Lending Frictions in the Corporate Bond Market: Evidence from Life Insurance Companies*

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Comments welcome.

Abstract

This paper documents that adverse financial shocks to life insurance companies propagate to firms in the real economy that borrow from them via the corporate bond market. First, I show that lending relationships are sticky beyond the refinancing of corporate bonds and that holdings are concentrated among few, large institutional investors. Then, I estimate the effect of a negative financial shock, measured by **?**, on borrowings, interest rates, capital expenditures, and employment growth. I find negative effects that are about half of what has been measured in the literature on relationship banking. This is evidence that lending frictions also prevail in the open market for credit.

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JEL codes: E44, G22, G32

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1 Introduction

Recent literature on relationship banking has shown how negative financial shocks to banks affect the firms that borrow from them (**???**). However, banking is only one source of debt financing. In 2018, U.S. corporations had $6.3 trillion of outstanding corporate bond debt compared to $3.3 trillion loans. In this paper, I study to what degree lending frictions prevail in the corporate bond market.

Life insurance companies are large investors in the corporate bond market and experienced sizeable financial shocks in recent decades. I use security-level corporate bond holdings information and the shadow cost of regulatory capital estimated by **?** to calculate a borrower-specific average health of its life insurance lenders. The estimated shadows cost of capital of life insurance companies propagate differentially to borrowers based on their preexisting lending relationship. I exploit institutional details to argue for exogeneity in a regression which explains different financial and real outcomes of firms in the same industry and during the same time period. I find that borrowers who are more exposed reduce their investment and employment by more and also pay higher interest rates and reduce debt.

I begin by documenting two facts about borrowing through the corporate bond market. First, lending relationships in the corporate bond market are sticky. I find that conditional on rolling over all bond debt the average firm retains 62% of lenders compared to one year ago. Furthermore, conditional on no new debt issuance the average firm retains 90% of lenders compared to one year ago. Second, lenders are concentrated. The average firm that borrows 5 $ billion via corporate bonds has only 15 lenders, while the average firm that borrows 1.5 $ billion has only 10 lenders.

I establish exogeneity of the average shadow cost of capital among life insurance company lenders under two different assumptions. First, "shares are exogenous" if firms care about the concentration of their lenders, the fraction they borrow from life insurance companies and the similarity of their lenders over time, but not about their specific identity. Second, "shocks are exogenous" if adverse, within time-industry group shocks to firms propagate to their lenders through their bond holdings, but are uncorrelated with their lender's overall health. I argue that the source of variation of life insurance companies' health is the realization of aggregate risk to which insurers are differently exposed to and that the degree of exposure is orthogonal to their bond portfolio. To substantiate this claim I show that adverse shocks caused by bond downgrades in an insurer's portfolio are insignificantly and inversely related to the insurer's health in the cross-section.

My estimates allow me to compare two firms whose average health among life insurance company lenders is at the 25th and 75th percentile and I find that they have different financial and real outcomes. The lower health firm decreases corporate bond borrowing by 4.3% more and overall debt by 1.8% more and hence is not able to fully substitute to other forms of debt. The lower health firm pays a 0.29% higher interest rate on its bonds and a 0.17% higher interest rate overall. It reduces employment growth by 1.6% more and invests 0.5% less.

These results are qualitatively identical to what the empirical literature on relationship banking finds. A large body of work shows that lending relationships are vital to stable firm debt financing. Borrowers cannot perfectly substitute credit between banks, and there are consequences in the borrower's real activity when a relationship bank is impaired. On the contrary, open market credit is commonly thought of as suffering less from frictions. Large, publicly traded, and creditworthy firms should be able to competitively raise debt financing on the capital markets. My evidence shows that even for these most transparent firms lending frictions still matter.

Related Literature This paper relates to the empirical literature on lending relationships. Perhaps most closely related in spirit is **?**. They make the case that arm's length lending through the money market is not fully arm's length. They find that relationships between money market mutual funds and borrowers are persistent and that fund outflows due to losses on European banks in 2011 lead to a decreased lending activity which the U.S. borrowers cannot fully compensate for by finding other lenders. Since they focus on the commercial paper market their issuers are typically very large firms, and many of them are in the financial sector. I make the same point for corporate bonds issued by non-financial, corporate businesses in the U.S. which borrowed 123 $ billion via commercial papers and 2,870 $ billion via corporate bonds at the end of 2007 according to Flow of Funds data. I too find patterns of imperfect substitutability of different forms of debt. However, in contrast to their findings, I uncover a statistically and economically significant decline in investment following a weakening of lender's health. Assuming that long-term investments are funded with long-term debt and not commercial papers this is not surprising.

Many empirical papers document the real effects of bank lending frictions using various sources of shocks. In **?**, **?**, **?** internationally active banks suffer losses in one country and cut lending in another. **?** study how innovations in monetary policy propagate to the real economy. Another source of shocks is the housing market to which many banks are exposed to. **?**, **?**, and **?** argue that during the financial crisis of 2007-08 banks' losses on their mortgage-related portfolio are the source of the lending cuts which adversely affect borrowers. Similarly to them, I focus on financial and real effects on firms, however, given data limitations I can only study real effects on publicly traded companies and financial effects on firms with public debt.

The theoretical work on the bank lending channel offers explanations for the limited substitutability between lenders and forms of debt with asymmetric information being at the center. For example, costly state verification or moral hazard prevents efficient outcomes, however, repeated interaction mitigates these problems. A break in a long-term relationship can serve as a signal to other lenders or create a lemons problem for borrowers that seek new lenders, as in **?**. More transparent firms with stricter reporting requirements and larger borrowers are better equipt to overcome informational frictions. **?** introduce a model in which banks are better equipt to monitor firms. This leads to limited substitutability between forms of debt. On a different note, **?** model loans that can be renegotiated, whereas open market credit cannot. This feature is valuable to firms.

Institutional Background Non-financial corporate firms in the U.S borrowed \$ 3,348 billion via bonds and \$ 2,979 billion via loans in 2007 according to Flow of Funds data. The Integrated Macroeconomic Accounts show that they pay 54 % of all compensation received by employees in the U.S.

The steps involved in issuing a corporate bond are the following. The borrower must decide on the bond's characteristics and register the issue with the Security and Exchanges Commission. With the help of an investment bank, they find underwriters who participate in the distribution of the new bond and guarantee a price and minimum sales. The underwriters and the issuer's investor relations division then market the bond to institutional investors, like pension funds, insurance companies, or mutual funds. Along the whole process, there is direct contact between the borrower and the institutional investors. Even before the decision to issue a bond is made a firm may conduct non-deal roadshows to build a relationship with investors. After the initial registration with the

SEC investment bankers and firm executives may "test the waters" with institutional investors. Orders or binding commitments are not allowed in such interactions, but the participants may get an indication about interest for the bond. Deal roadshows are an integral part of the marketing phase of a bond issue during which underwriters may take bona fide orders from investors.

Public bonds can be bought by any investors, hence they can be advertised in financial publications or marketed to private households. However, they must adhere to strict regulation and disclosure rules. Privately-placed bonds can only be bought by qualified institutional buyers, but are subject to less scrutiny by the SEC which allows for smaller bond issues that are attractive to smaller firms.

Life insurance companies are large investors in the corporate bond market. In 2007, about one-quarter of investment-grade, and one-fifth of all corporate bonds are held by them. Vice versa, one-third of life insurer's assets are invested in corporate bonds.

The source of these funds are the premia paid by the holders of various policies. The most conventional policies insure against early death (life insurance), late death (annuities), or a combination of both (whole life insurance). The insurer receives and invests the premium and records future liabilities in its books according to statutory accounting. State regulators with coordination by the National Association of Insurance Commissioners (NAIC) impose a risk-based capital constraint. Life insurance policies are guaranteed by a state guaranty fund in the case that an insurer should default.

In recent decades non-traditional insurance business lines grew. Life insurance companies offer equity mutual funds with a return guaranty (guaranteed annuities). The inherent long-dated put option sold by the insurer generates losses when the long-term expected return on the stock markets drops. Furthermore, life insurers sell insurance in the market for credit default swaps and engage in securities lending activities.

This exposure to the aggregate stock market and business cycle risk caused a number of large life insurance companies to suffer big losses that were accompanied by a reduction in assets between the years 2000 and 2010. Most prominently, AIG failed in 2008 because of losses on its credit default swaps, mortgage-related investments, and securities lending business. Excessive risk-taking was possible due to regulatory loopholes and off-balance sheet activities that **?** call shadow insurance. Many other insurance companies were hit hard and had to either raise equity or accumulate capital by selling new policies at a bargain. The latter observation is the basis of the structural model in **?**. They note that during most of the time since the year 2000 selling a life insurance policy at the actuarial price led to a relaxation of the regulatory capital constraint. During these episodes, the markup between the actutal and the actuarial price is informative about the severity of the constraint. In the early 2000's and in 2008 many life insurance companies sold policies at a price below the actuarial value.

2 Data

I construct a novel panel dataset that combines firm balance sheet and income statement information with the composition of lenders. The universe of firms is U.S. non-financial, corporate firms. Details on the structure of debt I gather from Standard & Poor's CapitalIQ data set which provides information on individual components of debt, for example term loans or specific bond issues. Many firms in this data set are privately-owned companies that borrow from the capital market via corporate bonds and have to the file form 10-K with the Security and Exchanges Commission. I retrieve yearly balance sheets and income statements of publicly-traded companies from Standard & Poor's COMPUSTAT data set. Security-level holdings information is provided by Thomson Reuters' eMAXX data set which covers the corporate bond holdings of 2400 institutional investors on a quarterly basis between the years 2000 and 2016. Estimates for life insurance company health are taken from the data appendix of **?**.

First, I describe the selection of companies from CapitalIQ. I choose public or private firms in the U.S. that are non-financial according to CapitalIQ's industry classification system and which report to the Security and Exchanges Commission in a non-financial filing format. CapitalIQ provides the amount, maturity, interest rate, and other modalities of every component of debt on the liability side of the balance sheet on a yearly basis.

Second, I merge balance sheet and income statement data. COMPUSTAT and CapitalIQ have two different primary keys, GVKEY in COMPUSTAT and companyId in CapitalIQ. I merge COMPUSTAT data using the linking table between the two sets of primary keys provided by Standard & Poor's. Unmatched firms for which there is a publicly traded stock CUSIP identifier I try to match the issuer part of that CUSIP with the entries in the linking table that reference securities to companyIds.

	Q5	Q25	Median	Mean	Q75	Q95
Assets	\$500M	\$1.4B	\$3.1B	\$8.7B	\$7.4M	\$29B
Debt	\$235M	\$501M	\$1B	\$2.4B	\$2.1B	\$7.7B
Bond Debt	\$161M	\$344M	\$717M	\$1.8B	\$1.6B	\$6.2B
Employees	1524	3963	9517	22146	24716	87788
Employment Growth	-18 %	-5.8 %	-0.6 %	-0.8 %	4.5 %	15 %
Investment Rate	0.8 %	1.7 %	3.1 %	4.4 %	5.3 %	12 %
Interest Rate	3.7 %	5.4 %	6.5 %	6.6 %	7.7 %	9.6 %

Table 1: Descriptive statistics of cross-sectional variation in firm characteristics
Note: The displayed numbers are calculated moments within each time period and averaged over time periods.

Third, I process eMAXX data set. Information about bond issues are compared to and if necessary supplemented by the Mergent FISD data set. This ensures the most accurate information on the coupon, maturity, amount outstanding, and other characteristics of a bond issue. The bond holdings data is purged of double reporting by multiple managers of the same portfolio.

Fourth, I match bond issues to firms. Publicly traded bonds and privately placed bonds of a company that has other public securities are easily matched via issuer part of the CUSIP and the linking table.

Lastly, I hand-match the life insurance companies for which **?** provide estimated health to their respective portfolios in eMAXX.

Table 1 shows characteristics for the subset of publicly traded firms. The borrowers in this data set are large firms with the median borrowing 1 \$ billion, owning 3.1 \$ billion in assets, and employing 9517.

2.1 Lending Relationships

I define two measures that capture firm characteristics concerning its lending relationships in the bond market. The similarity of the composition of lenders if compared to one year ago is the **?** coefficient. Let firm j borrow a fraction $\omega_{j,i,t} = \frac{\text{Holding}_{i,j,t}}{\text{Bond Debt}_{j,t}}$ of its outstanding bond debt from investors $i \in I$ at time t, then the similarity measure is:

$$BC_{i,t} = \sum_{i \in I} \sqrt{\omega_{j,i,t}\omega_{j,i,t-1}}$$

	Q5	Q25	Median	Mean	Q75	Q95
Bond Coverage	13 %	32 %	45 %	45 %	57 %	75 %
Share held by LI	3 %	16 %	35 %	39 %	64 %	82 %
Lender Similarity	45 %	71 %	82 %	77 %	88 %	94 %
Number of Lenders	5	13	23	28	37	62

Table 2: Borrowing relationships

Note: The displayed numbers are calculated moments within each time period and averaged over time periods.

Suppose two extreme cases: If a firm's lenders change completely, then $BC_{i,t} = 0$, and if a firm's lenders do not change at all, then $BC_{i,t} = 1$. In a more realistic case, suppose a firm has four symmetric lenders, each lending one-fourth of the outstanding debt. If one of these lenders has been replaced by a new lender wihtin the last year, then $BC_{i,t} = 0.75$.

The concentration of lender composition is measured as the Herfindahl–Hirschman index of $\omega_{j,i,t}$:

$$HHI_{i,t} = \sqrt{\sum_{i \in I} \omega_{j,i,t}^2} \cdot 10000$$

For a firm that has only symmetric lenders the HHI has a natural interpretation as the number of lenders:

$$Lenders_{i,t} = \frac{10000}{HHI_{i,t}}$$

Table 2 shows that the eMAXX data set contains holdings information on 45 % of bond debt for the median firm, of which 35 % is held by life insurance companies. The median firm's lender composition changes as if 18 % of its bond debt moves from one investor to another within one year. That firm would have 23 lenders if they were all symmetric.

The right panel of figure 1 shows the cross-sectional distribution of $BC_{j,t}$ plotted over time. Some noticeable churn occurs in 2009 and 2010 during which the similarity measure drops from 83 % to 79 % and 73 %. This pattern robustly appears when comparing the lender composition two years apart in appendix C.1. The left panel displays the similarity measure conditional on the fraction of bonds that have been issued within the last year. In the absence of bond trades on secondary markets and assuming that there is no stickiness of lending relationships beyond a

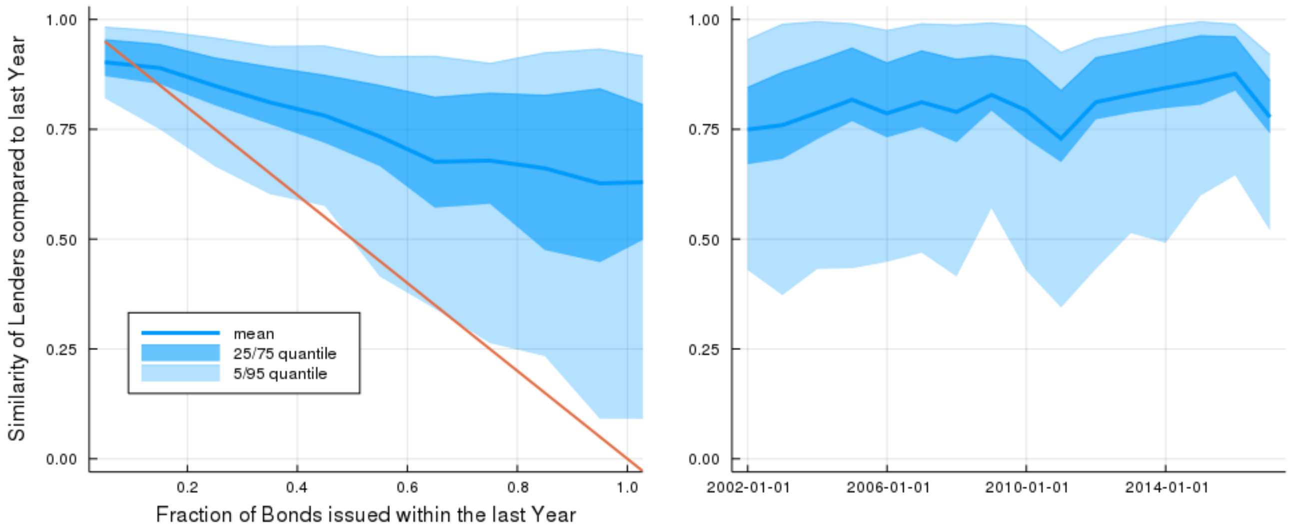

Figure 1: Similarity of lenders compared to one year ago

specific bond issue, the similarity measure should lie on the orange line. This is not the case. There is trade on the secondary market which pushes the distributions down. Despite this, the distribution lies firmly above the orange line, which indicates stickiness of lending relationships beyond a bond rollover. Investors who held maturing bonds from a firm before also buy the newly issued bonds.

The left panel of figure 2 shows the distribution of the number of symmetric lenders conditional on the outstanding amount of bond debt. A firm that has bonds with a total notional of 5 \$ billion outstanding has on average 15 symmetric lenders, each lending 333 \$ million. A smaller firm with only 1.5 \$ billion in bond debt has on average 10 symmetric lenders, each lending 150 \$ million. This shows a high degree of concentration among lenders. The right panel shows the unconditional distribution over time. The average firm has 10 lenders.

2.2 Life Insurer Health

The estimates for the health of life insurance companies are taken from **?**. They introduce a model of insurance pricing under regulatory constraints that I briefly explain here for convenience and as the basis for a discussion on exogeneity later. Let i be a life insurance company with assets A_t, statutory reserves L_t, and statutory capital $K = A - \phi L$, where ϕ is the leverage constraint. The

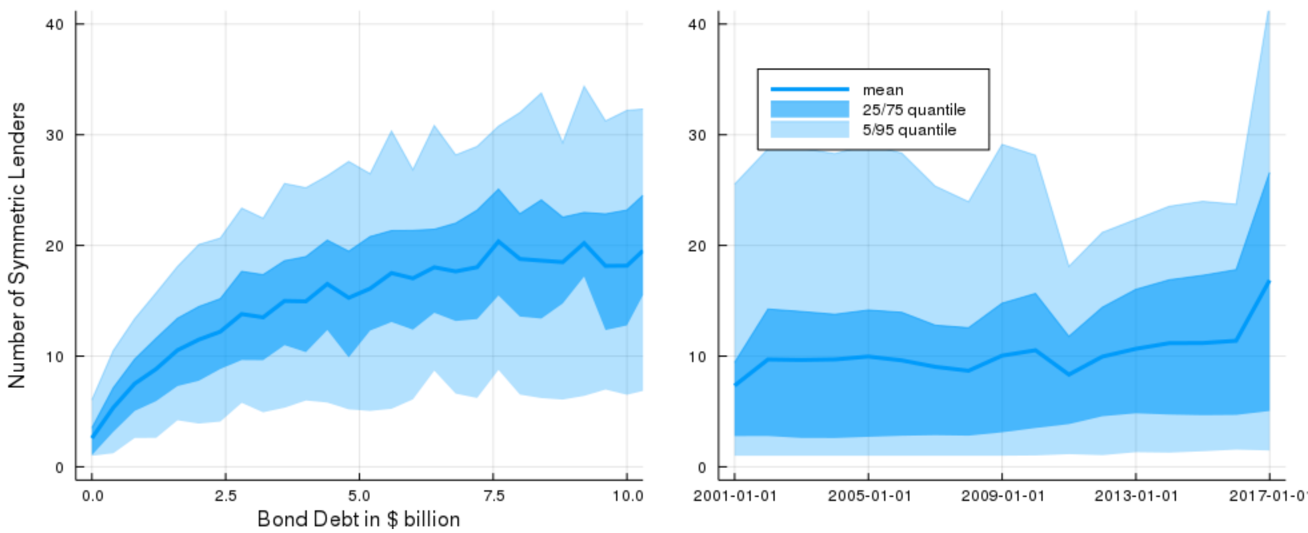

Figure 2: Concentration of lenders

regulator imposes the constraint:

$$K \geq 0 \iff \frac{L}{A} \leq \phi \iff \frac{A - L}{\rho L} \geq \psi$$

where ρ is the risk charge based on the asset and liability portfolio and ψ is a constant that triggers regulatory action. Let λ be marginal value of an extra Dollar of statutory capital, that is $\lambda_t = \lambda_t^{\text{flow}} + \mathbb{E}\left[M_{t+1}\frac{\partial J_{t+1}}{\partial K}\right]$ where M is the stochastic discount factor and J is the continuation value of the insurer's problem. Having more statutory capital relaxes current and future regulatory constraints, hence λ is the sum of the marginal flow payoff and the marginal continuation value. λ has the interpretation of how many $ loss the insurer is willing to incur in order to raise the internal capital by one $. If the constraint is not binding this number is zero, otherwise, it is weakly positive.

The insurer faces a downward sloping demand curve for its policies. The sale of a new policy increases assets A by the selling price P, increases liabilities L by the statutory reserve value $\hat{V}$, and it affects economic profits by comparing the selling price and the actuarial price V. The authors show that if the regulatory constraint is binding, then the sell price is lower than the Bertrand price if and only if selling an extra policy relaxes the constraint. During most of the time between the years 2000 and 2011 selling an extra policy did relax the regulatory constraint. Episodes of stress on the health of a life insurance company were accompanied by low prices on policies.

The authors use variation over different policies p that are on offer by the same life insurer at

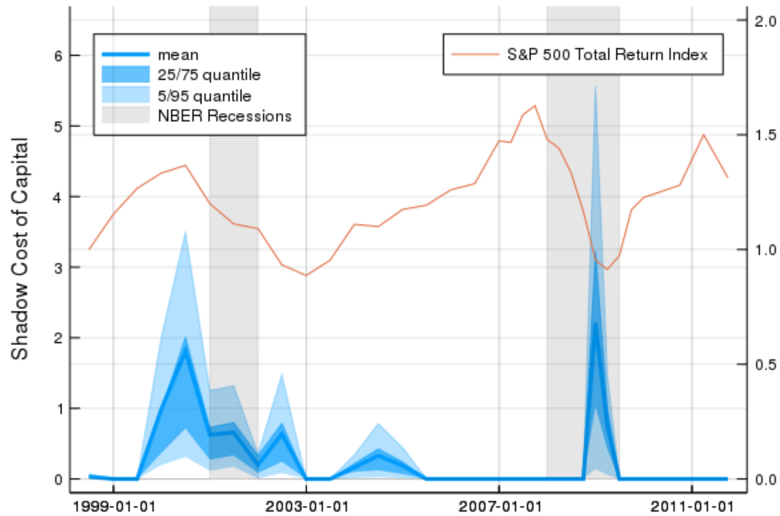

Figure 3: Shadow costs of capital of life insurance companies

the same time to estimate their empirical specification which is a log-linearization of the first-order condition on the selling price:

$$\log\left(\frac{P_p}{V_p}\right) = -\log\left(1 - \frac{1}{\epsilon_p}\right) + \log\left(\frac{1 + \lambda\big(L/A\big)^{-1}\big(\hat{V}_p/V_p\big)}{1 + \bar{\lambda}}\right) + e_p$$

where ϵ_p is the negative price elasticity of demand for policy p, which is also estimated parametrically.

Figure 3 shows that there are time-series and cross-sectional variation in the health of insurers. The time-series shows that life insurance companies experience stress during economic downturns and when stock markets fall. In between, there are calm periods, where all insurance companies have zero shadow cost of capital. The graph also reveals the dispersion of health across different insurers. In late 2008, the mean life insurance company was willing to make a 2 \$ loss in order to raise 1 \$ of capital by selling new policies, while some other insurers appear not to be under much stress.

2.3 Data Limitations

I focus on borrowers for which I observe detailed information on the debt on the liability side of the balance sheet. This is necessary because eMAXX and Mergent FISD often contain errors on the outstanding amount of a bond due to unreported life-cycle events. Overallotment options allow underwriters to sell typically 15 % more of the targetted amount. Premature repayments like exercised puts, calls or convertibility, or the firm buying back bonds on the secondary market can reduce the amount outstanding without an adjustment in either eMAXX or FISD. The balance sheet information is audited and reliable up to errors in CapitalIQ's data processing.

On average eMAXX shows who owns 45 % of the bond debt of a firm. The holders of the remaining fraction of bonds are unknown. eMAXX covers corporate bond holdings of all insurance companies that do business in the U.S., all public pension funds, and all mutual funds that U.S. investors can invest in. The main groups among the investors for which I have no holdings information are foreigners, private pension funds, banks, hedge funds, and households. About 20 % of all corporate bonds are held abroad, 5 % are owned by private pension funds, 8 % by banks and the household sector (including hedge funds) owns 10 % according to Flow of Funds data.

The similarity and concentration measures above are calculated based on the observable holdings only. Changes in the ownership from an observed to an unobserved investor, or vice versa, are accounted for correctly in the similarity measure. However, if changes in the ownership among unobserved investors occur more often than in the observed sample, then the similarity measure is biased upward. If unobserved investors held infinitesimally small fractions of a firm's bond debt, then the $HHI_{j,t}$ of the median firm would be too high by the factor 2, and the number of lenders would be too low by the same factor. However, unobserved investors largely are institutional investors too. Particularly among the foreign investors the fraction of institutional investors is likely very high.

The concept of an investor who does not change its identity, purpose, or clientele over time is not easily transferred to the definition of managing firms and account numbers in eMAXX. I calculate the similarity and concentration measures by defining an investor to be a managing firm. When it comes to life insurance company holdings I only regard account numbers that concern general accounts as opposed to separate accounts. Many life insurance companies offer and manage mutual funds, which are pass-through investment vehicles that are kept in separate accounts. A change of the managing firm of a fund may be accounted for as a change of investor in the similarity measure, despite the fund not changing at all. This introduces a downward bias.

? only provide estimates for about 100 life insurance companies, among them are all the largest. According to the American Council of Life Insurers, there were around 900 companies in 2011. This may lead to measurement error when I calculate the average health of a firm's lenders.

3 Empirical Strategy and Identification

The goal of the empirical strategy is to identify the effect of the lender's health on the borrower's financial and real outcomes. Concretely, I study the average interest rate paid on all debt, changes in bond and overall debt levels, investment rate and employment growth. Those are the left-hand side variables $y_{j,t}$ in the regression:

$$y_{j,t} = \alpha_{t,S(j)} + \beta\bar{\lambda}_{j,t} + x'_{j,t} \cdot \gamma + \epsilon_{j,t} \tag{1}$$

where $\bar{\lambda}_{j,t} = \sum_i \omega_{i,j,t-1}\lambda_{i,t}$ is the average shadow cost of capital among previous lenders of firm j in industry $S(j)$, $\omega_{i,j,t} = \frac{\text{Holding}_{i,j,t}}{\text{Bond Debt}_{j,t}}$ is the fraction of outstanding bond debt held by investor i and $x_{j,t}$ is a vector of covariates.

The weighted average of the lender's health is calculated using the bond holdings from one year ago. This is necessary since contemporary bond holdings may change due to worsening lender health. **?** show that insurance companies which are more constraint are more likely to sell a recently downgraded bond, possibly at fire-sale prices. For example, suppose a life insurance company i experiences a binding regulatory constraint and sells all bonds it held from borrower j. Then $\omega_{i,j,t} = 0$ and this situation would not be reflected in the average health if calculated with contemporary holdings, hence I use $\omega_{i,j,t-1}$. This makes $\bar{\lambda}_{j,t}$ a shift-share or Bartik instrument.

I view the empirical specification 1 as a reduced form of a richer model. The state space of a firm financing problem may be very high dimensional, containing the bond maturity structure, expected probabilities of successful bond rollovers, or expected future interest rate schedules. In this sense, the regressions explaining the average interest rate and changes in debt levels can be viewed as the first-stage. However, given the complexities mentioned and the lack of other instruments an instrumental variable estimation would be under-indentified, so I rather view all regressions as reduced form.

Following **?** the key exogeneity assumption is that the average shadow cost among lenders weighted by ex-ante weights is asymptotically uncorrelated with the regression error within each time t and industry S group conditional on observables:

$$\frac{1}{|S|}\sum_{j\in S}\bar{\lambda}_{j,t}\epsilon_{j,t}=\frac{1}{|S|}\sum_{j\in S}\sum_{i}\omega_{i,j,t-1}\lambda_{i,t}\epsilon_{j,t}=\underset{p}{\rightarrow}0\quad\forall S,t \tag{2}$$

I discuss two different identifying assumptions:

First, following the “shares are exogenous” assumption of **?** demands that the ex-ante investment activity of a life insurer within an industry is uncorrelated with the regression error:

$$\frac{1}{S}\sum_{j\in S}\omega_{i,j,t-1}\epsilon_{j,t}\underset{p}{\rightarrow}0\quad\forall i,s,t \tag{3}$$

This means that no investor’s ex-ante lending within an industry sector is correlated with unobservables that drive the explained variable. This assumption seems not fulfilled in the light of investor relations activities. Borrowers actively seek out institutional investors to advertise their debt issues, and the degree of success may well influence capital expenditure, employment growth, and borrowing costs. However, if there are sufficient statistics for the degree of success, I can control for them. In this spirit, I control for three such measures: the share of debt held by life insurance companies, the concentration of lenders as the number of symmetric lenders, and the similarity of lenders.

Another identification strategy follows the “shocks are exogenous” assumption of **?** who derive conditions under which weighted regression errors are asymptotically uncorrelated with investor health:

$$\frac{1}{|S|}\sum_{j\in S}\bar{\lambda}_{j,t}\epsilon_{j,t}=\frac{1}{|S|}\sum_{j\in S}\sum_{i}\omega_{i,j,t-1}\lambda_{i,t}\epsilon_{j,t}=\sum_{i}\hat{\omega}_{i,S,t-1}\bar{\epsilon}_{i,S,t}\lambda_{i,t}\underset{p}{\rightarrow}0 \tag{4}$$

where $\hat{\omega}_{i,S,t-1}=\frac{1}{|S|}\sum_{j\in S}\omega_{i,j,t-1}$ is the average fraction of bond debt investor i holds in industry S and $\bar{\epsilon}_{i,S,t}=\frac{\sum_{j\in S}\omega_{i,j,t-1}\epsilon_{j,t}}{\sum_{j\in S}\omega_{i,j,t-1}}$ is the weighted average of regression errors in the industry S

part of the bond portfolio of investor i.

Three assumptions are together sufficient for shock exogeneity:

$$\mathbb{E}\Big[\lambda_{i,t} \,|\, \hat{\omega}_{i,S,t-1}, \bar{\epsilon}_{i,S,t}\Big] = \mu_{t,S} \quad \forall i, S, t \tag{5}$$

$$\mathbb{E}\Big[\big(\lambda_{i_1,t} - \mu_{t,S}\big)\big(\lambda_{i_2,t} - \mu_{t,S}\big) \,|\, \hat{\omega}_{i_1,S,t-1}, \bar{\epsilon}_{i_1,S,t}, \hat{\omega}_{i_2,S,t-1}, \bar{\epsilon}_{i_2,S,t}\Big] = 0 \quad \forall i_1 \neq i_2, t, S \tag{6}$$

$$\sum_i \hat{\omega}^2_{i,S,t} \xrightarrow{p} 0 \quad \forall t, S \tag{7}$$

Assumption 5 means that based on an investor's importance as a lender within an industry and the exposure-weighted unobservables in that industry, every investor is expected to have equal health. Assumption 6 ensures enough variation such that a shock-level law of large numbers holds. Again conditional on importance and within weighted time-industry errors, there must be no correlation between two investors' shadow cost beyond the time-industry fixed effect. Assumption 7 demands that no investor is too important within an industry and implies that the number of investors grows with the sample.

Concerning the last assumption, I calculate the sample average of $\hat{\omega}_{i,S,t-1}$ over investors at the managing firm level. The 95th quantile of the empirical distrubtion function over time periods and industries is 0.2 % and the 99th quantile is 3 %. Hence, no single investor seems too important. However, if borrower-specific, within time-industry shocks affect their investors' health, then the assumptions may be violated. Hence, a discussion about reverse causality is in order.

I argue that the source of variation of life insurer health is the realization of aggregate shocks, to which insurers are differently exposed. Furthermore, I argue that this exposure is orthogonal to their corporate bond portfolio. Figure 3 shows that shadow costs spike when stock prices are falling, which coincided with the bursting housing bubble during 2008. This lead to immediate losses on the life insurer's assets and liabilities. Furthermore, these episodes may have induced a correction in the long-term return expectations of these investors[1]. Shocks from the housing

[1] **?** and many privately conducted surveys show that return expectations of institutional investors appear be extrapolative.

market are plausibly orthogonal to both the investor's corporate bond portfolio composition and the regression error, and hence are no threat to identification as in **?**. I focus now on shocks from the real economy.

On the asset side of the balance sheet statutory accounting allows life insurers to record almost all corporate bonds at historical cost[2]. Hence, the risk-based capital constraint $\frac{A-L}{\rho L} \geq \psi$ does not become more binding when the market-based value of its bond portfolio decreases. However, the bond rating does have an effect through a higher risk-based capital charge ρ.

I analyze this relation empirically. In a regression of insurer health $\lambda_{i,t}$ on innovations in the portfolio-weighted average risk-based capital charge:

$$\text{shock}_{i,t}^{\text{RBC}} = \frac{\sum_b (\text{charge}_{b,t} - \text{charge}_{b,t-t}) \cdot \text{Holding}_{i,b,t-1}}{Portfolio_{i,t-1}}$$

where b is a corporate bond in the portfolio which incurscharge$_{b,t}$ according to the schedule displayed in appendix B. Table 3 shows that the cross-sectional health of insurers is weakly negative related to bond downgrades, meaning that insurers with ex-post worse health held bonds that have not been subject to a downgrading. The shocks from the risk charge on corporate bonds only explain 4 % variation in this regression. However, the times series variation is related to bond downgrades. About 1 % of time-series variation is explained by downgraded bonds. This is a result of the high-quality bond portfolio of insurers. In my main specification 1 I only exploit cross-sectional variation over borrowers, but as a robustness test I leave out observations in which the borrower received a bond downgrade and report the results in appendix C.2.

Furthermore, the corporate bond portfolios of life insurance companies that did have poor health ex-post do not differ from those with good ex-post health. Table 4 reports observable characteristics of those portfolios. They are about as risky according to average NAIC SVO rating category and risk-based capital charge. There is no sorting towards high-yield bonds either way. Ex-post unhealthier life insurance companies have a lower average time-to-maturity in their bond portfolio. This may expose them to more interest rate risk due to a higher duration mismatch between assets and liabilities, depending on their hedging activity with interest rate swaps. Insurers with higher shadow cost of capital are more diversified over borrowers and exhibit about the same

[2]**?** provide details on the regulations.

	λ	
RBC shock	-0.24	0.54***
	(0.22)	(0.11)
Time FE	Yes	
Investor FE		Yes
N	1451	1440
R^2 within	0.04	0.01

Table 3: Life insurer's health and bond downgrades
Note: Life insurer's health is explained by innovation in the risk-based capital charge of their bond portfolio and either time fixed effects or insurer fixed effects. Standard errors are displayed in paranthesis and are clustered at the fixed effect level.

concentration over industries.

Also on the asset side, life insurance companies hold only a small stock portfolio. Flow of Funds data show that in 2007 only 5 % of life insurer's assets are invested in corporate equity. A risk-based capital charge of 30 % makes holding an equity portfolio costly from the regulatory perspective. **?** display the asset allocation of large insurance companies. Comparing the ex-ante fraction invested in equities and the ex-post insurer health there seems to be no correlation.

On the liability side, life insurance companies are differentially exposed to aggregate stock market risk via guaranteed annuities and to corporate default risk via credit default swaps. If an insurer's lending activity to a specific borrower j is not influenced by its exposure to the aggregate stock market, then there is no threat to the identification. More worrisome is a possible correlation between the composition of the bond portfolio and of the credit default swap portfolio. If an insurer holds bonds of a firm and also sells default insurance on this firm cross-sectional, then variation in the shadow cost is endogenous. However, the regression in table 3 speaks against that. There may be some week negative correlation, namely that insurers buy credit default swaps on the bonds they own and sell insurance on bonds they do not own. But the evidence on this is weak. Hence, I think of corporate default risk again as an aggregate risk that insurers are differently exposed to.

average	Shadow Costs above	below
NAIC Rating Category	1.77	1.75
	(0.15)	(0.13)
RBC Charge (%)	1.6	1.5
	(0.04)	(0.3)
Offering Yield (%)	7.20	7.26
	(0.25)	(0.39)
Time-to-maturity (years)	11.1	13.1
	(5.7)	(5.5)
Portfolio Concentration (HHI)	95	264
	(70)	(512)
Industry Concentration (HHI)	652	670
	(206)	(251)

Table 4: Ex-ante portfolio characteristics of insurers with above or below average ex-post shadow costs
Note: The displayed numbers are calculated moments for each time period and averaged over time periods. I condition on life insurance companies with a shadow cost of at least 0.01 \$. Standard deviations are reported in brackets.

4 Results

Figure 4 shows the distribution of borrower-specific average health among lenders. The most variation occurs during the financial crisis, but there is some during 2001, 2002 and 2004. In order to interpret the estimated coefficients of the main specification 1 I consider the dispersion of average lender health in late 2008. The difference between a firm at the zeroth quantile and the mean firm is 0.41 \$, the interquartile range is 0.53 \$, and the difference between the 10th and 90th quantile is 1.01 \$.

I first present results on how the average lender's health drives the financial outcomes of a borrower. Table 5 shows the estimated coefficients of the main specification 1. Firms with poorer average lender's health decrease bond borrowing by more, and also overall debt levels decline by more. This means that firms cannot fully substitute bond debt with other forms of debt. Those firms also borrow at a higher interest rate both on bond and on overall debt.

Next, I turn to real outcomes. Table 6 presents estimated coefficients on investment and

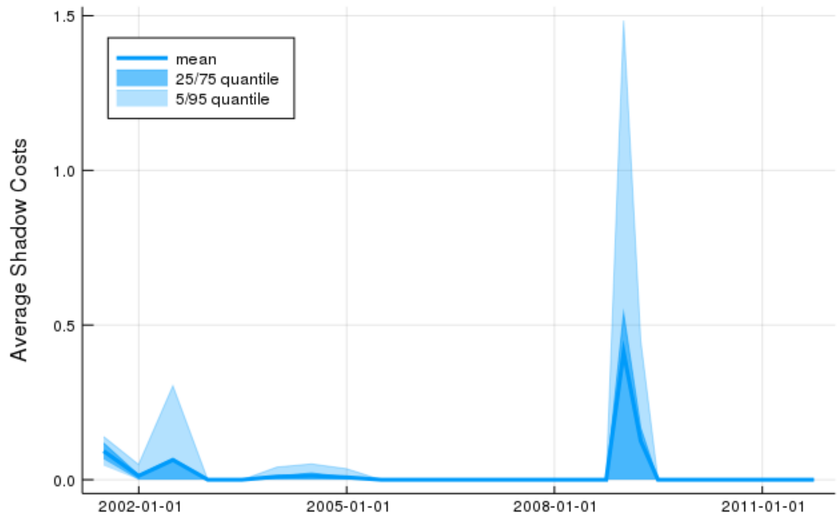

Figure 4: Average shadow cost of capital among lenders

	(1)	(2)	(3)	(4)	(5)
	Debt Growth	Loan Growth	Bond Debt Growth	Debt Interest Rate	Bond Interest Rate
Average Shadow Costs	-3.351***	1.152***	-8.254***	0.321*	0.544***
	(0.796)	(0.038)	(1.717)	(0.158)	(0.114)
Share held by LI	0.015	-0.025	0.171**	-0.012***	-0.011***
	(0.039)	(0.028)	(0.057)	(0.002)	(0.003)
Symmetric Lenders	0.063	0.067	0.217*	0.005	0.001
	(0.295)	(0.799)	(0.097)	(0.057)	(0.002)
Lender Similarity	0.007	0.003	-0.401	0.011***	0.010***
	(0.006)	(0.015)	(0.481)	(0.002)	(0.003)
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes
Time-Industry FE	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	OLS	OLS	OLS
N	2,661	1,944	2,639	2,640	2,612
R^2	0.110	0.044	0.092	0.506	0.592

Table 5: Financial outcomes

Note: Borrower characteristics include log assets, age, leverage, revenue over assets, and return on assets. Standard errors are clustered at the time-industry level and are reported in parentheses. Each time-industry cluster must have at least 12 observations.

	(1)	(2)
	Investment Rate	Employment Growth
Average Shadow Costs	-0.903***	-3.046***
	(0.054)	(0.735)
Share held by LI	-0.022	-0.049
	(0.019)	(0.062)
Symmetric Lenders	0.003	-0.029
	(0.006)	(0.027)
Lender Similarity	-0.001	0.001
	(0.142)	(0.400)
Borrower Characteristics	Yes	Yes
Time-Industry FE	Yes	Yes
Rating FE	Yes	Yes
N	2,537	2,301
R^2	0.380	0.201

Table 6: Real outcomes

Note: Borrower characteristics include log assets, age, leverage, revenue over assets, and return on assets. Standard errors are clustered at the time-industry level and are reported in parentheses. Each time-industry cluster must have at least 12 observations.

employment growth of the main specification 1. Firms with poorer average lender's health have both lower investment and employment growth rates than firms with healthier lenders.

It is worth comparing these results to what other studies found. Comparing two firms with an interquartile difference in firm-specific commercial paper lender's health **?** find a $11.5 * -0.10\% = -1.15\%$ reduction in commerical paper borrowing, a $11.5 * 0.14\% = 1.61\%$ increase in long-term debt issuance and an insignificant decrease of both cash holdings and investment activities. In my estimation most variation comes from the financial crisis, which was a more severe event than the European debt crisis for U.S. investors. Hence, a direct comparison between the effects of disruptions in the commercial paper market versus the corporate bond market is not possible. If I compare two firms with an interquartile difference in firm-specific life insurance lenders' health I find $0.53 * -8.2\% = -4.3\%$ decrease in corporate bond borrowings and a $0.53 * 1.15\% = 0.6\%$ increase in bank credit. Moreover, I find a which is $0.53 * -0.9\% = -0.47\%$ lower investment rate.

? compares firms at the 10th and 90th percentile and finds a 0.33% to 0.48% higher interest rate on new loans for firms who borrowed from lenders with ex-post lower health. I find a higher interest rate on both bond debt and overall debt by $1.01 * 0.54\% = 0.55\%$ and $1.01 * 0.32\% = 0.32\%$. The author reports employment growth differences of between 4% and 5.5%, while I estimate $1.01 * 3\% = 3\%$.

5 Conclusion

In this paper, I show that firm financing through the corporate bond market exhibits similar patterns of frictions as found in relationship banking. I use cross-sectional variation in the health of life insurance companies and security-level corporate bond holdings information to calculate a borrower-specific measure of average health among its lenders. This variation is then used to explain differences in financial and real outcomes of firms in the same industry sector and during the same time period. Firms with worse average lenders' health decrease borrowing, pay higher interest rates, decrease investment and employment compared to firms with healthier lenders. This evidence speaks for limited substitutability of lenders and types of debt. It also suggests that life insurance companies are an important source of debt financing.

A Proofs of Identifying Assumptions

Under the "shares are exogenous" assumption:

$$\frac{1}{S}\sum_{j\in S}\omega_{i,j,t-1}\epsilon_{j,t} \underset{p}{\rightarrow} 0 \quad \forall i,s,t$$

the key exogeneity assumption is fulfilled:

$$\frac{1}{S}\sum_{j\in S}\bar{\lambda}_{j,t}\epsilon_{j,t} = \sum_{i}\lambda_{i,t}\underbrace{\frac{1}{S}\sum_{j\in S}\omega_{i,j,t-1}\epsilon_{j,t}}_{\underset{p}{\rightarrow}0} \underset{p}{\rightarrow} 0 \quad \forall S,t$$

for finitely many investors I.

B NAIC Bond Rating and Charges

Life insurance companies must hold higher reserves if their bond portfolio is more risky according the NAIC bond rating. U.S. government bond receive no risk charge.

<table>
<tr><th></th><th>Moody’s</th><th>S&P</th><th>Fitch</th><th>NAIC SVO Category</th><th>Risk Charge</th></tr>
<tr><td rowspan="10">Investment grade</td><td>Aaa</td><td>AAA</td><td>AAA</td><td rowspan="7">1</td><td rowspan="7">0.004</td></tr>
<tr><td>Aa1</td><td>AA+</td><td>AA+</td></tr>
<tr><td>Aa2</td><td>AA</td><td>AA</td></tr>
<tr><td>Aa3</td><td>AA−</td><td>AA−</td></tr>
<tr><td>A1</td><td>A+</td><td>A+</td></tr>
<tr><td>A2</td><td>A</td><td>A</td></tr>
<tr><td>A3</td><td>A−</td><td>A−</td></tr>
<tr><td>Baa1</td><td>BBB+</td><td>BBB+</td><td rowspan="3">2</td><td rowspan="3">0.013</td></tr>
<tr><td>Baa2</td><td>BBB</td><td>BBB</td></tr>
<tr><td>Baa3</td><td>BBB−</td><td>BBB−</td></tr>
<tr><td rowspan="13">Non-investment grade</td><td>Ba1</td><td>BB+</td><td>BB+</td><td rowspan="3">3</td><td rowspan="3">0.046</td></tr>
<tr><td>Ba2</td><td>BB</td><td>BB</td></tr>
<tr><td>Ba3</td><td>BB−</td><td>BB−</td></tr>
<tr><td>B1</td><td>B+</td><td>B+</td><td rowspan="3">4</td><td rowspan="3">0.1</td></tr>
<tr><td>B2</td><td>B</td><td>B</td></tr>
<tr><td>B3</td><td>B−</td><td>B−</td></tr>
<tr><td>Caa1</td><td>CCC+</td><td rowspan="5">CCC</td><td rowspan="3">5</td><td rowspan="3">0.23</td></tr>
<tr><td>Caa2</td><td>CCC</td></tr>
<tr><td>Caa3</td><td>CCC−</td></tr>
<tr><td rowspan="2">Ca</td><td>CC</td><td rowspan="4">6</td><td rowspan="4">0.3</td></tr>
<tr><td>C</td></tr>
<tr><td>C</td><td rowspan="2">D</td><td>DDD</td></tr>
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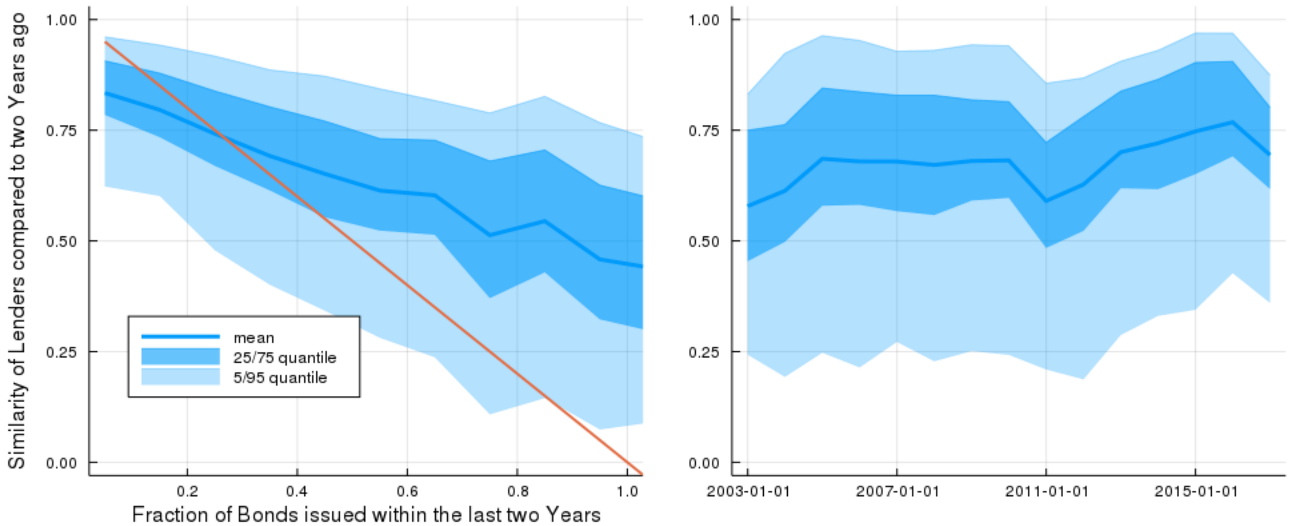

Figure 5: Similarity of lenders compared to two years ago

C Robustness

C.1 Similarity of lenders two years apart

The similarity measure $BC_{j,t}$ is not cumulative. For example, suppose firm j has two symmetric lenders and two consecutive estimates $BC_{j,1} = BC_{j,2} = 0.5$. This is consistent with the firm having the same lender composition if compared two years apart, if one of the lenders leaves in the first year, is substituted with a new investor, but again replaces that new investor in the second year. Hence, to make a case for higher lender turnover in 2009 and 2010 I calculate $BC^2_{i,t} = \sum_{i \in I} \sqrt{\omega_{j,i,t}\omega_{j,i,t-2}}$ and find the same drop.

C.2 Estimates leaving out downgraded Borrowers

	Debt Growth	Loan Growth	Bond Debt Growth	Debt Interest Rate	Bond Inter
Average Shadow Costs	-1.371	6.372*	-5.670**	0.348***	0
	(1.893)	(3.071)	(1.740)	(0.103)	
Share held by LI	0.029	-0.048	0.139	-0.014	
	(0.368)	(0.253)	(0.084)	(0.008)	
Symmetric Lenders	0.065***	0.100	0.235	0.004	
	(0.014)	(0.572)	(0.993)	(0.004)	
Lender Similarity	0.008	0.015	-0.372***	0.014***	
	(0.310)	(0.035)	(0.047)	(0.001)	
Borrower Characteristics	Yes	Yes	Yes	Yes	
Time-Industry FE	Yes	Yes	Yes	Yes	
Rating FE	Yes	Yes	Yes	Yes	
N	1,890	1,352	1,871	1,875	
R^2	0.114	0.051	0.090	0.515	

Table 7: Financial outcomes

Note: Borrower characteristics include log assets, age, leverage, revenue over assets, and return on assets. Standard errors are clustered at the time-industry level and are reported in parentheses. Each cluster must have at least 12 observations.

	Investment Rate	Employment Growth
Average Shadow Costs	-0.327**	-2.544***
	(0.125)	(0.333)
Share held by LI	-0.005	-0.055
	(0.622)	(0.059)
Symmetric Lenders	-0.002	-0.046***
	(0.002)	(0.010)
Lender Similarity	-0.001	0.008
	(0.118)	(1.502)
Borrower Characteristics	Yes	Yes
Time-Industry FE	Yes	Yes
Rating FE	Yes	Yes
Estimator	OLS	OLS
N	1,206	1,206
R^2	0.524	0.166

Table 8: Real outcomes

Note: Borrower characteristics include log assets, age, leverage, revenue over assets, and return on assets. Standard errors are clustered at the time-industry level and are reported in parentheses. Each cluster must have at least 12 observations.