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Bank stability and the price of loan commitments

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ABSTRACT

Firms insure themselves from liquidity shocks by contracting on credit lines from banks. I document novel empirical evidence on how the risk of contract nonperformance by banks is priced. Firms pay a higher price for loan commitments from safer banks. A one standard deviation increase in the cross-sectional mean of bank capital increases the commitment fees by 5%. To investigate a potential causal effect of lender stability on commitment fees, I exploit exogenous variation in the market value of banks' assets from natural disasters. The sensitivity of the fees is higher for firms with higher short-term liabilities and higher income uncertainty.

1. Introduction

The financial crisis provided substantial evidence that financial instability has ramifications in the broader economy. Several papers have explored the channels through which financial instability impacts firms and businesses. One such channel is the possibility of banks cutting back on pre-committed loans. This is an important channel because loan commitments (or credit lines) are the most popular source of bank financing for firms.[1] Over 80% of new commercial loans in an average US bank's portfolio are under loan commitments.[2] Access to these credit lines, however, depends on the financial health of the lender. Firms lose their credit lines when banks go bankrupt. Even if banks survive, there is evidence of credit rationing by distressed banks. For example, banks that were more vulnerable during the financial crisis were tougher in waiving covenant violations under credit line arrangements (Acharya et al., 2020, Chodorow-Reich and Falato, 2022).[3] Hence, banks' ability and willingness to service their loan commitments is an important channel through which financial instability spills over onto the broader economy.

What, however, remain relatively unexplored are the *ex-ante* implications of lender instability. In this paper, I explore the question that if firms can anticipate the uncertainty stemming from their lenders' ability to honor commitments, do they price it in when they contract on these credit lines? To put it differently, how does the financial health of the *lender* influence the price in the equilibrium contract? If firms can distinguish vulnerable banks from safer ones, then the resilience or safety of the bank should be reflected in the prices of these contracts. Surprisingly little evidence exists in this regard. I attempt to fill this gap.[4]

The main contribution of this paper is to document novel empirical evidence on how the spillover of lender instability is priced in loan commitments. I find that after controlling for firm characteristics, the financial health of a bank has a positive effect on the price of loan commitments. Firms pay a higher price when they sign credit line contracts with safer and stable banks. This empirical finding suggests that, in the equilibrium contract, firms internalize the stability of their lender and hence the reliability of the loan commitment. I further document that firms pay this higher price when revocation is costly for them.

The theoretical literature views credit lines as insurance contracts. Firms pay an insurance premium to banks for the assurance to provide money in contingencies where the firm may become cash constrained. For example, Thakor (2005) rationalizes the existence of such loans-under-commitments as insurance against credit rationing in the future.

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[1] In this paper, I interchangeably use the words credit line, line of credit, and loan commitment.

[2] Analysis of the Federal Reserve's Survey of Terms of Business Lending.

[3] Several studies demonstrate that banks had cut back on loans and credit lines during the financial crisis (Acharya et al., 2021, Campello et al., 2011, Ivashina and Scharfstein, 2010).

[4] In a closely related paper, Bord and Santos (2014) document *ex-post* evidence of the effect of the collapse of the market for asset-backed commercial paper (ABCP) on the cost of liquidity provisions to firms. In this paper, I focus on *ex-ante* pricing implications of bank stability in general.

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One feature of these contracts is that they are discretionary. Boot et al. (1993) argue in favor of the efficiency of such discretionary contracts, as they allow banks to preserve financial capital. The premium of such an insurance contract will be driven by the probability with which a firm is hit by a liquidity need (and thus draws down the credit line) and also the probability with which the bank is able to pay the cash on demand. Aggregate economy-wide shocks hit firms and banks at the same time. The positive correlation between the two events drives up the cost of insurance (Acharya et al., 2013). Anecdotal evidence suggests that CFOs internalize this mechanism and care about the risk of these spillovers. When firms form relations with banks, the stability and resilience of the lender become an important consideration (Schwert, 2018).

Using loan origination data from syndicated loan deals from 1990 to 2016, I estimate the magnitude of the effect of lender resilience on the pricing of loan commitments. Since the price of a credit line is not a single number, rather a complex structure of fees and spreads, I focus on a specific fee that is part of the pricing of credit lines. Namely, I focus on the commitment fees that are very commonly levied on all credit lines and are charged exclusively on the undrawn amount of a loan commitment. It is intuitively relatable to the insurance premium of the liquidity insurance provided by banks to firms.

I use a two-pronged strategy to isolate the economic mechanism that relates the financial strength of the bank to the commitment fees of credit lines. First, I proxy for bank financial strength using bank capital. There is overwhelming evidence that higher bank capital is associated with greater bank stability, higher liquidity creation, and higher probabilities of surviving crises (see Thakor, 2014 for review). Thus, better-capitalized banks are *ex-ante* better positioned to honor their future commitments. Since better-capitalized banks offer a better product in terms of these credit lines, they could charge a higher price.

I find that firms pay higher commitment fees on credit lines when they borrow from better capitalized-banks. A move from one standard deviation below to one standard deviation above the cross-sectional mean of the equity-over-assets increases the commitment fees by almost 2.5 basis points (i.e., 11% of its mean). For the average credit line, this amounts to, a 3.2% increase in the total cost of borrowing. These empirical findings are consistent with the theoretical prediction of Boot et al. (1993), where the authors show that banks with high capital charge higher fees to guarantee contingent claims.

The results indicate that the capital of the bank influences the price of the insurance provided by banks. This is consistent with the argument that firms price the uncertainty concerning banks servicing their future commitments. Higher bank capital lowers this uncertainty and demands a higher insurance premium (i.e., higher commitment fees).

Identification using pooled panel regressions has its fair share of limitations, primarily due to non-random assignment. For example, if firms and banks match on unobservable characteristics unrelated to bank stability, then this could bias the estimates (including the sign) of the effect of bank capital on prices (Roberts and Whited, 2013). This impedes an empiricist to draw correct inferences regarding the relation.

To overcome these endogeneity concerns, I use a second empirical approach. I exploit natural disasters as a source of exogenous variation of a bank's financial health to identify the causal effect of bank resilience on the pricing of loan commitments. Natural disasters impact the local businesses and cause higher delinquencies for exposed banks. Thus, major natural disasters reduce the market values of exposed banks' assets and thereby make them more vulnerable. After being hit by a negative shock, a bank's loan commitment will be less reliable than before, and therefore, when firms contract with this bank, they will apply a discount for the increased uncertainty regarding future drawdowns.[5]

I find that a negative shock to bank stability reduces the commitment fees charged by banks. The shock on average decreases commitment fees by almost 8% (that is around 2.4% of the average total borrowing cost). The underlying economic mechanism here is the same as with the positive relationship between capital and commitment fees. Firms pay a higher insurance premium to stable banks. If the stability of a bank is exogenously shocked, then this encumbers the bank's ability to charge a higher price.

The second dimension that I explore in this paper is the sensitivity of the commitment fees to changes in bank safety across several firm characteristics. The differences in sensitivity are driven by the costs of credit line revocation of firms (and also differences in the likelihood that firms are hit by liquidity shocks). Firms that are more likely to incur large losses (if credit lines are revoked) are willing to pay higher premiums for a marginal decrease in the probability of bank distress.

These costs are arguably higher for firms with higher short-term liabilities. Firms with higher operating liabilities (relative to their current assets) rely heavily on credit lines. For example, the inability to pay suppliers on time can subsequently entail stricter trade credit terms, thus increasing a firm's costs of operation. The change in the equilibrium fee for these firms, for a marginal change in bank safety, is higher. Consistent with these arguments, I find that the relation between bank safety and commitment fee is stronger for firms with high short-term liabilities.

Next, I focus on the income uncertainty of firms.[6] Firms with higher income uncertainty are more vulnerable to liquidity shocks. Furthermore, the liquidity needs of the firms with higher income uncertainty are more sensitive to aggregate economy-wide shocks. Thus, the joint probability of a liquidity shock faced by a firm and a negative shock faced by a bank is higher. Consistently, I find that the relation between bank safety and commitment fees is larger in magnitude for firms with higher income uncertainty. It is important to note that firms with high income uncertainty and high short-term liabilities pay a higher commitment fee by virtue of being riskier entities. What I disentangle is that the sensitivity of the fees to changes in the financial health of a bank is larger.

Finally, I do not find any evidence that the effect of bank safety on prices is any different for smaller firms. Firms that are larger, and arguably unconstrained in their access to capital markets, also face costs when a bank reneges on its credit lines. This could be because raising capital on short notice may be difficult for unconstrained firms as well. This evidence points to the importance of lender stability even among large unconstrained firms.

My findings inform the policy debate on the regulation of banks. Forcing banks to finance themselves with more equity and maintain sufficient liquidity may constrict credit supply in the short run. However, being well-capitalized and/or liquidity-rich may enhance credit facilitation in the future. The possibility of credit rationing by banks that are under-capitalized and/or liquidity-constrained in the future is *ex-ante* understood by firms, and hence priced in.

Related Literature. Several studies have explored how bank health spills over onto the real economy. One such mechanism involves banks cutting back on pre-committed loans. If the liquidity needs of banks and firms are correlated with aggregate risk, then the ability of a bank to serve the liquidity need of a firm would be impaired during downturns (Acharya et al., 2013, Acharya et al., 2014). Banks also use their discretion in enforcing covenant violations to ration credit when they are under distress. When firms violate covenants, banks in poor health renegotiate tougher deals (Acharya et al., 2020; Chaderina et al., 2020, Chodorow-Reich and Falato, 2022, Huang, 2010). These have real implications for firms (Chodorow-Reich, 2014). My paper documents the *ex-ante* pricing implications of these *ex-post* effects.

[5] I remove firms that were hit by natural disasters to mitigate the direct effect that the disasters might have had on exposed firms. In the online appendix, I also deal with the concern that the negative shock may cause banks to contract with fundamentally different firms.

[6] I measure income uncertainty as the standard deviation of a firm's past 3 years EBITDA/Sales.

There is also some evidence that firms internalize these risks *ex-ante*. Schwert (2018) documents that firms self-select into banks based on banks' financial health. Bank-dependent firms form lending relationships with safer banks. Detragiache et al. (2000) provide a theory, and accompanying empirical evidence, of how potential adverse real effects, because of internal problems faced by firms' relationship banks, may cause firms to have multiple lending relationships.[7] Marchuk (2021) documents that the equity returns of firms that form lending relations with highly leveraged banks outperform those firms with relations with well-capitalized banks. In other words, equity holders of firms demand compensation for the risks emanating from firms' lenders.[8] To the best of my knowledge, my paper is the first to document that firms price these risks when they contract on credit lines with banks.

Finally, my paper also contributes to our understanding of banks as liquidity providers. Banks provide liquidity to agents on both sides of their balance sheets (Kashyap et al., 2002, Gatev and Strahan, 2006). The deposit rate is primarily determined by the uncertainty faced by the depositor. My results demonstrate that borrowers price the uncertainty of liquidity provision as well. Similar to depositors, borrowers consider the financial condition of their banks *ex-ante* and price the risk associated with the uncertainty of future drawdowns.

The remainder of this paper is organized as follows. In Section 2, I develop the testable hypotheses. Section 3 outlines the strategy to identify and pin down the economic mechanism and briefly describes the data. In Section 4, I present the results of the panel regression analysis. Section 5 reports the results of the analysis using natural disasters as exogenous shocks. Section 6 concludes.

2. Theoretical motivation and hypotheses development

There is a large theoretical literature that rationalizes the existence of credit lines or loan commitments as liquidity insurance for firms. For example, Holmström and Tirole (1998) demonstrate that if a firm faces a liquidity shock then (in a setting where entrepreneurs have to be additionally incentivized to overcome a moral hazard problem) the firm will have to abandon some profitable projects because it will not be able to raise the needed capital to continue. In such a scenario, the optimal contract would be that the firm purchase an insurance via a credit line. Similarly, a credit line is also the optimal contract in some settings of information asymmetry where there is a need for intermediate investment (Berkovitch and Greenbaum, 1991, Boot et al., 1987). In these models, credit lines allow firms to avoid suboptimal investment decisions.

Credit lines are not immediately drawn down. The average rated firm in the USA (that has a credit line) has more than two-thirds of its credit line remaining undrawn after the first 3 years (Berg et al., 2017). This delay exposes firms to risk emanating from the side of the bank. If a lender declares bankruptcy, then the borrowers lose their right to draw down on their credit lines. Thus, there is uncertainty regarding a firm's ability to access its credit line, which emanates from the risk that the firm's lender faces.

Moreover, lender default is not a necessary condition for firms to lose access to their credit lines. One feature that is prevalent among credit lines is that they are discretionary in nature. Nearly all credit lines have an "escape clause". This allows banks to withdraw the commitment when it observes "material adverse changes" in the borrower's condition or if a borrower violates a covenant. Acharya et al. (2020) find that banks that had higher exposure to the Asset-Backed Commercial Paper (ABCP) market were significantly less likely to waive covenant violations. Similarly, Chodorow-Reich and Falato (2022) find that lenders in worse financial health are more likely to force a reduction in the loan commitments after a violation.

What are the pricing implications of this uncertainty faced by firms when purchasing credit lines from banks? To explore this question, I fall back on the idea of viewing credit lines as insurance contracts, providing liquidity insurance to firms. Consider a simple model in the spirit of Doherty and Schlesinger (1990). A risk-averse firm suffers a liquidity shock and faces a loss of L with probability p if it is unable to meet the liquidity demand. The firm will insure a proportion α ($0 < \alpha < 1$) of the loss L. The firm aims to draw down on its pre-arranged credit line to manage the liquidity demand and minimize the loss. Conditional on the occurrence of a loss, a bank will be able to provide the demanded liquidity (i.e., provide indemnity for the loss) with probability q. With probability $1 - q$, the bank will be unable to honor its commitment and will renege on the credit line.

Assuming full information, in a world of perfect competition the premium, f, charged is actuarially fair and equals the expected value of the losses covered by the bank. Thus,

$$f = \alpha p q L. \tag{1}$$

Doherty and Schlesinger (1990) show that in the case of perfect competition (and for CARA utility function) there is a monotonic relationship between α and q. Then it is straightforward to show that the partial derivative of f with q is strictly positive. Thus, there will be a positive relation between the probability of the bank serving its commitment and the price of those commitments. A credit line from a safer bank has less uncertainty regarding future drawdowns (i.e., higher q). Thus, credit lines from safer banks would, in principle, demand a higher price.

Perfect competition may not necessarily be useful for empirically relevant predictions. Firms (especially bank-dependent ones) may be constrained in their choice of lenders. Thus, banks may enjoy sufficient bargaining power in setting these insurance premiums, and the stability of a bank need not necessarily be positively related to them. A useful comparison then is to explore the comparative statics under a monopolist insurer.

In the case of a monopoly, an insurer (i.e., the bank) will keep the firm at its reservation utility without the insurance, and the premium will be above the actuarially fair value. In Fig. 1, I plot the relation between f and q under monopoly (and also under perfect competition) for different levels of L.[9] The figure demonstrates that under both perfect competition and monopoly, there is a positive relation between the probability of a bank serving its commitment and the price of the commitments. Also noteworthy in the figure is that the sensitivity of the premium, f, to q is larger under monopoly.[10] Thus, irrespective of the level of competition, the uncertainty at the end of the lender will be priced. Whether firms actually pay this higher price for safety is ultimately an empirical question. The formal hypothesis is as follows:

Hypothesis 1. Keeping firm characteristics fixed, safer banks charge a higher price for credit lines.

The above hypothesis needs a deeper analysis as to what exactly is the price of a credit line and what can be a good measure of the fee, f, in credit lines. The price of a credit line is a combination of multiple fees and spreads. Shockley and Thakor (1997) document a complex

[7] My results also contribute to the literature on bank–firm lending relationships. Firms and banks match endogenously based on several factors. These include bank and firm size (Petersen and Rajan, 1994, Berger et al., 2005, Stein, 2002), geographical distance (Degryse and Ongena, 2005), past relationships (Bharath et al., 2007, Bolton et al., 2016) and growth opportunities (Ongena and Smith, 2001), among others. I show that banks and firms also match on lenders' ability to serve future commitments. This is reflected in the price that borrowers pay for credit lines.

[8] Slovin et al. (1993) document that the share prices of client firms react negatively to their banks' impending insolvency.

[9] For both the case of monopoly and perfect competition I have used a CARA utility function for expositional purposes.

[10] It, however, must be noted that this simple model does not allow us to explore how bargaining power may impact the relation between q and f.

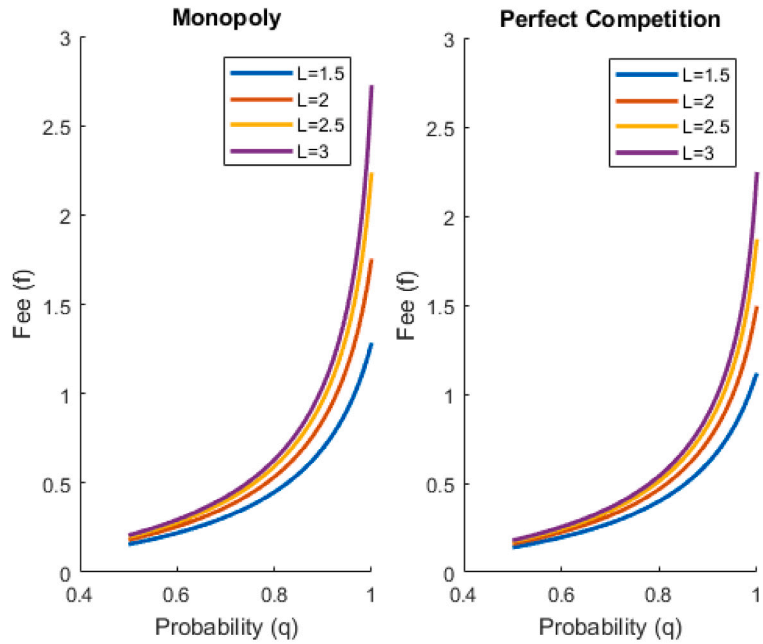

Fig. 1. Relation between probability of credit line payout and insurance premium.
This figure plots the relation between the probability that the bank honors the credit line agreement (q) and the insurance premium/fee (f) charged. The utility function for the firm is a CARA utility function, and L denotes the loss the firm suffers with probability p (set fixed at 0.75).

pricing structure of loan commitments and rationalize this multiple fee structure as a means to confront both pre and post contract private information problems with respect to the borrower. Berg et al. (2016) also provide a comprehensive analysis of the various fees in credit line contracts and the purpose they serve. The interest rate (i.e., LIBOR spread) aside, the other fees that are frequently levied on credit lines are upfront fees, annual fees, and commitment fees.

The fee that is noteworthy in credit lines is commitment fee. The commitment fee is paid by borrowers on undrawn amounts of the credit lines.[11] A firm's exposure to a bank's stability is on the undrawn portions of the line.[12] Commitment fees can be interpreted as the *insurance premium* for the liquidity insurance that the credit line provides to the firm. They are intuitively relatable to the fee, f, in the above discussed model. Thus, the specific hypothesis to test is as follows:

Hypothesis 1a. Keeping firm characteristics fixed, safer banks charge higher commitment fees of credit lines.

The other empirically relevant exercise is to explore the sensitivity of changes to bank stability to the price of the insurance. We return to the simple model to glean insights regarding this sensitivity. As can be clearly seen from Fig. 1, the sensitivity (both in cases of perfect competition and monopolist insurer) depends on the losses incurred, L (i.e., for a given q, the slope is higher for higher L). The sensitivity also depends on the probability of a liquidity shock, p. The higher the losses (or the higher the likelihood of loss), the higher the correlation between the commitment fees and bank stability. With a monopolist insurer, the insurance premium is higher than the actuarially fair value. In this case, the premium *additionally* depends on the willingness to pay of the firm (which, in turn, depends on its risk aversion parameter). Therefore, the sensitivity would also depend on the risk aversion parameter. In Fig. 2,

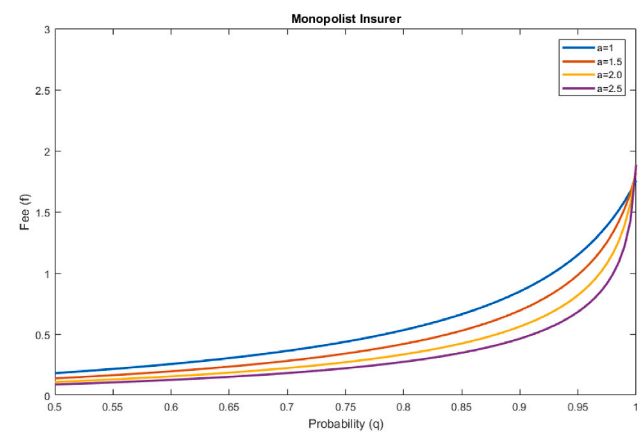

Fig. 2. Insurance premium for varying risk aversion coefficients.
This figure plots the relation between the probability that the bank honors the credit line agreement (q) and the insurance premium/fee (f) charged for varying risk aversion coefficients a. The utility function used is a CARA utility function.

I again plot the relation between f and q but for varying levels of risk aversion coefficients.

The empirically relevant takeaways from this simple model is that if there is heterogeneity in the costs of revocation (e.g., owing to opportunity costs, and financial distress), or in the likelihood of being hit by a shock, then the impact of changes in bank stability is higher for those firms with higher costs and higher likelihood. The level of competition among banks will have an impact on this sensitivity. However, the testable predictions will remain the same. The testable hypothesis is as follows:

Hypothesis 2. The relation between bank safety and commitment fees is larger in magnitude for firms with higher costs of revocations or higher likelihood of loss.

[11] To give an example, if a firm contracts on a credit line of \$100 million and immediately draws \$20 million it will pay commitment fees only on the \$80 million that remain undrawn.

[12] If a firm draws down majority of its credit line soon after contracting, the firm will have little exposure to the lender's stability. In practice too, this firm would pay negligible commitment fees.

What are the firm-level observables along which these elements vary? In this paper, I focus on three firm-level observables along which I argue the costs of revocation, the likelihood, and the willingness to pay varies. My choice of these three observables is motivated by the recent findings regarding the usage of credit line. These three variables can also be directly related to the model parameters p and L.

I first focus on the income uncertainty of the firm. Firms with more uncertain cash flows are more likely to be hit by a shock (higher p). Furthermore, the liquidity needs of the firms with higher income uncertainty are more sensitive to aggregate economy-wide shocks (Acharya et al., 2013) (positive correlation between p and q). Thus, the joint probability of a liquidity shock faced by the firm and a negative shock faced by the bank are higher. Therefore,

Hypothesis 2a. The relation between bank safety and commitment fees is larger in magnitude for firms with higher income uncertainty.

Second, I focus on the short term liabilities of a firm relative to its liquid assets. Firms use credit lines to fund operating liabilities and growth opportunities (Demiroglu and James, 2011). Firms with higher current liabilities are more dependent on these credit lines. Revocation of credit lines for these firms can increase operating costs. For example, inability to pay suppliers on time can subsequently entail stricter trade credit terms, thus increasing the firm's costs of operation. This can viewed as firms having a higher L. Thus,

Hypothesis 2b. The relation between bank safety and commitment fees is larger in magnitude for firms with higher short term liabilities.

Finally, I focus on the size of the firm. Smaller firms are generally financially constrained (Beck et al., 2005) and have a higher likelihood of being unable to fund their liquidity shocks. Smaller firms are also likely to suffer greater consequences of having their credit lines revoked. Thus,

Hypothesis 2c. The relation between bank safety and commitment fees is larger in magnitude for smaller firms.

Hypothesis 2 (and its subparts) deserve a particular discussion regarding the effect of higher losses (or higher likelihood of losses) on the insurance premium. A higher p or L has a direct impact on the insurance premium, f. However, these hypotheses deal with the sensitivity of q on f when one changes p and/or L. The empirical challenge is to separate these effects. I deal with some of these identification challenges in the next section.

The underlying theory behind the hypotheses developed thus far does not consider the reputation concerns of banks in honoring loan commitments. In a multiperiod setting, a bank's decision to honor a commitment will not only be influenced by the payout probability, q, but also by utility concerns of lending in future periods. Chemmanur and Fulghieri (1994) model this choice, albeit in a different theoretical setting, and show how banks can use reputation as a commitment device to convince firms of their willingness to honor commitments.[13] The impact of reputation on the price of commitments is not immediately clear. Higher reputation banks may naturally be more willing to honor commitments, thus increasing the price. However, reputation concerns may also cause banks to overlend in economic booms, which may increase the possibility of reneging in economic busts (Thakor, 2005). It is, however, challenging to assess this empirically as reputation, in itself, is a difficult idea to quantify.

[13] Boot et al. (1993) rationalize the existence of discretionary loan contracts by demonstrating that legally unenforceable and discretionary contracts can be optimal even in an environment where legally enforceable contracts are feasible. In a model that trades-off reputational capital against financial capital, the authors demonstrate that discretionary contracts achieve higher efficiency than enforceable contracts.

3. Identification strategy and data

My aim is to identify the effect of the financial health of a lender on the pricing of loan commitments. The ideal dataset to identify this effect is one where a cross-section of identical firms is randomly assigned to banks that vary in their degree of financial health (but otherwise identical). The matched firms and banks then contract on identical credit lines. If there is a variable that perfectly quantifies the financial health of a bank, then a simple OLS estimation would suffice to identify the effect.

However, such an ideal setup is almost impossible when one is working with observational data. There could be strategic reasons (unrelated to bank stability), and not randomly, why some firms match with certain kinds of banks. In the following subsections, I describe the two strategies I employ to isolate the economic mechanism and test the hypotheses developed in the previous section. I also discuss the shortcoming of each of the techniques in greater detail and how I address some of the concerns.

3.1. OLS approach using bank capital

I estimate the effect of the financial health of the bank on the commitment fees of credit lines in a pooled OLS setting. I proxy for bank stability using bank capital.[14] There is overwhelming evidence that higher bank capital is associated with greater bank stability, higher liquidity creation and higher probabilities of surviving crises. Higher capital implies lower cost of funding (Flannery and Rangan, 2008), lower liquidity costs (Allen and Santomero, 1997 and Allen and Gale, 2004), stronger incentive to monitor the borrower (Holmström and Tirole, 1997 and Mehran and Thakor, 2011), and greater capacities to absorb risk (Berger and Bouwman, 2009). Thus, better-capitalized banks are *ex-ante* better positioned to honor their future commitments. The specification I employ is as follows:

$$Price_{ijdt} = \beta_1 \frac{Equity}{Assets}_{it-1} + \boldsymbol{\alpha} B_{it-1} + \lambda F_{jt-1} + \theta L_d + \gamma_i + \upsilon_t + \epsilon_{ijdt} \quad (2)$$

where i indexes for banks; j, firms; d, loan deals; and t, time. B, F, and L denote bank, firm, and loan controls respectively. γ_i controls for bank fixed effects and υ_t for time fixed effects. In some specifications, I also include industry fixed effects and industry-time fixed effects (not shown in the equation), which remove any industry-specific or industry-time-specific unobservable effects.

The idea here is to identify the effect of bank stability on credit line pricing off of the variation in bank capital controlling for all other bank, loan, and firm observables. A positive correlation between bank capital and credit line pricing (i.e., a positive and significant β_1) would indicate that better-capitalized banks charge a higher insurance premium (i.e., commitment fees). This higher insurance premium can be interpreted as a premium for stability, one that is charged by banks better equipped to absorb future unexpected shocks and hence provide less uncertainty about future drawdowns.

Firms differ from each other on several measures which can directly influence the price of the credit line (e.g., credit risk, liquidity, profitability.). I control for several firm observables that could potentially influence the price. The main firm controls included are Altman Z-Score (for credit risk) and firm leverage. I also control for various measures of firm profitability, firm liquidity, and firm tangibility. Past relations with banks can also influence prices (Bharath et al., 2011). I control for past relation between firms and the lead banks. Ideally, to control for demand-side unobservables, one would want to estimate the specification with firm-year fixed effects as in Khwaja and Mian (2008). However, this is not possible because very few firms borrow from multiple banks simultaneously. In fact, an attempt to estimate

[14] I measure bank capital as a simple equity over total assets. I also use a risk weighted measure of bank capital and the results are qualitatively similar.

the specification with simple firm fixed effects removes much of the variation from the data. This is because more than half of the firms in the sample do only one deal during the entire sample period.[15]

Banks would also vary on several dimensions (other than risk profile), which could drive prices. For example, more profitable banks could charge lower prices owing to their cost advantage over other banks. Thus, I include controls such as return on assets, deposits, and bank size. I also control for several loan characteristics such as loan amount, loan maturity, covenants, collateral, lead bank's share of the loan, and number of lenders associated with the loan.

An important motivation for using bank capital is that it is easily observable to firms and (even with lagged observability) serves as a predictive variable for bank stability. The same cannot be said of other call report variables of banks (such as nonperforming loans) observable to firms, which tend to be backward-looking. Metrics computed from current market prices may be useful substitutes to bank capital; however, the vast majority of banks in my sample are privately held and do not have share prices or CDS spreads.

Perhaps, the biggest concern with Eq. (2) is that firms and banks do not match randomly. Firms could strategically choose banks. This strategic choice could influence my inference. There could be alternative reasons (unrelated to bank risk or stability) why firms match up with certain kinds of banks. For example, better-capitalized banks provide better add-on services, and hence, a positive correlation between bank capital and prices has nothing to with bank stability but rather a payment for a better service. Similarly, if weak firms (with higher probability of shock p) match with weak banks and strong firms match with strong banks, then one would empirically observe a negative relation between bank capital and the premium charged. This negative relation would be driven the variation in the probability of the firm seeking loss indemnity (i.e., variation in p). This mechanism would then attenuate the effects of the relation between bank safety and the premium. Moreover, if the reason why certain firms match up with certain banks is not directly observable then the specification of Eq. (2) would have a missing variable inside of the error term which would be correlated to firm and bank characteristics. This makes the estimates of β_1 biased and inconsistent. Although I draw my list of controls from the extensive research on bank–firm lending relations, this would not solve the endogeneity problem.

3.2. Using natural disasters as exogenous shocks to bank stability

To overcome the aforementioned endogeneity problem, I make use of a quasi-natural experiment methodology to isolate the effect of bank stability on prices. The idea here is to look for a shock to the financial health of some banks and then employ a difference-in-differences estimation on the set of shocked (treated) and non-shocked (control) banks. If treated banks contract on credit line both before and after the shock, then comparing the effects of the shock on the prices of treated and control banks (controlling for firm characteristics) would help uncover whether there is a causal relation between bank stability and credit line pricing.

I focus on natural disasters as exogenous shocks to bank stability. Natural disasters are unexpected (or at least cannot be forecasted with precision in advance). There is evidence that natural disasters affect the asset side of the balance sheet of banks. This is because, even though insurance payments cover for damages in disaster-struck areas, there is disruption in the normal working of businesses. This leads to delinquencies in loan repayments and hence reduction in the market value of the bank's assets. Hence, major natural disasters can be viewed as negative exogenous shocks to the financial stability of exposed banks.

The identification strategy is to exploit the exogenous variation in bank health induced by natural disasters and identify the effect of bank health on loan commitment pricing. I do this in a difference-in-differences setting as follows:

$$Price_{ijdt} = \beta_1 Treat_i * EventWindow_t + \boldsymbol{\alpha} B_{it-1} + \lambda F_{jt-1} + \theta L_d + \gamma_i + \upsilon_t + \epsilon_{ijdt} \tag{3}$$

where i indexes for banks; j, firms; d, loan deals; and t, time. B, F, and L denote bank, firm, and loan controls, respectively.

Eq. (3) is similar to a difference-in-differences analysis. Here, $treat$ is set equal to 1 when a bank is headquartered in a county that has experienced a major natural disaster. My definition of a major natural disaster is a natural disaster for which a Federal Emergency Management Agency (FEMA) emergency was declared and the Hazard Mitigation Assistance (HMA) program was announced. I describe the natural disaster data in greater detail in the next section. For now, it suffices to say that these are disasters that caused massive damages to selected counties. The $EventWindow$ is an indicator set equal to 1 for those calendar dates that fall between 180 days from the start date of a natural disaster in my list of disasters.[16] I put in bank fixed effects γ_i to control for time-invariant bank unobservables. Bank fixed effect also obviates the need to estimate $treated$. I also employ year fixed effects υ_t to control for time-varying unobservables.

The interaction term $treat * EventWindow$ will identify the average effect of a natural disaster on credit line pricing. In other words, it will identify the effect a negative exogenous shock on bank stability has on credit line prices. If the coefficient of the interaction term is negative and significant, it would imply that banks that are negatively shocked charge a lower price on their loan commitments. The rationale here would be that the control banks (not exposed to the negative shock) are more stable than the treated banks, and hence, on average, there is a discount on the prices charged by the treated bank. This would be akin to an instability discount.

The underlying economic mechanism, in both this subsection and the previous one, is the same. Stable banks can charge a stability premium. If the stability of a bank is exogenously shocked then this would hinder its ability to charge a premium in loan commitment. Then borrowers would no longer be willing to pay this premium.

The assignment into treated and control is arguably random as the occurrence of natural disaster hitting some counties of USA is random. Some counties might be more prone to natural disasters than others. Bank fixed effects deal with unobservable county specific factors affecting the price.

Although the setup of Eq. (3) makes use of an exogenous variation in bank stability, there is an implicit assumption that merits some discussion. The choice of the kind of firms to contract with can, however, be influenced by the fact that the bank faced a major shock. For example, a bank can lend to firms that also faced the same shock, and hence, the contracting dynamics would be different. I take remedial measures by removing deals done by firms in counties hit by natural disasters. This, however, does not resolve the issue that even when "shocked" banks lend to "unshocked" firms, banks could be strategic in the choice of firms they lend to. Here, I make an assumption that the choice of loans is uncorrelated with whether a bank was shocked or not.

It would have been ideal if the bank received a mandate before the shock and finalized the contracting terms, including the price, after the shock. Then, by construction, the choice of firm that a bank

[15] In the online appendix, I report the results of the estimation using various combinations of firm fixed effects. Although the point estimates are similar to the ones reported here in the baseline specifications, the standard errors are often high because of smaller sample sizes. This highlights the concern regarding statistical power when employing more saturated models in estimation.

[16] I repeat the analysis with event windows of 120 and 150 days, and the results remain unaltered.

lends to is uncorrelated with the shock and only the contracting terms are impacted by the shock. However, applying such a restrictive filter hardly leaves any data to work with.

To assuage concerns, I show that the choice of firm is not influenced by whether the bank faced a shock or not. This is suggestive evidence that my assumption is supported by the data. I discuss this further in the online appendix.

3.3. Variation in the effects across subgroups

Hypothesis 2 deals with how the effect varies across certain groups of firms with, for example, higher income uncertainty. The empirical challenge is to disentangle the direct effect of income uncertainty on commitment fees as opposed to the effect of income uncertainty on the relation between bank stability and commitment fees. To this effect, I use the two identification strategies separately. First, I use an interaction term with the measure of bank capital (i.e., bank capital) as follows:

$$Price_{ijdt} = \beta_1 * Vol_j + \beta_2 * \frac{Equity}{Assets}_{it-1} + \beta_3 * \frac{Equity}{Assets}_{it-1} * Vol_j + \alpha B_{it-1} + \lambda F_{jt-1} + \theta L_d + \gamma_i + \upsilon_t + \epsilon_{ijdt} \quad (4)$$

Next, for the identification using the shock of natural disasters, I use a triple interaction as follows:

$$\begin{aligned} Price_{ijdt} = \beta_1 * Vol_j + \beta_2 * Treat_i * EventWindow_t \\ + \beta_3 * Treat_i * EventWindow_t * Vol_j \\ + \alpha B_{it-1} + \lambda F_{jt-1} + \theta L_d + \gamma_i + \upsilon_t + \epsilon_{ijdt} \end{aligned} \quad (5)$$

In the above equations, Vol_i is an indicator variable set equal to 1 when a firm is classified as a high income-uncertainty firm. More specifically, it is set equal to 1 if the firm is in the top quintile of the cross-sectional distribution of profit volatility among firms.[17] The coefficient of interest, for both the estimation strategies, is β_3. In the first empirical setting (Eq. (4)), it measures whether the relation between bank capital and price is different for firms with more uncertain income. For the estimation using natural disaster shocks (Eq. (5)), it isolates the differences between treatment and control across the two different groups with high and low income uncertainty. Thus, it measures the difference in the sensitivity of the bank stability on the insurance premium for two distinct groups. I repeat this exercise dividing groups based on other observables, such as short-term liabilities and size, as discussed in Section 2.

3.4. Data

My data comes primarily from four sources. I collect loan-level data (loan origination only) from LPC Dealscan. Bank data is collected from SNL Financial, which is essentially a collection of the different call reports (FR Y-9C, FR Y-9LP,FR Y-9SP, FFIEC 031/041) filed by all bank holding companies, commercial banks, and savings banks with regulators in the United States. There is some heterogeneity on how frequently a bank files a call report. Based on certain characteristics (e.g., bank type, bank size), the filing frequency varies from quarterly to annually. All banks have to submit regulatory filings at least once a year. It is for this reason that I collect bank data on a yearly frequency basis. Compustat provides firm-level data in my sample.

I also collect data on natural disasters in the USA from the Federal Emergency Management Agency (FEMA) website. FEMA has a codified declaration process, which the US President follows to declare a disaster in specific regions of the country. The data for these declarations, type of disaster, counties included in the disaster declarations, and other such details are maintained by FEMA. I filter FEMA declarations for disasters for which the Hazard Mitigation Assistance (HMA) had been declared.[18] The HMA program is declared in response to disasters to prevent or reduce long-term risk to life and property from natural hazards. The idea here is to keep disasters that caused massive disruptions and losses. In Fig. 3, I plot a county-wise heat map of the natural disasters based on the number of times a county has been placed under FEMA disaster declaration between 1990 and 2016.

3.4.1. Summary of the sample

Table 1 presents the summary statistics of the sample. Panel A reports the summary statistics of the loans in my sample at the loan level. Since the economic mechanism that I highlight is active in credit lines it is useful to make a distinction between term loans and credit lines in my sample. Of the 13,480 loans in my sample 10,598 are credit lines and 2882 are term loans. The average deal size (approximately \$520 million) is similar among both the loan types; however, both the distributions are right-skewed with significantly lower medians.

The median Libor spreads charged on term loans are higher than those charged on credit lines. This is consistent with the fact that Libor spreads are only charged on the drawn portion of the credit lines. There are additional fees charged on the undrawn portion of the credit lines, and these fees constitute an important part of the pricing of the loan deal. The average fee charged on the undrawn portion of credit lines is approximately 28.5 basis points. This undrawn spread is the sum of the commitment fee, which is charged exclusively on the undrawn amount, and the annual fee, which is charged on the whole loan amount irrespective of whether a part of the loan has been drawn or not. In Fig. 4, I plot the year-wise distribution of the commitment fees in the sample. There was large spike in commitment fees following the financial crisis. The average commitment fee, over the entire sample period, is approximately 22.5 basis points. Finally, the average total cost of borrowing for credit lines is 76.19 basis points (estimated as per Berg et al., 2016).[19]

Panel B reports the summary statistics of the lead banks in my sample. The observational level is bank-year. There are 488 distinct banks in the sample. The average bank has \$10 billion in assets and 8% equity. The risk-weighted measures (Common equity Tier 1 and the Total Tier 1) of capital are on average 10% of the risk-weighted asset. In this paper, I use the simple equity over assets as the measure of bank capital. During the period of 1990–2016, several changes were made to both the computation of risk weights and the computation of tier 1 capital. Thus, there are cross-sectional variations in the computation of these capital measures. Two similar banks can have different measures of risk-weighted capital ratios depending on what approach they use to compute the risk weights. Hence, some of the variation in the risk-weighted capital measures may not be driven by bank fundamentals but by changes in capital regulation and differences in computing risk weights. For this reason, I rely on equity over assets as the more appropriate measure of bank capital.[20]

Panel C of Table 1 reports the summary statistics of the firms in my sample. There are 4506 distinct firms in my sample with around 9500 firm-year observations. My main measure of credit risk of the firm is the Altman Z-Score (Altman, 1968). This measure is standard in the banking industry to price loans (cite paper). An Altman-Z Score of 2.6 or above is considered safe. Over 25% of the sample is below this "safety threshold". The average firm has about 27% of the assets financed by debt. About 35% of the sample have long-term credit ratings, and approximately 21% are investment grade.

[17] Income uncertainty is measured as the standard deviation of the firms past 3 years EBITDA/Sales.

[18] Disaster declarations can be of two types: emergency and disasters. I exclude emergency declarations and focus only on disaster declarations where an event has occurred as opposed to emergency declaration, which in some cases are declared in anticipation of a disaster.

[19] It is bit surprising that the average total cost of borrowing is below the average spread, but this implies that usage rates are low, and hence, the actual cost is lower than the spread.

[20] Nevertheless, I repeat the analysis using risk-weighted capital measures and the results are qualitatively similar.

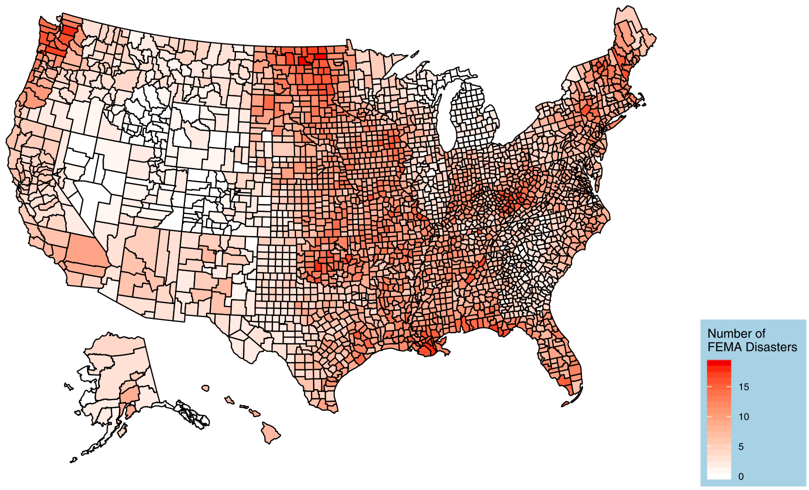

Fig. 3. County-wise major FEMA natural disasters from 1990–2016.
This figure plots the number of times a FEMA disaster was declared in a given county. The darker shade indicates greater exposure to natural disasters.

Table 1
Summary statistics.
This table reports the summary statistics of the loan data, the bank data, and the firm data. In panel A, the observation level is loan level. In panel B, the observation level is bank-year. In panel C, the observation level is firm-year.

Panel A: Loan data								
	Credit lines				Term loans			
	Obs.	Mean	Std. Dev	Median	Obs	Mean	Std. Dev	Median
Deal Amount ($ millions)	10,598	525.85	1,355.12	125.00	2,882	516.89	1,513.10	80.00
Maturity (in months)	10,351	39.41	21.32	36	2,806	53.02	22.00	60
Commitment Fee (bps)	8,715	22.40	19.40	25.00	196	32.22	21.29	25.00
LIBOR Spread (bps)	8,254	136.95	90.92	125.00	1,964	213.19	96.30	200.00
Annual Fee (bps)	8,717	5.82	10.68	0.00	212	14.44	17.31	8.25
AIUD Spread (bps)	8,707	28.50	17.44	25.00	97	35.05	25.47	25.00
TCB (bps)	6,677	76.19	52.45	64.02	1,865	228.12	97.04	217.69
Upfront Fee (bps)	2,739	42.77	45.83	25.00	973	60.46	56.45	50.00
No. of Lenders	10,598	8.39	9.01	5	2,882	7.61	10.63	3
No. of Leads	10,598	1.69	2.05	1	2,882	1.79	2.22	1
Secured (1/0)	10,598	0.50	0.50	0	2,882	0.72	0.45	1
Covenant Count	10,598	1.55	1.50	1	2,882	1.75	1.66	2
Lead Share (%)	10,598	42.67	36.64	25	2,882	50.49	38.74	39.81
Panel B: Bank data								
	Obs.	Mean	Std. Dev	p10	p25	Median	p75	p90
Log(Assets)	1,780	16.36	2.23	13.46	15.04	16.20	17.76	19.34
Assets ($ billions)	1,780	128.57	364.95	0.70	3.41	10.81	51.82	251.76
Equity/Assets	1,780	0.08	0.03	0.06	0.07	0.08	0.09	0.12
Deposits/Assets	1,780	0.72	0.15	0.54	0.65	0.74	0.83	0.88
Cash/Assets	1,773	0.31	0.12	0.17	0.23	0.30	0.38	0.47
ROA	1,780	0.01	0.01	0.00	0.01	0.01	0.01	0.02
RWAs/Assets	1,773	0.76	0.15	0.56	0.67	0.76	0.85	0.95
NPLs/Loans	1,778	0.02	0.03	0.00	0.01	0.01	0.03	0.05
Loss Reserve/Assets	1,780	1.24	0.69	0.57	0.81	1.08	1.52	2.15
Panel C: Firm data								
	Obs.	Mean	Std. Dev	p10	p25	Median	p75	p90
Log(Firm Assets)	9,443	6.07	2.22	3.12	4.45	6.04	7.61	9.08
Firm Assets ($ billions)	9,443	4.22	18.30	0.02	0.09	0.42	2.02	8.75
Firm Profitability	9,360	0.13	0.19	0.02	0.07	0.12	0.19	0.30
Firm Alt Z-Score	7,698	4.22	3.40	1.44	2.29	3.36	5.03	7.83
Firm Leverage (D/A)	9,413	0.27	0.21	0.01	0.12	0.25	0.39	0.54
Firm EBITDA/Int Expense	8,906	34.79	404.22	1.24	3.44	7.17	15.77	40.97
Firm Debt/EBITDA	9,361	2.14	3.47	0.00	0.51	1.62	3.04	5.14
Firm Market-to-Book Equity	8,225	2.85	3.36	0.79	1.30	2.10	3.38	5.65
Firm Net PPE/Assets	9,042	1.96	2.64	0.20	0.45	0.98	2.27	4.91
Firm Cash/Assets	9,433	0.10	0.14	0.01	0.02	0.05	0.13	0.26
Firm Current Ratio	9,004	2.06	1.32	0.85	1.22	1.74	2.50	3.57
Firm Rating (1/0)	9,633	0.35	0.48	0.00	0.00	0.00	1.00	1.00
Firm Investment Grade (1/0)	9,633	0.21	0.41	0.00	0.00	0.00	0.00	1.00

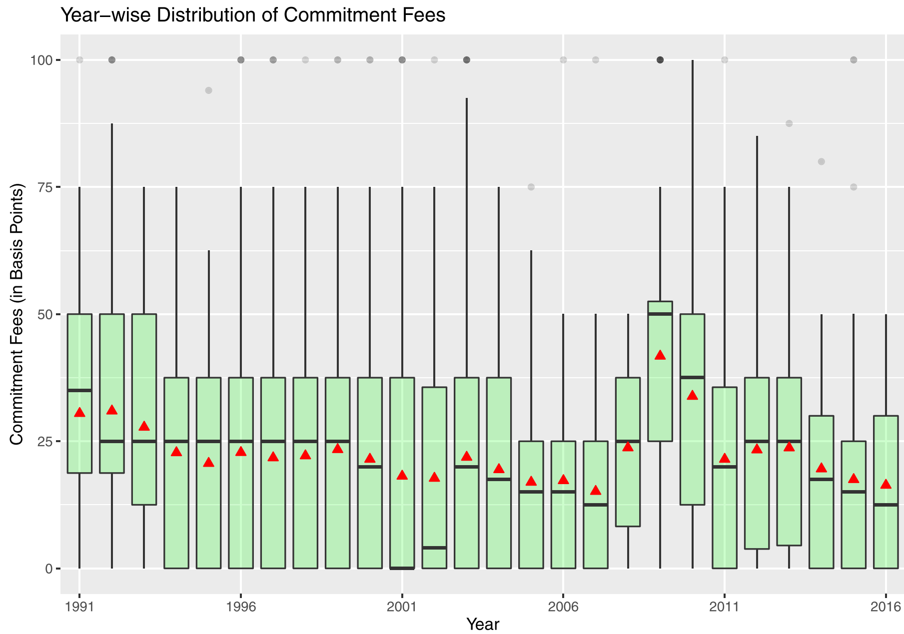

Fig. 4. Distribution of commitment fees over years.
This figure plots the distribution of the commitment fees (in basis points) across years. The bottom and top end of each box represent the 1st and 3rd quartile, respectively. The median is marked inside the box. The red triangles denote the mean values in respective years. The vertical lines above and below each box extend up to 1.5 times the inter-quartile range. The dots represent the outliers.

4. Results

4.1. Baseline results with bank capital

I test the first hypothesis that relates the bank resilience to the price of the credit lines. Table 2 presents the results of the relation between bank stability and the commitment fee. I find a strong positive correlation between bank capital and the commitment fees. Taking the strictest specification (column (4) with industry-by-year fixed effects), I find a coefficient of around 39.9. A move from one standard deviation below to one standard deviation above the cross-sectional mean of the equity/assets increases the commitment fees by almost 2.5 basis points (i.e., 11% of its mean). For the average credit line, this amounts to approximately a 3.2% increase in the total cost of borrowing.

The results presented in Table 2 provide evidence supporting the first Hypothesis 1a that there is a relation between the financial health of the bank and the fees paid on loan commitments. The positive relation between bank capital and commitment fees can be interpreted as better-capitalized banks charging a premium because these banks are better equipped to handle correlated liquidity shocks and unexpected losses (Boot et al., 1993, Castiglionesi et al. (2014)). As a result, it is less likely, for well-capitalized banks, that there is a spillover of negative shocks on bank commitments to serve future drawdowns.

The use of bank capital as a measure of bank safety raises some caveats for inference. An alternative explanation for positive relation between bank capital and commitment fees is that capital is expensive and banks with higher capital simply charge higher prices because of higher regulatory compliance costs (Kisin and Manela, 2016, Plosser and Santos, 2018). One has to however note that higher regulatory costs may not correspond, one-to-one, to higher prices. In equilibrium, firms need to agree to the higher price from banks with higher regulatory costs, and thus the dynamics of bargaining power and market structure become important. Contrasting that with the theoretical setting developed in Section 2, the premium for safety is priced irrespective of the market structure (perfect competition or monopoly). Thus, the positive relation between capital and commitment fees is arguably a reflection of the safety premium inbuilt in insurance contracts. Additionally, I perform robustness checks with other measures of bank stability.

I construct additional measures of bank stability, to augment the above results. The first measure is based on Z-Score. I follow the procedure of Laeven and Levine (2009) and construct a Z-Score measure for banks. Z-Score is given as $(ROA+(E/A))/\sigma(ROA)$ and measures the probability of insolvency for a bank. A higher Z-score indicates that the bank is more stable.

Next, I construct market based measures of bank risk. Of the 488 banks in my sample, only about 50 have actively traded stock prices around the time periods when those banks signed contracts on credit lines. Thus, the sample size gets reduced. Nevertheless, I compute *Distance-to-Default* based on the methodology of Bharath and Shumway (2008) and *Systemic Expected Shortfall* as per the methodology of Acharya et al. (2016). Distance-to-Default (DD) measures the probability of a bank defaulting on its liabilities, a higher DD implying a safer bank. Systemic Expected Shortfall (SES) calculates the reduction in the capital of a bank, conditional on the market being in its left tail. The shortfall has a negative sign, and thus a higher SES here implies a safer bank.

I report the results of the regression with these alternate measures in Table 3. First, I find that stable banks, as measured by their Z-Scores, charge higher commitment fees. The results and the economic magnitudes are in sync with the baseline results. Similarly, I find a positive relation between DD and the commitment fees charged, and a positive relation between SES and the commitment fees as well. Taken together, I find evidence that the premiums that banks charge for their loan commitments (i.e., the commitment fees) are positively associated with measures of bank safety. The evidence is consistent with Hypothesis 1a in Section 2.

The use of syndicated lending data and the focus on lead lenders to establish the hypothesis deserve some attention. First, in syndi-

Table 2
Impact of lender stability on commitment fees of credit lines.
This table reports the results of the regression of commitment fees on loan, bank, and firm characteristics. The sample is restricted to loan facilities that are credit lines. The observation level is bank-firm-year, and the sample runs from 1990 to 2016. The dependent variable is commitment fee in basis points. The table reports the results where bank stability is measured using bank capital. *Equity/Assets* is the measure of lead banks' capital and is a proxy for lender stability. The coefficients of firm profitability, firm Alt-Z score, and firm leverage are displayed for exposition. All variables and controls are defined in Table A.1. The standard errors are double clustered at the firm and bank level, and are reported in parenthesis. Significance of the parameters are indicated as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Commitment fees (bps)			
	(1)	(2)	(3)	(4)
Equity/Assets	42.074**	41.274**	41.972**	39.877**
	(17.630)	(18.714)	(18.774)	(19.342)
Firm Profitability	−3.098	−4.354*	−6.672***	−5.901***
	(2.173)	(2.280)	(2.248)	(2.245)
Firm Alt Z-Score	−0.485***	−0.508***	−0.464***	−0.514***
	(0.114)	(0.109)	(0.109)	(0.121)
Firm Leverage(D/A)	8.722***	8.230***	9.379***	10.745***
	(2.589)	(2.482)	(2.503)	(2.487)
Year Fixed Effects	Yes	Yes	Yes	No
Bank Fixed Effects	No	Yes	Yes	Yes
Industry Fixed Effects	No	No	Yes	No
Industry x Year Fixed Effects	No	No	No	Yes
Loan Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Observations	8157	8091	8089	7925
R^2	0.435	0.468	0.486	0.592

Table 3
Impact of lender stability on commitment fees - other measure of bank stability.
This table reports the results of the regression of commitment fees on loan, bank, and firm characteristics. The sample is restricted to loan facilities that are credit lines. The observation level is bank-firm-year, and the sample runs from 1990 to 2016. The dependent variable is commitment fee in basis points. The table reports the results where bank stability is measured using 3 different measures. In columns (1) and (2) bank stability is measured using Z-Score as used in Laeven and Levine (2009). In columns (3) and (4) bank stability is measured by Distance-to-Default (Bharath and Shumway (2008)). Finally, in columns (5) and (6) stability is measured by Systemic Expected Shortfall as measured by Acharya et al. (2016). All variables and controls are defined in Table A.1. The standard errors are double clustered at the firm and bank level, and are reported in parenthesis. Significance of the parameters are indicated as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Commitment fees (bps)					
	(1)	(2)	(3)	(4)	(5)	(6)
Bank Z-Score	0.189***	0.178***				
	(0.064)	(0.059)				
Distance-to-Default			0.160**	0.162**		
			(0.066)	(0.070)		
Systemic Expected Shortfall					4.264***	2.923**
					(1.478)	(1.305)
Year Fixed Effects	Yes	No	Yes	No	Yes	No
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	No	Yes	No	Yes	No
Industry x Year Fixed Effects	No	Yes	No	Yes	No	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8089	7925	2949	2720	2949	2720
R^2	0.486	0.592	0.539	0.680	0.539	0.679

cated lending, since there are more than one lender, even if the lead lender gets into trouble the participant lenders, in theory, could step in to honor the draw down claims of borrowers (see Santos and Viswanathan, 2020). Hence, there should not really be the need to pay a premium when a firm borrows from a particular safe bank because there is a large syndicate behind the loan. This however goes against finding any premium. The fact that I find a premium is indicative that channel is active even in case of multiple-lender syndicated loans. The magnitudes could potentially be much larger in single lender credit lines. Second, an important control in the all the tests is the fraction of the lead arranger's share of the syndicate. The lead banker's share is important to control for any effect that might be driven by the (relative) size of the loan share that the lead arranger keeps with itself.

4.2. Cross-sectional heterogeneity of price sensitivity

I further analyze the sensitivity of the relation between bank stability and commitment fees across heterogeneous firms and banks. I focus on three firm characteristics and one bank characteristic across which the effects could potentially vary. For firms I focus on income uncertainty, liquidity, and size. For banks I focus on the fraction of previously contracted loan commitments left unused by firms.

In column 1 of Table 4, I report the results of the analysis for varying income uncertainty. I measure income uncertainty as the standard deviation of the firms past 3 years' EBITDA/Sales. The table reports the results of the analysis focusing on the moderating effect of higher income uncertainty on the relation between bank capital and the commitment fees of credit lines.

Table 4
Variation in price sensitivity across bank and firm characteristics.
This table reports the results of the regression of commitment fees on loan, bank, and firm characteristics. The sample is restricted to loan facilities that are credit lines. The observation level is bank-firm-year, and the sample runs from 1990 to 2016. The dependent variable is commitment fee in basis points. The table reports the interaction between *Equity/Assets* and indicator variables separating the firms/banks into distinct groups. The indicator variables are defined as follows: *High Volatility* is an indicator variable that is set to 1 for those firms with profit volatility above the top quintile. *Low Liquidity* is an indicator variable set equal to 1 if the current ratio of the firm is below the bottom quintile (i.e, the firm has low current assets as a fraction of its short term liabilities). *Small Firm* is an indicator variable set equal to 1 if the size of the firm is below the bottom quintile. *High Unused* is an indicator variable set equal to 1 if the bank is above the top quintile of unused commitments (as of fraction of liquid assets). All variables and controls are defined in Table A.1. The standard errors are double clustered at the firm and bank level, and are reported in parenthesis. Significance of the parameters are indicated as follows: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	Commitment fees (bps)			
	(1)	(2)	(3)	(4)
Equity/Assets	34.065**	28.141**	34.600**	39.487***
	(17.041)	(11.991)	(15.474)	(12.780)
Equity/Assets x High Volatility	56.322**			
	(24.987)			
Equity/Assets x Low Liquidity		40.665**		
		(19.438)		
Equity/Assets x Small Firm			37.280	
			(42.440)	
Equity/Assets x High Unused				−31.449*
				(18.150)
Year Fixed Effects	No	No	No	No
Bank Fixed Effects	Yes	Yes	Yes	No
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Observations	7925	7990	7930	7978
R^2	0.532	0.565	0.588	0.566

The dummy variable *High Volatility* is set equal to 1 if the firm is in the top quintile of the cross-sectional distribution of income uncertainty among firms. The interaction term, *Equity/Assets * High Volatility*, captures how the relation between bank capital and commitment fees of credit lines differs among firms with high income uncertainty. The coefficient of the interaction term is positive and significant. This suggests that the relation between bank stability and commitment fees is stronger for firms with uncertain income. The magnitude more than doubles. This finding is consistent with Hypothesis 2a. Thus the correlation between bank stability and the price of commitments is higher for firms with more uncertain income.

Similarly, in column 2 of Table 4, I document evidence on how the relation between bank stability and credit line pricing is stronger for firms with higher short term liabilities (relative to their current assets). The table reports the results of the analysis, focusing on the ability of the firm to pay off its short-term liabilities. The dummy variable *Low Liquidity* is set equal to 1 if the firm lies in the bottom quintile of the cross-sectional distribution of the current ratio (ratio of current assets to current liabilities) across firms. These are firms that have the highest short term liabilities relative to their current assets.

Here too the interaction term, *Equity/Assets * Low Liquidity*, captures how the relation between bank capital and the commitment fees of credit lines differs among firms with high relative short term liabilities. The coefficient of the interaction term is positive and significant with a magnitude 1.5 times the baseline effect. Therefore, the sensitivity of the price to the safety of the bank more than doubles. This finding is again consistent with Hypothesis 2b. The correlation between bank stability and the price of commitments are higher for firms with higher short term liabilities. Firms with higher current liabilities are more dependent on these lines of credit. Revocation of credit lines for these firms can increase operating costs. For example, inability to pay their suppliers on time can subsequently entail stricter trade credit terms, thus increasing the firm's costs of operation.

In column 3 of Table 4, I report the results of the analysis of how the relation between bank stability and credit line pricing is different for smaller (and hence more constrained) firms. The table presents the results of the analysis, focusing on the differences in effects that vary with firm size. The dummy variable *Small Firm* is set equal to 1 if the firm lies in the bottom quintile of the cross-sectional distribution of firm size.

Surprisingly, I do not find differences in the effects of bank stability on the fees in smaller firms. The interaction term, *Equity/Assets * Small Firm*, is statistically insignificant. Thus, the correlation between the stability of the bank and the insurance fees on credit lines does not vary with the size of the firm. One interpretation of this result is that the costs of revocation are not necessarily higher for smaller firms. Hence, firms that are larger and unconstrained in their access to capital markets also face costs when a bank reneges on its credit lines. This could be because raising capital on a short notice at favorable terms may be difficult for unconstrained firms as well. This evidence points to the importance of lender stability even among large unconstrained firms.

Finally, I analyze whether the price sensitivity varies across bank characteristics. In column 4 of Table 4 presents the results of the analysis of how the relation between bank stability and credit line pricing is different for banks with more unused commitments. The results focus on the differences in effects that vary with the level of unused bank commitments. The dummy variable *High Unused* is set equal to 1 if the bank has unused commitments (as a fraction of liquid assets) above the top quintile of the cross-sectional distribution. The interaction term, *Equity/Assets * High Unused*, captures how the price sensitivity differs among banks with high unused commitments. The coefficient of the interaction term is negative and significant, but the sum of the coefficient is still positive. This suggests that for an increase in bank safety, the commensurate increase in commitment fees is lower. This is intuitive because these banks have higher levels of pre-committed loans and are relatively worse-of than similar banks with lower pre-commitments to charge a premium for safety.

Table 5
Impact of natural disasters on the commitment fees of new credit lines.
This table reports the results of the regression analysis where some banks are exposed to negative shocks from natural disasters. The sample is restricted to loan facilities that are credit lines. The observation level is bank-firm-year, and the sample runs from 1990 to 2016. The dependent variable is commitment fee in basis points. *Treat* is an indicator variable to indicate whether a bank was exposed to natural disasters. *Event Window* is an indicator variable to indicate if the deal active date of a package is less than 6 months starting from a disaster event date. *Treat * Event Window* measures the average treatment effect of natural disasters on commitment fees. In both panels, the coefficients of firm profitability, firm Alt-Z score, and firm leverage are displayed for exposition. All variables and controls are defined in Table A.1. The standard errors are double clustered at the firm and bank level, and are reported in parenthesis. Significance of the parameters are indicated as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Commitment fees (bps)		
	(1)	(2)	(3)
Treat * Event Window	−1.891**	−1.474***	−1.648***
	(0.820)	(0.483)	(0.531)
Firm Profitability		−5.180**	−5.191**
		(2.178)	(2.319)
Firm Alt Z-Score		−0.359***	−0.373***
		(0.112)	(0.118)
Firm Leverage(D/A)		4.431*	3.985
		(2.414)	(2.545)
Year Fixed Effects	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Loan Controls	No	Yes	Yes
Bank Controls	No	No	Yes
Firm Controls	No	Yes	Yes
Observations	10410	8138	7177
R^2	0.217	0.528	0.528

5. Natural disasters as exogenous shocks on bank stability

5.1. Estimation of baseline results using FEMA disasters

One can argue that a simple regression of commitment fees on measures of bank safety may not be informative of a 'safety premium'. Two banks with similar observable safety measures could still be very different on many unobservable aspects (e.g., off-balance sheet derivative exposures). This is where the approach using the natural disasters comes in handy. The negative shock to the financial health of the bank is uncorrelated with bank fundamentals. Under the assumption that the decision to lend is unrelated to the negative shock, the estimation helps me uncover the average treatment effect of natural disasters on the contract terms of the credit line. The negative effect of natural disasters can be interpreted as the fact that banks that face a negative shock are comparatively in a worse position to honor future claims. Hence, their ability to charge an extra fee for commitment is reduced. I present those results in this section.

The results of the analysis of the impact of natural disasters on the commitment fees are reported in Table 5. Here, $Treat$ is a term set equal to 1 when a bank is located in a county that has been exposed to a natural disaster. $EventWindow$ is set equal to 1 if the deal activation date of the loan falls within 6 months from the recorded start date of the natural disaster. The coefficient of the interaction term $Treat * EventWindow$ measures the average treatment of the natural disaster on the commitment fees. In the full model specification with all controls I find a negative and significant effect of natural disasters on the commitment fees. In terms of economic magnitudes the effects are very similar to Panel A. The shock reduces the commitment fees by about 1.7 basis point, which is about 8% of the mean (2.4% of the total cost of borrowing).

The definition of *treated* in my empirical setup merits some discussion. Those banks are considered treated that are headquartered in a county hit by a natural disaster. Control groups, by extension, are those headquartered in counties that were not exposed to natural disasters. Is this separation based on headquarter a reasonable segregation of treatment and control? Banks, especially large banks, may have assets spread over several counties, and thus, even though a bank may be headquartered in a county not directly hit by a disaster, it may still find itself substantially impacted by disasters in other counties. One way to deal with this "approximation error" is to use county-wise asset distribution of banks and create a continuous variable of treatment based on the fraction of assets in the exposed county. However, public access of such datasets is a challenge.[21] I do, however, proxy for this county-wise asset distribution from two separate data sources. First, I use the Home Mortgage Disclosure Act (HMDA) data on mortgages to create a proxy for continuous treatment. Second, I use the county-wise summary of deposits (SOD) data from FDIC to create another proxy for continuous treatment.

I compute *Treat HMDA* as the fraction of the mortgages (of the total new mortgages) generated in affected counties in the past 2 years from the date of a disaster event. Similarly, I create *Treat SOD* as the fraction of the deposits (of the total deposits) held in affected counties in the past 2 years from the date of a disaster event.

Thus, *Treat HMDA* and *Treat SOD* are now continuous variables between 0 and 1. I report the results in Table 6. The results corroborate the main findings of the previous table. In fact, the magnitudes are larger than when using the discrete treatment variable.[22]

It is possible that natural disasters do not actually hurt banks. There is evidence that lending increases in areas hit by disasters, for rebuilding measures (Cortés and Strahan, 2017, Koetter et al., 2020, Brown et al., 2021). The increased demand could cushion the

[21] I am comforted by the fact that approximation error would err on the side of considering treated group as controls and not vice-versa. Thus, the estimates are likely to be attenuated.

[22] It, however, must be noted that the standard errors of the estimates in some specifications are high wherein I lose significance of the parameters. The analysis using HMDA and FDIC SOD data are also approximations of the geographic distribution of the assets of a bank. The assumption here is that the geographic distribution of assets is similar to the distribution of mortgages and deposits. This may not necessarily be the case and hence this does not fully eliminate the identification challenge. However, it is comforting to note that the results do hold in this setting as well.

Table 6
Measuring exposure to natural disasters using continuous variables.
This table reports the results of the regression analysis where some banks are exposed to negative shocks from natural disasters. Exposure to the negative shock is measured with continuous variables computed from HMDA mortgage data and FDIC Summary of Deposit data. The observation level is bank-firm-year, and the sample runs from 1990 to 2016. The dependent variable is commitment fee in basis points. *Treat SOD* is a continuous variable between 0 and 1, computed as the fraction of deposits of a bank in disaster struck counties in the previous 2 years prior to a disaster. *Treat HMDA* is a continuous variable between 0 and 1, computed as the fraction of mortgages (as filed under HMDA) generated by a bank in disaster struck counties in the previous 2 years prior to a disaster. *Event Window* is an indicator variable to indicate if the deal active date of a package is less than 6 months starting from a disaster event date. All other variables and controls are defined in Table A.1. The standard errors are double clustered at the firm and bank level, and are reported in parenthesis. Significance of the parameters are indicated as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Commitment fees (bps)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat SOD x Event Window	−3.390***	−2.577**	−3.339***	−3.684***				
	(0.954)	(1.123)	(0.973)	(0.995)				
Treat HMDA x Event Window					−6.115*	−8.734***	−6.564*	−3.092
					(3.312)	(2.974)	(3.398)	(3.353)
Year Fixed Effects	Yes	No	No	Yes	Yes	No	No	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8138	7179	7177	7177	7083	6146	6146	7177
R^2	0.479	0.426	0.442	0.481	0.805	0.793	0.810	0.481

Table 7
Differences in price impact of natural disasters across firm and bank characteristics.
This table reports the results of the regression analysis where some banks are exposed to negative shocks from natural disasters. The sample is restricted to loan facilities that are credit lines. The observation level is bank-firm-year, and the sample runs from 1990 to 2016. The dependent variable is commitment fee in basis points. *Treat* is an indicator variable to indicate whether a bank was exposed to natural disasters. *Event Window* is an indicator variable to indicate if the deal active date of a package is less than 6 months starting from a disaster event date. *High Volatility* is an indicator variable that is set to 1 for those firms with profit volatility above the top quintile. *Low Liquidity* is an indicator variable set equal to 1 if the current ratio of the firm is below the bottom quintile (i.e, the firm has low current assets as a fraction of its short term liabilities). *Small Firm* is an indicator variable set equal to 1 if the size of the firm is below the bottom quintile. *High Unused* is an indicator variable set equal to 1 if the bank is above the top quintile of unused commitments (as of fraction of liquid assets). All variables and controls are defined in Table A.1. The standard errors are double clustered at the firm and bank level, and are reported in parenthesis. Significance of the parameters are indicated as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Commitment fees (bps)			
	(1)	(2)	(3)	(4)
Treat * Event Window	−1.174*	−0.689	−1.385**	−0.936
	(0.695)	(0.700)	(0.631)	(0.671)
Treat * Event Window * High Volatility	−3.499*			
	(2.032)			
Treat * Event Window * Low Liquidity		−2.881**		
		(1.319)		
Treat * Event Window * Small Firm			−2.582	
			(6.732)	
Treat * Event Window * High Unused				−5.756***
				(2.189)
Year Fixed Effects	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Observations	7177	6923	6923	7181
R^2	0.481	0.487	0.487	0.480

shock for exposed banks. In fact, there is evidence that the long run impact of natural disaster on banks is negligible (Blickle et al., 2022). The estimation strategy that I use in this paper relies on the short-term impact of disasters. For identification purposes, I require that the immediate impact of the natural disasters on bank value is negative, even if there is a strong possibility of recovery in the future. As long as the immediate impact of the shock is negative, and the borrowers perceive it as such, this will be reflected in the price of newly contracted credit lines. There is evidence that the short term impact of natural disasters is well and truly negative (Schüwer et al., 2018, Noth and Schüwer, 2018).[23]

[23] In the online appendix, I present evidence that these disasters had a negative impact on the banks in my sample.

5.2. Cross-sectional heterogeneity of impact of shocks

In this section I explore how the impact of the natural disasters across heterogeneous firms and banks. The analysis is similar to Section 4.2. The only difference here is that I use the triple interactions with natural disasters (estimation of Eq. (5)).

In column 1 of Table 7, I report the results of the analysis for varying income uncertainty. The column reports the results of the analysis focusing on the effect of higher income uncertainty on the impact of shocks to banks on the commitment fees of credit lines. The triple interaction term, *Treat * Event Window * High Volatility*, captures how the treatment effect of natural disasters on the commitment fees of credit lines differs among firms with high income uncertainty. The coefficient of the triple interaction term is negative and significant. This suggests that the reduction in the commitment fees, once a lender is shocked, is higher for firms with higher income uncertainty. The difference is about 3.5 basis points. This finding is consistent with Hypothesis 2a.

Similarly, in column 2 of Table 7, I document evidence on how the relation between bank stability and credit line pricing is stronger for firms with higher short term liabilities (relative to their current assets). The triple interaction term, *Treat * Event Window * Low Liquidity*, captures how the treatment effect of natural disasters on the commitment fees of credit lines differs among firms with high relative short term liabilities. The coefficient of the triple interaction term is negative and significant. This suggests that the reduction in the commitment fees, once a lender is shocked, is higher for firms with higher relative short-term liabilities. This finding is consistent with Hypothesis 2b. Firms with higher current liabilities are more dependent on these lines of credit. Revocation of credit lines for these firms can increase operating costs. Therefore, these firms apply a higher discount on the 'safety premium' once a bank is shocked.

In column 3 of Table 7, I report the results of the analysis of how the relation between bank stability and credit line pricing is different for smaller (and hence more constrained) firms. Similar to the results of Section 4.2, here too, I do not find evidence supporting H2c. That is, the impact of the negative shock on banks do not seem to have a stronger effect on the commitment fees for smaller firms.

In column 4 of Table 7 presents the results of the analysis of how the relation between bank stability and credit line pricing is different for banks with more unused commitments. The triple interaction term, *Treat * Event Window * High Unused*, captures how the treatment effect of natural disasters differs among banks with high unused commitments. The coefficient of the triple interaction term is negative and significant. This suggests that the reduction in the commitment fees, once a lender is shocked, is higher for banks with higher unused commitments. Banks that have high unused commitments at the time of the shock are relatively worse-off to provide credit on demand in the future. Therefore, these banks experience a sharper reduction in the commitment fees. The findings are in line with viewing credit lines as liquidity insurance contracts. Banks with a large amount of unused commitments are highly extended in insurance provision. In the event of a shock, banks may default on existing insurance contracts and their ability to credibly offer new insurance contracts is negatively impacted.

6. Conclusion

In this paper, I document empirical evidence that firms care about the financial health of their lender and price it in when they contract on loans that will be drawn down in the future. Keeping the firm side constant, there is an uncertainty about the accessibility of credit lines because the lender might face duress in the future. This uncertainty is priced in credit line contracts. I document a positive relation between the bank capital level and the commitment fees charged in credit lines. I also show that exogenous shocks on bank stability have an effect on the commitment fees of newly contracted credit lines. The evidence is consistent with a causal link.

Furthermore, I find that the correlation between bank stability and the price paid for the commitment is higher for firms with high income uncertainty and high short-term liabilities. These are firms who are arguably more likely to draw down their credit lines and also suffer higher costs if the bank reneges on its commitment. Consistent with this hypothesis, I find that a change in bank safety has a larger impact on fees for these firms. I also find that the relation does not depend on the size of the firm. Firms that are larger (and unconstrained in their access to capital markets) also face costs when a bank reneges on its credit lines.

This result provides useful insights into several economic mechanisms. First, revocation of credit lines is costly for firms, and hence, the safety of the bank directly affects the insurance fee in credit lines. Second, the findings also highlight a channel through which shock to lenders spill over onto the real economy. When lenders face financial distress, they tighten their standards and cut back credit. Firms anticipate this behavior of lenders. Finally, my findings also inform the policy debate on the regulation of banks. Forcing banks to finance themselves with more equity and maintain sufficient liquidity may constrict credit supply in the short run. However, being well capitalized and/or liquidity-rich may enhance credit facilitation in the future.

Data availability

The authors do not have permission to share data.

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Appendix

See Table A.1.

Table A.1
Explanation of variables.

Variable	Source	Definition
Loan Characteristics		
Credit Line	Dealscan	Loans with type "Revolver/Line < 1 Yr.","Revolver Line > 1 Yr.","364-Day Facility", "Limited Line" or "Revolver/Term Loan" as indicated in the facility table in Dealscan.
Term Loan	Dealscan	Loans with type "Term Loan", "Term Loan A"-"Term Loan H" or "Delay Draw Term Loan" as indicated in the facility table in Dealscan.
Log(Deal Amount)	Dealscan	Natural logarithm of the amount of the facility
Maturity	Dealscan	The number of months of facility maturity
Commitment Fees	Dealscan	Fees paid (in basis points) on the unused amount of commitments. If it does not exist and AIUD exists, it is set to 0
LIBOR Spread	Dealscan	Spread over Libor paid on the drawn amounts of a credit line (in basis points)
Annual Fees	Dealscan	Fees paid (in basis points) on the entire loan facility amount. If it does not exist and AIUD exists, it is set to 0
AIUD spread	Dealscan	The sum of the commitment fees (in basis points) and the annual fees (in basis points) charged on a loan facility
TCB	Dealscan	The total cost of borrowing (in basis points) computed as per (Berg et al., 2016)
Upfront Fees	Dealscan	The upfront fees (in basis points) paid on a loan facility
No. of Lenders	Dealscan	Count of the unique number of lenders to a given facility
No. of Leads	Dealscan	Count of the number of lenders in a given facility who either have LeadArrangerCredit column equal to 'Yes' or have lender role of Arranger, Admin agent, Agent, Lead Bank, or Sole Lender

(*continued on next page*)

Table A.1 (*continued*).

Variable	Source	Definition
Secured (1/0)	Dealscan	Dummy variable set equal to 1 if the column Secure in the Facility table equals 'Yes'
Covenant Count	Dealscan	The number of covenants attached to a loan deal (i.e., package)
Prior Relation (1/0)	Dealscan	Dummy variable set equal to 1 if the lender and the borrower have contracted on a loan before
Lead Share	Dealscan	The lead's share of the loan facility as indicated by the column BankAllocation in table LenderShares
Bank Characteristics		
Log(Assets)	SNL Financial	Natural logarithm of the total assets of a bank
Equity/Assets	SNL Financial	Ratio of total book equity to total assets
Deposits/Assets	SNL Financial	Ratio of total deposits to total assets
Cash/Assets	SNL Financial	Ratio of total cash to total assets
ROA	SNL Financial	Ratio of net income to total assets
RWAs/Assets	SNL Financial	Ratio of risk-weighted assets to total assets
NPLs/Loans	SNL Financial	Ratio of nonperforming loans to total loans
Loss Reserve/Assets	SNL Financial	Ratio of allowance for loan losses in balance sheet to total assets
Treat	FEMA	Dummy variable set equal to 1 if a bank is headquartered in county which was exposed to a natural disaster
Treat HMDA	HMDA	A continuous variable between 0 and 1 measuring the fraction of HMDA mortgages generated in the past two years from a disaster event date, in affected counties
Treat SOD	Summary of Deposits	A continuous variable between 0 and 1 measuring the fraction of deposits in affected counties, in the past two years from a disaster event date
Event Window	FEMA & Dealscan	Dummy variable set equal to 1 if the deal active date of a package is less than 6 months starting from a disaster event date
Liquidity Ratio	SNL Financial	Ratio of total liquid assets to total liabilities
Demand Deposits/Assets	SNL Financial	Ratio of demand deposits to total assets
Repo Financing/Assets	SNL Financial	Ratio of repurchase loan financing to total assets
High Unused	SNL Financial	Dummy variable set equal to 1 if the ratio of unused commitments over liquid assets is above the top quintile
High Mkt Power	SNL Financial	Dummy variable set equal to 1 if the Lerner index of a bank is above the top quintile
Firm Characteristics		
Log(Firm Assets)	Compustat	Natural logarithm of the total assets (at) of a firm
Firm Profitability	Compustat	Ratio of EBITDA (ebitda) to Sales (sale)
Firm Alt Z-Score	Compustat	Altman's Z-Score for a borrower at the end of the fiscal year prior to a loan. Z-score is calculated as Z= 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + X5, where X1 is working capital (act-lct) /total assets (at), X2 is retained earnings (re)/total assets (at), X3 is EBIT (ebit) /total assets (at), X4 is market value of equity (csho*prcc_f) /book value of total liabilities (lt), and X5 is sales (sale) /total assets (at)
Firm Leverage (D/A)	Compustat	Ratio of total debt (dlc+dltt) to total assets
Firm EBITDA/Int Expense	Compustat	Ratio of EBITDA (ebitda) to interest expenses (xint)
Firm Debt/EBITDA	Compustat	Ratio of total debt (dlc+dltt) to EBITDA (ebitda)
Firm Market-to-Book Equity	Compustat	Ratio of market value of equity (csho * prcc_f) to book value of equity (ceq)
Firm Net PPE/Assets	Compustat	Ratio of net property plant and equipment (ppent) to total assets (at)
Firm Cash/Assets	Compustat	The ratio of cash and equivalents (che) to total assets (at)
Firm Current Ratio	Compustat	Ratio of current assets (act) to current liabilities (lct)
Firm Rating (1/0)	Compustat	Dummy variable set equal to 1 if a firm has a long term credit rating (splticrm) in a given fiscal year
Firm Investment Grade (1/0)	Compustat	Dummy variable set equal to 1 if a firm has investment grade long term credit rating (splticrm) in a given fiscal year
Firm Debt/Tang. Net Worth	Compustat	Ratio of total debt (dlc+dltt) to tangible equity (ceqt)
Firm Past Violation (1/0)	SEC Filings	Dummy variable set equal to 1 if a firm has violated a covenant in the past. Courtesy (Roberts and Sufi, 2009)
Firm Profit Volatility	Compustat	Standard deviation of EBITDA/Sales 3 years prior to deal origination
High Volatility	Compustat	Dummy variable set equal to 1 if the profit volatility of a firm is above the top quintile
Low Liquidity	Compustat	Dummy variable set equal to 1 if the current ratio of a firm is below the bottom quintile
Small Firm	Compustat	Dummy variable set equal to 1 if the log(firm assets) of a firm is below the bottom quintile

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfi.2023.101027.

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