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No. 544

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Prestige and Loan Pricing

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Prestige and Loan Pricing*

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First Version: October 19, 2015
This Version: January 28, 2016

Abstract

We find that prestigious companies pay lower spreads and upfront fees on their loans despite the fact that prestige does not predict default risk over the life of the loan. Using survey data on firm-level prestige, we show that a one standard deviation increase in prestige reduces loan spreads by 6.18% per year and upfront fees by 22.86%. We identify causal effects (i) using fraud by industry peers as an instrument for borrower prestige and (ii) exploiting a regression discontinuity around rank 100 of the prestige survey. Banks that lend to prestigious firms attract more business afterwards compared to otherwise similar institutions. Moreover, the effect of prestige on upfront fees is particularly strong for new bank relationships. Our findings suggest that prestigious firms receive cheaper funding because the associated lending relationship helps banks establish valuable credentials they use to compete for future borrowers.

JEL-Classification: G21, G30, G32

Keywords: Loan Pricing, Firm Prestige, Bank Incentives

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1 Introduction

We show that banks provide prestigious firms with favourable loan conditions despite the fact that prestige does not predict default risk over the life of the loan.[1] Using *Fortune's Most Admired Companies* survey to quantify borrower prestige, we find that an increase in prestige by one standard deviation reduces loan spreads by 6.18% per year and upfront fees by 22.86%. These results are robust to different methodologies (OLS, IV, RDD) and hold over and above firm fundamentals, loan characteristics, and fixed effects. Studying the impact of borrower prestige on loan pricing is important for understanding how intangible assets affect financing conditions.

Prestige can have an influence on loan pricing through several channels. The prestige or public admiration of a company might carry information that is relevant within the contracting relationship between the bank and the borrowing firm. For example, prestige can be a proxy for unobservable firm characteristics, such as management skills, that are relevant for the credit risk of firms. In addition, firms of high quality might acquire prestige to signal their credit risk to banks. If prestige influences loan pricing within the bank-borrower-relationship through these channels, it should predict the firm's credit rating over the life of the loan. Since our empirical tests do not document such an effect, we infer that providing a loan to a prestigious firm must be valuable to the bank outside the specific contracting relationship.

When banks compete for underwriting loans to borrowers, it is common business practice to present credentials to their potential future clients. An important part of these credentials are loans that banks structured in the recent past. Providing loans to prestigious firms enables banks to create valuable credentials, which help them win future

[1] We use the terms "firm" and "borrower" interchangeably.

business. **Figure 1** illustrates the common practice of banks using loans with prestigious borrowers as a marketing tool to attract future business.[2] Since banks compete for high profile credentials, they provide cheaper funding to prestigious firms. Our empirical tests provide strong support for this channel: Banks that lend to prestigious firms attract significantly more business afterwards compared to otherwise similar institutions. This result is not driven by an expansion strategy of the bank or overall macroeconomic conditions. Moreover, we find that banks charge lower upfront fees to *start* new lending relationships with prestigious companies, suggesting that lending to admired firms is valuable to banks. Thus, prestige is an intangible good which is transferable between contracting parties. By contracting with a prestigious firm, banks raise their level of prestige which is valuable for contracting with other borrowers in the future. The reduction in loan spreads and upfront fees resembles a lower bound for the value that banks attach to the prestige transfer.

We use *Fortune's Most Admired Companies* survey to quantify borrower prestige. Since 1982, Fortune Magazine annually asks around 15000 analysts, outside directors, and executives to evaluate the prestige of companies in the Fortune 1000. To quantify 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

[2]The graph at the top shows US syndicated loan credentials that Royal Bank of Canada (RBC) used in client presentations in 2009. In terms of loan volume, RBC belongs to the top 10 lenders in the US syndicated loan market. Many borrowers on RBC's credentials page are classified as highly prestigious companies according to Fortune's Most Admired Companies survey (e.g., Merck, Pfizer, Verizon, etc.). Importantly, none of the borrowers in RBC's presentation is classified as a company with low prestige. The figure at the bottom shows European syndicated loan credentials for UniCredit in 2013. Again, many firms on Unicredit's credentials page are widely regarded as prestigious companies (e.g., Daimler/Mercedes-Benz, Carlsberg, E.On, OMV, etc.).

the final ranking because respondents are not directly affiliated to the firms they evaluate (Focke et al. (2015)). Moreover, survey questions and variables are determined by a third party (Hay Group) and do not change over time. We hand collect the data on firm-level prestige from printed editions of the survey between 1982 and 2009. For our empirical tests, we use (i) the firm's score in the prestige survey and (ii) membership among the 100 most admired companies as our measures of borrower prestige.

We focus on syndicated loans to US borrowers issued between 1982 and 2009. Our analysis yields several interesting results. First, we find that higher borrower prestige is associated with lower loan spreads and upfront fees. These effects are statistically significant and robust to controlling for a large number of loan features, borrower characteristics, and fixed effects. The inverse relation between borrower prestige and loan pricing is also significant in economic terms. An increase in borrower prestige by one standard deviation reduces loan spreads by 6.18% per year and upfront fees by 22.86%. For the median loan of our sample, this is equivalent to a reduction in loan costs of USD 108,150 annually and USD 85,700 upfront.

Second, borrower prestige does *not* predict default risk at loan maturity, measured as the firm's credit rating. Therefore, prestige is not a proxy for credit risk capturing unobservable firm characteristics that we cannot control for in our baseline OLS regressions. In other words, the lower spreads and fees that banks charge to prestigious borrowers do not seem to be justified by a lower default probability over the life of the loan. Moreover, these findings imply that the effect of prestige on loan pricing is *not* driven by asymmetric information: If prestige served as a signal of borrower quality at loan issuance, we should find an inverse relation between prestige and default risk *ex-post* due to adverse selection.

Third, banks that lend to prestigious firms attract more borrowers and underwrite more loans *thereafter*.[3] Manually merging our loan and prestige data with bank fundamentals from SNL Financial, we show that this result is not driven by an expansion strategy of the bank or macroeconomic conditions. Moreover, we find that the effect of prestige on upfront fees is stronger for firms that borrow from a lender for the first time. Thus, banks seem to make upfront fee concessions to *start* new lending relationships with prestigious firms.

Fourth, our identification strategy suggests that the effects of borrower prestige on loan pricing and default risk are *causal*. A key challenge in our empirical analysis is to obtain exogenous variation in borrower prestige such that we are able to establish causal relations. In our setting where the dependent variables are loan pricing or default risk, "raw" prestige measures are likely endogenous. Specifically, unobservable firm characteristics, such as CEO skill, may drive both the outcome variables and firm prestige, thereby biasing our coefficients due to omitted variables. We address the endogeneity of borrower prestige with an instrumental variable and a regression discontinuity design.

In our two-stage least squares approach, we introduce corporate fraud committed by industry peers as an instrument for borrower prestige. The main intuition is that fraudulent activities of industry rivals likely affect the prestige of borrowers in that particular industry although the borrowers themselves did not commit fraud. We argue that the industry-fraud induced variation in prestige is plausibly exogenous to loan contracting on the borrower level. The key identifying assumption is that our instrument is valid, i.e. the fraudulent activities of industry peers affect the borrower's loan terms via prestige but not directly (e.g., Roberts and Whited (2012)). In this context, one might be concerned that fraud waves within an industry might induce loan officers to update their believes about industry

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

risk, which could give rise to a direct effect. Therefore, we assess the validity of our instrument in an "out-of-sample" test period which covers the years 1982 to 1995. The coefficients of our instrumental variable are never statistically significant, irrespective of whether we consider loan spreads, upfront fees, or credit ratings as our dependent variables. This suggests that the instrument is valid as it has no direct effect on our dependent variables. Moreover, in nearly all model specifications our instrument is strong such that weak identification is unlikely a concern in our analysis. We estimate our two-stage least squares model both for the "in-sample" period from 1996 to 2009 and the whole sample (1982 to 2009). We find that the negative effect of borrower prestige on loan spreads remains highly significant.[4] Moreover, prestige still does not predict default risk. These findings support a causal interpretation of our baseline results. In the first-stage models, the coefficients of our instrument are negative and highly statistically significant, suggesting that fraudulent activities of industry peers adversely affect a borrower's prestige.

As an alternative identification approach, we perform a regression discontinuity analysis around rank 100 of the prestige survey to exploit locally exogenous changes in borrower prestige.[5] The print media focuses on the top 100 companies in the Fortune survey. For example, the New York Times and the Wall Street Journal do not print the entire survey but only include information on the top 100. We argue that the additional media coverage for the 100 most admired firms leads to a positive, discontinuous jump in borrower prestige around rank 100. Importantly, local changes in prestige are plausibly exogenous around this threshold since random factors determine whether a company is ranked just below or just above 100 (e.g., mood of survey participants at the day of evaluation). We focus on

[4]Unfortunately, we cannot interpret the estimate for upfront fees because the corresponding prestige coefficient is the only one that is weakly identified (1st-stage F-statistics of 2.61 and 4.92).

[5]We adopt this approach from Focke et al. (2015) 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.

firms with ranks 80 to 120 and make sure that loans on both sides of the threshold are virtually identical in terms of other borrower and loan characteristics. Consistent with our baseline results, we find a significant, negative jump in loan pricing but no break in default risk for borrowers ranked below 100. As a robustness test, we perform a placebo RDD around rank 140. As expected, we do not find any discontinuity in our outcome variables at this threshold.

Taken together, this paper provides novel evidence on the relation between intangible assets and financing conditions. Our main finding is that prestigious firms receive cheaper funding because the associated lending relationship helps banks establish valuable credentials they use to compete for future borrowers. To the best of our knowledge, we are the first to empirically examine the role of borrower prestige in bank lending.

Related Literature. We contribute to the literature on firm-creditor relationships.[6] 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)). These relationship benefits accrue *inside* the relationship, but they might be reduced by credit market competition (Petersen and Rajan (1995)) or by banks extracting monopoly rents due to their informational advantage (Sharpe (1990), Rajan (1992), Degryse and Ongena (2005), Agarwal and Hauswald (2010)). Fama (1985) and Diamond (1991) argue that bank relationships also generate value to borrowing firms *outside* the relationship since the renewal of bank loans (inside debt) serves as a positive signal to other lenders (outside debt). By comparison, we posit that financing a prestigious borrower creates value to the lending bank *outside* the relationship

[6] Ongena and Smith (1998) provide a survey of this literature.

since it serves as a credential that helps to compete for future clients.

We also 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. (forthcoming) investigate which dimensions of corporate culture are relevant for firm performance. They document that performance is stronger when employees view their top managers as trustworthy and ethical. Both of these studies rely on surveys conducted among employees (insiders). In our paper, we study whether the company's perception by outsiders affects loan pricing. Hong and Liskovich (2015) find that socially responsible firms pay USD 2 million less in fines for bribery of foreign officials although corporate social responsibility is uncorrelated with bribe characteristics and 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 default probability over the loan's life. We argue that bank-level incentives are the main driver of our results.

Malmendier and Tate (2009) and Focke et al. (2015) 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. (2015) 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. Our economic explanation is related to Focke et al. (2015) since we argue that prestige is an intangible, valuable good which is transferable between contracting parties.

The remainder of this paper is structured as follows. In Section 2, we describe our data and sample. In Section 3, we present our baseline results from panel regressions. In Section 4, we investigate the channels through which prestige may impact loan pricing. In Section 5, we address the potential endogeneity of borrower prestige. We conclude in Section 6.

2 Data

2.1 Quantifying Borrower Prestige

We collect data on borrower-level prestige from Fortune's Most Admired Companies survey. This survey is conducted once a year during fall among approximately 15000 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 on 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 attributes' meaning is left to the respondents. The average of the 8 attribute scores determines the overall score of a company, which Fortune publishes every spring.

Using Fortune's Most Admired Companies ranking to define and quantify prestige has the advantage that firms cannot actively influence their inclusion or position in the survey (Focke et al. (2015)). 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.[7] We hand collect the Most Admired Companies surveys from printed editions of Fortune magazine between 1982 and 2009 and manually match them to our loan-level data.

2.2 Loan, Borrower, and Bank Data

We obtain data on all USD-denominated syndicated loans issued by US firms from LPC Dealscan.[8] 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). One syndicated loan (or deal) typically consists of multiple facilities, which are initiated at the same time. Ivashina (2009) documents 1.4 facilities per deal on average. Facilities that comprise a deal are not independent as general loan terms and pricing are determined at the deal level (Hertzel and Officer (2012)). Therefore, our unit of observation is a deal. For syndicated loans with more than one facility, we

[7] As discussed by Focke et al. (2015), 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.

[8] Carey et al. (1998) and Chava and Roberts (2008) provide a detailed description of the Dealscan database.

follow the literature and choose the largest tranche to represent the deal. Ivashina (2009) and Carey et al. (1998) show that this selection procedure does not significantly affect the distribution of loans. As a robustness test, we use individual facilities as the unit of observation and find that our results remain qualitatively unchanged.

We collect financial statement data on the borrower level from Compustat, using the Dealscan-Compustat linking file by Chava and Roberts (2008). We obtain firm-level data on financial misconduct (corporate fraud) from the SEC Accounting and Auditing Enforcement Releases (AAER) dataset of UC Berkeley's Center for Financial Reporting and Management. This database was compiled by Dechow et al. (2011) and covers 1330 firm misstatement events.[9] Finally, we collect bank fundamentals from SNL Financial, which we manually link with our other data.

2.3 Sample Selection and Descriptive Statistics

Our merged sample covers the time period 1982 to 2009.[10] We exclude loans without a borrower ID (gvkey) and without information about the loan spread. We winsorize all continuous and unbounded variables at the 1% and 99% level to mitigate the effects of outliers.[11] These selection criteria result in an initial sample of 38019 loans to 9304 unique borrowers. For our empirical analysis we create the continuous variable *Score*, which equals the borrower's overall score in the Fortune Most Admired Companies survey. As this measure is only defined for companies that are featured in the survey, our final sample is smaller and consists of 2242 loans (507 borrowers). To also use the larger, initial

[9]We match the AAER data to our other datasets using the 10-digit CIK code.

[10]While the prestige data (overall score) from Fortune magazine covers the years 1982 to 2009, the loan data from Dealscan and the financial statement data from Compustat are available from 1982 to 2015. Therefore, the merged sample covers the years 1982 to 2009.

[11]Our results remain qualitatively unchanged if we do not winsorize or if we winsorize at the 2.5% or 5% level in each tail instead.

sample, we follow Focke et al. (2015) and additionally create a dummy variable called *Top 100*, which is equal to one if a borrower is ranked among the 100 most admired companies in the Fortune survey in a given year and zero otherwise. This measure of borrower prestige is defined both for companies that are featured in the survey and for companies that are not. Therefore, it is available for all 38019 loans of our initial sample. In **Table 1**, we define all variables we use in our empirical analysis and indicate their respective data source.

Table 2 reports descriptive statistics for our sample. Panel A provides statistics for the prestige-related variables. Approximately 3% of all loans in our sample are granted to borrowers which belong to the 100 most admired companies in the U.S. according to the Fortune survey. Among the loans of borrowers that are featured in the survey, the average prestige score is 6.33 and its standard deviation is 1.03. **Figure 2** shows that the distribution of the Score variable is bell-shaped with a small, negative skew. There is substantial variation in borrower prestige. Specifically, the range of the prestige score equals 7.5, with a minimum of 1.25 and maximum of 8.75. Panel B summarizes the loan characteristics. The typical loan in our sample has an all-in-spread drawn (loan spread) of roughly 200 basis points, an upfront fee of 63 basis points, and a maturity of 41.82 months. Approximately 24% of the loans feature an upfront fee, which is consistent with the findings of previous studies (e.g., Berg et al. (forthcoming)). The facility amount is skewed towards large loans with a mean of USD 310.89 million and a median of USD 100 million. 49% of the loans are collateralized and 44% feature financial covenants. Panel C presents the statistics for firm fundamentals. The average borrowing company has total assets of USD 8.65 billion with an annual return on assets of 10% and a market-to-book ratio (Q) of 1.67. The distribution of total assets is widely dispersed. In particular, the 1st and the 99th percentile of total assets are USD 0.01 billion and USD 151.10 billion respectively. Thus, our sample covers both small and large borrowers. The average default barrier equals 21%. Among the rated borrowers, the average S&P senior debt rating at loan origination is BBB-. The rating worsens by 0.34 notches until loan maturity on average. In Panel D, we provide descriptive statistics for the bank-level variables. The typical (lead) bank in our sample has a tier 1 capital ratio of 10% and total assets of USD 483.67 billion, of which 51% are loans. On average, a bank underwrites 12.41 syndicated loans per year with a median overall volume of roughly USD 250 million. Finally, Panel E shows that 1% of our sample loans are granted to borrowers which the SEC caught engaging in some form of financial fraud during the year of loan origination. On average, the SEC detects 8.82 companies per year committing financial misconduct in any given SIC 1 industry.

3 Borrower Prestige and Loan Pricing

3.1 Panel Regression Model

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

$$\mathrm{y}_{\mathrm{l,i,t}} = \alpha + \beta \cdot \mathrm{Prestige}_{\mathrm{i,t\text{-}1}} + \gamma' \cdot \mathrm{X}_{\mathrm{l,i,t(\text{-}1)}} + \delta' \cdot \mathrm{Fixed\ Effects}_{\mathrm{l,i,j,b,t}} + \epsilon_{\mathrm{l,i,t}} \quad . \tag{1}$$

Subscripts l, i, j, b, and t(-1) denote the loan, borrowing firm, industry, lead bank, and (lagged) time period respectively. The dependent variable y is the logarithm of the all-in-spread drawn or the logarithm of the upfront fee.[12] Upfront fees and all-in-spreads drawn capture two different cost components of borrowing in the syndicated loan market. The all-in-spread drawn is the lender's annual compensation for providing the loan. It equals the annual spread that the borrower pays to the lender(s) in basis points over LIBOR (or

[12]We use the logarithm to account for skewness in loan spreads and upfront fees. Our results remain qualitatively unchanged if we use the level instead.

LIBOR equivalent) for each dollar drawn down plus the (annual) facility fee (Berg et al. (forthcoming)). In contrast, the upfront fee is a one-time fee (in basis points) that the borrower pays to the lender(s) at the syndication date for arranging the loan. We look at both cost components as it is not clear ex-ante whether firm prestige should affect the all-in-spread drawn or the upfront fee (or both).

In our analysis, we consider two different measures of borrower prestige. Prestige is either the borrower's overall score in Fortune's Most Admired Companies survey (*Score*) or a dummy variable which equals one if a borrower is ranked among the 100 most admired companies in a given year and zero otherwise (*Top 100*). While the *Score* variable is only available for companies that are featured in the survey, the *Top 100* indicator is defined both for borrowers that are part of the survey and for borrowers that are not. Our main coefficient of interest is β, which captures the relation between borrower prestige and loan pricing. We lag the prestige variables by one year to ensure that our measures capture survey results prior to loan origination. This timing convention implies that the variables do 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, collateralization, financial covenants, prime as base rate, and performance pricing. On the borrower level, we control for the return on assets, firm size, market-to-book ratio (Tobin's Q), as well as default barrier. All borrower characteristics are lagged by one year to avoid an overlap with the period of loan issuance. Fixed Effects is a vector of loan type, loan purpose, rating, industry, as well as year dummies and ϵ denotes the vector of regression disturbances.

We estimate the above regression model by ordinary least squares. As loans to the same borrower might be correlated with each other, we adjust standard errors for within firm-clusters (e.g., Valta (2012), Hertzel and Officer (2012), and Petersen (2009)).[13]

3.2 Baseline Results

In **Figure 3**, we take a first look at the relation between borrower prestige and the cost of bank debt. The horizontal axis of the two scatter plots reports the prestige score and the vertical axis shows the natural logarithm of the all-in-spread drawn or the upfront fee respectively. The red solid lines of fitted OLS values show that borrower prestige is strongly negatively related to loan spreads and upfront fees. Therefore, prestigious companies seem to pay unconditionally less for their bank loans, both at the syndication date (upfront fee) and over the life of the loan (spread).

Table 3 reports the coefficient estimates of model (1) for loan spreads with the prestige score as key explanatory variable. In the first column, we only control for loan and borrower characteristics. We find that the coefficient of the lagged prestige score is negative and highly statistically significant. The estimate remains negative and significant once we include loan purpose, loan type, year, industry, rating notch, and lender fixed effects. In the full regression model (column 8), the coefficient of the prestige score equals -0.060 and is significant at the 1% level. Importantly, the negative relation between borrower prestige and loan spreads is also economically large. An increase in borrower prestige by one standard deviation (1.03) reduces the loan spread by 6.18% on average. For the median

[13]As a robustness check, we cluster standard errors at the lead bank, year or industry level instead and find that this does not change our inferences.

loan of our sample, this translates into an annual reduction of the all-in-drawn spread by 10.81 basis points. In dollar terms, the spread reduction is equivalent to USD 108,150 that the borrowing firm has to pay less in interest per year.

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. The negative but insignificant estimate for Ln(Total Assets_{t-1}) is also consistent with this interpretation. In contrast, the number of facilities is positively related to loan spreads. One likely explanation might be that loans with a large number of tranches are more difficult to structure and arrange for the bank. Consequently, the lender demands higher spreads from the borrower as compensation. Surprisingly, collateralized loans have significantly higher spreads. As discussed by Hertzel and Officer (2012), this is a common finding of nearly all empirical studies using Dealscan data and 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 positive and highly significant, suggesting that loans which are based on the US prime rate have higher spreads compared to loans which are tied to LIBOR. Consistent with structural credit risk models (e.g., Black and Scholes (1973), Merton (1974)), spreads are significantly higher for borrowers with low profitability (ROA) and a high default barrier. The directional effects of the remaining control variables are in line with the existing literature although their statistical significance varies. In particular, spreads are higher for loans with shorter maturities, loans with financial covenants, and borrowers with little growth opportunities (Q).

Table 4 reports the estimation results for loan spreads with the Top 100 indicator as our measure of borrower prestige. The findings are very similar to the preceding analysis, even though we now use a much larger sample which is arguably less selected than the previous sample in which we only consider loans to borrowers that are featured in the Fortune survey.[14] The coefficient of the lagged Top 100 dummy is negative and statistically significant, irrespective of whether we only control for loan and borrower characteristics or additionally include fixed effects. In the full regression model (column 8), the coefficient of the Top 100 indicator equals -0.048, implying that borrowers which belong to the 100 most admired companies in the US pay a 4.8% lower annual spread on newly issued loans next year. For the median loan, the coefficient translates into a spread reduction of 8.40 basis points or USD 84,000 less interest per year. These numbers are large in economic terms and similar to the magnitudes we obtained using the prestige score as our measure of borrower prestige. The directional effects of the control variables remain unchanged compared to the preceding analysis. However, several controls which were previously insignificant are now statistically significant (Ln(Maturity$_t$), Performance Pricing$_t$, Ln(Total Assets$_{t-1}$), Q$_{t-1}$), which is due to the larger sample size and the increased power of our tests.

In **Table 5**, we investigate the relation between borrower prestige and upfront fees. Unlike spreads, upfront fees are one-off costs that the borrower pays to the lender(s) at the start of the contract for arranging the loan. We find that for both measures of borrower prestige, the point estimates are negative and statistically significant. This suggests that lead banks charge lower upfront fees to prestigious borrowers. In the full regression models (columns 2 and 4), the coefficients of the prestige score and the Top 100 dummy are -0.222 and -0.236 respectively.[15] Interestingly, the effect of borrower prestige on upfront fees is even larger in economic terms than for loan spreads. An increase in the prestige score (Top

[14]As discussed in Section 2, the Top 100 dummy is equal to one if a borrower is ranked among the 100 most admired companies in the Fortune survey in a given year and zero otherwise. This measure of borrower prestige is defined both for companies that are featured in the survey and for companies that are not. Therefore, it is available for all 38019 loans of our initial sample.

[15]The number of observations is smaller compared to the previous two tables because only 23.90% of all loans feature an upfront fee (see Section 2 and Berg et al. (forthcoming)).

100 indicator) by one standard deviation (one unit) reduces the upfront fee by 22.86% (23.60%). This is equivalent to 8.57 (8.85) basis points or USD 85,700 (USD 88,500) for the median loan.

4 Why Does Borrower Prestige Affect Loan Pricing?

We have documented that banks charge significantly lower spreads and upfront fees to prestigious firms. In this section, we investigate two different channels through which prestige may impact the cost of bank loans. First, we examine if prestige is a predictor of credit risk reflecting unobservable information about the borrower. Second, we test whether lending to prestigious firms is valuable to banks since it helps them attract more business afterwards.

4.1 Default Risk Channel

Borrower prestige might capture unobservable firm characteristics (e.g. CEO skill) that banks take into account when deciding on the financing terms at loan issuance. In this context, our measures of borrower prestige would pick up unobserved heterogeneity across firms which we cannot control for in our baseline panel regression model. If this channel is driving our results, we expect that borrower prestige also has predictive power for the company's default risk at loan maturity since unobservable firm characteristics that are relevant for loan pricing will have an impact on the default probability as well. To study whether borrower prestige is related to future default risk, we modify our baseline empirical model as follows:

$$\text{Default Risk}_{\text{l,i,m}} = \alpha + \beta \cdot \text{Prestige}_{\text{i,t-1}} + \gamma' \cdot \ \text{X}_{\text{l,i,t(-1)}} + \delta' \cdot \text{Fixed Effects}_{\text{l,i,j,b,t}} + \epsilon_{\text{l,i,m}} \ . \quad (2)$$

The dependent variable is the borrower's default risk at loan maturity m. Our measures of default risk are the S&P long-term rating at maturity (Rating_{m}) or the change in rating between loan issuance and maturity ($\Delta\text{Rating}_{\text{m}}$).[16] The explanatory variables are equivalent to the baseline panel regression (model (1)). We add the logarithm of the loan spread to the vector of control variables X to take into account the mechanical effect of interest rate payments on default risk. The timing of the covariates is identical to the baseline model since we want to mimic the bank's information set at the time of structuring the loan.

Panel A of **Table 6** presents the baseline results of our default risk analysis. The coefficients of our prestige variables are insignificant, irrespective of whether we consider Rating_{m} or $\Delta\text{Rating}_{\text{m}}$ as our measure of credit quality. Therefore, borrower prestige is not a proxy for credit risk capturing unobservable firm characteristics. In other words, the lower spreads and upfront fees that banks charge to prestigious borrowers do not seem to be "justified" by a lower default probability over the life of the loan. One might argue that if banks comprehensively account for all default relevant information contained in borrower prestige when deciding on loan pricing, prestige *should not* have an effect on default risk over and above the loan spread. To test whether the insignificant relation between prestige and default risk is governed by this effect, we also estimate model (2) without the loan spread as control variable. In Panel B of **Table 6**, we find that without controlling for the

[16] We map ratings into natural numbers using a scale from 1 to 22 (AAA=1, . . . , D=22).

spread, borrower prestige still does not predict default risk at loan maturity.[17]

The results of our default risk analysis imply that the effect of prestige on loan pricing is also not driven by asymmetric information: If prestige served as a signal of borrower quality at loan issuance, we should find an inverse relation between prestige and default risk *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.[18]

4.2 Bank Channel

4.2.1 Lending to Prestigious Firms and Future Bank Business

Incentives at the bank level are an alternative explanation for 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 win future business. In this context, prestige is an intangible, valuable good which is transferable between contracting parties. By contracting with a more prestigious firm, banks raise their level of prestige which is valuable for contracting with other parties in the future. The reduction in loan spreads and upfront fees resembles the value that banks attach to the prestige transfer.

Based on this argument, we hypothesize that banks which lend to prestigious firms at-

[17]Without controlling for the loan spread, the coefficients of our prestige variables are downward biased since borrower prestige and spreads are negatively related (see Table 3 and Table 4) while spreads and default risk are positively related. However, this bias does not affect our inferences since it only makes it more difficult *not* to find an effect of borrower prestige on default risk. Throughout the paper, we include the loan spread as control variable whenever we predict default risk to properly account for the mechanical effect of interest payments on the default probability.

[18]We acknowledge that due to data availability, we cannot investigate whether prestige has an impact on the borrower's loss given default (LGD). However, it is well established that there is little cross-sectional variation in LGD compared to the probability of default (default risk). Banks typically make LGD assumptions based on the loan's seniority, collateralization, covenants, as well as the borrower's industry. Nearly all loans in our sample are senior (98%), a feature which is common among syndicated loans. Moreover, in our empirical tests, we control for collateralization, covenants, and industry. Therefore, it seems unlikely that prestige could drive the limited cross-sectional variation in loss given default and thereby justify the lower spreads and upfront fees that banks charge to prestigious borrowers.

tract more business afterwards. To test this conjecture, we estimate the following regression on the lead bank-year level:[19]

$$\begin{aligned} \text{Business}_{\text{b,t+1}} = \alpha + \beta \cdot \text{Ln}(1 + \text{Top 100 Loans}_{\text{b,t}}) \\ + \gamma' \cdot \text{X}_{\text{b,t}} + \delta' \cdot \text{Fixed Effects}_{\text{b,t,ind}} + \epsilon_{\text{b,t+1}} \quad . \end{aligned} \tag{3}$$

Subscripts b, t(+1), and ind denote the lead bank, (future) time period, and bank type, respectively. We focus on lead banks since these institutions initiate, arrange, and manage the loan. Therefore, it is the lead bank that is primarily associated with the loan and most likely benefits from lending to a prestigious borrower. We consider four different measures of the lead bank's annual business activities. Depending on the specification, our dependent variable $\text{Business}_{\text{b,t+1}}$ equals (i) the logarithm of the annual loan volume underwritten, (ii) the logarithm of the average volume per loan, (iii) the logarithm of the total number of loans per year, or (iv) the logarithm of the number of unique borrowers per year. The key explanatory variable $\text{Top 100 Loans}_{\text{b,t}}$ captures the number of loans that a particular bank has underwritten for borrowers ranked among the 100 most admired companies.[20]

To control for bank characteristics (vector X), we manually merge our loan data from Dealscan with the bank fundamentals database of SNL Financial. We account for the bank's size, tier 1 capital ratio, and market-to-book ratio since larger, better capitalized banks with a lot of growth opportunities originate more loans and have a larger borrower base. Moreover, we include the growth of the bank's loan book as well as the fraction

[19]We follow the literature and define lead banks as "administrative agent", "agent", "lead arranger", "lead bank", "lead manager", or "bookrunner" according to Dealscan.

[20]We use the logarithm to account for skewness in these variables. Our inferences do not change if we use the level instead. We add 1 to the Top 100 Loan variable before we take the logarithm since it can take values of zero (in which case the logarithm is not defined).

of loans to total assets as covariates to filter out the effects of a general loan expansion strategy that the bank may pursue. Fixed Effects is a vector of lead bank, year, and bank type dummies. We add lead bank and bank type indicators to capture unobserved heterogeneity that is constant within banks or bank types and include year dummies to control for macroeconomic conditions. In terms of bank types, we differentiate between commercial banks, broker-dealers (i.e. investment banks), and savings banks.

In **Table 7**, we report the results of our bank-level analysis. Consistent with our hypothesis, we find that the coefficients of the Ln(1 + Top 100 Loans) variable are positive and almost always statistically significant. Therefore, banks that lend to prestigious borrowers seem to attract more business in the subsequent year.[21] Overall deal volume can rise because of an increase in loans and/or an increase in the volume per loan. Looking at these two constituents, we find that the increase in deal volume is driven by an increased 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 firms. Interestingly, not only the number of loans but also the number of unique borrowers (customer base) increases after banks lend to prestigious firms. In economic terms, a one-standard deviation increase in "high profile lending" increases the number of loans and number of unique borrowers by roughly 17% in the subsequent year. We also estimate model (3) with time gaps of two years. In untabulated results, we find that the directional effects of our analysis remain the same. However, the coefficients of the Ln(1 + Top 100 Loans) variable become insignificant or only marginally significant. One explanation for why the effect weakens after one year

[21] For robustness, we also ran model (3) with a lagged dependent variable as control to account for potential autocorrelation that is not already absorbed by the other covariates. Models with lagged dependent variables are challenging to estimate due to a violation of strict exogeneity, which can lead to biased coefficients (especially in combination with fixed effects). That being said, we find that including a lagged dependent variable does not change our inferences qualitatively.

might be that banks mainly use credentials with prestigious firms from the previous year to attract new business.

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

4.2.2 New Bank Relationships with Prestigious Borrowers

As an alternative test of the bank channel, we investigate whether our baseline results from Section 3 depend on cross-sectional differences in relationship banking. If lending to prestigious firms is valuable to lenders, then non-relationship banks might offer extra favourable pricing terms to prestigious borrowers in order to compete against relationship banks that already established themselves, created entry barriers, and therefore have a competitive advantage in doing business with the firm. To investigate this argument, we extend our baseline loan-level regression as follows:

$$\begin{aligned} \mathrm{y}_{\mathrm{l,i,t}} = \alpha &+ \beta \cdot \mathrm{Prestige}_{\mathrm{i,t\text{-}1}} \cdot \mathrm{New\ Bank\ Relationship}_{\mathrm{l,i,t}} + \gamma \cdot \mathrm{Prestige}_{\mathrm{i,t\text{-}1}} \\ &+ \delta \cdot \mathrm{New\ Bank\ Relationship}_{\mathrm{l,i,t}} + \zeta' \cdot \mathrm{X}_{\mathrm{l,i,t(\text{-}1)}} + \eta' \cdot \mathrm{Fixed\ Effects}_{\mathrm{l,i,j,t}} + \epsilon_{\mathrm{l,i,t}} \quad . \end{aligned} \tag{4}$$

The dependent variable is either the logarithm of the all-in-spread drawn or the logarithm of the upfront fee. New Bank Relationship$_{\mathrm{l,i,t}}$ is a dummy variable equal to one if the lead bank lends to the borrower for the first time, and zero otherwise.[22] The key explanatory variable is the interaction term between Prestige$_{\mathrm{i,t\text{-}1}}$ and New Bank Relationship$_{\mathrm{l,i,t}}$. It quantifies whether the effect of borrower prestige on loan pricing is stronger for new bank

[22]Since our sample starts in 1982, we cannot observe the entire lending history of our borrowers. We do not define the New Bank Relationship$_{\mathrm{l,i,t}}$ variable for the first loan of every borrower to make sure that the dummy does not artificially equal one. Our results are qualitatively unchanged if we start defining the New Bank Relationship$_{\mathrm{l,i,t}}$ dummy at each borrower's third or fourth loan instead.

relations.[23]

In **Table 8**, we find that the coefficient of the interaction term is negative and statistically significant for upfront fees but insignificant for loan spreads. These results hold for both measures of borrower prestige. Therefore, banks seem to make upfront fee concessions to start new lending relationships with prestigious firms. Consistent with our previous analysis, these findings suggest that lending to prestigious borrowers is valuable to banks. The insignificant interaction for loan spreads implies that non-relationship banks use lower upfront fees, not annual reductions in interest payments, to compete against relationship banks of prestigious borrowers.

5 Causal Identification

The panel regression model in Section 3 is not able to identify the *causal* effect of borrower prestige on loan pricing since our prestige variables are likely endogenous. In particular, unobservable firm characteristics could drive both loan contracting and firm prestige. Fortune's Most Admired Companies survey may partly reflect unobservable information such as quality of management or community and environmental responsibility. To the extend that we cannot control for this unobserved heterogeneity in our panel regression framework, the prestige coefficient will be biased due to omitted variables. To cleanly identify causal effects in our setting, we need to obtain exogenous variation in borrower prestige. Conceptually, this is a challenging task because any variation that is related to borrower fundamentals is subject to the same endogeneity concerns as our raw measures of firm prestige. In this section, we address the endogeneity of borrower prestige by (1) estimating an instrumental variable model and (2) employing a regression discontinuity

[23] In the full regression model, we do not include bank dummies since these are highly collinear with the New Bank Relationship$_{\mathrm{l,i,t}}$ variable.

design.

5.1 Instrumental Variable Model

Firms that engage in financial misconduct and get caught face severe legal and financial penalties (e.g., Karpoff et al. (2008)). Moreover, the fraudulent activities of one company likely affect the prestige of its industry peers. Based on this argument, we introduce corporate fraud committed by industry peers as an instrument for our prestige score.[24] The main intuition is that fraudulent activities of industry rivals likely affect the prestige of borrowers in that particular industry although the borrowers themselves did not commit fraud. The industry-fraud induced variation in prestige is likely exogenous to loan contracting on the borrower level. First, the roots of financial misconduct are typically closely linked to individual character traits of key executives or peer-firm specific incentives such as the vesting of CEO or CFO stock options. Second, the revelation of corporate fraud by enforcement agencies such as the SEC is very difficult to anticipate and therefore quasi-random.

We define the industry fraud intensity experienced by borrower i in year t as

$$\text{Industry Fraud}_{\text{i,t}} = \text{Fraud SIC1}_{\text{j,t}} - \text{Borrower Fraud}_{\text{i,t}}$$

where Fraud $\text{SIC1}_{\text{j,t}}$ is the number of firms that the Securities and Exchange Commission investigates for financial fraud in SIC1-industry j in year t and Borrower $\text{Fraud}_{\text{i,t}}$ is a dummy variable equal to one if borrower i is investigated for fraud in year t. We subtract fraud cases against the borrower to make sure that the variation in our instrument is only driven by the fraudulent activities of the borrower's industry peers. In our two-stage least

[24]We do not instrument the Top 100 indicator with the industry fraud intensity since we lack the statistical power to do so (partial F-statistics of below 4). Intuitively, this is not surprising because there is substantially less variation in the Top 100 dummy compared to the continuous prestige score.

squares model, we separately control for borrower-level fraud to capture the direct effect of financial misconduct on loan terms (Graham et al. (2008)). We take the logarithm of *Industry Fraud* to account for skewness in the data.

To identify causal effects, our instrument must satisfy the exclusion restriction which requires that the industry-fraud intensity affects loan pricing *only* via borrower prestige but not directly (Roberts and Whited (2012)).[25] Although the exclusion restriction cannot be formally tested, we can support its validity using out-of-sample evidence (e.g., Giroud et al. (2012)). Therefore, we split our sample into two equally-sized time periods (1982 to 1995 and 1996 to 2009) and investigate if industry fraud has any direct effect on our dependent variables using the earlier subsample and regression model (1). Afterwards, we will estimate our two-stage least squares model both for the time period from 1996 to 2009 and the whole sample. In **Table 9**, we find that the coefficients of *Ln(Industry Fraud)* are never statistically significant, irrespective of whether we consider loan spreads, upfront fees, or credit ratings as our dependent variable. Moreover, these results are robust to controlling for the prestige score. Therefore, out-of-sample evidence suggests that our instrument is valid as it has no direct effect on loan pricing.

Our two-stage least squares model is given by

$$\mathrm{z_{l,i,t}} = \alpha + \beta \cdot \widehat{\mathrm{Score}}_{\mathrm{i,t\text{-}1}} + \gamma \cdot \mathrm{X_{l,i,t(\text{-}1)}} + \delta' \cdot \text{Fixed Effects}_{\mathrm{l,i,j,t}} + \epsilon_{\mathrm{l,i,t}} \tag{5}$$

$$\mathrm{Score_{i,t\text{-}1}} = \zeta + \eta \cdot \mathrm{Ln(Industry\ Fraud)_{i,t\text{-}2}} + \theta \cdot \mathrm{X_{l,i,t(\text{-}1)}} + \iota' \cdot \text{Fixed Effects}_{\mathrm{l,i,j,t}} + \kappa_{\mathrm{i,t\text{-}1}} \tag{6}$$

where (5) is a second-stage OLS regression and (6) is the corresponding first-stage model. The dependent variable z is either the logarithm of the loan spread, the logarithm of the upfront fee, or our default risk measures at loan maturity. Contrary to our baseline panel

[25]In econometric terms, the correlation between the instrument and the error term of the original regression must be zero.

regression, we do not use the *raw* prestige score as our explanatory variable in model (5). Instead, we use the fitted values ($\widehat{\text{Score}}_{\text{i,t-1}}$) from the first-stage regression, in which we instrument our prestige score with the logarithm of the industry fraud intensity. In the first-stage model, we include our instrumental variable with a lag of two periods to make sure that we only capture fraudulent activities that get revealed *before* the survey is conducted. The vector of control variables again contains loan features and borrower characteristics (including the borrower-fraud indicator). Fixed Effects is a vector of loan type, loan purpose, rating, and industry dummies.[26] We estimate the above system of equations in two stages.

Table 10 provides the coefficient estimates of our instrumental variable model for both the *in-sample* period from 1996 to 2009 (Panel A) and the whole sample (Panel B). In Panel A, the coefficients of the lagged prestige score are negative and statistically significant for the loan spread (columns (1) to (3)). This suggests that borrower prestige has a negative causal effect on the all-in-spread drawn. The negative coefficient of -0.366 in the full regression model (column (3)) implies that a typical, fraud-related prestige shock induced by industry peers increases the borrower's loan spread by 20.64%.[27] In economic terms, this effect is larger compared to our OLS regressions, suggesting that the baseline estimates might be downward biased by omitted variables. The Wald exogeneity test confirms that the raw prestige score in the loan spread models is indeed endogenous and that our instrument successfully removes the negative bias in the prestige coefficient (p-values of 0.009, 0.038, and 0.000 respectively).

[26] We do not include year dummies because a substantial fraction of the variation in Ln(Industry Fraud) comes from the time dimension. To control for overall economic conditions, we include (yearly) real GDP growth instead.

[27] A one standard-deviation increase in the number of frauds committed by industry rivals (8.70) translates into an decrease in the borrower's prestige score by 0.564 units (Ln(Industry $\text{Fraud}_{\text{t-1}}$) coefficient of -0.261 times ln(8.70)). This negative prestige shock increases the loan spread (second stage) by 20.64% (-0.564 times -0.366).

In the first-stage regressions, the coefficients of Ln(Industry Fraud) are negative and highly statistically significant. This suggests that the fraudulent activities of industry peers adversely affect a borrower's prestige. The industry fraud-intensity must be strongly correlated with the lagged prestige score such that the prestige coefficient is consistent. We quantify the strength of our instrument via a partial F-test and find that the test statistics in columns (1) to (3) are 7.69, 7.56, and 37.20 respectively. These values are larger than the 20% critical threshold (6.66) by Stock and Yogo (2005). For the full regression model (column (3)), the value of the partial F-statistic is also larger than the rule of thumb for strong instruments (partial F-statistic ≥ 10) by Staiger and Stock (1997). Therefore, weak identification is unlikely a concern for the loan spread regressions.

Surprisingly, the estimate of the prestige score is positive and marginally significant for upfront fees (column (4)). However, the F-statistic of 4.92 in the first stage model reveals that this parameter is weakly identified, making a reliable statistical inference impossible. In contrast, the specifications with the default risk measures as dependent variables (columns (5) and (6)) do not suffer from weak identification issues (F-statistics of 34.25 and 36.58). Consistent with the OLS results, the coefficients of the rating at maturity (Rating_{m}) and the rating change from loan issuance to loan maturity ($\Delta\text{Rating}_{\text{m}}$) are not statistically significant.

In Panel B, we estimate our instrumental variable models for the full sample period (1982-2009) and find that our results remain qualitatively unchanged. Borrower prestige still has a negative causal effect on loan spreads but does not predict default risk. In these specifications, our instrument is even stronger with partial F-statistics ranging from 11.57 to 53.05. Interestingly, the coefficient of the prestige score is no longer significant for upfront fees. The corresponding F-statistic is 2.61 and smaller compared to the in-sample period. Again, we cannot interpret the result for upfront fees in a meaningful way because the coefficient of the prestige score is weakly identified (column (4)).

5.2 Regression Discontinuity Design

As an alternative identification strategy, we perform a regression discontinuity analysis around rank 100 to exploit locally exogenous changes in our *Top 100* dummy.[28] Fortune magazine publishes its Most Admired Companies 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) 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 loan spreads around rank 100.[29] We need to make sure 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

[28] We adopt this approach from Focke et al. (2015), 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.

[29] We do not perform a regression discontinuity analysis for upfront fees since there are not enough observations around rank 100 to do so.

regressions that control for these fundamentals.[30] We only consider loans that are originated between April and December because Fortune magazine publishes its Most Admired Companies survey between January and March each year. Following Lee and Lemieux (2010), we examine the discontinuity at rank 100 using non-parametric (local polynomial) regressions. We apply the optimized bandwidth by Imbens and Kalyanaraman (2012) and vary the size of the bandwidth by factors 0.75 and 1.25 for robustness.

Figure 4 provides graphical evidence for our regression discontinuity analysis. Consistent with our previous results, we find a discontinuous, negative jump in spreads for loans ranked below 100. In contrast, we do not find any statistically and economically significant jump in default risk around rank 100.[31] Panel A of **Table 11** reports the corresponding point estimates. The coefficient for loan spreads (column (1)) is -0.564, statistically significant, and robust to different bandwidths. The treatment effect of the residual spread (column (2)) remains negative and statistically significant for a bandwidth factor of 0.75.[32] Importantly, the treatment coefficients for the default risk measures (columns (3) and (4)) are never statistically significant (low z-statistics of around 0.5). To corroborate our findings, we perform a range of placebo tests around rank 140. Borrower prestige should not change exogenously since there is no "media effect" at this threshold. In Panel B of **Table 11**, we find that there is indeed no discontinuity in loan terms (and default risk) around rank 140.

Taken together, the results of our regression discontinuity analysis are in line with the findings from our two-stage least squares models: Borrower prestige reduces loan spreads but does not predict default risk.

[30] We calculate the residuals from linear regressions in which we control for ln(amount$_t$), ln(maturity$_t$), ROA$_{t-1}$, ln(total assets$_{t-1}$), the default barrier$_{t-1}$, and year-fixed effects.

[31] We use the change in credit rating as our measure of default risk to control for the borrower's credit quality at the time of loan origination.

[32] The p-value for the benchmark bandwidth (1.00) is 20.10%.

6 Conclusion

We find that prestigious companies pay lower spreads and upfront fees on their loans despite the fact that prestige does not predict default risk over the life of the loan. Using survey data on firm-level prestige, we show that a one standard deviation increase in prestige reduces loan spreads by 6.18% per year and upfront fees by 22.86%. Banks that lend to prestigious firms attract significantly more business afterwards compared to otherwise similar institutions. In addition, we find that banks charge lower upfront fees to start new lending relationships with prestigious companies. Our causal identification strategy is based on instrumental variables and a regression discontinuity design. Studying the impact of borrower prestige on loan pricing is important for understanding how intangible assets affect financing conditions.

Our findings suggest that prestigious firms receive cheaper funding because the associated lending relationship helps banks establish valuable credentials they use to compete for future borrowers. We argue that prestige is an intangible good which is transferable between contracting parties. By contracting with a prestigious firm, banks raise their level of prestige which is valuable for contracting with other firms in the future. The reduction in loan spreads and upfront fees resembles a lower bound for the value that banks attach to the prestige transfer.

References

Agarwal, S. and Hauswald, R. (2010), 'Distance and Private Information in Lending', *Review of Financial Studies* **23**(7), 2757–2788.

Berg, T., Saunders, A. and Steffen, S. (forthcoming), 'The Total Cost of Corporate Borrowing in the Loan Market: Don't Ignore the Fees', *Journal of Finance* .

Berger, A. N., Miller, N. N., Petersen, M. A., Rajan, R. G. and Stein, J. C. (2005), 'Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks', *Journal of Financial Economics* **76**(2), 237–269.

Berger, A. N. and Udell, G. F. (1995), 'Relationship Lending and Lines of Credit in Small Firm Finance', *Journal of Business* **68**(3), 351–382.

Black, F. and Scholes, M. (1973), 'The Pricing of Options and Corporate Liabilities', *Journal of Political Economy* **81**(3), 637–654.

Carey, M., Post, M. and Sharpe, S. A. (1998), 'Does Corporate Lending by Banks and Finance Companies Differ? Evidence on Specialization in Private Debt Contracting', *Journal of Finance* **53**(3), 845–878.

Chava, S. and Roberts, M. R. (2008), 'How Does Financing Impact Investment? The Role of Debt Covenants', *Journal of Finance* **63**(5), 2085–2121.

Dechow, P. M., Ge, W., Larson, C. R. and Sloan, R. G. (2011), 'Predicting Material Accounting Misstatements', *Contemporary Accounting Research* **28**(1), 17–82.

Degryse, H. and Ongena, S. (2005), 'Distance, Lending Relationships, and Competition', *Journal of Finance* **60**(1), 231–266.

Diamond, D. W. (1991), 'Monitoring and Reputation: The Choice between Bank Loans and Directly Placed Debt', *Journal of Political Economy* **99**(4), 689–721.

Edmans, A. (2011), 'Does the Stock Market Fully Value Intangibles? Employee Satisfaction and Equity Prices', *Journal of Financial Economics* **101**(3), 621–640.

Fama, E. F. (1985), 'What's Different About Banks?', *Journal of Monetary Economics* **15**(1), 29–39.

Focke, F., Maug, E. and Niessen-Ruenzi, A. (2015), 'Pride and Promotion: How Prestigious Firms Pay their CEOs less', *Working Paper* .

Giroud, X., Mueller, H. M., Stomper, A. and Westerkamp, A. (2012), 'Snow and Leverage', *Review of Financial Studies* **25**(3), 680–710.

Graham, J. R., Li, S. and Qiu, J. (2008), 'Corporate Misreporting and Bank Loan Contracting', *Journal of Financial Economics* **89**(1), 44–61.

Guiso, L., Sapienza, P. and Zingales, L. (forthcoming), 'The Values of Corporate Culture', *Journal of Financial Economics* .

Hertzel, M. G. and Officer, M. S. (2012), 'Industry Contagion in Loan Spreads', *Journal of Financial Economics* **103**(3), 493–506.

Hong, H. and Liskovich, I. (2015), 'Crime, Punishment and the Halo Effect of Corporate Social Responsibility', *Working Paper* .

Imbens, G. W. and Kalyanaraman, K. (2012), 'Optimal Bandwidth Choice for the Regression Discontinuity Estimator', *Review of Economic Studies* **79**(3), 933–959.

Ivashina, V. (2009), 'Asymmetric Information Effects on Loan Spreads', *Journal of Financial Economics* **92**(2), 300–319.

Karpoff, J. M., Lee, S. D. and Martin, G. S. (2008), 'The Cost to Firms of Cooking the Books', *Journal of Financial and Quantitative Analysis* **43**(3), 581–611.

Lee, D. S. and Lemieux, T. (2010), 'Regression Discontinuity Designs in Economics', *Journal of Economic Literature* **48**(2), 281–355.

Malmendier, U. and Tate, G. (2009), 'Superstar CEOs', *Quarterly Journal of Economics* **124**(4), 1593–1638.

Merton, R. C. (1974), 'On the Pricing of Corporate Debt: The Risk Structure of Interest Rates', *Journal of Finance* **29**(2), 449–470.

Ongena, S. and Smith, D. C. (1998), Bank Relationships: A Review, *in* H. P. and Z. S. A., eds, 'The Performance of Financial Institutions', Cambridge University Press, Cambridge, UK.

Petersen, M. A. (2009), 'Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches', *Review of Financial Studies* **22**(1), 435–480.

Petersen, M. A. and Rajan, R. G. (1995), 'The Effect of Credit Market Competition on Lending Relationships', *Quarterly Journal of Economics* **110**(2), 407–443.

Rajan, R. G. (1992), 'Insiders and Outsiders: The Choice Between Informed and Arm's-Length-Debt', *Journal of Finance* **47**(4), 1367–1400.

Roberts, M. R. and Whited, T. M. (2012), 'Endogeneity in Empirical Corporate Finance', *Handbook of the Economics of Finance* **2**.

Sharpe, S. A. (1990), 'Asymmetric Information, Bank Lending and Implicit Contracts: A Stylized Model of Customer Relationships', *Journal of Finance* **45**(4), 1069–1087.

Staiger, D. and Stock, J. H. (1997), 'Instrumental Variables Regression with Weak Instruments', *Econometrica* **65**(3), 557–586.

Stein, J. C. (2002), 'Information Production and Capital Allocation: Decentralized versus Hierarchical Firms', *Journal of Finance* **57**(5), 1891–1921.

Stock, J. H. and Yogo, M. (2005), Testing for Weak Instruments in Linear IV Regression, *in* D. K. Andrews and J. H. Stock, eds, 'Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg', Cambridge University Press, Cambridge, UK, pp. 80–108.

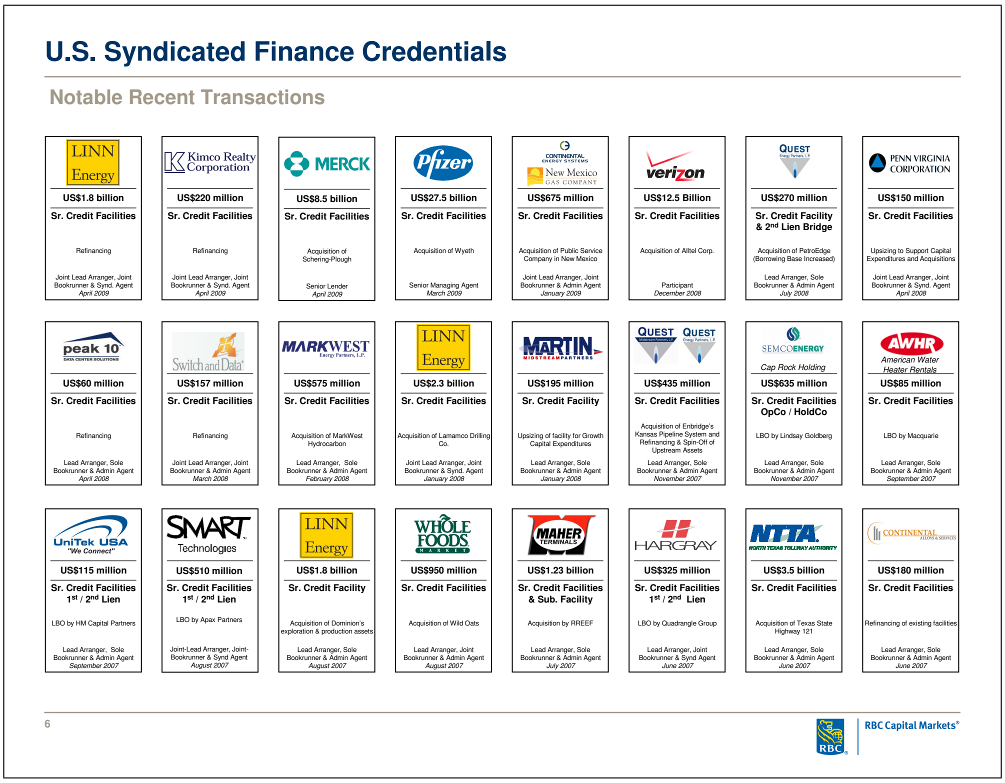
Valta, P. (2012), 'Competition and the Cost of Debt', *Journal of Financial Economics* **105**(3), 661–682.

von Thadden, E.-L. (1995), 'Long-Term Contracts, Short-Term Investment and Monitoring', *Review of Economic Studies* **62**(4), 557–575.

Tables and Figures

Figure 1: Syndicated Loan Credentials of Banks

This figure illustrates the common practice of banks using loans with prestigious borrowers as a marketing tool to win future business (credentials). The graph at the top shows US syndicated loan credentials that Royal Bank of Canada (RBC) showed in client presentations in 2009. The figure at the bottom shows European syndicated loan credentials of UniCredit for 2013.



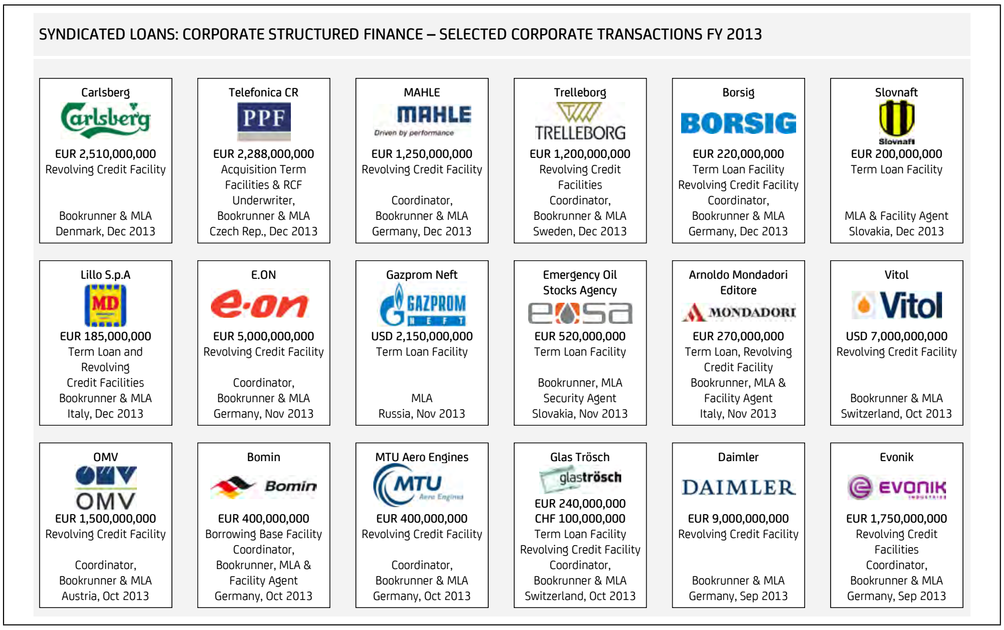


Table 1: Variables Definition and Data Sources

Variable [Units]	Definition	Data Source
Prestige Variables		
Score [0-10]	Prestige score of the borrower as defined by *Fortune's Most Admired Companies* (FMAC) survey	Fortune
Top 100 [0/1]	Dummy variable equal to one if the borrower is ranked among the top 100 firms in the FMAC survey (by score), zero otherwise	Fortune
Loan Characteristics		
Loan Spread [bps]	*All-in-spread drawn*, defined as the spread the borrower pays in basis points (bps) over LIBOR or LIBOR equivalent for each dollar drawn down plus the facility (annual) fee paid to the lender(s)	Dealscan
Ln(Loan Spread) [number]	Natural logarithm of Loan Spread	Dealscan
Upfront Fee [bps]	One-time fee paid by the borrower to the lender(s) at loan origination	Dealscan
Ln(Upfront Fee) [number]	Natural logarithm of Upfront Fee	Dealscan
Amount [USD mn.]	Size of the largest facility within the loan package	Dealscan
Ln(Amount) [number]	Natural logarithm of Facility Amount	Dealscan
Facilities [number]	Number of facilities in loan package	Dealscan
Maturity [months]	Maturity of the largest facility within the loan package	Dealscan
Ln(Maturity) [number]	Natural logarithm of Maturity	Dealscan
Collateral [0/1]	Dummy variable equal to one if the loan is secured, zero otherwise	Dealscan
Financial Covenants [0/1]	Dummy variable equal to one if the loan has financial covenants, zero otherwise	Dealscan
Prime Base Rate [0/1]	Dummy variable equal to one if the base rate is prime, zero otherwise	Dealscan
Performance Pricing [0/1]	Dummy variable equal to one if the loan has performance pricing, zero otherwise	Dealscan
New Bank Relationship [0/1]	Dummy variable equal to one if the lead banks lends to the borrower for the first time, zero otherwise	Dealscan
Borrower Characteristics		
Total Assets [number]	Total book assets (*at*)	Compustat
Ln(Total Assets) [number]	Natural logarithm of Total Assets	Compustat
ROA [number]	Operating income before depreciation (*oibdp*) divided by average book assets (*at*)	Compustat
Q [number]	Market value of assets divided by book value of assets (*at*). Market value of assets equals the book value of assets plus the market value of equity (*csho*prcc_f*) minus the book value of equity (*ceq*)	Compustat
Default Barrier [number]	0.5 * long-term debt (*dltt*) plus debt in current liabilities (*dlc*), divided by book assets	Compustat
Rating_{m} [number]	S&P senior debt rating (AAA=1, AA+=2, etc...) at loan maturity	Compustat
$\Delta\text{Rating}_{\text{m}}$ [number]	Change in S&P senior debt rating (AAA=1, AA+=2, etc...) between loan origination and maturity	Compustat
Bank-Level Variables		
Top 100 Loans [number]	Number of loans underwritten for borrowers that are ranked among the top 100 firms in the FMAC survey (by score)	Fortune, Dealscan
Ln(1+Top 100 Loans) [number]	Natural logarithm of the sum of 1 + Top 100 Loans	Fortune, Dealscan
Loan Volume [number]	Total volume of all loans underwritten during the year	Dealscan
Ln(Loan Volume) [number]	Natural logarithm of Loan Volume	Dealscan
Volume / Loan [number]	Loan Volume divided by Loans	Dealscan
Ln(Volume / Loan) [number]	Natural logarithm of Volume / Loan	Dealscan
Loans [number]	Total number of loans underwritten during the year	Dealscan
Ln(Loans) [number]	Natural logarithm of Loans	Dealscan
Unique Borrowers [number]	Number of unique borrowers that the bank provided with loans during the year	Dealscan
Ln(Unique Borrowers) [number]	Natural logarithm of Unique Borrowers	Dealscan
Bank Size [number]	Total bank assets (book value)	SNL Financial
Ln(Bank Size) [number]	Natural logarithm of Bank Size	SNL Financial
Total Loans [number]	Total amount of loans held on the bank's balance sheet	SNL Financial
Loan Fraction [number]	Total Loans divided by Bank Size	SNL Financial
Loan Growth [number]	Ln(Total Loans) - Ln($\text{Total Loans}_{\text{t-1}}$)	SNL Financial
Tier 1 Ratio [number]	Tier 1 Capital Ratio	SNL Financial
MtB [number]	Market value of bank assets divided by Bank Size. Market value of bank assets equals the book value of assets (Bank Size) plus the market value of equity minus the book value of equity	SNL Financial
Corporate Fraud Variables		
Borrower Fraud [0/1]	Dummy variable equal to one if an SEC AAER has been filed against the borrower during the year, zero otherwise	UC Berkeley
Industry Fraud [number]	Number of AAERs in SIC1 industry per year minus Borrower Fraud	UC Berkeley
Ln(Industry Fraud) [number]	Natural Logarithm of Industry Fraud	UC Berkeley

Table 2: Descriptive Statistics
This table reports descriptive statistics for key variables of the empirical analysis. For each variable the number of observations (N), mean, standard deviation (SD), 1% quantile ($Q_{0.01}$), 25% quantile ($Q_{0.25}$), median ($Q_{0.50}$), 75% quantile ($Q_{0.75}$), and 99% quantile ($Q_{0.99}$) are reported. Panel A provides statistics for the prestige-related variables. Panels B, C, D, and E report summary statistics for loan characteristics, borrower characteristics, bank-level variables, and corporate fraud variables. The prestige variables are obtained from *Fortune's Most Admired Companies* surveys. Loan and borrower characteristics are collected from *Dealscan* and *Compustat* respectively. Bank fundamentals are obtained from *SNL Financial* and fraud-related variables are obtained from *UC Berkeley* (AAER dataset). The overall dataset covers 38019 loans to 9304 US borrowers between 1982 and 2009. We define all variables in Table 1.

	N	Mean	SD	$Q_{0.01}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.99}$
Panel A: Prestige Variables								
Score [0-10]	2242	6.33	1.03	3.38	5.69	6.41	7.05	8.32
Top 100 [0/1]	38019	0.03	0.16	0.00	0.00	0.00	0.00	1.00
Panel B: Loan Characteristics								
Loan Spread [bps]	38019	199.52	146.34	17.50	75.00	175.00	275.00	655.00
Upfront Fee [bps]	9090	63.05	80.43	2.17	15.63	37.50	90.00	350.00
Amount [USD mn.]	38019	310.89	784.16	1.00	26.50	100.00	300.00	3030.00
Facilities [number]	38019	1.44	0.81	1.00	1.00	1.00	2.00	4.00
Maturity [months]	36062	41.82	26.14	3.00	17.00	36.00	60.00	108.00
Collateral [0/1]	38019	0.49	0.50	0.00	0.00	0.00	1.00	1.00
Financial Covenants [0/1]	38019	0.44	0.50	0.00	0.00	0.00	1.00	1.00
Prime Base Rate [0/1]	38019	0.14	0.35	0.00	0.00	0.00	0.00	1.00
Performance Pricing [0/1]	38019	0.34	0.47	0.00	0.00	0.00	1.00	1.00
New Bank Relationship [0/1]	26368	0.51	0.50	0.00	0.00	1.00	1.00	1.00
Panel C: Borrower Characteristics								
Total Assets [USD bn.]	34635	8.65	62.29	0.01	0.15	0.66	2.84	151.10
ROA [number]	32854	0.10	0.13	-0.46	0.07	0.11	0.16	0.41
Q [number]	30773	1.67	1.10	0.68	1.08	1.33	1.84	6.74
Default Barrier [number]	34466	0.21	0.15	0.00	0.10	0.19	0.28	0.77
Rating_m [number]	14129	10.41	3.69	2.00	8.00	10.00	13.00	22.00
$\Delta\text{Rating}_\text{m}$ [number]	11519	0.34	1.96	-4.00	0.00	0.00	1.00	8.00
Panel D: Bank-Level Variables								
Top 100 Loans [number]	1618	0.42	1.82	0.00	0.00	0.00	0.00	12.00
Loan Volume [USD bn.]	1618	6.66	26.42	0.00	0.03	0.25	2.17	160.70
Loans [number]	1618	12.41	37.47	1.00	1.00	2.00	8.00	206.00
Unique Borrowers [number]	1618	11.35	33.34	1.00	1.00	2.00	7.00	186.00
Bank Size [USD bn.]	1108	483.67	697.67	0.12	12.54	94.96	719.45	2814.47
Loan Fraction [number]	1044	0.51	0.21	0.00	0.37	0.58	0.67	0.84
Loan Growth [number]	871	0.10	0.23	-0.30	0.01	0.08	0.16	0.77
Tier 1 Ratio [number]	890	0.10	0.06	0.04	0.08	0.09	0.11	0.29
MtB [number]	1012	1.06	0.08	0.94	1.01	1.04	1.10	1.36
Panel E: Corporate Fraud Variables								
Borrower Fraud [0/1]	38019	0.01	0.11	0.00	0.00	0.00	0.00	1.00
Industry Fraud [number]	38019	8.82	8.70	0.00	3.00	6.00	13.00	38.00

Figure 2: 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 borrowers with loan data in *Dealscan* (2242 loans to 507 US borrowers). The horizontal axis reports the prestige score, which can take any value between 0 and 10. The vertical axis shows the frequency of the respective bin in percent. The prestige data is manually collected from printed editions of *Fortune Magazine*.

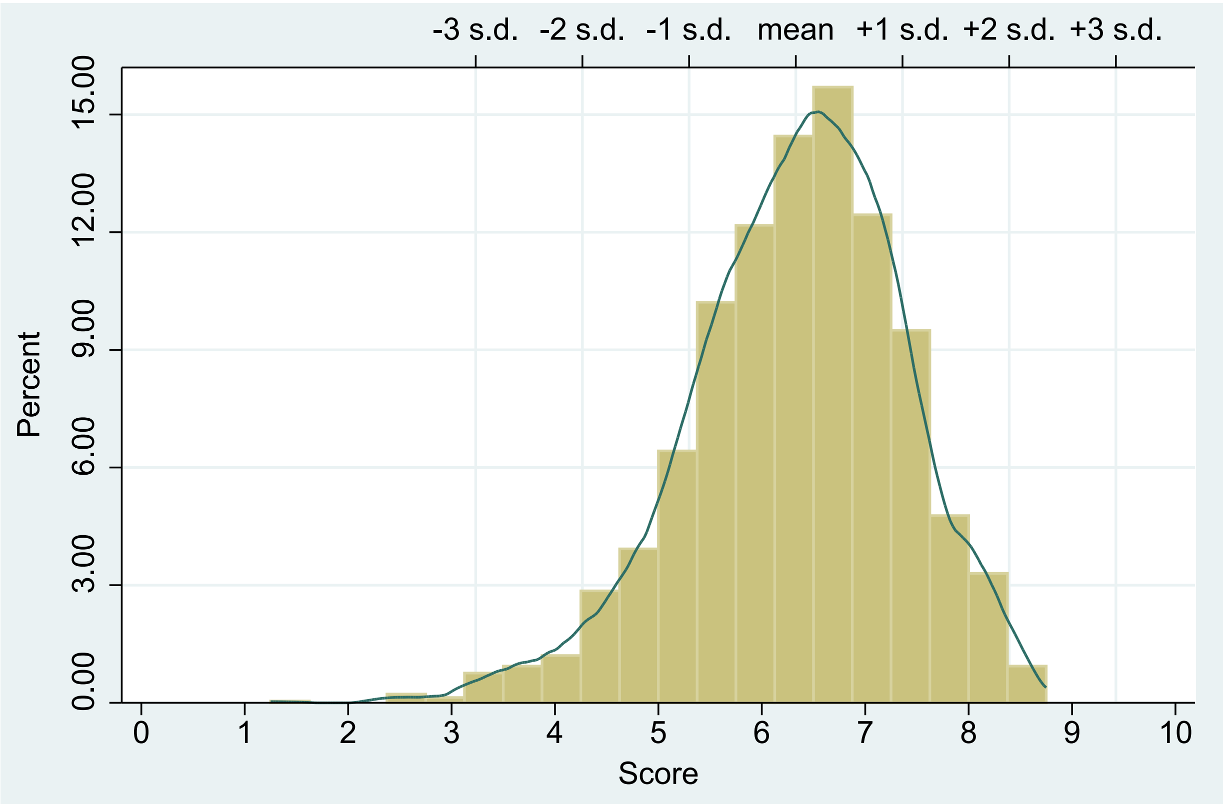
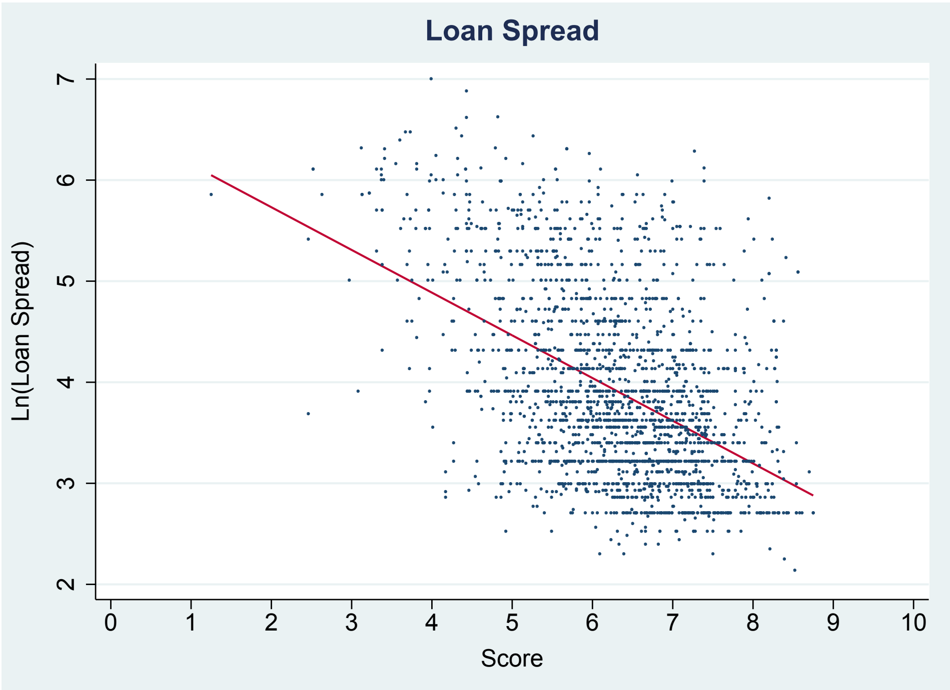


Figure 3: Borrower Prestige and the Cost of Bank Loans

This figure illustrates the strong negative relation between borrower prestige and the cost of bank loans. The scatter plot at the top shows the relation for loan spreads. The graph at the bottom illustrates the relation for upfront fees. In both plots the horizontal axis reports the prestige score, which can take any value between 0 and 10. The vertical axis shows the natural logarithm of the all-in-spread drawn or the upfront fee. The solid lines display the fitted values from an OLS regression of ln(loan spread) or ln(upfront fee) on the prestige score. Loan spreads and upfront fees are obtained from *Dealscan* and the prestige score is manually collected from printed editions of *Fortune Magazine*. This sample covers the time period 1982 to 2009.



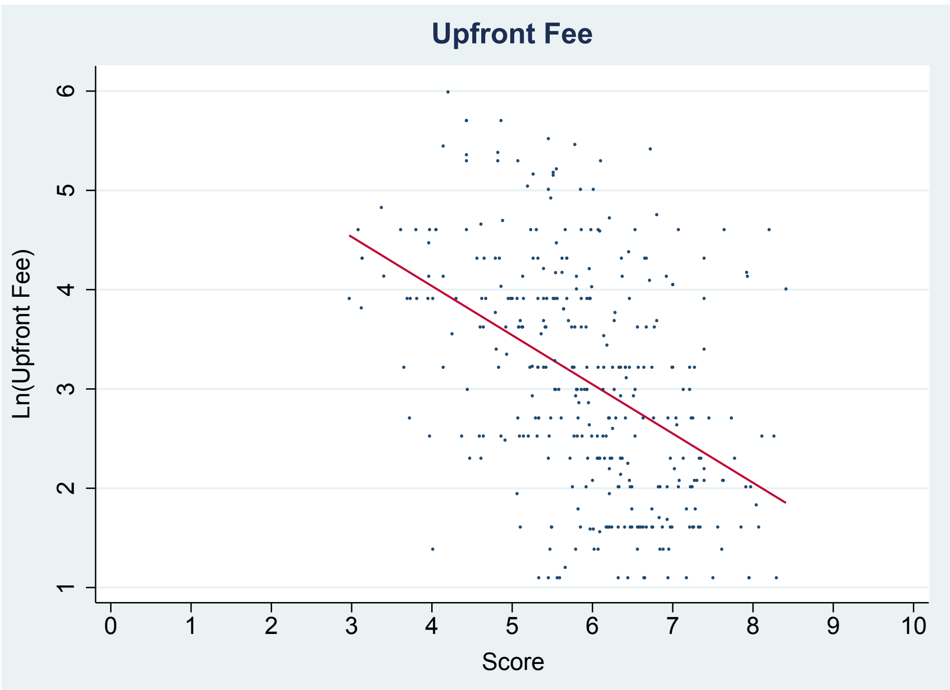


Table 3: Impact of Borrower Prestige on Loan Spreads

This table provides results for linear regressions of the loan spread on the prestige score and control variables (model (1)). The dependent variable is the logarithm of the all-in-spread drawn. 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. In all regression specifications, we control for loan and borrower characteristics. Column (1) presents the estimates without any fixed effects. In column (2), we include loan purpose and loan type fixed effects. In column (3), we add year fixed effects and in column (4) we control for real GDP growth instead. In columns (5) to (7), we separately include industry (one digit SIC code), rating, and bank fixed effects. In column (8), we report the estimates for the complete regression model. This 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 1. Clustered standard errors at the borrower level (e.g. Petersen (2009)) are given in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Ln(Loan Spread)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Score_{t-1}$	**-0.172*** (0.028)**	**-0.168*** (0.025)**	**-0.159*** (0.027)**	**-0.168*** (0.028)**	**-0.166*** (0.027)**	**-0.048* (0.026)**	**-0.157*** (0.030)**	**-0.060*** (0.019)**
Ln(Amount)	-0.107*** (0.027)	-0.102*** (0.020)	-0.100*** (0.026)	-0.109*** (0.027)	-0.121*** (0.027)	-0.095*** (0.028)	-0.098*** (0.031)	-0.078*** (0.019)
Facilities	0.130*** (0.029)	0.060** (0.025)	0.157*** (0.026)	0.143*** (0.028)	0.126*** (0.029)	0.158*** (0.028)	0.130*** (0.029)	0.119*** (0.021)
Ln(Maturity)	-0.012 (0.025)	-0.109** (0.048)	0.064*** (0.024)	-0.012 (0.024)	-0.015 (0.025)	-0.065*** (0.023)	-0.010 (0.024)	-0.009 (0.047)
Collateral	0.869*** (0.073)	0.591*** (0.063)	0.817*** (0.062)	0.851*** (0.071)	0.868*** (0.073)	0.633*** (0.067)	0.805*** (0.080)	0.398*** (0.062)
Financial Covenants	0.328*** (0.061)	0.265*** (0.058)	0.191*** (0.054)	0.324*** (0.059)	0.300*** (0.061)	0.160*** (0.047)	0.238*** (0.058)	0.030 (0.040)
Prime Base Rate	0.907*** (0.181)	0.835*** (0.171)	0.967*** (0.198)	0.863*** (0.192)	0.957*** (0.183)	0.978*** (0.182)	0.981*** (0.184)	1.177*** (0.202)
Performance Pricing	-0.075 (0.047)	-0.015 (0.042)	-0.095** (0.044)	-0.079* (0.046)	-0.060 (0.046)	-0.071* (0.038)	-0.078* (0.046)	-0.024 (0.032)
Ln(Total $Assets_{t-1}$)	-0.051** (0.022)	-0.059*** (0.019)	-0.108*** (0.025)	-0.054** (0.023)	-0.029 (0.022)	0.037* (0.020)	-0.105*** (0.027)	-0.026 (0.018)
ROA_{t-1}	-2.266*** (0.399)	-1.814*** (0.357)	-2.304*** (0.377)	-2.186*** (0.400)	-2.472*** (0.395)	-1.456*** (0.297)	-2.437*** (0.405)	-1.365*** (0.260)
Q_{t-1}	-0.097*** (0.025)	-0.092*** (0.024)	-0.095*** (0.025)	-0.091*** (0.025)	-0.083*** (0.026)	-0.030 (0.020)	-0.086*** (0.027)	-0.018 (0.018)
Default $Barrier_{t-1}$	0.528** (0.207)	0.588*** (0.179)	0.735*** (0.210)	0.601*** (0.207)	0.729*** (0.209)	0.272 (0.170)	0.779*** (0.221)	0.562*** (0.167)
Real GDP $Growth_{t-1}$				-10.684*** (1.782)				
Constant	7.662*** (0.457)	8.130*** (0.391)	7.966*** (0.508)	8.021*** (0.449)	7.815*** (0.504)	5.537*** (0.468)	9.565*** (0.626)	6.461*** (0.556)
Observations	1894	1894	1894	1894	1894	1894	1894	1894
Adjusted R^2	0.501	0.601	0.597	0.518	0.515	0.618	0.549	0.784
Fixed Effects								
Loan Type & Loan Purpose	No	Yes	No	No	No	No	No	Yes
Year	No	No	Yes	No	No	No	No	Yes
Industry	No	No	No	No	Yes	No	No	Yes
Rating	No	No	No	No	No	Yes	No	Yes
Bank / Lender	No	No	No	No	No	No	Yes	Yes

Table 4: Alternative Measure of Borrower Prestige

This table provides results for linear regressions of the loan spread on the Top 100 dummy and control variables (model (1)). The dependent variable is the logarithm of the all-in-spread drawn. The key explanatory variable is the lagged Top 100 indicator, which equals one if a borrower is ranked among the top 100 firms in Fortune's Most Admired Companies survey in a given year and zero otherwise. In all regression specifications, we control for loan and borrower characteristics. Column (1) presents the estimates without any fixed effects. In column (2), we include loan purpose and loan type fixed effects. In column (3), we add year fixed effects and in column (4) we control for real GDP growth instead. In columns (5) to (7), we separately include industry (one digit SIC code), rating, and bank fixed effects. In column (8), we report the estimates for the complete regression model. This 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 1. Clustered standard errors at the borrower level (e.g. Petersen (2009)) are given in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Ln(Loan Spread)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top 100$_{t-1}$	**-0.531*** (0.043)**	**-0.418*** (0.036)**	**-0.470*** (0.044)**	**-0.513*** (0.043)**	**-0.510*** (0.042)**	**-0.118*** (0.036)**	**-0.465*** (0.043)**	**-0.048* (0.029)**
Ln(Amount)	-0.036*** (0.008)	-0.038*** (0.007)	-0.034*** (0.007)	-0.031*** (0.008)	-0.039*** (0.008)	-0.037*** (0.008)	-0.052*** (0.007)	-0.048*** (0.007)
Facilities	0.114*** (0.006)	0.035*** (0.006)	0.124*** (0.006)	0.122*** (0.006)	0.119*** (0.006)	0.108*** (0.005)	0.111*** (0.006)	0.055*** (0.005)
Ln(Maturity)	0.012 (0.008)	-0.094*** (0.010)	0.042*** (0.008)	0.013* (0.008)	0.009 (0.008)	-0.048*** (0.007)	0.010 (0.008)	-0.064*** (0.009)
Collateral	0.540*** (0.013)	0.451*** (0.011)	0.492*** (0.012)	0.523*** (0.012)	0.530*** (0.013)	0.397*** (0.011)	0.482*** (0.013)	0.297*** (0.010)
Financial Covenants	0.195*** (0.013)	0.140*** (0.012)	0.084*** (0.015)	0.202*** (0.013)	0.189*** (0.013)	0.124*** (0.011)	0.130*** (0.014)	0.003 (0.012)
Prime Base Rate	0.486*** (0.016)	0.471*** (0.015)	0.571*** (0.017)	0.490*** (0.017)	0.484*** (0.016)	0.555*** (0.015)	0.518*** (0.018)	0.604*** (0.016)
Performance Pricing	-0.140*** (0.013)	-0.054*** (0.012)	-0.138*** (0.013)	-0.137*** (0.013)	-0.140*** (0.013)	-0.107*** (0.011)	-0.105*** (0.013)	-0.043*** (0.010)
Ln(Total Assets$_{t-1}$)	-0.103*** (0.007)	-0.098*** (0.006)	-0.142*** (0.007)	-0.112*** (0.007)	-0.099*** (0.007)	-0.036*** (0.008)	-0.118*** (0.007)	-0.068*** (0.006)
ROA$_{t-1}$	-0.665*** (0.048)	-0.628*** (0.043)	-0.588*** (0.047)	-0.686*** (0.048)	-0.675*** (0.047)	-0.629*** (0.041)	-0.632*** (0.051)	-0.511*** (0.039)
Q$_{t-1}$	-0.083*** (0.005)	-0.081*** (0.005)	-0.081*** (0.005)	-0.078*** (0.005)	-0.083*** (0.005)	-0.053*** (0.004)	-0.087*** (0.006)	-0.053*** (0.004)
Default Barrier$_{t-1}$	0.677*** (0.046)	0.611*** (0.040)	0.734*** (0.044)	0.692*** (0.045)	0.677*** (0.045)	0.443*** (0.040)	0.697*** (0.045)	0.466*** (0.034)
Real GDP Growth$_{t-1}$				-9.120*** (0.366)				
Constant	5.752*** (0.103)	6.116*** (0.102)	5.424*** (0.103)	5.974*** (0.103)	5.820*** (0.136)	4.757*** (0.105)	5.924*** (0.148)	4.645*** (0.195)
Observations	23707	23707	23707	23706	23707	23707	23707	23707
Adjusted R^2	0.534	0.604	0.596	0.550	0.540	0.638	0.585	0.739
Fixed Effects								
Loan Type & Loan Purpose	No	Yes	No	No	No	No	No	Yes
Year	No	No	Yes	No	No	No	No	Yes
Industry	No	No	No	No	Yes	No	No	Yes
Rating	No	No	No	No	No	Yes	No	Yes
Bank / Lender	No	No	No	No	No	No	Yes	Yes

Table 5: Impact of Borrower Prestige on Upfront Fees

This table provides results for linear regressions of the upfront fee on borrower prestige and control variables (model (1)). The dependent variable is the logarithm of the upfront fee. The key explanatory variable is either the lagged prestige score (columns (1) and (2)) or the Top 100 dummy (columns (3) and (4)) from *Fortune's Most Admired Companies* survey. In all regression specifications, we control for loan and borrower characteristics. Columns (1) and (3) present the estimates without any fixed effects. In columns (2) and (4), we report the estimates for the complete regression model including loan purpose, loan type, year, industry (one digit SIC code), rating, and bank fixed effects. This 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 1. Clustered standard errors at the borrower level (e.g. Petersen (2009)) are given in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Ln(Upfront Fee)			
	(1)	(2)	(3)	(4)
$Score_{t-1}$	**-0.186** **(0.074)**	**-0.222** **(0.099)**		
Top 100_{t-1}			**-0.646***** **(0.133)**	**-0.236**** **(0.119)**
Ln(Amount)	0.005 (0.069)	0.057 (0.110)	-0.007 (0.017)	-0.061*** (0.018)
Facilities	0.152*** (0.057)	0.075 (0.104)	0.152*** (0.016)	0.076*** (0.017)
Ln(Maturity)	0.180** (0.088)	0.169 (0.210)	0.098*** (0.022)	0.075*** (0.029)
Collateral	0.633*** (0.160)	0.316 (0.272)	0.535*** (0.033)	0.361*** (0.034)
Financial Covenants	0.293* (0.155)	0.261 (0.197)	-0.147*** (0.036)	-0.131*** (0.042)
Prime Base Rate	0.467 (0.379)	-0.053 (0.967)	0.351*** (0.041)	0.367*** (0.042)
Performance Pricing	-0.035 (0.152)	0.164 (0.208)	-0.275*** (0.039)	-0.146*** (0.040)
Ln(Total $Assets_{t-1}$)	-0.114** (0.055)	-0.100 (0.122)	-0.019 (0.014)	-0.022 (0.017)
ROA_{t-1}	-2.458** (0.991)	-3.834** (1.537)	-0.823*** (0.110)	-0.626*** (0.121)
Q_{t-1}	-0.304* (0.161)	-0.028 (0.229)	-0.056*** (0.012)	-0.029** (0.013)
Default $Barrier_{t-1}$	0.221 (0.441)	0.822 (0.790)	0.659*** (0.102)	0.393*** (0.098)
Constant	4.498*** (1.407)	5.860** (2.565)	2.944*** (0.242)	2.252*** (0.427)
Observations	326	326	6027	6027
Adjusted R^2	0.324	0.520	0.207	0.416
Fixed Effects				
Loan Type & Loan Purpose	No	Yes	No	Yes
Year	No	Yes	No	Yes
Industry	No	Yes	No	Yes
Rating	No	Yes	No	Yes
Bank / Lender	No	Yes	No	Yes

Table 6: Default Risk Channel

This table provides results for linear regressions of measures of default risk (ratings) on borrower prestige and control variables (model (2)). The dependent variable is either the borrower's credit rating at loan maturity (columns (1) and (2)) or the change in credit rating between loan issuance and maturity (columns (3) and (4)). The key explanatory variable is the lagged prestige score (columns (1) and (3)) or the Top 100 dummy (columns (2) and (4)) from *Fortune's Most Admired Companies* survey. In all regression specifications, we control for loan and borrower characteristics as well as loan purpose, loan type, year, industry (one digit SIC code), rating, and bank fixed effects. In Panel A we include the all-in-drawn spread (log) as control variable and in Panel B we exclude it. This 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 1. Clustered standard errors at the borrower level (e.g. Petersen (2009)) are given in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	$Rating_m$		$\Delta Rating_m$	
Panel A	(1)	(2)	(3)	(4)
$Score_{t-1}$	**0.034**		**0.032**	
	(0.094)		**(0.093)**	
Top 100_{t-1}		**0.346**		**0.184**
		(0.235)		**(0.219)**
Observations	1671	10429	1622	8887
Adj. R2	0.744	0.707	0.302	0.133
Controls / Fixed Effects (FE)				
Loan Features (incl. Spread)	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes
Loan Type & Purpose FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes
Bank / Lender FE	Yes	Yes	Yes	Yes

	$Rating_m$		$\Delta Rating_m$	
Panel B	(1)	(2)	(3)	(4)
$Score_{t-1}$	**-0.006**		**0.013**	
	(0.090)		**(0.088)**	
Top 100_{t-1}		**0.225**		**0.127**
		(0.215)		**(0.199)**
Observations	1954	11848	1894	10103
Adj. R2	0.749	0.703	0.281	0.125
Controls / Fixed Effects (FE)				
Loan Features (excl. Spread)	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes
Loan Type & Purpose FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes
Bank / Lender FE	Yes	Yes	Yes	Yes

Table 7: Bank-Level Analysis

This table provides results for linear regressions of lead banks' business activities on a measure capturing lending to prestigious borrowers and control variables (model (3)). The dependent variable is the future loan volume (columns (1) and (2)), volume per loan (columns (3) and (4)), number of loans underwritten (columns (5) and (6)), or number of unique borrowers (columns (7) and (8)). The key explanatory variable is the Ln(1 + Top 100 Loans) variable, which is based on *Fortune's Most Admired Companies* survey. In all regression specifications, we include bank, bank type, and year fixed effects. Depending on the column, we also control for the bank's size (log), loan fraction, loan growth, tier 1 capital ratio, and market-to-book ratio. This sample is based on lead banks 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 data is obtained from *Dealscan* and *SNL Financial*. We define all variables in Table 1. Clustered standard errors at the bank level (e.g. Petersen (2009)) are given in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	$Ln(Loan\ Volume_{t+1})$		$Ln(Volume_{t+1} / Loan_{t+1})$		$Ln(Loans_{t+1})$		$Ln(Unique\ Borrowers_{t+1})$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1 + Top 100 Loans)	**0.620*** **	**0.430*** **	**0.086**	**-0.002**	**0.534*** **	**0.432*** **	**0.522*** **	**0.427*** **
	(0.186)	**(0.160)**	**(0.111)**	**(0.092)**	**(0.116)**	**(0.153)**	**(0.114)**	**(0.149)**
Ln(Bank Size)		0.989**		0.431**		0.558*		0.571*
		(0.402)		(0.206)		(0.311)		(0.303)
Loan Fraction		2.352		0.402		1.950		1.992
		(1.884)		(0.939)		(1.354)		(1.311)
Loan Growth		-0.332		-0.098		-0.234		-0.263
		(0.451)		(0.276)		(0.299)		(0.291)
Tier 1 Ratio		-0.047		-0.008		-0.040		-0.035
		(0.115)		(0.072)		(0.065)		(0.063)
MtB		0.565		0.942		-0.377		-0.246
		(1.934)		(1.017)		(1.423)		(1.414)
Observations	1083	515	1083	515	1083	515	1083	515
Adjusted R^2	0.802	0.835	0.796	0.834	0.678	0.730	0.684	0.731
Fixed Effects								
Bank Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Borrower Prestige and New Bank Relationships

This table provides results for linear regressions of measures of loan pricing on borrower prestige and control variables with a focus on new bank relationships (model (4)). The dependent variable is either the logarithm of the all-in-spread drawn (columns (1) and (2)) or the logarithm of the upfront fee (columns (3) and (4)). The key explanatory variable is an interaction term of the new bank relationship dummy with either the lagged prestige score (columns (1) and (3)) or the Top 100 indicator (columns (2) and (4)). In all regression specifications, we control for loan and borrower characteristics as well as loan purpose, loan type, year, industry (one digit SIC code), and rating fixed effects. This 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 1. Clustered standard errors at the borrower level (e.g. Petersen (2009)) are given in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Ln(Loan Spread)		Ln(Upfront Fee)	
	(1)	(2)	(3)	(4)
$Score_{t-1}$ * New Bank Relation	**0.005**		**-0.254****	
	(0.024)		**(0.120)**	
Top 100_{t-1} * New Bank Relation		**0.039**		**-0.317***
		(0.034)		**(0.173)**
$Score_{t-1}$	-0.052**		-0.085	
	(0.020)		(0.078)	
Top 100_{t-1}		-0.050*		-0.080
		(0.030)		(0.131)
New Bank Relation	-0.037	0.010	1.570**	0.134***
	(0.154)	(0.007)	(0.738)	(0.030)
Observations	1686	18813	274	4267
Adj. R^2	0.796	0.734	0.538	0.340
Controls / Fixed Effects (FE)				
Loan Features	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes
Loan Type & Purpose FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes
Bank / Lender FE	No	No	No	No

Table 9: Exclusion Restriction

Panel A provides results for linear regressions of measures of loan pricing on Ln(Industry Fraud), the prestige score, and control variables for the time period 1982 to 1995 (out-of-sample). The dependent variable is either the logarithm of the all-in-spread drawn (columns (1) to (6)) or the logarithm of the upfront fee (columns (7) and (12)). Panel B provides results for linear regressions of measures of default risk (ratings) on Ln(Industry Fraud), the prestige score, and control variables for the out-of-sample period. The dependent variable is either the borrower's credit rating at loan maturity (columns (1) to (6)) or the change in credit rating between loan issuance and maturity (columns (7) to (12)). The key explanatory variable is the 2-year lagged logarithm of the industry fraud intensity. In all regression models, we control for loan and borrower characteristics (including borrower-level fraud) as well as loan purpose, loan type, and rating fixed effects. Depending on the specification, we additionally control for real GDP growth, industry fixed effects (one digit SIC code), and the loan spread (default risk as dependent variable). This sample is based on loans in the US syndicated loan market. The prestige data is manually collected from printed editions of *Fortune Magazine*. Loan and borrower characteristics are obtained from *Dealscan* and *Compustat* respectively. Fraud-related variables are obtained from *UC Berkeley* (AAER dataset). We define all variables in Table 1. Clustered standard errors at the borrower level (e.g. Petersen (2009)) are given in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Ln(Loan Spread)						Ln(Upfront Fee)					
Panel A (1982 – 1995)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ln(Industry Fraud$_{t-2}$)	**0.017**	**0.002**	**0.102**	**0.015**	**0.001**	**0.089**	**-0.078**	**-0.102**	**-0.243**	**-0.015**	**-0.043**	**0.015**
	(0.048)	**(0.046)**	**(0.064)**	**(0.046)**	**(0.045)**	**(0.062)**	**(0.233)**	**(0.233)**	**(0.416)**	**(0.203)**	**(0.200)**	**(0.353)**
Score$_{t-1}$				-0.121***	-0.115***	-0.130***				-0.590***	-0.613***	-0.571***
				(0.035)	(0.036)	(0.036)				(0.157)	(0.164)	(0.166)
Observations	529	529	529	529	529	529	136	136	136	136	136	136
Adjusted R2	0.659	0.672	0.660	0.667	0.679	0.670	0.333	0.340	0.324	0.439	0.456	0.413
Controls / Fixed Effects (FE)												
Loan Features	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics (incl. Fraud)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type & Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Real GDP Growth	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Industry FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank / Lender FE	No	No	No	No	No	No	No	No	No	No	No	No

	Rating$_m$						ΔRating$_m$					
Panel B (1982 – 1995)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ln(Industry Fraud$_{t-2}$)	**-0.106**	**-0.086**	**0.145**	**-0.106**	**-0.087**	**0.172**	**-0.135**	**-0.113**	**0.089**	**-0.139**	**-0.117**	**0.153**
	(0.224)	**(0.225)**	**(0.335)**	**(0.225)**	**(0.225)**	**(0.321)**	**(0.218)**	**(0.217)**	**(0.325)**	**(0.219)**	**(0.217)**	**(0.307)**
Score$_{t-1}$				0.185	0.182	0.216				0.389	0.388	0.444
				(0.313)	(0.314)	(0.299)				(0.326)	(0.325)	(0.305)
Observations	443	443	443	443	443	443	420	420	420	420	420	420
Adjusted R2	0.658	0.659	0.663	0.659	0.659	0.663	0.464	0.467	0.474	0.469	0.472	0.481
Controls / Fixed Effects (FE)												
Loan Features (incl. Spread)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics (incl. Fraud)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type & Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Real GDP Growth	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Industry FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank / Lender FE	No	No	No	No	No	No	No	No	No	No	No	No

Table 10: Instrumental Variable Regressions

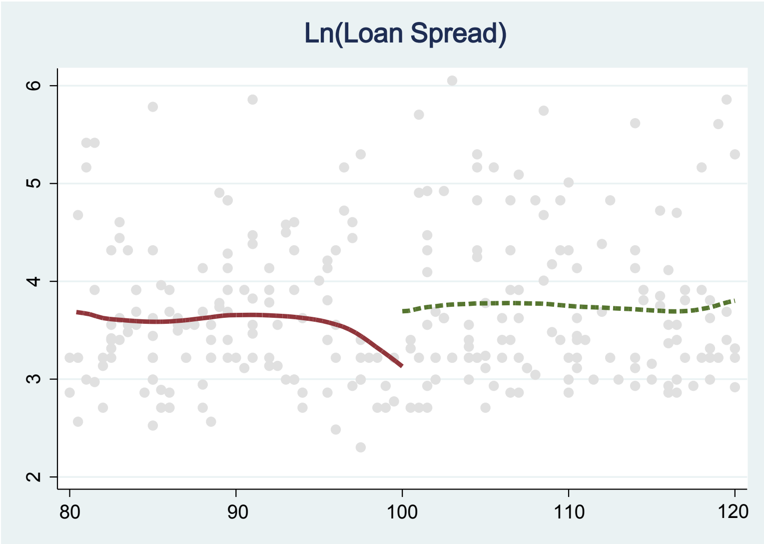
This table provides results for two-stage least squares regressions of measures of loan contracting on the prestige score and control variables (model (5)), using *Ln(Industry Fraud)* as an instrument for borrower prestige (model (6)). Panel A reports the results for the time period 1996 to 2009 (in-sample period) and Panel B provides the estimates for the whole sample (1982 to 2009). The dependent variables are the logarithm of the all-in-spread drawn, the logarithm of the upfront fee, or measures of the borrower's default risk (rating). The key explanatory variable is the lagged prestige score from Fortune's Most Admired Companies surveys. The instrumental variable in the first-stage regression (model (6)) is the 2-year lagged logarithm of the industry fraud intensity. In all regression models, we control for loan and borrower characteristics (including borrower-level fraud) as well as loan purpose, loan type, and rating fixed effects. Depending on the specification, we additionally control for real GDP growth, industry fixed effects (one digit SIC code), and the loan spread (default risk as dependent variable). The Wald exogeneity test is a test of the null that the lagged prestige score is not endogenous. It rejects the null at any significance level higher than the reported p-value. The partial F-statistic quantifies the strength of the (excluded) instruments. This sample is based on loans in the US syndicated loan market. The prestige data is manually collected from printed editions of *Fortune Magazine*. Loan and borrower characteristics are obtained from *Dealscan* and *Compustat* respectively. Fraud-related variables are obtained from *UC Berkeley* (AAER dataset). We define all variables in Table 1. Standard errors are given in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Ln(Loan Spread)			Ln(Upfront Fee)	$Rating_m$	$\Delta Rating_m$
Panel A (1996 – 2009)	(1)	(2)	(3)	(4)	(5)	(6)
Second Stage						
$Score_{t-1}$	-0.582**	-0.462*	-0.366***	0.734*	-0.357	-0.395
	(0.285)	(0.256)	(0.110)	(0.413)	(0.331)	(0.313)
Wald Exogeneity Tests						
Chi^2-Statistic	6.813	4.264	11.853	5.413	1.006	1.397
p-value	0.009	0.038	0.000	0.020	0.315	0.237
Observations	1343	1343	1343	186	1208	1182
First Stage	$Score_{t-1}$					
Ln(Industry $Fraud_{t-2}$)	-0.075***	-0.075***	-0.261***	-0.283**	-0.263***	-0.275***
	(0.027)	(0.027)	(0.042)	(0.127)	(0.045)	(0.045)
Weak Instrument Tests						
Partial F-Statistic	7.69	7.56	37.20	4.92	34.25	36.58
Stock-Yogo 20% Threshold	6.66	6.66	6.66	6.66	6.66	6.66
Controls / Fixed Effects (FE)						
Loan Features	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics (incl. Fraud)	Yes	Yes	Yes	Yes	Yes	Yes
Ln(Loan Spread)	No	No	No	No	Yes	Yes
Loan Type & Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Real GDP Growth	No	Yes	No	No	No	No
Industry FE	No	No	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank / Lender FE	No	No	No	No	No	No

	Ln(Loan Spread)			Ln(Upfront Fee)	$Rating_m$	$\Delta Rating_m$
Panel B (1982 – 2009)	(1)	(2)	(3)	(4)	(5)	(6)
Second Stage						
$Score_{t-1}$	-0.527**	-0.434**	-0.435***	1.059	-0.465	-0.349
	(0.229)	(0.211)	(0.104)	(0.928)	(0.335)	(0.318)
Wald Exogeneity Tests						
Chi^2-Statistic	6.323	4.198	17.323	4.173	2.477	1.755
p-value	0.011	0.040	0.000	0.041	0.115	0.185
Observations	1872	1872	1872	322	1651	1602
First Stage	$Score_{t-1}$					
Ln(Industry $Fraud_{t-2}$)	-0.079***	-0.080***	-0.247***	-0.143	-0.263***	-0.271***
	(0.023)	(0.023)	(0.035)	(0.088)	(0.036)	(0.037)
Weak Instrument Tests						
Partial F-Statistic	11.57	11.58	49.49	2.61	51.21	53.05
Stock-Yogo 20% Threshold	6.66	6.66	6.66	6.66	6.66	6.66
Controls / Fixed Effects (FE)						
Loan Features	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics (incl. Fraud)	Yes	Yes	Yes	Yes	Yes	Yes
Ln(Loan Spread)	No	No	No	No	Yes	Yes
Loan Type & Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Real GDP Growth	No	Yes	No	No	No	No
Industry FE	No	No	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank / Lender FE	No	No	No	No	No	No

Figure 4: Regression Discontinuity (Graphical Evidence)

This figure graphically shows non-parametric estimates of two local polynomial regressions based on either the logarithm of the all-in-spread drawn (chart at top) or the change in the borrower's credit rating between loan issuance and maturity (chart at bottom). The cut-off equals rank 100 in Fortune's Most Admired Companies survey. We only consider companies with ranks between 80 and 120. In both charts, the horizontal axis reports the rank in Fortune survey based on the prestige score. The vertical axis shows the natural logarithm of the all-in-spread drawn or the change in rating notches. This 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 1.



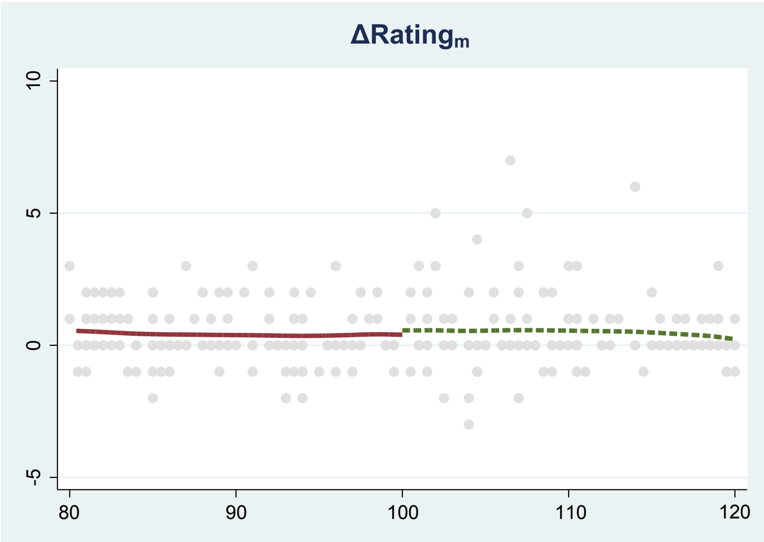


Table 11: Regression Discontinuity Analysis

This table provides non-parametric estimates for a sharp regression discontinuity design. Panel A reports the results for our main specification (threshold value of 100 with interval [80;120]). Panel B provides the results for our placebo test (hypothetical threshold value of 140 with interval [120;160]). The dependent variables are the logarithm of the all-in-spread drawn, the residual of ln(spread), the change in credit rating between loan issuance and maturity, and the residual of ΔRating_m. Our treatment variable equals one for borrowers ranked less or equal than 100 (Panel A) or 140 (Panel B) in the Fortune Most Admired Companies survey, and zero otherwise. We estimate kernel regressions applying a triangular (Epanechnikov) kernel and the optimized bandwidth (1.00) by Imbens and Kalyanaraman (2012). We vary the bandwidth by factors 0.75 and 1.25 for robustness. We obtain the residuals of ln(spread) from linear regressions of ln(spread) on $\ln(\text{amount}_t)$, $\ln(\text{maturity}_t)$, $\text{ROA}_{t\text{-}1}$, $\ln(\text{total assets}_{t\text{-}1})$, the default $\text{barrier}_{t\text{-}1}$, and year-fixed effects. We estimate the residuals of ΔRating_m based on linear regressions of ΔRating_m on ln(spread), $\ln(\text{amount}_t)$, $\ln(\text{maturity}_t)$, $\text{ROA}_{t\text{-}1}$, $\ln(\text{total assets}_{t\text{-}1})$, the default $\text{barrier}_{t\text{-}1}$, and year-fixed effects. This sample covers 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 1. Standard errors are given in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

Panel A: Baseline RDD Threshold 100; Interval: [80;120]	Ln(Loan Spread) (1)	Residual Ln(Loan Spread) (2)	ΔRating_m (3)	Residual ΔRating_m (4)
Treated	-0.725**	-0.530*	-0.219	-0.295
(bandwidth = 0.75)	(0.329)	(0.314)	(0.475)	(0.511)
Treated	-0.564*	-0.362	-0.165	-0.194
(bandwidth = 1.00)	(0.309)	(0.283)	(0.424)	(0.446)
Treated	-0.495*	-0.266	-0.201	-0.285
(bandwidth = 1.25)	(0.283)	(0.258)	(0.374)	(0.406)
Observations	266	256	272	222

Panel B: Placebo RDD Threshold 140; Interval: [120;160]	Ln(Loan Spread) (1)	Residual Ln(Loan Spread) (2)	ΔRating_m (3)	Residual ΔRating_m (4)
Treated (Placebo)	-0.165	-0.449	-0.170	0.256
(bandwidth = 0.75)	(0.421)	(0.448)	(0.586)	(0.614)
Treated (Placebo)	-0.201	-0.452	-0.258	0.022
(bandwidth = 1.00)	(0.383)	(0.409)	(0.518)	(0.550)
Treated (Placebo)	-0.044	-0.305	-0.310	-0.078
(bandwidth = 1.25)	(0.354)	(0.377)	(0.487)	(0.527)
Observations	217	197	213	173

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