The Financial Intermediation Premium in the Cross Section of Stock Returns

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Abstract

This paper documents a significant risk premium for financial intermediation risk in the cross section of equity returns. Firms that borrow from highly levered financial intermediaries have on average 4% higher expected returns relative to firms with low-leverage lenders. This difference cannot be attributed to differences in firm characteristics and is driven by firms' exposure to the financial sector. The dispersion in the leverage of financial intermediaries in the debt market forecasts the growth of macroeconomic aggregates. To shed light on the underlying mechanism behind the intermediation risk, I provide a tractable model with state-dependent borrowing costs.

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1 Introduction

In the aftermath of the Great Recession, public attention has once again been drawn to risks emerging in the financial sector. The financial industry has proved to be an important cogwheel in the economic mechanism. In good times, it is an essential source of financing for firms and a stimulus of growth. However, as Minsky (1969) argues, this economic stability and growth may be illusory, because highly levered financial intermediaries are more susceptible to negative shocks to their assets, as their equity is not sufficiently high to absorb these shocks (Haldane et al., 2010). When aggregate economic conditions deteriorate, high-leverage financial intermediaries may face losses in their loan portfolios, forcing them to contract their lending volume. The risk accumulated in the financial sector thus is transmitted by intermediaries to the whole economy, and as a result, even relatively safe firms can become risky if they borrow from high-leverage intermediaries and bear a higher cost of capital.

In this paper, I study the risk premium for financial intermediation that is incorporated in the cross section of equity returns of nonfinancial firms. I proxy for a firm's exposure to the financial intermediation risk using the average market leverage of financial intermediaries that provide external debt financing for this firm.[1] More precisely, I first retrieve the information on linkages between nonfinancial firms and financial institutions from the syndicated loan data. Next, I introduce a novel firm characteristic, namely the firm-specific financial intermediary leverage (*FILe*). For each firm I examine its current connections to financial intermediaries via lending relationships, that is, whether there exists an outstanding syndicated loan between a firm and a syndicate of intermediaries. After computing market leverage of each financial intermediary and aggregate resulting values in different ways, the *FILe* characteristic represents the average leverage of financial intermediaries associated with the firm.[2] Finally, I estimate the financial intermediation premium as an average return on high-minus-low portfolio strategy that goes long in top 30% *FILe* firms and goes short in bottom

[1] Throughout the paper I use market leverage unless book leverage is mentioned explicitly. As is standard in the literature, I define market leverage as the ratio of total debt to the sum of total debt and market equity. I relegate the discussion of differences between market and book leverage to the Appendix E.

[2] The process of matching between firms and banks is certainly endogenous. With this in mind, I suggest that the newly computed *FILe* characteristic reflects unobserved firm characteristics that determine firm's matching properties with a bank. In other words, *FILe* serves as a proxy for firm's matching choice of financial intermediaries.

30% *FILe* firms.

I document that firms which borrow from high-leverage financial intermediaries have on average 4% higher risk-adjusted annualized returns relative to firms with low-leverage lenders. The spread in expected returns cannot be explained by risk factors based on differences in traditional firm characteristics, such as size, book-to-market, investment, or operating profits factors. In line with findings from Chodorow-Reich (2014), the intuition behind the risk premium is that firms that borrow from high-leverage financial intermediaries may face refinancing risk, as their lenders may be in distress in bad times. Importantly, I show that the result is unlikely to be driven by 'bad matching', that is, riskier firms borrowing from riskier banks. The analysis of firm fundamentals in extreme portfolios indicates that high-*FILe* firms can be classified as safer investments for their financial intermediaries.[3]

I investigate the determinants of the risk premium in more detail and show that the firm's operational risk can offer a potential explanation for the return differential. Given that firms with high operating leverage, as measured by the ratio of operating costs to total assets, are largely affected during recessions, it could be the case that financial intermediary leverage risk is driven exclusively by firm operational risk. In actuality, this channel is important, but it cannot fully account for the observed premium. On the financial intermediary side, I uncover evidence that firms which borrow from high-leverage intermediaries have greater exposure to shocks stemming from the financial sector. This leads me to conclude that the documented risk premium is driven by the financial intermediation risk. Moreover, my robustness analysis reveals that the documented risk premium is significant under alternative specification of the sorting procedure. Among other cases, I consider a sample of firms with access to corporate bond financing, or an alternative computation of *FILe*, where only commercial banks-lenders are taken into account.

In the second part of my paper, I construct the financial intermediary leverage risk factor as a traditional high-minus-low portfolio strategy described above. I then demonstrate that this risk factor is distinct from factors commonly used in literature and that it is priced in the cross section of equity returns. Since my FILe risk factor incorporates the information on network

[3]The matching between riskier firms and safer banks and the other way around aligns with the notion of join capital structure decision of firms and banks (Gornall and Strebulaev, 2018)).

linkages between firms and financial intermediaries, it is distinct from factors derived from the time variation of aggregate values of financial intermediary leverage (Adrian et al., 2014; He et al., 2017).

Motivated by my asset pricing results, I construct a macroeconomic indicator that captures the spread in *FILe* in the cross section of nonfinancial firms. This indicator delivers a novel link between credit and business cycles. In particular, it positively forecasts industrial production growth and negatively predicts unemployment growth up to 4 quarters ahead. The results continue to hold after including macroeconomic controls, such as term and default spread, inflation and consumer credit growth. In anticipation of a recession, the spread in *FILe* shrinks that is associated with a contraction in lending volume. Following this, investment in the corporate sector falls and consequently industrial output growth decreases and unemployment rises. Importantly, the *FILe*-based indicator compares with other forward-looking predictors, such as price-dividend ratio, and offers up to 10% improvement in R-squared of predictive regressions.

To rationalize my empirical findings and offer a potential explanation behind the financial intermediation risk premium, I provide a reduced-form, Leland-type model with state-dependent borrowing costs. My empirical findings serve as main assumptions in my model. First of all, I document that on average high-*FILe* firms face lower borrowing costs on their loans compared to low-*FILe* firms. This result is in line with a rationing that large, high-leverage banks can undercut low-leverage banks and offer firms better lending terms. Second, I show that high-*FILE* firms face an increase in their borrowing cost in bad times, that is, if their lender is in distress. In the economy with ex ante identical nonfinancial firms with respect to their capital and productivity, I compare firms which borrow from high- and low-leverage intermediaries. Ex post firms differ with respect to their borrowing cost. Precisely, there is a trade off between cheap financing that may become extremely costly in bad times and more expensive, but stable funding. As a result, firms associated with high leverage banks face refinancing risk, which is priced by investors. The firm's probability of default increases and shareholders demand higher expected equity returns.

My work is related to a recent study by Schwert (2018), who examines the implication of the matching mechanisms between banks and firms for credit provision. In contrast to his work, this paper takes existing lending relationships as given and focuses on the asset pricing implications of the matching between firms and banks.

My study complements the growing literature on intermediary asset pricing. Among others, Adrian et al. (2014), Adrian et al. (2010), and He et al. (2017) argue that financial institutions, such as security broker dealers or prime dealers, represent the marginal investor in the economy, since they hold and trade assets in multiple financial markets. Therefore, the wealth and leverage of financial intermediaries exhibit strong predictive power for macroeconomic fluctuations, as well as for expected returns in numerous asset classes. In addition, Muir (2017) shows that the health of the financial sector is essential in understanding why risk premia vary over time.

The common thread of previous studies is that they investigate properties of financial intermediaries in the aggregate. In contrast to this approach, I focus on more granular borrower-lender relations and analyze how returns of an individual firm are affected by the leverage of a (group of) financial intermediaries. Importantly, this allows me to examine the differential impact of financial shocks on nonfinancial firms. To my knowledge, this paper is the first to study the asset pricing implications of the leverage of a firm's financial intermediary.

My theoretical model contributes to the literature on equilibrium asset pricing models with financial intermediaries, like He and Krishnamurthy (2012, 2013) and Brunnermeier and Sannikov (2014), to name just a few. Building on the work of Gomes and Schmid (2010), who establish a link between stock returns and firm leverage, I propose a simple mechanism by which the leverage of a firm's lender can influence the expected return on the firm's equity.

This paper proceeds as follows. In Section 2, I describe the data set and the empirical strategy used to quantify the financial intermediation premium. Moreover, I analyze the determinants of the premium on both the borrower and lender sides. In Section 3, I introduce the financial intermediary leverage risk factor and study its asset pricing properties. Then, in Section 4, I present a stylized theoretical framework to rationalize the observed intermediation risk premium. Section 5 concludes.

2 Financial Intermediary Leverage Risk

In this section, I develop an approach to measure the financial intermediation risk premium in the cross section of nonfinancial firms' equity returns. In particular, I sort firms based on their exposure to financial intermediation risk, as measured by financial intermediary leverage, and document a significant spread between extreme portfolios. I further show that the identified risk premium is robust to alternative specifications of portfolio sorting procedures. Moreover, I analyze lender and borrower characteristics to distinguish between risks on the firm side and those originating within the financial intermediation sector.

2.1 Data

To connect nonfinancial corporate firms to their financial intermediaries, I retrieve information on lender-borrower links from the DealScan syndicated loans database provided by Thomson Reuters. This data set allows me to identify a group of financial institutions (a syndicate) that supplies external debt financing to a firm. For the period from the origination of the loan until its maturity date, I consider the firm to be linked to its lenders, that is, to be exposed to the shocks of its lender. Unlike in Europe, the syndicate loan market is well developed in the US. For instance, Ivashina and Scharfstein (2010) document that the syndicated loan market represents up to 80% of the debt financing market. The data set coverage starts in 1986 and represents a significant share of the market from early 1990 on. A further discussion on the representativeness of the sample can be found in the appendix.

In addition to the existing link to Capital IQ's *Compustat* balance sheet information for DealScan borrowers first developed by Chava and Roberts (2008), I manually create an analogous linking table for DealScan lenders.[4] Importantly, in the case of subsidiary banks I track their bank holding company and link firms to this holding company. An argument in favor of looking at the balance sheet data and leverage of bank holding companies instead of their subsidiaries is as follows. When a subsidiary is in distress, its parent company may choose to liquidate the subsidiary or to reallocate available funds in order to rescue the daughter

[4] The coverage of bank balance sheet data provided by Compustat is rather scarce after 2009. However, I require only the statement on debt outstanding for my analysis.

company. However, when the bank holding company finds itself in distress, the poor financial health of a subsidiary provides an reinforcing signal about the increased financing risk to the nonfinancial corporate sector.

When linking a firm to its lenders, I consider all participants of the syndicate, instead of only focusing on lead-arrangers in the syndicate (e.g., Schwert, 2018). Although the lead-arrangers have an important monitoring role in the lending process, the risk is shared among all participants in the case of an adverse event. This strategy enables me to achieve a higher dispersion in the firm exposure to financial intermediation risk.[5]

Since the main analysis of the paper employs market leverage as an indicator of the intermediaries' financial conditions, I require the equity of financial institutions to be publicly traded. I collect monthly stock returns and market equity values from CRSP/Compustat Merged. The information on corporate bond financing comes is Mergent FISD and Compustat S&P ratings. The final sample represents approximately 7,000 borrowers and 500 lenders and covers the period from 1986 to 2014. The time frame is short compared to those of the samples used in the asset pricing literature. However, before 1980 the process of financial intermediation was less developed and lacked economic significance (Haldane et al., 2010). Finally, the data on the 3-months LIBOR rate and the credit spread (Baa-Aaa) are retrieved from Federal Reserve Economic Data (FRED) from the Federal Reserve Bank of St. Louis.

2.2 Portfolio Sorting

In this section, I outline the sorting procedure of nonfinancial firms into portfolios based on the leverage of their financial intermediaries. In contrast to the analysis of time variation in the aggregated leverage of financial intermediaries, as studied, for example, by Adrian et al. (2014) and He et al. (2017), this sorting exercise focuses on the cross-sectional heterogeneity in the firms' exposure to risks stemming from the providers of their external debt financing.

In my benchmark specification, I construct three portfolios with low, medium, and high fi-

[5]In general, the debt contract is signed between a firm and an entire syndicate. Therefore, any changes to loan terms have to be negotiated with the syndicate not a particular financial intermediary. Even though the lead bank is in charge of arranging the deal, it still needs an approval of the syndicate to alter it.

nancial intermediary leverage (FILe) as follows. First, based on information from syndicated loans, I establish links (borrower-lender relationships) between firms and the financial institutions from which these firms borrow. I consider each link valid for the duration of the loan, from the date of origination until maturity. Second, for each borrower I compute the simple average of the market leverage of the financial intermediaries (lenders) linked to this firm by an outstanding lending relationship.

Market leverage is defined as the ratio of book value of total debt (debt in short-term liabilities plus long-term debt) over the sum of market equity and book value of total debt. The choice of leverage as an indicator of the financial sector condition is justified by recent findings by Adrian et al. (2010, 2014), who show that the change in aggregate financial intermediary leverage is a strong predictor of macroeconomic activities and a key determinant of risk premia.[6] In addition, large financial institutions, such as prime dealers in He et al. (2017), are active in a wide spectrum of financial markets and represent a systemically important component of the economy. It is thus reasonable to expect that shocks to their leverage, that is, risk bearing capacity, potentially affect asset returns in multiple markets.

Based on the average leverage of their lenders, I sort all connected borrower firms into three portfolios, using the 30th and 70th percentiles of the leverage distribution as cutoff points. The time series of *FILe* of the constructed portfolios is depicted in Figure 1. The data indicate the significant dispersion in *FILe* in the syndicated loan markets and that this dispersion varies over time. Since the accounting information on debt I use to compute leverage becomes public to investors only with a delay, I form portfolios in March and then compute corresponding value-weighted portfolio returns. The results of this sorting procedure are documented in Table 1.

The main finding is that firms that borrow from high-leverage financial intermediaries earn a risk premium of 3.80% annually relative to firms that deal with low-leverage lenders. This premium can be viewed as an estimate of financial intermediation costs derived from the cross section of stock returns. In this case, investors demand a premium for being exposed to financial intermediation risk in addition to firm-specific risks.

[6] In these studies, the authors use book leverage as a predictor. My main findings hold for both the market and book leverage of financial intermediaries.

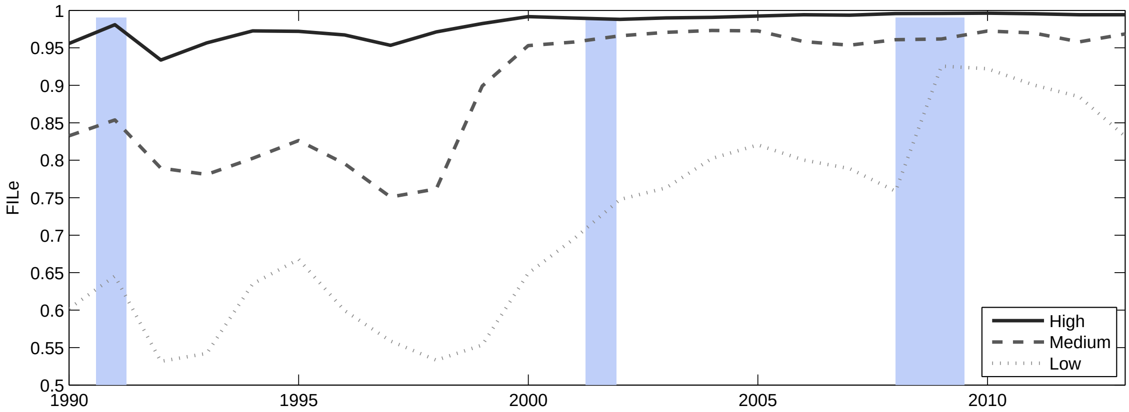

FIG. 1: Dispersion in Leverage of Financial Intermediaries (Syndicated Loans Market)

This figure depicts annual time series of the dispersion in market leverage of financial intermediaries in the syndicated loans market. I observe a cross section of firms together with their lenders as of the end of each year. For each firm in the cross section I compute the average market leverage of the syndicate from which this firm borrows. In the next step, I determine the 30th and 70th percentiles of the financial intermediary leverage (FILe) distribution and assign the firm into one of three groups: low, medium, or high *FILe*. I then compute an average leverage value for each group. Firms are reassigned into the groups each year. The sample spans the period from 1988 to 2014.

Next I show that the premium remains significant after controlling for Fama and French (1993) three factors and Fama and French (2016) five factors. Importantly, the sign of the spread in average returns is opposite to that of the difference in firm leverage. In fact, both the book and market leverage of firms in the high financial intermediary leverage portfolio are significantly lower. This finding highlights that high-leverage banks are not necessarily matched with high-leverage firms.[7] Furthermore, firms in extreme portfolios are similar in their exposures to market risk, as measured by market β in the Fama-French three factor model, as well as their total and idiosyncratic volatilities. Finally, firms in the high-*FILe* portfolio are smaller in terms of log market equity and have lower book-to-market ratios. Since these differences are not statistically significant, the uncovered risk premium is unlikely to be attributable to the size or value anomaly.

Overall, the evidence indicates that the risk premium earned by firms in the high financial

[7]Indeed, the matching of high-leverage banks with low-leverage firms can be optimal for banks from a risk management perspective (Gornall and Strebulaev, 2018). A large bank which lends to low-leverage firms is able to achieve high leverage since the issued loans are safe. On the contrary, a bank that chooses to invest in high-leverage firms tends to limit risks by lowering its own leverage.

TABLE 1: Financial Intermediation Risk Premium

	Low	Mid	High	High−Low
Excess return	6.50*	7.13**	10.30***	3.80*
	(1.88)	(2.41)	(3.38)	(1.92)
CAPM α	−1.05	0.15	3.23***	4.28**
	(−0.78)	(0.18)	(2.61)	(2.40)
FF3 α	−1.34	−0.32	3.63***	4.97***
	(−0.89)	(−0.35)	(2.90)	(2.57)
FF5 α	−1.20	−0.78	2.73**	3.93**
	(−0.79)	(−0.76)	(2.23)	(2.08)
Sharpe ratio	0.35	0.44	0.61	0.40
FILe	0.71	0.89	0.98	0.27***
σ(*FILe*)	0.29	0.16	0.27	−0.02*
Id. Vol.	0.25	0.23	0.24	−0.01
Tot. Vol.	0.32	0.31	0.32	0.01
Firm market leverage	0.33	0.32	0.29	−0.04**
Firm book leverage	0.23	0.22	0.20	−0.03***
Firm log(ME)	6.13	6.74	5.93	−0.20
Firm BE/ME	0.83	0.79	0.77	−0.06
FF3 β_{MKT}	1.09	1.10	1.09	0.00
$[\beta^5_{MKT}, \beta^{95}_{MKT}]$	[0.90, 1.33]	[0.98, 1.25]	[0.97,1.29]	–

Notes - This table provides annualized value-weighted returns of portfolios of nonfinancial firms sorted according to the market leverage of their financial intermediary (*FILe*). First, using the data on syndicated loans I establish a link between a nonfinancial firm and a group of financial intermediaries from which the firm obtains a loan. Next, for each firm I compute the average of the market leverage ratios of the linked financial intermediaries and assign the resulting value to the firm. I then sort firms into three portfolios according their average financial intermediary leverage. I select the 30th and 70th percentiles of the leverage distribution as cutoff points. Return data are monthly over the period 1986:07–2014:12. *FILe* denotes the average of financial intermediaries' leverage ratios, σ(*FILe*) denotes the average standard deviation of financial intermediaries' leverage ratios. Id. Vol. and Tot. Vol. represent the average idiosyncratic and total volatiles of stock in a portfolio. *CAPM* α, *FF3* α, and *FF5* α denote average excess returns unexplained by the CAPM, Fama-French three factor, and the Fama-French five factor models, respectively. Definitions of firm-related characteristics are provided in Appendix A. The numbers in parentheses are t-statistics adjusted according to the Newey and West (1987) procedure. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

intermediary leverage portfolio cannot be directly explained by the firm fundamentals commonly used in the literature. The results in Table 1 in contrast suggest, if anything, that expected returns for these firms should be even lower than those for firms in the low-*FILe* portfolio. I therefore conclude that the risk premium comes from the differential exposure to the financial intermediation risk. An investor demands a higher expected return for a reasonably safe firm that borrows from a highly levered bank as a fair compensation for financial intermediation risk.

Before investigating the properties of firms and their financial intermediaries in greater detail, I show that the intermediation risk premium is robust to alternative specifications of the portfolio sorting procedure.

2.3 Robustness

In this section, I perform a series of robustness checks with respect to the described baseline specification. Expected returns on a strategy that is long in firms with high financial intermediation risk exposure and short in firms with low intermediation risk under alternative specifications are presented in Table 2.

Rated firms. The first specification focuses on a more homogeneous subsample of firms. In particular, I select only firms that in addition to bank financing have access to the corporate bond market. Following Chava and Purnanandam (2011) I use the S&P Domestic Long Term Issuer rating to distinguish between bank-dependent and non-bank-dependent borrowers, since rated firms have access to public debt markets.

In my sample, 37.3% of firms are rated by Standard& Poor's.[8] The first column in Table 2 indicates that there is a significant risk premium for firms that borrow from high-leverage intermediaries even if these firms have an opportunity to substitute bank financing with public debt. The financial intermediation risk becomes highly relevant in bad times, when banks face financial constraints and are unable to issue new loans to firms. Unfortunately, at the same time, the public debt markets become unattractive to investors. This intuition suggests that firms are prevented from switching to corporate bond financing in bad times. This result is in line with findings of Carvalho et al. (2015), who show that access to corporate bond financing does not enable firms to alleviate financial intermediation risk.

In the case of S&P-rated firms, the premium is highly significant and is of a higher magnitude than in the benchmark specification. Given that rated firms are generally larger and more

[8]The stated share is based on the total number of firms. In terms of market-value shares and the economic significance, the number is higher, since it is usually larger firms that participate in public debt markets.

TABLE 2: FILe Factor: Alternative Specifications

	Subsample of loans		All loans			
	S&P-rated firms	Commercial banks	Loan weighted	Book leverage	Market leverage *Recessions*	Market leverage *Booms*
Excess return	4.53***	3.92**	2.92*	2.28	7.67	3.35*
	(4.21)	(2.38)	(1.68)	(1.40)	(1.31)	(1.76)
CAPM α	4.88***	3.67**	3.34**	2.81*	6.87	3.96**
	(4.01)	(2.34)	(1.98)	(1.76)	(1.10)	(2.11)
FF3 α	5.18***	4.26***	3.73**	3.27**	6.99	4.82**
	(3.77)	(2.87)	(2.25)	(2.32)	(1.13)	(2.40)

Notes - This table reports annualized value-weighted returns of the financial intermediary leverage factor (FILe) for alternative specifications. The FILe factor is defined as a portfolio strategy which is long in nonfinancial firms that borrow from highly levered financial institutions and short in firms with low-leverage lenders. The first section, "Subsample of loans," provides information on the FILe factor specification, which includes only firms with a long-term issuer rating by Standard & Poor's ("S&P rated") and the specification with firms borrowing from financial intermediaries classified as commercial banks based on their SIC code ("Commercial banks"). The second section, "All Loans," includes the same set of loans as the benchmark specification. Columns "Loan weighted," and "Book leverage" present returns of the FILe factor constructed by sorting nonfinancial firms on market leverage of lenders weighted by loan amount, and average book leverage, respectively. Columns "Recessions" and "Booms" reflect results of the benchmark specification across NBER recessions and booms. *CAPM* α, *FF3* α, and *FF5* α denote average excess returns unexplained by the CAPM, Fama-French three factor, and Fama-French five factor models, respectively. The monthly return data span the period 1986:07–2014:12. The numbers in parentheses are t-statistics adjusted according to the Newey and West (1987) procedure. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

transparent to investors, the information about the firms' sources of funds becomes more important for the valuation.

Commercial banks. The participant pool of the syndicated loan market covers a broad range of financial institutions: commercial banks, security broker dealers, insurance companies, and various nondepository institutions, among others. To address potential heterogeneity in the business structure and accounting standards, I modify the calculation of financial intermediary leverage by considering only commercial banks within each syndicate. The second column in Table 2 presents results of this sorting. I find the risk premium earned by firms in the high-*FILe* portfolio is significant even after adjusting for the market, size, value, investment, and operating profitability factors. Contrary to the conclusion of Adrian et al. (2010) that only the leverage of security broker dealers but not commercial banks has predictive power for future expected returns, I document that the firms' differential exposure to the commercial banking sector is reflected in their expected returns. In particular, a firm that borrows from a highly levered commercial bank earns a risk premium of 3.92% annually relative to a firm with a low-leverage lender. These findings support my approach of accounting for all participants within a syndicate when measuring a firm's exposure to the financial sector. Commercial banks, although smaller relative to security broker dealers, are still an important part of the financial sector.

Loan weighted. My next robustness check addresses my decision to weigh the leverage of all of a firm's lenders equally when computing the *FILe* characteristic. Since the data on each financial intermediary's contribution to the syndicate are scarce, I modify the procedure only for cases in which a firm has two or more loans outstanding at the same time. Under these conditions, I first compute the *FILe* for each loan using equal weighting and then aggregate these values into the firm's *FILe* by weighting each loan-specific *FILe* by the respective loan amount. The results of this exercise are presented in the fourth column in Table 2. My main findings remain valid with respect to loan-weighting modification.

Book leverage. Results presented in the fifth column in Table 2 are analogous to the benchmark specification, with the only difference being that instead of computing market leverage of lenders I use book leverage. In this case, book leverage is defined as the ratio of total debt over total assets. The results still hold, but they are comparatively weaker. In Appendix E, I argue that market rather than book leverage is a more appropriate measure of financial intermediary leverage despite the fact that intermediary balance sheets are marked-to-market.

Booms versus recessions. Finally, I separately estimate the risk premium for boom and recession periods as defined by the NBER. The rightmost two columns of Table 2 indicate that the risk premium is statistically significant during booms and insignificant during recessions.

The lack of significance during market downturns is driven by gradually resolving uncertainty about the firm's future refinancing risk. In fact, the financial intermediation risk materializes only for a fraction of high-*FILe* firms, while lenders of remaining firms either survive the recession periods or they are saved by the government ('too-big-to-fail'). As a result, the point estimate of the risk premium becomes insignificant.

To summarize, the above results provide evidence that my main findings are robust to alternative specifications.[9] I document the results of additional robustness tests with respect to the weighting scheme of individual bank leverages within *FILe*, as well as loan importance to a firm and types of loans in Appendix C.

2.4 Borrower and Lender Characteristics

In this section, I analyze the properties of the extreme portfolios in greater detail. I start by investigating the existing lending relationships by comparing firm fundamentals, characteristics of firms' financial intermediaries, and properties of outstanding loans. My main findings are summarized in Table 3.

The top panel of Table 3 shows financial intermediary characteristics for the firms in the high- and low-*FILe* portfolio. First, in line with Laeven et al. (2014) I find that high-leverage financial intermediaries are larger in terms of total assets. As a result, firms which borrow from these intermediaries inherit their greater vulnerability to systemic financial shocks through the lending relationship. Second, firms in the high-*FILe* portfolio obtain their external debt financing from syndicates with a smaller number of participants and larger loan amount per participant. Such syndicates enjoy arguably lower diversification benefits, since in the case of the firm's default each participating intermediary faces larger losses. The lower degree of diversification is supported by significantly lower variation in individual financial intermediary leverage that contribute to high-*FILe* values (see Table 1). Moreover, in the extreme case of the default of one of the syndicate participants, surviving intermediaries will have to cover the funding promised by the failed intermediary.

Furthermore, the composition of the high-*FILe* portfolio syndicates is shifted towards financial institutions with higher systemic risks, such as security broker dealers. In contrast, the share of commercial banks is lower in these syndicates. Finally, I find no significant difference in terms of the loan loss provision by financial intermediaries or the collateralization of loans

[9] Results of the double sorts of the FILe factor portfolio with respect to different firm characteristics are presented in Table G5.

TABLE 3: Portfolios Sorted on FILe

Financial intermediary characteristics	Low	High	High−Low
log($Size$)	10.95	12.66	1.71***
# Intermediaries in syndicate (merged data)	3.52	1.59	−1.93***
# Intermediaries in syndicate (loan data)	8.53	4.64	−3.88***
Share of commercial banks	0.87	0.80	−0.07***
Share of security broker dealers	0.03	0.05	0.02*
Loan amount per intermediary (in $ millions)	37.97	49.95	11.98
Secured loans	0.45	0.46	0.01
Loan loss provision (%)	0.32	0.37	0.05

Debt financing characteristics	Low	High	High−Low
Firm total cost of borrowing (bps)	272.47	167.36	−105.11***
Interest Expenses (%)	2.28	1.91	−0.36*
Loan amount over firm total assets (%)	36.42	25.81	−10.62***
Corporate bonds issued over total assets (%)	29.34	29.97	0.62
Bond issuer rating	11.06	10.37	−0.69***
Short-term debt over total debt (%)	18.02	21.22	3.20***
Cash over total assets (%)	7.93	10.08	2.15***
Net equity issuance (%)	1.58	1.44	−0.14

Notes - This table contrasts properties of firms and their respective lenders in the high and low financial intermediary leverage portfolios. Using the sorting procedure on the lender leverage, I assign nonfinancial firms into three portfolios with low, medium, and high leverage of their financial intermediaries. Subsequently, I collect balance sheet and loan information for the firms in the portfolios. Statistics in the table represent average values across firms in a portfolio and over time. Data are annual and span the period from 1987 to 2014. The row "# Intermediaries in syndicate (loan data)" states how many financial institutions form a syndicate that lends to a firm, while the row "# Intermediaries in syndicate (merged data)" specifies how many of these lenders are present in the merged DealScan/Compustat/CRSP dataset. Variable definitions with their respective data sources are provided in Appendix A. The last column shows the difference between high- and low-*FILe* portfolio and its significance based on a two-sided t-test with unknown variance. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

by firms between the high- and low-*FILe* portfolios.

While the evidence in the top panel of Table 3 clearly points towards high intermediation risk in the high-*FILe* portfolios, the results presented in the bottom panel indicate that firms in the high-*FILe* portfolio ought to be less risky. In addition to having lower leverage and a lower book-to-market ratio (see Table 1), these firms face lower total costs of borrowing as measured by Berg et al. (2016) and total interest expenses, have better credit ratings, and are less bank-financing dependent.[10] The latter can be seen from a lower average ratio of the loan amount to firm total assets and a higher ratio of public debt amount (corporate bonds) to total assets. Table 3 additionally shows that high-*FILe* firms have a higher exposure to refinancing risk through significantly higher share of short-term borrowings in their debt portfolio compared to low-*FILe* firms. Unsurprisingly, to compensate for this exposure high-*FILe* firms choose to hold about 2% more cash and cash-like securities. Finally, although high-*FILe* face high cost of equity, they do not significantly differ from low-*FILe* firms with respect to net equity issuance, as one would expect high-*FILe* firms to repurchase their equity in order to decrease their external financing cost.

In the next step, I gather additional evidence that, solely based on balance sheet data, firms in the high-*FILe* portfolio do not appear to be riskier than firms in the low-*FILe* portfolio. Table 4 provides estimates for the panel linear probability model that investigates the determinants of whether a firm is assigned to the high-*FILe* portfolio.[11] More specifically, I estimate the following probability model:

$$\mathbb{P}\{Firm_{ij} \in \textit{High portfolio at } t+1 | X_{ij,t}\} = X'_{ij,t}\beta + f_i + a_{j,t} + u_{ij,t+1}, \tag{1}$$

where $X_{ij,t}$ represents a set of firm-specific balance sheet variables of firm i in industry j, and f_i and $a_{j,t}$ control for firm and year-industry fixed effects.

In line with my previous findings, the regression results in columns (1)–(4) in Table 4 show that firms in the high-*FILe* portfolio have lower market leverage, higher operating leverage, and lower interest expenses. In addition, I document that higher tangibility of assets and higher working capital significantly increase the probability that a firm will borrow from a high-leverage intermediary.

The negative effect of size, as measured by sales, on probability comes from the largest firms in the sample being assigned to the middle portfolio (see Table 1). When I exclude the middle portfolio, the coefficient of log(*Sales*) becomes insignificant.

[10]For credit ratings, I assign numerical values for each category starting from 1 for AAA, with an increment of 1 for each subsequent category. Higher numerical values imply lower credit ratings.

[11]I discuss the results of the linear probability model here due its greater tractability. Table G3 reports the results of the probit model. All conclusions from the main analysis continue to hold.

TABLE 4: Firm-Level Determinants of High-FILe Portfolio Firms

Linear probability model: $\mathbb{P}\{\text{ Firm}_{ij} \in \text{High-FILe portfolio at } t+1 | X_{ij,t}\} = X'_{ij,t}\beta + f_i + a_{j,t} + u_{ij,t+1}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm leverage	−0.159***	−0.148***	−0.129***	−0.124***	−0.112***	−0.129***	−0.132***	−0.126***
	(−9.77)	(−9.05)	(−7.27)	(−6.52)	(−4.94)	(−4.49)	(−6.74)	(−6.37)
log(*Sales*)		−0.030***	−0.031***	−0.022***	−0.025***	−0.021**	−0.018***	−0.026***
		(−5.83)	(−5.83)	(−3.49)	(−3.66)	(−2.21)	(−2.72)	(−3.85)
Profitability			0.097***	0.061*	0.059	0.020	0.052	0.037
			(2.93)	(1.67)	(1.61)	(0.34)	(1.35)	(0.86)
Tangibility			0.097***	0.164***	0.164***	0.180***	0.181***	0.150***
			(2.77)	(4.34)	(4.32)	(3.20)	(4.59)	(3.84)
Operating leverage			0.007**	0.041***	0.038***	0.089**	0.052***	0.043***
			(2.36)	(2.93)	(2.63)	(2.47)	(3.62)	(2.91)
Bond issuer			−0.017*	−0.008	−0.007	−0.004	−0.011	−0.006
			(−1.80)	(−0.85)	(−0.71)	(−0.26)	(−1.10)	(−0.56)
Book-to-market				−0.001	−0.001	−0.001	−0.001	−0.001
				(−0.65)	(−0.64)	(−0.35)	(−0.81)	(−0.82)
Working capital				0.122***	0.110***	0.103***	0.141***	0.113***
				(4.68)	(3.98)	(2.71)	(5.20)	(4.06)
Interest expenses				−0.001**	−0.001***	−0.001	−0.002***	−0.001***
				(−2.54)	(−2.59)	(−1.19)	(−2.75)	(−2.66)
log(*Sales*)*Op. leverage				−0.007***	−0.006**	−0.010**	−0.009***	−0.007***
				(−2.66)	(−2.35)	(−2.12)	(−3.43)	(−2.68)
O-score					−0.004			
					(−1.13)			
DD						−0.000		
						(−1.19)		
KZ-index							0.000	
							(0.62)	
Z-score								0.004
								(0.97)
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year-industry FE	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.079	0.081	0.082	0.087	0.087	0.120	0.090	0.087
# Obs.	30523	30470	30364	27724	27630	14547	26349	26662

Notes - This table provides panel regression estimates of the linear probability model that determines the probability of a firm to be assigned to the high-*FILe* portfolio. The dependent variable is zero for the low- and medium–*FILe* portfolios and one for the high-*FILe* portfolio. I utilize accounting data at the end of year t to determine the probability that a firm will be assigned to the high-*FILe* portfolio in the next period. Variable definitions are provided in Appendix A. Data is annual and span the period from 1987 to 2014. I report t-statistics in parentheses. All regressions include firm and year-industry fixed effects. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Reported R^2s do not take fixed effects into account.

The only firm characteristic that can explain the riskiness of high-*FILe* portfolio firms is operating leverage.[12] In this regard, Novy-Marx (2011) shows that firms with higher operating leverage earn higher returns. I discuss the operating leverage channel in greater detail in Section 2.5. Lastly, I do not find supporting evidence that either firms' profitability or their book-to-market ratio is an important determinant for membership in the high-*FILe* portfolio.

[12]In line with Novy-Marx (2011), I measure operating leverage as the ratio of operating expenses to total assets.

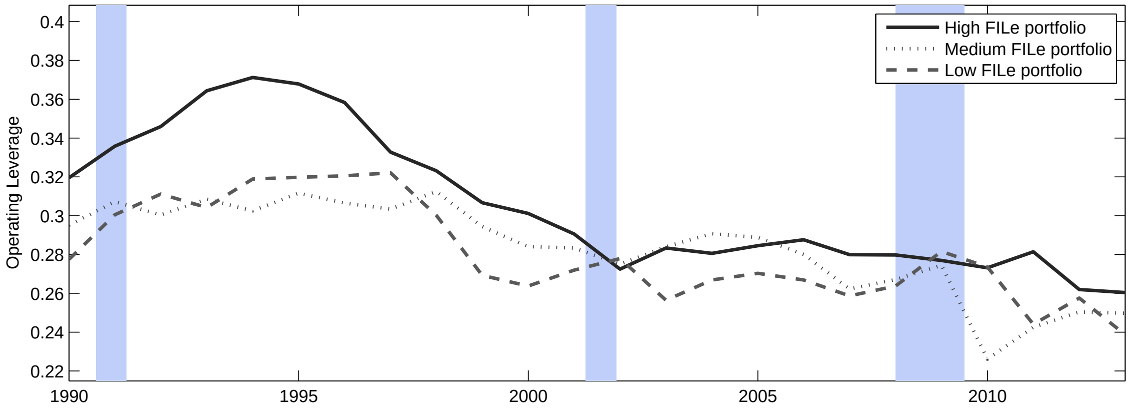

FIG. 2: Operating Leverage of Portfolios Formed on Financial Intermediary Leverage

This figure depicts annual time series of the equally weighted average firm operating leverage for three portfolios constructed by sorting firms on their *FILe*. I observe a cross section of firms together with their lenders as of the end of each year. For each firm in the cross section I compute the average market leverage of the syndicate from which this firm borrows. In the next step, I determine the 30th and 70th percentiles of the *FILe* distribution and assign each firm into one of three groups: low, medium, or high *FILe*. I then compute the average operating leverage, as the ratio of operating costs (costs of goods sold [COGS] and administrative and general expenses [XSGA]) to total assets. The firm balance sheet data span the period from 1988 to 2014.

Specifications (5)–(8) in Table 4 show that indicators of firm financial constraints or distress have no predictive power regarding the likelihood that a firm will borrow from high-leverage intermediaries. Further results on the relation between firm constraints measures and the leverage of its lender are presented in Appendix Tables D2 and D3.

2.5 Operating Leverage Channel

In this section, I turn to the discussion of the operating leverage channel as a potential source of riskiness of firms in the high-*FILe* portfolio. In a theoretical model, Obreja (2013) and Carlson et al. (2004) show that operating leverage is especially problematic during recessions. In times when profits decrease, firms with high operating leverage, that is, high production costs, incur additional losses if they cannot easily scale down their production. In particular, Obreja argues that due to abnormally high losses, high operating leverage firms experience a decrease in their equity value and at the same time an increase in the equity risk premium during economic downturns.

My first piece of empirical evidence highlighting the importance of the operating leverage channel with regard to financial intermediation risk is presented in Figure 2. In this figure, I depict equally weighted averages of operating leverage in three portfolios constructed by sorting firms on their *FILe*. The operating leverage of firms in the high-*FILe* portfolio (solid line) is almost always larger than the operating leverage of the low-*FILe* portfolio firms (dashed line), with two exceptions during the recent recessions. However, sorting on financial intermediary leverage does not translate into monotonic sorting with respect to operating leverage. Note that operating leverage of the medium-*FILe* portfolio (dotted line) travels outside the bounds outlined by the high- and low-*FILe* portfolios.

My second set of results is based on an industry analysis. To determine which types of firms are more likely to deal with high-leverage financial intermediaries, I divide all firms into industries based on their one- and two-digit SIC codes and compare the types of financial intermediaries (high or low leverage) which are predominant in those industries. I find that high-leverage intermediaries finance a larger share of manufacturing firms, particularly, firms that specialize in the production of chemicals and industrial, commercial, and electronic equipment. Moreover, these intermediaries also deal with transportation manufacturers (including railroad, aircraft, and ship builders) and durable goods wholesale traders. On average, a firm with high production costs and procyclical profits is more likely to borrow from a high-leverage intermediary. In contrast, I document that low-leverage intermediaries are more active in the communication and service industries. In my benchmark sample, a typical firm from an industry with a larger share of low-leverage intermediaries has a 16.6% smaller operating leverage than a comparable firm from an industry financed by high-leverage intermediaries.

In the final part of my analysis, I construct two versions of the operating leverage factor developed by Novy-Marx (2011). The first is constructed from the entire cross section of stocks, while the second factor includes only firms from my sample. The operating leverage factor that takes into account the entire cross section yields a negligible correlation with the FILe factor. However, with the operating leverage factor constructed using my sample, the correlation increases to 10.1% for monthly returns and 26% for quarterly returns. In light of this correlation, I conclude that the financial intermedation risk premium is unlikely to be fully explained by firm operating leverage.

Overall, these findings suggest that operational risk, although a potentially important driver of the equity premium earned by high-*FILe* portfolio firms, does not entirely explain this premium. Based on theoretical and empirical evidence, operating leverage and FILe risk are distinct dimensions that mutually amplify each other in the cross section of equity returns.

3 Asset Pricing

In this section, I study the asset pricing properties of the financial intermediary leverage factor (FILe factor). First, I explore whether the FILe factor can be spanned by existing risk factors common in the empirical asset pricing literature. In particular, I focus on the factors reflecting firms' investment and profitability risks together with factors constructed by aggregating the balance sheet data of the largest financial institutions. Second, I employ Fama-MacBeth regressions to measure the market price of risk associated with the FILe factor in the cross section of equity returns. Finally, I document that financial intermediation risk presents a systemic risk in the economy by highlighting the properties of the spread in intermediary leverage growth as a predictor of key macroeconomic variables.

3.1 Time-Series Analysis of the FILe Factor

In order to assess whether the risk coming from the financial intermediation sector is novel to the risk factors common in the literature, I use a time-series factor regression of the form:

$$FILe_t = \alpha_{FILe} + \beta F_t + \varepsilon_t, \tag{2}$$

where F_t denotes a set of factors. If the risk captured by the FILe factor can be spanned by a set of factors F_t, then α_{FILe} should be insignificant. Unconditional correlations between the FILe factor and other factors are presented in Table G2.

Estimation results of regression (2) for the selected asset pricing models are provided in Ta-

TABLE 5: Time-Series Analysis of the FILe Factor

Carhart		FF5		QMJ		HXZ		AEM & HKM	
α_{FILe}	3.29**	α_{FILe}	3.93**	α_{FILe}	3.49*	α_{FILe}	3.36*	α_{FILe}	3.34*
	(2.44)		(2.16)		(1.82)		(1.74)		(1.84)
MKT	−0.03	MKT	−0.05	MKT	−0.02	MKT	−0.04	MKT	0.14
	(−0.99)		(−1.39)		(−0.66)		(−1.43)		(1.16)
HML	−0.08	HML	−0.23**	HML	−0.13*	ME	−0.01	FIvw	0.01
	(−1.28)		(−2.17)		(−1.74)		(−0.16)		(0.44)
SMB	−0.11**	SMB	−0.08	SMB	−0.03	I/A	−0.11	mHKM	−0.19*
	(−2.49)		(−1.29)		(−0.56)		(−1.11)		(−1.90)
MOM	0.17***	RMW	0.11	QMJ	0.18***	ROE	0.21**	mAEM	0.03
	(2.78)		(1.49)		(2.95)		(2.28)		(0.40)
		CMA	0.15						
			(0.92)						
Adj. R^2	0.12	Adj. R^2	0.04	Adj. R^2	0.05	Adj. R^2	0.05	Adj. R^2	0.02
# Obs.	324	# Obs.	324	# Obs.	324	# Obs.	324	# Obs.	309

Notes - This table provides results of time-series regressions with the FILe factor as the dependent variable. I consider the Carhart (1997), Fama and French (2016), Asness et al. (2018) and Hou et al. (2014) asset pricing models. α_{FILe} denotes the annualized return of the FILe factor that is not explained by these models. The rightmost column of the table represents the FILe factor alpha unexplained by factors based on financial intermediary leverage characteristics of Adrian et al. (2014) and He et al. (2017). The monthly return data span the period 1987:04–2014:12. The numbers in parentheses are t-statistics adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

ble 5. In particular, I focus on the four-factor model of Carhart (1997) (henceforth Carhart), the five factor model of Fama and French (2016) (FF5), the Asness et al. (2018) model with the quality-minus-junk factor (QMJ), and q-factors model of Hou et al. (2014) (HKZ). My last specification combines the financial intermediary leverage factors proposed by Adrian et al. (2014) (AEM) and He et al. (2017) (HKM).[13] Given that the leverage factors are not portfolio returns, I use factor-mimicking portfolios constructed from 25 size and book-to-market portfolios. The resulting mimicking portfolios capture roughly 70% of the variation in leverage factors.

[13]Data provided by He et al. (2017) end in 2012. This explains the lower number of observations.

Importantly, I find that the unexplained returns (α_{FILe}) are similar in magnitude and significant across all specifications, and they are also similar in magnitude to the raw return difference, as shown in Table 1. Moreover, the R^2s in Table 5 are relatively low, ranging from 2% for the intermediary leverage model to 12% for the four-factor Carhart model. This finding implies that common risk factors can explain up to 12% of the risk premium captured by the FILe factor. Additionally, I find that the FILe factor is positively correlated and significantly linked to investment and profitability factors such as QMJ and the ROE profitability factor of HKZ. This evidence suggests that the financial intermediary leverage risk factor is related to factors that pick up firms' investment and profitability risk. Indeed it can potentially offer an explanation for documented riskiness of 'quality' firms in QMJ factor.

Finally, the results of the regression of the FILe factor on the financial intermediary leverage factors of Adrian et al. (2014) and He et al. (2017) show that it is not only the time variation of aggregate leverage that is relevant to asset valuation, but also the dispersion of leverage within the cross section of financial intermediaries and, more importantly, existing lending relationships. In untabulated results, I find that both long and short sides of FILe portfolio load significantly on aggregate leverage factors with difference in laodings being at most weakly significant. This suggests that in order to measure the firm's exposure to the financial intermediation risk, it is not sufficient to compute an equity β with respect to the aggregate leverage factor. That is to say, the information obtained by analyzing firm's lending relationships, the structure of a syndicate and individual financial intermediary leverage is extremely richer in content. I provide further evidence that the spread in the leverage growth of financial intermediaries potentially represents a systemic risk in Section 3.3.

3.2 Market Price of Financial Intermediary Leverage Risk

In this section, I explore whether the FILe factor is priced in the cross section of stock returns. Note, that FILe factor is constructed using a subsample of firms which borrow from banks in the syndicated loan market. Therefore, the FILe factor is not expected to price the entire cross section of non-financial firms. I employ the two-step generalized method of moments procedure to estimate the linear factor model

$$\begin{aligned} R^{ex}_{i,t} &= a_i + \beta_{MKT,i}MKT_t + \beta_{SMB,i}SMB_t + \beta_{HML,i}HML_t + \beta_{FILe,i}FILe_t + u_{i,t} \\ E[R^{ex}_{i,t}] &= \beta_{MKT,i}\lambda_{MKT} + \beta_{SMB,i}\lambda_{SMB} + \beta_{HML,i}\lambda_{HML} + \beta_{FILe,i}\lambda_{FILe} + v_i, \end{aligned} \tag{3}$$

where $R^{ex}_{i,t}$ denotes the time-t return of the ith test asset in excess of risk-free rate, and MKT, SMB and HML represent the Fama and French (1993) market, size, and value factors, respectively. Let f denote the matrix of risk factors $f = [MKT_t\ SMB_t\ HML_t\ FILe_t]$ and λ be a vector of market prices of risk $\lambda = [\lambda_{MKT}\ \lambda_{SMB}\ \lambda_{HML}\ \ \lambda_{FILe}]$. By linearly projecting the stochastic discount factor m on the factors ($m = \overline{m} - f'b$), I can determine the pricing kernel coefficients as $b = E[ff']^{-1}\lambda$, where $b = [b_{MKT}\ b_{SMB}\ b_{HML}\ \ b_{FILe}]$. Estimation results of (3) for different sets of test assets are presented in Table 6.[14]

The main finding of this exercise is that the market price of risk for the FILe factor is significant across different sets of test assets and also is of a similar magnitude (all estimates range between 1.03 and 1.77). Moreover, I find that the FILe factor helps to price the cross section of test assets, as shown by the significant b_{FILe} (Cochrane, 2005). Together with the FILe factor, the Fama and French three factors explain the cross section of test portfolios with average time-series R^2s ranging between 76% and 94%. Based on overall performance of the FILe factor, I conclude that the financial intermediation risk is a distinct factor priced in the cross section of equity returns.

3.3 Macroeconomic Effects of Financial Intermediation Risk

After presenting the evidence that the FILe factor is priced in the cross section of equity returns, I am interested whether the financial intermediation risk derived from the cross section of financial firms constitutes a source of systemic risk for the economy, that is, risk affecting the entire economic system.

To address this question, I first construct a time series of the spread in the financial intermediary leverage between the high- and low-*FILe* portfolios (see Figure 1). Since the

[14]Before estimating regression (3) I demean all factors, and consequently the market price of risk λ does not represent the average return on corresponding factors.

TABLE 6: Market Price of Financial Intermediary Leverage Risk

Test portfolios	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{FILe}	$\overline{R^2}$
25 BtM/ME	0.58**	0.11	0.35	0.37**	0.94
	(0.26)	(0.17)	(0.22)	(0.17)	
25 ME/Inv	0.61**	0.03	0.67***	0.32*	0.89
	(0.26)	(0.17)	(0.23)	(0.18)	
25 ME/OP	0.54*	0.01	0.80**	0.27*	0.89
	(0.27)	(0.17)	(0.40)	(0.17)	
25 Inv/OP	0.59**	−0.50	0.56**	0.32*	0.76
	(0.27)	(0.32)	(0.26)	(0.20)	
	b_{MKT}	b_{SMB}	b_{HML}	b_{FILe}	
25 BtM/ME	0.04***	0.02	0.07**	0.07***	
	(0.01)	(0.02)	(0.03)	(0.02)	
25 ME/Inv	0.05***	0.02	0.11***	0.07***	
	(0.01)	(0.02)	(0.03)	(0.02)	
25 ME/OP	0.05***	0.02	0.12**	0.06***	
	(0.01)	(0.02)	(0.05)	(0.02)	
25 Inv/OP	0.05***	−0.04	0.08**	0.06**	
	(0.01)	(0.04)	(0.04)	(0.03)	

Notes - This table presents estimates of factor risk premia and the exposures of the pricing kernel to the Fama and French (1993) three factors (MKT, SMB, HML) and the financial intermediary leverage risk factor ($FILe$). Using the two-step generalized method of moments (GMM) I estimate the linear factor model

$$\begin{aligned} R^{ex}_{i,t} &= a_i + \beta_{MKT,i} MKT_t + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + \beta_{FILe,i} FILe_t + u_{i,t} \\ E[R^{ex}_{i,t}] &= \beta_{MKT,i}\lambda_{MKT} + \beta_{SMB,i}\lambda_{SMB} + \beta_{HML,i}\lambda_{HML} + \beta_{FILe,i}\lambda_{FILe} + v_i. \end{aligned}$$

By linearly projecting the stochastic discount factor m on the factors ($m = \overline{m} - f'b$), I determine the pricing kernel coefficients as $b = E[ff']^{-1}\lambda$. The table presents pricing results for different sets of test portfolios: 25 portfolios sorted on book-to-market and size (25 BtM/ME), 25 portfolios sorted on size and investment (25 ME/Inv), 25 portfolios sorted on size and operating profitability (25 ME/OP), 25 portfolios sorted on investment and operating profitability (25 Inv/OP); and a set of 40 portfolios consisting of 10 portfolios univariately sorted on each of size, book-to-market, investment, and operating profitability (40 FF). $\overline{R^2}$ denotes the average R^2 of time-series regressions across the test portfolios. Monthly portfolio returns are obtained from Kenneth French's webpage and cover the period from April 1987 to December 2014. The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

portfolio leverage ratio is a persistent process, I compute the spread in changes in leverage $\Delta(FILe^{High} - FILe^{Low})$ to avoid spurious results. Afterwards, I use this time series to predict changes in the growth in industrial production growth and unemployment. The results of these predictive regressions are presented in Table 7.

TABLE 7: Predictive Properties of Dispersion in FILe

ΔZ_t	γ_0	γ_1	γ_2	γ_3	γ_4
Industrial-production growth rate	0.31**	0.34**	0.33**	0.31**	0.28**
	(2.26)	(2.07)	(2.02)	(1.99)	(1.99)
Adj. R^2	0.17	0.20	0.20	0.18	0.16
Unemployment growth rate	−0.94*	−1.12**	−1.13**	1.11**	−1.06**
	(−1.93)	(−2.02)	(−2.06)	(−2.11)	(−2.22)
Adj. R^2	0.11	0.16	0.16	0.16	0.16
Banks tightening standards	−2.13***	−2.01***	−1.61**	−1.50**	−1.19*
	(−2.56)	(−2.60)	(−2.48)	(−2.32)	(−1.84)
Adj. R^2	0.19	0.17	0.10	0.09	0.05

Notes - This table investigates the predictive properties of the spread in the leverage growth between high and low financial leverage portfolios. From the quarterly time series of the average portfolio ***FILe*** I construct a predictor as the difference between the current-quarter and the same-quarter-last-year growth rates of the lender leverage in high- and low-***FILe*** portfolios, $\Delta_t(FILe^{High} - FILe^{Low})$.
I then use this variable to study the contemporaneous and predictive relation of the ***FILe*** spread to macroeconomic quantities such as the industrial-production and unemployment growth rates. In the bottom panel, the predicted variable is net share of domestic banks tightening standards for commercial and industrial loans to large and middle-market firms from Senior Loan Officer Opinion Survey. The table provides the slope coefficients of contemporaneous regressions (denoted as γ_0)

$$\Delta Z_t = \alpha + \gamma_0 \Delta_t(FILe^{High} - FILe^{Low}) + \varepsilon_t,$$

and predictive regressions (denoted as γ_j)

$$\Delta Z_{t+1\to t+j} = \alpha + \gamma_j \Delta_t(FILe^{High} - FILe^{Low}) + \varepsilon_{t+1\to t+j},\ j = 1, .., 4,$$

where $\Delta Z_{t\to t+j}$ is the horizon j growth rate of the macroeconomic variable. The numbers in parentheses are t-statistics adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

I document that the spread in the leverage growth between high- and low-***FILe*** firms positively predicts industrial production growth and negatively predicts unemployment for up to four quarters ahead. The interaction mechanism underlying these predictive properties could be as follows. When the spread increases, financial institutions increase their leverage by borrowing more and lending more to firms. The latter in turn stimulates investment and leads to higher output growth. At the same time the unemployment rate declines.

These results continue to hold when I include various controls of macroeconomic conditions in the predictive regression. In particular, I choose credit spread, term spread, consumer credit growth, and inflation as my control variables. I present the estimation results of the adjusted regressions in Appendix Table G4.[15]

Additionally, I consider the connection between the spread in *FILe* across extreme portfolios and the net share of banks tightening standards for commercial and industrial loans to large and middle-market firms. The latter time series comes from the Senior Loan Officer Survey. I find the strong negative relation between the time series. Put differently, a decrease in the spread in *FILe* forecasts an increase in the share banks which tighten their lending standards up to 4 quarters ahead.

It is important to highlight that the outstanding loan composition, that is, the connection between the real and financial sectors, plays a crucial role in the predictive regression. Consider an analogous spread in the leverage growth constructed by sorting all financial institutions based on their leverage into three portfolios, disregarding existing lending relationships. Time series of average portfolio leverages resulting from this sorting procedure are depicted in Figure G1. I find that the spread in the leverage growth for the depicted time series has no predictive power for macroeconomic variables.

To sum up, the robustness of my results indicate that the spread in financial intermediary leverage captures the systemic risk and predicts the key macroeconomic variables at a horizon of up to four quarters.

4 Theoretical Model

In this section, I present a model of endogenous default and state-dependent debt costs in the spirit of Leland and Toft (1996) and Gomes and Schmid (2010) to rationalize the risk premium I discover in the data. Although the financial sector is not modeled explicitly, the model provides a simple mechanism explaining how the capital structure of a firm's lender constitutes a source of risk for the firm. In line with the empirical evidence, a firm receiving external financing from a high-leverage bank enjoys the benefits of lower borrowing costs

[15] All results are valid when include the lagged growth rate of the dependent variable. These results are available upon request.

in normal times, but it has to bear an additional risk in bad times when the high-leverage financial intermediary becomes constrained and external financing is scarce and expensive.

4.1 Model assumptions

Before describing the model, I collect additional empirical evidence to justify my main assumptions.

Assumption 1. In the model, I assume that firms which borrow from high-leverage intermediaries face on average lower debt financing costs. This assumption is based on empirical findings presented in Table 3. Intuitively, these costs may significantly increase in bad times, when high-leverage intermediaries become constrained and are forced to cut their lending. Moreover, at the same time the costs of switching to alternative sources of financing, for example corporate bonds, are also higher.

Assumption 2. I assume that firms which borrow from high-leverage intermediaries have higher debt costs in bad times. To support my second assumption, I analyze firm borrowing costs during the period from 2006 to 2011, which covers the Great Recession. In particular, I consider a portfolio of high-*FILe* firms whose financial intermediaries failed or were acquired by other institutions during this period (High Affected FILe firms). For these firms the financial intermediation leverage risk was realized during the last recession. As benchmarks for comparison, I consider high- and low-*FILe* portfolios from the baseline specification. Figure 3 depicts the results of this analysis.

I measure borrowing costs in two ways: as the ratio of total interest expenses over total assets (left panel) and as the total cost of borrowing value provided by Berg et al. (2016) (right panel). The latter measure includes only debt costs associated with firms' syndicated loans. Each panel of Figure 3 contains two lines: the dotted line depicts the difference in debt costs between high- and low-*FILe* baseline portfolios, while the solid line represents the cost difference between a portfolio of firms whose financial intermediaries were affected during the recession and the low-*FILe* benchmark portfolio.

The left panel of the figure indicates that, in general, high-*FILe* firms have on average lower

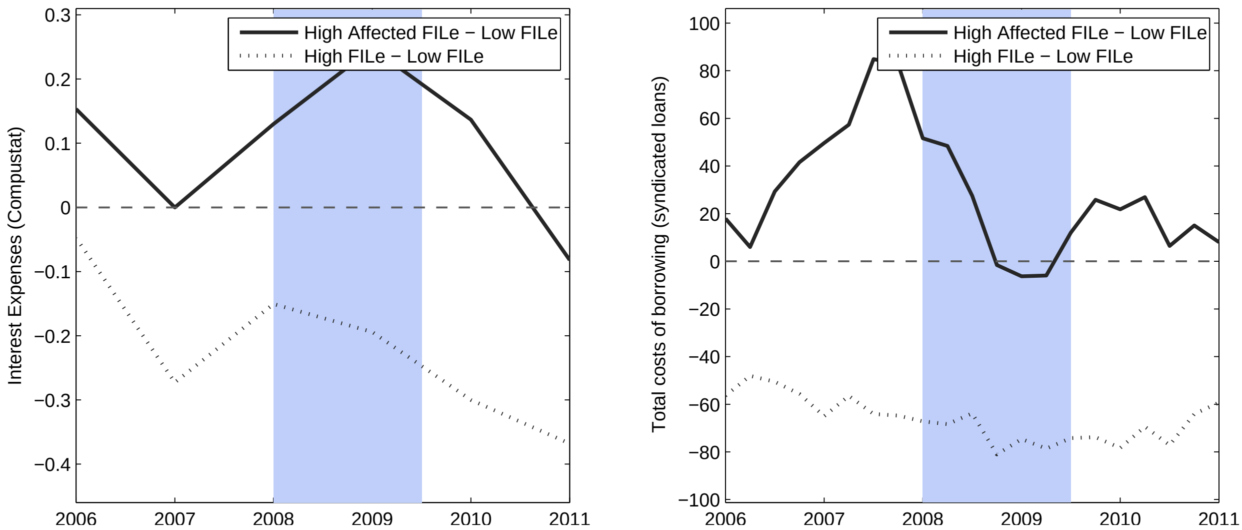

FIG. 3: Debt Financing Cost during the Great Recession

This figure contrasts the debt financing costs of high financial intermediary leverage firms with those of firms with low-leverage lenders. High *FILe* and Low *FILe* portfolios are constructed as in the baseline specification of the paper. The High Affected *FILe* portfolio includes firms that borrowed from high-leverage intermediaries which failed during the Great Recession, such as Lehman Brothers, Wachovia, and Morgan Stanley. Interest expenses are computed using annual data (Compustat item XINT over total assets [AT]). Quarterly total costs of borrowing from Berg et al. (2016) include only costs associated with the outstanding syndicated loans.

total interest expenses, even during the recession period. However, when I consider only firms with constrained financial intermediaries, the difference in borrowing costs switches sign. In particular, the figure shows that during the recession, High Affected *FILe* firms had relatively higher costs of borrowing. Analogous results hold when I examine only interest expenses associated with firms' outstanding syndicated loans. The difference is positive for affected firms in the run up to the recession. Overall, the data suggest that high-*FILe* firms indeed experience an increase in debt costs in bad times.

4.2 Model Setup

The economy is populated by value-maximizing firms. The state of aggregate productivity level X_t is exogenous and is described by the stochastic process

$$dX_t = \mu X_t dt + \sigma X_t dWt, \tag{4}$$

where W_t is a Brownian motion. Denoting the corporate tax rate by τ and capital by K, I can write the after-tax profits of firm i as $\Pi_{it} = (1-\tau)X_t K^{\alpha}$, where $0 < \alpha < 1$. In this economy, firms are homogeneous with respect to their profits, but they face different borrowing costs in the debt market.

Similar to the setup of Gomes and Schmid (2010), I assume that the debt of the firm i mirrors a consol bond with a fixed coupon c_i per period. In the case of adverse conditions in the financial intermediation market, the firm's debt can be restructured in a way such that existing debt is retired and new debt is issued under new financing conditions.

Firm equity. In the model, I consider two types of firms. Firm 1 borrows from a low-leverage financial intermediary. The firm's intermediary chooses to hold less debt and as a result has enough equity to be less susceptible to negative shocks to aggregate productivity. Consequently, debt is issued at initial date 0 and is never restructured.

The dynamics of firm 1's equity value solves the following Bellman equation:

$$V(X, c_1) = (1-\tau)(XK^{\alpha} - c_1)dt + (1 + rdt)^{-1}\mathbb{E}\left[V(X + dX, c_1)\right], \tag{5}$$

where c_1 is a fixed coupon paid by firm 1. When the aggregate state of the economy worsens and the firm's profits become insufficient to repay its debt, shareholders may choose to default on their debt obligations and liquidate the firm. I assume that the firm defaults whenever the aggregate productivity level X falls below the default threshold $X_{D,1}$. Formally, the solution to equation (5) should satisfy the following boundary conditions:

$$\begin{aligned} V(X_{D,1}, c_1) &= 0 \\ V'(X_{D,1}, c_1) &= 0. \end{aligned} \tag{6}$$

The system of equations (6) states that once the firm's equity value becomes zero, it is liquidated and no further operations are possible.

Firm 2 borrows from a high-leverage financial intermediary. Unlike the low-leverage lender of firm 1, the high-leverage financial intermediary becomes financially constrained in bad states of the economy and chooses to restructure the firm's debt and to demand a higher coupon payment. To compensate for this additional risk, during good times firm 2 faces lower borrowing costs than firm 1, which borrows from a low-leverage financial intermediary; that is, firm 2 pays out a lower coupon $c_2 < c_1$. In the case of debt restructuring, firm 2's coupon payment increases, such that the new coupon c_2^* exceeds the coupon of firm 1 c_1. Assuming that the restructuring occurs when the aggregate productivity level X reaches a level below a threshold X_R, the equity value of firm 2 $W(X, c_2, c_2^*)$ can be modeled as the sum of $V(X, c_2^*)$, the value of a firm paying out a fixed coupon c_2^*, plus $\nu(X, \bar{c})$, a value of a claim which pays out $\bar{c} = (1-\tau)(c_2^* - c_2)$ every period whenever $X > X_R$. Here, the 'wedge' $\nu(X, \bar{c})$ represents a cost adjustment function due to state-dependent coupon payments. More precisely, firm 2's value can be written in the following form:

$$\begin{aligned} W(X, c_2, c_2^*) &= V(X, c_2^*) + \nu\left(X, (1-\tau)(c_2^* - c_2)\right) \mathbb{I}\left\{X > X_R\right\} && (7) \\ V(X, c_2^*) &= (1-\tau)(XK^\alpha - c_2^*)dt + (1+rdt)^{-1}\mathbb{E}\left[V(X+dX, c_2^*)\right] && (8) \\ \nu(X, \bar{c}) &= \bar{c}dt + (1+rdt)^{-1}\mathbb{E}\left[\nu(X+dX, \bar{c})\right]. && (9) \end{aligned}$$

Note that equation (8) is equivalent to equation (5), describing the dynamics of firm 1's equity.

In the next step, I specify the appropriate boundary conditions to select a solution to the system of equations (7)–(9). As in the case of firm 1, I first determine the endogenous default threshold $X_{D,2}$: once the aggregate level of productivity reaches level $X_{D,2}$ shareholders choose to liquidate the firm and firm equity value becomes zero. In this case shareholders choose to fail on their debt obligations.

The second set of boundary conditions arises due to the lender's decision to alter the financing conditions of the firm (coupon c_2) when the aggregate productivity level X falls below the exogenously specified threshold level X_R. This is consistent with the usual notion of systemic risk, where shocks spread from the financial to the real sector, so that financial distress would be propagated from the intermediary to the firm. I therefore choose X_R to be above the firm's default threshold. Here, it is reasonable to assume that $X_R > X_{D,2}$, as the debt restructuring decision of the lender is irrelevant otherwise.

Combining all boundary conditions together yields the following system of equations:

$$\begin{aligned} W(X_{D,2}, c_2, c_2^*) &= 0 \\ W'(X_{D,2}, c_2, c_2^*) &= 0 \\ \nu(X_R, \bar{c}) &= 0. \end{aligned} \tag{10}$$

The last condition of system (10) accounts for the change in coupon at the time of the debt restructuring.

Firm debt. After specifying the dynamics of firms' equity values, I determine the market value of firms' debt. Let $B(X, c)$ denote the market value of debt when the aggregate productivity level is equal to X and the firm pays a fixed coupon c. In the case of firm 1, the debt dynamics can be described by the following Bellman equation:

$$B(X, c_1) = c_1 dt + (1 + r dt)^{-1} \mathbb{E}\left[B(X + dX, c_1)\right]. \tag{11}$$

Equation (11) holds as long as no default of firm 1 occurs. In the case of default, debt holders are able to recover a share ξ of the firm's asset value. Formally, this assumption yields a boundary condition:

$$B(X_{D,1}, c_1) = \xi \frac{(1-\tau) X_{D,1} K^{\alpha}}{r - \mu}. \tag{12}$$

In the case of firm 2, I modify the equations (11)–(12) to account for the fact that the intermediary demands a higher debt payment when the aggregate productivity X is below the restructuring threshold X_R. Under the assumptions of the model, firm 2 pays a coupon c_2 when $X > X_R$ and a coupon $c_2^* > c_2$ when $X_{D,2} < X < X_R$.

Let $D(X, c_2, c_2^*)$ denote the market value of firm 2's debt. It can be computed as the difference of the value of a consol bond $B(X, c_2^*)$, which pays a coupon c_2^* and defaults whenever X reaches the default threshold $X_{D,2}$, and the value of a bond $b(X, c_2^* - c_2)$, which pays a coupon equal to $c_2^* - c_2$ as long as $X > X_R$. The bond value $b(X, c_2^* - c_2)$ becomes zero when the aggregate state X reaches the threshold X_R, that is, at the point when firm 2's lender forces the firm to restructure its debt. Consequently, the dynamics of debt value are fully specified by the following set of equations:

$$
\begin{aligned}
D(X, c_2, c_2^*) &= B(X, c_2^*) - b(x, c_2^* - c_2)\mathbb{I}\{X > X_R\} && (13)\\
B(X, c_2^*) &= c_2^* dt + (1 + rdt)^{-1}\mathbb{E}\left[B(X + dX, c_2^*)\right] && (14)\\
b(X, c_2^* - c_2) &= (c_2^* - c_2)dt + (1 + rdt)^{-1}\mathbb{E}\left[b(X + dX, c_2^* - c_2)\right]. && (15)
\end{aligned}
$$

Assuming the same default procedure as for firm 1, I can specify the boundary conditions for firm 2's debt as

$$
\begin{aligned}
D(X_{D,2}, c_2, c_2^*) &= \xi \frac{(1-\tau)X_{D,2}K^\alpha}{r - \mu} && (16)\\
b(X_R, c_2^* - c_2) &= 0. && (17)
\end{aligned}
$$

The wedge $b(X, c_2, c_2^*)$ reflects the adjustment in coupon payments, and condition (17) ensures the continuity of the debt value at the restructuring threshold. In fact, no new debt is issued at this point, but debt financing costs increase instead. This assumption follows the intuition that in bad times the financial intermediary is constrained and will prefer to cut its lending rather than to increase it.

Firm problem. In this model, firm 1 is maximizing its total value by choosing the threshold value $X_{D,1}$ and coupon c_1. Formally, c_1 is determined as a solution to the value maximizing problem

$$c_1 = \arg\max_c V(X_0, c) + B(X_0, c),$$

where X_0 is some initial level of aggregate productivity.

For firm 2 the restructuring threshold X_R and coupon c_2^* are set exogenously.[16] Consequently, firm 2 only determines the default threshold $X_{D,2}$ and coupon c_2 in good times. The coupon payment c_2 is chosen to match the debt and equity values of firm 1 in expected values. This results in firm 2's capital structure matching the optimally determined capital structure of

[16]In a model with a fully specified financial intermediation sector, the threshold X_R and the coupon c_2^* will follow from the intermediary's problem.

firm 1. Under these assumptions, c_2 is a solution the following optimization problem:

$$c_2 = \arg\min_c \int_X |V(X, c_1) - W(X, c, c_2^*)| dF(X) + \int_X |B(X, c_1) - D(X, c, c_2^*)| dF(X).$$

When the total values of firms 1 and 2 are equal, the firms are precluded from switching between high- and low-leverage intermediaries. Specifically, the market value of debt with a fixed coupon payment will correspond to the market value of debt with a state-dependent coupon. Hence, both firms will have comparable book leverages, so that the difference in expected returns between the two firms cannot be attributed to a difference in firm leverage.

4.3 Model Solution

For given values of coupon payments c_1, c_2, and c_2^*, the equity and debt values of firms 1 and 2 can be solved in closed form. I first apply Ito's Lemma to the corresponding Bellman equations: (5), (8), and (9) for equity values; and (11), (14), and (15) for debt values. Next I solve the associated second-order differential equations. This procedure yields a family of functions; hence I utilize the boundary conditions to determine unknown coefficients and select the solution to the firm's problem.

Let $\eta_1 < 0$ denote the negative root of the quadratic equation $0.5\sigma^2\eta^2 + (\mu - 0.5\sigma^2)\eta - r$. Then the solutions to firm 1's and firm 2's problems are

$$\begin{aligned}
V(X, c_1) &= \frac{(1-\tau)XK^\alpha}{r-\mu} - \frac{(1-\tau)c_1}{r} + A_1 X^{\eta_1} && (18)\\
B(X, c_1) &= \frac{c_1}{r} + \left(\xi \frac{(1-\tau)X_{D,1}K^\alpha}{r-\mu} - \frac{c_1}{r}\right)\left(\frac{X}{X_{D,1}}\right)^{\eta_1} && (19)\\
W(X, c_2, c_2^*) &= \frac{(1-\tau)XK^\alpha}{r-\mu} - \frac{(1-\tau)c_2^*}{r} + A_2 X^{\eta_1} && (20)\\
&+ \left(\frac{(1-\tau)(c_2^* - c_2)}{r} - D_1 X^{\eta_1}\right)\mathbb{I}(X \geqslant X_R) \\
D(X, c_2, c_2^*) &= \frac{c_2^*}{r} + \left(\xi \frac{(1-\tau)X_{D,2}K^\alpha}{r-\mu} - \frac{c_2^*}{r}\right)\left(\frac{X}{X_{D,2}}\right)^{\eta_1} && (21)\\
&- \left(\frac{c_2^* - c_2}{r} + G_1 X^{\eta_1}\right)\mathbb{I}(X \geqslant X_R)
\end{aligned}$$

Unknown coefficients A_1, A_2, D_1, and G_1, as well as the default threshold levels $X_{D,1}$ and $X_{D,2}$, can be determined by plugging the solutions into the boundary conditions and solving the associated equations.

4.4 Numerical Example

In this section, I present a parametrized example to assess the model's implications for firms' returns and leverage.

Firm conditional expected equity returns can be derived within the model by considering a conditional one-factor model with a constant factor risk premium λ.[17] This model takes the form

$$\mathbb{E}_t\left[R_{i,t+1}\right] = r + \beta_{i,t}\sigma\lambda,\ i = 1,2 \tag{22}$$

where $R_{i,t+1}$ denotes the time $t+1$ return on firm i's equity, and $\beta_{1,t} = \frac{d\log V(X_t,c_1)}{d\log X_t}$ and $\beta_{2,t} = \frac{d\log W(X_t,c_2,c_2^*)}{d\log X_t}$ are the elasticities of firm equity value to changes in the aggregate state of the economy. Note that in this one-factor model a higher beta automatically translates into a higher expected return on equity.

Using the closed-form solutions (18) and (20), I derive the corresponding expressions for firms' βs

$$\beta_{1,t} = 1 + \frac{(1-\tau)c_1}{rV(X_t,c_1)} + \frac{A_1(\eta_1-1)X^{\eta_1}}{V(X_t,c_1)} \tag{23}$$

$$\begin{aligned}\beta_{2,t} &= 1 + \frac{(1-\tau)c_2^*}{rV(X_t,c_2,c_2^*)} + \frac{A_2(\eta_1-1)X^{\eta_1}}{V(X_t,c_2,c_2^*)} \\ &- \left[\frac{(1-\tau)(c_2^*-c_2)}{rV(X_t,c_2,c_2^*)} + \frac{D_1(\eta_1-1)X^{\eta_1}}{V(X_t,c_2,c_2^*)}\right]\mathbb{I}(X \geqslant X_R).\end{aligned} \tag{24}$$

Expression (24) shows that, in comparison to firm 1, firm 2's β incorporates an additional risk exposure associated with an increase in the size of coupon payments in bad states of the economy.

To assess the quantitative implications of the model, Figure 4 depicts the βs and leverages

[17] In this stylized model, λ is unspecified, since the agent's preferences and the implied pricing kernel are left unspecified for greater tractability of results.

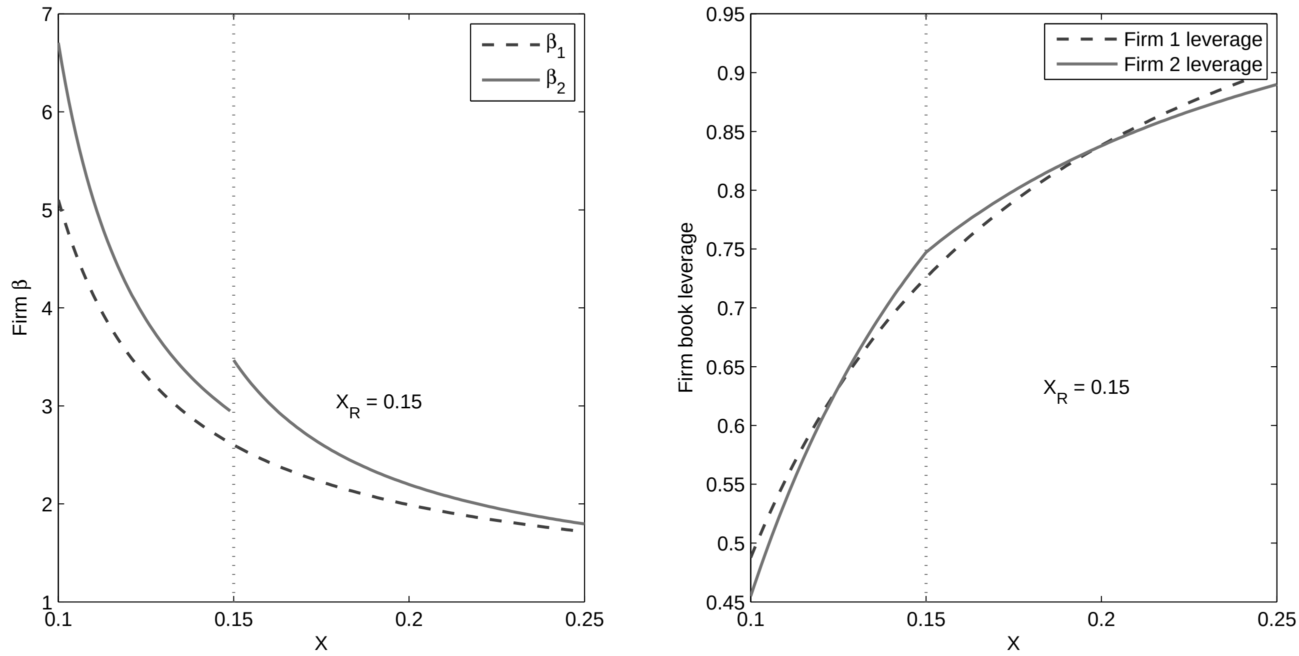

FIG. 4: Firm βs and Leverage Implied by the Model

This figure depicts the β and leverage implied by the model. βs are computed from the solution (23)–(24). Firm leverage is defined as the value of debt divided by total assets: $B(X, c)/K$. Model parameters are set as follows: $K = 10$, $\alpha = 0.65$, $\tau = 0.2$, $\xi = 0.25$, $r = 0.05$, $\mu = 0$, $\sigma = 0.2$, $X_R = 0.15$.

of firm 1 and firm 2 under a standard parametrization (see Gomes and Schmid, 2010). The right panel of the figure shows that firm 2's exposure to aggregate risk is higher than firm 1's exposure, and the former increases significantly in bad times. At the same time, the average leverage ratio of firm 2, defined as the ratio of debt (B or D) over total assets K, is similar to firm 1's leverage. Both results are in line with the main empirical finding of the paper that firms which borrow from high-leverage financial intermediaries have significantly higher expected returns.

4.5 Endogenous Matching

The developed modelling framework can deliver predictions on the matching between firms and financial intermediaries. In this section, I assume that firms differ with respect to the volatility of their productivity. In particular, firm profits are now driven by *firm-specific* productivity X_i that follows

$$dX_i = \mu X_i dt + \sigma_i dW_t. \tag{25}$$

To assess the model's ability to explain the matching between firms and banks, I run the following exercise. First, I determine the menu of borrowing cost c_1, c_2, and c_2^*, charged by low- and high-leverage banks, as a solution to the problem with ex ante identical borrowers. At this point I set the volatility of aggregate productivity to an initial level $\sigma_0 = 0.2$. Note that, at the optimum the expected equity values are equalized. Next, keeping the borrowing cost fixed, I compute expected equity values of high- and low-*FILe* firms for different values of the volatility of the productivity. The resulting functions are depicted in Figure 5.

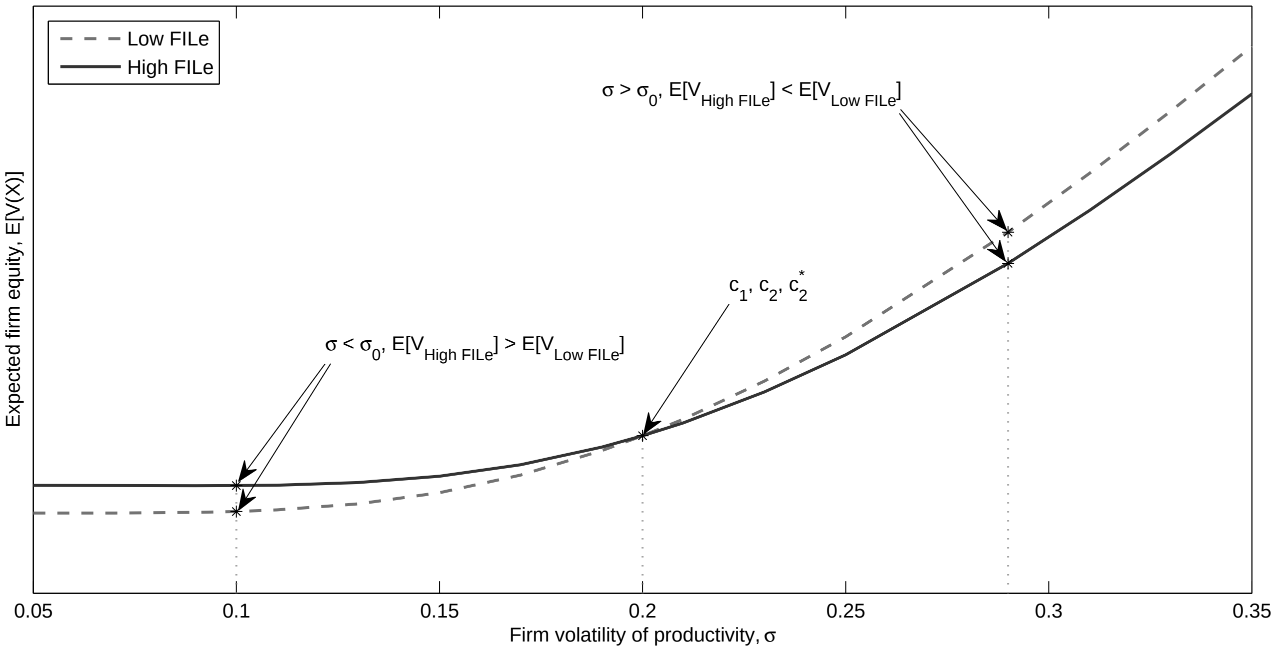

FIG. 5: Expected Firm Equity and Volatility of Productivity

This figure depicts expected values of equity for high- and low-*FILe* firms for different levels of volatility of productivity σ. Expected values are computed over 1-year distribution of firm productivity X. Borrowing cost c_1, c_2, c_2^* are determined by matching equity values of both firms with volatility of productivity $\sigma_0 = 0.2$. Other model parameters are set as follows: $K = 10$, $\alpha = 0.65$, $\tau = 0.2$, $\xi = 0.25$, $r = 0.05$, $\mu = 0$, $X_R = 0.15$.

First, as it can be seen from the figure, the firm equity is increasing in the volatility of the productivity. In general, firm's equity represents a call option on firm's cash flows after all debt claims have been satisfied. Therefore, equity values are higher for higher volatility.

Second, by comparing the expected equity values for high- and low-*FILe* firms, I notice that for volatility values below σ_0 a lending relationship with a *high-leverage* bank yields a higher expected equity value. Consequently, for a given menu of borrowing cost, a less risky firm benefits from borrowing from a high-leverage financial intermediary. At the same time, according to the model, a riskier firm, that is, a firm with volatility of productivity $\sigma > \sigma_0$, should optimally borrow from a low-leverage bank.

The intuition behind this result as follows. Due to high volatility of the productivity, profits of the riskier firm have a large upside potential, but they are also subject to the substantial downside risk. Hence shareholders are able to achieve a higher equity value by borrowing from low-leverage banks, as they are ready to give up a fraction of their profits' upside potential in good times in exchange for a protection from the downside risk during bad times.

On the other hand, safer firms choose to borrow high-leverage banks, since their downside risk is limited. Additionally, such firms greatly benefit from lower borrowing cost in good times. Thus, my stylized model with state-dependent borrowing cost is able to rationalize the endogenous matching between lenders and borrowers. An alternative explanation for matching with a focus on the financial intermediary's objectives is discussed in Appendix F.

5 Conclusion

In this paper, I quantify the risk premium demanded by investors for a firm's exposure to the financial sector. In the cross section, I find that firms which borrow from high-leverage financial intermediaries have on average 4% higher risk-adjusted annualized returns relative to firms with low-leverage lenders.

Interestingly, the difference in expected returns cannot be explained by risk factors based on the difference in firm balance sheets. In fact, by looking at firm balance sheet statements one can conclude that firms with high-leverage financial intermediaries are less risky than firms with low-leverage lenders and, consequently, the risk premium should have the opposite sign. One potential channel I discover that can explain the greater riskiness of these firms is operational risk. However, while important, operational risk cannot fully explain the risk premium for financial intermediation risk.

On the other hand, I present evidence in support of the hypothesis that firms which borrow from high-leverage intermediaries are more exposed to shocks originating in the financial sector. Funding for these firms comes from syndicates of fewer but larger banks. Although this matching is optimal from the risk management perspective (banks lend to less-risky firms and therefore can maintain higher leverage), in bad times the financial intermediation risk spills over to firms as the risk-bearing capacity of banks dries up.

I document that the financial intermediary leverage risk is priced in the cross section of equity returns. Moreover, the spread in the leverage growth between high- and low-leverage financial intermediaries represents a source of systemic risk in the economy. In particular, the dispersion in financial intermediary leverage predicts the growth in industrial production and unemployment for up to four quarters ahead. More importantly, these predictive properties strongly rely on the existing lending relationships between firms and financial intermediaries, as they are crucial in linking the financial and real sectors.

Finally, I propose a tractable model of endogenous default and state-dependent borrowing costs to shed light on the main mechanism behind the financial intermediation risk premium. In the model, the firms matched with high-leverage intermediaries enjoy the benefits of favorable loan conditions during good times. In bad times, these firms are faced with an increase in debt costs, since their financial intermediaries become constrained. As a result, firms with high-leverage lenders earn a risk premium for being exposed to shocks stemming from the financial sector.

References

Acharya, V., R. Engle, and D. Pierret. 2014. Testing Macroprudential Stress Tests: The Risk of Regulatory Risk Weights. *Journal of Monetary Economics* 65:36–53.

Adrian, T., E. Etula, and T. Muir. 2014. Financial Intermediaries and the Cross-Section of Asset Returns. *Journal of Finance* 69:2557–2596.

Adrian, T., E. Moench, and H. S. Shin. 2010. Financial Intermediation, Asset Prices, and Macroeconomic Dynamics. Staff Reports 422, Federal Reserve Bank of New York.

Allen, F., E. Carletti, and R. Marquez. 2011. Credit Market Competition and Capital Regulation. *Review of Financial Studies* 24:983–1018.

Altman, E. I. 1968. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *Journal of Finance* 23:589–609.

Asness, C. S., A. Frazzini, and L. H. Pedersen. 2018. Quality Minus Junk. *Review of Accounting Studies* pp. 1–79.

Berg, T., A. Saunders, and S. Steffen. 2016. The Total Cost of Corporate Borrowing in the Loan Market: Don't Ignore the Fees. *Journal of Finance* 71:1357–1392.

Bharath, S. T., and T. Shumway. 2008. Forecasting Default with the Merton Distance-to-Default Model. *Review of Financial Studies* 21:1339–1369.

Brunnermeier, M. K., and Y. Sannikov. 2014. A Macroeconomic Model with a Financial Sector. *American Economic Review* 104:379–421.

Carhart, M. M. 1997. On Persistence in Mutual Fund Performance. *Journal of Finance* 52:57–82.

Carlson, M., A. Fisher, and R. Giammarino. 2004. Corporate Investment and Asset Price Dynamics: Implications for the Cross-Section of Returns. *Journal of Finance* 59:2577–2603.

Carvalho, D., M. Ferreira, and P. Matos. 2015. Lending Relationships and the Effect of Bank Distress: Evidence from the 2007-2009 Financial Crisis. *Journal of Financial and Quantitative Analysis* 50:1165–1197.

Chava, S., and A. Purnanandam. 2011. The Effect of Banking Crisis on Bank-Dependent Borrowers. *Journal of Financial Economics* 99:116–135.

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

Chodorow-Reich, G. 2014. The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008-9 Financial Crisis. *Quarterly Journal of Economics* 129:1–59.

Chodorow-Reich, G., and A. Falato. 2017. The Loan Covenant Channel: How Bank Health Transmits to the Real Economy. NBER Working Paper No. w23879.

Cochrane, J. H. 2005. *Asset Pricing*. Princeton: Princeton University Press.

Davis, J. L., E. F. Fama, and K. R. French. 2000. Characteristics, Covariances, and Average Returns: 1929 to 1997. *Journal of Finance* 55:389–406.

Fama, E. F., and K. R. French. 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33:3–56.

Fama, E. F., and K. R. French. 2016. Dissecting Anomalies with a Five-Factor Model. *Review of Financial Studies* 29:69–103.

Farre-Mensa, J., and A. Ljungqvist. 2016. Do Measures of Financial Constraints Measure Financial Constraints? *Review of Financial Studies* 29:271–308.

Gande, A., and A. Saunders. 2012. Are Banks Still Special When There Is a Secondary Market for Loans? *Journal of Finance* 67:1649–1684.

George, T. J., and C.-Y. Hwang. 2010. A Resolution of the Distress Risk and Leverage Puzzles in the Cross Section of Stock Returns. *Journal of Financial Economics* 96:56–79.

Gomes, J. F., and L. Schmid. 2010. Levered Returns. *Journal of Finance* 65:467–494.

Gornall, W., and I. A. Strebulaev. 2018. Financing as a supply chain: The capital structure of banks and borrowers. *Journal of Financial Economics* 129:510–530.

Haldane, A., S. Brennan, and V. Madouros. 2010. *What Is the Contribution of the Financial Sector: Miracle or Mirage?*, vol. 87. London, England: The London School of Economics and Political Science.

Haldane, A., and V. Madouros. 2012. The Dog and the Frisbee. *Proceedings of the Economic Policy Symposium — Jackson Hole* pp. 109–159.

He, Z., B. Kelly, and A. Manela. 2017. Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics* 126:1–35.

He, Z., and A. Krishnamurthy. 2012. A Model of Capital and Crises. *Review of Economic Studies* 79:735–777.

He, Z., and A. Krishnamurthy. 2013. Intermediary Asset Pricing. *American Economic Review* 103:732–770.

Hou, K., C. Xue, and L. Zhang. 2014. Digesting Anomalies: An Investment Approach. *Review of Financial Studies* .

Irani, R. M., and R. R. Meisenzahl. 2017. Loan Sales and Bank Liquidity Management: Evidence from a U.S. Credit Register. *Review of Financial Studies* 30:3455–3501.

Ivashina, V., and D. Scharfstein. 2010. Bank Lending during the Financial Crisis of 2008. *Journal of Financial Economics* 97:319–338.

Kaplan, S. N., and L. Zingales. 1997. Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints? *Quarterly Journal of Economics* 112:169–215.

Laeven, L., L. Ratnovski, and H. Tong. 2014. Bank Size and Systemic Risk. IMF Staff Discussion Notes 14/4, International Monetary Fund.

Leland, H. E., and K. B. Toft. 1996. Optimal Capital Structure, Endogenous Bankruptcy, and the Term Structure of Credit Spreads. *Journal of Finance* 51:987–1019.

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

Minsky, H. P. 1969. Notes on the Susceptability of the US Economy to a Financial Crisis. *Hyman P. Minsky Archive* 61.

Muir, T. 2017. Financial Crises and Risk Premia*. *Quarterly Journal of Economics* 132:765–809.

Newey, W., and K. West. 1987. A Simple, Positive Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55:703–708.

Novy-Marx, R. 2011. Operating Leverage. *Review of Finance* 15:103–134.

Obreja, I. 2013. Book-to-Market Equity, Financial Leverage, and the Cross-Section of Stock Returns. *Review of Financial Studies* 26:1146–1189.

Ohlson, J. A. 1980. Financial Ratios and the Probalistic Prediction of Bankruptcy. *Journal of Accounting Research* 18:109–131.

Schwert, M. 2018. Bank Capital and Lending Relationships. *The Journal of Finance* 73:787–830.

Appendices

A Data Definitions

Market Equity (ME)	=	price×shares outstanding
Book-to-Market (BE/ME)	=	(stockholder equity + deferred taxes and investment tax credit − preferred stock liquidating value)/market equity (Davis et al., 2000)
Total Debt	=	short-term debt + long-term debt
Market Leverage	=	total debt/(total debt + market equity)
Book Leverage	=	total debt/total assets
Operating Leverage	=	(cost of goods sold + administrative and general expenses)/total assets
Profitability	=	operating income before depreciation/total assets
Tangibility	=	net property, plant, and equipment/total assets
Bond Issuer	=	corporate bond issuer dummy
Working Capital	=	(current assets − current liabilities)/total assets
Interest Expenses	=	total interest expenses/total assets

Total Cost of Borrowing (Berg et al., 2016):

$$\begin{aligned} TCB &= \textit{Upfront Fee}/\textit{Expected Loan Maturity in Years} \\ &+ (1 - PDD) \times (\textit{Facility Fee} + \textit{Commitment Fee}) \\ &+ PDD \times (\textit{Facility Fee} + \textit{Spread}) \\ &+ PDD \times \mathbb{P}(\textit{Utilization} > \textit{Utilization Threshold} | \textit{Usage} > 0) \times \textit{Utilization Fee} \\ &+ \mathbb{P}(\textit{Cancellation}) \times \textit{Cancellation Fee}, \end{aligned}$$

where PDD is the likelihood that the credit line is drawn down.

O-score (Ohlson, 1980; George and Hwang, 2010):

$$
\begin{aligned}
O-score \quad = \quad & -1.32 - 0.407\log(at) + 6.03\left(\tfrac{lt}{at}\right) - 1.43\left(\tfrac{wcap}{at}\right) + 0.076\left(\tfrac{lct}{act}\right) \\
& -1.72\,\mathbb{I}_{(at>lt)} - 2.37\left(\tfrac{ni}{at}\right) - 1.83\left(\tfrac{ffo}{lt}\right) + 0.285\,\mathbb{I}_{(ni_t+ni_{t-1}<0)} \\
& -0.521\left(\tfrac{ni_t-ni_{t-1}}{|ni_t|+|ni_{t-1}|}\right)
\end{aligned} \tag{A.1}
$$

Here, at denotes total assets, lt is total liabilities, $wcap$ is working capital, act is total current assets, lct is total current liabilities, ni is net income, and ffo is funds from operations.

Altman's Z-score (Altman, 1968):

$$
Z-score = 3.3\,pi + sale + 1.4\,re + 1.2\frac{act - lct}{at} \tag{A.2}
$$

Here, pi denotes pretax income, $sale$ is total revenue, re is retained earnings, act and lct are current assets and liabilities, respectively.

KZ-index (Kaplan and Zingales, 1997):

$$
\begin{aligned}
KZ \quad = \quad & -1.001909(ib_t + dp_t)/ppent_{t-1} + 0.2826389(at_t + prcc_{f,t} \times csho_t - ceq_t - txdb_t)/at_t \\
+ \quad & 3.139193(dltt_t + dlc_t)/(dltt_t + dlc_t + seq_t) - 39.3678(dvc_t + dvp_t)/ppent_{t-1} \\
- \quad & 1.314759\ che_t/ppent_{t-1}
\end{aligned} \tag{A.3}
$$

Here, ib denotes income before extraordinary items; dp is depreciation and amortization; $ppent$ is property, plant, and equipment; at is total assets; prc is close price; $csho$ is common shares outstanding; ceq is common equity; $txdb$ is balance sheet deferred taxes; $dltt$ is long-term debt; dlc is debt in current liabilities; seq is stockholder's equity; dvc is dividends on common stocks; dvp is dividends on preferred stocks; and che is cash and short-term investments.

Distance-to-Default of Merton (1974), following the estimation approach of Bharath and Shumway (2008):

$$
DD = \frac{\log((E+F)/F) + r + 0.5\sigma^2}{\sigma}, \tag{A.4}
$$

where $E = |prc| * shrout/1000$, $F = dlc + 0.5dllt$, $r = \prod_{i=1}^{12} (1 + ret_{t,i}) - 1$.

$$\sigma \approx \frac{E}{E+F}\sigma_E + \frac{F}{E+F}(0.05 + 0.25\sigma_E) \quad \text{(A.5)}$$

σ_E is the annualized percentage standard deviation of returns, estimated from monthly stock returns over the previous 12 months. The probability of default is defined as $N(-DD)$. If F is equal to zero, DD is not defined and the probability of default is set to 0.

B DealScan Data Coverage

The database used in my study is constructed by merging the data on syndicated loans with the balance sheet and market equity data of lenders and borrowers. Figure B1 addresses potential concerns about representativeness of the merged sample by depicting the shares of financial and nonfinancial firms covered in the sample. The shares are computed in terms of market capitalization with respect to the universe of CRSP stocks. Figure B1 demonstrates that the DealScan database contains data on up to 80% non financial firms and up to 50% of financial firms. When instead of market capitalization I consider the number of firms, I find that my sample contains 6,250 firms, which comprise more than a third of the total number of firms during the sample period. The large number of financial intermediaries (more than 400) follows from the inclusion of all participants in the syndicates under consideration.

C *FILe* Robustness

This section provides a discussion of alternative specification of the FILe portfolio strategy.

***FILe* calculation.** The benchmark specification of *FILe* assumes equal weights for all financial intermediaries. This assumption is necessary due to the scarcity of reported loan shares by each individual institution in DealScan. However, financial intermediaries that serve as lead-arrangers of the syndicate carry arguably more important functions than other banks, and, therefore, their leverage is more essential in determining the firm's exposure to finan-

FIG. B1: Market Share of Financial and Nonfinacial Firms in DealScan

This figure represents the ratio of total market capitalization of financial and nonfinancial firms represented in the DealScan database to the respective aggregate market capitalization of firms in the CRSP universe. The quarterly sample covers the period from 1986:Q1 to 2014:Q4.

cial intermediation risks. I address this concern by doubling weights of lead-arrangers when computing the *FILe* characteristic. The first column of Table C1 shows that the modified FILe portfolio strategy yields around 3.5% annually. An alternative approach to account for the heterogeneity in the lender leverage's importance is to weigh each individual leverage by total assets of banks (column 2, Table C1). Resulting excess and risk-adjusted returns are smaller in magnitude, but remain weakly significant. This observation is not surprising since the procedure assigns large weights to the largest banks in the U.S. and attenuates the diversification benefits of having a larger number of banks and smaller banks within a syndicate.

Loan importance. Unlike bank financing dependent firms in Europe, a large fraction of US firms has access to public debt markets and is able to obtain external financing through corporate bond issuance. *FILe* characteristic which is computed for two firms that borrow from the same set of banks may mismeasure their exposure to financial intermediation risk if

TABLE C1: FILe Factor: Alternative Specifications

	FILe calculation		Loan importance		Loan type	
	Over-weigh lead banks	Asset-weighted	w=Loan/ Total Debt	w=Bank Debt/ Total Debt	Term loans	Credit lines
Excess return	3.46*	1.79	6.02**	4.21**	6.48***	3.03
	(1.91)	(1.23)	(2.21)	(1.98)	(2.68)	(1.43)
CAPM α	3.86**	2.44*	5.62*	4.27**	6.51***	3.19*
	(2.28)	(1.67)	(1.77)	(2.07)	(2.64)	(1.69)
FF3 α	4.24**	2.80*	4.67**	4.68**	4.87*	4.03**
	(2.46)	(1.87)	(2.20)	(2.24)	(1.79)	(1.98)

Notes - This table reports annualized value-weighted returns of the financial intermediary leverage factor (FILe) for alternative specifications. The FILe factor is defined as a portfolio strategy which is long in nonfinancial firms that borrow from highly levered financial institutions and short in firms with low-leverage lenders. The first section, "FILe calculation," provides information on the FILe portfolio where firm-level *FILe* is computed either by doubling the weights of the lead-arrangers within the syndicate ("Over-weigh lead banks") or by weighting lenders leverage by their total assets ("Asset-weighted"). In the "Loan importance" section of the table I scale the equally weighted *FILe* either by total loan amount over total debt (see column "w = Loan/Total Debt, term loans only) or by ratio of total bank debt over total debt from Capital IQ ("Bank Debt/Total Debt"). The rightmost section reports results for two types of loans: term loans and revolving lines of credit. *CAPM* α, *FF3* α, and *FF5* α denote average excess returns unexplained by the CAPM, Fama-French three factor, and Fama-French five factor models, respectively. The monthly return data span the period 1986:07–2014:12. The numbers in parentheses are t-statistics adjusted according to the Newey and West (1987) procedure. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

one of the firms heavily relies on bank financing and the other funds its operations in the bond market and compliments its main source with a small fraction of bank loans. In my analysis, I incorporate the degree of bank financing importance in two ways. The first approach uses the total loan amount over total debt as scaling for the *FILe* characteristic (column 3, Table C1). In the cross section, firms with low reliance on bank financing will have lower *FILe* compared to firms that load more on bank loans, given that both groups of firms borrow from the same set of banks. Importantly, in this exercise I rely on a subsample of firms that have at least one term loan outstanding. Results are insignificant when I include revolver loans. In the latter case, the scaling factor becomes very noisy, since the eventual usage of credit lines varies substantially across firms and, as a result, total loan amount overestimates the importance of bank funding. In my second approach, I use the actual weight of bank debt in the firm debt composition collected from Capital IQ (see column 4). This variable reflects the loan amounts held by firms. The financial intermediation premium is very close in magnitude and significance to the benchmark specification.

Loan type. Two rightmost columns of Table C1 document results for two subsamples of firms with different types of loans outstanding: term loans and revolvers. In this exercise, I compute the *FILe* characteristic in the exact same way as in the benchmark specification, that is, using all connections between nonfinancial firms and their financial intermediaries. The purpose of the analysis is twofold. First, the results show that the exposure to refinancing risk comes from both potential repricing of term loans and unavailability of credit line financing when financial intermediary becomes constrained. Second, highly significant premia through the term loan exposure justifies the importance of the "loan covenant channel" (Chodorow-Reich and Falato, 2017).

Secondary Market for Loans. FILe characteristic as a proxy for firm's risk exposure to a group of intermediaries is severely biased if banks that originate a loan do not retain their shares up to the loan maturity date. The secondary market for loans has been growing since 2003 and plays an important part in mitigating the banks' liquidity constraints in times of market-wide distress (Irani and Meisenzahl, 2017). Following the re-sale of the loan share, the lending relationship link between a firm and a bank weakens, so does the stream of associated benefits and cost (Gande and Saunders, 2012). Untabulated results show that the financial intermediation risk premium was about 6.5% before 2003 and its magnitude declines after the introduction of the secondary market with the full sample average being 3.80%.

D FILe and Firm Financial Constraints

A recent paper by Gornall and Strebulaev (2018) develops a theoretical framework to rationalize a joint capital structure decision of financial intermediaries and their lenders. In their model, firms borrowing from high-leverage intermediaries decide optimally to maintain low leverage to limit risk accumulated by their lenders. Using the syndicate lending data, I inves-

TABLE D2: Firm and Financial Intermediary Leverage

	Firm leverage			
$FILe$	0.003	0.006	0.005	0.006
	(0.29)	(0.55)	(0.46)	(0.59)
Bond issuer		0.117***	0.095***	0.092***
		(14.59)	(12.50)	(11.76)
log(Sales)			0.039***	0.028***
			(10.01)	(8.62)
Profitability			−0.176***	−0.163***
			(−6.07)	(−6.09)
Tangibility			0.234***	0.293***
			(9.34)	(11.71)
Credit spread				0.045***
				(16.45)
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	NO
R^2	0.070	0.100	0.152	0.106
# Obs.	29367	29367	29117	29095

Notes - This table presents results from panel OLS regressions of firm market leverage on financial intermediary leverage with a set of controls. The merged data are annual and cover the period from 1986 to 2014. Variable definitions are provided in Appendix A. The numbers in parentheses are t-statistics computed using standard errors adjusted for heteroskedasticity and clustered on the firm level. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Reported R^2 does not take firm fixed effects into account.

tigate a potential link between the leverage of firms and that of their financial intermediaries. In particular, I run a set of panel OLS regressions of a firm's market leverage on its financial intermediary leverage,

$$Lev_{i,t} = FILe_{i,t} + X_{i,t} + f_i + a_t + \varepsilon_t,$$

where $Lev_{i,t}$ denotes the leverage of firm i at time t. $X_{i,t}$ contains firm-specific control variables, such as a bond issuer dummy, size, profitability, and tangibility. f_i and a_t represent firm and year fixed effects. The results of this regression analysis are presented in Table D2. Judging by the insignificance of the regression estimates (in the first row), I fail to find any supporting evidence that the capital structure of financial intermediary leverage influences the leverage of the intermediaries' borrowers.

As a robustness check, I estimate the same regressions using different measures of financial constraints and distress as a dependent variable. Specifically, I use firm book leverage, O-

Table D3: FILe and Firm Financing Constraint Measures

	Book lev	O-score	DD	Z-score	KZ-index
			Without controls		
$FILe$	0.005	−0.003	0.506	−0.078	14.307
	(0.28)	(−0.03)	(0.37)	(−0.36)	(1.56)
R^2	0.005	0.020	0.097	0.005	0.001
# Obs.	29431	29304	16152	28423	27786
			With controls		
$FILe$	0.012	0.010	0.683	0.071	0.875
	(0.92)	(0.13)	(0.48)	(0.59)	(0.32)
R^2	0.128	0.183	0.094	0.473	0.008
# Obs.	27656	27533	15153	26813	26215
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Notes - This table presents results from panel OLS regressions of measures of firm financial constraint on financial intermediary leverage with a set of controls. The merged data are annual and cover the period from 1986 to 2014. Variable definitions are provided in Appendix A. The numbers in parentheses are t-statistics computed using standard errors adjusted for heteroskedasticity and clustered on the firm level. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Reported R^2 does not take firm fixed effects into account.

score by Ohlson (1980), the Merton (1974) distance-to-default measure (DD), the predictor of bankruptcy Z-score by Altman (1968) and the KZ-index of financial constraints proposed by Kaplan and Zingales (1997). I report the results of the robustness analysis in Table D3.

Taking into account the critique of Farre-Mensa and Ljungqvist (2016), I focus on the distance-to-default measure, as it has been shown to be more reliable in identifying firm financial constrainability. Once again, I do not find sufficient evidence of a strong relation between the measures of firm's financial constraints and distress and the leverage of the firm's lender.

E Book versus Market Leverage

In my benchmark specification, I employ the market leverage of financial intermediaries to sort firms into portfolios. Although weaker results hold for book leverage, I choose to use market leverage in my main analysis for the following reasons. First, the market capitalization of a financial intermediary should more precisely reflect the underlying value of its equity. For instance, unwilling to write off bad loans, banks may still keep these loans on their balance sheets with a large discount. At the same time, the market price of such loans may be virtually zero. As a result, book leverage would underestimate the intermediary's leverage, as it is uses a larger book value of equity in the ratio's denominator (Acharya et al., 2014; Haldane and Madouros, 2012).

Secondly, book leverage reacts with a delay to changes in the assets' value. To support this claim, I study the cross-correlation between quarterly time series of current-quarter to same-quarter-previous-year changes in an individual institution's book and market leverages. I consider a subsample of 100 banks with the longest data available. Although results obtained using the quarterly data should be treated as suggestive rather than normative, I find that for 11 banks the changes in book leverage are more strongly correlated with future values of market leverage than with their contemporaneous counterparts. In comparison, book leverage leads market leverage for only four banks.

Finally, when I analyze the turnover of portfolios sorted on financial intermediary book and market leverage, I observe that the sorting based on market leverage yields lower turnover values. This finding suggests that the market leverage measure is more stable in the cross section.

F The Financial Intermediary's Problem

Recent work in the banking literature provides potential explanations of the matching process between firms and financial intermediaries. Among others is a theory of a joint capital structure decision of firms and banks by Gornall and Strebulaev (2018). According to this theory, firms internalize the cost they put on banks' balance sheets, and they choose to hold less leverage if their banks are already highly levered.

In the model in Section 4.2, the high-leverage financial intermediary imposes higher borrowing cost on its borrowers when in distress. The increase in borrowing cost can be justified by the bank's leverage constraint becoming binding due to a drop of bank's equity capital, or, alternatively, due to an increase in risk of bank's liabilities (for example, lack of liquidity in the interbank market). In light of these events, the bank decides to cut lending, as it needs to decrease its debt level, and to charge higher interest rates as a compensation for an increase in the borrowers' risk.

The baseline model can be extended by introducing a banking sector in spirit of Allen et al. (2011). The bank faces a trade off between holding more equity capital and charging borrowers higher loan rates. Optimal values are determined such that social welfare is at optimum.

Firms. Consider an economy populated by risk-neutral agents. There is a cross section of firms that differ in their transparency to investors. While some firms represent established long-run businesses with well-structured business models, other firms are rather opaque to investors. Firms require external financing of one unit to operate their projects.

From the dynamics (4), one-period payoff of a project by firm i is defined as $X_i K^\alpha - c_i$, where $X_i = e^{y_i},\ y_i \sim \mathcal{N}(\mu - \frac{1}{2}\sigma^2, \sigma^2)$ is the firm-specific productivity level, and c_i is the firm's repayment on the bank loan. As before, each firm endogenously determines the default threshold $X_{D,i}$, such that the firm's payoff is zero when X falls below $X_{D,i}$. Consequently, the payoff structure can be summarized in the form of the two-state discrete random variable:

$$\text{Payoff}_i = \begin{cases} \mathbb{E}\left[X_i K^\alpha | X_i \geqslant X_{D,i}\right] - c_i, & \text{with probability } q_i = \mathbb{P}\left[X_i \geqslant X_{D,i}\right] \\ 0, & \text{with probability } 1 - q_i = \mathbb{P}\left[X_i < X_{D,i}\right]. \end{cases} \tag{F.1}$$

Denoting $R_i = \mathbb{E}\left[X_i K^\alpha | X_i \geqslant X_{D,i}\right]$, I can write the firm surplus as $q_i(R_i - c_i)$.[18]

Banks. In the economy, banks act as financial intermediaries between firms and households: banks convert households' deposits into loans to firms. For a unit of funding, a firm has to repay c_i, while a bank repays r_D to its depositors for each unit of deposits. In addition to deposit financing, which represents a $(1-k)$ share of bank's assets, banks raise equity capital k at a cost r_E per unit. In line with the literature, I assume that equity financing is more expensive to banks and hence $r_E \geqslant 1$. In addition, I consider a case of deposit insurance provided by the government and hence $r_D = 1$.

Banks provide monitoring for firms and in this way they can improve their performance or

[18] For the simplicity of notation, I will drop the index i in the following computations.

decrease their default probability. Precisely, the bank's monitoring effort q represents the success probability of a firm's project. Monitoring is costly for banks and incurs cost $\frac{1}{2}q^2$. Since some firms require more monitoring than others, for example, due to riskiness of their projects, firms borrow from banks that are capable to provide a sufficient monitoring effort q^*.

The bank chooses the unobserved effort level q to maximize its profit function:

$$\max_q \Pi = q(c-(1-k)) - kr_E - \frac{1}{2}q^2, \tag{F.2}$$

where the first term results from the profit on the loan to the firm, the second term represents the cost of holding the capital and the third term is the monitoring cost. Optimal monitoring effort is then $\tilde{q} = \min[c-(1-k), 1]$.

F.1 Market Equilibrium

The competitive market equilibrium is a solution to the maximization problem

$$\begin{aligned} \max_{k,c} \quad & \tilde{q}(R-c) \\ \text{s.t. } \tilde{q} \;&=\; \min[c-(1-k), 1] \\ \Pi \;&=\; \tilde{q}(c-(1-k)) - kr_E - \tfrac{1}{2}\tilde{q}^2 \geqslant 0 \\ \tilde{q}(R-c) \;&\geqslant\; 0 \\ 0 \;&\leqslant\; k \leqslant 1, \end{aligned} \tag{F.3}$$

where capital k and borrowing cost c are chosen to maximize the firm surplus. The constraints in (F.3) guarantee that both firm's and bank's profits are nonnegative and the monitoring effort $\tilde{q}$ is optimal for given level of the bank capital.

Following *Proposition 4* of Allen et al. (2011), the solution to the problem (F.3) is defined for two regions:[19]

$$\begin{aligned} R \geqslant \overline{R}: \quad & \tilde{k} = \tfrac{1}{2r_E},\ \tilde{c} = 2 - \tfrac{1}{2r_E},\ \text{and } \tilde{q} = 1; \\ R < \overline{R}: \quad & \tilde{k} = \left(\tfrac{\sqrt{2r_E} - \sqrt{2r_E - 3(R-1)}}{3}\right)^2 < \tfrac{1}{2r_E},\ \tilde{c} = 1 - \tilde{k} + \sqrt{2r_E\tilde{k}},\ \tilde{q} = \sqrt{2r_E\tilde{k}}. \end{aligned} \tag{F.4}$$

[19] The cutoff point $\overline{R}$ is determined as $\overline{R} = \frac{3}{2} - \frac{3}{8r_E} + \frac{r_E}{2}$ for $r_E < \frac{3}{2}$ and $\overline{R} = 3 - \frac{3}{2r_E}$ for $r_E \geqslant \frac{3}{2}$.

Importantly, for all values R bank's profit is exactly zero, such that all profits are accrued to firms. In the equilibrium, the bank trades off the costly capital and firm borrowing cost: while the bank prefers to hold as little capital as possible and charge higher loan rates, the firm prefers the bank to hold enough capital to monitor and face lower borrowing cost. The bank equity capital serves a commitment device for the bank monitoring, as $\tilde{q}$ increases with equity capital share $\tilde{k}$.

F.2 Matching Between Banks and Firms

The framework of Allen et al. (2011), described in (F.3), allows to generate predictions for matching nonfinancial firms and financial intermediaries. The key mechanism in the model is the monitoring effort of the bank that represents the success probability of a firm's project. The solution to the bank optimization problem (F.2) indicates that the monitoring efforts increases with the equity capital the bank holds. As a result, riskier non-financial firms, that require a high level of project monitoring, optimally borrow from well-capitalized banks that hold higher levels of capital.[20]

Computing the derivative of $\tilde{c}$ with respect to $\tilde{k}$, it can be shown that for all R the optimal borrowing cost $\tilde{c}$, charged by banks, decreases with capital $\tilde{k}$. This result is inline with my empirical findings that firms that borrow high-leverage financial intermediaries face significantly lower cost of borrowing. It can be argued that high-leverage banks, that are usually larger banks, have access to a large set of debt markets and a better investment technology. Consequently, these banks are able to provide relatively cheap financing to their borrowers. Since the high-leverage banks optimally hold low levels of capital, they choose to lend to high-quality firms, that require less monitoring.

F.3 Shocks to Cost of Bank Equity

In this section, I describe the potential channel that constitutes an additional source of risk for borrowers of high-leverage banks. Due to the high inter-connectivity of the banking sector,

[20]Note, assuming the identical amount of deposits across banks, a higher level of capital automatically translates in lower bank leverage and the other way around.

large high-leverage financial intermediaries are voluntarily exposed to the risk of markets where they are active. Moreover, banks often rely on the presence of sufficient liquidity in the interbank lending market. In case of adverse events in the financial sector, such as a liquidity dry-up or negative shocks to assets of a large borrower, high-leverage lenders become first victims to face financial constraints.

Within the current modelling framework, financial constraints can be introduced as a shock to bank's cost of capital r_E.[21] The solution of the problem (F.3) implies that when the cost of equity r_E increases, the optimal level of bank capital decreases when firm projects are profitable enough, that is, when $R \geqslant \overline{R}$. However, in this case the monitoring effort $\tilde{q}$ should decrease as well. Less monitoring, in turn, can be insufficient from the stand point of borrowing firms forcing them to seek alternative sources of external financing.

In case when the bank invests in firms with lower expected payoff $R < \overline{R}$, an increase in cost of equity r_E leads to an increase in the optimal level of bank capital $\tilde{k}$. Unfortunately, raising new capital, when its prices goes up, is unattractive for the bank. Given high cost of equity capital, the bank can actually decide to hold less equity than it is optimal. As a result, a shock to *cost* of bank's equity is amplified by the associated decrease in the lending volume. The low level of equity capital may lead to a violation of the bank's participation constraint $\Pi \geqslant 0$, or even to a violation of regulatory capital requirements.

To alleviate the effect of shock amplification, the bank can alternatively adjust the loan rates keeping the monitoring effort $\tilde{q}$ and capital $\tilde{k}$ unchanged. Let $\hat{r}_E > r_E$ denote a new cost of bank's capital, then from the bank participation constraint $\Pi = 0$, I can derive the expression for the new cost of borrowing $\hat{c}$:

$$\hat{c} = \begin{cases} (1-\tilde{k}) + \tilde{k}\hat{r}_E + \frac{1}{2}, & \text{if } R \geqslant \overline{R} \\ (1-\tilde{k}) + \frac{\sqrt{\tilde{k}}(\hat{r}_E + r_E)}{\sqrt{2r_E}}, & \text{if } R < \overline{R}. \end{cases} \tag{F.5}$$

Comparing the above expression with the cost of borrowing $\tilde{c}$ in (F.4), I obtain that the derived value $\hat{c}$ is larger than the previously optimal value, that is, to compensate an increase of cost

[21]Alternatively, the result of a financial shocks can be modelled as a decrease in the bank's equity $\tilde{k}$. Qualitatively results are identical for both situations.

of equity $\hat{r}_E > r_E$ the bank can charge a higher loan rate $\hat{c} > \tilde{c}$ and keep the monitoring effort $\tilde{q}$ and capital $\tilde{k}$ unaltered.

$$\hat{c} - \tilde{c} = \begin{cases} \frac{1}{2}\left(\frac{\hat{r}_E}{r_E} - 1\right), & \text{if } R \geqslant \overline{R} \\ \frac{\sqrt{\tilde{k}}(\hat{r}_E - r_E)}{\sqrt{2r_E}}, & \text{if } R < \overline{R} \end{cases} > 0, \text{if } \hat{r}_E > r_E. \tag{F.6}$$

The suggested mechanism aligns with the menu of borrowing cost offered by high-leverage banks in Section 4.5.

G Additional Tables and Figures

TABLE G1: Financial Intermediation Premium: Daily Returns

	Low	Mid	High	High−Low	H−L: Recession	H−L: Boom
Panel A: Value-weighted Returns						
Excess return	7.61**	8.81***	12.19***	4.58**	6.21	4.39**
	(2.24)	(2.87)	(3.95)	(2.45)	(1.10)	(2.20)
$CAPM\ \alpha$	−0.82	0.67	4.29***	5.10***	5.15	4.82**
	(−0.67)	(0.73)	(3.45)	(2.80)	(0.89)	(2.45)
$FF3\ \alpha$	−1.23	0.84	4.69***	5.92***	6.36	5.88***
	(−1.01)	(0.85)	(3.80)	(3.24)	(1.15)	(3.00)
$FF5\ \alpha$	−1.21	0.17	3.80***	5.01***	4.22	5.20***
	(−0.94)	(0.15)	(3.08)	(2.71)	(0.85)	(2.64)
Panel B: Equally weighted returns						
	Low	Mid	High	High−Low	H−L: Recession	H−L: Boom
Excess return	16.58***	14.87***	19.25***	2.67***	−0.47	3.05***
	(3.69)	(3.34)	(4.18)	(2.72)	(−0.17)	(2.90)
$CAPM\ \alpha$	8.58***	6.79***	11.42***	2.84***	−0.49	3.35***
	(3.29)	(2.59)	(4.07)	(2.81)	(−0.18)	(3.11)
$FF3\ \alpha$	5.98***	4.50***	9.05***	3.07***	−0.44	3.73***
	(3.76)	(2.78)	(5.50)	(3.09)	(−0.15)	(3.66)
$FF5\ \alpha$	5.30***	3.45**	8.58***	3.28***	−0.77	3.93***
	(3.25)	(2.07)	(5.11)	(3.20)	(−0.24)	(3.79)

Notes - This table provides annualized value-weighted returns (Panel A) and equally weighted returns (Panel B) on portfolios of nonfinancial firms sorted according to the market leverage of their financial intermediary. First, using the data on syndicated loans I establish a link between a nonfinancial firm and a group of financial intermediaries from which the firm obtains a loan. Next, for each firm I compute the average of the market leverage ratios of the linked financial intermediaries and assign the resulting value to the firm. I then sort firms into three portfolios according the average financial intermediary leverage. I select the 30th and 70th percentiles of the leverage distribution as cutoff points. Return data are daily over the period 1986:07–2014:12. $CAPM\ \alpha$, $FF3\ \alpha$, $FF5\ \alpha$ denote average excess returns unexplained by the CAPM, Fama-French three factor, and Fama-French five factor models, respectively. The rightmost two columns, "H−L: Boom" and "H−L: Recession," present expected returns on the high-*FILe* minus low-*FILe* portfolio strategy as measured during NBER booms and NBER recessions, respectively. The numbers in parentheses are t-statistics adjusted according to the Newey and West (1987) procedure. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

TABLE G2: Correlation between Common Risk Factors and the FILe Factor

Fama and French (2016) factors				
MKT	HML	SMB	RMW	CMA
-0.113**	-0.099*	-0.111**	0.088	-0.002
(0.042)	(0.076)	(0.046)	(0.113)	(0.965)

Hou et al. (2014) q-factors			Novy-Marx (2009)	Asness et al. (2014)
ME	I/A	ROE	sOL	QMJ
-0.084	-0.022	0.225***	0.101*	0.199***
(0.133)	(0.691)	(0.000)	(0.071)	(0.000)

He et al. (2015) and Adrian et al. (2014) leverage factors				
FIvw	mHKM	mAEM	HKM	AEM
-0.062	-0.152***	-0.069	-0.083	0.022
(0.275)	(0.006)	(0.212)	(0.145)	(0.694)

Notes - This table reports the pairwise time-series correlation between the financial intermediary leverage factor (FILe) and a set of asset pricing factors. The analysis includes five Fama and French (2016) factors: MKT (market), SMB (size), HML (value), operating profitability (RMW), and investments (CMA); the Hou et al. (2014) q-factors: size (ME), investment-to-assets (I/A), and profitability (ROE); and the operating leverage factor similar to the Novy-Marx (2011) (sOL), the Asness et al. (2018) quality-minus-junk factor (QMJ). The sOL is constructed using the cross section of firms linked with their borrowers. I also consider the value-weighted return of financial intermediaries (FIvw), the security broker dealer leverage (AEM) from Adrian et al. (2014) and the primary dealers leverage from He et al. (2017). mAEM and mHKM correspond to factor-mimicking portfolios for the AEM and HKM leverages, respectively. The monthly data span the period from 1987:04 to 2014:03. The significance of the correlation coefficients is determined by p-values (in parentheses). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

TABLE G3: Firm-Level Determinants of High-FILe Portfolios: Logit Regressions

Logit model: $\mathbb{P}\{\text{ High-}\mathit{FILe}\text{ portfolio at } t+1|X_{i,t}\} = \frac{e^{\beta X_{i,t}}}{1+e^{\beta X_{i,t}}} + f_i + u_{i,t+1}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm leverage	−1.007***	−0.920***	−0.729***	−0.639***	−0.631***	−0.636***	−0.722***	−0.689***
	(−8.20)	(−7.44)	(−5.42)	(−4.35)	(−3.57)	(−2.82)	(−4.69)	(−4.51)
log(*Sales*)		−0.265***	−0.281***	−0.204***	−0.204***	−0.123*	−0.141***	−0.204***
		(−7.10)	(−7.18)	(−4.37)	(−4.15)	(−1.74)	(−2.71)	(−4.24)
Profitability			0.948***	0.765***	0.757***	0.312	0.370	0.494
			(3.68)	(2.64)	(2.61)	(0.68)	(1.19)	(1.48)
Tangibility			0.650**	1.196***	1.184***	1.465***	1.553***	1.204***
			(2.50)	(4.21)	(4.17)	(3.47)	(5.13)	(4.10)
Operating leverage			0.067**	0.383***	0.375***	0.975***	1.074***	0.396***
			(2.17)	(3.74)	(3.63)	(3.56)	(5.32)	(3.68)
Bond issuer			−0.122*	−0.084	−0.073	−0.030	−0.100	−0.053
			(−1.72)	(−1.10)	(−0.95)	(−0.27)	(−1.24)	(−0.68)
Book-to-market				−0.013	−0.013	−0.003	−0.015	−0.017
				(−0.67)	(−0.67)	(−0.07)	(−0.80)	(−0.88)
Working capital				1.123***	1.089***	1.111***	1.309***	1.090***
				(5.33)	(4.90)	(3.68)	(5.87)	(4.84)
Interest expenses				−0.014**	−0.014**	−0.003	−0.012*	−0.015**
				(−2.12)	(−2.10)	(−0.60)	(−1.74)	(−2.13)
log(*Sales*)*Op. leverage				−0.059***	−0.058***	−0.119***	−0.133***	−0.063***
				(−3.26)	(−3.15)	(−3.41)	(−5.13)	(−3.31)
O-score					−0.005			
					(−0.22)			
DD						−0.001		
						(−0.92)		
KZ-index							0.001	
							(0.45)	
Z-score								0.031
								(0.93)
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.034	0.038	0.039	0.042	0.042	0.043	0.047	0.043
# Obs.	18959	18931	18857	16732	16662	7179	15840	16002

Notes - This table provides panel regression estimates of the probit model that determines the probability of a firm to be assigned to the high-leverage financial intermediary portfolio. The dependent variable is zero for the low- and medium-*FILe* portfolios and one for the high-*FILe* portfolio. I utilize accounting data at the end of year t to determine the probability that a firm will be assigned to the high-*FILe* portfolio in the next period. Variable definitions are provided in Appendix A. Data are annual and span the period from 1987 to 2014. I report t-statistics in parentheses. All regressions include firm fixed effects. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

TABLE G4: Predictive Properties of Dispersion in FILe: With Control Variables

ΔZ_t	γ_0	γ_1	γ_2	γ_3	γ_4
Industrial-production growth rate	0.24***	0.23**	0.22**	0.20*	0.18*
	(3.54)	(2.25)	(2.04)	(1.88)	(1.77)
Adj. R^2	0.54	0.66	0.70	0.70	0.67
Unemployment growth rate	−0.57*	−0.72*	−0.75*	−0.76*	−0.78**
	(−1.78)	(−1.87)	(−1.91)	(−1.95)	(−2.05)
Adj. R^2	0.52	0.55	0.57	0.56	0.55

Notes - This table investigates the predictive properties of the spread in the leverage growth between high- and low-***FILe*** financial leverage portfolios. From the quarterly time series of the average portfolio ***FILe*** I construct a predictor as the difference between current-quarter to same-quarter-last-year growth rates of the lender leverage in high- and low-***FILe*** portfolios, $\Delta_t(FILe^{High} - FILe^{Low})$.
I then use this variable to study the contemporaneous and predictive relation to macroeconomic quantities such as the industrial-production and unemployment growth rates. The table provides the slope coefficients of contemporaneous regressions (denoted by γ_0)

$$\Delta Z_t = \alpha + \gamma_0 \Delta_t(FILe^{High} - FILe^{Low}) + X_t + \varepsilon_t,$$

and predictive regressions (denoted by γ_j)

$$\Delta Z_{t+1\to t+j} = \alpha + \gamma_j \Delta_t(FILe^{High} - FILe^{Low}) + X_t + \varepsilon_{t+1\to t+j},\ j = 1, .., 4,$$

where $\Delta Z_{t\to t+j}$ is the horizon j growth rate of the macroeconomic variable. Matrix X_t includes a set of controls for aggregate macroeconomic conditions, such as default and term spreads, consumer credit growth, and inflation. The numbers in parentheses are t-statistics adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

TABLE G5: FILe Factor: Double Sorts

	Size		BE/ME		Tangibility		Op. Leverage		Fin. Leverage		ST Debt	
	Small	Large	Low	High	Low	High	Low	High	Low	High	Low	High
Excess return	1.37	4.12**	1.29	7.23***	−1.33	5.75***	5.81**	−1.59	2.3	3.99	0.98	5.05*
	(0.93)	(1.99)	(0.56)	(2.69)	(−0.41)	(2.67)	(2.06)	(−0.54)	(1.17)	(1.60)	(0.55)	(1.65)
CAPM α	0.88	4.60**	1.55	7.46***	−1.56	6.38***	6.78**	−2.28	2.68	4.13*	0.46	5.96**
	(0.61)	(2.44)	(0.63)	(2.68)	(−0.48)	(3.32)	(2.47)	(−0.72)	(1.35)	(1.68)	(0.23)	(2.03)
FF3 α	0.54	5.26***	2.00	7.29***	−1.07	7.39***	6.93**	−0.85	3.05	5.95**	1.05	6.60**
	(0.32)	(2.57)	(0.74)	(2.88)	(−0.29)	(3.82)	(2.54)	(−0.28)	(1.47)	(2.35)	(0.49)	(2.06)
FF5 α	1.50	4.29**	0.62	5.59**	−0.96	6.64***	4.34*	0.46	1.6	5.99**	0.26	5.34*
	(0.94)	(2.11)	(0.20)	(2.32)	(−0.27)	(3.35)	(1.72)	(0.14)	(0.79)	(2.50)	(0.11)	(1.67)

Notes - This table reports annualized value-weighted returns of the financial intermediary leverage factor (FILe) for subsamples of stocks. These subsamples are constructed by splitting firms into two portfolios using a median of a firm characteristic as cutoff point. I use size, book-to market ratio ("BE/ME"), tangibility, operating leverage ("Op. Leverage"), financial firm leverage ("Fin. Leverage"), and the share of short-term debt relative to the total debt ("ST Debt") to form subsamples. For each subsample, the FILe factor is defined as a portfolio strategy which is long in nonfinancial firms that borrow from highly levered financial institutions and short in firms with low-leverage lenders. *CAPM* α, *FF3* α, and *FF5* α denote average excess returns unexplained by the CAPM, Fama-French three factor, and Fama-French five factor models, respectively. The monthly return data span the period 1986:07–2014:12. The numbers in parentheses are t-statistics adjusted according to the Newey and West (1987) procedure. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

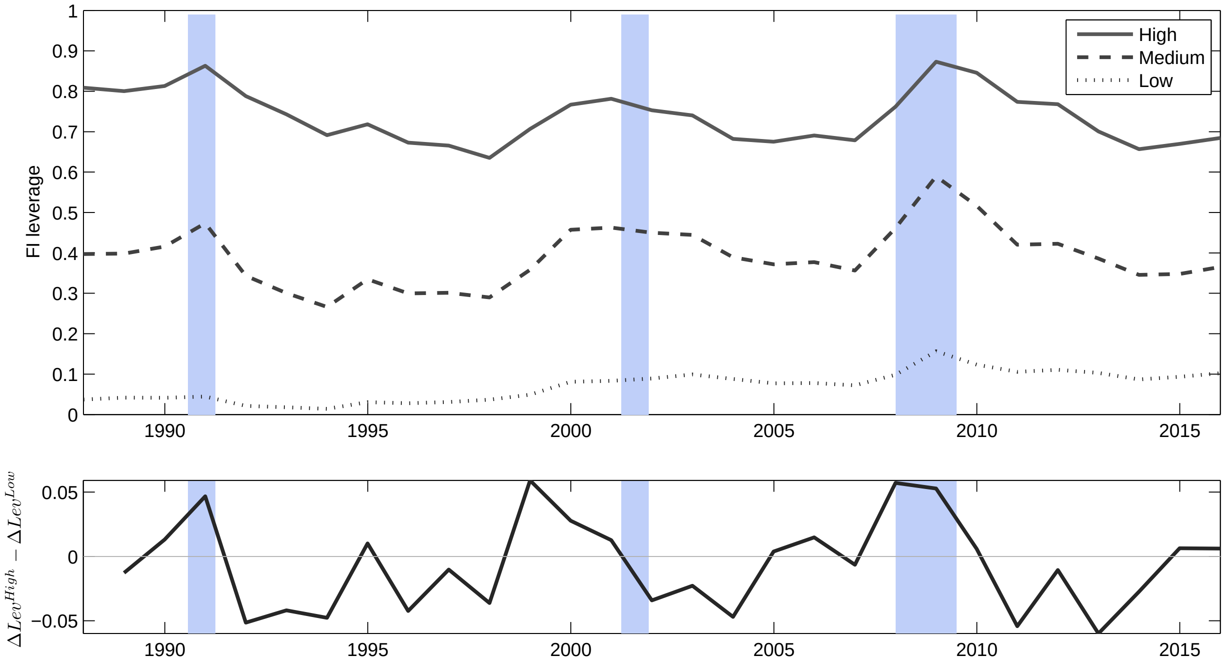

FIG. G1: Spread in Leverage of Financial Intermediaries

This figure depicts quarterly time series of the dispersion in market leverage in the cross section of financial intermediaries. I observe a cross section of financial intermediaries as of the end of each year. For each financial firm in the cross section I compute market leverage and then construct three portfolios using the 30th and 70th percentiles of the leverage distribution as cutoff points. The top panel of the figure presents the time series of simple average leverage for each portfolio. The bottom panel shows the difference between the changes in the leverage of high and low portfolios. The sample spans the period from 1989:Q1 to 2015:Q2.