The Pass Through of Uncertainty Shocks: Evidence from the Banking System

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Abstract

Using loan-level regulatory data, this paper finds that banks reduce risk-taking in their loan book after positive bank-level uncertainty shocks, as measured by the idiosyncratic volatility of the bank's stock price. Interest rates and the use of collateral in loan contracts also increase after positive uncertainty shocks. These precautionary responses are strongest among banks with less regulatory capital that are also subject to mark-to-market accounting regulations. Public firms react to bank-level uncertainty shocks by holding more cash, and reducing share repurchases, investment and employment. Riskier private firms that are exposed to these uncertainty shocks turn to shorter-term higher cost credit, such as credit cards and trade credit, increasing illiquidity. We also find that local employment declines after bank uncertainty increases. Taken together, uncertainty shocks in the banking system significantly affect the economy.

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Using the near-universe of corporate lending by large US banks, this paper studies the impact of bank-level uncertainty shocks on loan-level outcomes, as well as the real and financial consequences of these bank-level shocks on public and private firms, and the broader economy. Microeconomic responses to uncertainty are important and can help explain aggregate fluctuations (Bloom 2009, Baker, Bloom et al. 2016, Leduc and Liu 2016).[1] Moreover, some recent theoretical arguments note that even small positive uncertainty shocks, *inter alia,* at a big institution or at a key node within a production network can potentially induce large aggregate fluctuations (Gabaix 2011, Christiano, Motto et al. 2014, Acemoglu, Ozdaglar et al. 2021). But while there has been important progress in mapping the transmission of firm-level uncertainty shocks, we know relatively less about the consequences of uncertainty shocks emanating from the financial system (Guiso and Parigi 1999). Yet bank credit is a key node in most production networks, and a few large banks often dominate the supply of credit in many local markets, potentially allowing bank-level uncertainty to cascade through the broader economy.

In particular, arguments that emphasize the precautionary motive predict that banks that face increased uncertainty over their future profitability will reduce risk-taking in their loan portfolios, reallocating credit away from riskier towards safer firms. These precautionary responses can also increase the price of credit; for a given level of borrower risk, a bank might charge a higher interest rate, and or rely more on collateral to hedge against borrower default (Hart and Moore 1998, Benmelech and Bergman 2009). Well known arguments also predict that the pass-through of bank-level uncertainty shocks onto firms can depend on a bank's risk bearing capacity. Banks that are closer to regulatory insolvency or face other sources of balance sheet risk have less risk-bearing capacity and will reduce risk in their loan book even more sharply when uncertainty increases.

However, risk-shifting arguments offer more nuanced predictions, noting that a bank's response to volatility can depend on the regulatory environment and the presence of agency conflicts between shareholders, creditors and management. One classic argument notes for example that because shareholder losses are bounded at zero, and depositors and other creditors

[1] A non-exhaustive list of important contributions in this area include (Bernanke 1983, Abel and Eberly 1994, Gourinchas and Parker 2002, Bertola, Guiso et al. 2005). See also the surveys in (Pindyck 1991) and (Bloom 2014).

are dispersed, banks might increase risk-taking in their loan book when volatility increases and regulatory oversight is limited, especially when the bank is closer to insolvency (Dewatriport and Tirole 1994). Also, whether these bank-level decisions in response to uncertainty pass-through onto firms and the broader economy depend on the substitutability of bank finance. If firms can easily switch to non-bank lenders and bond-financing, then bank-level responses to uncertainty would be irrelevant for firms' decisions and aggregate fluctuations. But if financial frictions are present so that substitutability across different sources of finance difficult, then a bank can be a "star node" in a production network and idiosyncratic bank volatility shocks can potentially have large effects on firms' production, capital structure decisions, and the broader economy.

Identifying the pass-through of bank-level uncertainty shocks is difficult. Bank-level uncertainty or second moment shocks are often correlated with first moment shocks to bank earnings, as well as with firm level shocks that can independently drive lending decisions and loan demand. Aggregate factors, such a geopolitical events or monetary policy, as well as local economic factors are common examples of latent factors that can simultaneously affect firms' demand for credit, as well as both the mean and volatility surrounding a bank's expected profitability, making it hard to tell apart the bank's supply response to uncertainty from latent firm-level demand. In addition, measuring a bank's response to uncertainty shocks when making new loans requires a standardized and consistent measure of loan risk across banks and time.

To address these concerns, we use granular regulatory Y14Q credit register data from the Federal Reserve that cover the near universe of large bank lending in the US economy from just after the 2008-2009 financial crisis to just before the 2020 Covid event, comprising nearly $4 trillion in bank loans and lines—just under 80 percent of all bank lending in the US. In addition to identifying the firm, its location and other key firm-level observables, the data also consistently measure loan risk using a standardized scale. We can thus measure the effects of bank-level uncertainty on loan-risk taking, while absorbing firm-level demand and local economic shocks. Moreover, for the public firms in the database, we merge the Y14Q data with other databases to measure the effects of these bank-level shocks on a variety of firm-level decisions. We use a credit bureau to study the effects of bank uncertainty on private firms.

To measure bank-level uncertainty, we build on the fact that stock prices are informative about an institution's future profitability, and use the daily idiosyncratic volatility of a bank's stock price

to measure the uncertainty surrounding the path of the bank's future profits in each quarter (Gilchrist, Sim et al. 2014, Di Maggio, Kermani et al. 2022). This approach has the advantage of purging market-wide first and second moment shocks through the standard Fama-French factors, but of course restricts the focus to public banks. We also control for first moment idiosyncratic bank-level shocks using the same methodology and include year-by-quarter fixed effects, bank fixed effects, firm fixed effects and even city-by-year-quarter fixed effects to absorb alternative narratives.

We find evidence that banks reduce risk-taking in the loan book after increased uncertainty. The ordered logit estimates suggest that the probability of observing a loan with a rating of 1 (the riskiest) declines about 5.7 percent after a one percentage point increase in uncertainty, while the odds of a loan with a rating of 3 (safer) jumps by 7.1 percent. To assuage concerns about endogeneity and better identify the mechanism, we also show that the impact of uncertainty on this precautionary behavior is much larger among less well capitalized banks. For a bank at the 25^{th} percentile of the distribution of the ratio of tier 1 capital to risk weighted assets (RWA), a one percentage point increase in uncertainty suggests a 4.2 percentage point drop in the odds of observing a category 1 loan (safer is higher); while there is a corresponding 4.6 percentage point increase in the odds of observing a category 3 loan. There is no significant response among banks at the 75^{th} percentile of the tier 1 RWA ratio distribution. Simple OLS estimates also suggest that bank capital mediates the precautionary response to uncertainty in new lending.

During our sample period, regulations that altered the risk bearing capacity of some banks changed sharply over time, and we use the variation in some of these regulations to further identify the effects of uncertainty. In particular, we focus on the implementation of the Accumulated Other Comprehensive Income (AOCI) rule. Banks' can classify their holdings of financial assets such as US Treasuries and mortgage-backed securities as either hold to maturity (HTM) or available for sale (AFS). Market fluctuations in the value of HTM assets do not pass through onto bank earnings and regulatory capital, as these assets are valued at historical cost. Similarly, for banks not subject to the AOCI rule, movements in the price of AFS assets are also valued at historical cost. But for banks that are subject to the AOCI rule, unrealized gains and losses in AFS assets are classified as AOCI and pass through directly onto end-quarter earnings and regulatory capital.

Thus, because banks that are subject to the AOCI rule face increased earnings volatility from their AFS bond holdings, then the AOCI rule along with low levels of capital should greatly amplify the impact of uncertainty shocks on lending decisions. That is, because such a bank would already have limited risk bearing capacity and the AOCI rule would further subject the bank to additional risk via AFS bond price fluctuations, the bank would be expected to reduce risk-taking in its loan book even more when idiosyncratic volatility increases in the previous quarter. In keeping with this channel, we find that the biggest drop in the odds of observing the riskiest loans after an uncertainty shock occurs among the least capitalized banks that are also subject to the AOCI rule. There is also significant evidence that increased uncertainty is associated higher interest rates and a greater use of collateral for the riskiest borrowers among AOCI banks with less capital.

We next study the impact of these uncertainty induced shifts in bank credit policy on firms' real decisions and capital structure choices. For each public firm in the Y14Q database, we construct the firm's time-varying weighted exposure to uncertainty shocks among its bank lenders. The weight is based on each bank's share in the firm's total outstanding debt. We find that increased bank uncertainty materially affects firms' decisions. After controlling for firm and year-quarter fixed effects along with first moment banking shocks, we find that a mean volatility shock among a firm's bank lenders in the previous quarter is associated with a 0.38 percentage point drop in the growth in firm-level investment, as proxied by plant, property and equipment spending, while employment growth declines by 0.87 percentage points. These lender uncertainty shocks also appear to induce firms to hoard liquidity. A mean volatility shock among the firm's lenders implies a 1.5 percentage point increase in the growth cash, and a decline in share buybacks. Firms' stock returns are also negatively affected after increased lender volatility. And consistent with the financing channel, these effects are larger among the more financially constrained firms.

We next use credit bureau data to study the effects of bank uncertainty shocks on a panel of 3.5 million private businesses. There is less information available for these businesses, but we find evidence that increased uncertainty among banks is associated with a decline in the odds of new bank loans to very small riskier businesses, and a shift towards short-term more expensive sources of liquidity such as credit card and trade credit financing (Diamond 1991). This shift towards riskier short-term financing after increased banking system volatility is also associated with greater

illiquidity at these small private businesses, as the odds of late payments and high credit balances rise. There is also evidence that overall employment in the county declines when local lenders are subject to more idiosyncratic volatility.

These results add to several literatures and are important for policy. To our knowledge, this is the first paper to rely on loan-level data to document the impact of bank-level uncertainty shocks on loan contract terms and firms' responses. Taken together, the results suggest bank-level uncertainty shocks are a plausible source of aggregate fluctuations, and these estimates can help inform the parameter choices in the theoretical literature focused on quantifying the impact of uncertainty on the macro-economy. [2] These estimates thus add to the literature on the microeconomic origins of aggregate fluctuations (Di Giovanni, Levchenko et al. 2014). Of course, a large literature emanating from the seminal contributions in (Bernanke 1983, Peek and Rosengren 2000, Khwaja and Mian 2008) have studied the transmission of banking sector shocks. Much of this literature however has focused on crisis periods using "first moment" banking shocks.[3] This paper shows that even during relatively tranquil time periods, "second" moment shocks in the banking system can also be first order.

The results in this paper also add to the evidence showing that asset prices are a powerful sources of information, and that economic agents, in this case, banks and perhaps regulators, use the information in asset prices to make decisions that can cascade through the real economy (Edmans, Goldstein et al. 2015, Dow, Goldstein et al. 2017, Goldstein 2023). Our use of loan-level data that afford various non-parametric controls for common information and other shocks also help address the typical endogeneity concerns in this literature. The results on bank capital and the AOCI rule also informs the policy discussion on post crisis financial regulation. In particular, the

[2] (Kim, Lee et al. 2023) use Korean micro data to examine the impact of firm-level uncertainty shocks on bank loan contracts, while (Correa, Giovanni et al. 2024) use the Y14 Q data to study the impact of trade uncertainty on loan terms, while (Alessandri and Bottero 2020) use Italian micro data to study the impact of aggregate policy uncertainty on lending.(Soto 2020) create a text-level measure of bank uncertainty and study its impact on balance sheet aggregates.

[3] The literature is large. See (Richardson and Troost 2009, Rajan and Ramcharan 2016) for the pre-WWII period; (Gan 2004, Ashcraft 2005) focus on the 1980s banking crisis, while (Chodorow-Reich 2014, Ramcharan, Verani et al. 2016, Granja, Matvos et al. 2017, Jiménez, Ongena et al. 2017) are examples of papers focused on the more recent period.

estimates show that the sizeable increases in bank capital after 2009 appear to indeed augment the risk-bearing capacity of the banking system. But other regulations, such as the AOCI rule—a major piece of the post-crisis Basel regulatory framework—have the potential to transmit more forcefully banking system volatility onto the economy.[4] The next section discusses the data, while Section 2 presents the main bank-loan level results, while Section 3 reports the firm responses. Section 4 concludes.

1. Data

In order to study the impact of bank-level uncertainty shocks on loan risk-taking, we focus on the time variation in idiosyncratic bank-level risk. This approach builds on the recent literature that uses stock returns residuals after taking into account the standard five factor Fama-French factors (Gilchrist, Sim et al. 2014, Di Maggio, Kermani et al. 2022). Methodologically, these factors absorb "first moment" market wide shocks and some of the other major characteristics that have been hypothesized to explain stock returns. The square of the residual from these regressions thus represent the idiosyncratic volatility or bank-specific uncertainty about future earnings, limiting the potential for common shocks that might drive bank loan supply and firm credit demand. To further assuage endogeneity concerns, the baseline lags this residual-based volatility measure and includes year-quarter and bank-fixed effects, along with the first moment from the residual to help ensure that the estimated effects of uncertainty are not due to aggregate shocks or differences in time-invariant bank characteristics like their risk scoring methodology or pool of clients. With the loan-level data, we can also include the city in which the firm is located by time fixed effects in the most conservative specifications to non-parametrically absorb time-varying local economic shocks.

[4] A small literature has begun to focus on the AOCI rule. (Greenwald, Krainer et al. 2024, Orame, Ramcharan et al. forthcoming) study the AOCI rule and monetary policy; (Fuster and Vickery 2018) examine the impact of this rule on banks' securities holdings, while (Kim, Kim et al. 2019) examine the broader effects of the AOCI rule using public bank balance sheet data.

To be precise, we use data from CRSP to obtain the daily stock prices for the 20 large banks in our sample that report Y14Q data.[5] We then risk adjust each bank's stock price using the standard Fama-French 5 factor model—the data are obtained from Kenneth French's website. To be consistent with the Y14Q data, we run these factor models over the same 2012-2019 sample period as the Y14Q when extracting the daily residuals from these regressions. The residuals are bank-specific or idiosyncratic shocks to future profitability. Because the Y14Q and Y9C regulatory data are reported quarterly, we next aggregate these daily residuals up to the quarterly frequency, computing both the mean and standard deviation in each quarter over the sample period. These quarterly aggregates measure respectively mean idiosyncratic shocks to future profits, as well as idiosyncratic realized volatility or uncertainty surrounding a bank's future profits.

Figure 1 Panel A plots idiosyncratic volatility at the 25th, 50th and 75th percentiles of the distribution in each quarter, while Panel B repeats this exercise for mean idiosyncratic returns over the 2012-2019 sample period. Panel A shows a decline in bank-level uncertainty after the financial crisis, and a corresponding increase in uncertainty over bank-level future profitability in the first quarter of 2016 when the Federal Reserve first implemented the capital conservation buffer for the banks in our sample. To wit, financial regulation appears to significantly affect uncertainty around market equity valuation—a fact that we return to in our identification strategy. Panel B shows that the introduction of the capital conservation buffer in Q1 2016 also coincides with large first moment shocks to the residual value of market equity returns among the banks in our sample.

Table 1 examines the correlation between the information extracted from the stock prices of these banks and standard measures of solvency, profitability and liquidity from the regulatory data in the Y9Cs, which are available quarterly. The dependent variable in column 1 is the idiosyncratic volatility of the stock price residual, and the regression includes the baseline bank and year-quarter fixed effects—the latter absorbs time-varying macro shocks, while the former absorbs time-invariant differences in banks such as their opacity and overall business model. Intuitively, bigger banks, as well as those that rely more on stable deposit funding tend to have lower idiosyncratic

[5] References to CRSP herein refer to data from Center for Research in Security Prices, LLC (CRSP) via Wharton Research Data Services (WRDS).

volatility. For example, a 1 one percent increase in asset size suggests a 0.61 percentage point drop in volatility, while a one standard deviation increase in the ratio of deposits to assets imply a 0.24 percentage point drop in volatility next quarter. There is also evidence that volatility is lower among banks with a higher return on assets. Because these balance sheet observables could be related to the riskiness of bank's corporate clients, we control for these variables in subsequent specifications to exclude endogenous matching. Also consistent with expectations, column 2 shows that these lagged balance sheet variables do not predict mean idiosyncratic shocks.

Our focus is on how information in a bank's stock price influences its lending decisions at the extensive margin, and Table 2 next summarizes the loan-level data from the Y14Q used in our sample. During our sample period, there are 157,628 new term loans and credit lines. Of which 94,613 are new credit lines (60.0%) and 63,015 (39.9 %) are new term loans. Table 2 also shows that the credit facilities in our sample are relatively large. The mean term loan size in the sample is $18.3 million with a standard deviation of $109 million, while the mean credit line is $27.8 million with a standard deviation of $64.4 million. Figure 2 plots the total amount of new loans and lines and each quarter. On average, there are $9.4 billion in new lines, and $4.13 billion in new term loans each quarter, so that over the sample period we study the impact of bank-level stock price movements on over $2.6 trillion in new lines and $1.16 trillion in new bank loans—the near universe of large bank lending in the US economy.

A key component of our analysis is the standardized risk rating used to evaluate each loan and credit line in the Y14Q dataset. Note that bank uses their own internal rating system to give borrowers a grade, as defined in their normal course of lending business. Even though the systems used by banks are proprietary and can vary by the methods used to calculate these ratings, banks are instructed to report ratings that reflect each loan's probability of default rating. Banks are also separately required to provide a detailed description their internal risk rating system, including the specific ratings used and descriptions of each rating level. Note that during our sample period, all corporate loans were assigned a capital weight of 100 percent regardless of risk, and so banks had little incentive to engage in regulatory arbitrage by underpricing risk in order to reduce the capital weight.

Nevertheless, to make sure the ratings used in our analysis are comparable across banks, we use the standardized risk ratings that reflect a borrower's probability of default. The

standardization was conducted by regulators to compute a measure such that the same grade given to a borrower would mean the same probability of default across different lenders. The standardization process takes the bank-reported internal ratings described above and the reported detailed description of probability of default corresponding to each rating within a bank, and turn those various internal ratings into a harmonized version of probability of default into a 10-point scale, ranging from AAA to D. Panel B of Table 2 shows that a rating of 6 (BB) is the modal rating, accounting for about 46% of all loans and lines in our sample, followed by those with a rating of 7 (BBB) (28.3%). Roughly 10 percent of the loans in the sample are rated "A" (8) or higher. Because some rating buckets are sparse, we transform this 10-point scale into a coarser 4 point ordinal ranking, where loans rated below 6 are classified as 1 (17.2%); those rated 6 in the 10 point scale are classified as 2 (46.2%); those rated 7 are classified as 3 (28.3 %) and those above 7 are classified as 4 (8.3%).

In what follows, we show that the main results are not sensitive to these choices, though the estimates tend to be more precise given that each of the 4 ratings bucket now contains more information. In addition to the ratings, the Y14Q dataset also contains other key information about the loan, such as the interest rate, whether collateral is used, and the maturity. There is also borrower-level balance sheet information such as the firms' liquidity (cash and marketable securities); leverage; debt service; net income and assets, usually observed in the same year as the loan is originated. Panel C of Table 2 summarizes these variables, where we winsorize the variables at the 1 percent level to address outliers. Loan rates are relatively low over the sample period, and the median interest rate is 2.6 percent, while about 38 percent of loans are collateralized. The median firm also has a cash to assets ratio of 0.16; a return on assets of 15.7 percent; a debt service burden of 2.8 percent relative to assets, and a leverage ratio of 71.2 percent.

Before examining the impact of uncertainty on bank risk-taking, Table 3 shows that the risk rating correlates in intuitive ways with these firm and contract observables. For example, the size of the loan is positively related to the risk score (higher is safer); while higher interest rates are associated with lower (riskier) scores; similarly longer duration loans tend to be made to safer borrowers, and collateral is less likely to be observed when the risk score is higher and the loan is thus safer. Column 2 includes firm-level observables. Ratings are higher among more profitable

firms, as well as among those with more cash and lower debt service burdens. More leveraged firms, with a history of past credit access, also have higher ratings.

The loan rating is on a four-point ordinal scale, and column 3 uses an ordinal logit model to interpret better the estimates. The coefficients are qualitatively similar to the OLS estimates. The odds of a higher risk rating declines for example by 30.5 percent when collateral is used in the loan contract. Finally, column 4 uses the original regulatory 10-point risk scale (higher is safer) as the dependent variable in the ordered logit model. The estimates are nearly identical to those in column 4. For example, the odds of a higher risk rating declines for example by about 29 percent when collateral is used in the loan contract. Using these regulatory risk ratings, we next examine the role of uncertainty surrounding a bank's future profitability as embedded in its stock price, *inter alia,* in shaping risk taking in its loan book at the extensive margin.

2. Main Results

Table 4 examines the impact of uncertainty on the riskiness of a bank's new loans and lines originated in the current quarter. We measure uncertainty using the idiosyncratic realized volatility of the bank's stock price, observed in the previous quarter. In all specifications, we use bank fixed effects to absorb time-invariant bank-level factors that can both help explain volatility shocks and the endogenous matching between bank and borrower risk type. We also include year-quarter fixed effects to non-parametrically absorb all aggregate time-varying shocks, like geopolitical, monetary and other similar shocks that could simultaneously affect bank volatility and loan demand. All specifications also control for the mean idiosyncratic returns, as first and second moment shocks can also be correlated.

Moreover, because term loans and credit lines can have different risk implications for a lender, we begin by estimating the effects of uncertainty separately for these two types of credit instruments. For example, term loans are generally not callable, and if a bank faces increased uncertainty over its own future profitability and ability to meet its regulatory solvency requirements, it cannot easily cancel or "call" an existing term loan in order to reduce its risk weighted assets and deleverage. At the same time, credit lines can be especially risky for a bank if firms draw on these lines during periods when the bank also faces deposit outflows or is capital constrained (Kashyap, Rajan et al. 2002).

The dependent variable in column 1 is the 4-point risk rating (higher is safer) and the sample is restricted to term loans. The OLS estimate in column 1 is positive and significant at better than the one percent level, suggesting that increased uncertainty over future profits is significantly associated with less risk-taking in the loan book in the next quarter. The coefficient implies that a one percentage point increase in volatility—the mean volatility shock is 0.79–is associated with a 0.19 point increase in the risk rating (higher is safer); the mean rating in the sample is 2.2 with a standard deviation of 0.77 or a about 0.25 standard deviations. The coefficient on the mean return residuals is also positive but insignificant (p-value=0.18).

The risk rating is an ordinal ranking on a 4-point scale and column 2 uses an ordered logit model to better interpret the evidence. Column 2 reports the odds ratio along with standard errors that are clustered at the bank-level. The impact of uncertainty on the loan risk rating remains positive and highly statistically significant. It suggests that a one percentage point increase in uncertainty is associated with a 58 percent increase in the odds of moving to a higher loan rating. Figure 3 visualizes these marginal effects over the distribution of risk measures. In Panel A, there is clear evidence that risk taking declines after an increase in uncertainty. The probability of observing a loan with a rating of 1 declines about 5.8 percent after a one percentage point increase in uncertainty, while the odds of a loan with a rating of 3 jumps by 7.1 percent.

Columns 3 and 4 repeat this exercise for credit lines. The evidence suggests that increased uncertainty has a smaller impact on loan risk among the sample of credit lines. From column 3 for example, a one percentage point increase in volatility suggests a 0.1 point increase in the mean loan risk-rating (p-value=0.04). The ordered logit estimates in column 4 mirror these results, and Panel B of Figure 3, which plots the marginal effect of an increase uncertainty on the odds of observing particular rating outcomes, also show a smaller risk response. A one percentage point increase in uncertainty for example implies a 1.9 percentage point drop in the odds of observing a loan with a rating of "1", and a corresponding 2.9 percentage point increase in the likelihood of observing a safer "3" rated loan.

The baseline OLS and ordered logit models in columns 5 and 6 combine both the sample of loans and lines and formally tests for differences in the impact of uncertainty across these two instruments. The interaction term for credit lines is not significant at conventional levels (p-value=0.15). We thus use the combined sample of both loans and lines in all subsequent analysis.

Also, we will generally use the OLS model to conduct robustness checks, especially when perturbing the fixed effects assumptions, as the linear model is robust to the incidental parameter problem that can affect the ordered logit estimator. We have seen suggestive evidence that banks reduce risk-taking in their loan book at the extensive margin when uncertainty spikes. But common shocks to firm and bank profits along with endogenous matching between banks and firms could contaminate these results. In what follows, we conduct a number of robustness tests to address these concerns.

To this end, column 1 of Table 5 uses firm fixed effects, along with the baseline bank and year-quarter fixed effects. Firm fixed effects absorb time invariant factors that might produce endogenous matching between a firm and bank. For example, firms with particular business models might systematically borrow from banks that are more prone to uncertainty shocks. But if these firms that are matched to riskier banks are themselves riskier, then our results might reflect these latent firm-level factors rather than the causal effect of uncertainty on a bank's risk-taking decisions in its loan book. There are 25,178 firms in our sample that borrowed from more than one bank over the sample period, and our sample size shrinks by about 48 percent. The impact of uncertainty declines by about 45 percent, but remains significant at the 10 percent level—dropping the firm fixed assumption on the same sample yields a coefficient of 0.16.

A key concern remains that common time-varying sectoral or spatial shocks that affect the future profitability of a bank might also affect firm credit demand, making it hard to tell apart the impact of bank-level uncertainty on risk-taking from these other shocks. To address the issue of common time-varying shocks, column 2 uses a firm's two digit sector NAICS code to absorb non-parametrically sector-level shocks that vary by year-quarter over the sample period. Column 3 addresses time-varying spatial shocks using city by year-quarter fixed effects in addition to bank fixed effects. This approach controls for time-varying city-level shocks that might contaminate inference—affecting simultaneously bank-level uncertainty and the risk rating assigned to local firms. Across the specifications, the results are largely unchanged.

Next, column 4 linearly includes a set of bank-level controls to help control for the possibility that existing bank-level balance sheet characteristics might drive these results rather idiosyncratic volatility (Claessens, Law et al. 2018). That is, we saw previously that larger banks tend to suffer from smaller idiosyncratic volatility shocks, and these banks in turn might lend to safer firms,

making bank size an important omitted variable. The controls in column 4 include the log of bank assets; deposits to assets; the return on assets; the ratio of tier 1 capital to risk weighted assets; loans to assets and bank's ratio of reserves and cash (liquid assets) to assets—all lagged one quarter. The results are little changed. We next perturb the loan risk measure. Column 5 replaces the ordinal risk rating dependent variable, with a simple binary variable that equals 1 if the loan is rated BBB or lower and 0 otherwise. The linear probability model in column 5 shows that the odds of observing a new riskier loan declines by about 1.5 percentage points after a one standard deviation uncertainty shock. Finally, column 6 uses the finer 10 point regulatory measure of loan risk as the dependent variable; the impact of uncertainty remains little changed.

In sum, across a variety of non-parametric, parametric and risk measure assumptions, we have seen evidence that banks facing greater uncertainty over future earnings increasingly lend to safer borrowers in the subsequent quarter. Clearly, this apparent shift in the supply of credit can have consequences at both the firm level and on local economies. For example, increased credit rationing to riskier firms can lead to lower investment and employment among these firms, and if substitution is imperfect, then these bank-level shocks can worsen local economic outcomes. Before tackling these more general transmission questions however, we next develop a suite of tests that can help discern the underlying bank-level mechanisms and help exclude alternative interpretations.

2.1 The role of financial regulation

This section uses the variation in financial regulation and bank-level balance sheet heterogeneity to understand how volatility affects risk-taking decisions. The first set of tests are premised on the idea that if these results reflect a precautionary response to uncertainty, then a bank's distance from its minimum regulatory capital requirement should mediate the effects of uncertainty on risk-taking. Under the risk-bearing hypothesis, because higher levels of regulatory capital increase a bank's distance to default and augment its risk bearing capacity, we would expect that banks with more regulatory capital will evince less sensitivity to uncertainty shocks. In contrast, for a bank that is closer to the minimum regulatory capital requirement, an increase in the variance of future earnings can significantly increase the odds of failure, potentially reducing its risk-taking incentives. Well known risk-shifting arguments can however predict the opposite,

noting that an undercapitalized bank might have a greater incentive to take on riskier loans when the variance of future earnings increase and other stakeholders are dispersed.

To implement this test, column 1 of Table 6 interacts both the uncertainty and first moment profitability one quarter lag shocks with a bank's ratio of tier 1 capital to risk weighted assets observed in the previous quarter—this is a standard measure of regulatory capital that captures a bank's distance from regulatory insolvency. The specification also linearly includes the suite of other time varying bank-level controls, along with the baseline bank fixed effects and year-quarter fixed effects, and the sample includes both loans and lines. The panel at the bottom of Table 6 evaluates the marginal effect of a one percentage point increase in realized idiosyncratic volatility in the previous quarter on the risk rating of the loan (higher values imply safer loans) for banks at the 25th and 75th percentiles of the tier 1 risk weighted assets ratio distribution.

There is striking evidence that the effects of increased uncertainty on reduced risk-taking is significantly larger among less well capitalized banks. A one percentage point increase in uncertainty implies a 0.14 unit increase in the average loan's risk-rating in the next quarter for a bank at the 25th percentile of the distribution of the tier 1 capital to RWA ratio (tier 1 RWA ratio) distribution. The coefficient estimate is highly statistically significant with the p-value less than 0.01. But for a bank at the 75th percentile of this distribution, a similar increase in uncertainty implies an effect that is both statistically insignificant (p-value=0.25) and about 5 times smaller in magnitude.

To illustrate more intuitively the mediating role of risk based capital in shaping a bank's response to uncertainty, column 2 uses the ordered logit specification, reporting the odds ratio, while Figure 4 plots the marginal impact of an increase in uncertainty on the relative odds of observing the four risk outcomes for banks at the 25th and 75th percentiles of the credit distribution. For a bank at the 25th percentile of the tier 1 RWA ratio distribution, a one percentage point increase in uncertainty suggests a 4.2 percentage point drop in the odds of observing a category 1 loan (safer is higher); while there is a corresponding 4.6 percentage point increase in the odds of observing a category 3 loan. Figure 4 also shows that there is no significant response among banks at the 75th percentile of the tier 1 RWA ratio distribution.

The variation in the implementation of the Accumulated Other Comprehensive Income (AOCI) rule over our sample period provides an especially helpful way to identify further the mechanism

through which earnings volatility affects banks' risk-taking decisions. Banks classify their holdings of financial assets such as US Treasuries and mortgage-backed securities as either hold to maturity (HTM) or available for sale (AFS). Market fluctuations in the value of HTM assets do not pass through onto bank earnings and regulatory capital, as these assets are valued at historical cost. Similarly, for banks not subject to the AOCI rule, movements in the price of AFS assets are also valued at historical cost. But for banks that are subject to AOCI rule, unrealized gains and losses in AFS assets are classified as AOCI and pass directly through onto quarterly earnings and regulatory capital.

The variation in the AOCI rule across banks can help identify further the precautionary motive in banks' responses to uncertainty. If these results reflect the precautionary motive, the effect of a volatility shock on a bank's lending decision should be particularly large for banks that are both closer to their regulatory solvency minimum and subject to the AOCI rule. To wit, AOCI banks already face greater uncertainty about future profits and solvency risk, as fluctuations in their AFS bond portfolio directly affect their earnings, the value of their market equity and the bank's distance to regulatory insolvency. Therefore, if an AOCI bank also has limited regulatory capital, then the precautionary motive suggests that such a bank would become even more conservative in its lending when earnings volatility increases, as the bank both has less risk bearing capacity and is also subject to earnings volatility from its AFS bond holdings via the AOCI rule: The AOCI rule should further amplify the effects of uncertainty on risk-taking in the loan book.

During our sample period, the AOCI rule—the pass through of AFS valuation changes onto earnings and regulatory capital—was introduced in January 2014 and affected 10 percent of the banks in the sample. The rule was expanded to cover more banks, and by 2018 more than 40 percent of the banks became subject to the AOCI rule ("AOCI banks"). The 2017 deregulation bill allowed some banks to exit from the AOCI rule, and the fraction of AOCI banks fell to about a 25 percent in 2019, when our sample ends--see Figure 5. We thus have both cross-sectional and time variation in the application of the AOCI rule in our sample. The OLS specification in column 3 of Table 6 exploits this variation, using a triple interaction term between the lagged uncertainty shock; tier 1 RWA ratio and an indicator variable that equals 1 if a bank is subject to the AOCI rule and 0 otherwise. We include all subcomponents of these interaction terms, and also include a similar interaction term using the first moment shock to stock prices. Finally, the specification linearly

includes the suite of bank time-varying controls along with bank and year-quarter fixed effects; standard errors are clustered at the bank-level.

The OLS estimates in column 3 suggests that the AOCI rule amplifies the impact of uncertainty on loan risk-taking, especially among banks with less regulatory capital. A one percentage point increase in uncertainty suggests 0.16 (p-value<0.01) increase in the loan risk rating for a bank at the 25th percentile of tier 1 RWA ratiothat is also subject to the AOCI rule. But for a bank with the same amount of capital, but not subject to the AOCI rule, a similar increase in uncertainty implies a 0.10 (p-value=0.01) increase in the risk rating. For banks at the 75th percentile of capital that are subject to the AOCI rule, the impact of uncertainty on risk ratings is even smaller at 0.08 (p-value=0.04). And in keeping with this monotonicity, for banks at the 75th percentile of capital that also face no earnings volatility from their AFS holdings, stock price volatility does not affect loan risk-taking. The coefficient is the wrong sign, small and not different from zero (p-value=0.41).

To better interpret these estimates, column 4 uses an ordinal logit model, and Figure 6 plots the marginal effects of an increase in uncertainty for the set of possible risk ratings for non AOCI and AOCI banks at the 25th and 75th percentiles of tier 1 RWA ratio. The magnitudes mirror the OLS estimates, showing that the biggest drop in the odds of observing the riskiest loans after an uncertainty shock occurs among the least capitalized banks that are also subject to the AOCI rule. For these banks, a percentage point increase in uncertainty implies a 5.1 percentage point drop in the odds of observing a new loan with a rating of "1"—the riskiest in the 4-point classification scheme. Likewise, there is a corresponding 5.2 percentage point increase in the odds of a new loan with a rating of "4"—the safest—after a one percentage point uncertainty shock among the least capitalized banks that are also subject to the AOCI rule.

In addition to reducing the supply of credit to riskier firms, AOCI banks that are also closer to their tier 1 RWA ratios might also charger higher interest rates for riskier loans after an increase in bank-level uncertainty. Column 5 investigates this hypothesis. The dependent variable in column 5 is the interest rate on the loan, and to study the effects of uncertainty and a bank's risk-bearing capacity on risk-based loan pricing, the specification uses a quadruple interaction term, interacting uncertainty with the tier 1 RWA ratio, the indicator for whether the bank is subject to the AOCI rule, and the risk rating of the loan. There is significant evidence that increased uncertainty is associated higher interest ratings for the riskiest borrowers when the bank itself has limited risk-

bearing capacity. In particular, a one percentage point increase in uncertainty suggests a 0.9 percentage point higher interest rate for loans with a rating of "1" when the bank is also subject to the AOCI rule and its tier 1 RWA ratio is at the 25th percentile—the mean interest rate in the sample is 2.6 percent.

Lenders can also use collateral to protect themselves when lending to riskier borrowers. We would expect then that the use of collateral might increase when a lender faces greater uncertainty over future profits and have more limited risk bearing capacity. Column 6 investigates this hypothesis using a linear probability model, where the dependent variable equals 1 if the loan is collateralized and 0 otherwise. Increased uncertainty is associated with a higher probability of a collateralized loan for the riskiest borrowers when the bank itself has limited risk-bearing capacity. The effects are also economically large. A one percentage point increase in uncertainty is associated with 37.5 percentage point increase in the odds of a collateralized loan when the rating is "1" and the bank is subject to the AOCI rule and its tier 1 RWA ratio is at the 25th percentile.

Taken together then, this evidence suggests that after bank-level uncertainty shock, banks increase the odds of lending to safer firms, and conditional on observing a loan, the cost of credit and the probability of collateral usage rises especially for riskier firms when banks also have limited risk-bearing capacity and are exposed to asset price volatility via the AOCI rule. Indeed, simple bank-panel regressions available upon request show that conditional on bank and year-quarter fixed effects, a mean volatility shock is associated with a 16 percent decline in the total new loans in the subsequent quarter (p-value=0.09). There is thus evidence of feedback from asset price fluctuations onto lending decisions. But whether this feedback affects the real economy depends on the substitutability of bank finance. We turn to this question next.

3. Firm-level effects of bank uncertainty shocks

3.1 Public firms

This subsection studies the transmission of bank-level uncertainty shocks onto firm-level outcomes. To this end, for each firm in the sample, we compute a firm's weighted one quarter lagged exposure to bank-level volatility using the firm's relative loan size from each of its banks as the weight. This measure thus captures a firm's exposure to volatility emanating from its own past bank lenders. Consider a firm with an outstanding stock of debt obtained from two banks in

our sample. The firm owes \$2 to bank A, and \$3 to bank B in the last quarter, and has an outstanding stock of debt of \$5.50—the firm might have borrowed \$0.50 from a bank not in our sample. Firm $i's$ exposure to bank-level volatility is thus: $0.36\sigma_{A,t-1} + 0.55\sigma_{B,t-1}$. Because most corporate-bank lending relationships are relatively sticky, this weighted average exposure variable is a reasonable proxy of the bank-level volatility that a firm faces. We also construct a similar weighted average for a firm's exposure to bank-level first moment shocks. To construct these measures, we use the individual loans from the Y14Q data, along with the firm's outstanding stock of debt from the Y14Q—Compustat also provides data on the stock of debt for public firms and the correlation between Compustat and the Y14Q measures of outstanding debt stock is 0.96.[6]

Table 7 examines the impact of these weighted average exposure measures on firm-level outcomes, such as investment, employment, as well as capital structure outcomes. To measure these firm-level outcomes, we merge the Y14Q data with Compustat, leaving behind a selected sample of public firms. Unfortunately, the Y14Q data cannot legally be merged with Census level micro data in order to study the impact of uncertainty on the universe of US firms, but we partially address these concerns using credit bureau data in the next section. The dependent variable in column 1 is the firm's quarterly growth in the value of plant, property and equipment (PPE) expenditures.

Given the previous loan-level evidence that bank volatility shocks can reduce loan supply, we would expect that a firm exposed to these shocks would face greater financing constraints in the following quarters, leading to slower investment growth. The baseline regression includes firm and year-quarter fixed effects, along with a suite of time-varying firm-level controls to address endogenous matching concerns. The firm-level controls include the log size of assets; the return on assets; debt service as a share of assets; Tobin's Q; and the firm's capital intensity. Endogenous matching can arise for example if firms that have slower investment growth on account of their size or some other factor also systematically borrow from lenders subject to more volatility shocks. The loan-level evidence with the suite of various fixed effects weigh against this narrative.

[6] Compustat herein refer to Compustat data from S&P Global Market Intelligence via WRDS.

Consistent with our previous results at the loan-level, the coefficient on a firm's weighted exposure to bank-level uncertainty shocks is negative and significant at better than one percent. A mean weighted average volatility shock is associated with a 0.38 percentage point drop in PPE growth the next quarter—an effect about 10 percent of the mean PPE growth in the sample. The coefficient on the weighted exposure to idiosyncratic first moment bank-level shocks is not significant. We view the magnitude of this response as indicative of signaling about future credit conditions, as firms anticipate that future bank credit might become more expensive and less available given the stock market volatility among the firm's relationship lenders.

In column 2, the dependent variable is the log of firm employment. This variable is available annually in Compustat and we use the fourth quarter exposure measures in each year to measure a firm's weighted exposure bank-level shocks. The coefficient on the weighted average bank volatility exposure is again negative and highly significant (p-value<0.01). A mean volatility shock implies a 0.87 percentage point drop in employment growth, which is about 30 percent of the mean employment growth in the sample.

Tighter financing constraints on account of bank-level uncertainty shocks can also induce firms to hoard liquidity, such as by retaining more cash and short-term reserves to insure against the possible loss of access to external finance. To measure liquidity hoarding, the dependent variable in column 3 is the growth in cash and short-term investments. Consistent with a cash hoarding motive, the coefficient on bank volatility is now positive and statistically significant (p-value<0.01). A mean volatility shock implies a 1.5 percentage point increase in the growth cash—the mean growth rate in the sample is 0.9, so the effect of bank volatility on liquidity hoarding among the banks' corporate clients is economically large. Liquidity hoarding is also commonly associated with a decrease in share repurchases, and column 4 uses the growth in such repurchases as the dependent variable. A mean volatility shock implies a 0.81 percentage point decline in the growth of share repurchases.

Corroborating the earlier loan-level evidence on volatility and bank lending, column 5 also shows that a firm's growth in long-term debt—typically bank loans—also declines after its lenders face greater volatility. In this case, a mean volatility shock suggests a 9.4 percentage point decline in loan growth (p-value=0.09). Taken together then, these results imply that a volatility induced decline in risk-taking at banks can lead to slower credit growth at firms, greater liquidity hoarding,

and slower investment and employment. If firms are less able to capitalize on growth opportunities on account of tighter credit supply, then greater lender volatility can depress a firm's stock returns. This is exactly what column 6 suggests. The dependent variable is a firm's mean daily stock returns over the quarter. A mean volatility shock implies a 0.5 percentage point lower stock return (p-value=0.06).

The extent to which a firm adjusts its investment, employment and capital structure decisions in response to bank-level volatility shocks depends on the availability of alternative sources of finance, either internal resources or from other external sources. Firms that lack these resources then—the more financially constrained firms—would thus be forced to make bigger adjustments to volatility shocks. To test this hypothesis, we use the AZ index of financing constraints, lagged one year; this measure is based on a firm's age and size (Hadlock and Pierce 2010). We create a dummy variable that equals 1 if a firm is in the top-quartile of the index—most constrained. We then interact this dummy with both our volatility and firm moment shocks, as well as including the dummy linearly, along with the standard baseline controls and firm and year-quarter fixed effects.

The evidence in Table 7B is strongly suggestive that the impact of bank-level volatility shocks tend to be larger among the more financially constrained firms. Financially constrained firms may not be able to adjust investment and employment any faster than other firms in response to bank volatility shocks, and the interaction term is in the expected direction but not precisely estimated. For example, investment growth shrinks by about 0.25 percentage points more after a similar sized volatility shock among the more constrained firms (p-value=0.12). But the differences are much sharper in the case of cash, where firms have more flexibility. A mean volatility shock implies a 1.1 percentage point increase in cash growth at firms below the top quartile of the AZ index, but a 2.6 percentage point increase for those firms in the top quartile of the AZ index the previous year (p-value=0.04). These results suggest than that asset price volatility at lenders can feedback onto real decisions in the economy. But while public firms are economically important, they are only a slice of corporate finance decisions. We address this gap next.

3.2 Private firms

This section uses credit bureau data from Experian to help understand the impact of bank volatility on the very small private firms that are absent from most databases. Credit bureaus like

Experian collect detailed information on small private businesses' credit usage and repayment histories, which can be useful in designing tests of the precautionary motive for this set of businesses. In particular, the precautionary motive predicts that positive bank uncertainty shocks should restrain the supply of bank credit to these businesses, especially among riskier businesses. And as the latter lose access to longer duration cheaper bank credit, riskier businesses might be forced to substitute towards short term more expensive credit, such as credit card debt (Diamond 1991).

Moreover, because many private businesses use external financing to fill their working capital gaps, greater substitution to expensive short term credit to fund these gaps after an uncertainty induced decline in bank credit should lead to more illiquidity at riskier private businesses.[7] Increased bank uncertainty can also indirectly increase working capital gaps through the local demand channel. That is, small private businesses are generally concentrated in local non-tradables—non-chain coffee shops and restaurants for example—and a bank uncertainty shock that shrinks credit to bigger firms and weakens the local economy can also yield larger working capital shortfalls and greater illiquidity at these small private businesses that operate locally.

To test these predictions, we use a panel of about 3.5 million small private businesses observed in the final quarter of 2013, 2016, 2017 and 2018; businesses that exit the panel are replaced, so that each cross-section consists of 3.5 million businesses. In each observation year and for each business, the panel reports the latitude and longitude of the business; an estimate of the number of employees; and the exact date upon which a business obtained a new credit facility at any point in the sample period. In the final quarter of each observation year, Experian also provides information on the business' repayment profile, such as whether the business was late on its debt service obligations in the calendar year, or whether the businesses is running an unusually high balance on a credit facility—these are two common measures of illiquidity in small business finance (Liu, Parker et al. 2023). The data also have important limitations. Information on the dollar size of a

[7] See (Cooley and Quadrini 2001, Jermann and Quadrini 2012) for theoretical models that embed this working capital channel.

facility is not consistently available, and the name of the lender is masked. And unlike Compustat, we cannot observe investment, employment, cashflow and other measures businesses activity.

Despite these limitations, the data provide a novel opportunity to study the consequences of bank uncertainty on the capital structure outcomes at small private firms. Table 8 Panel A shows that in our 2012-2019 sample period, we observe 5,676,911 new credit originations, of which about 41 percent came from banks in the form of bank term loans and credit lines; 22 percent as credit cards (both retail stores and banks); 17 percent from non-bank lenders; and 16 percent from new leases. Panel B shows however that in any given year, relatively few private businesses obtain new credit. In the 11,723,671 business-year observations that constitute the main sample, the odds of observing a new credit facility is about 1.5 percent—most of the credit tend to flow to a few businesses. But on average, the probability that a private business becomes less than 90 days late on a credit facility is about 9.1 percent while reaching the maximum on a credit facility such as a credit card—occurs about 23.1 percent of the time.

We do not observe the lender, and in order to measure the impact of bank uncertainty shocks on these private business outcomes, the research design builds on the large literature showing that small businesses generally obtain bank financing mainly from nearby lenders (Petersen and Rajan 1995, Granja, Leuz et al. 2022, Adams, Brevoort et al. 2023). The median distance for example between a bank and a small business borrower is just 5.6 miles in (Adams, Brevoort et al. 2023). Practically then, the fact that most small businesses borrow from nearby banks means that we can use geospatial data on both bank and business locations to proxy for a business' exposure to lender level shocks based on a weighted average of shocks to all lenders within a business' zipcode.

To implement this approach, for each business, we identify its zipcode from Experian. We then use the FDIC's Summary of Deposits data to locate all bank branches within the business' zipcode. Next, for the universe of public banks in the zipcode—not just the Y14Q banks—we compute each bank's idiosyncratic volatility and mean returns over the 2013-2019 sample period using the daily Fama-French regressions. The final step computes the weighted average zipcode level bank idiosyncratic volatility and mean returns in each year. The weight in the baseline weighted average

zipcode level measure uses each bank's deposits in each branch in the zipcode.[8] Of course, because a bank's market share of deposits might imperfectly capture its market share of small business loans, we also compute the weighted average based on the count of branches in the zipcode. Figure 7 plots the median weighted average zipcode-level volatility shock over the sample period at a quarterly frequency. The dynamics of these shocks are similar regardless of the choice of weights and reassuringly resemble closely the dynamics of the Y14Q bank-level series. To be sure, a natural limitation of these market-based measures is that they exclude banks without publicly traded equity.

Column 1 of Table 9 Panel A examines the impact of the zipcode-year level bank uncertainty and idiosyncratic mean returns on the probability that a private business forms a new banking relationship in the calendar year. Note that these regressions are at the business-year level and all specifications use business fixed effects to absorb time invariant business, location and other possible confounders, while year fixed effects control for aggregate shocks. Consistent with the Y14Q loan-level and the public firm results, there is evidence that increased banking system uncertainty in the zipcode-year is associated with a decline in the odds that a private businesses forms a new bank credit relationship in the year. A volatility shock equal to the mean of the distribution is associated with a 0.04 percentage point decline in the probability that a business obtains a new bank loan or credit line in the calendar year. And intuitively, a positive mean first moment idiosyncratic zipcode level bank shock implies a 0.2 percentage point increase in the odds of a new credit relationship. These estimates are economically large, as the unconditional probability of a new bank loan is just 0.09 percent. Column 2 repeats this exercise using the branch weighted idiosyncratic shock measures. The results are unchanged, and in what we follows we use the deposit based measures.

[8] Consider a zipcode with 3 bank branches from 3 separate bank holding companies in a given quarter, then the weighted average volatility in the zipcode based on the branching density in the zipcode is $0.3(\sigma_1^2 + \sigma_2^2 + \sigma_3^2)$, where σ_i^2 is the squared residuals in the quarter obtained after regressing a bank's daily stock returns on a five factor Fama-French model. The weighted average volatility in the zipcode based on deposit shares is $\frac{1}{d_1+d_2+d_3}(d_1\sigma_1^2 + d_2\sigma_2^2 + d_3\sigma_3^2)$, where d_i is the value of deposits in branch *i* in the zipcode.

Column 3 allows the impact of these local banking sector shocks to vary by firm risk. As in the case of public firms, small and younger firms are generally riskier, and to help measure the role of business risk in mediating the effects of volatility shocks, we create an indicator that equals 1 if a business is "small"—has less than 10 employees (Hadlock and Pierce 2010)—we do not have reliable data on age. The baseline specification interacts this indicator variable with the zipcode-year banking shock measures. We do not find any evidence that firm size mediates the effects of the local banking sector uncertainty shock on the probability of a new bank loan. The interaction term in the case of mean shocks is negative, suggesting that positive idiosyncratic first moment shocks might increase lending more to bigger firms.

Column 4 examines the impact of these shocks on non-bank sources of credit—trade credit and credit cards. Because of their more limited internal cash flow, small firms are more likely to demand non-bank sources of credit when increased bank uncertainty reduces the flow of bank credit into the zipcode. This is indeed what we find. The interaction term between the local volatility measure and the small indicator variable is positive and significant. The point estimates suggest that a mean volatility shock implies a 0.2 percentage point increase in the probability that a small business obtains new non-bank financing—the unconditional probability of such a relationship is 1.5 percent. But for larger businesses, a similar sized shock suggests a 0.14 percentage point drop in the odds of new non-bank sources of credit, as these credit sources can be more expensive than internal sources of financing for larger firms.

Column 5 studies the impact of these shocks on illiquidity. The dependent variable equals 1 if the business is 90 days late or delinquent on a credit account. The direct effect of uncertainty is not significant, but the coefficient on the interaction term between volatility and "small" is positive and highly statistically significant (p-value<0.00). These estimates imply that a mean uncertainty shock increases the odds that a small business becomes late or delinquent on an account by about 0.25 percentage points—the unconditional mean is 9.2 percent. Column 6 uses a "high" credit balance to measure illiquidity; the dependent variable equals 1 if an account has hit its maximum in the calendar year and 0 otherwise. Consistent with the prediction that uncertainty can increase illiquidity for smaller businesses, a mean uncertainty shock increases the odds that a small business reaches a "high" balance on an account by about 0.18 percentage points. For a larger business, a

similar shock suggests a 0.24 percentage point drop in observing a high balance, as these businesses likely reduce their credit exposures amid uncertainty.

The business-year level tests suggests that bank uncertainty shocks pass through onto the capital structure and liquidity outcomes of small private businesses. But the annual-level variation is relatively coarse, and other explanations remain possible. Perhaps for example higher frequency time varying shocks in the local area both cause illiquidity among small businesses and coincide with increased volatility at banks. One way to help address this short-coming is to use the time-stamp on a new loan and pool all new credit facilities in the database. We can then examine how bank volatility shocks in the previous quarter within a zipcode affects the probability of observing a new bank loan relative to credit cards; non-bank credit; and leasing facilities within a zipcode-quarter. This higher frequency approach thus studies the extensive margin, and allows us to use county-by-year-quarter fixed effects to absorb time-varying local shocks.

The results from this research design that uses the pool of new loan level originations are consistent with the business-year level evidence. The dependent variable in column 1 of Table 9 Panel B equals 1 if a particular new account at a business in a zipcode-year quarter cluster is a bank loan and 0 if it is either a credit card; trade credit; or leasing. A mean volatility shock in the previous quarter implies a 0.31 percentage point increase in the odds of observing a new bank loan among businesses with more than 10 employees (p-value<0.01), but a 0.58 percentage point decline in the odds of new bank credit to small businesses in the zipcode (p-value<0.01). The remaining columns of Table 9B examine how businesses might substitute to other sources of financing.

The dependent variable in column 2 equals 1 if the credit facility is a credit card, and 0 otherwise. Among bigger businesses, the odds of new credit card issuances drop after an increase in local banking system volatility, as a mean volatility shock implies a 0.51 percentage point decline in the odds of a new credit card. And as before, the odds of new card issuances increase among small businesses increases, so that a mean volatility shock implies a 0.12 percentage point increase in the odds of a new credit card. Column 3 examines substitution through trade credit. The implied effect is similar to credit cards, though the estimates are less precise. Both the business-year and loan-level evidence suggest that when local banks face increased uncertainty over their future profits, new lending declines and smaller businesses fill some of that decline in

bank credit using credit cards and vendor credit. Bank volatility shocks are also associated with increased odds of illiquidity at small businesses.

4. Conclusion

This paper studies the impact of bank-level uncertainty shocks—the idiosyncratic volatility of a bank's stock price—on loan-level risk-taking. Consistent with the precautionary motive, we find that banks facing increased uncertainty are less likely to lend to riskier firms. These banks also increase the cost of credit per quanta of risk, and are more likely to demand collateral. These precautionary responses to uncertainty are especially strong among the less well capitalized banks that also face earnings volatility from their bond portfolio. We also show that public firms react to these bank-level shifts in credit policy by reducing their investment and employment, well increasing their holdings of cash assets and reducing share buy backs. Small private firms shift their borrowing towards more expensive sources of short-term liquidity.

Taken together, the results suggest that bank-level uncertainty shocks are a plausible source of aggregate fluctuations, and add to the broader literature on the micro origins of aggregate fluctuations. More generally, the paper shows that even during tranquil time periods, "second" moment shocks in the banking system can also be first order importance, pointing to the importance of banking regulations in managing economic fluctuations. More precisely, the increases in bank capital after 2009 augment the risk-bearing capacity of the banking system and dampen the transmission of banking sector shocks onto the real economy. But other key regulations like the AOCI rule appears to have the opposite effect. Also, that uncertainty extracted from stock prices matter for loan terms and firm outcomes supports the idea that asset prices are a powerful sources of information in the economy that can cascade through the real economy.

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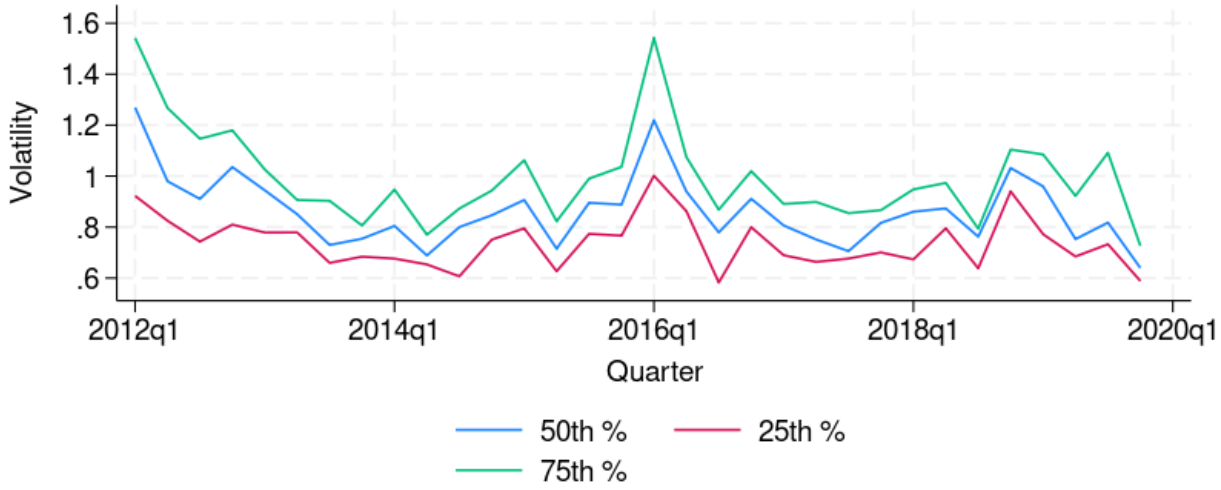
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Figures and Tables

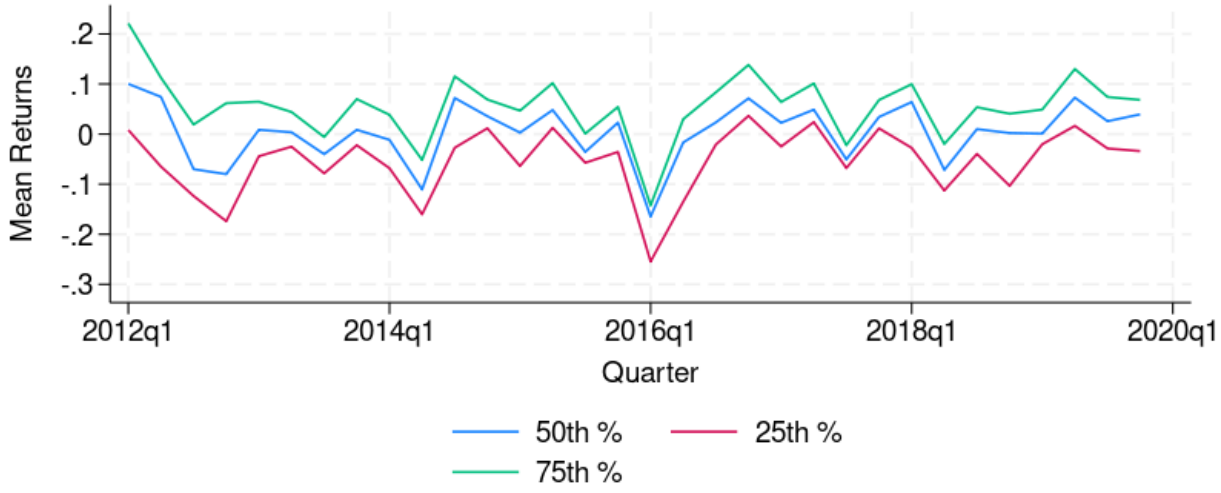
Figures

Figure 1. Idiosyncratic Returns, 2013-2019

Panel A. Volatility

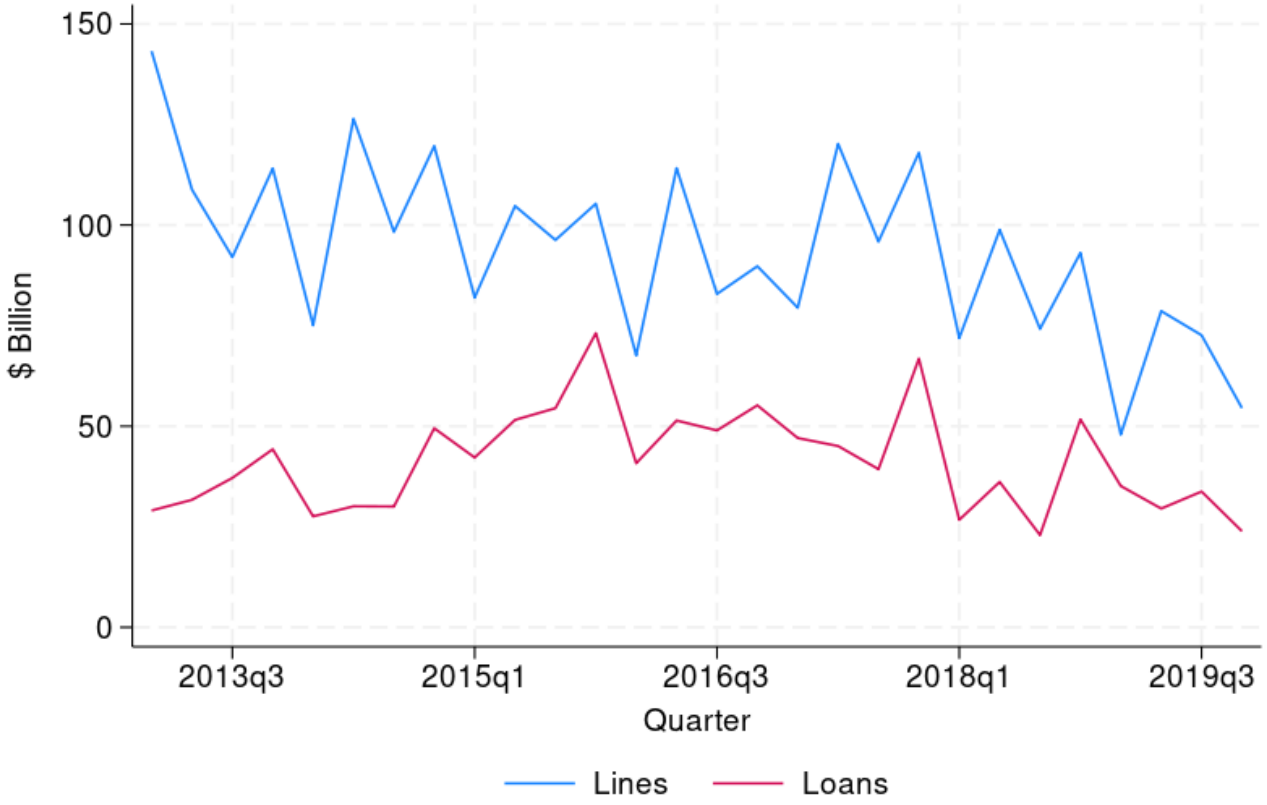


Panel B. Mean



Notes: Panel A plots the 25th, 50th, and 75th percentiles of the standard deviation of daily idiosyncratic stock returns computed in each quarter for the 19 banks in our sample that report Y-14Q corporate loans in Schedule H.1. The idiosyncratic returns are extracted using a 5-factor Fama-French regression with the data obtained from Kenneth French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html accessed on September 2024). Panel B reports the mean idiosyncratic stock returns for the 25th, 50th, and 75th percentiles using the same methodology.

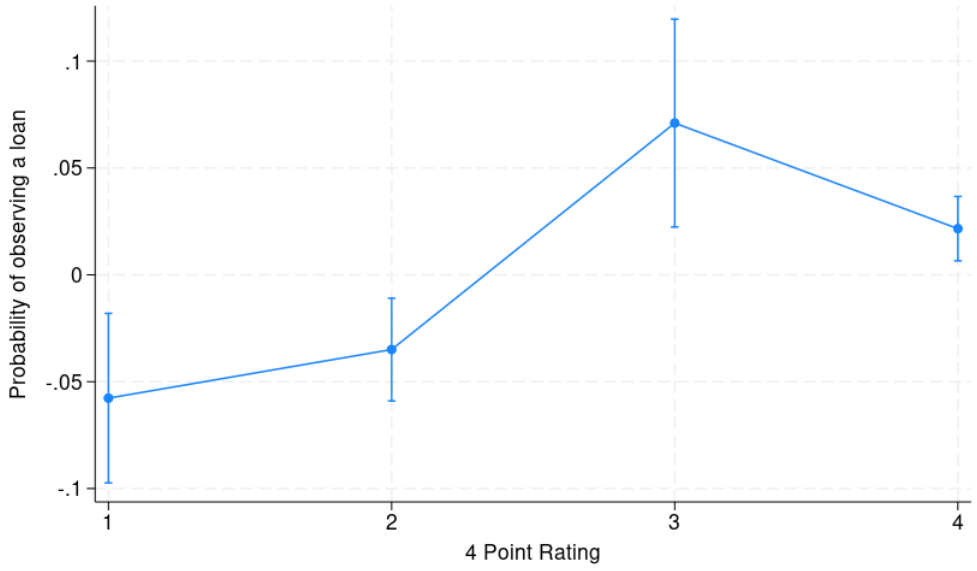
Figure 2. The Volume of Loans and Lines



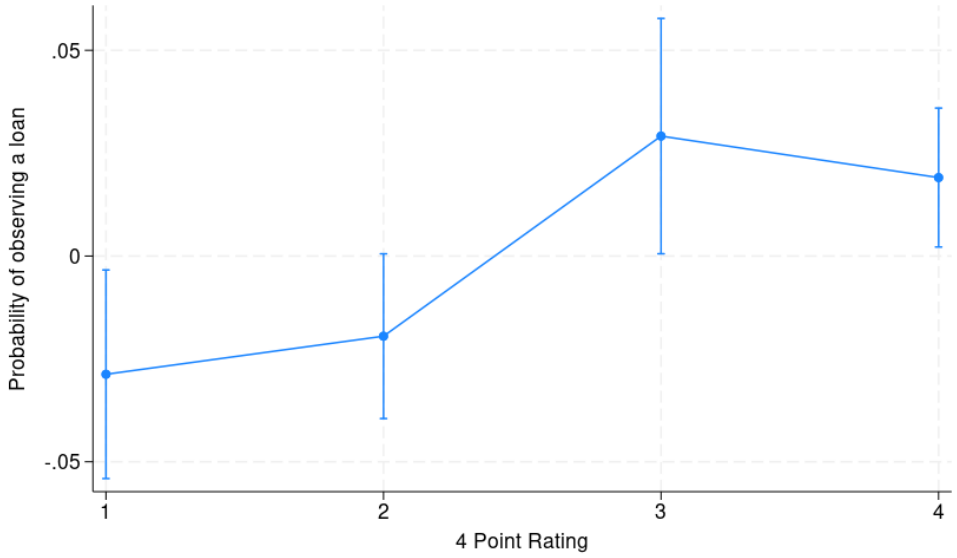
This figure plots the amount of new loans and credit lines from the Y-14Q, Schedule H.1 originated in each quarter by the banks in the sample.

Figure 3. The marginal impact of uncertainty on risk outcomes

Panel A. Term Loans

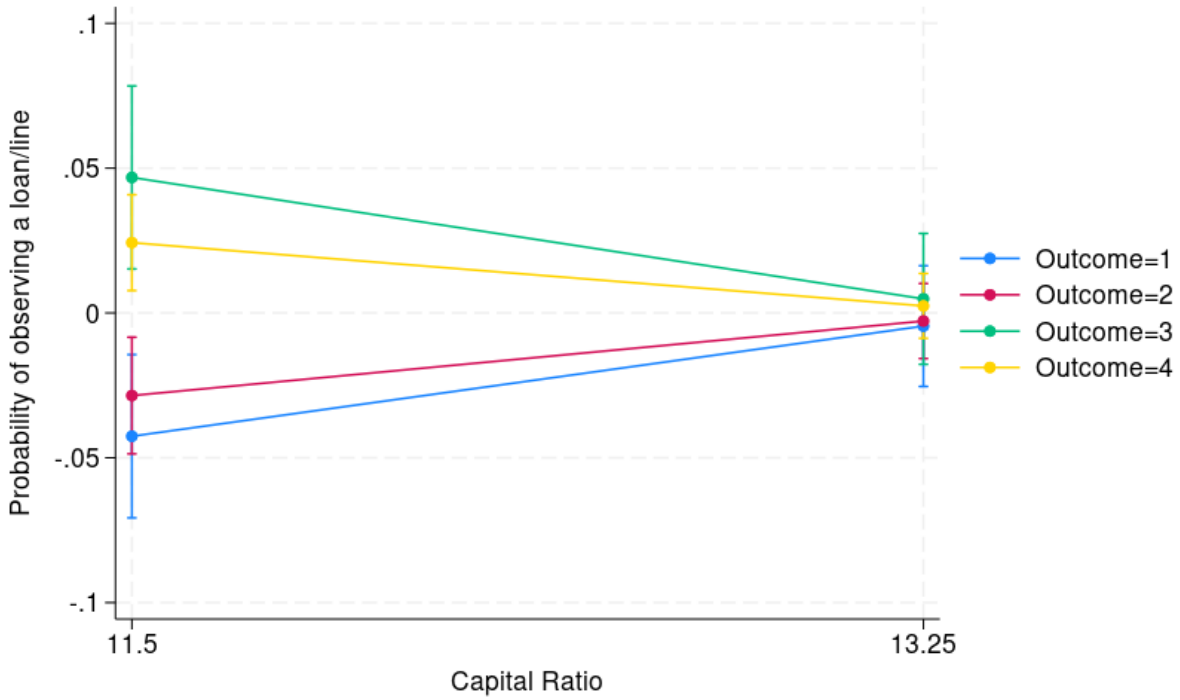


Panel B. Credit Lines



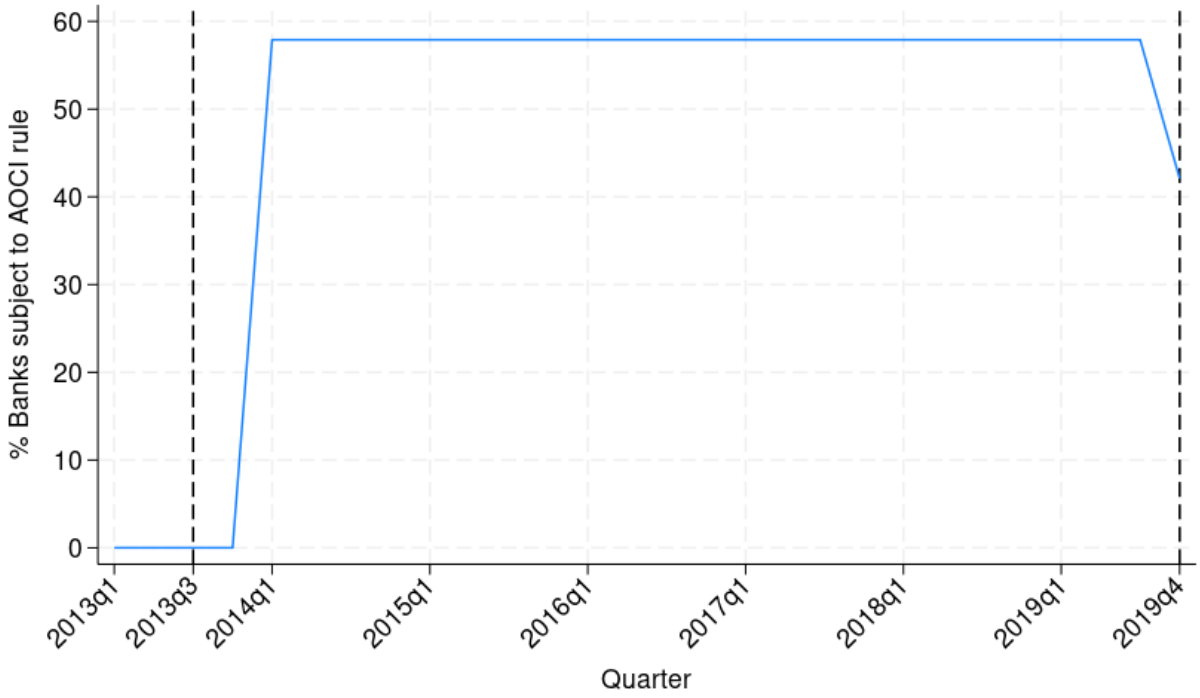
These figures plot the marginal effects of increase in bank-level volatility on the odds of observing a term loan (Panel A) and credit line (Panel B) across the loan risk distribution. The estimates are taken from columns 2 and 4 of Table 4. Source Y-14Q U.S. C&I Loans and CRSP Stock Prices (2013-19)

Figure 4. The marginal impact of uncertainty on risk outcomes, by regulatory solvency



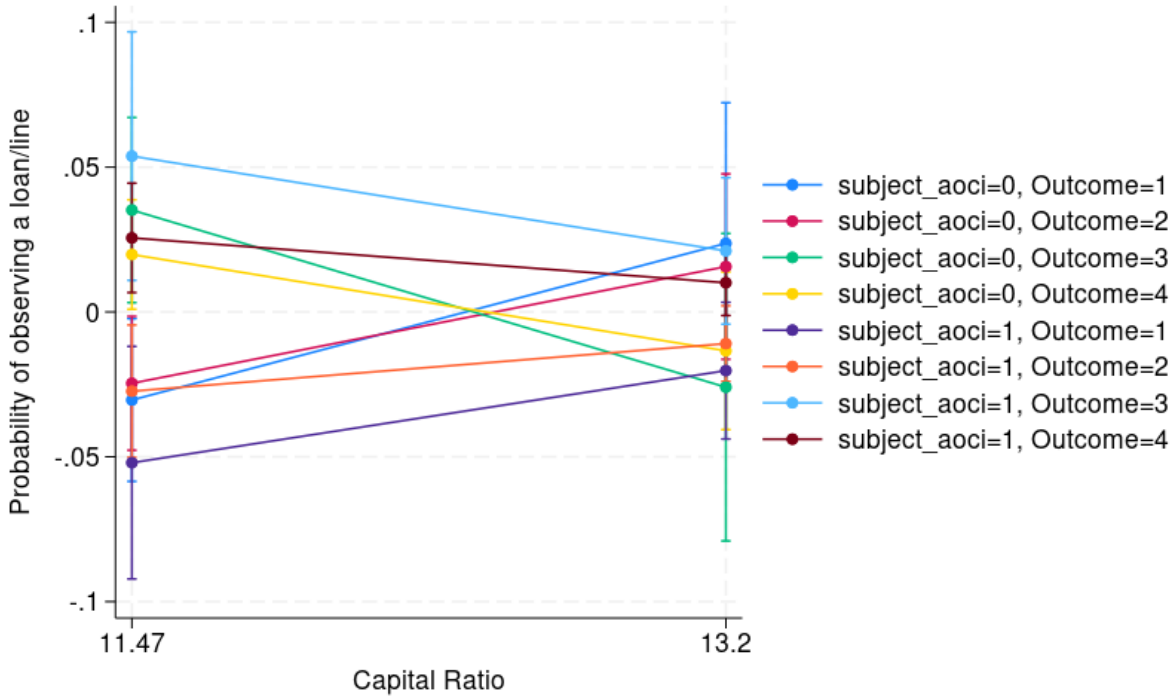
This figure uses the coefficients from column 2 of Table 6 to plot the marginal effects of uncertainty on the odds of loan risk scores (higher is safer) for banks at the 25th and 75th percentiles of the tier 1 RWA ratio distribution. Source Y-14Q U.S. C&I Loans and CRSP Stock Prices (2013-19)

Figure 5. The evolution of the AOCI rule, 2013-2019



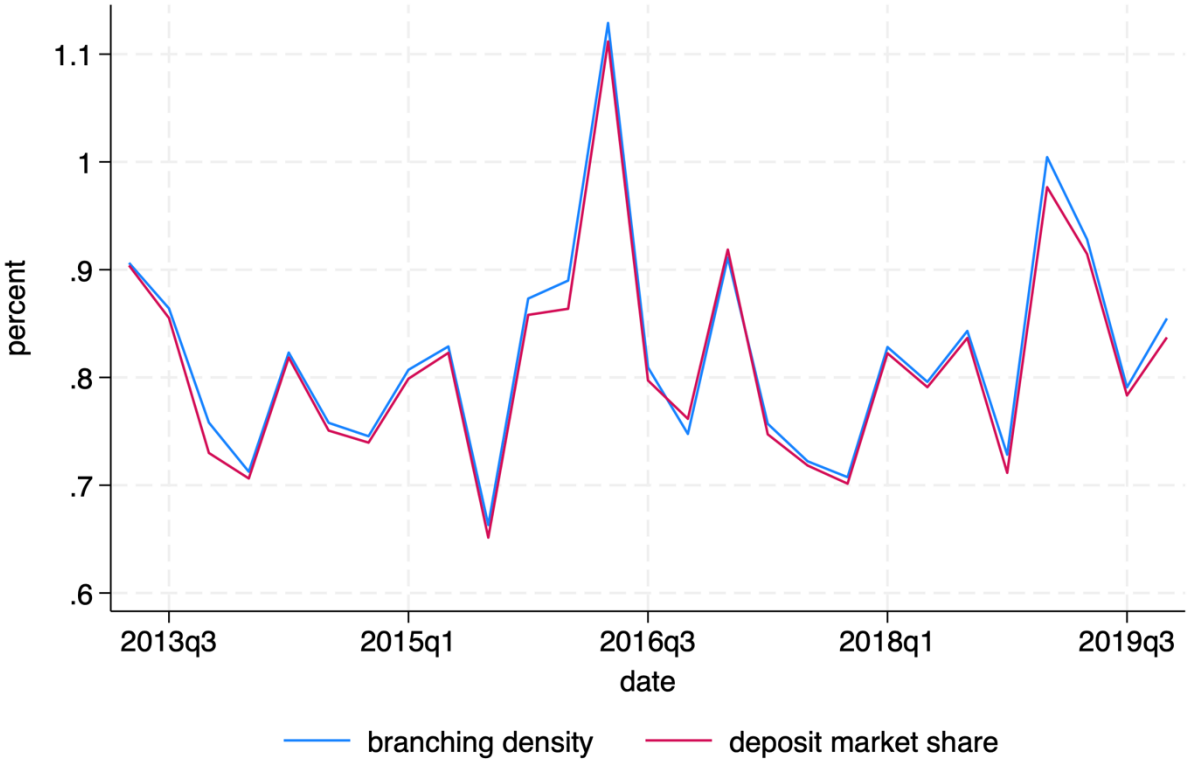
Source: FR Y-9C (2013-19). Sample includes 19 Bank Holding Companies that report Y-14Q, Schedule H.1.
Vertical lines represent the introduction of the AOCI filter removal (2013Q3) and Tailoring Rules (2019Q4)

Figure 6. The marginal impact of uncertainty on risk outcomes, by AOCI rule and regulatory solvency



This figure uses the estimates in column 4 of Table 6 to plot the marginal effects of an uncertainty shock on the odds of loan risk scores for banks at the 25th and 75th percentiles of the tier 1 RWA ratio distribution, and whether these banks are subject to the AOCI rule. Source Y-14Q U.S. C&I Loans and CRSP Stock Prices (2013-19)

Figure 7. Zipcode level weighted idiosyncratic bank volatility, 2012-2019



Source: Authors' calculations using FDIC Summary of Deposits, CRSP Stock Returns and Experian

Tables

Table 1. Idiosyncratic returns and bank observables

	(1) Volatility	(2) Mean Returns
Loan to Assets	-0.689	-0.248
	(0.538)	(0.173)
Deposits to Assets	-1.204**	0.181
	(0.464)	(0.159)
Return on Assets	-12.127**	0.523
	(5.522)	(0.998)
Log Assets	-0.601***	0.028
	(0.146)	(0.059)
Tier 1 Leverage	-0.021	0.012*
	(0.016)	(0.006)
Tier 1 Capital	-0.006	0.004
	(0.009)	(0.004)
BHC FE's	Yes	Yes
Year-Quarter FE's	Yes	Yes
R-squared	0.562	0.359
N	483	483

This table studies the impact of lender regulatory balance variables on lender idiosyncratic volatility (column 1) and mean returns (column 2). All models include Year-Quarter and Bank Holding Company (BHC) fixed effects. Standard Errors are clustered by BHC. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2. Summary Statistics

Panel A. Loans and Lines in the Sample

Summary Statistics

	LOC	Loans	All
Committed Exposure	27,752,187	18,331,816	23,986,202
	(64,432,958)	(108,994,970)	(85,219,651)
N	94,613	63,015	157,628

Source: Y-14Q U.S. C&I Loans and FR Y-9C (2013-19). Means and (standard deviations) in USD

Panel B. Distribution of Loans by Risk Rating on 10 point scale

10 Point Rating	N	Percent	Cumulative Percent
1	418	0.27	0.27
2	79	0.05	0.32
3	672	0.43	0.74
4	2,840	1.80	2.54
5	23,043	14.62	17.16
6	72,887	46.24	63.40
7	44,584	28.28	91.69
8	9,746	6.18	97.87
9	2,847	1.81	99.68
10	512	0.32	100.00
Total	157,628	100.00	

Panel C. Loan and borrower characteristics

	mean	median	sd
Interest Rate	.0247466	.0264005	.0206543
Collateral=1	.3857754	0	.4867795
Maturity	25.84934	25.78329	2.167933
Cash and reserves/assets	.2662016	.1652124	.2774885
Total debt/assets	2.121806	.7117593	4.469813
Debt service/assets	.1039829	.0282517	.2235338
Return on assets	.3210002	.1578173	.813419
Observations	157628		

Source: Y-14Q U.S. C&I Loans and FR Y-9C (2013-19). Means and (standard deviations) in USD

Table 3. The Determinants of Risk Ratings

	(1)	(2)	(3)	(4)
		4-point risk rating (higher is safer)		10-point risk rating (higher is safer)
	OLS	OLS	Ordered Logit	Ordered Logit
main				
Committed Exposure	0.099***	0.126***	0.333***	0.324***
	(0.013)	(0.016)	(0.038)	(0.037)
Interest Rate	-9.928***	-9.686***	-27.426***	-27.119***
	(0.851)	(0.659)	(2.331)	(2.230)
Credit Line=1	-0.066	-0.093***	-0.258***	-0.237***
	(0.048)	(0.029)	(0.082)	(0.084)
Maturity	0.036**	0.025***	0.066***	0.069***
	(0.014)	(0.007)	(0.019)	(0.020)
Collateral=1	-0.071	-0.113*	-0.300**	-0.282**
	(0.043)	(0.055)	(0.142)	(0.142)
ROA		0.133***	0.384***	0.387***
		(0.014)	(0.040)	(0.036)
Leverage		0.010**	0.033***	0.033***
		(0.004)	(0.011)	(0.011)
Liquidity		0.250***	0.640***	0.623***
		(0.050)	(0.123)	(0.117)
DSCR		-0.726***	-2.235***	-2.176***
		(0.066)	(0.212)	(0.199)
R-squared	0.173	0.208		
Pseudo R-squared			0.101	0.089
N	155,465	106,864	106,864	106,864

This table reports OLS (Columns 1, 2) and Ordered Logistic (Columns 3, 4) regressions of loan ratings outcomes on loan-level and firm-level (i.e. borrower) risk measures. The dependent variable in columns 1 through 3 is a ratings measure on a 4 point scale constructed using the 10 point scale reported by lenders in the Y-14Q. Column 4 directly uses the 10 point rating scale from the Y-14Q. Ratings in the Y-14Q come from the lender's internal risk-rating system and correlate with probability of default. Source: Y-14Q U.S. C&I Loans and FR Y-9C (2013-19). All models include Year-Quarter and Bank Holding Company (BHC) fixed effects. Column 1 uses loan-level controls, columns 2 through 4 add firm-level controls. Standard Errors are clustered by BHC. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. The impact of bank-level uncertainty on loan risk, basic results.

Effect of Uncertainty on Loan Ratings

	(1)	(2)	(3)	(4)	(5)	(6)
	Loans		Line of Credit		Both	
	OLS	Ordered Logit	OLS	Ordered Logit	OLS	Ordered Logit
Volatility	0.190***	0.457***	0.100**	0.214**	0.149***	0.288*
	(0.057)	(0.156)	(0.045)	(0.103)	(0.069)	(0.164)
Mean	0.109	0.278	-0.063	-0.134	0.055	0.141
	(0.078)	(0.204)	(0.083)	(0.188)	(0.088)	(0.208)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.099		0.088		0.087	
Pseudo R-squared		0.052		0.040		0.041
N	63,015	63,015	94,613	94,613	157,628	157,628

This table studies the impact of bank-level idiosyncratic volatility on the loan risk ratings. The dependent variable is a 4-point ordinal ranking of loan risk (1,2,3,4) with higher values denoting a safer loan. All regressions include bank and year-quarter fixed effects, and standard errors are clustered at the bank-level. Columns 2, 4 and 6 report the odds ratio from the ordered logit regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. The impact of bank-level uncertainty on loan risk, robustness tests.

	(1)	(2)	(3)	(4)	(5)	(6)
	4-point risk rating (higher is safer)				BBB<=1	10-point risk rating (higher is safer)
Volatility	0.086*	0.132***	0.112**	0.089**	-0.064**	0.165***
	(0.048)	(0.043)	(0.045)	(0.032)	(0.027)	(0.053)
Mean	0.048	0.002	0.033	-0.059	0.017	0.004
	(0.054)	(0.056)	(0.058)	(0.073)	(0.039)	(0.068)
Bank FE's	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE's	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE's	Yes	No	No	No	No	No
NAICSxQuarter	No	Yes	No	No	No	No
CityxQuarter	No	No	Yes	No	No	No
Bank Controls	No	No	No	Yes	No	No
R-squared	0.757	0.140	0.365	0.080	0.062	0.070
N	104,484	156,826	136,990	155,164	157,628	157,628

This table studies the impact of bank-level idiosyncratic volatility on the loan risk ratings. The dependent variable in columns 1-4 is the 4-point ordinal ranking of loan risk (1,2,3,4) with higher values denoting a safer loan. In column 5, the dependent variable equals 1 if the loan is BBB or lower, and 0 otherwise; column 5 uses the regulatory 10 point scale. All regressions include bank and year-quarter fixed effects, and standard errors are clustered at the bank-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. The impact of bank-level uncertainty on loan risk—financial regulation

	(1)	(2)	(3)	(4)	(5)	(6)
	4-point risk rating (higher is safer)				Interest rate	Collateral =1
	OLS	Ordered Logit	OLS	Ordered Logit	OLS	OLS
Volatility	0.856***	2.229***	1.197**	3.062**	-0.006	-0.154
	(0.246)	(0.621)	(0.458)	(1.227)	(0.015)	(0.551)
Capital	0.035	0.105*	0.042	0.132	-0.000	-0.033
	(0.023)	(0.054)	(0.033)	(0.090)	(0.001)	(0.050)
Volatility#Capital	-0.062***	-0.166***	-0.095**	-0.246**	0.001	0.006
	(0.018)	(0.047)	(0.039)	(0.104)	(0.001)	(0.048)
Volatility#Capital# AOCI			0.049	0.115	-0.000	-0.061
			(0.047)	(0.133)	(0.001)	(0.067)
Volatility#Capital# AOCI#Rating					-0.004**	-0.051
					(0.002)	(0.061)
R-squared	0.080		0.081		0.145	0.542
Pseudo R-squared		0.038		0.038		
N	155,164	155,164	155,164	155,164	153,099	155,147
25th pct	0.1419	-0.0426	0.1592	-0.0515	0.0094	0.3747
p	0.0047	0.0031	0.0096	0.0112	0.0084	0.0311
75th pct	0.0333	-0.0045	0.0793	-0.0193	0.0011	0.2518
p	0.2919	0.6701	0.0378	0.1048	0.7056	0.0232

This table studies the interaction between capital (tier 1/risk weighted assets ratio); volatility and the Accumulated Other Comprehensive Income (AOCI) rule. The dependent variable in columns 1-4 is the 4-point risk rating (higher is safer). In column 5 the dependent variable is the interest rate on the loan, while in column 6 the dependent variable equals 1 if the loan uses collateral and 0 otherwise. All regressions include the mean idiosyncratic returns linearly, and interacted with capital and or the AOCI indicator variable along with all subcomponents. All regressions also include bank and year-quarter fixed effects, and standard errors are clustered at the bank-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. The impact of bank-level uncertainty on firm-level outcomes

Panel A. Full Sample

	(1) PPE	(2) Emp	(3) Cash	(4) Buy -backs	(5) Firm Debt	(6) Stock Price
Volatility	-0.011***	-0.016***	0.042***	-0.022*	-0.189	-0.016**
	(0.003)	(0.004)	(0.013)	(0.012)	(0.113)	(0.008)
Mean Returns	-0.005	0.055	-0.009	-0.084*	-0.596	0.004
	(0.013)	(0.063)	(0.053)	(0.048)	(0.426)	(0.035)
Quarter FE's	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE's	Yes	No	Yes	Yes	Yes	Yes
R^2	0.209	0.315	0.025	0.024	0.017	0.062
N	63,522	11,337	64,256	40,500	46,741	67,338

This table studies the impact of a firm's weighted exposure to bank idiosyncratic volatility on public firms' real and capital structure outcomes. The dependent variable in column 1 is the growth in property, plant and equipment spending; column 2: growth in employment; column 3: growth in cash and short-term reserves; column 4: growth in share buybacks; column 5: growth in debt; and column 6: mean daily stock returns. All models include a firm's weighted exposure to bank idiosyncratic mean returns; year-quarter and firm fixed effects along with time-varying firm financials including book to market, log assets, return on assets, income over assets, Tobin's Q, Short-Term Financial Constraint and Capital Intensity. Standard Errors are double-clustered by firm and year-quarter. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All variables are quarterly, except for firm employment which is annual (Column 2).

Panel B. Financial Constraints

	(1) PPE	(2) Employment	(3) Cash	(4) Buybacks	(5) Firm Debt	(6) Stock Price
Volatility	-0.009***	-0.013***	0.034**	-0.022*	-0.157	-0.012
	(0.003)	(0.005)	(0.012)	(0.011)	(0.123)	(0.008)
High financial constraints	0.011	0.023**	-0.006	0.016	0.120	0.009
	(0.010)	(0.010)	(0.010)	(0.011)	(0.131)	(0.011)
Volatility#High financial constraints	-0.007	-0.010	0.041**	0.001	-0.186	-0.011
	(0.009)	(0.009)	(0.020)	(0.018)	(0.205)	(0.014)
Quarter FE's	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE's	Yes	No	Yes	Yes	Yes	Yes
R^2	0.210	0.318	0.025	0.024	0.018	0.062
N	63,212	11,286	63,946	40,348	46,503	67,015
The marginal impact of volatility evaluated across the financial constraints distribution						
Below top quartile of financial constraints	-0.0093	-0.0133	0.0337	-0.0219	-0.1573	-0.0124
p-value	0.0017	0.0089	0.0070	0.0496	0.2002	0.1124
Top quartile of financial constraints	-0.0160	-0.0237	0.0746	-0.0208	-0.3438	-0.0238
p-value	0.0719	0.0017	0.0005	0.3722	0.0761	0.0811

This table allows the impact of a firm's weighted exposure to bank idiosyncratic volatility to vary depending on whether the firm is in the top quartile of financial constraints in the previous year, using the (Hadlock and Pierce 2010) AZ Index. The dependent variable in column 1 is the growth in property, plant and equipment spending; column 2: growth in employment; column 3: growth in cash and short-term reserves; column 4: growth in share buybacks; column 5: growth in debt; and column 6: mean daily stock returns. All models include a firm's weighted exposure to bank idiosyncratic mean returns linearly and interacted with the financial constraint indicator variable; year-quarter and firm fixed effects along with time-varying firm financials including book to market, log assets, return on assets, income over assets, Tobin's Q, Short-Term Financial Constraint and Capital Intensity. Standard Errors are double-clustered by firm and year-quarter. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All variables are quarterly, except for firm employment which is annual (Column 2).

Table 8. Credit to private businesses

Panel A. New credit originations

	Credit cards	Non-banks	Banks	Leases
Number of Originations in sample	1,224,992	982,661	2,348,333	891,059
Percent of total originations in sample	21.6	17.31	41.37	15.70

Panel B. Loan outcomes

	Mean	Standard deviation
Probability of a new credit facility	0.152	0.122
Probability of a late payment	0.092	0.289
Probability of a high balance	0.231	0.421

Source: Experian

Table 9A. The impact of bank volatility shocks on private businesses—business-year

	(1)	(2)	(3)	(4)	(5)	(6)
		new bank		New nonbank	late	high
Volatility (deposits)	-0.000446***		-0.000498***	-0.00165***	-0.000647	-0.00297***
	(0.0000872)		(0.0000909)	(0.000403)	(0.000692)	(0.000990)
mean shocks (deposits)	0.00244***		0.00342***	0.0425***	0.0267***	-0.00889*
	(0.000456)		(0.000431)	(0.00250)	(0.00337)	(0.00506)
Volatility (branches)		-0.000579***				
		(0.0000962)				
small			-0.000681***	-0.00490***	-0.000671	-0.0268***
			(0.0000800)	(0.000491)	(0.000932)	(0.00120)
Volatility (deposits) #small			0.000114	0.00386***	0.00360***	0.00517***
			(0.0000809)	(0.000539)	(0.00103)	(0.00129)
mean shocks (deposits) #small			-0.00223***	-0.0710***	-0.0577***	-0.0442***
			(0.000402)	(0.00311)	(0.00467)	(0.00658)
R-squared	0.645	0.645	0.645	0.315	0.590	0.623
Obs	11723671	11723671	11723671	11723671	11723671	11723671

The table studies the impact of zipcode level bank idiosyncratic volatility and mean shocks on credit usage at private business. The data are a panel of about 3.5 million private businesses observed in 2013, 2016, 2017 and 2018. The dependent variable in columns 1-3 equals 1 if the business obtained a new bank liability (loan or credit line) in the calendar year, and 0 otherwise. In column 4, the dependent variable equals 1 if a business obtained a new non-bank liability (credit card/trade credit/lease) and 0 otherwise. The dependent variable in column 5 equals 1 if the business is late (more than 30 days) or delinquent on an account. The dependent variable in column 6 equals 1 if the business is at its maximum on a credit account in the calendar year, and 0 otherwise. All regressions include business and year fixed effects, and standard errors are clustered at the zipcode level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9B. The impact of bank volatility shocks on private businesses—loan-year-quarter

	(1) bank loan	(2) credit card	(3) non-bank
volatility(deposits)	0.00356*	-0.00598***	-0.00190
	(0.00188)	(0.00161)	(0.00189)
volatility(deposits)#small	-0.0103***	0.00732***	0.00322*
	(0.00286)	(0.00167)	(0.00168)
mean shocks (deposits)	-0.0412***	0.00439	0.0254***
	(0.00690)	(0.00538)	(0.00719)
mean shocks (deposits)#small	0.113***	-0.0510***	-0.0277***
	(0.0100)	(0.00674)	(0.00710)
R-squared	0.082	0.058	0.073
Obs	5676911	5676911	5676911

The table uses the pool of all new accounts at small businesses to study the impact of zipcode level bank idiosyncratic volatility and mean shocks on the probability of observing a new bank loan (column 1); a new credit card (column 2); and a new non-bank account (column 3) in particular quarter. All regressions include county-by-year-quarter fixed effects, and standard errors are clustered at the zipcode level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.