratio. Bank-Dependent is an indicator equal to one if the borrower does not have a S&P long-term issuer rating. Distance-to-default is the naive distance-to-default from Bharath and Shumway (2008). Control Variables include borrower tangibility, profitability, cash, operating leverage, Tobin's Q, years since IPO, industry and state dummies, loan type and purpose dummies, and loan maturity. Calendar quarter fixed effects are included to account for time trends. *t*-statistics based on standard errors clustered by bank are reported in brackets.

Bank Capital (%)	(1)	(2)	(3)	(4)	(5)
Borrower Bank-Dependent*Lead	1.612***	0.883*	0.866**	0.694*	0.053
	[2.82]	[1.92]	[2.01]	[1.95]	[0.53]
Borrower Bank-Dependent	0.275	-0.040	-0.029	0.039	0.032
	[1.27]	[-0.20]	[-0.19]	[0.26]	[0.83]
Borrower Distance-to-Default*Lead		-0.037	-0.037	-0.028	0.014
		[-1.32]	[-1.35]	[-1.04]	[0.80]
Borrower Distance-to-Default		0.031*	0.018	0.003	-0.001
		[1.85]	[1.29]	[0.21]	[-0.14]
Quarter FEs	X	X	X	X	X
Lead Indicator	X	X	X	X	X
Bank Log(Assets)		X	X	X	X
Control Variables			X	X	X
Borrower FEs				X	
Bank FEs					X
Observations	69,622	69,622	69,622	69,622	69,622
R^2	0.54	0.61	0.61	0.65	0.84

Table 6: Reduced-Form Matching Regressions - Revolvers and Term Loans

This table reports regressions of lead arranger capital on borrower and loan characteristics. The sample is restricted to revolving credit facilities and term loans. Bank Capital is defined as the market equity ratio. Bank-Dependent is an indicator equal to one if the borrower does not have a S&P long-term issuer rating. Revolving Facility Indicator equals one if the loan is a revolving credit facility. The interaction terms Borrower Bank-Dependent*Revolver and Borrower Distance-to-Default*Revolver allow for different coefficients for revolving credit facilities and term loans. Distance-to-default is the naive distance-to-default from Bharath and Shumway (2008). Control Variables include borrower tangibility, profitability, cash, operating leverage, Tobin's Q, years since IPO, industry and state dummies, loan type and purpose dummies, and loan maturity. Calendar quarter fixed effects are included to account for time trends. *t*-statistics based on standard errors clustered by bank are reported in brackets.

Bank Capital (%)	(1)	(2)	(3)	(4)	(5)
Borrower Bank-Dependent*Revolver	-0.241	-0.262	-0.188	0.007	0.006
	[-1.55]	[-1.54]	[-1.30]	[0.09]	[0.07]
Borrower Bank-Dependent	1.955***	1.111**	0.933**	0.427***	0.149
	[3.11]	[2.33]	[2.43]	[3.35]	[1.25]
Borrower Distance-to-Default*Revolver		-0.016	-0.023*	-0.012	-0.015
		[-1.10]	[-1.86]	[-1.43]	[-1.36]
Borrower Distance-to-Default		-0.004	-0.012	-0.019	0.009
		[-0.19]	[-0.59]	[-1.15]	[0.77]
Revolving Facility Indicator	X	X	X	X	X
Quarter FEs	X	X	X	X	X
Bank Log(Assets)		X	X	X	X
Control Variables			X	X	X
Borrower FEs				X	
Bank FEs					X
Observations	19,553	19,553	19,553	19,553	19,553
R^2	0.59	0.65	0.67	0.81	0.84

Table 7: Bank Effects on Loan Spreads

This table reports regressions of loan spreads on bank capital and control variables. The dependent variable is the all-in-drawn loan spread, expressed in basis points. Bank Capital is defined as the market equity ratio. Bank-Dependency is defined in two ways here. Non-Rated is an indicator equal to one if the borrower does not have a S&P long-term issuer rating. Below Index Cut-Off is an indicator equal to one if the borrower's book assets multipled by the sample median book leverage of 34% are below the minimum issue size in the Barclays/Lehman Brothers Corporate Bond Index. The minimum issue sizes in the index are $1 million from 1986 to 1988, $50 million from 1989 to 1992, $100 million from 1993 to 1998, and $150 million from 1999 to present. Bank Capital is interacted with the borrower bank-dependent indicator to obtain different effects for bank-dependent and rated borrowers. Borrower Credit Risk includes naive distance-to-default and credit rating dummies. Borrower Controls include log assets, tangibility, profitability, cash, operating leverage, Tobin's Q, years since IPO, industry and state dummies, and indicators for whether the borrower issued debt or equity during the life of the loan. Loan controls include loan amount as a percentage of borrower assets, the bank's position as a percentage of bank book equity, loan maturity, and dummies for loan type and purpose. Relationship Length is the number of years since the first loan between the bank and the borrower. Calendar quarter fixed effects are included to account for time trends. *t*-statistics based on standard errors clustered by bank are reported in brackets.

Bank-Dependency Proxy	Non-Rated		Below Index Cut-Off			
Loan Spread (bps)	(1)	(2)	(3)	(4)	(5)	(6)
Bank Capital*Borrower Bank-Dependent	0.674	1.064	1.486	2.576***	2.788**	2.297**
	[0.92]	[1.53]	[1.52]	[2.73]	[2.46]	[2.43]
Bank Capital	-0.122	-0.032	-0.335	-0.107	-0.028	-0.074
	[-0.32]	[-0.10]	[-0.74]	[-0.34]	[-0.12]	[-0.28]
Quarter FEs	X	X	X	X	X	X
Borrower Bank-Dependent	X	X	X	X	X	X
Bank Log(Assets)	X	X	X	X	X	X
Borrower Controls	X	X	X	X	X	X
Loan Controls	X	X	X	X	X	X
Borrower FEs		X		X		
Borrower-Year FEs		X			X	
Borrower-Year-Bank-Dependent FEs		X				X
Observations	16,659	16,659	16,659	16,659	16,659	16,659
R^2	0.62	0.79	0.62	0.79	0.84	0.84

Table 8: Semi-Parametric Matching Model

This table reports estimates from a semi-parametric matching model. All borrower and bank-specific characteristics are demeaned each quarter. Bank Capital is defined as the market equity ratio. The coefficient on the Prior Relationship indicator is normalized to provide scale for the other coefficients, except in column (4), where Borrower Log(Assets)*Bank Log(Assets) is normalized. 95% confidence intervals, based on subsampling, are included in brackets, with the double asterisk ** indicating that the confidence interval does not include zero. Inequalities Satisfied is the fraction of matches deemed pairwise stable using the vector of parameter estimates. Number of Inequalities is the total number of inequalities considered, which are based on all pairs of matches within each quarterly market. In-Sample Prediction reports the fraction of observed matches that are the same under the matching assignment generated by the estimated model parameters.

	(1)	(2)	(3)	(4)
Panel A: Parameter Estimates				
Borrower Bank-Dependent*Bank Capital	5.348**		12.48**	5.375**
	[2.66, 8.09]		[9.93, 15.6]	[3.84, 13.9]
Borrower Log(Assets)*Bank Capital		-1.058**		
		[-1.70, -0.66]		
Distance between Headquarters	-0.178**	-0.195**	-0.181**	-0.198**
	[-0.22, -0.18]	[-0.23, -0.18]	[-0.20, -0.16]	[-0.29, -0.18]
Borrower Log(Assets)*Bank Log(Assets)	42.74**	44.84**		42.74**
	[39.8, 56.2]	[39.8, 55.5]		[-]
Borrower in Bank's Top 3 FF30 Industries	158.7**	137.2**	153.7**	117.4**
	[144, 212]	[133, 194]	[139, 188]	[109, 182]
Prior Relationship	1000**	1000**	1000**	
	[-]	[-]	[-]	
Number of Inequalities	688,663	688,663	688,663	688,663
Inequalities Satisfied	0.914	0.914	0.904	0.761
Panel B: In-Sample Prediction				
Prediction of All Matches	0.532**	0.531**	0.523**	0.241**
(Random Matching Null)	(0.141)	(0.142)	(0.143)	(0.141)

Table 9: Matching Model Counterfactual - Financial Crisis Loan Supply

This table reports estimates of the loan supply growth faced by bank-dependent borrowers during the financial crisis under endogenous matching relative to counterfactual matching assignments. Counterfactuals are generated by altering coefficients in the semi-parametric matching model. The model is estimated between 2004Q1 and 2007Q2, to capture borrowers that have active relationships with the bank during the crisis period. Loan Supply Growth is the percentage change in each bank's total loan volume between the periods October 2004 to June 2007 and October 2008 to June 2009. The column labeled Bank-Dep. Firms reports the average loan supply growth for the last bank (most recent relationship) matched with each bank-dependent firm in the pre-crisis period under each counterfactual scenario. The reported 95% confidence intervals are based on 50 subsamples of the original matching model inequalities to obtain a sampling distribution of parameter estimates and 20 random draws of the counterfactual scenario for each subsampling run. The value function from the matching model, for reference in the counterfactuals, is:

$$V(b,f) = \beta_{BD} BankDep_f Capital_b + \beta_{Dist} Distance + \beta_{Size} Size_f Size_b + \beta_{Special} Specialization_{fb} + \beta_{Prior} Prior.$$

Counterfactual Loan Supply for Bank-Dependent Firms
(1,221 Observations, 581 Bank-Dependent Observations)

	Loan Supply Growth (%)		
Counterfactual	Bank-Dep. Firms	Obs. - Counter.	95% Conf. Int.
Observed	-65.96		
Model Prediction	-65.86	-0.10	[-0.71, 1.61]
Shut off β_{BD}	-67.57	1.61**	[1.11, 2.08]
"Reverse" $\beta_{BD} = -\beta_{BD}$	-72.59	6.63**	[2.46, 7.35]
Shut off β_{Dist}	-65.94	-0.02	[-0.89, 0.19]
Shut off β_{Size}	-65.44	-0.52	[-0.60, 1.57]
Shut off $\beta_{Special}$	-64.86	-1.10	[-1.43, 1.06]
Shut off β_{Prior}	-65.19	-0.77	[-1.55, 1.27]
Below 75th Size Match by Distance	-68.33	2.37**	[0.78, 3.10]
All Match by Distance	-68.17	2.21**	[1.77, 2.57]
All Match Randomly	-68.88	2.92**	[2.05, 3.93]

9 Figures

Figure 1: Changes in Loan Volume during the Financial Crisis by Bank Capital

This figure reports percentage changes in loan volume between the periods October 2004 to June 2007 and October 2008 to June 2009 for each bank in my sample, plotted against the bank's capital in the fourth quarter of 2006. The pre-crisis period excludes the third quarter of each year, to avoid issues with seasonality. Total volume is annualized for comparability across periods of different length. Bank capital is defined as the market equity ratio. Loan volume includes amounts lent in my sample by both lead arrangers and participants.

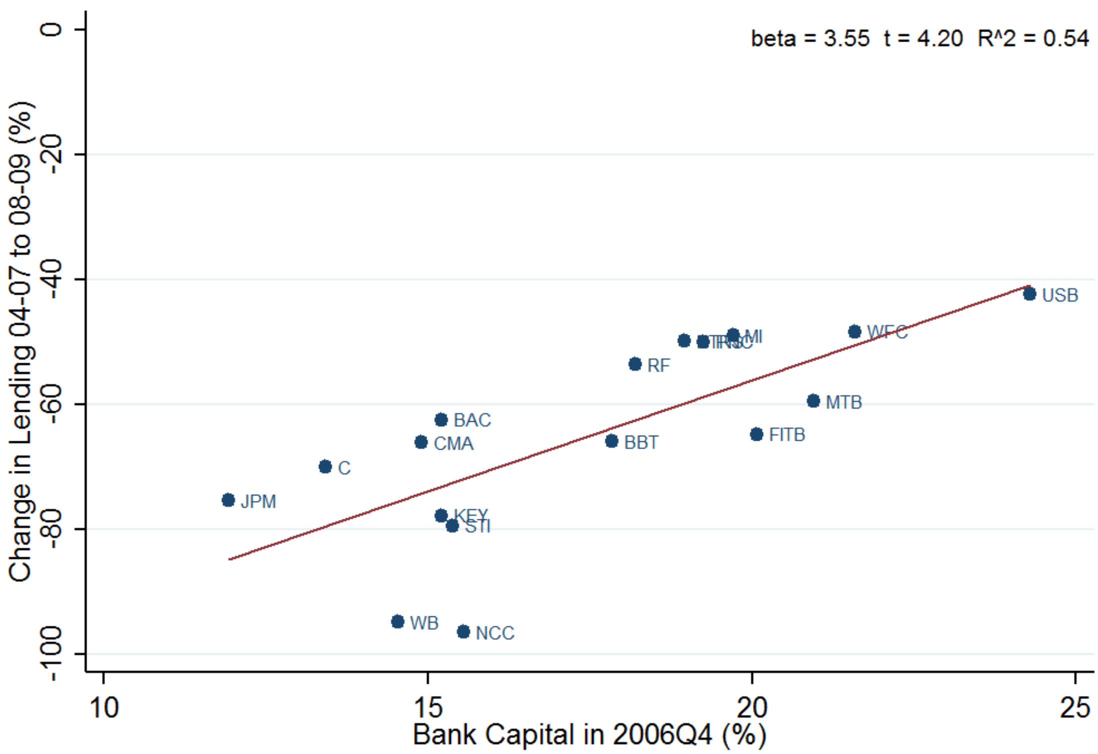

Figure 2: Borrower Substitution into Bonds during the Financial Crisis

This figure reports the percentage of borrowers issuing bonds between October 2008 and December 2009 plotted against the bank's capital in the fourth quarter of 2006. Bank capital is defined as the market equity ratio.