Fishing with Pearls: The Value of Lending Relationships with Prestigious Firms*

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Abstract

We provide novel evidence of banks establishing lending relationships with prestigious firms to signal their quality and attract future business. Using survey data on firm-level prestige, we show that lenders compete more intensely for prestigious borrowers and offer lower upfront fees to initiate lending relationships with prestigious firms. We also find that banks expand their lending after winning prestigious clients. Prestigious firms benefit from these relations as they face lower costs of borrowing even though prestige has no predictive power for credit risk. Our results are robust to matched sample analyses and a regression discontinuity design.

JEL Classification: G20; G21; G30; G32; L14; N20

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1 Introduction

A large literature examines the economic benefits of private information production by banks *within* lending relationships (e.g., Diamond, 1984; Rajan, 1992; Petersen and Rajan, 1994). However, lending relationships are also valuable to banks *outside* of specific firm-creditor ties. In practice, lenders frequently advertise their participation in syndicated loan transactions through "tombstone announcements" in financial magazines to raise their public profile (Carter and Manaster, 1990) and use existing lending relationships as a marketing tool to attract new borrowers.[1] Despite anecdotal evidence that banks value the public recognition from high profile transactions, we know little about how lending relationships with prestigious firms shape debt contracting.

In this paper, we examine the economic consequences of borrower prestige in the U.S. syndicated loan market. If firms have difficulties in assessing lenders' underwriting abilities, banks may use lending relationships with prestigious firms as credentials to signal their quality (e.g. Nelson, 1974; Bagwell and Ramey, 1994). Since lenders compete for high profile credentials, they may trade-off loan terms against the public recognition of their relationships and provide cheaper loans to prestigious firms. Our empirical tests provide strong support for this channel. We find that lenders compete more intensely for prestigious clients and offer lower upfront fees to initiate lending relationships with prestigious firms. After winning a prestigious borrower, banks expand their lending (to new firms) relative to otherwise similar institutions. Prestigious borrowers benefit from these relationships as they face lower costs of borrowing even though prestige has no predictive power for credit risk.

We use *Fortune's Most Admired Companies* survey to quantify borrower prestige. Since 1982, Fortune Magazine annually asks close to 15,000 analysts, outside directors, and executives to evaluate the public admiration of firms in the Fortune 1,000. To quantify

[1] Figure 1 shows US syndicated loan credentials that Royal Bank of Canada (RBC) used in client presentations in 2009. Figure 2 shows European syndicated loan credentials for UniCredit in 2013.

prestige, survey participants rate firms in their industry based on how much they admire them using a score between 0 (poor) and 10 (excellent). The questionnaire explicitly states that prestige ratings should be based on "respondents' firsthand knowledge of the companies or on anything they may have observed or heard about them." Using this particular survey to quantify prestige has the advantage that firms cannot actively influence their position in the final ranking since respondents are not directly affiliated with the firms they evaluate (Focke et al., 2017). Moreover, survey questions and variables are determined by a third party and do not change over time. We manually collect our prestige data from printed editions of the Fortune survey and use firms' overall score as our main measure of borrower prestige.

We begin our empirical analysis by investigating the impact of borrower prestige on firms' financing costs. We document that more prestigious firms face lower (total) costs of borrowing (Berg et al., 2016). The effect holds for different loan types and cost components and is robust to controlling for a large set of borrower characteristics, loan features, and (high-dimensional) fixed effects. The coefficient magnitude in our most conservative specification implies that a one standard deviation increase in prestige is associated with a reduction in total borrowing costs of 4.85% for the median loan.

Next, we show that borrower prestige is *not* associated with firms' credit ratings, credit default swap spreads, and implied recovery rates over the life of the loan. Thus, the cheaper financing for prestigious firms does not seem to be justified by a lower default probability, loss given default, or systematic risk. These results mitigate the concern that firm prestige does not causally impact borrowing costs but is rather associated with loan pricing because prestige is a proxy for credit risk capturing unobservable, time-varying firm characteristics.

We address the endogeneity of firm prestige more explicitly by exploiting discontinuous changes in prestige around rank 100 of the Fortune survey. The print media only focuses on the top 100 firms in the prestige ranking. For example, the New York Times and the Wall Street Journal do not print the entire ranking, but only include information on the top 100. The additional media coverage for firms within the top 100 leads to a positive, discontinuous jump in borrower prestige. Local changes in prestige are plausibly exogenous since random factors determine whether a firm is ranked just below or above 100 (e.g., mood of survey participants at the day of evaluation). We focus on firms with ranks 80 to 120 and make sure that loans on either side of the cutoff are virtually identical in terms of other borrower and loan characteristics. Consistent with our baseline results, we find a negative, significant jump in loan pricing but no break in credit risk for borrowers ranked below 100.

We validate the inferences from our regression discontinuity design by employing matched sample regressions as an alternative identification approach. Again, we consider firms as prestigious if they are included in the top 100 of the Fortune survey. Inclusion in the top 100 is likely based on criteria such as profitability or size and therefore not random. We alleviate this endogeneity concern by using (i) coarsened exact matching, (ii) nearest-neighbor matching, and (iii) propensity score matching to construct appropriate control samples based on a large set of pre-treatment financial characteristics. The results mirror those of our previous analyses.

Having established our main results, we next provide evidence that signaling by banks is a likely channel for the observed effects. First, we document that loan originations for prestigious firms experience fiercer bank competition. Holding everything else constant (including loan volume and firm size), borrower prestige is positively associated with both syndicate size and the portion of the loan that lead arrangers retain on their books. Moreover, the inverse effect of prestige on firms' financing costs is particularly strong for large syndicates, suggesting that banks' competition for prestigious clients drives down the cost of credit. Second, we document that prestigious firms pay lower upfront fees when they contract with a lead arranger for the first time. Thus, banks seem to make up-front fee concessions to *initiate* lending relationships with prestigious borrowers. Finally, banks that start lending to prestigious firms attract new borrowers and underwrite more syndicated loans *afterwards*.[2] We show that this result is not driven by an expansion strategy of the bank or concurrent but unrelated macroeconomic or regulatory changes.

Related Literature. We make two contributions relative to the existing literature. First, we contribute to the literature on firm-creditor relationships.[3] If there are informational frictions between investors and firms, banks generate private information by monitoring firms and thereby become inside creditors (Rajan, 1992; Berger and Udell, 1995; Stein, 2002; Berger et al., 2005). The informational advantage of banks creates value for firms by reducing agency conflicts and allowing for more efficient contracting (von Thadden, 1995; Rajan, 1992). Empirically, Bharath et al. (2011) find that repeated borrowing from the same lender yields lower spreads (in particular when borrower transparency is low), while banks are more likely offer further fee generating services to existing relationship borrowers (e.g., Drucker and Puri, 2005; Yasuda, 2005; Burch et al., 2005; Bharath et al., 2007). Fama (1985) and Diamond (1991) argue that bank relationships also generate value to borrowing firms outside the relationship since the renewal of bank loans serves as a positive signal to other lenders. By comparison, we document that financing a prestigious borrower creates value for the lender outside of the relationship since it serves as a credential which helps to compete for future clients.

Second, we contribute to a growing body of research that investigates the economic consequences of intangible assets. Edmans (2011) finds that companies with high levels of employee satisfaction generate superior long-run returns. Guiso et al. (2015) document that performance is stronger when employees view their top managers as trustworthy and

[2] In our bank-level analysis, we focus on lead arrangers since these institutions initiate, arrange, and manage the loan. It is the lead arranger that is primarily associated with the loan and most likely benefits from lending to a prestigious borrower.

[3] We refer to Ongena and Smith (1998) for a survey of this literature.

ethical. Both of these studies rely on surveys conducted among employees (insiders). In contrast, we study whether a company's perception by outsiders affects debt contracting. Hong and Liskovich (2015) find that socially responsible firms pay lower fines for bribing foreign government officials although corporate social responsibility is uncorrelated with bribe characteristics and judicial cooperation. The authors show that this bias is a halo effect and not prosecutorial conflict of interest. Our results are similar in spirit since the lower spreads and upfront fees that banks charge to prestigious borrowers are not justified by a lower credit risk over the life of the loan. We argue that bank-level incentives are the main driver of our results. Malmendier and Tate (2009) and Focke et al. (2017) examine the role of prestige in executive compensation. Malmendier and Tate (2009) show that prestigious CEOs with superstar status extract compensation benefits. Focke et al. (2017) document that the reverse also holds. They find that CEOs accept lower pay to work for prestigious firms because of status preferences and better subsequent career prospects. In contrast, we investigate the impact of firm prestige on loan contracting and show that prestige matters for the pricing of debt instruments over and above credit risk because lenders value relationships with prestigious firms.

2 Economic Mechanism and Empirical Predictions

Information asymmetry between lenders and borrowers is at the core of financial intermediation. Lenders invest in costly information production to assess the creditworthiness of potential borrowers, thereby reducing inefficiencies that arise from adverse selection. After loan contracting, lenders monitor borrowers to alleviate agency conflicts between managers and shareholders. Bank monitoring yields borrower-specific information that is durable, reusable (Boot and Thakor, 2000), and valuable if borrowers and lenders engage in repeated interactions.[4] Relationship borrowers may even be locked in due to the information asymmetries between outside lenders and the relationship lender (Sharpe, 1990; Rajan, 1992).

Lenders differ in their ability to underwrite and structure a loan for potential borrowers in a cost-efficient and timely manner. This heterogeneity in lenders' quality is particularly prevalent among lead arrangers in the syndicated loan market. Structuring a syndicated loan requires experience and a reliable network of other lenders that trust the lead arranger and are thus willing to timely commit to the syndicate. Potential borrowers might be less informed and therefore worry about the lender's quality. In this setting of asymmetric information, prestige can serve a signal about lenders' quality and thereby enhance the efficiency of lending (e.g. Nelson, 1974; Bagwell and Ramey, 1994).

Prestige is publicly observable, firm-specific information over which lenders compete to signal their quality to potential borrowers. The scarcity of lending relationships with prestigious borrowers equips them with bargaining power vis-à-vis lenders. Lenders in turn offer fee concessions to initiate high profile relationships. In the syndicated loan market, this translates into a higher number of participants in a deal and the lead arranger retaining a higher fraction of the loan.[5] For high-quality lenders, the benefit of signaling their quality to other clients is higher relative to low-quality lenders and they are willing to offer lower upfront fees to prestigious firms. The prestige of borrowers thus acts as a marketing tool that reveals lenders' quality and thereby reduces the inefficiency in lending due to asymmetric information.

This economic mechanism leads to the following empirical predictions. First, acquiring prestige as a valuable signal is costly and implies lower cost of borrowing for prestigious

[4]The association between past lending relationships and future bank business has been examined by Bharath et al. (2007) for the syndicated loan market, Drucker and Puri (2005) for seasoned equity offerings, and Yasuda (2005) and Burch et al. (2005) for public debt underwritings. They all find that existing lending relationships translate into a higher probability of repeated interaction.

[5]Ivashina (2009) shows that a higher lead bank's ownership of a loan also reduces asymmetric information between the lead and participants.

companies. Prestige is thus negatively related to the cost of borrowing. Second, prestige is unrelated to the creditworthiness of the borrower. Thus, prestige does not predict credit risk over the life of the underlying loan. Third, lenders compete for underwriting loans with prestigious borrowers. Prestige is thus positively related to the size of the syndicate and to the percentage retained by the lead arranger. Fourth, lenders use loans with prestigious borrowers as credentials and benefit by attracting more business with other clients. Underwriting loans with prestigious firms is therefore positively associated with the lead arranger's loan volume afterwards.

3 Data and Sample Selection

3.1 Measuring Borrower Prestige

We collect data on borrower-level prestige from Fortune's *Most Admired Companies* (MAC) survey. This survey is conducted once a year during fall among approximately 15,000 financial analysts, senior executives, and outside directors in the U.S. since 1982. Fortune magazine publishes the results in spring the following year and widely-read business newspapers such as the New York Times or the Wall Street Journal also provide coverage of the survey. To quantify firm-level prestige, Hay Group (on behalf of Fortune) asks survey participants to rate 10 companies in their industry among the Fortune 1000 based on how much they admire them in 8 different categories using a scale from 0 (poor) to 10 (excellent). The 8 categories are: (1) quality of management, (2) quality of products or services, (3) ability to attract, develop, and retain talented people, (4) wise use of corporate assets, (5) financial soundness, (6) innovativeness, (7) community and environmental responsibility, and (8) long-term investment. These attributes did not change since the inception of the survey in the 1980s. They were developed through interviews with executives and industry analysts to determine the qualities that make a company worthy of admiration. In the survey, only the attribute names are listed without any additional explanation or interpretation. Fortune asks survey participants to rate companies based on their firsthand knowledge or on anything they may have observed or heard about them. Therefore, the interpretation of the meaning of attributes is left to the respondents. The average of the 8 attribute scores determines the overall score of a company, which Fortune publishes every spring. In 2010, however, Fortune stopped reporting scores and only publishes industry ranks ever since.

Using Fortune's MAC ranking to define and quantify prestige has the advantage that firms cannot actively influence their inclusion or position in the survey (Focke et al., 2017). First, respondents are not directly affiliated to the companies they evaluate. Second, survey questions and variables are determined by a third party (Hay Group) and do not change over time. Third, it is arguably impossible for companies to find out the names of all survey respondents and to influence them accordingly. The number of firms included in the survey ranges from 183 to 535 per year with an average of 352.[6] We hand-collect the MAC surveys from printed editions of Fortune magazine between 1982 and 2009 and manually match them to our loan-level data.

3.2 Loan, Borrower and Bank Data

We obtain data on all dollar-denominated syndicated loans issued by U.S. firms from the Dealscan database maintained by the Loan Pricing Corporation (LPC).[7] We collect information on loan pricing, fees, size, maturity, seniority, type, collateral, covenants, and lenders. The unit of observation in the Dealscan database is a facility (or loan tranche). A syndicated loan package (or deal), however, typically consists of multiple potentially very

[6]Focke et al. (2017) point out that this variation is mainly driven by the number of industries included in the pool. Although the survey covers most industries, a significant fraction of companies comes from industries such as manufacturing, business equipment, and materials.

[7]We refer to Carey et al. (1998) and Chava and Roberts (2008) for a detailed description of the Dealscan database.

different facilities initiated at the same time. When we analyze the pricing implications of prestige on various fee and loan types, we use the loan-level information. We augment the Dealscan loan-level data by merging it with the comprehensive total cost of borrowing measure of Berg et al. (2016).[8]

For analyses that are based on variables determined at the deal level (syndicate size, lead share and measures for borrower-lender relationships), we follow the literature and choose the largest tranche to represent the deal. Carey et al. (1998) and Ivashina (2009) show that this selection procedure does not significantly affect the distribution of loans.

Using the Dealscan-Compustat Linking Database of Chava and Roberts (2008), we collect annual financial statement information for each borrower from Compustat. We use data from the fiscal year prior to the calendar year of loan origination to ensure that we only use accounting information that is publicly available at loan origination. For our bank level analysis, we also match annual financial statement information for lenders using the linking table provided by Schwert (2017) to our sample. We only focus on deals where we can identify a single lead arranger.[9] We define all variables we use in our empirical analysis and their respective data sources in Table A1.

3.3 Sample Selection and Descriptive Statistics

Our merged sample covers the time period 1982 to 2009. We exclude loans without an existing link to borrower information or missing borrower characteristics. We also exclude loans with non-positive facility amounts and maturities. We winsorize all continuous and unbounded variables at the 1% and 99% level to mitigate the effects of outliers. We are left with 45,837 loans to 7,328 U.S. borrowers between 1982 and 2009. Our key explanatory

[8]We are grateful for Tobias Berg providing the data on his homepage. We provide a detailed description of this measure in Section 4.

[9]Similar to Bharath et al. (2011) and Berg et al. (2016), we define a lender as a lead arranger if the lender is the sole lender or the lender role is reported as "Agent", "Admin Agent", "Arranger", or "Lead bank".

variable – the prestige score – is only defined for companies that are featured in Fortune's MAC survey. Therefore, our final sample consists of 4,285 loans to 540 borrowers. We draw on the larger initial sample, when we perform matching analyses between companies that are ranked among the top 100 MAC and those that are not featured in the survey.

Table 1 reports descriptive statistics for our sample. The average prestige score in our sample is 6.28 with a standard deviation of 0.99. About 3% of all loans in our sample are granted to borrowers which belong to the top 100 MAC. Figure 3 shows that the distribution of the prestige score is bell-shaped with a small negative skew. There is substantial variation in borrower prestige. Specifically, the range of the prestige score equals 6.76 with a minimum of 1.99 and a maximum of 8.75.

The average loan in our sample has a total cost of borrowing of about 140 basis points and a maturity of 47.72 months. The total cost of borrowing measures is available for about 48% of all loans in the sample. Approximately 24% of all loans have a reported upfront fee, 37% have a reported commitment fee, and 18% have a reported facility fee. The facility amount is skewed towards large loans with a mean of USD 321.21 million and a median of USD 100 million. 49% of all loans are secured and 42% feature financial covenants.

The average borrower in our sample has total assets of USD 11.67 billion. The distribution of assets is widely spread, in particular, the first and last decile of total assets are USD 0.05 billion and USD 16.91 billion, respectively. Thus, our sample covers both small and large borrowers. The average coverage is 34 with a median of 4.87 which is similar to Bharath et al. (2011). The average borrower has a leverage ratio of 34%, a profitability of -7%, tangibility of 35%, a current ratio of 61%, and a market-to-book ratio of 169%. About a third of all loans belong to borrowers with an investment grade rating, while 53% of all borrowers have no rating at all.

4 Borrower Prestige, Loan Pricing, and Credit Risk

We take a first look at the relation between borrower prestige and the cost of bank debt in Figure 4. The horizontal axis of the three scatter plots reports the prestige score and the vertical axes show the logarithm of the total cost of borrowing, the interest spread over LIBOR, and the upfront fee. The fitted lines indicate a strong negative unconditional relationship between borrower prestige and all three measures for the cost of borrowing.

We use three approaches to identify the effect of borrower prestige on outcome variables related to loan pricing. First, we apply fixed effects regressions with lagged firm controls to isolate the effect of borrower prestige on the cost of borrowing. Second, we exploit exogenous variation around rank top 100 of firms in the MAC rankings in a regression discontinuity analysis. Third, we use different matching estimators to evaluate the average treatment effect on a firm being ranked among the top 100 in the MAC ranking.

4.1 Fixed-Effects Regressions

To formally study the effect of borrower prestige on loan pricing, we estimate the following panel regression model

$$y_{l,i,t} = \alpha + \beta \cdot \text{Prestige}_{l,i,t-1} + \gamma \cdot X_{l,i,t(-1)} + \delta \cdot \text{Fixed Effects}_{l,i,j,t} + \varepsilon_{l,i,t}, \tag{1}$$

where subscripts l, i, j, and $t(-1)$ denote the loan, borrowing firm, industry, and (lagged) time period respectively. The dependent variable y is the logarithm of different measures for the cost of borrowing.[10]

Berg et al. (2016) show that the pricing structure of loan commitments is complex and includes a variety of fees. The most important fee types are the spread (interest margin above LIBOR paid on drawn portion of loan), the upfront fee (one-time fee paid at loan

[10]We use the logarithm to account for skewness in the data. Our results remain qualitatively unchanged if we use the level instead.

closing date), the commitment fee (one-time fee paid on unused loan commitments), and the facility fee (annual fee paid on total committed amount regardless of usage).[11] Importantly, different fees are used to price options embedded in loan contracts. For instance in credit lines, borrowers do not have to pay the committed spread until they actually choose to use the credit line. Furthermore, different fees can be used to screen borrowers' private information about the likelihood of future credit line usage. Lenders, therefore, typically use a combination of these fee types depending on borrower risk and loan type.

The total cost of borrowing (TCB) measure of Berg et al. (2016) reflects the option characteristics of bank loans and takes the likelihood of exercising these options as well as the different fees into account. The measure is defined as

$$\begin{aligned}
\text{TCB} = & \text{Upfront Fee/Expected Loan Maturity in Years} \\
& + (1 - PDD) \cdot (\text{Facility Fee} + \text{Commitment Fee}) \\
& + PDD \cdot (\text{Facility Fee} + \text{Spread}) \\
& + PDD \cdot \text{Prob(Utilization} > \text{Utilization Threshold} \mid \text{Usage} > 0) \cdot \text{Utilization Fee} \\
& + \text{Prob(Cancellation)} \cdot \text{Cancellation Fee},
\end{aligned}$$

where PDD is the likelihood that a credit line is used, Prob(Utilization $>$ Utilization Threshold |Usage $>$ 0) is the probability that the utilization of the credit line is higher than the threshold specified in the contract conditional on observing usage, and Prob(Cancellation) is the probability that the loan will be canceled. We use TCB as the main measure of loan pricing throughout the most part of our analysis.

Our measure of prestige is the borrower's overall score in Fortune's MAC survey. Our main coefficient of interest is β, which captures the relation between borrower prestige and

[11] Unfortunately, we do not have enough observations to test the effect of borrower prestige on other less common fee types such as utilization and cancellation fees.

the cost of borrowing. We lag the prestige score by one year to ensure that our measure captures survey results prior to loan origination. This timing convention implies that the variable does not reflect elements that result from the issuance of the loan (reverse causality). For example, it might be the case that survey participants (e.g., financial analysts) take into account recent news on loan contracting when evaluating the prestige of a particular borrower.

X denotes the vector of control variables. It includes loan and borrower characteristics that directly affect the cost of bank loans or simultaneously drive borrower prestige and loan pricing. On the loan level, we follow the literature and control for loan size, maturity, number of facilities, whether the loan is secured, has financial covenants, prime as base rate, or performance pricing. On the borrower level, we control for firm size, the coverage ratio, leverage, profitability, tangibility, the current ratio, and the market-to-book ratio. All borrower characteristics are lagged by one year to avoid an overlap with the period of loan issuance. Throughout most of our analysis and following the literature on loan pricing, Fixed Effects is a vector of loan type, loan purpose, rating, industry, as well as year dummies. ϵ denotes the vector of regression disturbances.

We estimate the above regression model with multi-level fixed effects by applying the feasible and computationally efficient estimator of Correia (2016). Importantly, the estimator eliminates singleton observations which typically arise in model with multi-level fixed effects and which might overstate statistical significance. As loans to the same borrower might be correlated with each other, we adjust standard errors for within firm-clusters (e.g., Petersen, 2009; Valta, 2012; Hertzel and Officer, 2012).

Table 2 reports the coefficient estimates of model (1) for TCB with the prestige score as the key explanatory variable. In the first column, we report our main regression specification – controlling for loan features and borrower characteristics, including rating, industry, year, loan type and purpose fixed effects, and standard errors clustered at the firm level. We find that the coefficient of the lagged prestige score is negative and highly statistically significant (coefficient: -0.049, t-statistic: -3.11). To alleviate concerns, that the time fixed-effect does not appropriately account for industry dynamics, we include industry-year fixed effects. The results remain virtually the same (coefficient -0.048, t-statistic: 3.24). Similarly, results do not change either when we include loan-purpose-year and loan-type-year fixed effects (coefficient: -0.042, t-statistic: 2.70) to account for purpose and type specific invariant unobservables. We also replace rating fixed effects by firm fixed effects in our baseline specification to control for firm-specific time-invariant observables which yields a lower point estimate (coefficient: -0.072, t-statistic: 3.77). We also employ state-level clustering for some specifications which, however, does not impair the significance of our estimates.

Overall, the coefficient estimate is similar across most of the specifications. In our main regression specification, the coefficient of the prestige score equals -0.049 and is significant at the 1% level. Importantly, the negative relation between borrower prestige and the cost of borrowing is also economically significant. An increase in borrower prestige by one standard deviation (0.99) reduces the TCB by 4.85% on average. For the median loan in our sample, this translates into an annual reduction of the TCB by about 5 basis points.

The estimates of the control variables have the expected sign. The coefficient of the loan amount is negative and statistically significant which suggests that firms with larger financing needs receive cheaper funding due to positive economies of scale. In contrast, the number of facilities is positively related to the TCB. One likely explanation might be that loans with a higher number of tranches are more difficult to structure and arrange for banks. Consequently, the lender demands higher spreads from the borrower as compensation. Surprisingly, secured loans have significantly higher borrowing costs. As discussed by Hertzel and Officer (2012), this is a common finding in nearly all empirical studies using Dealscan data. It is the result of this variable capturing variation in credit risk that is not picked up by the other control variables. The coefficient of the prime base rate dummy is negative and weakly statistically significant which suggests that loans which are based on the U.S. prime rate have lower borrowing costs compared to loans which are tied to LIBOR. In line with the existing literature, the TCB is higher for loans with shorter maturities, loans with financial covenants and loans which feature a performance pricing schedule. Moreover, the costs of borrowing are significantly higher for borrowers with high leverage, consistent with structural models of credit risk (e.g. Black and Scholes, 1973; Merton, 1974). Borrowers with higher interest coverage and market-to-book ratios (i.e. higher growth opportunities), on the other hand, face lower borrowing costs.

Next, we investigate the impact of borrower prestige on alternative measures for the cost of borrowing and individual fee types in Table 3. In Panel A, we find that the coefficients of prestige are negative and highly statistically significant for the spread (interest spread over LIBOR), AISD (spread plus facility fee), AISU (commitment fee and facility fee). On the fee level, we find a statistically significant negative impact of borrower prestige on upfront fees and the facility fee in Panel B. We do not find strong evidence that prestigious borrowers pay lower commitment fees (i.e. fees on unused loan commitments).

As discussed above, loan contracts differ substantially with respect to embedded option characteristics. In particular, the spread of term loans and credit lines are fundamentally different objects – in term loan contracts, borrowers have to pay the spread on a regular basis, while in credit line contracts, borrowers pay the spread only when they decide to exercise the option to draw on the credit line. We test whether there are significant differences between the effect of prestige on term loans and credit lines. Therefore, we restrict our sample to loans that we can identify as either of the two loan types. The results are reported in Table 4. We find evidence for lower TCB, loan spreads, and upfront fees for credit lines of prestigious borrowers compared to term loans. We do not find that facility fees are significantly different between the two loan types. We also perform F-tests to test whether the effect of prestige is also negative and significant for credit lines overall. Indeed, we find that prestige negatively affects all four measures of borrowing costs for credit lines.

We have established that prestigious borrowers face lower costs of borrowing. However, borrower prestige might just capture unobservable firm characteristics that banks take into account when negotiating loan contracts. Our measure of borrower prestige would thus pick up unobserved heterogeneity across firms and time which we cannot control for in our baseline panel regression model. If this channel is driving our result, we expect borrower prestige to have predictive power for companies' credit risk. The credit risk channel has at least three components which should matter for loan contracting – the probability of default, the recovery in default, and a firm's systematic risk.

We use three measures for credit risk to account for these three dimensions – the average S&P long-term rating from loan issuance to maturity ($\overline{Rating}$), the average Markit implied recovery from loan issuance to maturity ($\overline{Recovery}$), and the average five year Markit CDS spread from loan issuance to maturity ($\overline{CDS\ Spread}$).[12] We take averages over a loan's life to account for the different paths these variables might have over time.[13] The model specification is essentially the same as in (1). We also add the loan spread as an additional control variable to take into account the mechanical effect of interest rate payments on credit risk. Without controlling for the loan spread, the coefficients of our prestige variables are downward biased since borrower prestige and spreads are negatively related, while spreads and credit risk are positively related. However, this bias does not

[12] While S&P ratings are available for the whole sample period, Markit CDS spreads and implied recoveries are only available from 2001 on.

[13] As a robustness, we conduct the same analysis using values at maturity and changes from issuance to maturity. The results are the same and are available in the Internet Appendix Table IA1.

affect our inference since it only makes it more difficult *not* to find an effect of borrower prestige on default risk.

Table 5 presents the results of our credit risk analysis. The coefficients of our prestige measure are insignificant for all three measures of credit risk and irrespective of whether we include the spread as a control. The lower costs of borrowing thus do not seem to be justified by lower credit risk over the life of a loan.

The results of our credit risk analysis imply that the effect of borrower prestige on loan pricing is not driven by asymmetric information either. If prestige served as a signal of borrower quality at loan issuance, we should find an inverse relation between prestige and default *ex-post* due to adverse selection. Overall, banks seem to provide prestigious firms with better pricing terms for reasons that are unrelated to default-relevant fundamentals.

4.2 Regression Discontinuity Design

To support the results of the fixed effects regressions, we perform a regression discontinuity analysis around rank 100 to exploit locally exogenous changes around this threshold.[14] Fortune magazine publishes its MAC ranking every spring and widely-read business newspapers then provide coverage on the survey. In this context, the print media focuses on the top 100 firms in the ranking. For example, the New York Times and the Wall Street Journal do not print the entire ranking but only include information on the top 100. Moreover, companies themselves frequently issue press releases if they are ranked among the top 100 most admired companies. We argue that the *additional* media and press coverage for companies within the top 100 leads to a discontinuous, positive jump in borrower prestige. Importantly, local changes in borrower prestige are exogenous around rank 100 since random factors (e.g., mood of survey participants at the time of evaluation)

[14]We adopt this approach from Focke et al. (2017), who perform a regression discontinuity analysis around rank 100 using Fortune's list of the *Best Companies to Work for* and Fortune's *Most Admired Companies* ranking.

determine whether a company is ranked just below or just above 100.

In our regression discontinuity analysis, we focus on firms ranked between 80 and 120. These companies are differentially affected by the treatment but very similar with respect to other firm characteristics (e.g., profitability, size, etc.). If borrower prestige has a causal effect on loan pricing, we should find a discontinuous jump in the TCB around rank 100. We have to ensure that the estimates of the treatment effect are not biased by heterogeneity in other firm characteristics. Therefore, we perform our analysis not only for the raw outcome variables but also for their residuals, which we obtain from linear regressions that control for these fundamentals. We only consider loans that are originated between April and December because Fortune magazine publishes its MAC survey between January and March each year.

Figure 5 provides graphical evidence for our regression discontinuity analysis. Consistent with our previous analysis, we see a discontinuous, negative jump in the total cost of borrowing for loans ranked below 100. In contrast, we do not find any statistically and economically significant jump in credit risk around rank 100.[15] In Table 6 we report the corresponding point estimates. We find a negative statistically significant coefficient for the total cost of borrowing both without controlling for any firm or loan characteristics and with including covariates. The results are still significant when we apply the bias-corrected robust variance estimator of Calonico et al. (2017). For credit risk, we find a significant negative coefficient without controlling for firm and loan characteristics, however, the effect vanishes once we include covariates. To corroborate our findings, we perform placebo tests around rank 150. Borrower prestige should not change exogenously since there is no media effect at this threshold. Indeed, we find that there is either a positive effect for the total cost of borrowing, or no effect at all for all other models.

[15] We use the average borrower rating over a loan's life as our measure of credit risk. Unfortunately, we do not have enough observations to perform the analysis on our other measures of credit risk, i.e. CDS spreads and implied recovery.

Taken together, the results support out notion that borrower prestige reduces the cost of borrowing, but does not predict credit risk. Next, we use the top 100 cutoff to construct a further measure of prestige – a dummy variable which indicates whether a company is in the top 100 of the MAC ratings.

4.3 Matched Sample Analyses

Because being in the top 100 was not randomaly assigned, the pretreatment covariates differ between treated and control groups. To account for this endogeneity problem, we apply several matching estimators.

The first class of matching estimators we use is coarsened exact matching (CEM) (Iacus et al., 2012). CEM is a matching method where the balance between treated and control group is chosen ex ante through coarsening. The CEM algorithm coarsens variables into groups and assigns them the same numerical value. Then, exact matching is applied to the coarsened data to determine matches and prune unmatched observations. Only uncoarsened values of the matched data are then used in regressions. The CEM procedure thereby automatically restricts the matched data to areas of common empirical support.

As a fist step, we calculate the imbalance between treated and untreated observations by computing the $\mathcal{L}_1$ distance which is a measure of imbalance bounded between 0 (perfect balance) and 1 (complete separation). Table 7 shows the imbalance and the differences in mean and median between treated and control groups before and after CEM. The imbalance is largest with respect to total assets, coverage, leverage and market-to-book ratio. We first apply the CEM algorithm on total assets and leverage and use the resulting matches in our baseline regressions specification. Table 8 shows the regression results on the coarsened-exact matched samples. We find a significant negative effect of the top 100 dummy on the total cost of borrowing (coefficient: -0.081, t-statistic: -3.26). We then apply the CEM algorithm on total assets, coverage, leverage, and market-to-book ratio to further reduce the imbalance. The estimate remains essentially unchanged (coefficient: -0.085, t-statistic: -3.39).[16] Also consistent with our previous results, we do not find any effect of the top 100 dummy on credit risk as measured by the average rating for both matched samples.

The second class of matching estimators belongs to approximate matching methods which specify some metric to find a control group that is close to the treated observations. We apply two commonly used approximate matching methods as robustness checks – nearest-neighbor matching (NNM) and propensity score matching (PSM). In both cases, we are interested in the average treatment effect on the treated (ATET) of firms ranked in the top 100 of the MAC.

NNM uses some distance metric between covariate patterns of treated firms to find the closest matches among control firms. Since using more than one continuous covariate in NNM introduces a large sample bias, we employ the bias-adjustment proposed by Abadie and Imbens (2006, 2011). Panel A of Table 9 shows the ATET for different NNM specifications. We match on borrower characteristics in all models and find a negative significant coefficient on the top 100 dummy for 1 or 10 neighbors. Since there might also be an endogeneity problem with respect to the loans prestigious companies actually issue, we also match on loan features in addition to firm characteristics. The results are statistically significant and consistent with our previous analyses across all models. When we also match on loan features, the magnitudes are similar to previous point estimates.

PSM matches on the estimated probability of being treated (propensity score). Estimating the ATET only requires finding matches for the treated observations. Since the typical derivative-based standard error estimators cannot be used in this case, we rely on the non-parametric method derived in Abadie and Imbens (2016) to compute standard

[16]Matching on all borrower characteristics unfortunately does not yield enough observations for meaningful statistical inference.

errors. Again, we apply different models – matching on firm characteristics only, matching on loan features and firm characteristics, using different number of neighbors – and find a statistically significant negative coefficient on the top 100 dummy in Panel B of Table 9. However, the results for the PSM are quantitatively lower by a magnitude of two compared to our previous analyses and should therefore interpreted with caution.

5 Why Does Prestige Affect Loan Pricing?

5.1 Borrower Prestige and Bank Competition

After having established that prestigious borrowers get better terms in their loan contracting, we investigate which channel drives these results. Our third hypothesis states that lenders compete for prestigious borrowers. Since the additional key variables are determined at the deal level, we focus on the largest facility of each package to represent the deal in the following analyses.

Competition for prestigious borrowers creates a tension between the number of lenders able to participate in a deal and the allocation the lead bank retains. Prestigious borrowers attract more (potential) lenders who value the participation in a deal with these companies and therefore compete for being part of the syndicate. Prestige should therefore positively predict the syndicate size (i.e. the number of participating lenders). The lead bank, however, might have an incentive to retain a larger allocation of a deal with a prestigious company for various reasons, e.g. build up a lending relationship or strengthen the signal that it is a high quality lender. Indeed, we find that prestige positively predicts the syndicate size and the lead share in Table 10.

Table 10 also provides evidence that lenders are willing to accept concessions for being part of a deal as measured by including the interaction of prestige and syndicate size in our main regression specification – deals with a larger syndicate have higher total cost of borrowing, but prestigious companies seem to get a rebate when they contract with a larger syndicate. We do not find significant evidence for a similar effect for higher lead shares.

5.2 The Role of Lending Relationships

If lending to prestigious borrowers is valuable to lenders, then lenders might offer extra favorable pricing terms in order to attract prestigious borrowers. We thus define the variable *New Relation* as a dummy variable equal to one if the lead bank lends to the borrower for the first time, and zero otherwise.[17] It quantifies whether the effect of borrower prestige on loan pricing is stronger for new bank relationships.

In Table 11, we find that the coefficient of the interaction term is negative and statistically significant for upfront fees but insignificant for the total cost of borrowing. Therefore, banks seem to make upfront fee concessions to start new lending relationships with prestigious firms. This results is consistent with the competition channel we highlight above – lenders use lower upfront fees to compete for lending relationships with prestigious borrowers. The insignificant interaction term for the total cost of borrowing implies that lenders only use a rebate in upfront fees rather than a reduction in the overall cost.

We also examine how lending relationships with prestigious companies evolve over time. We construct the relationship lending variables in the spirit of Bharath et al. (2011) who find that repeated borrowing from the same lender translates into lower spreads. The measures of relationship lending include a dummy variable equal to one if a borrower and a lender interacted in the last five years before a deal (*Old Relation (Dummy)*), the share of the number of loans between a borrower and a lender as a fraction of the total number

[17]Since our sample starts in 1982, we cannot observe the entire lending history of our borrowers. We do not define the relationship dummy variables for the first loan of every borrower to make sure that they are not artificially equal to one. Our results are qualitatively unchanged if we start defining these variable at each borrower's third or fourth loan instead.

of loans of a borrower in the last five years before a deal (*Old Relation (Number)*), and the share of the loan amount between a borrower and a lender as a fraction of the total loan amount of a borrower in the last five years before a deal (*Old Relation (Amount)*). We find that existing relationships reduce the average upfront fees paid by lenders, prestigious companies, however, pay higher upfront fees in repeated interactions. We do not find any statistically significant evidence for the effect of lending relationships on the total cost of borrowing.

Taken together, these results indicate that lenders are willing to make price concessions to establish a relationship with a prestigious borrower. These borrowers then pay relatively higher upfront fees in the following deals. This is consistent with our hypothesis that lending to prestigious companies yields attractive future lending opportunities.

5.3 Future Bank Business

As we have established above, incentives at the bank level might provide an explanation of the effect of borrower prestige on loan pricing. It is common practice that banks use loans with prestigious borrowers as a marketing tool in client presentations to attract future business (see Figures 1 and 2). The reduction in borrowing costs resembles the value that banks attach to the value of relationships with prestigious companies.

In this analysis, we collapse the deal-level data to bank-year level variables and examine whether lending to prestigious companies in a given year leads to higher bank business in subsequent years. We consider four different measures of annual bank business – the total annual loan volume underwritten, the average volume per loan, the total number of loans per year, and the number of unique borrowers a lead bank contracted with. The key explanatory variable *Top 100 Loans* is defined as the number of loans that a lead bank has underwritten for borrowers ranked among the top 100 most admired companies. We control for banks' total assets, market-to-book ratios, and deposits over assets ratios.[18] See Table 12 for descriptive statistics of the bank-level sample. We include bank fixed-effects to control for unobserved heterogeneity that is constant within banks and year fixed-effects to control for macroeconomic conditions.

We report the results of our bank-level analysis in Panel A of Table 13. Consistent with our hypothesis, we find that the effect of the number of top 100 loans on the total loan volume in subsequent years is positive and statistically significant. We further show that this increase in deal volume is not driven by an increase in the average volume per loan, but rather by an increase in the number of loans that the lead bank underwrites. The insignificant estimate for the volume per loan is in line with borrowers having financing needs that are unrelated to the intensity with which banks lend to prestigious companies. Interestingly, not only the number of loans but also the number of unique borrowers – a measure of the broadness of a bank's customer base – increases after banks lend to prestigious firms. In Panel B of Table 13, we show that these findings hold up to a two year lag. One explanation for the lack of persistence in the effect might be that banks mainly use credentials with prestigious firms from recent deals to attract new business.

Overall, our findings support the idea that prestigious firms receive cheaper funding because the associated lending relationship helps banks to establish valuable credentials they use to successfully compete for future business.

6 Conclusion

Despite anecdotal evidence that banks value the public recognition from high profile transactions, we know little about how lending relationships with prestigious firms shape debt contracting. In this paper, we provide novel evidence of banks establishing lending relationships with prestigious firms to signal their quality and attract future business.

[18]The results remain qualitatively unchanged if we include tier 1 ratios as a measure of banks' financial constraints. The results can be found in Internet Appendix Tables IA2 and IA3.

Using survey data on firm-level prestige, we show that lenders compete more intensely for prestigious clients and offer lower upfront fees to initiate lending relationships with prestigious firms. We also find that banks expand their lending after winning prestigious borrowers. Prestigious firms benefit from these relationships as they face lower costs of borrowing even though prestige has no predictive power for credit risk.

Our results should be interpreted with the following caveats in mind. First, although the negative association between firm prestige and financing costs is statistically significant across our different econometric approaches, its economic magnitude varies and readers should therefore interpret the corresponding coefficients with care. Second, firm prestige might have sizeable volume effects on other financial services. For instance, banks may use credentials from the syndicated loan market to cross-sell equity underwritings or M&A advisory and vice-versa (e.g., Laux and Walz, 2009). Finally, firm prestige might also matter in other service industries such as auditing. We leave the investigation of these other settings to future research.

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Tables

Table 1: Descriptive Statistics for Facility-Level Sample

This table reports descriptive statistics for key variables of the empirical analysis. For each variable, the number of observations (N), mean, standard deviation (SD), 10% quantile ($Q_{0.10}$), 25% quantile ($Q_{0.25}$), median ($Q_{0.50}$), 75% quantile ($Q_{0.75}$), and 99% quantile ($Q_{0.99}$) are reported. Prestige variables are obtained from *Fortune's Most Admired Companies* surveys. Loan and borrower characteristics are collected from *Dealscan* and *Compustat*, respectively. The overall sample covers 45,837 loans to 7,328 US borrowers between 1982 and 2009. We define all variables in Table A1.

	N	Mean	SD	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
Prestige Variables								
Prestige [0-10]	4,285	6.28	0.99	5.05	5.66	6.34	6.97	7.50
Top 100 [0/1]	45,837	0.04	0.19	0.00	0.00	0.00	0.00	0.00
Loan Characteristics								
TCB [bps]	22,207	139.56	124.19	26.94	49.15	102.94	187.05	308.95
AISD [bps]	37,957	200.09	148.43	37.50	75.00	175.00	275.00	380.00
AISU [bps]	22,237	31.44	23.93	8.00	13.00	25.00	50.00	50.00
Spread [bps]	31,522	170.00	130.95	27.50	62.50	150.00	250.00	325.00
Upfront Fee [bps]	11,350	63.22	82.70	9.00	16.66	38.05	87.50	150.00
Commitment Fee [bps]	16,767	36.88	54.74	12.50	25.00	37.50	50.00	50.00
Facility Fee [bps]	8,115	19.27	24.25	6.00	8.00	12.50	22.22	37.50
Amount [USD mn.]	45,837	321.21	864.30	6.00	24.96	100.00	300.00	750.00
Maturity [months]	45,837	47.72	33.46	12.00	23.00	47.00	60.00	84.00
Facilities [number]	45,837	1.90	1.25	1.00	1.00	2.00	2.00	3.00
Secured [0/1]	45,837	0.49	0.50	0.00	0.00	0.00	1.00	1.00
Financial Covenants [0/1]	45,837	0.42	0.49	0.00	0.00	0.00	1.00	1.00
Prime Base Rate [0/1]	45,837	0.58	0.49	0.00	0.00	1.00	1.00	1.00
Performance Pricing [0/1]	45,837	0.31	0.46	0.00	0.00	0.00	1.00	1.00
Credit Line [0/1]	45,837	0.60	0.49	0.00	0.00	1.00	1.00	1.00
Term Loan [0/1]	45,837	0.27	0.44	0.00	0.00	0.00	1.00	1.00
Number of Lenders	45,720	7.09	8.75	1.00	1.00	4.00	9.00	18.00
Lead Share [0-1]	14,572	0.58	0.39	0.10	0.19	0.50	1.00	1.00
New Relation [0/1]	36,439	0.64	0.48	0.00	0.00	1.00	1.00	1.00
Old Relation (Dummy) [0/1]	36,439	0.35	0.48	0.00	0.00	0.00	1.00	1.00
Old Relation (Number) [0-1]	26,070	0.34	0.41	0.00	0.00	0.00	0.67	1.00
Old Relation (Amount) [0-1]	26,069	0.36	0.43	0.00	0.00	0.00	0.88	1.00
Average Rating [1-15]	18,909	10.16	3.55	5.86	7.67	10.00	13.00	14.46
Average Recovery [number]	4,036	0.39	0.04	0.37	0.40	0.40	0.40	0.40
Average CDS Spread [number]	3,971	0.02	0.04	0.00	0.01	0.01	0.02	0.04
Borrower Characteristics								
Total Assets [USD bn.]	45,837	11.67	70.32	0.05	0.16	0.72	3.56	16.91
Coverage [number]	45,837	34.06	813.58	0.81	2.38	4.87	10.56	24.93
Leverage [number]	45,837	0.34	0.26	0.07	0.18	0.32	0.46	0.62
Profitability [number]	45,837	-0.07	9.36	0.02	0.07	0.13	0.22	0.36
Tangibility [number]	45,837	0.35	0.24	0.06	0.14	0.29	0.52	0.73
Current Ratio [number]	45,837	0.61	6.17	0.07	0.16	0.31	0.52	0.89
Market-to-Book [number]	45,837	1.69	1.73	0.95	1.09	1.36	1.84	2.66
Investment Grade [0/1]	21,655	0.33	0.47	0.00	0.00	0.00	1.00	1.00
Not Rated [0/1]	45,837	0.53	0.50	0.00	0.00	1.00	1.00	1.00

Table 2: Impact of Borrower Prestige on Total Cost of Borrowing

This table provides results for linear regressions of the total cost of borrowing (TCB) on the prestige score, loan features, and borrower characteristics. The dependent variable is the logarithm of the TCB. The key explanatory variable is the lagged prestige score from Fortune's Most Admired Companies surveys, which can take any value between 0 and 10. Column (1) shows results for our main regression model with rating, industry (one-digit IC code), year, loan type and loan purpose fixed effects. In column (2), we replace industry and year fixed effects by industry-year fixed effects. In column (3), we replace loan type and purpose fixed effects by loan-type-year and loan-purpose-year fixed effects. Column (4) shows the results for firm fixed effects instead of rating fixed effects. In column (5), we use industry-year, loan-type-year, loan-purpose-year, and firm fixed effects. Standard errors are clustered at the borrower level in columns (1)-(5). Columns (6)-(8) show the results for state-level clustering of the specifications used in columns (1), (2) and (5). The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the firm or state level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Log(TCB)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prestige_{t-1}	-0.049***	-0.048***	-0.042***	-0.072***	-0.093***	-0.046**	-0.048***	-0.105***
	(-3.11)	(-3.24)	(-2.70)	(-3.77)	(-5.38)	(-2.52)	(-2.85)	(-6.18)
Log(Amount)_t	-0.066***	-0.071***	-0.061***	-0.071***	-0.043***	-0.065***	-0.070***	-0.044***
	(-4.39)	(-4.97)	(-4.47)	(-4.27)	(-2.98)	(-4.74)	(-5.82)	(-3.44)
Log(Maturity)_t	-0.274***	-0.266***	-0.263***	-0.276***	-0.257***	-0.253***	-0.253***	-0.241***
	(-8.05)	(-8.54)	(-7.00)	(-8.24)	(-7.24)	(-9.03)	(-8.92)	(-5.72)
Facility Number_t	0.054***	0.055***	0.056***	0.057***	0.048**	0.057***	0.059***	0.058*
	(3.78)	(3.85)	(3.77)	(3.09)	(2.44)	(4.04)	(4.12)	(1.89)
Secured_t	0.539***	0.550***	0.591***	0.553***	0.555***	0.519***	0.530***	0.567***
	(13.28)	(14.07)	(12.25)	(12.10)	(11.25)	(14.32)	(14.93)	(10.66)
$\text{Financial Covenants}_t$	0.065**	0.047	0.040	0.000	-0.012	0.054*	0.035	-0.021
	(2.06)	(1.46)	(1.17)	(0.01)	(-0.30)	(1.84)	(1.06)	(-0.55)
Prime Base Rate_t	-0.056*	-0.050	-0.061*	-0.007	-0.011	-0.046	-0.041	-0.008
	(-1.66)	(-1.50)	(-1.73)	(-0.19)	(-0.25)	(-1.45)	(-1.29)	(-0.23)
$\text{Performance Pricing}_t$	-0.211***	-0.216***	-0.188***	-0.216***	-0.190***	-0.221***	-0.225***	-0.187***
	(-6.73)	(-6.73)	(-5.76)	(-6.53)	(-5.78)	(-7.62)	(-8.05)	(-6.35)
$\text{Log(Total Assets)}_{t-1}$	0.024	0.022	0.017	0.015	0.011	0.015	0.013	-0.038
	(1.55)	(1.55)	(1.14)	(0.28)	(0.19)	(1.16)	(1.11)	(-0.74)
Coverage_{t-1}	-0.001**	-0.001**	-0.001***	-0.001	-0.002	-0.001**	-0.001**	-0.002
	(-2.32)	(-2.40)	(-2.65)	(-0.98)	(-1.48)	(-2.29)	(-2.47)	(-1.27)
Leverage_{t-1}	0.343***	0.334***	0.362***	0.436***	0.498***	0.365***	0.357***	0.406***
	(3.62)	(3.33)	(3.65)	(2.85)	(3.46)	(3.64)	(4.70)	(3.06)
$\text{Profitability}_{t-1}$	-0.120	-0.133	-0.189	-0.547*	-0.536	-0.129	-0.189	-0.594*
	(-0.88)	(-1.05)	(-1.42)	(-1.83)	(-1.61)	(-0.95)	(-1.28)	(-1.78)
Tangibility_{t-1}	0.082	0.087	0.087	-0.125	0.014	0.099	0.089	-0.032
	(1.03)	(1.12)	(1.17)	(-0.59)	(0.07)	(1.29)	(1.23)	(-0.15)
$\text{Current Ratio}_{t-1}$	0.008	0.012	0.014	-0.029	-0.035	0.024	0.018	-0.034
	(0.22)	(0.34)	(0.37)	(-0.57)	(-0.58)	(0.60)	(0.45)	(-0.56)
$\text{Market-to-Book}_{t-1}$	-0.051***	-0.048**	-0.038*	-0.085***	-0.055**	-0.054***	-0.050**	-0.054***
	(-2.75)	(-2.47)	(-1.84)	(-3.39)	(-2.15)	(-2.84)	(-2.43)	(-2.76)
Rating FE	Yes	Yes	Yes	No	No	Yes	Yes	No
Industry FE	Yes	No	No	No	No	Yes	No	No
Year FE	Yes	No	No	No	No	Yes	No	No
Loan Type FE	Yes	Yes	No	Yes	No	Yes	Yes	No
Loan Purpose FE	Yes	Yes	No	Yes	No	Yes	Yes	No
Industry x Year FE	No	Yes	Yes	Yes	Yes	No	Yes	Yes
Loan Type x Year FE	No	No	Yes	No	Yes	No	No	Yes
Loan Purpose x Year FE	No	No	Yes	No	Yes	No	No	Yes
Firm FE	No	No	No	Yes	Yes	No	No	Yes
Observations	2,278	2,269	2,217	2,194	2,140	2,133	2,124	1,991
Adjusted R^2	0.855	0.862	0.872	0.882	0.894	0.860	0.867	0.896
Cluster Variable	Firm	Firm	Firm	Firm	Firm	State	State	State
Number of Clusters	394	392	388	311	307	42	42	38

Table 3: Borrower Prestige and Different Financing Cost Components

This table provides results of linear regressions of individual components of the total cost of borrowing on lagged prestige score and control variables. Panel A shows the results for the all-in-spread-drawn (AISD), the all-in-spread-undrawn (AISU), and the interest rate spread over LIBOR. Panel B shows the results for upfront fees, commitment fees, and facility fees. All dependent variables are log-transformed. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the firm level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

Panel A: Alternative Measures for the Cost of Borrowing

	Log(AISD)		Log(AISU)		Log(Spread)	
	(1)	(2)	(3)	(4)	(5)	(6)
Prestige_{t-1}	-0.163***	-0.078***	-0.119***	-0.066***	-0.173***	-0.088***
	(-4.47)	(-3.53)	(-4.79)	(-4.13)	(-4.21)	(-3.72)
Loan Features	No	Yes	No	Yes	No	Yes
Borrower Characteristics	No	Yes	No	Yes	No	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes
Loan Type FE	No	Yes	No	Yes	No	Yes
Loan Purpose FE	No	Yes	No	Yes	No	Yes
Observations	3,239	3,232	2,375	2,366	2,974	2,968
Adjusted R^2	0.438	0.744	0.507	0.763	0.469	0.778
Cluster Variable	Firm	Firm	Firm	Firm	Firm	Firm
Number of Clusters	504	503	469	466	481	480

Panel B: Fee Types

	Log(Upfront Fee)		Log(Commitment Fee)		Log(Facility Fee)	
	(1)	(2)	(3)	(4)	(5)	(6)
Prestige_{t-1}	-0.157*	-0.113**	-0.080*	-0.025	-0.102***	-0.048***
	(-1.96)	(-2.11)	(-1.75)	(-0.81)	(-4.97)	(-3.18)
Loan Features	No	Yes	No	Yes	No	Yes
Borrower Characteristics	No	Yes	No	Yes	No	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes
Loan Type FE	No	Yes	No	Yes	No	Yes
Loan Purpose FE	No	Yes	No	Yes	No	Yes
Observations	812	801	956	950	1,688	1,678
Adjusted R^2	0.159	0.581	0.279	0.592	0.525	0.742
Cluster Variable	Firm	Firm	Firm	Firm	Firm	Firm
Number of Clusters	254	252	324	323	335	332

Table 4: Impact of Borrower Prestige on Pricing of Credit Lines and Term Loans
This table provides results of linear regressions of the total cost of borrowing (TCB), and the three most commonly used fee types – spread over LIBOR, facility, and upfront fee – on prestige score and the a credit line dummy. We only look at loans that can be classified as either credit line or term loans. Including the loan type fixed effects leads to omission of the credit line dummy in columns (2), (4), (6), and (8). All dependent variables are log-transformed. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the firm level in parentheses for the top three rows of controls. We report values of the F-test of the null of zero in the fourth row. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Log(TCB)		Log(Loan Spread)		Log(Facility Fee)		Log(Upfront Fee)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prestige$_{t-1}$	-0.056	0.006	-0.013	0.008	-0.005	0.022	0.047	0.041
	(-1.17)	(0.21)	(-0.24)	(0.21)	(-0.03)	(0.13)	(0.50)	(0.46)
Prestige * Credit Line	-0.112**	-0.070***	-0.210***	-0.121***	-0.105	-0.070	-0.280***	-0.197***
	(-2.27)	(-2.65)	(-4.04)	(-3.84)	(-0.64)	(-0.42)	(-3.24)	(-2.66)
Credit Line	-0.723**	-	0.379	-	0.234	-	0.936*	-
	(-2.59)		(1.29)		(0.21)		(1.87)	
Prestige + Prestige * Credit Line	-0.168***	-0.064***	-0.223***	-0.113***	-0.11***	-0.048***	-0.233***	-0.156***
	(46.80)	(16.72)	(49.07)	(22.19)	(28.26)	(9.85)	(8.82)	(9.39)
Loan Features	No	Yes	No	Yes	No	Yes	No	Yes
Borrower Characteristics	No	Yes	No	Yes	No	Yes	No	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Loan Type FE	No	Yes	No	Yes	No	Yes	No	Yes
Loan Purpose FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	2,278	2,274	2,785	2,781	1,641	1,636	737	729
Adjusted R^2	0.665	0.856	0.578	0.784	0.544	0.749	0.257	0.580
Cluster Variable	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Number of Clusters	394	394	474	474	332	330	246	244

Table 5: Borrower Prestige and Credit Risk

This table provides results of linear regressions of measures of credit risk on borrower prestige and control variables. In columns (1) and (2), the dependent variable is the average S&P rating of a borrower over the loan maturity. In columns (3) and (4), the dependent variable is the average implied recovery from Markit CDS spreads of a borrower over the loan maturity. In columns (5) and (6), we use the average 5-year Markit CDS spread of a borrower over the loan maturity as a dependent variable. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the firm level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	$\overline{\text{Rating}}$		$\overline{\text{Recovery}}$		$\overline{\text{CDS Spread}}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Prestige_{t-1}	0.034	0.052	0.003	0.002	0.004	0.006
	(0.54)	(0.80)	(1.24)	(0.93)	(0.52)	(0.84)
Log(Spread)		0.374***		-0.004**		0.023**
		(4.18)		(-2.27)		(1.99)
Loan Features	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,660	2,590	993	781	991	779
Adjusted R^2	0.899	0.901	0.221	0.240	0.282	0.313
Cluster Variable	Firm	Firm	Firm	Firm	Firm	Firm
Number of Clusters	452	402	179	169	179	169

Table 6: Regression Discontinuity Analysis

This table presents non-parametric estimates for a regression discontinuity (RD) analysis with a kernel regression using a triangular kernel as implemented by Calonico et al. (2017). We report two different models – conventional RD estimates with conventional variance estimator (Conventional), and bias-corrected RD estimates with robust variance estimator (Robust). A sharp RD design is assumed in which the treatment variable – ranking in *Fortune Magazine's Most Admired Companies* – jumps from one to zero at rank 100. We run the analysis for all firms ranked between 80 and 120 (Panel A) and a placebo test for a hypothetical cutoff set to 150 and all firms ranked between 130 and 170 (Panel B). In columns (1) and (3), we report results without including any covariates. In columns (2) and (4), we report results with the covariates facility amount, maturity, total assets, leverage and market-to-book. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

Panel A: Threshold Value of 100

	Log(TCB)		$\overline{\text{Rating}}$	
	(1)	(2)	(3)	(4)
Conventional	-0.638*	-0.825**	-3.091**	-0.167
	(-1.93)	(-2.17)	(-2.23)	(-0.18)
Robust	-0.709*	-1.008**	-3.811**	-0.633
	(-1.75)	(-2.14)	(-2.33)	(-0.59)
Observations	280	280	494	494

Panel B: Threshold Value of 150 (Placebo)

	Log(TCB)		$\overline{\text{Rating}}$	
	(1)	(2)	(3)	(4)
Conventional	1.883***	-0.177	-0.485	-1.435
	(2.84)	(-0.43)	(-0.33)	(-1.26)
Robust	2.342***	-0.258	-0.865	-1.500
	(2.99)	(-0.48)	(-0.50)	(-1.06)
Observations	197	197	402	402

Table 7: Covariate Imbalances Before and After Coarsened Exact Matching

This table reports measures of imbalance before and after applying the coarsened exact matching (CEM) algorithm of Iacus et al. (2012). $\mathcal{L}_1$ measures the unidimensional imbalance between firms ranked in the top hundred of Fortune Magazine's Most Admired Companies (treated) and firms that are not (untreated) where $\mathcal{L}_1$ is bounded between zero and one. A lower $\mathcal{L}_1$ statistic indicates lower imbalance. We also report differences in means and medians between treated and untreated groups. CEM (1) refers to matching on total assets and leverage. CEM (2) refers to matching on total assets, leverage, market-to-book, and coverage. Matching on all borrower characteristics does not yield enough observations for meaningful statistical inference. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1.

	Before CEM			After CEM (1)			After CEM (2)		
	$\mathcal{L}_1$	ΔMean	ΔMedian	$\mathcal{L}_1$	ΔMean	ΔMedian	$\mathcal{L}_1$	ΔMean	ΔMedian
Log(Total Assets)	0.711	3.011	3.110	0.548	1.687	1.894	0.400	1.016	0.060
Coverage	0.301	0.692	3.883	0.200	3.252	2.965	0.191	3.735	1.284
Leverage	0.291	-0.076	-0.074	0.209	-0.024	-0.039	0.221	-0.035	-0.047
Profitability	0.183	0.023	0.024	0.120	0.005	0.010	0.130	-0.013	-0.007
Tangibility	0.217	0.004	0.020	0.205	-0.014	-0.003	0.163	-0.023	-0.021
Current Ratio	0.123	-0.054	0.006	0.123	-0.021	0.006	0.132	-0.020	-0.006
Market-to-Book	0.257	0.452	0.271	0.245	0.475	0.283	0.220	0.275	0.132

Table 8: Matched Sample Regressions

This table provides results of linear regressions of the total cost of borrowing (TCB) and the average borrower rating over loan maturity on a dummy variable indicating whether a company is ranked among the top 100 companies in *Fortune Magazine's Most Admired Companies* and control variables. Columns (1) and (4) show the results without applying any matching algorithm. In columns (2) and (5), we apply the coarsened exact matching (CEM) algorithm of Iacus et al. (2012) on borrowers' total assets and leverage to reduce the imbalance between observations which are among the top 100 companies (treated) and those that are not (untreated). In columns (3) and (6), we match on total assets, leverage, market-to-book, and coverage. Matching on all borrower characteristics does not yield enough observations for meaningful statistical inference. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the firm level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Log(TCB)			$\overline{\text{Rating}}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Top 100_{t-1}	-0.021	-0.081***	-0.085***	0.092	-0.011	0.049
	(-0.75)	(-3.26)	(-3.39)	(0.83)	(-0.10)	(0.56)
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Loan Features	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,864	9,989	5,012	10,531	7,315	4,227
Adjusted R^2	0.835	0.855	0.850	0.912	0.895	0.905
Cluster Variable	Firm	Firm	Firm	Firm	Firm	Firm
Number of Clusters	3,842	1,772	1,010	1,583	1,149	814

Table 9: Average Treatment Effect for Alternative Matching Estimators

This table provides matching results for different set of control variables and numbers of neighbors. The variable of interest is the average treatment effect on the treated of firms ranked among the top 100 most admired companies. In Panel A, we apply nearest neighbor matching including the bias-adjustment of Abadie and Imbens (2006, 2011) to correct for the bias that arises due to the use of continuous control variables. In Panel B, we apply propensity score matching including standard errors derived in Abadie and Imbens (2016) to account for the fact that the propensity score is an estimated quantity. We use a probit model to estimate propensity scores. We drop observations if they violate the overlap assumption for a specific model. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1.

Panel A: Nearest Neighbor Matching

	Log(TCB)			
	(1)	(2)	(3)	(4)
Top 100_{t-1}	-0.121**	-0.065**	-0.237***	-0.095***
	(-2.17)	(-2.22)	(-7.20)	(-4.31)
Borrower Characteristics	Yes	Yes	Yes	Yes
Loan Features	No	Yes	No	Yes
Neighbors	1	1	10	10
Observations	22,207	19,752	22,207	17,064

Panel B: Propensity Score Matching

	Log(TCB)			
	(1)	(2)	(3)	(4)
Top 100_{t-1}	-0.339***	-0.251***	-0.476***	-0.243***
	(-6.67)	(-5.12)	(-12.14)	(-6.81)
Borrower Characteristics	Yes	Yes	Yes	Yes
Loan Features	No	Yes	No	Yes
Neighbors	1	1	10	10
Observations	22,207	22,207	22,207	22,207

Table 10: Borrower Prestige and Bank Competition

This table provides results for linear regressions with measures of competition. In columns (1) and (2) we regress syndicate size (i.e. the number of participants in a deal) on borrower prestige and lead share (i.e. percentage of loan retained the lead arranger at loan origination). In columns (3) and (4), we regress the lead share on borrower prestige and syndicate size. In columns (5)-(8), the dependent variable is the total cost of borrowing (TCB). The sample is based on loans in the US syndicated loan market between 1982 and 2009. For each deal in the sample, we select the the largest facility to represent the deal. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the firm level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Syndicate Size		Lead Share		Log(TCB)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prestige$_{t-1}$	1.143***	0.885**	4.183*	2.645**	-0.061	0.010	-0.069	-0.063*
	(2.66)	(2.06)	(1.96)	(2.29)	(-1.23)	(0.48)	(-1.17)	(-1.82)
Prestige * Syndicate Size					-0.003	-0.003***		
					(-1.49)	(-2.78)		
Syndicate Size			-1.268***	-0.432***	0.010	0.012**		
			(-6.39)	(-3.65)	(0.75)	(2.04)		
Lead Share	-0.249***	-0.092***					0.036***	0.006
	(-16.34)	(-4.36)					(4.56)	(0.84)
Prestige * Lead Share							-0.005***	-0.001
							(-3.71)	(-0.98)
Loan Features	No	Yes	No	Yes	No	Yes	No	Yes
Borrower Characteristics	No	Yes	No	Yes	No	Yes	No	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Loan Type FE	No	Yes	No	Yes	No	Yes	No	Yes
Loan Purpose FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	698	694	698	694	1,651	1,645	521	515
Adjusted R^2	0.359	0.580	0.400	0.639	0.415	0.824	0.373	0.825
Cluster Variable	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Number of Clusters	266	266	266	266	389	388	211	211

Table 11: Borrower Prestige and Lending Relationships

This table provides results for linear regressions of measures of loan pricing on borrower prestige and control variables with a focus on bank relationship variables. The dependent variable is either the total cost of borrowing (TCB) in columns (1)-(4) or the upfront fee in columns (5)-(8). The key explanatory variables are the interaction terms of lagged prestige score with variables related to the relationship between a borrower and a lender. In columns (1) and (5), the relevant variable is a dummy which indicates whether a borrower and a lender interact for the first time in a given deal (New Relation). In columns (2) and (6), the relevant variable is a dummy which indicates whether a borrower and a lender interacted in the last five years before a deal (Old Relation (Dummy)). In columns (3) and (7), we use the share of the number of loans between a borrower and a lender as a fraction of the total number of loans of a borrower in the last five years before a deal (Old Relation (Number)). In columns (4) and (8), we use the share of the loan amount between a borrower and a lender as a fraction of the total loan amount of a borrower in the last five years before a deal (Old Relation (Amount)). The sample is based on loans in the US syndicated loan market between 1982 and 2009. For each deal in the sample, we select the the largest facility to represent the deal. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the firm level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Log(TCB)				Log(Upfront Fee)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prestige * New Relation	-0.026				-0.287**			
	(-1.04)				(-2.54)			
Prestige * Old Relation (Dummy)		0.021				0.238**		
		(0.85)				(2.13)		
Prestige * Old Relation (Number)			0.006				0.358**	
			(0.19)				(2.02)	
Prestige * Old Relation (Amount)				-0.001				0.197
				(-0.03)				(1.18)
Prestige_{t-1}	-0.026	-0.049**	-0.034	-0.032	-0.102	-0.337***	-0.308***	-0.260**
	(-1.60)	(-2.00)	(-1.46)	(-1.32)	(-1.12)	(-3.55)	(-2.91)	(-2.39)
New Relation	0.172				1.911***			
	(1.07)				(2.77)			
Old Relation (Dummy)		-0.138				-1.616**		
		(-0.86)				(-2.35)		
Old Relation (Number)			-0.040				-2.144**	
			(-0.19)				(-2.02)	
Old Relation (Amount)				-0.009				-1.207
				(-0.04)				(-1.20)
Loan Features	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,236	1,236	1,168	1,168	222	222	191	191
Adjusted R^2	0.842	0.842	0.848	0.848	0.580	0.576	0.523	0.515
Cluster Variable	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Number of Clusters	337	337	320	320	153	153	133	133

Table 12: Descriptive Statistics for Bank-Level Sample

This table reports descriptive statistics for variables used in the bank level analysis. For each variable, the number of observations (N), mean, standard deviation (SD), 10% quantile ($Q_{0.10}$), 25% quantile ($Q_{0.25}$), median ($Q_{0.50}$), 75% quantile ($Q_{0.75}$), and 99% quantile ($Q_{0.99}$) are reported. Loan volume, loan number, average loan volume and the number of unique borrowers are based on aggregating deals from *Dealscan* to an annual level. Top 100 loans refers to the number of loans originated for companies ranked among the top 100 companies according to *Fortune's Most Admired Companies* surveys. The remaining bank characteristics are collected from *Compustat*. The panel of yearly bank level observations spans from 1982 to 2009. We define all variables in Table A1.

	N	Mean	SD	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
Loan Volume [USD bn.]	1,187	6.05	20.63	0.02	0.08	0.54	3.33	12.07
Loan Number	1,187	17.68	34.85	1.00	2.00	6.00	18.00	38.00
Average Loan Volume [USD mn.]	1,187	210.42	493.67	10.00	25.00	82.50	234.64	497.63
Unique Borrowers [number]	1,187	16.21	31.56	1.00	2.00	6.00	16.00	36.00
Top 100 Loans [number]	1,187	0.69	2.42	0.00	0.00	0.00	0.00	2.00
Total Assets [USD bn.]	946	227.13	442.66	9.46	21.82	58.62	219.23	632.57
Market-to-Book [number]	862	1.06	0.07	0.99	1.01	1.04	1.09	1.14
Deposits/Assets [number]	946	0.67	0.13	0.55	0.62	0.68	0.75	0.80
Tier 1 Ratio [0-100]	596	8.82	1.80	7.10	7.68	8.44	9.54	10.92

Table 13: Bank-Level Regressions

This table provides results for linear regressions of lead arrangers' business activities on a measure that captures the lending to prestigious borrowers and control variables. The dependent variable is the future loan volume in columns (1) and (2), average volume per loan in columns (3) and (4), the number of loans underwritten in columns (5) and (6), and the number of unique borrowers in columns (7) and (8). The key explanatory variable is the Log(1+ Top 100 Loans) variable which is based on *Fortune' Most Admired Companies* survey. In all regression specification, we include bank and year fixed effects. Depending on the column, we also control for the bank's total assets, market-to-book ratio and deposits over assets ratio. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The main results are displayed in Panel A. Panel B shows the results for up to 5 lags in the key explanatory variable. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and bank characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the bank level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

Panel A: Main Bank-Level Analysis

	Log(Volume)_t		$\text{Log}\left(\frac{\text{Volume}}{\text{Loans}}\right)_t$		Log(Loans)_t		Log(Borrowers)_t	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Log(1 + Top 100 Loans)}_{t-1}$	0.483***	0.296**	0.076	-0.059	0.407***	0.355***	0.382***	0.333***
	(4.21)	(2.13)	(0.85)	(-0.50)	(7.15)	(6.17)	(6.49)	(5.85)
$\text{Log(Total Assets)}_{t-1}$		1.044***		0.363***		0.681***		0.675***
		(4.03)		(2.87)		(4.39)		(4.34)
$\text{Market-to-Book}_{t-1}$		-1.193		-1.356**		0.163		0.037
		(-1.18)		(-2.13)		(0.23)		(0.05)
$\text{Deposit/Assets}_{t-1}$		1.320		-0.073		1.392**		1.317**
		(1.30)		(-0.10)		(2.38)		(2.27)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,186	860	1,186	860	1,186	860	1,186	860
Adjusted R^2	0.772	0.815	0.688	0.696	0.766	0.810	0.770	0.814
Cluster Variable	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Number of Clusters	100	75	100	75	100	75	100	75

Panel B: Bank-Level Analysis With Additional Lags

	Log(Volume)_t		$\text{Log}\left(\frac{\text{Volume}}{\text{Loans}}\right)_t$		Log(Loans)_t		Log(Borrowers)_t	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Log(1 + Top 100 Loans)}_{t-1}$	0.456***	0.187*	0.079	-0.063	0.377***	0.249***	0.347***	0.234***
	(3.61)	(1.70)	(1.01)	(-0.77)	(5.06)	(4.41)	(4.51)	(4.08)
$\text{Log(1 + Top 100 Loans)}_{t-2}$	0.258***	0.231**	0.133**	0.099*	0.125**	0.131**	0.126***	0.120**
	(3.16)	(2.46)	(2.39)	(1.68)	(2.58)	(2.45)	(2.64)	(2.32)
$\text{Log(1 + Top 100 Loans)}_{t-3}$	-0.132	0.137	-0.061	0.041	-0.071	0.096	-0.063	0.092
	(-1.06)	(1.50)	(-0.89)	(0.61)	(-0.95)	(1.60)	(-0.90)	(1.62)
$\text{Log(1 + Top 100 Loans)}_{t-4}$	-0.011	-0.034	-0.041	-0.078	0.030	0.044	0.032	0.039
	(-0.09)	(-0.31)	(-0.53)	(-1.24)	(0.44)	(0.60)	(0.50)	(0.55)
$\text{Log(1 + Top 100 Loans)}_{t-5}$	-0.106	-0.099	-0.091	-0.111	-0.015	0.013	-0.010	0.014
	(-0.75)	(-0.75)	(-1.10)	(-1.37)	(-0.20)	(0.19)	(-0.14)	(0.22)
$\text{Log(Total Assets)}_{t-1}$		1.026***		0.367***		0.660***		0.655***
		(3.97)		(2.85)		(4.30)		(4.26)
$\text{Market-to-Book}_{t-1}$		-1.152		-1.369**		0.217		0.086
		(-1.14)		(-2.09)		(0.31)		(0.12)
$\text{Deposit/Assets}_{t-1}$		1.411		-0.111		1.521**		1.438**
		(1.33)		(-0.15)		(2.60)		(2.49)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,186	860	1,186	860	1,186	860	1,186	860
Adjusted R^2	0.772	0.815	0.688	0.696	0.766	0.812	0.770	0.815
Cluster Variable	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Number of Clusters	100	75	100	75	100	75	100	75

Figures

Figure 1: U.S. Syndicated Loan Credentials

This figure illustrates the common practice of banks using loans with prestigious borrowers as a marketing tool to win future business (credentials). The graph shows US syndicated loan credentials that Royal Bank of Canada (RBC) used in client presentations in 2009.

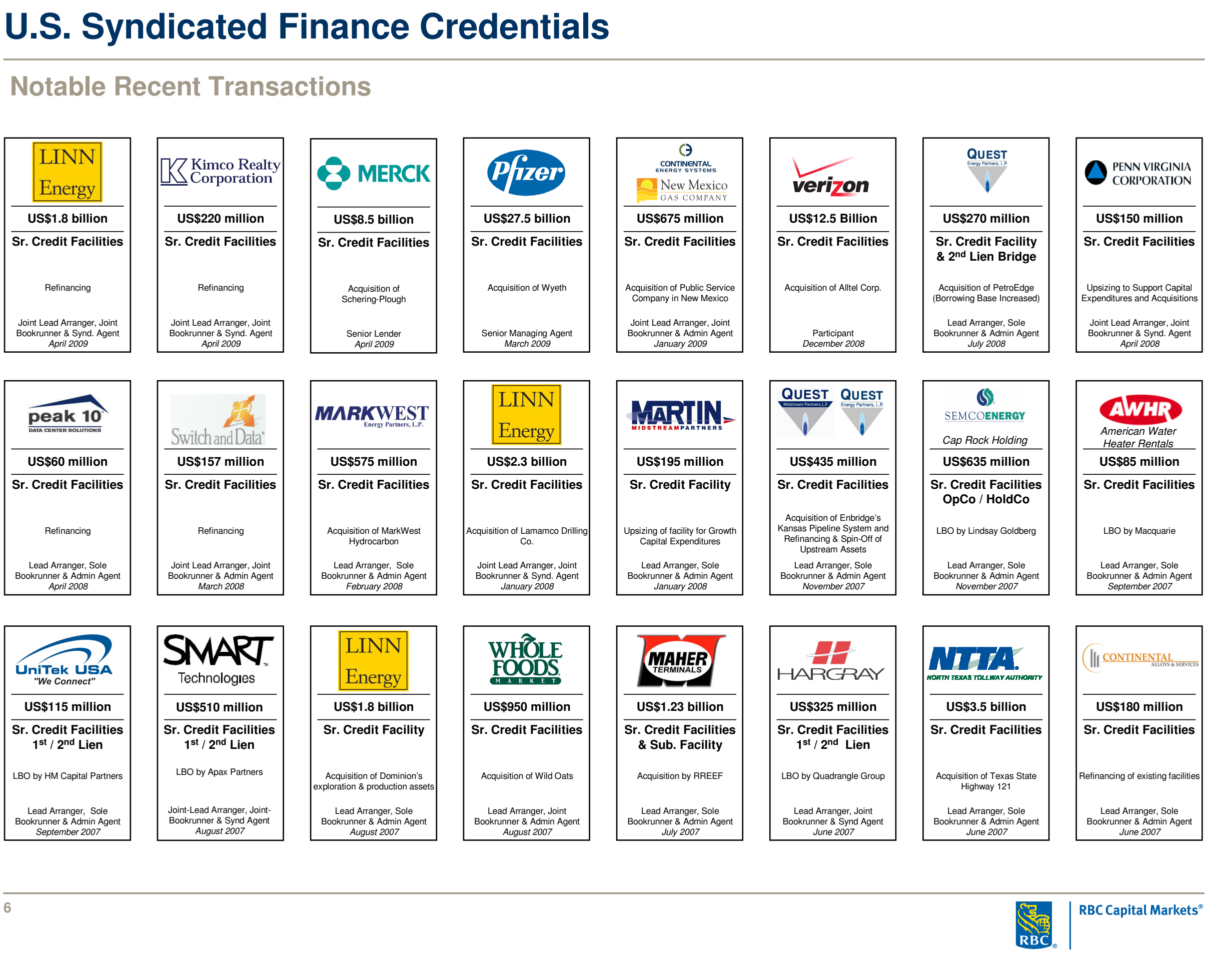


Figure 2: European Syndicated Loan Credentials

This figure illustrates the common practice of banks using loans with prestigious borrowers as a marketing tool to win future business (credentials). The graph shows European syndicated loan credentials for UniCredit in 2013.

Figure 3: Distribution of Borrower Prestige

This histogram shows the distribution of the prestige score from *Fortune's Most Admired Companies* surveys between 1982 and 2009 for borrower with loan data in *Dealscan*. The horizontal axis reports the prestige score which can take any value between zero and ten. The vertical axis shows the frequency of the respective bin in percent. The prestige data is manually collected from printed editions of *Fortune Magazine*.

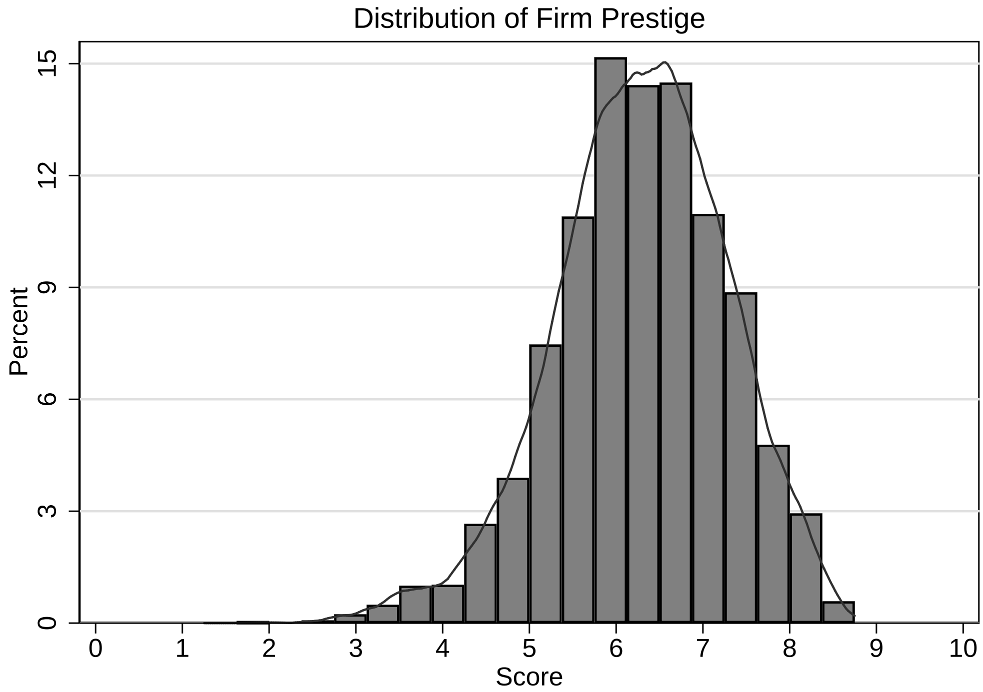


Figure 4: Borrower Prestige and the Cost of Borrowing

These figures illustrate the strong negative relationship between borrower prestige and the cost of borrowing. The scatter plot in the top shows the relation for the total cost of borrowing (TCB) of Berg et al. (2016). The graph in the middle illustrates the relationship for the loan spread over LIBOR. The bottom plot shows the relation for upfront fees. In all plots, the horizontal axis reports the prestige score, which can take any value between zero and ten. The solid lines represent fitted values from an OLS regressions. Loan spreads and upfront fees are obtained from *Dealscan* and the prestige score is manually collected from printed editions of *Fortune Magazine*. The sample covers the time period 1982 to 2009.

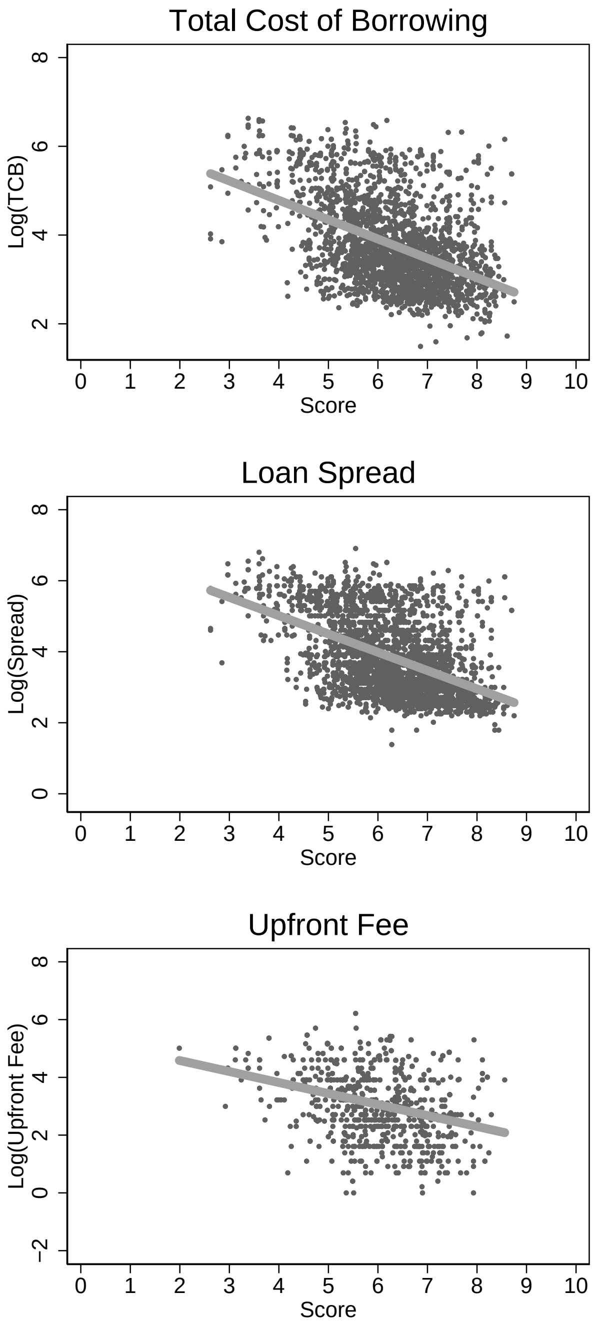
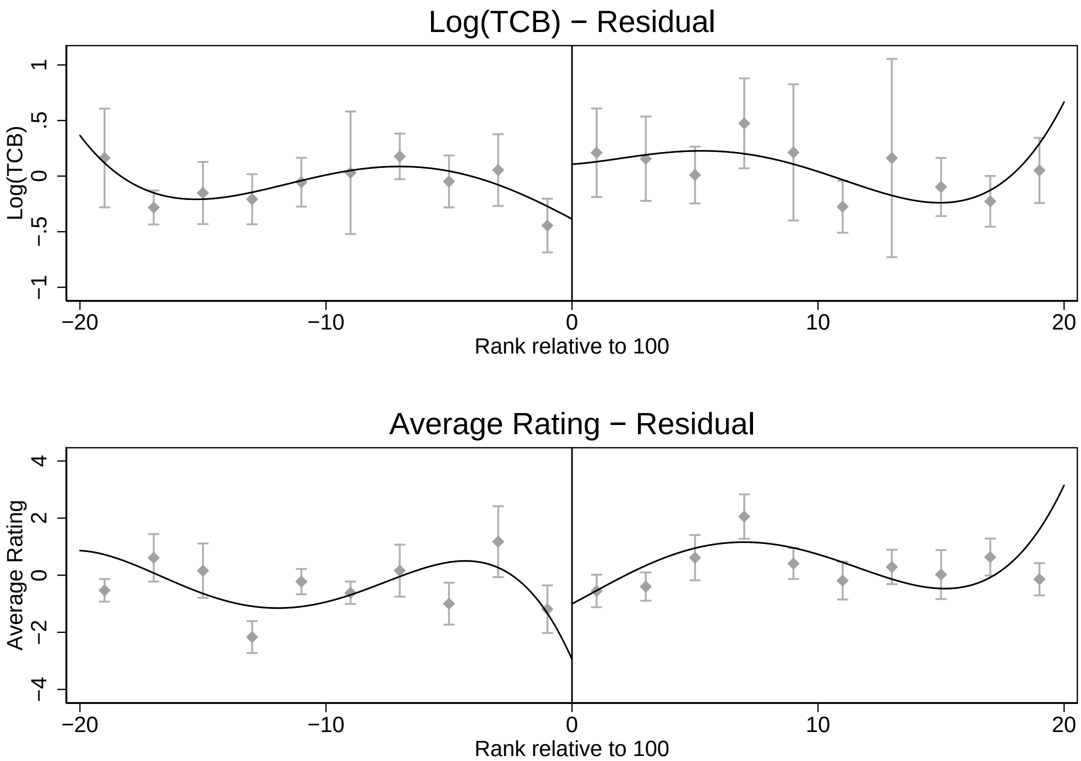


Figure 5: Regression Discontinuity around Rank 100 of Prestige Survey

This figure shows non-parametric estimates of two local polynomial regressions using a triangular kernel as implemented by Calonico et al. (2015). The dependent variables are the residuals of the regression of the total cost of borrowing (TCB) and the average rating over loan maturity on facility amount, maturity, total assets, leverage and market-to-book. The cutoff equals rank 100 in *Fortunes' Most Admired Companies* survey. We only consider companies with ranks between 80 and 120. In both charts, the horizontal axis reports the rank based on the prestige score as reported in the survey. The vertical lines represent 90% confidence intervals for each bin. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1.



A Appendix

Table A1: Variable Definitions and Data Sources

Variable [Units]	**Source**	**Definition**
Prestige Variables		
Prestige [0-10]	Fortune	Prestige score of the borrower as defined by *Fortune's Most Admired Companies* survey.
Top 100 [0/1]	Fortune	Dummy variable equal to one if the borrower is ranked among the top 100 firms in the *Fortune's Most Admired Companies* survey (by score).
Loan Characteristics		
TCB [bps]	Dealscan	Total Cost of Borrowing (TCB) developed and provided by Berg et al. (2016). The TCB measure reflects option characteristics of loans, differentiates between credit lines and term loans, and takes various fees paid to lenders into account.
AISD [bps]	Dealscan	All-in-spread-drawn, defined as the sum of the spread over LIBOR plus the facility fee.
AISU [bps]	Dealscan	All-in-spread-undrawn, defined as the sum of the facility fee and the commitment fee.
Spread [bps]	Dealscan	Spread over LIBOR paid on drawn amounts on credit lines.
Upfront Fee [bps]	Dealscan	Fee paid upon completion of syndicated loan deal.
Commitment Fee [bps]	Dealscan	Fee paid on the unused amount of loan commitments.
Facility Fee [bps]	Dealscan	Fee paid on the total committed amount independent of usage.
Amount [USD mn.]	Dealscan	Facility amount as indicated in the field *FacilityAmt* in the Dealscan facility table.
Maturity [months]	Dealscan	Facility maturity in months as indicated in the field *Maturity* in the Dealscan facility table.
Facilities [number]	Dealscan	Number of facilities in a package.
Secured [0/1]	Dealscan	Dummy variable equal to one if facility is secured as indicated by the field *Secured* in the Dealscan facility table.
Financial Covenants [0/1]	Dealscan	Dummy variable equal to one if the loan has financial covenants as indicated by appearing the Dealscan financial covenants table.
Prime Base Rate [0/1]	Dealscan	Dummy variable equal to one if the base rate is prime as indicated by the field *Baserate* in the Dealscan current facility pricing table.
Performance Pricing [0/1]	Dealscan	Dummy variable equal to one if the loan has performance pricing as indicated by appearing in the Dealscan performance pricing table.
Credit Line [0/1]	Dealscan	Loans with type "364-Day Facility", "Revolver/line < 1 Yr.", "Revolver/Line >= 1 Yr.", or "Revolver/Term Loan" as indicated in the field *Loantype* in the Dealscan facility table.
Term Loan [0/1]	Dealscan	Loans with type "Term Loan", "Term Loan A"-"Term Loan K", and "Delay Draw Term Loan" as indicated in the field *Loantype* in the Dealscan facility table.
Syndicate Size [number]	Dealscan	Number of lenders (lead arranger and participants) of a syndicated loan facility as indicated by the Dealscan lender shares table.
Lead Share [0-1]	Dealscan	Share of the loan that is retained by the lead bank at loan origination as indicated by the field *BankAllocation* in the Dealscan lender shares table.

New Relation [0/1]	Dealscan	Dummy variable equal to one if the lead banks lends to the borrower for the first time. The variable is set to missing for the first loan of each company in our sample.
Old Relation (Dummy) [0/1]	Dealscan	Dummy variable equal to one if the borrower and lender had at least one lending relationship in the last 5 years before loan origination.
Old Relation (Number) [0-1]	Dealscan	Number of loans by bank j to borrower i in the last 5 years before loan origination divided by the total number of loans by borrower i in the last 5 years.
Old Relation (Amount) [0-1]	Dealscan	Amount of loans by bank j to borrower i in the last 5 years before loan origination divided by the total amount of loans by borrower i in the last 5 years.
$\overline{\text{Rating}}$ [1-15]	Compustat	Average S&P rating over loan maturity.
$\overline{\text{Recovery}}$ [number]	Markit	Average implied recovery over loan maturity.
$\overline{\text{CDS Spread}}$ [number]	Markit	Average 5-year CDS spread over loan maturity.
Borrower Characteristics		
Total Assets [number]	Compustat	Total book assets (*at*) in USD million.
Coverage [number]	Compustat	Ratio of EBITDA (*ebitda*) to interest expenses (*xint*).
Leverage [number]	Compustat	Ratio of book value of total debt (*dltt* + *dlc*) to book value of assets (*at*).
Profitability [number]	Compustat	Ratio of EBITDA (*ebitda*) to sales (*sale*).
Tangibility [number]	Compustat	Ratio of property, plant, and equipment (*ppent*) to total assets (*at*).
Current Ratio [number]	Compustat	Ratio of current assets (*aco*) to current liabilities (*lco*).
Market-to-Book [number]	Compustat	Ratio of book value of assets (*at*) - book value of equity (*ceq*) + market value of equity (*csho*prcc_f*) to book value of assets (*at*).
Investment Grade [0/1]	Compustat	Dummy variable equal to one if the S&P rating is BBB- or higher and missing for non-rated borrowers.
Not Rated [0/1]	Compustat	Dummy variable equal to one if no S&P rating for the borrower exists.
Bank Level Variables		
Loan Volume [USD bn.]	Dealscan	Total volume of all loans underwritten by lead bank in a given year.
Loans [number]	Dealscan	Total number of loans underwritten by lead bank in a given year.
Loans / Volume [number]	Dealscan	Average loan volume issued by lead bank in a given year.
Unique Borrowers [number]	Dealscan	Number of unique borrowers that the lead bank provided with loans during the year.
Top 100 Loans [number]	Dealscan	Number of loans underwritten for borrowers that are ranked among the top 100 firms in the *Fortune's Most Admired Companies* survey.
Total Assets [USD bn.]	Compustat	Total book assets (*at*).
Market-to-Book [number]	Compustat	Ratio of book value of assets (*at*) - book value of equity (*ceq*) + market value of equity (*csho*price*) to book value of assets (*at*) where *price* is the month-end price from CRSP at the fiscal-year end.
Deposits/Assets [number]	Compustat	Deposits (*dptc*) over total assets (*at*).
Tier 1 Ratio [0-100]	Compustat	Risk-adjusted tier 1 capital ratio (*capr1*).

Internet Appendix to

Fishing with Pearls: The Value of Lending Relationships with Prestigious Firms

Alexander Mürmann Thomas Rauter Christoph Scheuch

November 15, 2017

Table of Contents

A Robustness Tests for Credit Risk Regressions

Table IA1: Borrower Prestige and Credit Risk at Loan Maturity

This table provides results of linear regressions of measures of credit risk on borrower prestige and control variables. In Panel A, the dependent variables describe credit risk at maturity. In columns (1) and (2), the dependent variable is the S&P rating of a borrower at loan maturity. In columns (3) and (4), the dependent variable is the implied recovery from Markit CDS spreads of a borrower at loan maturity. In columns (5) and (6), we use the 5-year Markit CDS spread of a borrower at loan maturity as a dependent variable. In panel B, we use the changes in these variables from origination to maturity as dependent variables. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the firm level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

Panel A: Credit Risk at Maturity

	Rating_m		Recovery_m		CDS Spread_m	
	(1)	(2)	(3)	(4)	(5)	(6)
Prestige_{t-1}	0.065	0.081	0.003	0.001	-0.001	-0.000
	(0.52)	(0.66)	(1.20)	(0.62)	(-0.68)	(-0.20)
Log(Spread)		0.524***		-0.008**		0.006**
		(3.41)		(-2.17)		(2.38)
Loan Features	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3626	2555	811	640	804	634
Adjusted R^2	0.725	0.731	0.224	0.302	0.381	0.376
Cluster Variable	bgvkey	bgvkey	bgvkey	bgvkey	bgvkey	bgvkey
Number of Clusters	454	411	164	154	162	152

Panel B: Changes in Credit Risk

	ΔRating		ΔRecovery		ΔCDS Spread	
	(1)	(2)	(3)	(4)	(5)	(6)
Score_{t-1}	0.094	0.104	-0.003	-0.004*	-0.001	-0.002
	(0.76)	(0.85)	(-1.65)	(-1.91)	(-0.88)	(-1.43)
Log(Spread)		0.501***		0.002		-0.009***
		(3.21)		(0.59)		(-2.76)
Loan Features	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3492	2474	639	482	629	474
Adjusted R^2	0.312	0.358	0.539	0.599	0.463	0.529
Cluster Variable	bgvkey	bgvkey	bgvkey	bgvkey	bgvkey	bgvkey
Number of Clusters	439	392	112	103	110	101

B Robustness Tests for Bank-Level Analyses

Table IA2: Baseline Regressions with Additional Controls

This table provides results for linear regressions of lead arrangers' business activities on a measure that captures the lending to prestigious borrowers and control variables. The dependent variable is the future loan volume in columns (1) and (2), average volume per loan in columns (3) and (4), the number of loans underwritten in columns (5) and (6), and the number of unique borrowers in columns (7) and (8). The key explanatory variable is the Log(1+ Top 100 Loans) variable which is based on *Fortune' Most Admired Companies* survey. In all regression specification, we include bank and year fixed effects. Depending on the column, we also control for the bank's total assets, market-to-book ratio, deposits over assets, and the tier 1 capital ratio. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and bank characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the bank level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Log(Volume)_t		$\text{Log}\left(\frac{\text{Volume}}{\text{Loans}}\right)_t$		Log(Loans)_t		Log(Borrowers)_t	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(1 + Top 100 Loans)$_{t-1}$	0.483***	0.245*	0.076	-0.012	0.407***	0.257***	0.382***	0.242***
	(4.21)	(1.88)	(0.85)	(-0.14)	(7.15)	(4.18)	(6.49)	(3.96)
Log(Total Assets)$_{t-1}$		0.722**		0.230		0.492***		0.494***
		(2.25)		(1.36)		(2.77)		(2.82)
Market-to-Book$_{t-1}$		-0.630		-1.346**		0.717		0.703
		(-0.67)		(-2.61)		(1.02)		(1.02)
Deposit/Assets$_{t-1}$		0.471		-0.718		1.189*		1.183*
		(0.44)		(-0.98)		(1.86)		(1.93)
Tier 1 Ratio$_{t-1}$		-0.039		0.002		-0.041		-0.047
		(-0.79)		(0.08)		(-1.03)		(-1.22)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,186	542	1,186	542	1,186	542	1,186	542
Adjusted R^2	0.772	0.857	0.688	0.750	0.766	0.855	0.770	0.859
Cluster Variable	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Number of Clusters	100	66	100	66	100	66	100	66

Table IA3: Baseline Specification with Longer Lag Structure

This table provides results for linear regressions of lead arrangers' business activities on a measure that captures the lending to prestigious borrowers and control variables. The dependent variable is the future loan volume in columns (1) and (2), average volume per loan in columns (3) and (4), the number of loans underwritten in columns (5) and (6), and the number of unique borrowers in columns (7) and (8). The key explanatory variable is the Log(1+ Top 100 Loans) variable which is based on *Fortune' Most Admired Companies* survey. In all regression specification, we include bank and year fixed effects. Depending on the column, we also control for the bank's total assets, market-to-book ratio, deposits over assets, and the tier 1 capital ratio. The sample is based on loans in the US syndicated loan market between 1982 and 2009. This table shows the results for up to 5 lags in the key explanatory variable. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and bank characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the bank level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Log(Volume)_t		$\text{Log}\left(\frac{\text{Volume}}{\text{Loans}}\right)_t$		Log(Loans)_t		Log(Borrowers)_t	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Log(1 + Top 100 Loans)}_{t-1}$	0.456***	0.202*	0.079	-0.031	0.377***	0.232***	0.347***	0.220***
	(3.61)	(1.68)	(1.01)	(-0.41)	(5.06)	(3.55)	(4.51)	(3.33)
$\text{Log(1 + Top 100 Loans)}_{t-2}$	0.258***	0.122	0.133**	0.090	0.125**	0.032	0.126***	0.022
	(3.16)	(1.59)	(2.39)	(1.63)	(2.58)	(0.61)	(2.64)	(0.40)
$\text{Log(1 + Top 100 Loans)}_{t-3}$	-0.132	0.087	-0.061	0.028	-0.071	0.059	-0.063	0.053
	(-1.06)	(0.79)	(-0.89)	(0.36)	(-0.95)	(0.84)	(-0.90)	(0.80)
$\text{Log(1 + Top 100 Loans)}_{t-4}$	-0.011	0.000	-0.041	-0.005	0.030	0.006	0.032	0.007
	(-0.09)	(0.00)	(-0.53)	(-0.09)	(0.44)	(0.07)	(0.50)	(0.08)
$\text{Log(1 + Top 100 Loans)}_{t-5}$	-0.106	-0.065	-0.091	-0.084	-0.015	0.019	-0.010	0.028
	(-0.75)	(-0.46)	(-1.10)	(-0.99)	(-0.20)	(0.26)	(-0.14)	(0.40)
$\text{Log(Total Assets)}_{t-1}$		0.712**		0.230		0.482***		0.484***
		(2.18)		(1.32)		(2.70)		(2.75)
$\text{Market-to-Book}_{t-1}$		-0.623		-1.328**		0.705		0.691
		(-0.66)		(-2.52)		(1.01)		(1.01)
$\text{Deposit/Assets}_{t-1}$		0.468		-0.711		1.179*		1.173*
		(0.43)		(-0.96)		(1.85)		(1.93)
$\text{Tier 1 Ratio}_{t-1}$		-0.043		0.002		-0.045		-0.050
		(-0.89)		(0.07)		(-1.11)		(-1.30)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,186	542	1,186	542	1,186	542	1,186	542
Adjusted R^2	0.772	0.856	0.688	0.748	0.766	0.854	0.770	0.858
Cluster Variable	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Number of Clusters	100	66	100	66	100	66	100	66