Investment Sensitivity to Lender Default Shocks*

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ABSTRACT

We investigate how idiosyncratic lender shocks impact corporate investment. Lenders with recent default experience write stricter loan contracts, leading to a reduction in real investment for borrowing firms. The decline in investment is not attributable to loan riskiness, borrower's agency costs, the lender-borrower relationship nexus, lender capitalization, or to borrower interest rate sensitivity, but is more pronounced when the lender faces higher incentives to learn. The evidence suggests that defaults inform lenders about investment opportunities and their screening ability, and adjustments to this information have real economic consequences.

JEL classification: E22, G21, G31, G32, G33.

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I. Introduction

Managers must make investment choices under uncertainty based on their forecast of future consumer demand or future prices (Lucas and Prescott, 1971). Similarly, lenders make loan decisions and write credit contracts based on both hard and soft information known at the time of contracting. Under uncertainty, agents can learn from the past (e.g., Marcet and Sargent, 1989). Recent research has investigated how lenders learn from shocks within their lending portfolio and modify their screening and contracting processes (Murfin, 2012). In this paper, we examine how these supply-side shocks to lender screening affect the corporate investment decisions of firms.

Although the broad association between financing and investment are well established (e.g., Stein, 2003; Chava and Roberts, 2008), the precise mechanisms that drive the relationship are relatively less known. A large literature focuses on the role of demand side factors, but are relatively silent about how supply-side frictions influence firm investment. Murfin (2012) examines how lender's recent default experience can influence the strictness of their loan contracts and finds that banks write stricter contracts compared to peer banks. The results suggest that banks learn about their own screening process when they experience defaults in their portfolio. We employ this idiosyncratic shock to credit terms to examine investment choices of affiliated firms. We find that this supply-side credit shock leads to a reduction in corporate investment for other firms borrowing from the same lenders.

We focus our attention on recent default events because large corporate defaults provide a unique opportunity for several reasons. First, corporate defaults damage lender profitability significantly, inducing changes to lending behavior. For example, Chava and Purnanandam (2011) show that banks affected by the Russian sovereign debt default reduce lending. Gopalan, Nanda, and Yerramilli (2011) show that lender defaults dent lead arranger reputations and negatively affect their activity in the syndicated loan market. A reduction in supply side lending activity following default shocks suggests possible variation in the intensive margin of lending by affecting the terms of new lending and impacting borrowers' investment. Second, defaults may alter the beliefs and processes of the lender. Defaults contain valuable information for the lenders, allowing them to update their beliefs about economic conditions. Also, defaults can lead to lenders reassessing their own credit risk models and internal controls (Murfin, 2012), thereby influencing future lending arrangements. Third, to the extent that default risk in the lender portfolio is correlated, it is easier for the lender to make alterations incrementally through new loans rather than reassessing the entire loan portfolio. Reassessing the entire portfolio is made difficult by state contingent allocation of control rights and ex-post limits to managerial attention.

How can supply-side frictions affect borrower's investment? Ideally, if lenders make independent lending decisions, defaults in a few loans should not affect other borrowers. However, we hypothesize that a lender's default experience may reduce borrower investment for several possible reasons. First is a 'learning' hypothesis where lenders learn about their own credit assessment ability and evaluation of future investment opportunities. Defaults contain valuable information about possible weaknesses in the lender's screening and monitoring mechanisms as well as information about the investment opportunities in the economy, which allows them to assess future firm prospects better or in a more conservative manner. These assessments incentivize the lenders to influence borrower investment at the time of contracting. For example, the lenders may explicitly discourage borrowers from investing in over optimistic projects, require borrowers to make safer investment choices when deciding among projects, or require them to reduce the scale of investment in a project. Beyond such explicit actions, contract terms may reduce investment implicitly. For example, a lender who believes that having control rights earlier can minimize losses will prefer a transfer of control rights from the borrower to the lender at the slightest hint of trouble, especially after having a recent default experience. As a consequence the lender is motivated to write stricter contracts (Murfin, 2012).[1] Stricter contracts may lead to changes in a firm's investment policy by changing the incentives of the manager due to the changed nature of the allocation of control rights. The manager may choose an investment policy that minimizes the probability of a future covenant violation and the subsequent transfer of control rights to the lender.

Second is a 'borrowing cost' hypothesis, where the lenders with recent default experience externalize their losses by charging higher interest rates on its subsequent loans, leading to a higher cost of capital for borrowing firms. Lenders with recent default experience may charge higher interest rates for several reasons. To overcome the negative profitability shock of the default, lenders may charge more for a given level of credit risk. Also, if they discover any weakness in their screening and monitoring processes, rectifying them will also incur costs, which inflates the interest rates charged to new borrowers. In the syndicated loan market, corporate defaults may harm the reputation of the lead arranger, making them unattractive for other lenders to join their syndicate (Gopalan et al., 2011). Therefore, the lenders with recent default experience may charge higher loan spreads, retain a larger fraction of the loans (Gopalan et al., 2011), and offer stricter contracts to borrowers (Murfin, 2012), so as to facilitate syndicate participation. All else equal, the higher cost of capital may make some profitable projects unviable or reduce their scale, thus decreasing corporate investment.

However, there is one possibility that is not considered in the above hypotheses that can potentially

[1] We confirm the findings of Murfin (2012) in our setting, in untabulated tests, where we examine how recent default experience influences contact strictness. Specifically, we find that recent default experience is negatively associated with *Covenant Slack*, defined as the difference between initial current ratio (net worth) and covenant specified threshold of current ratio (net worth) scaled by the standard deviation of current ratio (net worth).

explain why borrowers invest less when their lenders face recent default experience. To the extent that firms with poor investment opportunities borrow from lenders facing capital constraints, any negative association can be simply due to the endogenous matching between lenders and borrowers (Schwert, 2018). We perform a series of tests to rule out this potential explanation in subsequent sections. Specifically, we control for lender characteristics, examine changes in investment behavior, perform panel data regressions, and examine cross-sectional variation in the main findings according to borrower, lender, loan, and lender-borrower relationship characteristics.

Using data between 1987 and 2016 on bilateral and syndicated loans from LPC DealScan and data on corporate credit ratings from Compustat ratings database, we first identify the lenders with recent default experience. Next, we identify the firms that borrow from such lenders facing defaults. We find that these borrowers are more likely to have a pre-existing relationship with the lender with default experience (i.e., lend to relationship borrowers) and approximately on average pay 4.4% higher spreads (coefficient of 0.044 on *Lender Shock −−90 Days* and mean log spreads (*AIDS*) of 5.2861 in Table II). These findings suggest that when faced with defaults, lenders face stronger incentives to contract with familiar borrowers and charge them higher spreads.

Next, we examine the quarterly investment activity at the new borrowers and find that firms that borrow from a lender with a recent default reduce investment by 6.22% after controlling for the standard determinants of investment. The economic effect when compared to the effect of one standard deviation changes in Q, *Cash Flow*, and *Firm Size* of 27.91%, 2.48%, and -35.47%, respectively, is economically large and comparable to the standard determinants of investment. We also find that this negative effect on investment persists for at least two years after the default event.

To rule out the possibility that these findings are due to capital constraints faced by the lenders or because of overall macroeconomic conditions, we control for various measures of lender capital constraints and macroeconomic variables which do not meaningfully alter our findings. Our results also prevail when examining the changes in borrower's investments, performing panel data regressions with a sample of borrowers till the maturity of the loan, and when recent default experience is redefined by excluding defaults that happen within the same industry or geographic region.

In further analyses, to mitigate the concern that lender default experiences proxy for unobservable macroeconomic conditions, we perform a nested matched sample analysis of borrowers' corporate investment. Specifically, each quarter we match a borrower contracting with a lender with recent default experience to a borrower contracting from a lender without such experience using a propensity-score matching algorithm based on observable borrower characteristics. Our findings on borrower corporate investment remain qualitatively unaltered using the matched sample approach.

Finally, we examine cross-sectional variation according to loan, borrower, relationship, and lender characteristics, lender incentives to learn, borrower's interest rate sensitivity, and changes in credit markets. Systematic variation in our findings according to loan riskiness, borrower agency problems, lender-borrower familiarity, or lender capitalization status would support the endogenous matching interpretation of the results. For example, if lenders with recent default experience make more risky loans, or lend more to high agency cost borrowers, or face more severe information asymmetry problems, or lend under dire lender circumstances, the reduction in corporate investment may be due to correlation between defaults and lender-borrower matching. However, we find that our results are robust across all subsamples, irrespective of any of the characteristics of the loan, the borrower, the relationship, or the lender, thus mitigating concerns of endogenous matching.

Next, we examine whether our findings vary systematically according to measures of the lender's incentives to acquire information or 'learn' about their borrowers. We find that our baseline findings are stronger among high R&D and high Q firms and when the borrowers operate in more unique and volatile product markets, i.e., when lenders have stronger incentives to 'learn'. Additionally, we also examine whether our findings vary systematically by the borrower's interest rate sensitivity according to whether the borrower is highly levered, has underfunded pension funds, faces higher debt rollover in near future, and whether they belong to mining and construction industries. However our results remain robust irrespective of interest rate reliance of borrowers.

Recently, the participation of non-bank lenders in the corporate lending market has increased as witnessed by the proliferation of covenant-lite loans and increase in institutional participation. Such changes have lowered the necessity and importance of bank monitoring of corporate loans (Becker and Ivashina, 2016). Consistent with such an evolution in the credit markets, we find that our results are weaker for covenant-lite loans, loans with high institutional participation, and in years when the leveraged loan activity picked up, suggesting that bank incentives to monitor moderate the relationship between recent default experience and corporate investment. Thus, all these findings further support the 'learning' hypothesis over the 'borrowing cost' hypothesis, the latter although not ruled out is dominated by the 'learning' hypothesis in our sample.

We also investigate how the recent default experience of a syndicate participant affects borrower's investment. Syndicate participants usually have comparable economic exposure to the loan as the lead arranger, and if lenders are highly connected to each other in the form of small and closed syndicates, a default experience of a syndicate member can also have a 'learning' effect on any new lending. Alternatively, if lenders are largely independent, forming different syndicates over time, then it is not necessary that a default experience of one particular syndicate member affects the contractual arrangement in subsequent lending. In our analysis, we find that a shock to syndicate participants also has a similar effect on corporate investment.

Chava and Roberts (2008) show that financial covenant violations are negatively associated with firm investments. If firms that borrow from lenders with recent default experience receive stricter contracts on average (Murfin, 2012), then it is possible that actual covenant violations are a potential channel through which investments decrease. In other words, lender default experience influences the covenant thresholds, and affects the investment through covenant violations as documented in Chava and Roberts (2008). On the other hand, if covenant violations are not related to lender's recent default experience, it suggests that there are other potential channels through which lenders succeed in restricting the borrowing firm's investment. To investigate how default experience affects the probability of covenant violation, we estimate quantitative financial covenant violations including both current ratio and net worth covenants by comparing covenant thresholds in the loan contracts with quarterly financial reports. We find only weak evidence that lender's recent default experience is positively associated with future covenant violations. Also, examining the time to first covenant violation, we again find weak support that borrowers from lenders with recent default experience violate covenants sooner. Thus, these findings suggest that actual covenant violations may be an alternative channel through which firm investment decreases. However, our main finding of the immediate decrease in firm investment following the loan (i.e., in the quarter after the loan contract) suggests that covenant violations cannot explain the entire decrease in investment, but only provides complementary evidence for how lender-borrower nexus can impact investment.

Our paper is related to the literature investigating frictions to loan supply and its real consequences. Murfin (2012) documents the tightening of loan contracts when lenders are faced with recent default experience. Similarly, Gopalan et al. (2011) find that large-scale bankruptcies on lead arranger's portfolio harms their reputation and in subsequent syndication activity the lead arranger offers tighter contracts and retains larger fraction to attract syndicate participants. Our paper is also related to studies that examine how different kinds of shocks affect loan supply. For example, Bord, Ivashina, and Taliaferro (2018) examine how lenders exposed to counties that suffer adverse real estate shocks contract their loan supply to borrowers in different unaffected counties. Also, Chava and Purnanandam (2011) show that banks exposed to the 1998 Russian sovereign default shrink their lending. We extend these studies by documenting a new channel by which lenders can propagate their individual default experience to the real economy. Our findings also highlight who bears the costs of lender mistakes and further propagates the "too big to fail" view. Moreover, our results demonstrate a dark side of relationship borrowing, by suggesting that borrowers end up sharing the shocks faced by their relationship lenders. Finally, our paper is also related to studies that investigate the link between financing and investment and specifically show how financing market frictions in the lending market affects corporate investment (Whited, 1992; Hennessy, 2004; Chava and Roberts, 2008). We complement these studies by exploiting a new source of friction in the debt markets on investment.

The remainder of the paper proceeds as follows. Section II describes our data and sample construction. Section III presents our empirical findings examining the impact of recent default experience on investment. Section IV discusses the cross-sectional variation in the investment response to default experience, investment response to syndicate participant's default experience, and the effect of default experience on probability of covenant violations. In Section V we conclude.

II. Sample construction

A. Identification of recent default experience of lenders

To examine the effect of lender default experience on corporate investment, we begin our empirical analysis by identifying recent default experiences of lenders between 1987 and 2016, following Murfin (2012).[2] Our framework focuses on actual defaults instead of technical defaults like covenant violations as in Chava and Roberts (2008), for the following reasons. First, a technical violation like a covenant default is less likely to affect the profitability of the lender, and thus be less powerful in inducing any changes in their lending behavior to unaffected borrowers. Second, setting up of covenant thresholds is endogenous to the level and quality of monitoring desired by the lender. For example, a lender may substitute tight covenant thresholds with higher loan spreads, when they do not specialize in monitoring and interventions, and vice versa. Therefore, if we choose covenant violations as our source of shock, then our sample might be biased towards banks that specialize in active monitoring. Finally, Denis and Wang (2014) show that lenders and borrowers actively renegotiate covenants before their actual violation, which suggests that observed covenant violations might be understated and could systematically bias our sample in favour of lenders facing higher agency costs or lenders who are unwilling to actively monitor their loans i.e., prefer to behave like bondholders.

To identify recent default experience, first we create a list of firms that are reported to be in default (rating 'D') or selective default ('SD') in the Standard and Poor' (S&P) Compustat ratings database that is updated at a monthly frequency.[3] Such firms are reported to miss or delay one or more payments on any of their outstanding financial obligations. The S&P Compustat ratings database records all publicly listed firms in the US with a credit rating. Typically, these firms tend to be large and have access to alternative sources of funding, e.g., access to public bond markets. Specifically, during an economic crisis or contractions in the

[2]We begin our sample period in 1987 to coincide with the availability of S&P rating data and a sufficient sample of DealScan loans. However, in later tests on covenant violations and credit market changes, we restrict our attention to sample periods beginning in 1994 and 1997, respectively, to coincide with the availability of reliable covenant data (Chava and Roberts, 2008) and beginning of leveraged loans (Lim, Minton, and Weisbach, 2014).

[3]S&P rates a borrower 'SD' (selective default) or 'D' (default) when the borrower has failed to pay one or more of its financial obligations on either rated or unrated securities when the payments came due. A 'D' rating indicates that S&P believes the borrower will fail to pay all or substantially all of its obligations when they are due. A 'SD' rating indicates that S&P believes that the borrower has selectively defaulted on a specific obligation, but they will continue to meet their obligations on other issues or classes of obligations promptly.

money supply, these firms have better access to alternative sources of financing (Becker and Ivashina, 2014). With this caveat in mind, using this rich data provides us an empirical set up to test more meaningful idiosyncratic shocks in the form of corporate loan defaults of large borrowers to a new borrowing firm's investment behavior.

Second, we merge these borrowers in default with the Loan Pricing Corporation's DealScan (DealScan) loan database which largely consists of syndicated and bilateral loans made by financial institutions to publicly held firms. Different commercial loan measures in the DealScan data are available in different granularity. A tranche or facility is the most basic unit of observation, which is usually aggregated into a deal or package.[4] A facility refers to a specific loan amount and maturity available in the borrowing package. For example, a firm that enters into a revolving credit facility can be provided two or more facilities with different maturities and different amounts as part of a single loan package. Each facility in DealScan consists of information including terms of the deal like the loan size, interest rate spread, covenants, maturity, and other lending details, which may be the same within a loan package.[5]

[Figure 1 about here.]

Figure 1 plots the quarterly distribution of identified default shocks and the distribution of affected lenders during our sample period from 1987 to 2016, when a lender has experienced a default shock in the past 90 and past 360 days prior to the new loan issuance, respectively. Our data consists of a large number of defaults that occur after the burst of the "Dotcom Bubble" and prior to the "Great Recession", presumably during an era of high credit expansion. Unsurprisingly, the 360 day shocks are distributed more smoothly by virtue of their construction. Cross-sectional differences in lender exposure to default shock over the calendar quarter and calendar year help us to identify the role of these idiosyncratic shocks on corporate investment of new borrowers in Section III. The distribution of these aggregate shocks clearly show that idiosyncratic lender shocks occur even during the periods with relatively better economic performance, mitigating the concern that these shocks might simply capture business cycle fluctuations during our sample period.

B. Identification of new borrowers according to lender default experience

To examine whether the merging of Compustat and DealScan data introduces any bias, we first compare key firm characteristics before and after the merge. The comparison is presented in Panel A of Table I. In the first three columns, we provide the summary statistics of firms in the Compustat quarterly database, i.e.,

[4]A loan facility or tranche is the basic unit of observation in most studies that examine a borrowing firm's financial obligations from DealScan database (e.g., Chava and Roberts, 2008; Roberts and Sufi, 2009).

[5]When performing analysis of covenant violations, we aggregate the facility level information to package level by observing the maximum package maturity and the stricter current ratio and net worth covenants in case of multiple covenants (Chava and Roberts, 2008).

Compustat sample after excluding financial firms (i.e., SIC codes 6000-6999) for a total of 13,560 unique firms comprising of 507,592 observations. In the next three columns, we provide the summary statistics for the merged, i.e., Compustat-DealScan sample for a total of 4,002 unique firms comprising of 15,718 observations. Comparing the two samples, we can see that firms in the two databases are typically larger, highly levered, more profitable, have higher net worth and lower current ratios, have fewer growth opportunities, invest less, and face higher bankruptcy risks. The bias towards larger and more mature firms in the merged sample is consistent with lender preferences for a typical borrower (Schwert, 2018).

[Table I about here.]

Next, using DealScan database, we identify the lead lenders with recent default experience as explained in Section II.A. In the empirical analysis that follows, we mainly focus on the new loans that are originated by these lead lenders with default experience in the subsequent two (i.e., most recent quarter) to five quarters (i.e., most recent year) following default and compare them with those lead lenders who provide new loans but have no recent default experience. When identifying the lenders with recent default experience, we do not include the loans originated immediately in the quarter following the default (i.e., not included in the treated sample) as preparing the loan tear sheets and the syndication process on average takes a calendar quarter (Murfin, 2012). Specifically, loans originated by a lead lender who faces default in the previous quarter is included as a new loan from a lead lender without a recent default experience (i.e., included in the control sample). The default shock is unlikely to modify lender behavior in the subsequent immediate quarter when potential new loans are in advanced stages of negotiation already. Also, we limit the timing horizon to five quarters following the default as the effect of the default experience will become a distant memory for the lender after a year from the default, and thus less likely to modify lending behavior after a year. Furthermore, regular changes to lending practices and turnover of loan officers suggest that defaults that happened in the distant past might be less informative or relevant to the bank's current screening ability.

In the last three columns in Panel A of Table I, we provide the summary statistics for the subsample of firms in the Compustat-DealScan merged sample that has borrowed from a lender who had experienced at least one default in the most recent quarter (ignoring the immediate quarter after default as described above).[6] The subsample consists of 2,181 firm-quarter observations. Comparing the subsample to the Compustat and the Compustat-DealScan merged samples, we observe that most of the borrower firm characteristics are similar across subsamples.

[6]For all analysis in Table I, we use the most recent quarter to classify lenders into those with recent default experience and those without (i.e., *Lender Shock –90 Days*). But in later tests for robustness, we also use an alternative definition of recent default experience by examining those lenders who face default in the previous year (i.e., *Lender Shock –360 Days*).

C. *Loan and lender characteristics*

In Panel B of Table I, we compare the loan characteristics in the whole Compustat-DealScan sample, to the default and non-default experience subsamples. Other than the number of participants in the syndicate which is greater when lenders have recent default experience, other loan characteristics are quite similar between the two subsamples. In Panel C, we compare the characteristics of lenders based on whether or not they have recent default experience.[7] To the extent that poorly capitalized lenders face more default shocks, then their borrowers' investment behavior can simply be a manifestation of borrowers with poorer investment opportunities matching with poorly capitalized lenders, thus making borrower investments to be an endogenous outcome of the matching process (Schwert, 2018).[8]

To obtain lender characteristics without losing a significant amount of observations, we first link the DealScan loans data to Federal Deposit Insurance Corporation (FDIC) database, and second to Federal Reserve / National Information Center database. The FDIC and FED identifiers, i.e., RSSD allows us to link the lenders with the facility identifier in the DealScan database using a parsing, matching, and filtering algorithm proposed by Keil (2018).[9] Results in Panel C of Table I suggest that the lender capitalization and Tier-1 capital ratio is lower among lenders with recent default experience, which support the argument of Schwert (2018). However, these lenders also have a significantly larger amount of assets with respect to their counterparts in a sample of 821 (13,427) loans with a lender having (not having) experienced a recent default.

D. *Borrower characteristics*

For tracking investment behavior of new borrowers, we use quarterly data since utilizing high frequency accounting data can provide a better assessment of how lenders may influence borrowing firms' corporate policies. Also, borrowing firms are required to file periodic reports with their creditors detailing compliance with covenants and other loan requirements, which usually occur at the quarterly frequency (Chava and Roberts, 2008). Such additional information provides an opportunity for the lender to provide feedback to reinforce their preferred corporate policies even in the absence of a covenant violation. Panel D of Table I provides mean and median statistics of firm characteristics according to whether a borrowing firm obtains a

[7]As documented in the prior literature, bank capitalization and lending activity is significantly associated with each other (Cornett, McNutt, Strahan, and Tehranian, 2011; Beltratti and Stulz, 2012; Berger and Bouwman, 2013; Carlson, Shan, and Warusawitharana, 2013). Therefore, we use some of the important measures on lender characteristics as control variables in Table IV to control for endogenous lender-borrower matching process as suggested by Schwert (2018).

[8]Murfin (2012) shows that well-capitalized (poorly-capitalized) banks tend to offer less strict (strict) covenants. Schwert (2018) documents that bank dependent (non-bank dependent) firms borrow heavily from well-capitalized (poorly-capitalized) lenders.

[9]For more information on the matching procedure, please refer to Keil (2018). We confirm that this matching procedure is comprehensive enough by including the lender link table provided by Schwert (2018).

new loan from lenders with or without recent default experience in a sample of 2,181 and 37,278 firm-quarter observations, respectively.

We find that the borrower's whose lenders have no recent default experience have higher current ratios, lower net worth, higher growth opportunities, and are smaller, and invest more, with respect to borrowers that obtain a loan from a lender who has experienced a recent default shock. These differences in both mean and median are significant at least at the 5% level. Results on the differences in net worth and firm size suggest that firms who borrow from lenders facing recent default experience are not systematically less creditworthy than their counterparts, thereby lowering the concern that our findings are affected by endogenous matching, as discussed in Schwert (2018).

III. Empirical Findings

A. Effect of lender default experience on new lending

After experiencing a default on their portfolios, lenders tend to write stricter loan contracts (Murfin, 2012).[10] Provisions like tighter covenants can ensure that lenders learn about potential trouble at borrowing firms sooner rather than later, and thereby have greater control when borrower performance begins to deteriorate. Bradley and Roberts (2015) highlight trade-offs between covenants and interest rates and suggest that strict contracts are often accompanied by lower interest rates. However, if a lender experiences a recent default and offers stricter contracts with low interest rates, then inevitably they will face a double-whammy of a negative profitability shock from the default and low interest rates on new loans. Both of our key hypotheses predict an increase in interest rates on new lending following recent default experience. Specifically, when lenders try to fix gaps in their screening and monitoring mechanisms (the 'learning hypothesis') and attempt to reverse the negative profitability shocks or try to overcome reputation loss in syndicates (the 'borrowing cost hypothesis'), we predict that the new loans from lenders with recent default experience are more expensive.[11]

Bolton, Freixas, Gambacorta, and Mistrulli (2016) argue that relationship lending reduces defaults despite higher initial information acquisition costs, emphasizing the 'learning' by banks through their lending activity.

[10] Theoretical and empirical evidence strongly suggest a demand-side story, i.e., on average, riskier firms receive strict contracts in the form of number and strictness of covenants (Berlin and Mester, 1992; Billett, King, and Mauer, 2007; Rauh and Sufi, 2010, among others). On the other hand, Murfin (2012) explores the supply-side effect on the borrower-lender relationship and proposes a new measure of contract strictness to capture the ex-ante probability of a forced renegotiation between lender and borrower.

[11] It is also possible that lenders use higher interest rates as a screening mechanism to identify good borrowers. Also, higher interest rates may indicate a riskier portfolio of the lender. However, we believe such an explanation is less likely for the following reasons. First, we concentrate on large borrowers because of the nature of our samples where information asymmetry problems are less severe, thereby lowering the need for screening borrowers. Second, the lender faces stronger incentives to lower the riskiness of their total portfolio when experiencing default.

Thus, following recent defaults, banks may have greater incentives to lend to a familiar borrower rather than establishing a new relationship with higher uncertainty. From the borrower's perspective, relationship borrowers face higher switching costs to find new lenders. For example, Bharath, Dahiya, Saunders, and Srinivasan (2009) argue that on average transactional borrowers pay higher borrowing costs when compared to relationship based repeat borrowers, which incentivizes the borrowers to stick to their lenders even when their lenders face recent defaults. Therefore, the lenders can behave opportunistically by inflicting the costs of their default on their relationship borrower locked in due to information asymmetry problems and potential switching costs. Alternatively, when lenders face a default shock, any additional lending to an existing borrower can increase lending portfolio concentration, especially if the risks are correlated across the loan portfolio, such as through common geographic or industry exposure. Thus, the prediction of recent default experience on the choice between relationship and transactional borrower, is ex-ante not clear, and needs to be explored empirically. In this regard, both the 'learning' and 'borrowing cost' hypotheses suggest that when lenders experience idiosyncratic default shocks, they have stronger incentives to charge higher interest rates on the new loans.

[Table II about here.]

Using the merged Compustat-DealScan sample, we examine the interest rates on new loans and the nature of the borrowers according to lender's recent default experience. The results are presented in Table II based on standard errors clustered by lenders. In Panel A, the natural logarithm of the all-in-drawn spread is the dependent variable in all the models and the default shock to the lender observed in the recent past is the key explanatory variable. We adopt key control variables from Ivashina (2009) who examines the effect of asymmetric information among syndicate members on loan spreads. To control for time invariant borrower heterogeneity, business cycle changes in lending behavior, loan characteristics, and borrower creditworthiness, we control for borrower fixed effects, year-quarter fixed effects, and include dummies for loan types and S&P credit ratings, respectively. In Models (I)–(V), the main variable of interest is represented by an indicator for the shock and in Models (VI)–(X), we utilize a cardinal variable as the count of default shocks in the lead lender's portfolio. In Model (I), we find that a lender who has experienced a default in the past 90 days is likely to charge higher interest rates on the loan, where the coefficient on *Lender Shock - 90 Days* is significant at the 1% level. The coefficient estimate suggests that a default shock to the lender portfolio leads to a 4.4% increase in loan spreads to a new borrower. In Model (II), we further control for a default shock that happens between 90 and 180 days in the past. We observe that the coefficient on *Lender Shock - 90 Days* continues to be significant at conventional levels while *Lender Shock 90-180 Days* is insignificant, suggesting that lenders account for these shocks and immediately reflect their circumstances on the newly issued loans.[12] Results remain qualitatively similar in Models (III) and (IV), when we control for default shocks to lenders in the past between 180 and 270 days and between 270 and 360 days periods, respectively. In Model (V), we use an alternative definition of a default shock to the lender by accounting for any shocks that happen during the past 360 days. We find that the coefficient on *Lender Shock - 360 Days* remains significant at a level of 1%. The models using a cardinal variable, i.e., the number of default shocks in Models (VI)–(X) produce qualitatively similar results.

In Panel B of Table II we present the results on whether the new lending is likely to be transactional or relationship-based in nature, conditional on the lender experiencing a recent default shock. The dependent variable is an indicator for whether the borrower has had a relationship with the lead bank in the past. Using the specification as in Panel A in which we control for time invariant borrower heterogeneity, business cycle changes in lending behavior, loan characteristics, and borrower creditworthiness, and estimating linear probability models, we find that recent default experience is weakly and positively associated with the likelihood of the new borrower being a repeat borrower, i.e., positive coefficient in Model (1) on *Lender Shock - 90 Days*, significant at the 10% level. However, in Models (II), (IV), and (V), the coefficient becomes insignificant, suggesting a weak effect of recent default experience on choice between familiar and unfamiliar borrowers. In Models (VI)–(X), replacing the indicator with a cardinal variable, we find that the coefficient on *Lender Shock - 90 Days* is positive and significant in Models (VI) and (X), at least at the 10% level.[13] Overall, these findings show that when lenders experience default in their portfolios; they tend to charge higher interest rates on their new loans and prefer to lend to familiar borrowers.

B. *Effect of lender default experience on borrower investment: Cross-sectional regressions*

Lenders with recent default experience are incentivized to reduce their overall portfolio's risk and to charge higher interest rates for a given level of risk to overcome the negative profitability shock, to cover the increased fixed costs in improving screening and monitoring systems, and to fix their reputation among syndicate participants. Relying on these arguments, in this section, we provide evidence on how these lender incentives affect investments of the new borrower.

The new loans can have a negative effect on borrowing firm's investment for the following reasons. First, the 'learning' hypothesis suggests that stricter contract terms can explicitly prevent investment in risky projects which usually benefit shareholders more than creditors, i.e., asset substitution problems. Also, lenders could possess significant negative information about specific types of investment opportunities from

[12] In subsequent analysis, we focus on this efficiency in lenders immediate reaction following default and for the sake of brevity, only report the results using the measure over the 90-day window. Using these alternate definitions in the subsequent analysis does not significantly alter any of our interpretation of the findings that rely on the 90-day window.

[13] This result also complements the findings of Murfin (2012). The stricter contracts offered by lenders with recent default experience could also arise from increased negotiating power that lenders have with their relationship borrowers.

their default experience and thus forbade the new borrowers in investing in those opportunities. Second, 'borrowing cost' hypothesis suggests higher costs of loans can lower the profitability of positive NPV projects otherwise and make the potential projects less attractive to pursue. Also, bearing higher interest costs can reduce investment scale in committed projects. Thus, both the hypotheses predict a negative spillover effect on new borrower investment from the recent default experience.

[Figure 2 about here.]

Figure 2 plots the average quarterly investments around the borrowing. On the left (right) panel, we focus on eight quarters before and after borrowing a loan from a lender with (without) default experience in the previous 90 days. In the left panel, we see the average investments steeply declining and the sharp decline coincides with the start of the new loan. However, on the right panel when borrowers take a loan from lenders without any default experience, we see the average investments marginally increase or stay similar compared to the quarters before the loan. These graphs suggest that the lender's recent default experience can hurt corporate investment for borrowers. To further investigate this more rigorously, we employ cross-sectional regressions as detailed below.

[Table III about here.]

Using the lender's recent default experience from the most recent quarter, we perform cross-sectional regressions of new borrower's quarterly investment activity. We restrict the Compustat quarterly sample to those firm-quarters where the firms have just borrowed a loan from the banks in the DealScan database. The results are presented in Panel A of Table III based on standard errors clustered by borrower. Using investment defined as capital expenditures scaled by start of period capital stock, as the dependent variable, we include the standard control variables used in prior literature investigating the determinants of investment, e.g., Macro Q, cash flow, and size of the firm (Bond and Meghir, 1994; Erickson and Whited, 2006; Chava and Roberts, 2008). We also include borrower fixed effects to enhance our identification (Murfin, 2012). Holding the borrower fixed, we examine how their investment is affected when the lender has had a recent default experience. This allows us to rule out any unobservable and correlated time invariant borrower characteristics that may affect their investment.[14] In Model (I) we present the results without controlling

[14] Since our data is cross-sectional, we omit time fixed effects in the baseline analysis. However, to mitigate concern about specific events that may influence the observed association, we perform the following. First, in additional tests in Section III.F, we include various additional fixed effects such as borrower-lender, loan quarter and year-quarter fixed effects when we extend our sample to perform a panel data analysis. These additional fixed effects further help narrow the interpretation of our findings solely to lender specific idiosyncratic experiences. Second, in Section III.G, we use a matched sample approach to examine lenders that lend contemporaneously but with different default experiences, and examine the effect on borrower investment. Third, in Section III.D we explicitly control for various macroeconomic measures that correlate with economic circumstances and aggregate defaults to isolate the effect of idiosyncratic default experience. We present the above results and our interpretation in subsequent sections.

for conventional investment factors and we find a negative coefficient significant at the 1% level. In terms of economic magnitude, a borrower who obtains a loan from a bank with a recent default experience decreases her investment by 8.24% (coefficient of -0.486 divided by the sample mean investment of 0.0590 × 100 as investment is scaled by 100 in the regressions). In Models (II) and (III), we include the control variables in a simple investment regression model, i.e., *Macro Q* and *Cash flow*, and *Firm Size* and results remain significantly negative for *Lender Shock*.[15] Specifically, after controlling for the standard determinants of investment, we find that a borrower who takes a loan from a lender with a recent default experience invests 7.14% and 6.22% less on average (estimated coefficient on the variable, -0.421 and -0.367 divided by the sample mean investment of 0.0590 × 100) in Models (II) and (III), respectively. Comparatively, a one-standard-deviation change in the standard determinants of investment including *Macro Q, Cash flow,* and *Firm size* leads to an increase in investment by 27.91%, 2.48%, and -35.47%, respectively. Thus, the economic magnitude of the lender's recent default experience on corporate investment is comparable to the other standard determinants of investment. In Model (IV), we additionally control for *Altman's Z-score* to account for the effect of financial stability of a borrower on its investment behavior (Altman, 1968). In Model (V), we consider a potential non-linear relationship between a firm's investment opportunities and its investment and additionally control for the square of *Macro Q*. In Model (VI), we add lagged cash flow to our specification and consider the persistence in the firm's operating profitability (Chava and Roberts, 2008). All these additional specifications continue to yield robust results with the coefficient on *Lender Shock* remaining negative and significant at the 1% statistical level.

C. Persistence of the effect of lender default experience on borrower investment

In Panels B and C of Table III, we investigate the persistence in the effect of lender default experience on borrower investment. Using the cross-sectional framework in Panel A, we examine the investment activity of borrowing firms in the subsequent periods, i.e., two to eight quarters following the loan issuance. In Panel B, we compare the mean difference in investment between borrowers from lenders with and without default experience, we find that firms in the former group invest consistently lower than those in the latter. Although the difference is gradually decreasing over time, it remains strong and persistent as all of the differences in investment between quarters two to eight is statistically significant at the 1% level. To further test the long-term impact of lender default shock on corporate investment, in Panel C, we present the results regarding investment in two to eight quarters following a new loan issuance. Our empirical specification in similar to Model (IV) in Panel A, in which we fix the timing of control variables relative to the measurement of investment, except for *Lender Shock*, since it is time invariant. We find that the coefficient on *Lender*

[15] All the variable definitions are detailed in Appendix A.

Shock is significant at the 1% level in all the models, suggesting that there is a persistent effect of a lender default experience on borrower investment activity. An intuitive explanation for the persistent decrease in investments is that certain investment activities may happen gradually over time and when such projects are forfeited, the reduction in investment can happen gradually over time giving rise to persistence in investment cuts (e.g., (e.g., Veracierto, 2002; Khan and Thomas, 2008). This finding also supports the view of Eberly, Rebelo, and Vincent (2012), who attribute the lagged-investment effect to the adjustment cost function of investments (Christiano, Eichenbaum, and Evans, 2005).[16]

D. *Influence of lender and macroeconomic characteristics*

The negative effect of recent default experience on borrower investment can also be due to two alternative explanations: 1) endogenous matching of borrowers with lenders and 2) correlation of business cycle with investments. First, endogenous matching suggests that there can be a potential mechanical relationship between the shrinkage in borrower investment and lender default experience. When banks, especially weaker banks, are hit with a shock that depletes their capital, it is inevitable that they shrink their assets unless they raise new capital or shift to a lower capital to assets ratio (Kashyap, Stein, and Hanson, 2010). So, it is natural to assume that they will lend to less number of borrowers and make smaller loans to each. Also, endogenous matching suggests that borrowers with weaker investment opportunities may borrow from a bank with capital constraints, thereby setting up a mechanical relationship between default shock and investment activity at new borrowers. To test this prediction, we control for the lender's capitalization measured by the changes in the ratio of equity to book value, the changes in the lender's risk-weighted Tier-1 capital ratio, and the changes in the natural logarithm of the lender's total assets (Murfin, 2012; Schwert, 2018).[17] Additionally, we also control for the interest rates charged on these new loans, given that higher interest rates can indicate a higher level of borrower's risk assessment. This argument is in line with the intuition that risky borrowers may be financially constrained and be unable to fully finance their investment projects (Fazzari, Hubbard, and Petersen, 1988; Almeida and Campello, 2007).

[Table IV about here.]

The results when we control for lender characteristics are presented in Table IV with standard errors clustered by borrower. In Models (I)–(IV), we add each of the variable discussed above one at a time to our specification in Model (VII) of Table III. In all the four models, *Lender Shock* remains significant at the 1%

[16] In untabulated results, we test the robustness of our findings to an alternative definition of cash flow as in Eberly et al. (2012) and their double-log transformation of investment equation. Our original findings remain qualitatively unaltered.

[17] In addition, these control variables may also alleviate some of the concerns about the association between bank liabilities and relationship lending as argued by (Berlin and Mester, 1999).

level. In terms of these additional variables, we find that Δ *Lender Book Assets* is positive and significant in Model (III) and Δ *Lender Capitalization* and the *All-in-drawn spread* are negative and significant in Models (I) and (IV), respectively. These findings suggest that when firms borrow from banks with growing asset portfolios and those that borrow at cheaper interest rates can pursue investment projects more aggressively, having partialled out their recent default experience. However, results in Model (I) suggest that firms that borrow from lenders with improving market capitalization invest less when recent default experience is partialled out. In Model (V), we include all the controls together and still find that *Lender Shock* remains significant at the 1% level. In Models (VI), (VII), and (VIII), we replace the dependent variable by lead investment in the subsequent periods, i.e., quarters two, three, and four, respectively. We find the coefficient on *Lender Shock* remains negative.

Second, to the extent that defaults in the economy and investment opportunities are correlated, it is expected to find a negative relationship between defaults and future investment. To control for the influence of this alternative channel related to business cycles, we include the quarterly GDP growth, credit spreads between Baa-rated and Aaa-rated corporate bonds, quarterly return on the S&P 500, and finally an indicator for the level of aggregate defaults as reported by (S&P) Compustat ratings in our specifications. Controlling for aggregate defaults in the economy in the same frequency as we measure idiosyncratic default shocks faced by the lenders allows us to account for aggregate macroeconomic risk, allowing *Lender Shock* to capture risks solely from lender's idiosyncratic lending experience, orthogonal to other common observable macroeconomic risks as argued by Murfin (2012).

[Table V about here.]

The results when we control for observable macroeconomic variables are presented in Table V. All the specifications are exactly similar to those in Table IV. In all the models, *Lender Shock* remains significant at least at the 5% level. Additionally, we find that in Models (I)-(IV) when we add these control variables one at a time, all of the other variables are significant at the 1% level. Specifically, we find that lower GDP growth, lower credit spreads, higher S&P 500 return, and lower incidence of corporate defaults, are associated with greater level of corporate investment. In Model (V) with all the controls, *Lender Shock* remains significant. This finding is robust when we replace the dependent variable with lead investment measured in quarters two, three, and four, respectively (Models (VI)-(VIII)). The findings in Tables IV and V suggest that the negative effect of the lender's recent default experience on borrower investment is not because of a mechanical relationship between investment and lender capital constraints or business cycle fluctuations.

E. *Effect of lender default experience on changes in borrower investment*

We further address concerns of endogenous matching between lenders and borrowers by using a change specification. Instead of using the level of investment which may vary between a borrower with and without good investment opportunities, we use the changes in investment level, since it is less likely that the changes in investment activity are related to the differences in firms' investment opportunities and their lender preferences.

[Table VI about here.]

The changes in investment is measured as the difference between investment in the post-borrowing period (first quarter after loan issuance) and the investment in the third quarter in the pre-borrowing period (i.e., a lag of one year). Leaving a gap of two quarters between actual borrowing and measuring past investment allows past investment to not be influenced by the loan negotiation process (Murfin, 2012) and also mitigates concerns about the high auto-correlation in investment (Philippon, 2009). Computing the dependent and explanatory variables as changes (i.e., estimating a first-difference regression) helps overcome omitted unobservable borrower-specific characteristics in the cross-sectional sample. Additionally, to account for time heterogeneity, we demean all variables (except *Lender Shock*) by cross-sectional sample median. Adopting the specification of Model (VII) in Table III and estimating the regression as changes on changes, we report the findings in Table VI with standard errors clustered by borrower. In this analyses, we control for changes in lagged investment level (e.g., Alti, 2006; Eberly et al., 2012). We find that the coefficient on *Lender Shock* remains significant at least at the 10% level in all the columns except Model (IV). For example, in Models (I) and (II), the coefficients of -0.190 and -0.157 on *Lender Shock*, when compared to the mean change in investment of -0.210 are substantially large, and can account for 0.90 and 0.75 times the average change in investment. In Models (V)–(VIII), we replace the indicator *Lender Shock* with a variable for the count of the number of default shocks the lender experiences. Our results remain qualitatively similar to the earlier cross-sectional analysis.

F. *Effect of lender default experience on borrower investment: Panel data regressions*

We also provide supporting evidence to the changes specification by relying on a larger panel dataset to better control the influence of borrower-lender nexus and time fixed effects. Specifically, using the cross-sectional data on firms that enter into a new loan contract, we construct panel data by including quarterly observations for each firm till the maturity of the original loan. With this unbalanced panel data, we then perform regression analyses by accounting for borrower (or borrower-lender) fixed effects, event-quarter fixed effects, and year-quarter fixed effects. By fixing the pair of borrower and lender, we manage to pin down the effect precisely to lender circumstances at time of loan. This empirical exercise helps us to address the potential influence of time invariant borrower-lender characteristics in our framework. Similarly, controlling for the event quarter and year-quarter fixed effects allow us to capture the heterogeneous effects on investment over time. The results are reported in TableVII with standard errors clustered by borrower and quarter.

[Table VII about here.]

In Table VII, we present the findings including all the control variables as in Model (IV) of Table VI, measured as levels. We find that the coefficient on *Lender Shock* is significantly negative at the 1% level in the first two models with event-quarter and borrower (borrower-lender) fixed effects. In Model (III), we include year-quarter fixed effects instead of event-quarter fixed effects, and find that *Lender Shock* remains negative and significant. In Model (IV), we include all of the fixed effects (except borrower) and find that the key explanatory variable remains significant. In Models (V)–(VIII), we use a count measure of *Lender Shock* instead of indicator and find similar results.

In sum, the findings in Table VII reinforce our earlier findings while addressing more directly the concern about potential endogeneity issues of borrower-lender nexus and time heterogeneity.

G. *Effect of lender default experience on borrower investment: Propensity Score Matching*

In this section, we attempt to provide more direct evidence of how the investment of two borrowers is affected when they contract at the same time from lenders with different recent default experience. By fixing contracting time, this analysis further mitigates concerns about the effect of unobservable macroeconomic differences that may influence our findings. To implement such an analyses, we perform a propensity-score (nearest neighborhood) matching approach and compare investment of borrowers borrowing from a lender with and without recent default experience in the same quarter. Specifically, each quarter we estimate the probability (i.e., propensity score) of a borrower contracting with a lender with recent default experience by regressing an indicator for *Lender Shock* on borrower characteristics, including *Macro Q*, *Cash Flow*, *Firm Size*, and *Altman's Z-score*. We then match, without replacement, a lender-borrower pair where the lender faces a recent-default experience with a lender-borrower pair where the lender faces no recent-default experience. By performing the matching iteratively in each quarter, we eliminate the influence of macroeconomic differences on both loan contracting and subsequent investment of borrowers. The matched sample consists of 1,358 lender-borrower pairs without recent lender default experience and 1,358 lender-borrowers with recent default experience.

[Table VIII about here.]

In Panel A of Table VIII, we report the differences in mean and median matching variables between the two groups of borrowers and find that none of the differences are significant, suggesting that the matching has identified similar borrowers on observable characteristics, except from the nature of their lenders recent default experience. Panel B of Table VIII presents results of cross-sectional investment regressions using the matched sample with industry fixed effects and standard errors clustered by borrower. In Models (I)–(III), using *Lender Shock* as an indicator variable, we find that the coefficient on *Lender Shock* is negative and significant at least at the 10% level, irrespective of the inclusion of controls for other determinants of investment. In Models (IV)–(VI), measuring *Lender Shock* as a count variable, we see a similar negative relationship between lender recent default experience and borrower investment.

Overall, the results in Tables IV–VIII support our key findings, and methodically help to minimize concerns regarding the alternative explanations such as endogenous matching, macroeconomic conditions, or other unobservable factors that may be driving the negative relationship between recent lender default experience and borrower investment.

IV. Robustness Tests

A. Effect of industry/region -specific factors on defaults and investment

Another potential concern regarding our finding is that lender defaults and investment opportunities may be correlated across industries or geographical regions. For example, a bank may specialize in lending to a particular industry (or region), and the default intensity in the industry (or region) and investment rate of non-defaulting firms are likely to be correlated, which can raise concerns of spurious correlations. Although in most of our analysis so far, we control for unobserved heterogeneity across sample and time, these adjustments may not fully mitigate this concern. Hence, we examine our findings in Table III by excluding new borrowers that belong to the same industry and geographic region as the defaulting firm. Specifically, we redefine the *Lender Shock* variable to exclude the defaults that occur in loans that are issued to borrowers in the same industry and region. We use a borrower's one-digit SIC industry code to define industry relatedness and identify the location of borrower's headquarters, i.e., state, respectively.

[Table IX about here.]

The results are presented in Table IX with borrower fixed effects and standard errors clustered by borrower. In Models (I) and (III) (Models (II) and (IV)), the dependent variable is the investment in the first (second) quarter following the loan issuance. The control variables are measured with respect to the timing of the investment measure. In both Models (I) and (II), we find that the coefficient on *Lender Shock* is negative and significant at the 1% level. In Models (III) and (IV), when we use the count measure instead of indicator to compute *Lender Shock*, we confirm similar results. These findings suggest that the observed effect of lenders' default experience on borrower's investment is not driven by spurious correlations that may be due to the specialization of the lender in certain industries or lender's presence in certain regions.

B. *Cross-sectional variation in findings*

While our findings so far document an average negative effect of recent default experience on investment, there is good reason to expect cross-sectional variation in investment sensitivity to the recent default experience. For example, the borrowers investment might be more sensitive when lenders face greater uncertainties or when borrowers investment opportunities are decreasing with their cost of financing. The goal of this section is to establish whether the documented negative relationship is universal or shows systematic variation based on various factors.

B.1. Variation according to firm, borrower, relationship, and lender characteristics

One can predict that if the lender's effect on investment relates to borrower risk, then the effect of recent default experience will be more pronounced on risky loans, i.e., loans with stricter contracts, borrowers with higher levels of agency problems, and borrowers who are more likely to be first time borrowers with the syndicate. More risky borrowers will receive stricter contracts and have higher levels of agency problems, and consequently their investment will be most sensitive to borrowing from lenders with recent default experience. Similarly, if the negative effect on investment is due to the lender's fragility, then our results will be more pronounced among lenders with capital constraints.

In this regard, we test whether there is systematic variation in firm's investment sensitivity to default experience along the dimensions of: 1) the type of loan contracts; 2) the severity of agency problems associated with a borrower; 3) characteristics of the lender-borrower relationship; and 4) characteristics of the lender.

By using the specification of Chava and Roberts (2008) to document the differential effect on firm investment, we interact the *Lender Shock* variable with a particular proxy for each characteristic along the dimensions discussed above, as specified below:

$$\begin{aligned}\text{Investment}_{i,t} = &\ \beta_1\, I(\omega)_{i,t-1}\,\text{Lender Shock}_{i,t-1} + \beta_2\,(1 - I(\omega)_{i,t-1})\,\text{Lender Shock}_{i,t-1} \\ &+ \chi_0\, I(\omega)_{i,t-1}\,\text{X}_{i,t-1} + \chi_1\,(1 - I(\omega)_{i,t-1})\,\text{X}_{i,t-1} + \epsilon_{i,t}\end{aligned} \tag{1}$$

where $I(\omega)$ is an indicator function that takes the value of one for specific subsample according to the different proxy measures and zero otherwise.[18] Estimating the above equation is better than estimating our baseline specification over different subsamples as it allows easy comparison of the coefficients in the same model, since the errors are not interacted with the indicator function (Chava and Roberts, 2008).[19]

For measuring loan contract terms, we choose proxies from the prior literature (Bradley and Roberts, 2015; Chava and Roberts, 2008; Ivashina, 2009). First, risky loans are going to be costly. To that extent, we create an indicator variable for the *All-in-drawn Spread*, which takes the value of one if the spread is in the top tercile and zero if in the bottom tercile, respectively. Second, lenders are also more likely to lend smaller amount of loans if they consider new loans to be riskier. Therefore, we define an indicator variable for *Loan Amount / Assets* that takes the value of one or zero for loans that constitute the top or bottom tercile, respectively. Third, lenders prefer to lend on a *Secured* basis as opposed to unsecured, especially when they consider the loan to be risky. So, we define an indicator *Secured* to indicate the nature of the loan. Fourth, when making risky loans, lenders prefer to lend for shorter maturity. Hence, we define our fourth proxy *Maturity*, which takes the value of one for loans with maturity in top tercile and zero if in bottom tercile.

For measuring agency costs, we choose the following proxies based on prior studies that examine agency problems in the context of a firm's contractual environment (Jensen and Meckling, 1976; Jensen, 1986; Ashbaugh-Skaife, Collins, and LaFond, 2006; Almeida and Campello, 2007; Nikolov and Whited, 2014). As agency problems can be more severe when firms rely less on external capital and when information asymmetry problems between managers and investors are severe, we capture these dimensions of agency problems using the following measures: 1) whether the firm has high free cash flow; 2) whether the firm has high levels of cash holdings (*Cash Holding*); 3) whether the firm has a credit rating or not (*Rated*); and 4) the ratio of fixed assets to total assets (*Tangibility*), which can increase debt capacity of the firm.

For measuring whether the borrower has had a prior relationship with the lender, first we observe whether the current lead lender has been a past lead lender for the same borrower in the DealScan data on syndicated loans (Rosenfeld, 2014).[20] We characterize such a relationship as "*Strong Relationship*". Second, to account for the possibility that the current lead lender could have had an indirect relationship with the borrower by participating in a syndicate that provided a loan in the past, we define "*Weak Relationship*" as those pairs, where the borrower has borrowed a loan in the past from a syndicate which included the current lead lender as a participant. Third, to see if at all there is any overlap between the current syndicate participants

[18] When the characteristic used to create the subsamples is a continuous measure, we define the indicators $I(\omega)_{i,t-1}$ and $(1 - I(\omega)_{i,t-1})$ as one when the observation belongs to the top and bottom terciles, respectively.

[19] In additional untabulated tests, to examine the robustness of our findings with alternative specifications, we verify our findings by using two samples divided by the $I(\omega)$ function and then compare the coefficients on *Lender Shock* across the subsamples. All the results of test of difference in coefficients are qualitatively similar to those presented in Tables X and XI, and are available upon request.

[20] Rosenfeld (2014) define a relationship lender as a lender who has been a lead lender in the past five years.

and any syndicate participants in a past borrowing, we define "*Any Relationship*" as those pairs where at least one syndicate participant is common between the current loan and a past loan. Finally, to account for the home bias of lenders (Carey and Nini, 2007), we create a distance measure between the lead lender and the borrower, "*Distance From Lender*". The borrowers who are nearer to the lead lender are more likely to be familiar to the lender and thus suffer less severe information asymmetry problems from a lender's perspective.

For measures of lender characteristics, we borrow the measures from Schwert (2018) as used in Table IV. Specifically, we create subsamples based on the level of lender capitalization measured as the ratio of equity to book value, the changes in lender capitalization, the changes in the lender's risk-weighted Tier-1 capital ratio, and the changes in the natural logarithm of the lender's total assets.

[Table X about here.]

The results using these variables and the specification in Eq. (1) is presented in Table X, with borrower fixed effects and standard errors clustered by borrower. For the sake of brevity, we only present the coefficients on $I(\omega)\times$*Lender Shock* and $(1-I(\omega))\times$*Lender Shock*. We also present the F-statistics of the test of difference between these two coefficients and the associated p-value. In Panels A, B, C, and D, we use the proxies for loan contract terms, agency costs, relationship characteristics, and lender characteristics, respectively. In Panel A, we find that both the coefficients are negative in all columns using *All-in-drawn Spread*, *Loan Amount / Assets*, *Secured*, and *Maturity*. The coefficients are also mostly significant, except in two cases including the larger loans and loans with longer maturity. The F-statistics for the test of difference in the two coefficients is also not significant in any model. These findings suggest that the sensitivity of borrower investment to recent lender default experience does not vary by any loan characteristics (Berlin and Mester, 1992; Billett et al., 2007; Rauh and Sufi, 2010). Furthermore, these findings go beyond the contribution of Murfin (2012) in suggesting that even when new borrowers receive better terms, the recent default experience of a lender affects borrower investment. This lends credence to the view that lenders learn about investment opportunities through their recent default experience and hence discourage even the less risky borrowers to invest.

In Panel B, we find that all the coefficients on $I(\omega)\times$*Lender Shock* and $(1-I(\omega))\times$*Lender Shock* are negative (but insignificant for firms with low free cash flow and high or low tangibility). Also, the F-statistics of the test of difference is insignificant in all the four columns using *Free Cash Flow*, *Cash Holding*, *Rated*, and *Tangibility*. We interpret these results as indicating that the effect of default experience on the borrower is not directly related to the severity of borrower's agency problems as assumed by standard information models of credit markets, which overweight the demand side characteristics and remain silent about the supply side.

In Panel C, we find again that all the coefficients on $I(\omega)\times$*Lender Shock* and $(1-I(\omega))\times$*Lender Shock* are mostly negative (and significant in first three columns), and the F-statistics of the test of difference is insignificant in all the columns. These findings along with those in Panel B, suggest that the negative effect of recent default experience on borrower's investment is independent of any borrower or relationship characteristics.

Similarly, in Panel D, using measures for lender capital constraints, we find that the coefficients on $I(\omega)\times$*Lender Shock* and $(1-I(\omega))\times$*Lender Shock* are negative for both extremes in lender capital measures. The F-statistics of the test of difference is also insignificant in the last three columns, but significant in the first column. However, the difference in the coefficients in the first column suggest that well-capitalized lenders impose further investment cuts on their borrowers, counter-intuitive to the expected positive relationship between lender capitalization and borrower investment. Thus, these findings suggest that the lender's capacity constraints do not seem to drive the relationship between the lender's recent default experience and borrower's investment.

Overall the findings presented in Table X suggest that our baseline results of a negative effect of lender's recent default experience on borrower investment activity cannot be fully explained through observable loan contract terms or through the characteristics of the borrower or the relationship or the lender. The effect seems to be more universal and coming exclusively from the lender's idiosyncratic experience and an update of their beliefs and lending processes.

B.2. Variation according to learning incentives, interest rate sensitivity, and credit market characteristics

While we briefly discuss and analyze the potential economic channels of the impact of lender recent default experience on borrower investment, i.e., lenders' learning incentives and costly borrowing, it is ex-ante not clear if any of these mechanisms dominate the other. Such predominance might be simply due to the relative difference in the extent of influence of the borrower versus lender on investment following loan contracting. In this section, we examine these potential economic channels further and provide results variation according to 1) learning incentives of lenders; 2) interest rate sensitivities of borrowers; and 3) developments in creditor markets. Although our prior is that the two economic explanations may co-exist, in these cross-sectional variation tests, we expect to find systematic differences across each of the three dimensions in our sample.

Specifically, we predict that our results will be more pronounced when lender incentives to learn and borrower sensitivity to interest rates are higher, in order to further support the 'learning' and 'borrowing cost' hypotheses, respectively. Finally, to understand how recent evolutionary changes in the credit markets, such as the increased participation of institutions and development of 'cov-lite' loans (e.g., Becker and Ivashina, 2016) affect our findings, we predict that these recent developments by weakening lender incentives to monitor, will reduce the negative effect on borrower investment.

To measure lender incentives to learn, we make use of proxies that measure uncertainties in the investment environment either at the borrowing firm or in their industry. Innovation involves higher uncertainty, risk taking, probing, experimenting, and testing (Jorde and Teece, 1990). Thus, in many "high-risk" R&D efforts, firms are unlikely to be certain whether they will succeed, even when maintaining active R&D effort (Malueg and Tsutsui, 1997), suggesting that returns to learning can be greater for lenders. Therefore, we create an indicator variable for *R&D / Sales* based on whether borrowers are in the top or bottom tercile of the ratio of R&D expenditure to sales.

Similarly, lenders to firms with high investment opportunities have more incentives to learn about those investment choices. Thus, our second measure is an indicator for *Macro Q* based on whether borrowers are in the top or bottom tercile of our sample in terms of *Macro Q*. Also, lenders have greater incentives to learn about the borrowers when they operate in more unique product markets, which are characterized by high overheads, higher risks of financial distress risk, and lower prices during liquidation (Opler and Titman, 1993). Therefore, we compute the median ratio of selling expenses to sales in the SIC 2-digit industry of the borrower and define an indicator for *Industry Uniqueness* that takes the value of one when the annual industry median ratio is in the top quartile in our sample. Moyen and Platikanov (2013) find that industries characterized by a higher R&D intensity naturally face more technical uncertainty, and their investments respond less to profits, than in firms that operate in less volatile industries. Following their work, we define industries in the top (bottom) two quintiles of annual R&D intensities out of the Fama-French 48 industries as being high-volatility (low volatility) industries.

To measure interest rate sensitivities of the borrower directly, we utilize the measures of leverage, funded status of defined benefit pension plans, the debt maturity profile of borrowers, and whether they operate in interest-rate sensitive sectors. First, highly levered firms may underinvest to lower their financial distress risk (Myers, 1977), with the rate of underinvestment being highly sensitive to interest rates. Pension fund assets and liabilities can influence capital structure decisions (Shivdasani and Stefanescu, 2010) and also have implications for capital budgeting decisions (Jin, Merton, and Bodie, 2006). Therefore, we anticipate firms with underfunded pension plans to be more sensitive to interest rates. Following Balachandran, Duong, et al. (2019), we compute *Pension Deficit* as the difference between pension fund liabilities and pension fund assets, scaled by the borrower's market capitalization. We designate borrowers as 'under-funded' ('over-funded') when they have non-negative (negative) *Pension Deficit*. Also, borrowers with near-term maturing risk are more sensitive to interest rates. Thus, we define the debt rollover risk as the *Debt Maturity Profile* computed as the ratio of long-term debt to total debt. Finally, firms that operate in mining and construction sectors, are expected to be more sensitive to interest rates as the latter plays a crucial role in the demand for their goods and services. Therefore, we define an indicator variable that takes the value of one for firms with 2-digit SIC codes between 10 and 17 and zero otherwise.

Finally, to capture the structural changes in the credit markets, we rely on recent studies that emphasize their implications. The first decade in the twentieth century saw some significant structural developments in the corporate lending market, with non-bank institutional investors participating and playing increasingly larger roles in corporate lending (Lim et al., 2014). The increased participation of such investors broadened the syndication supply, narrowed the skills, and muddled the incentives of the lenders (Becker and Ivashina, 2016). These developments also seemed to have significantly altered the nature of contracting in the corporate lending market, with covenant-lite loans becoming more popular, as a result of the increased coordination costs of the institutional investors. Such changes in the market affect the role of a lender and their incentives to actively monitor the borrower. They face greater incentives to cater to the institutional demand to earn a fee income, instead of thoroughly screening and monitoring the borrowers.[21]To test how these changes influence our results, first, we define an indicator for whether the loans consist of a financial covenant or not. Second, we classify a loan as being covenant-lite, based on DealScan market segment file, which provides a tag for "Covenant lite" (Berlin, Nini, and Edison, 2020). Third, we classify loans as either having or not having institutional investor participation based on the primary SIC code of the lenders. Specifically, we categorize a loan to have institutional participation if at least one non-commercial bank institutional investor is present in the syndicate (Lim et al., 2014).[22] Finally, we construct an indicator for post 2010 years that coincides with a period of increased supply and consistent growth in the issuance of covenant-lite loans.[23]

[Table XI about here.]

We present the findings based on cross-sectional variation in lender incentives to learn, borrower interest rate sensitivity, and changes in credit markets in Table XI using the same specification as in Eq. (1) with

[21]Responding to a letter by Senator Elizabeth Warren in May 2019 that raised concerns of overheating in the leveraged loan markets, the Office of the Comptroller of the Currency (OCC) Joseph Otting, Fed Chair Jerome Powell, and FDIC Chair Jelena McWilliams replied "Agency examiners have observed in some transactions fewer and less stringent protective covenants, more liberal repayment terms, and incremental debt provisions that allow for increased debt that may inhibit deleveraging capacity and dilute repayment to senior secured creditors," acknowledging the potential risks. Furthermore, according to the OCC spokesperson "While bank risk management practices are satisfactory, we continue to see risk accumulate, primarily outside of the regulated banking system where there is much less transparency, making it more difficult to monitor. The OCC has been discussing with bank management and directors the need to consider the potential effect on the financial system from originating and distributing weakly underwritten loans to leveraged borrowers."

[22]A lender is classified as a commercial bank if its primary SIC code falls in 6011-6082 or 6712, and as an institutional investor, otherwise.

[23]According to Financial Stability Board's December 2019 report on "Vulnerabilities associated with leveraged loans and collateralised loan obligations", the leveraged loans market after grinding to a halt in 2009 and 2010, has witnessed steady and sustained growth since, and witnessed a steady shift to institutional lenders. See https://www.fsb.org/wp-content/uploads/P191219.pdf for further characteristics of these trends.

borrower fixed effects and standard errors clustered by borrower. For the sake of brevity, we only present the coefficients on $I(\omega)\times$*Lender Shock* and $(1-I(\omega))\times$*Lender Shock*. We also present the F-statistics of the test of difference between these two coefficients and the associated p-value.

In Panel A, we find that the coefficients are significantly negative among firms with high R&D, high growth opportunities, and those that operate in unique product markets and highly volatile industries. The coefficient for firms with low R&D firms, firms with low growth opportunities, and in less volatile industries are insignificant. However, firms that operate in less unique product markets also have a negative coefficient, but smaller in magnitude when compared to those operating in more unique product markets. The F-statistics for the test of difference in the two coefficients across all the four columns are significant at least at the 10% level. These findings suggest that the sensitivity of borrower investment to recent lender default experience is more pronounced when lenders face higher uncertainty and hence have greater incentives to learn more about the borrowers, further supporting the 'learning' hypothesis.

In Panel B, we find that the coefficient on *Lender Shock* is negative and significant among highly levered firms (also less levered firms), firms with under funded pension schemes, firms with higher debt rollover risk, and in firms not in the mining and construction industries. Although the results on leverage, pension funding status, and debt maturity profile seem to support the 'borrowing cost' hypothesis due to the higher sensitivity of these borrowers to interest rate costs, the F-statistics for the test of difference in the two coefficients across all the four columns are insignificant. These findings suggest that although the 'borrowing cost' hypothesis is not rejected, neither is it strongly supported in our sample.

In Panel C, in the first column using an indicator for financial covenants, we find that the coefficient on financial covenants is negative and significant. In the next column, categorizing according to covenant-lite status, we find that the negative effect of recent default experience on new borrower investment is only present among non-covenant-lite loans. In column (3), we find that the negative effect is only pronounced among loans without institutional investor participation. Finally in column (4), we find that the negative effect on borrower investment is only present during the pre 2010 years. The test of difference in coefficients between $I(\omega)$ *Lender Shock* and $(1-I(\omega))$ *Lender Shock* are significant at least at the 10% level in all the columns. These results in Panel C suggest that lenders negative effect on borrower investment due to their recent default experience materialize only when lenders are locked into these loans and have the right incentives to monitor their borrower.

Overall the findings in Table XI suggest that our main findings remain intact and more pronounced when lenders face more uncertainties about the borrower and when the loans cannot be divested, i.e., lenders have more incentives to learn and face more economic benefits from monitoring, supporting the 'learning' hypothesis. In comparison, we do not find strong support for 'borrowing cost' hypothesis.

C. *Influence of syndicate role*

Champagne and Kryzanowski (2007) show that there is a high degree of continuity among syndicates. Lenders face a high degree of information asymmetry with the lead lender in a syndicate, and therefore prefer familiar lead lenders (Champagne and Kryzanowski, 2007) or demand higher interest rate spreads and a greater proportion of loan retention by less familiar lead lenders (Ivashina and Scharfstein, 2010). Under such circumstances, how will the recent default experience of a syndicate participant affect a loan and the borrower's investment? To the extent that these syndicate networks are constant over time, any default shock to one of the syndicate participants can have the same learning effect as a shock to the lead lender. Furthermore, since the economic impact of default is similar when the lender is the lead or a syndicate participant, the incentives to ensure loan performance remain the same across the syndicate. On the other hand, if these syndicate networks change constantly and information asymmetry problems are more severe between less familiar lenders, then a default shock to a particular lender is unlikely to spill over to borrower investment under a different lead lender. We examine these opposing predictions on a recent default experience of a syndicate participant.

[Table XII about here.]

The results are presented in Table XII with borrower fixed effects and standard errors clustered by borrower. The main explanatory variables include *Lead Shock* and *Participant Shock*, where *Participant Shock* is an indicator whether a syndicate participant has had a recent default experience. We check the correlation between *Lead Shock* and *Participant Shock* in our sample and find it to be 0.072 significant at the 1% level, which suggests that there is a non-trivial possibility that the lead lenders and syndicate participants have recent default experience at the same time. We replicate all the seven models from Panel A of Table III with an additional explanatory variable for *Participant Shock*. In all the models, we find that the coefficient on *Participant Shock* is negative (significant in Models (I), (V), (VI), and (VII) at least at the 10% level or better). The magnitude of *Participant Shock* is slightly lower than the coefficient on *Lender Shock* in all the models. These findings suggest that even when a syndicate participant member has a recent default experience, the spillover to borrower investment happens in a similar, although weaker manner as when the lead lender has a recent default experience.

D. *Effect of lender default experience on covenant violations*

A key contribution of Chava and Roberts (2008) is that following covenant violations, borrowing firms decrease their investment levels as a result of the increase in the bargaining power of the creditor and the creditor's active intervention.[24] The average time to first covenant violation in Chava and Roberts (2008) sample is 23 months or half the maturity of the average loan. However, in our analysis we find that when a borrower takes a loan from a shocked lender, the negative effect on firm investment is strong in the first few quarters of the loan itself, suggesting that there is a pre-covenant violation effect of the lender on borrowing firm's investment depending on the circumstances facing the lender.[25]

In order to understand how recent default experience affects the probability of covenant violation and if that can be a channel through which the former affects investment, following Chava and Roberts (2008) we identify all the current ratio and net worth covenants on the new loans.[26] Having identified both the current ratio and net worth covenants, we examine whether a firm is in violation at the end of each quarter by comparing the accounting variable for current ratio and net worth in the firm's financial statements against the threshold specified by the covenant. If the current ratio or net worth falls below the covenant specification, then the firm is estimated to have violated and not otherwise.[27]

[Table XIII about here.]

In Panel A of Table XIII, we use an indicator variable for covenant violation as the dependent variable. Adopting the key control variables from Chava and Roberts (2008) and retaining our main explanatory variable *Lender Shock*, we estimate linear probability models with panel data of the probability of covenant violation with standard errors clustered by borrower. In Models (I) and (II), we use each type of covenant violation indicator, i.e., current ratio and net worth, estimated quarterly. In Model (III), we use an indicator

[24] In a related study, Denis and Wang (2014) show that lenders and borrowers engage in active renegotiation prior to covenant violation, often relaxing the limits, in which case firm investment increases significantly, consistent with the view that lenders learn more about their borrowers during the relationship which partially mitigates information asymmetry leading to a better outcome overall. However, in our setting it is unclear whether renegotiations happen more often or rarely prior to covenant violations. On the one hand, strict contracts from lenders with recent default experience predicts higher likelihood of renegotiations. On the other hand, the increased riskiness of the lender portfolio following default experience might incentivize lenders to take control following an explicit violation instead of offering greater flexibility to borrower.

[25] In the context of covenant violations, our findings have interesting and competing implications. If lenders with recent default experience are more likely to monitor the borrowing firms closely and actively intervene in corporate decision making, they can make it happen by offering stricter contracts, thereby increasing the probability of covenant violation and thus obtain greater bargaining power with the borrower. Once the covenant is violated, the creditor can obtain more say in the day-to-day operations, and decrease firm investment further. This argument suggests that borrowing from a lender with recent default experience can have permanent consequences on the borrower, and therefore be very significant to their future. Alternatively, when lenders offer stricter contracts to their new borrowers, they may ex-ante decide to intervene less among their borrowers on covenant violation. Furthermore, managerial attention is also limited when more than one borrower violates their covenants, reducing the probability of close monitoring ex post violation. Such a decision predicts a lower effect of covenant violation on firm investment. Both these views are consistent with our findings of a negative effect on investment by a lender with recent default experience. However, they have opposite predictions for the effect of covenant violation on post covenant violation investment. Since this is not our key research agenda, we leave this question unexamined and leave it open for future research.

[26] Covenants are available at the package level but typically applies to each facility as well. Thus, we assume the covenant to start at the earliest facility start date and end with maturity, i.e., assume conservatively that firms are subject to strict conditions for the term of the maturity of the loan.

[27] However, there are certain challenges in exactly identifying covenant violations. First, the definition of current ratio and net worth by the creditor can vary according to various adjustments they prefer to be made for the measures. Second, some of the covenants are dynamic, allowing adjustments to be made to the thresholds with time or when the firm makes profits or losses. Third, the borrower might amend the contract thereby making the threshold stale or irrelevant. Chava and Roberts (2008) argue that despite these misgivings, their simple static measure of covenant violation can estimate actual covenant violations quite closely and these challenges do not significantly affect their findings.

for any type of covenant violations, using data on annual covenant violations from Nini, Smith, and Sufi (2012). We find that *Lender Shock* is positive in all models and significant at the 5% level for current ratio covenants. In Models (IV)–(VI), we replace industry fixed effects with firm fixed effects and the dependent variable with a count measure of *Lender Shock*. However, the coefficient on *Lender Shock* becomes insignificant. The findings in Panel A of Table XI suggest that there may be a weak effect on future covenant violation depending on whether the lender has had a recent default experience or not.

In Panel B of Table XIII, we replace the indicator for covenant violation with the time to covenant violation. We measure the time to covenant violation as the number of quarters in between the loan issue date and the quarter in which the covenant violation is identified as in Chava and Roberts (2008). In the first three models, the specifications remain similar to those in Panel A of Table XIII. In the last three models, we measure *Lender Shock* as a count measure. We find all the coefficients on *Lender Shock* is positive, but only significant in Models (I) and (IV), i.e., current ratio covenant violation. This finding suggests that firms that borrow from lenders with one or more default shocks are likely to violate their current ratio covenant sooner rather than later.

When combined with the evidence of Chava and Roberts (2008), our results in Table XIII suggest that when firms borrow from lenders with recent default experience, they witness a complete cycle of investment dampening for the term of the maturity of the loan contract, brought on by the lender through their lending negotiation, strict contract terms, and increased violation of contracts.

E. Robustness to past year shocks

There are some quarters during our sample period when no lender in our sample experiences a recent default shock in the previous quarter. This raises sample selection issues. To further mitigate this concern, we re-estimate our regressions using a recent default shock experienced in the previous year instead of the previous quarter. As can be seen in Figure 1, the annual default shocks are much more smoothly distributed across our sample period.

[Table XIV about here.]

The results are presented in Table XIV with borrower fixed effects and standard errors clustered by borrower. In Models (I)–(IV) (Models (V)–(VII)), the dependent variable is the investment in the first (second) quarter following the loan issuance. The control variables are measured with respect to the timing of the investment measure. In both Models (I) and (II), we find that the coefficient on *Lender Shock* as an indicator or as a count measure is negative and significant in all models except Models (III) and (IV). In Models (III) and (IV), we add all the lender control and macroeconomic control variables used in Table IV and Table V, respectively. The coefficient on *Lender Shock*, continues to remain negative but is insignificant. The results in Models (V)–(VIII) are stronger with the coefficient being significant in all the models, when we examine the second quarter investment following loan issuance. Overall the findings in Table XIV relax the time scale of our findings, allowing them to be more generally applicable to the default experience of lenders.

V. Conclusion

This paper identifies a unique channel, namely a lender's idiosyncratic default experience, through which financing frictions can impact corporate investment. In this regard, we construct two hypotheses, i.e., the 'learning' and 'borrowing cost' hypotheses, and test their implications. Recent default experience allow lenders to 'learn' and update their beliefs about investment opportunities and their own screening ability, thereby affecting borrower investments. Also, borrower investments can decrease from the crowding out effect of higher 'borrowing costs' due to the alteration in incentives of the lender with recent default experience to expend more resources on screening, to charge higher spreads to attract syndicate participants, and to make up for lost profitability and reputation.

Examining the investment activity of a comprehensive sample of U.S. firms, we find that firms that borrow from a lender with a recent default reduce investment by 6.22% compared with their counterparts per quarter, after controlling for the standard determinants of investment. These findings are robust to controlling for lender and macroeconomic characteristics, and accounting for spillovers from defaulter's industry as well as geographical region. Furthermore, the decrease is evident irrespective of loan, borrower, and lender characteristics, lender-borrower nexus, or borrowers' interest rate sensitivity. However, our findings are more pronounced when lender incentives to learn are intact, which establishes a strong support for the 'learning' hypothesis.

Overall, our results highlight the importance of supply-side determinants of corporate investment and consequently the influence on the aggregate economy, thereby contributing to traditional work on investment that emphasizes mostly on the demand-side determinants. Our evidence also improves the understanding of how the contractual environment may be affected by lender's idiosyncratic experience and beliefs about economic prospects. It draws special attention to the implied costs of relationship borrowing, where the borrowers share the negative effects of lender default experiences. Finally, our findings complement the seminal work on flight-to-quality and financial accelerator theories (e.g., Bernanke, Gertler, and Gilchrist, 1996), which predict that lenders propensity to discriminate borrowers based on agency costs varies with the business cycle, by showing that when faced with defaults, lenders become conservative irrespective of borrower agency costs or business cycles.

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Table I: Sample Selection and Summary Statistics

This table presents summary statistics (mean, median, and standard error) of samples from Compustat and Compustat-Dealscan merged data sets between the sample period from 1987 to 2016. Panel A presents important variables for three samples of firm-quarter observations. Compustat sample consists of all firm-quarter observations for nonfinancial firms in the Compustat Quarterly files. The Compustat-Dealscan merged sample consists of all firm-quarter observations for nonfinancial firms with one or more new private loans covered by Dealscan. The lender shock sample consists of all firm-quarter observations for nonfinancial firms that have one or more new private loan from a lender who faces a default shock in the past 90 days when the loan is initiated and covered by Dealscan. Panel B presents loan characteristics for three samples of firm-quarter observations in Dealscan. We split the whole Compustat-Dealscan merged sample according to whether the lender faces a default shock in the past 90 days (Lender shock sample) or not (No lender shock sample), when the loan is initiated. Panel C presents lender characteristics for the Compustat-Dealscan merged sample, and subsamples according to whether the lenders face a default shock or not. Panel D presents the mean and the median differences in important borrower characteristics between lender shock and no lender shock samples in the Compustat-Dealscan merged data. Variable definitions are in Appendix A.

Panel A: Sample Statistics

	Compustat Sample			Compustat-Dealscan Merged Sample			Lender Shock Sample		
Variable	Mean	Median	S.E.	Mean	Median	S.E.	Mean	Median	S.E.
Current Ratio	2.5054	2.0312	0.0023	1.9224	1.6762	0.0087	1.7701	1.5860	0.0338
Net Worth	254.2730	67.9735	0.5174	380.7198	189.5410	3.2949	468.2930	313.9610	14.4550
Tangible Net Worth	121.4194	41.4570	0.4431	80.1470	58.9945	3.5326	102.1736	97.9880	16.3069
Assets ($ million)	166.5790	147.3311	1.0031	554.9870	581.5168	1.0147	952.9750	940.4797	1.0538
Firm Size	3.3933	3.3097	0.0038	4.8300	4.8610	0.0168	5.4093	5.4473	0.0635
MtB	1.8150	1.1928	0.0026	1.3894	1.1216	0.0080	1.2712	1.0686	0.0330
Macro Q	13.2225	5.6524	0.0232	8.3215	3.6702	0.0882	7.1770	3.3931	0.3423
ROA	0.0110	0.0265	0.0001	0.0312	0.0325	0.0003	0.0337	0.0327	0.0009
Tangibility	0.2822	0.2062	0.0003	0.3202	0.2576	0.0019	0.3261	0.2673	0.0086
Investment	0.0643	0.0478	0.0001	0.0590	0.0456	0.0004	0.0511	0.0388	0.0015
Cash Flow	-0.2742	0.0639	0.0022	0.0642	0.0769	0.0035	0.0700	0.0712	0.0132
Leverage	0.2350	0.1979	0.0003	0.3336	0.3110	0.0017	0.3362	0.3223	0.0072
Altman's Z-score	0.6941	0.7139	0.0008	0.6757	0.6378	0.0039	0.6527	0.5657	0.0165

Table I: Continued

Panel B: Loan Characteristics

	Compustat-Dealscan			Shock			No Shock		
	Mean	Median	S.E.	Mean	Median	S.E.	Mean	Median	S.E.
All-in-drawn Spread	5.2861	5.4161	0.0053	5.2800	5.4161	0.0227	5.2865	5.4161	0.0055
Loan Maturity	3.7410	4.0943	0.0052	3.7430	4.0604	0.0216	3.7409	4.0943	0.0054
Loan Amount	18.2093	18.4207	0.0141	18.6823	18.8261	0.0503	18.1838	18.4207	0.0145
Number of Participants	3.8968	3.9994	1.0084	5.5880	5.9991	1.0337	3.8220	3.9994	1.0086
Secured	0.7935	1.0000	0.0032	0.7631	1.0000	0.0150	0.7951	1.0000	0.0033
Fixed Charge Coverage Ratio	9.3882	2.5122	0.2375	10.1360	2.4974	1.1023	9.3480	2.5133	0.2431
Lender Shock - 360 Days	0.1774	0.0000	0.0030	1.0000	1.0000	0.0000	0.1332	0.0000	0.0028
Lender Shock - 90 Days	0.0510	0.0000	0.0018	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000

Panel C: Lender Characteristics

	Whole Sample			Shock			No Shock		
	Mean	Median	S.E.	Mean	Median	S.E.	Mean	Median	S.E.
Lender Capitalization	1.6406	1.6247	0.0055	1.5515	1.6765	0.0169	1.6461	1.6142	0.0057
Lender Tier-1 Capital Ratio	9.3429	8.5500	0.0161	8.9294	8.2000	0.0588	9.3682	8.5700	0.0166
Lender Book Assets	12.9411	13.1214	0.0118	13.7834	13.6122	0.0195	12.8896	12.9831	0.0123

Panel D: Firm Characteristics - Difference

	Mean				Median - Whole Sample			
	No Shock	Shock	Diff.	S.E.	Wilcoxon	Porder	No Shock	Shock
Current Ratio	1.9306	1.7701	0.1606***	(0.0396)	0.0000	0.5570	35,535	2,090
Net Worth	376.0112	468.2930	-92.2819***	(14.9560)	0.0000	0.4110	37,106	2,174
Tangible Net Worth	78.9626	102.1736	-23.2110	(16.0534)	0.0000	0.4682	37,106	2,174
Log (Assets)	6.2905	6.8603	-0.5698***	(0.0660)	0.0000	0.4018	37,278	2,181
Firm Size	4.7989	5.4093	-0.6104***	(0.0763)	0.0000	0.4138	37,100	2,176
MtB	1.3958	1.2712	0.1246***	(0.0365)	0.0000	0.5337	35,418	2,040
Macro Q	8.3831	7.1770	1.2061**	(0.4006)	0.0025	0.5208	32,295	1,864
ROA	0.0310	0.0337	-0.0026*	(0.0013)	0.9428	0.5005	34,371	2,009
Tangibility	0.3199	0.3261	-0.0062	(0.0086)	0.2226	0.4922	37,173	2,176
Investment	0.0594	0.0511	0.0083***	(0.0017)	0.0000	0.5451	36,201	2,133
Cash Flow	0.0639	0.0700	-0.0061	(0.0157)	0.0465	0.5128	35,973	2,122
Leverage	0.3335	0.3362	-0.0027	(0.0077)	0.0057	0.4824	37,194	2,176
Altman's Z-score	0.6769	0.6527	0.0242	(0.0175)	0.0000	0.5354	35,417	2,086

Table II: Characteristics of New Lending According to Recent Default Experience

This tables presents results of OLS regressions of all-in-drawn spreads and linear probability model regressions of likelihood of repeated lending, using loans from Dealscan. The sample consists of loan observations of nonfinancial firms between 1987 and 2016 covered in both Compustat and Dealscan database. *Lender Shock* is an indicator variable that takes one when a lead lender experiences one or more default shock in the past 90/180/270/360 days when the loan is initiated. Models I-V (Models VI-X) present the results for an indicator for default shock (natural logarithm of count of default shocks) to measure lender shocks. The dependent variable in Panel A is the all-in-drawn spread of the loan contract. The dependent variable in Panel B is an indicator variable that takes the value of one for loans, where the lead lender has had a relationship with the borrower in the past. Borrower and year-quarter fixed effects are included in all models. Other indicators for Loan-type and S&P Long-term Bond Rating are also included. t-statistics robust to within-lender correlation and heteroskedasticity are reported in parentheses. Variable definitions are in Appendix A.

Panel A: Loan Spreads According to Recent Default Experience

	Shock Indicator					**Shock Count**				
	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX	Model X
Lender Shock - 90 Days	0.044***	0.043***	0.043***	0.045***		0.033***	0.033***	0.032***	0.034***	
	(2.873)	(2.818)	(2.882)	(3.034)		(3.082)	(3.232)	(2.897)	(3.092)	
Lender Shock - 90-180 Days		0.004	0.004	0.008			0.002	-0.001	0.002	
		(0.149)	(0.115)	(0.239)			(0.115)	(-0.058)	(0.170)	
Lender Shock - 180-270 Days			0.003	0.014				0.013	0.020	
			(0.113)	(0.518)				(1.140)	(1.635)	
Lender Shock - 270-360 Days				-0.030					-0.027***	
				(-1.450)					(-2.657)	
Lender Shock - 360 Days					0.040***					0.006
					(2.863)					(1.082)
Maturity	-0.016	-0.016	-0.016	-0.016	-0.020*	-0.016	-0.016	-0.015	-0.013	-0.014
	(-1.422)	(-1.422)	(-1.423)	(-1.385)	(-1.822)	(-1.401)	(-1.372)	(-1.341)	(-1.121)	(-1.202)
Amount	-0.068***	-0.068***	-0.068***	-0.068***	-0.068***	-0.068***	-0.068***	-0.068***	-0.067***	-0.067***
	(-8.280)	(-8.286)	(-8.284)	(-8.320)	(-8.574)	(-8.287)	(-8.315)	(-8.158)	(-8.394)	(-8.315)
Secured	0.420***	0.420***	0.420***	0.420***	0.428***	0.420***	0.420***	0.422***	0.426***	0.426***
	(16.775)	(16.866)	(16.876)	(16.900)	(17.222)	(16.790)	(16.694)	(16.782)	(16.681)	(16.576)
Log (Participants)	-0.053***	-0.053***	-0.053***	-0.053***	-0.055***	-0.053***	-0.053***	-0.053***	-0.054***	-0.053***
	(-4.701)	(-4.665)	(-4.660)	(-4.684)	(-4.923)	(-4.720)	(-4.675)	(-4.665)	(-4.664)	(-4.608)
Altman's Z-score	-0.173***	-0.173***	-0.173***	-0.173***	-0.166***	-0.173***	-0.173***	-0.172***	-0.178***	-0.177***
	(-7.261)	(-7.279)	(-7.310)	(-7.341)	(-6.978)	(-7.289)	(-7.151)	(-6.944)	(-7.231)	(-7.042)
Leverage to Net Worth	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(-1.214)	(-1.214)	(-1.214)	(-1.235)	(-1.383)	(-1.234)	(-1.270)	(-1.116)	(-1.170)	(-1.077)
Fixed Charge Cov. Ratio	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(-3.019)	(-3.021)	(-3.021)	(-3.017)	(-3.063)	(-3.020)	(-2.970)	(-2.978)	(-2.827)	(-2.824)
Current Ratio	-0.003	-0.003	-0.003	-0.003	-0.001	-0.003	-0.003	-0.004	-0.005	-0.005
	(-0.381)	(-0.380)	(-0.377)	(-0.392)	(-0.109)	(-0.348)	(-0.351)	(-0.520)	(-0.616)	(-0.636)
Tangible Net Worh	-0.088***	-0.088***	-0.088***	-0.088***	-0.092***	-0.088***	-0.089***	-0.088***	-0.088***	-0.087***
	(-6.427)	(-6.421)	(-6.437)	(-6.413)	(-6.896)	(-6.451)	(-6.397)	(-6.253)	(-6.181)	(-6.114)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
S&P Rating Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan-type Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower and Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	13,301	13,301	13,301	13,301	13,797	13,301	13,175	13,041	12,882	12,882
Adj.R-square	0.704	0.704	0.704	0.704	0.702	0.704	0.704	0.706	0.707	0.707

Table II: Continued

Panel B: Likelihood of Repeat Borrower According to Recent Default Experience

	Shock Indicator					**Shock Count**				
	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX	Model X
Lender Shock - 90 Days	0.070*	0.058	0.059*	0.058		0.037*	0.024	0.020	0.014	
	(1.758)	(1.562)	(1.662)	(1.643)		(1.717)	(1.226)	(1.083)	(0.737)	
Lender Shock - 90-180 Days		0.060**	0.065**	0.062**			0.055***	0.050***	0.044***	
		(2.407)	(2.511)	(2.329)			(3.790)	(3.425)	(2.794)	
Lender Shock - 180-270 Days			-0.016	-0.023				0.027	0.017	
			(-0.404)	(-0.584)				(1.498)	(0.952)	
Lender Shock - 270-360 Days				0.020					0.052***	
				(0.799)					(3.778)	
Lender Shock - 360 Days					0.004					0.032***
					(0.190)					(4.876)
Maturity	-0.009	-0.009	-0.009	-0.010	-0.011	-0.009	-0.008	-0.008	-0.010	-0.009
	(-1.044)	(-1.082)	(-1.080)	(-1.099)	(-1.403)	(-1.019)	(-0.898)	(-0.899)	(-1.071)	(-1.020)
Amount	0.025***	0.025***	0.025***	0.025***	0.026***	0.025***	0.025***	0.025***	0.023***	0.023***
	(4.964)	(4.983)	(4.988)	(4.999)	(5.094)	(4.988)	(4.852)	(4.879)	(4.640)	(4.544)
Secured	0.018	0.017	0.017	0.017	0.024	0.018	0.015	0.020	0.021	0.022
	(0.872)	(0.829)	(0.824)	(0.818)	(1.212)	(0.869)	(0.739)	(0.948)	(1.022)	(1.041)
Participants	0.060***	0.060***	0.060***	0.060***	0.064***	0.060***	0.060***	0.060***	0.060***	0.060***
	(6.742)	(6.717)	(6.750)	(6.744)	(7.244)	(6.760)	(6.650)	(6.774)	(6.624)	(6.650)
Altman's Z-score	-0.019	-0.020	-0.019	-0.019	-0.012	-0.019	-0.018	-0.012	-0.014	-0.014
	(-0.864)	(-0.894)	(-0.887)	(-0.878)	(-0.543)	(-0.861)	(-0.808)	(-0.548)	(-0.610)	(-0.636)
Leverage to Net Worth	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(1.450)	(1.457)	(1.456)	(1.470)	(1.314)	(1.435)	(1.477)	(1.347)	(1.253)	(1.197)
Fixed Charge Cov. Ratio	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.327)	(1.318)	(1.318)	(1.323)	(1.336)	(1.322)	(1.444)	(1.135)	(1.037)	(1.046)
Current Ratio	-0.004	-0.004	-0.004	-0.004	-0.008	-0.004	-0.004	-0.004	-0.002	-0.002
	(-0.470)	(-0.457)	(-0.473)	(-0.459)	(-0.912)	(-0.450)	(-0.477)	(-0.447)	(-0.266)	(-0.251)
Tangible Net Worh	-0.001	-0.001	-0.001	-0.001	0.000	-0.001	0.001	0.000	-0.001	-0.001
	(-0.045)	(-0.064)	(-0.072)	(-0.063)	(0.007)	(-0.057)	(0.079)	(0.019)	(-0.056)	(-0.089)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
S&P Rating Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan-type Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower and Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	13,887	13,887	13,887	13,887	14,510	13,887	13,749	13,598	13,429	13,429
Adj.R-square	0.211	0.211	0.211	0.211	0.215	0.211	0.213	0.213	0.214	0.213

Table III: Investment Regressions

This table presents results of cross-sectional investment regressions. The sample consists of firm-quarter observations of nonfinancial firms between 1987 and 2016 in the merged Compustat-Dealscan database. *Lender Shock* is an indicator variable that takes one when a lead lender experiences one or more default shock in the past 90 days when the loan is initiated. All the flow (stock) variables are measured during the fiscal quarter (end of the previous fiscal quarter). In Panel A, the dependent variable is investment in the quarter following the loan. Panel B presents univariate mean differences in investment between borrowers borrowing from shocked and not shocked lenders in two to eight quarters following the loan. Panel C presents the results of cross-sectional regressions of investments in two to eight quarters following the loan. In Panel C, the control variables are measured with respect to whether they are a flow or stock measure with respect to investment, except the shock variable that is measured 90 days prior to the loan. Investment measures are multiplied by 100 for readability. Borrower fixed effects are included in all models. t-statistics robust to within-borrower correlation and heteroskedasticity are reported in parentheses. Variable definitions are in Appendix A.

Panel A: Investment

	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII
Lender Shock	-0.486***	-0.421***	-0.367***	-0.339***	-0.288***	-0.341***	-0.293***
	(0.099)	(0.103)	(0.101)	(0.101)	(0.101)	(0.102)	(0.101)
Macro Q		0.179***	0.149***	0.142***	0.338***	0.140***	0.327***
		(0.007)	(0.007)	(0.007)	(0.017)	(0.007)	(0.017)
Cash Flow		0.293**	0.337***	0.101	0.051	0.080	0.035
		(0.116)	(0.116)	(0.121)	(0.116)	(0.117)	(0.113)
Firm Size			-0.992***	-0.795***	-0.804***	-0.815***	-0.825***
			(0.060)	(0.060)	(0.059)	(0.061)	(0.061)
Altman's Z-score				1.812***	1.658***	1.655***	1.534***
				(0.159)	(0.157)	(0.172)	(0.170)
Sq_Macro Q					-0.004***		-0.004***
					(0.000)		(0.000)
Lag Cash Flow						0.399***	0.335**
						(0.148)	(0.143)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	27,434	23,331	23,331	22,348	22,348	21,948	21,948
Adj.R-square	0.374	0.402	0.424	0.436	0.445	0.432	0.440

Panel B: Future Investment - Mean Difference

	Loan+2	Loan+3	Loan+4	Loan+5	Loan+6	Loan+7	Loan+8
Shock	5.258	5.200	5.168	5.137	5.148	5.078	5.049
No Shock	6.016	5.939	5.764	5.799	5.667	5.635	5.505
Difference	-0.758	-0.739	-0.596	-0.662	-0.519	-0.557	-0.456
t-statistic	-6.334	-6.226	-5.096	-5.610	-4.449	-4.761	-3.893

Panel C: Future Investment

	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII
Lender Shock	-0.281***	-0.310***	-0.194*	-0.352***	-0.240**	-0.275***	-0.221**
	(0.098)	(0.101)	(0.100)	(0.098)	(0.095)	(0.093)	(0.094)
Macro Q	0.149***	0.141***	0.141***	0.133***	0.138***	0.130***	0.140***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)
Cash Flow	0.325**	0.290***	0.058	0.381***	0.300**	0.436***	0.246**
	(0.129)	(0.110)	(0.125)	(0.129)	(0.130)	(0.127)	(0.108)
Firm Size	-0.646***	-0.624***	-0.567***	-0.664***	-0.617***	-0.668***	-0.644***
	(0.061)	(0.060)	(0.060)	(0.062)	(0.062)	(0.067)	(0.066)
Altman's Z-score	1.655***	1.840***	2.061***	1.825***	1.919***	1.877***	1.611***
	(0.176)	(0.167)	(0.156)	(0.176)	(0.191)	(0.174)	(0.171)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	22,047	21,700	21,343	20,783	20,326	19,817	19,341
Adj.R-square	0.435	0.432	0.431	0.419	0.427	0.413	0.422

Table IV: Investment Regressions with Lender Characteristics

This table presents results of cross-sectional investment regressions including controls for lender characteristics. The sample consists of firm-quarter observations of nonfinancial firms between 1987 and 2016 in the merged Compustat-Dealscan database. *Lender Shock* is an indicator variable that takes one when a lead lender experiences one or more default shock in the past 90 days when the loan is initiated. All the flow (stock) variables are measured during the fiscal quarter (end of the previous fiscal quarter) except Lender Capitalization, Tier-1 Capital Ratio, and Book Assets, which are measured as changes. The dependent variable is investment in the quarter following the loan. Model VI-VIII measure investment from two to four quarters following the loan. Investment measures are multiplied by 100 for readability. Borrower fixed effects are included in all models. t-statistics robust to within-borrower correlation and heteroskedasticity are reported in parentheses. Variable definitions are in Appendix A.

	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII
Lender Shock	-0.387***	-0.359***	-0.385***	-0.289***	-0.346***	-0.203*	-0.228*	-0.061
	(0.109)	(0.122)	(0.109)	(0.103)	(0.124)	(0.113)	(0.121)	(0.112)
Macro Q	0.323***	0.327***	0.322***	0.318***	0.325***	0.343***	0.325***	0.289***
	(0.021)	(0.022)	(0.021)	(0.018)	(0.023)	(0.021)	(0.023)	(0.021)
Cash Flow	0.125	0.082	0.129	-0.002	-0.006	0.170	0.529***	-0.099
	(0.169)	(0.181)	(0.170)	(0.118)	(0.186)	(0.220)	(0.139)	(0.160)
Firm Size	-0.836***	-0.989***	-0.827***	-0.840***	-0.991***	-0.685***	-0.704***	-0.657***
	(0.073)	(0.084)	(0.073)	(0.060)	(0.086)	(0.089)	(0.085)	(0.084)
Altman's Z-score	1.310***	1.297***	1.312***	1.291***	1.090***	1.297***	1.487***	1.523***
	(0.244)	(0.222)	(0.243)	(0.176)	(0.228)	(0.212)	(0.246)	(0.208)
Sq_Macro Q	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag Cash Flow	0.390**	0.431**	0.384**	0.282**	0.471***	0.190	-0.148	0.183
	(0.177)	(0.183)	(0.175)	(0.141)	(0.168)	(0.129)	(0.210)	(0.153)
Δ *Lender Capitalization*	-0.343**				-0.317	-0.011	0.034	0.173
	(0.167)				(0.206)	(0.192)	(0.194)	(0.185)
Δ *Lender Tier-1 Capital Ratio*		-0.033			0.084	0.020	-0.022	0.134
		(0.088)			(0.092)	(0.086)	(0.087)	(0.084)
Δ *Lender Book Assets*			0.778*		0.356	-0.172	0.123	-0.113
			(0.412)		(0.480)	(0.429)	(0.448)	(0.470)
All-in-drawn Spread				-0.686***	-0.607***	-0.729***	-0.744***	-0.768***
				(0.053)	(0.070)	(0.068)	(0.069)	(0.065)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	14,770	12,104	14,784	19,946	11,164	11,186	11,018	10,863
Adj.R-square	0.440	0.453	0.440	0.449	0.458	0.469	0.460	0.471

Table V: Investment Regressions with Macroeconomic Characteristics

This table presents results of cross-sectional investment regressions including controls for macroeconomic characteristics. The sample consists of firm-quarter observations of nonfinancial firms between 1987 and 2016 in the merged Compustat-Dealscan database. *Lender Shock* is an indicator variable that takes one when a lead lender experiences one or more default shock in the past 90 days when the loan is initiated. All the flow (stock) variables are measured during the fiscal quarter (end of the previous fiscal quarter). The dependent variable is investment in the quarter following the loan. Model VI-VIII measure investment from two to four quarters following the loan. Investment measures are multiplied by 100 for readability. Borrower fixed effects are included in all models. t-statistics robust to within-borrower correlation and heteroskedasticity are reported in parentheses. Variable definitions are in Appendix A.

	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII
Lender Shock	-0.261***	-0.245**	-0.262**	-0.634***	-0.371***	-0.395***	-0.283**	-0.333***
	(0.101)	(0.101)	(0.102)	(0.114)	(0.115)	(0.112)	(0.118)	(0.113)
Macro Q	0.363***	0.316***	0.325***	0.319***	0.343***	0.389***	0.366***	0.367***
	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)
Cash Flow	0.009	0.041	0.028	0.034	0.011	0.182	0.250**	-0.057
	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.133)	(0.108)	(0.124)
Firm Size	-0.505***	-0.774***	-0.829***	-0.826***	-0.539***	-0.245***	-0.350***	-0.197***
	(0.069)	(0.060)	(0.061)	(0.060)	(0.069)	(0.069)	(0.068)	(0.066)
Altman's Z-score	1.466***	1.498***	1.525***	1.515***	1.439***	1.832***	1.924***	2.016***
	(0.166)	(0.168)	(0.172)	(0.168)	(0.167)	(0.149)	(0.159)	(0.150)
Sq_Macro Q	-0.005***	-0.004***	-0.004***	-0.004***	-0.004***	-0.005***	-0.005***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag Cash Flow	0.303**	0.341**	0.308**	0.341**	0.294*	-0.151	-0.342***	-0.051
	(0.145)	(0.145)	(0.148)	(0.143)	(0.150)	(0.109)	(0.114)	(0.093)
Quarterly GDP growth	-0.000***				-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)				(0.000)	(0.000)	(0.000)	(0.000)
Baa - Aaa Credit Spreads		-1.118***			-0.843***	-0.454***	-0.819***	-0.463***
		(0.087)			(0.089)	(0.086)	(0.079)	(0.076)
S&P 500 Return			1.215***		0.758**	0.449	2.453***	0.417
			(0.364)		(0.359)	(0.339)	(0.336)	(0.340)
Aggregate Defaults (indicator)				-0.467***	-0.220***	-0.341***	-0.159***	-0.285***
				(0.060)	(0.062)	(0.060)	(0.061)	(0.061)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	21,948	21,948	21,672	21,948	21,672	21,737	21,405	21,030
Adj.R-square	0.444	0.445	0.440	0.442	0.449	0.460	0.456	0.454

Table VI: Changes in Investment Regressions

This table presents results of cross-sectional regressions of changes in investment with respect to pre-loan investment level. The sample consists of firm-quarter observations of nonfinancial firms between 1987 and 2016 in the merged Compustat-Dealscan database. *Lender Shock* is an indicator variable that takes one when a lead lender experiences one or more default shock in the past 90 days when the loan is initiated. Models I-IV (Models V-VIII) present the results for an indicator for default shock (natural logarithm of count of default shocks) to measure lender shocks. All the flow (stock) variables are measured during the fiscal quarter (end of the previous fiscal quarter). In all the models, the dependent variable is the change in investment in the quarter following the loan compared to the third quarter prior to the loan. All variables, except *Lender Shock* are demeaned by cross-sectional averages. All explanatory variables, except *Lender Shock* are also measured as changes similarly around loan issuance. Investment measures are multiplied by 100 for readability. Borrower fixed effects are included in all models. t-statistics robust to within-borrower correlation and heteroskedasticity are reported in parentheses. Variable definitions are in Appendix A.

	Shock Indicator				**Shock Count**			
	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII
Lender Shock	-0.190**	-0.157*	-0.140*	-0.121	-0.224***	-0.192**	-0.183**	-0.164*
	(0.083)	(0.090)	(0.084)	(0.085)	(0.085)	(0.091)	(0.084)	(0.084)
Δ *Macro Q*		0.161***	0.135***	0.296***		0.161***	0.135***	0.296***
		(0.006)	(0.006)	(0.016)		(0.006)	(0.006)	(0.016)
Δ *Cash Flow*		0.361***	0.384***	0.135		0.361***	0.385***	0.136
		(0.105)	(0.098)	(0.103)		(0.105)	(0.098)	(0.103)
Δ *Firm Size*			-0.776***	-0.539***			-0.775***	-0.538***
			(0.087)	(0.092)			(0.087)	(0.092)
Δ *Lag Investment*			-0.297***	-0.296***			-0.297***	-0.296***
			(0.007)	(0.007)			(0.007)	(0.007)
Δ *Altman's Z-score*				0.907***				0.907***
				(0.121)				(0.121)
Δ *Sq_Macro Q*				-0.003***				-0.003***
				(0.000)				(0.000)
Δ *Lag Cash Flow*				0.082				0.082
				(0.105)				(0.105)
Obs.	27,518	23,018	22,641	21,622	27,518	23,018	22,641	21,622
Adj.R-square	0.001	0.056	0.155	0.168	0.001	0.056	0.156	0.168

Table VII: Panel Investment Regressions

This table presents results of panel data investment regressions. The sample consists of firm-quarter observations of nonfinancial firms between 1987 and 2016 till the maturity of each loan in the merged Compustat-Dealscan database. *Lender Shock* is an indicator variable that takes one when a lead lender experiences one or more default shock in the past 90 days when the loan is initiated. Models I-IV (Models V-VIII) present the results for an indicator for default shock (natural logarithm of count of default shocks) to measure lender shocks. All the flow (stock) variables are measured during the fiscal quarter (end of the previous fiscal quarter). In all the Models, the control variables are measured with respect to whether they are a flow or stock measure with respect to investment, except the shock variable that is measured 90 days prior to the loan issuance. Additionally, *Lag Investment* is measured with respect to loan issuance time. Investment measures are multiplied by 100 for readability. t-statistics robust to within-borrower and quarter, and heteroskedasticity are reported in parentheses. Variable definitions are in Appendix A.

	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII
Lender Shock	-0.460***	-0.547***	-0.004*	-0.004**	-0.387***	-0.463***	-0.003	-0.003
	(0.093)	(0.136)	(0.002)	(0.002)	(0.089)	(0.141)	(0.002)	(0.002)
Macro Q	0.303***	0.150***	0.004***	0.004***	0.303***	0.150***	0.004***	0.004***
	(0.007)	(0.004)	(0.000)	(0.000)	(0.007)	(0.004)	(0.000)	(0.000)
Cash Flow	0.067*	0.987***	0.001*	0.001*	0.067*	0.986***	0.001*	0.001*
	(0.036)	(0.114)	(0.000)	(0.000)	(0.036)	(0.114)	(0.000)	(0.000)
Firm Size	-0.688***	-0.485***	0.007***	0.008***	-0.690***	-0.485***	0.007***	0.008***
	(0.030)	(0.036)	(0.001)	(0.001)	(0.030)	(0.036)	(0.001)	(0.001)
Altman's Z-score	1.320***	1.411***	0.018***	0.017***	1.320***	1.412***	0.018***	0.017***
	(0.075)	(0.059)	(0.001)	(0.001)	(0.075)	(0.059)	(0.001)	(0.001)
Sq_Macro Q	-0.004***	-0.000**	-0.000***	-0.000***	-0.004***	-0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag Cash Flow	-0.081**	-0.069***	-0.003***	-0.003***	-0.081**	-0.069***	-0.003***	-0.003***
	(0.036)	(0.023)	(0.000)	(0.000)	(0.036)	(0.023)	(0.000)	(0.000)
Lag Investment	0.108***	0.064***	0.001***	0.001***	0.108***	0.065***	0.001***	0.001***
	(0.006)	(0.010)	(0.000)	(0.000)	(0.006)	(0.010)	(0.000)	(0.000)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Event-Quarter FE	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Year-Quarter FE	No	No	Yes	Yes	No	No	Yes	Yes
Borrower FE	Yes	No	No	No	Yes	No	No	No
Borrower×Lender FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Obs.	76,570	76,487	77,849	77,845	76,570	76,487	77,849	77,845
Adj.R-square	0.438	0.468	0.483	0.484	0.438	0.467	0.483	0.484

Table VIII: Propensity-Score Matched Sample Investment Regressions

This table presents results of cross-sectional investment regressions using a matched sample of 2,716 firm-quarter observations constructed using the propensity score matching algorithm. Each quarter we match the borrowers obtaining loans from a lender with recent default experience with those borrowers obtaining loans from a lender without recent default experience, using the nearest neighbourhood algorithm without replacement. The variables used in the matching are *Macro Q*, *Cash Flow*, *Firm Size*, and *Altman's Z score*. The summary statistics of the matching variables and the difference in mean and medians in the matched sample are reported in Panel A. Panel B presents the results of cross-sectional investment regressions of firm-quarter observations of nonfinancial firms between 1987 and 2016 in the merged Compustat-Dealscan database. *Lender Shock* is an indicator variable that takes one when a lead lender experiences one or more default shock in the past 90 days when the loan is initiated. All the flow (stock) variables are measured during the fiscal quarter (end of the previous fiscal quarter). In Panel B, the dependent variable is investment in the quarter following the loan. Investment measures are multiplied by 100 for readability. Industry fixed effects based on 2-digit Standard Industrial Classification (SIC) codes are included in all models. In Panel A, the numbers in parentheses are t-statistics for the test of difference in means and t-statistics for the Wilcoxon rank-sum test of difference in medians. In Panel B, t-statistics robust to within-borrower correlation and heteroskedasticity are reported in parentheses. Variable definitions are in Appendix A.

Panel A: Descriptive Statistics for Firms Borrowing from Lenders With and Without Recent Default Experience

	Borrowers with Lender Shock = 1 (N = 1,358): A		Borrowers with Lender Shock = 0 (N = 1,358): B		Test of difference: (A - B)			
	Mean	Median	Mean	Median	Mean difference	t-test p-value	Median difference	Wilcoxon p-value
Macro Q	8.0285	3.9354	7.9137	3.4260	0.1148	0.7770	0.5094	0.1608
Cash Flow	5.6739	5.7085	5.6667	5.7203	0.0072	0.9271	-0.0118	0.7686
Firm Size	0.0867	0.0802	0.0925	0.0781	-0.0058	0.5965	0.0021	0.8894
Altman's Z-score	0.6716	0.6157	0.6669	0.6273	0.0047	0.7910	-0.0116	0.9794

Table VIII: Continued

Panel B: Investment Regressions Using Propensity-Score Matched Sample	Shock Indicator			Shock Count		
	Model I	Model II	Model III	Model IV	Model V	Model VI
Lender Shock	-0.307*	-0.248**	-0.211**	-0.299**	-0.261**	-0.225**
	(0.165)	(0.105)	(0.103)	(0.142)	(0.115)	(0.107)
Macro Q		0.101***	0.196***		0.100***	0.195***
		(0.010)	(0.029)		(0.010)	(0.028)
Cash Flow		-0.228	-0.384**		-0.228	-0.384**
		(0.201)	(0.184)		(0.201)	(0.183)
Firm Size		-0.263***	-0.238***		-0.263***	-0.238***
		(0.043)	(0.044)		(0.044)	(0.044)
Lag Investment		0.430***	0.419***		0.431***	0.420***
		(0.025)	(0.029)		(0.025)	(0.029)
Altman's Z-score			0.979***			0.976***
			(0.235)			(0.235)
Sq_Macro Q			-0.002***			-0.002***
			(0.001)			(0.001)
Lag Cash Flow			0.330			0.336
			(0.575)			(0.576)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2,716	2,628	2,519	2,716	2,628	2,519
Adj.R-square	0.132	0.412	0.415	0.132	0.412	0.416

Table IX: Investment Regressions Excluding Defaulter's Industry and Region

This table presents results of cross-sectional investment regressions. The sample consists of firm-quarter observations of nonfinancial firms between 1987 and 2016 in the merged Compustat-Dealscan database. *Lender Shock* is an indicator variable that takes one when a lead lender experiences one or more default shock from a borrower not in the same industry nor geographical region in the past 90 days when the loan is initiated, where industry refers to 1-digit Standard Industrial Classification (SIC) code and region refers to the U.S. state where headquarters are located (foreign headquartered firms are grouped as one region). All the flow (stock) variables are measured during the fiscal quarter (end of the previous fiscal quarter). The dependent variable is investment in the quarter following the loan. Investment measures are multiplied by 100 for readability. Borrower fixed effects are included in all models. t-statistics robust to within-borrower correlation and heteroskedasticity are reported in parentheses. Variable definitions are in Appendix A.

	Shock Indicator		**Shock Count**	
	Model I	Model II	Model III	Model IV
	Loan+1	Loan+2	Loan+1	Loan+2
Lender Shock	-0.328***	-0.275***	-0.354***	-0.316***
	(0.102)	(0.098)	(0.102)	(0.099)
Macro Q	0.142***	0.149***	0.142***	0.149***
	(0.007)	(0.007)	(0.007)	(0.007)
Cash Flow	0.101	0.325**	0.101	0.324**
	(0.121)	(0.129)	(0.121)	(0.129)
Firm Size	-0.795***	-0.647***	-0.795***	-0.647***
	(0.060)	(0.061)	(0.060)	(0.061)
Altman's Z-score	1.810***	1.654***	1.809***	1.653***
	(0.159)	(0.176)	(0.159)	(0.176)
Intercept	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes
Obs.	22,344	22,044	22,344	22,044
Adj.R-square	0.436	0.435	0.436	0.435

Table X: Cross-sectional Variation in Investment According to Lender - Borrower Relationship & Characteristics

This table presents variation in the results of cross-sectional investment regressions according to various cross-sectional loan, borrower, relationship, and lender characteristics. The sample consists of firm-quarter observations of nonfinancial firms between 1987 and 2016 in the merged Compustat-Dealscan database. *Lender Shock* is an indicator variable that takes one when a lead lender experiences one or more default shock in the past 90 days when the loan is initiated. All the flow (stock) variables are measured during the fiscal quarter (end of the previous fiscal quarter). The reported values correspond to investment response sensitivity with respect to *Lender Shock* variable interacted with two extreme subgroups of firms with respect to the characteristics variable. To form the subgroups, we create terciles based on the borrower and loan characteristics, when the measures are continuous or use the indicator for discrete measures. The high (low) group corresponds to loans/firms that comprise of the top (bottom) tercile. In Panel A, the loan characteristics variables include the all-in-drawn spread, loan amount scaled by assets, secured (indicator), and maturity of the loan. In Panel B, agency problem measures include the free cash flow, cash holdings, credit rating (indicator), and tangibility. In Panel C, the relationship measures include indicators for a strong relationship with lead lender, weak relationship with lead lender, any relationship with any lender in the syndicate, and distance between lead lender and borrower. In Panel D, the lender characteristics include the lender capitalization level and changes in lender capitalization, Tier-1 Capital ratio, and book assets. In all the Panels, we include all control variables as in Table III (Model IV) interacted with the loan and borrower characteristics subgroups. Investment measures are multiplied by 100 for readability. Borrower fixed effects are included in all models. t-statistics robust to within-borrower correlation and heteroskedasticity are reported in parentheses. Variable definitions are in Appendix A.

Panel A: Loan Characteristics

	All-in-drawn Spread		Loan Amount / Assets		Secured		Maturity
High	-0.807***	*Yes*	-0.314	*Yes*	-0.591***	*High*	-0.026
	(0.245)		(0.217)		(0.186)		(0.422)
Low	-0.448***	*No*	-0.283*	*No*	-0.462***	*Low*	-0.501***
	(0.135)		(0.150)		(0.171)		(0.168)
Test of diff		*Test of diff*		*Test of diff*		*Test of diff*	
F-stat	1.627	*F-stat*	0.014	*F-stat*	0.265	*F-stat*	1.095
p-value	0.202	*p-value*	0.905	*p-value*	0.606	*p-value*	0.295
Control	Yes	*Control*	Yes	*Control*	Yes	*Control*	Yes
Obs.	20,316	*Obs.*	22,348	*Obs.*	22,348	*Obs.*	22,311
Adj.R-sq.	0.388	*Adj.R-sq.*	0.380	*Adj.R-sq.*	0.389	*Adj.R-sq.*	0.370

Panel B: Agency Problems

	Free Cash Flow		Cash Holding		Rated		Tangibility
High	-0.453***	*Yes*	-0.380*	*Yes*	-0.342***	*High*	-0.218
	(0.148)		(0.211)		(0.112)		(0.177)
Low	-0.412	*No*	-0.639***	*No*	-0.329*	*Low*	-0.294
	(0.269)		(0.166)		(0.190)		(0.202)
Test of diff		*Test of diff*		*Test of diff*		*Test of diff*	
F-stat	0.018	*F-stat*	0.904	*F-stat*	0.004	*F-stat*	0.080
p-value	0.894	*p-value*	0.342	*p-value*	0.951	*p-value*	0.777
Control	Yes	*Control*	Yes	*Control*	Yes	*Control*	Yes
Obs.	22,055	*Obs.*	20,865	*Obs.*	22,348	*Obs.*	22,119
Adj.R-sq.	0.397	*Adj.R-sq.*	0.411	*Adj.R-sq.*	0.436	*Adj.R-sq.*	0.410

Table X: Continued

Panel C: Relationship Characteristics							
	Strong Relationship		**Weak Relationship**		**Any Relationship**		**Distance form Lender**
Yes	-0.470***	*Yes*	-0.614***	*Yes*	-0.505***	*Far*	-0.220
	(0.181)		(0.234)		(0.179)		(0.393)
No	-0.282**	*No*	-0.280**	*No*	-0.274**	*Close*	0.099
	(0.119)		(0.110)		(0.121)		(0.333)
Test of diff		*Test of diff*		*Test of diff*		*Test of diff*	
F-stat	0.780	*F-stat*	1.733	*F-stat*	1.173	*F-stat*	0.388
p-value	0.377	*p-value*	0.188	*p-value*	0.279	*p-value*	0.534
Control	Yes	*Control*	Yes	*Control*	Yes	*Control*	Yes
Obs.	22,348	*Obs.*	22,298	*Obs.*	22,298	*Obs.*	3,794
Adj.R-sq.	0.436	*Adj.R-sq.*	0.436	*Adj.R-sq.*	0.436	*Adj.R-sq.*	0.474
Panel D: Lender Characteristics							
	Lender capitalization		**Δ Lender capitalization**		**Δ Lender Tier-1 Capital Ratio**		**Δ Lender Book Assets**
High	-0.865***	*Yes*	-0.455**	*Yes*	-0.352*	*High*	-0.592***
	(0.195)		(0.195)		(0.207)		(0.173)
Low	-0.073	*No*	-0.231	*No*	-0.447**	*Low*	-0.490**
	(0.177)		(0.179)		(0.197)		(0.195)
Test of diff		*Test of diff*		*Test of diff*		*Test of diff*	
F-stat	9.164	*F-stat*	0.694	*F-stat*	0.120	*F-stat*	0.157
p-value	0.002	*p-value*	0.405	*p-value*	0.729	*p-value*	0.692
Control	Yes	*Control*	Yes	*Control*	Yes	*Control*	Yes
Obs.	16,069	*Obs.*	16,056	*Obs.*	13,575	*Obs.*	16,069
Adj.R-sq.	0.384	*Adj.R-sq.*	0.386	*Adj.R-sq.*	0.394	*Adj.R-sq.*	0.384

Table XI: Cross-sectional Variation in Investment According to Learning Incentives & Credit Market Characteristics

This table presents variation in the results of cross-sectional investment regressions according to cross-sectional variation in learning incentives and credit market characteristics. The sample consists of firm-quarter observations of nonfinancial firms between 1997 (when the leveraged loan markets began) and 2016 in the merged Compustat-Dealscan database. *Lender Shock* is an indicator variable that takes one when a lead lender experiences one or more default shock in the past 90 days when the loan is initiated. All the flow (stock) variables are measured during the fiscal quarter (end of the previous fiscal quarter). The reported values correspond to investment response sensitivity with respect to *Lender Shock* variable interacted with two extreme subgroups of firms with respect to the characteristics variable. In Panel A, the learning incentives measures include borrower's ratio of R&D expenditure to sales, macro Q, industry uniqueness, and industry volatility. In Panel B, the interest rate sensitivity measures include borrower's leverage, operating leases, debt maturity profile, and indicators for borrowers who belong to mining or construction industries or otherwise. In Panel C, credit market characteristics include indicators for covenant-lite loans, institutional investor participation, financial covenants, and for post-2010 loans. To form the subgroups, we create terciles based on the borrower and loan characteristics, when the measures are continuous or use the indicator for discrete measures. The high (low) group corresponds to loans/firms that comprise of the top (bottom) tercile. In all the Panels, we include all control variables as in Table III (Model IV) interacted with the credit market characteristics subgroups. Investment measures are multiplied by 100 for readability. Borrower fixed effects are included in all models. t-statistics robust to within-borrower correlation and heteroskedasticity are reported in parentheses. Variable definitions are in Appendix A.

Panel A: Learning Incentives

	R&D / Sales		**Macro Q**		**Industry Uniqueness**		**Industry Volatility**
High	-0.599***	*High*	-0.358**	*High*	-0.770***	*High*	-0.557*
	(0.160)		(0.171)		(0.184)		(0.287)
Low	-0.178	*Low*	0.049	*Low*	-0.274**	*Low*	0.063
	(0.143)		(0.151)		(0.123)		(0.242)
Test of diff		*Test of diff*		*Test of diff*		*Test of diff*	
F-stat	3.870	*F-stat*	3.704	*F-stat*	5.110	*F-stat*	2.736
p-value	0.049	*p-value*	0.055	*p-value*	0.025	*p-value*	0.098
Control	Yes	*Control*	Yes	*Control*	Yes	*Control*	Yes
Obs.	15,922	*Obs.*	15,922	*Obs.*	15,922	*Obs.*	15,922
Adj.R-sq.	0.452	*Adj.R-sq.*	0.453	*Adj.R-sq.*	0.458	*Adj.R-sq.*	0.412

Panel B: Interest Rate Sensitivity

	Leverage		**Pension Deficit**		**Debt Maturity Profile**		**Mining & Construction Industry**
High	-0.438**	*Underfunded*	-0.432***	*High*	-0.155	*2-digit SIC*	-0.254
	(0.191)		(0.131)		(0.183)	*02-17*	(0.440)
Low	-0.374*	*Overfunded*	-0.249	*Low*	-0.450**	*Other 2-digit*	-0.379***
	(0.198)		(0.190)		(0.192)	*SIC*	(0.108)
Test of diff		*Test of diff*		*Test of diff*		*Test of diff*	
F-stat	0.053	*F-stat*	0.669	*F-stat*	1.243	*F-stat*	0.076
p-value	0.818	*p-value*	0.413	*p-value*	0.265	*p-value*	0.783
Control	Yes	*Control*	Yes	*Control*	Yes	*Control*	Yes
Obs.	15,921	*Obs.*	7,199	*Obs.*	14,902	*Obs.*	15,922
Adj.R-sq.	0.412	*Adj.R-sq.*	0.444	*Adj.R-sq.*	0.407	*Adj.R-sq.*	0.458

Table XI: Continued

Panel C: Credit Market Characteristics

	Financial Covenant		**Covenant-lite**		**Ins. Investor Participation**		**Leveraged Loan Supply**
Yes	-0.529***	*Covenant-lite*	0.162	*Yes*	0.419	*Post 2010*	0.071
	(0.143)		(0.242)		(0.362)		(0.209)
No	-0.135	*Non-covenant-lite*	-0.381***	*No*	-0.288**	*Pre 2010*	-0.479***
	(0.147)		(0.106)		(0.127)		(0.119)
Test of diff		*Test of diff*		*Test of diff*		*Test of diff*	
F-stat	3.806	*F-stat*	4.240	*F-stat*	3.997	*F-stat*	5.252
p-value	0.051	*p-value*	0.040	*p-value*	0.046	*p-value*	0.022
Control	Yes	*Control*	Yes	*Control*	Yes	*Control*	Yes
Obs.	15,922	*Obs.*	15,922	*Obs.*	15,922	*Obs.*	15,922
Adj.R-sq.	0.458	*Adj.R-sq.*	0.457	*Adj.R-sq.*	0.449	*Adj.R-sq.*	0.458

Table XII: Investment Regressions - Shocks by Syndicate Role

This table presents results of cross-sectional investment regressions. The sample consists of firm-quarter observations of nonfinancial firms between 1987 and 2016 in the merged Compustat-Dealscan database. *Lender Shock* is an indicator variable that takes one when a lead lender experiences one or more default shock in the past 90 days. Participant Shock is an indicator variable that takes one when a syndicate participant in the lending syndicate experiences one or more default shock in the past 90 days. All the flow (stock) variables are measured during the fiscal quarter (end of the previous fiscal quarter). In Models I, II, and VII, the dependent variable is investment in the quarter following the loan. In Models III-VI, the dependent variable is investment in two to five quarters following the loan. In Models III-VI, the control variables are measured with respect to whether they are a flow or stock measure with respect to investment, except the shock variables that are measured 90 days prior to the loan. Investment measures are multiplied by 100 for readability. Borrower fixed effects are included in all models. *t*-statistics robust to within-borrower correlation and heteroskedasticity are reported in parentheses. Variable definitions are in Appendix A.

	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII
	Loan+1	Loan+1	Loan+2	Loan+3	Loan+4	Loan+5	Loan+1
Lead Shock (indicator)	-0.280***	-0.242**	-0.315***	-0.349***	-0.248***	-0.356***	
	(0.096)	(0.098)	(0.095)	(0.095)	(0.092)	(0.092)	
Participant Shock (indicator)	-0.204*	-0.159	-0.154	-0.139	-0.217**	-0.337***	
	(0.111)	(0.110)	(0.108)	(0.108)	(0.101)	(0.102)	
Lead Shock (count)							-0.301***
							(0.098)
Participant Shock (count)							-0.160
							(0.106)
Macro Q	0.149***	0.311***	0.142***	0.136***	0.141***	0.139***	0.310***
	(0.008)	(0.020)	(0.009)	(0.009)	(0.009)	(0.008)	(0.020)
Cash Flow	0.558***	0.186	0.340	0.558***	0.129	0.175	0.186
	(0.129)	(0.143)	(0.240)	(0.150)	(0.196)	(0.170)	(0.143)
Firm Size	-1.005***	-0.846***	-0.769***	-0.733***	-0.677***	-0.739***	-0.846***
	(0.068)	(0.070)	(0.070)	(0.067)	(0.068)	(0.068)	(0.070)
Sq_Macro Q		1.385***					1.381***
		(0.180)					(0.180)
Altman's Z-score		-0.004***	1.520***	1.559***	1.807***	1.844***	-0.004***
		(0.000)	(0.185)	(0.190)	(0.152)	(0.171)	(0.000)
Lag Cash Flow		0.459					0.460
		(0.282)					(0.283)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	18,024	16,961	16,992	16,760	16,523	16,114	16,961
Adj.R-square	0.455	0.470	0.457	0.451	0.452	0.441	0.470

Table XIII: Future Covenant Violation

This table presents results of a borrowers' probability of future covenant violation (Panel A) and the time to covenant violation (Panel B) using panel data. The sample consists of firm-quarter observations of nonfinancial firms between 1994 and 2016 for the duration of each loan in the merged Compustat-Dealscan database. *Lender Shock* is an indicator variable that takes one when a lead lender experiences one or more default shock in the past 90 days when the loan is initiated. All the variables are measured during the end of the previous fiscal quarter, except loan characteristics. In Panel A, the dependent variable is an indicator for whether the current ratio covenant (Models I and IV), the net-worth covenant (Models II and V), and any covenant (Models III and VI) are violated. In Panel B, the dependent variable is the time to violation for a current ratio covenant (Models I and IV), a net-worth covenant (Models II and V), and any covenant (Models III and VI). The current ratio and net-worth covenant based models are estimated at a quarterly frequency. Any covenant based models are estimated at an annual frequency. Borrower fixed effects are included in all models. t-statistics (z-statistics) robust to within-borrower correlation and heteroskedasticity are reported in parentheses in Panel A (Panel B). Variable definitions are in Appendix A.

Panel A: Probability of Future Covenant Violation - Logit Regression Model

	Shock Indicator			Shock Count		
	Model I	Model II	Model III	Model IV	Model V	Model VI
	Current Ratio	Net Worth	Any Other	Current Ratio	Net Worth	Any Other
Lender Shock	0.105**	0.019	0.007	-0.013	-0.016	0.020
	(2.24)	(0.63)	(0.61)	(-0.26)	(-0.45)	(1.30)
Amount	-0.034	-0.134***	-0.059***	-0.039	-0.075**	-0.035**
	(-0.91)	(-4.44)	(-4.79)	(-0.71)	(-2.13)	(-1.97)
Firm Size	-0.025***	-0.040***	-0.021***	0.036**	-0.084***	-0.013**
	(-2.98)	(-6.54)	(-6.64)	(2.07)	(-5.13)	(-2.16)
Investment Grade	-0.114	-0.009	-0.023***	0.034	-0.002	-0.048***
	(-1.42)	(-0.35)	(-2.91)	(0.48)	(-0.05)	(-2.72)
Cash Flow	-0.072***	-0.075***	-0.009**	-0.044***	-0.039***	-0.001
	(-3.82)	(-5.19)	(-2.26)	(-3.03)	(-3.76)	(-0.71)
Leverage	0.279***	0.564***	0.062***	0.072	0.552***	0.022
	(5.10)	(10.09)	(3.62)	(1.08)	(8.91)	(1.14)
Current Ratio	-0.102***	-0.019***	-0.009***	-0.089***	-0.024***	-0.003*
	(-11.40)	(-3.70)	(-6.15)	(-9.43)	(-4.96)	(-1.93)
Tangible Net Worth	0.000*	0.000**	0.000**	-0.000	-0.000*	-0.000
	(1.78)	(2.33)	(2.21)	(-0.18)	(-1.91)	(-0.93)
MtB	0.013	-0.009**	-0.007***	-0.011	-0.003	-0.005**
	(1.64)	(-2.20)	(-3.80)	(-1.16)	(-0.80)	(-2.15)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No	No	No
Borrower FE	No	No	No	Yes	Yes	Yes
Year-Quarter/Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	8,901	17,173	62,835	8,870	17,101	62,742
Adj.R-square	0.328	0.236	0.077	0.509	0.603	0.585

Table XIII: Continued

Panel B: Time to Covenant Violation - Cox Regression Model	Shock Indicator			Shock Count		
	Model I	Model II	Model III	Model IV	Model V	Model VI
	Current Ratio	Net Worth	Any Other	Current Ratio	Net Worth	Any Other
Lender Shock	0.313**	0.142	0.305	0.329**	0.238	0.425
	(2.01)	(0.50)	(0.64)	(2.06)	(0.87)	(1.08)
Amount	-0.156	-1.029***	-1.335**	-0.153	-1.032***	-1.326**
	(-1.05)	(-2.96)	(-2.02)	(-1.03)	(-2.96)	(-2.01)
Firm Size	-0.130***	-0.387***	-0.280***	-0.129**	-0.387***	-0.280***
	(-2.58)	(-7.39)	(-2.70)	(-2.57)	(-7.40)	(-2.71)
Investment Grade	-0.532	-0.289	-1.701***	-0.540	-0.288	-1.696***
	(-1.03)	(-0.90)	(-3.03)	(-1.05)	(-0.90)	(-3.01)
Cash Flow	-0.039	-0.178***	0.001	-0.038	-0.178***	0.003
	(-0.86)	(-3.38)	(0.01)	(-0.84)	(-3.38)	(0.03)
Leverage	0.228	3.905***	0.713	0.222	3.908***	0.705
	(1.03)	(10.97)	(1.23)	(1.00)	(10.97)	(1.21)
Current Ratio	-2.026***	-0.352***	-0.413***	-2.028***	-0.351***	-0.411***
	(-18.85)	(-4.30)	(-3.33)	(-18.87)	(-4.30)	(-3.32)
Tangible Net Worth	0.000**	0.000***	-0.000	0.000**	0.000***	-0.000
	(2.00)	(3.52)	(-0.12)	(2.05)	(3.52)	(-0.14)
MtB	0.004	-0.213**	-0.386**	0.003	-0.214**	-0.387**
	(0.05)	(-2.32)	(-2.26)	(0.05)	(-2.33)	(-2.27)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter/Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	8,902	17,175	14,973	8,902	17,175	14,973
Pseudo R-square	0.124	0.102	0.130	0.124	0.102	0.130

Table XIV: Investment Regressions Using Lender Shock in the Previous Year

This table presents results of cross-sectional investment regressions. The sample consists of firm-quarter observations of non-financial firms between 1987 and 2016 in the merged Compustat-Dealscan database. *Lender Shock* is an indicator variable that takes one when a lead lender experiences one or more default shock in the past 360 days when the loan is initiated. All the flow (stock) variables are measured during the fiscal quarter (end of the previous fiscal quarter). The dependent variable is investment in the quarter following the loan in Models I-IV. The dependent variable is investment in the second quarter following the loan in Models V-VIII. Investment measures are multiplied by 100 for readability. Borrower fixed effects are included in all models. t-statistics robust to within-borrower correlation and heteroskedasticity are reported in parentheses. Variable definitions are in Appendix A in the main manuscript.

	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII
Lender Shock (indicator)	-0.183***		-0.144	-0.107	-0.215***		-0.138*	-0.187***
	(0.067)		(0.088)	(0.069)	(0.065)		(0.082)	(0.069)
Lender Shock (count)		-0.145***				-0.224***		
		(0.056)				(0.056)		
Macro Q	0.330***	0.324***	0.322***	0.344***	0.367***	0.359***	0.342***	0.390***
	(0.017)	(0.018)	(0.023)	(0.018)	(0.016)	(0.017)	(0.021)	(0.017)
Cash Flow	0.068	0.051	-0.010	0.012	0.243*	0.190	0.181	0.181
	(0.109)	(0.117)	(0.186)	(0.113)	(0.127)	(0.145)	(0.220)	(0.133)
Firm Size	-0.800***	-0.815***	-0.988***	-0.538***	-0.659***	-0.667***	-0.677***	-0.245***
	(0.059)	(0.062)	(0.087)	(0.069)	(0.059)	(0.063)	(0.089)	(0.069)
Altman's Z-score	1.576***	1.559***	1.066***	1.443***	1.496***	1.577***	1.358***	1.831***
	(0.160)	(0.175)	(0.227)	(0.168)	(0.167)	(0.185)	(0.211)	(0.149)
Sq_Macro Q	-0.004***	-0.004***	-0.004***	-0.004***	-0.005***	-0.005***	-0.004***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag Cash Flow	0.280**	0.311**	0.485***	0.291*	-0.025	-0.025	0.177	-0.149
	(0.128)	(0.147)	(0.166)	(0.151)	(0.109)	(0.110)	(0.129)	(0.109)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Controls	No	No	Yes	No	No	No	Yes	No
Macroeconomic Controls	No	No	No	Yes	No	No	No	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	22,871	21,363	11,291	21,672	22,947	21,415	11,317	21,737
Adj.R-square	0.437	0.443	0.455	0.448	0.444	0.449	0.469	0.460

Appendix A: Variable definitions

Variable	Description
Aggregate Defaults (indicator)	An indicator with value one if the total number of defaults in all lender portfolios in the previous quarter is greater than the median
All-in-drawn Spread	Basis point loan spread over LIBOR plus the annual fee plus the upfront fee over the duration of the loan
Altman's Z-score	Sum of 3.3 times pre-tax income, sales, 1.4 times retained earnings, and 1.2 times net working capital all divided by total assets (Chava and Roberts (2008))
Any Relationship	An indicator that takes the value of one if the any syndicate member in the current loan has had any participation in a previous syndicate to the same borrower
Baa - Aaa Credit Spreads	Moody's Baa-rated bond yield minus Aaa-rated bond yield using corporate bonds
Cash Flow	Ratio of income before extraordinary items plus depreciation and amortization to start-of-period net property, plant, and equipment
Cash Holding	Ratio of cash and cash equivalents to total assets
Covenant-lite	An indicator that takes the value of one for loans that are tagged by Dealscan as "Covenant-lite" in the market-segment file (Berlin, Nini, and Yu (2020)
Current Ratio	Ratio of current assets to current liabilities
Debt Maturity Profile	Ratio of long-term debt to sum of short-term liabilities and long-term debt
Distance from Lender	Distance between the Headquarter locations of the borrower and the lead lender, based on their zip codes, computed using the haversince formula
Financial Covenant	An indicator which takes the value of one if the loan has one or more financial covenants
Firm Size	Natural logarithm of net property, plant, and equipment
Fixed Charge Cov. Ratio	The sum of rolling four-quarter operating income before depreciation scaled by the sum of rolling four-quarter interest expenses and debt in current liabilities
Free Cash Flow	Ratio of income before extraordinary items and depreciation reduced by dividends and capital expenditure to total assets
Industry Volatility	High (low) volatility industries are defined as indicators takes the value of one for firms that belong to Fama-French 48 industry classification (Fama and French (1997)) that is in the top (bottom) two quintiles in terms of the median R&D intensity, where R&D intensity is measured as R&D expenses scaled by beginning of period assets (Moyen and Platinakov (2013))
Industry Uniqueness	One if a firms 2-digit SIC industry is in the top quartile based on industry median ratio of selling expenses as a fraction of sales
Ins. Investor Participation	An indicator that takes the value of one when the loan syndicate includes at least one lender who is not a commercial bank (commerical banks have primary Standard Industrial Classification (SIC) codes between 6011-6082 or 6712)
Investment	Ratio of capital expenditures to start-of-period net property, plant, and equipment (Chava and Roberts (2008))
Investment Grade	An indicator which takes the value of one if the long-term S&P issuer rating of the firm is greater than or equal to BBB-
Lead Shock	One or more defaults on the lead lender portfolio in the previous quarter. Computed as either an indicator or as a count measure computed as the natural logarithm of one plus the number of defaults in the lead lender's portfolio
Lender Book Assets	Natural logarithm of total assets of the lender (Schwert (2018))
Lender Capitalization	Ratio of market value of equity to book value of equity of lender (Schwert (2018))

Appendix A: Continued

Variable	Description
Lender Shock	One or more defaults on lender portfolio in the previous quarter or year (Murfin (2012)). Computed as either an indicator or as a count measure computed as the natural logarithm of one plus the number of defaults in the lender portfolio
Lender Tier-1 Capital Ratio	Risk weighted Tier-1 capital ratio of the lender (Schwert (2018))
Leverage	Ratio of total debt to total assets
Loan Amount	Natural logarithm of loan amount
Log (Participants)	Natural logarithm of number of participants in the loan syndicate
Log (Assets)	Natural logarithm of total assets
Macro Q	Ratio of (market value of equity + book value of liabilities - net inventories) to net property, plant, and equipment
Maturity	Natural logarithm of loan maturity in months
MtB	Ratio of (market value of equity + book value of liabilities + preferred equity - deferred taxes and investment tax credit) to total assets
Net Worth	Total assets minus total liabilities
Participant Shock	One or more defaults on the syndicate participant portfolio in the previous quarter. Computed as either an indicator or as a count measure computed as the natural logarithm of one plus the number of defaults in the participant lender's portfolio
Pension Deficit	Difference between projected value of pension benefits and the fair value of pension assets, scaled by market capitalization. The changes in pension reporting standards and subsequent Compustat reporting are accounted for following procedures in Balasingham, Duong, and Vu (2018) and Franzoni and Marin (2006). Firms with Pension Deficit greater than zero (less than zero) are labelled as underfunded (overfunded)
Quarterly GDP growth	Real GDP growth rate measured two quarters prior to the new loan
Rated	An indicator that takes the value of one if a firm has a long-term S&P issuer rating
ROA	Ratio of operating income before depreciation to total assets
S&P 500 Return	Holding period quarterly return for S&P 500 index measured two quarters prior to the new loan
Secured	An indicator which takes the value of one if the loan is secured
Sq_Macro Q	Square of Macro Q
Strong Relationship	An indicator that takes the value of one if the borrower has borrowed a previous loan from the same lead lender as the current loan
Tangibility	Ratio of net property, plant, and equipment to total assets
Tangible Net Worth	Total assets minus total liabilities and intangible assets (Murfin (2012))
Weak Relationship	An indicator that takes the value of one if the borrower has borrowed a previous loan from the same lead lender as the current loan, provided the current lead lender was at least a syndicate participant in the previous loan

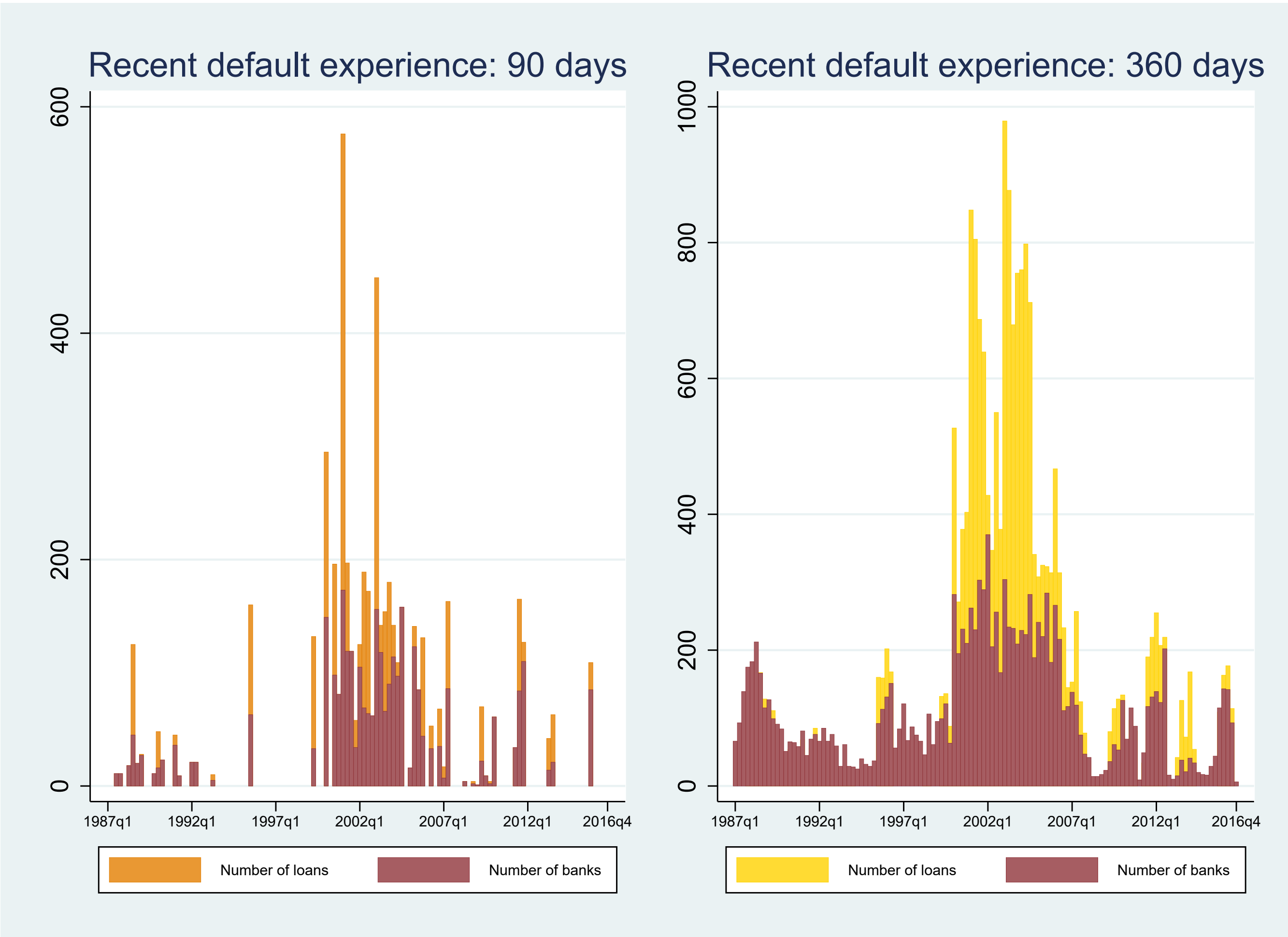

Figure 1. Distribution of Lender Default Shock

This figure presents the quarterly box-plot histogram of the distribution of default shocks and the affected lenders according to defaults in the 90 (left panel) and 360 (right panel) days prior to loan issuance during 1987 to 2016.

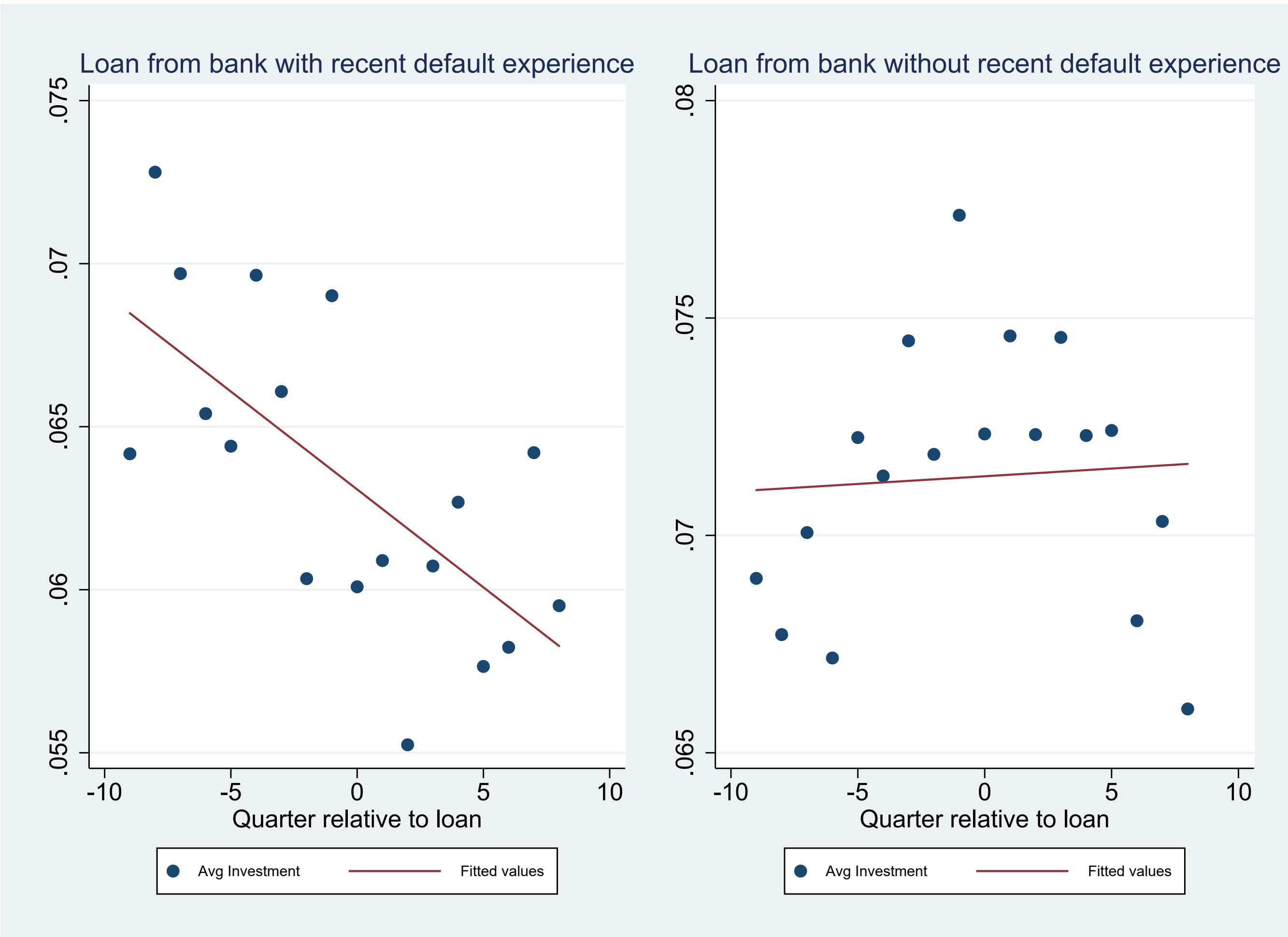

Figure 2. Average Investment According to Lender Default Experience

This figure presents the scatter plot of average investment in quarters around the loan borrowing. On the left (right) panel, we focus on eight quarters before and after borrowing a loan from a lender with (without) default experience in the prior 90 days during 1987 to 2016.