The Information Advantage of Banks: Evidence From Their Private Credit Assessments

Abstract

In classic theories of financial intermediation, banks mitigate information frictions by monitoring and producing information about borrowers. However, it is difficult to test these theories without being able to observe banks' private information. In this paper, we use supervisory data containing banks' *private* assessments of their loans' expected losses. We show that changes in expected losses predict firms' future stock returns, bond returns and earnings surprises. The predictability is concentrated among small firms and growth firms, and only occurs when banks become more pessimistic. Using within-firm variation in borrowing across banks, we identify sources of private information for banks and show that this information affects banks' credit allocation decisions. Our findings show that banks' information production and monitoring create an information advantage over financial markets, even among publicly traded firms.

1 Introduction

A fundamental role of banks is to collect and process information about borrowers. Because banks are better able to economize on the costs of information production and monitoring than financial markets, classic theories of financial intermediation predict that banks act as "informed investors" relative to public markets.[1] However, testing these important theories is challenging because banks' information is intrinsically private, and therefore unobservable. This empirical problem extends beyond just banks: without access to agents' private information, it is extremely difficult to test for asymmetric information in markets.[2] Many papers have attempted to test for banks' information advantage using indirect evidence; however, their inference regarding this and many other important questions is limited. For example, how do banks actually obtain this information? What type of information do banks specialize in? For which types of firms are banks' information advantages strongest? The answers to these questions have vast implications for how capital is allocated across firms and can help guide policies meant to spur credit growth and maintain financial stability.

In this paper, we address this empirical problem by using supervisory data containing banks' private risk assessments for corporate loans in the US. These assessments are not observable to other market participants and hence reflect banks' private information. We show that changes in banks' assessments of their loans' expected losses predict *future* changes in public stock/bond prices and analyst earnings surprises. Our effects are concentrated among small and growth firms and the predictability only occurs when banks become more pessimistic about firms' prospects. Using within-firm variation in borrowing across banks, we identify sources of banks' private information and show that banks use this information to allocate credit to firms. Finally, we provide evidence that banks' information advantage over public markets arises from both receiving non-public information earlier and actively producing information. Overall, our results provide direct evidence of banks as informed finance.

Our analysis uses Federal Reserve's Y-14Q Schedule H.1 data, which include all corporate loans over one million dollars extended by large bank holding companies (BHCs) in the United States. BHCs are required to report quarterly internal measures of the probability of default (PD) and loss given default (LGD) for each loan on their balance sheets. We use these measures to create an average quarterly expected loss (PD $\times$ LGD) variable for each bank/firm relationship, weighted by

[1] For example see Leland and Pyle (1977), Diamond (1984), Boyd and Prescott (1986), Sharpe (1990) and Rajan (1992).

[2] See Salanié (2017) for a discussion of these issues in the context of insurance markets.

the committed dollar amount of each loan. In order to test whether banks have an information advantage over public markets, we examine whether changes in banks' estimates of expected loss predict future asset prices as well as analyst earnings surprises. If banks have no informational advantage over public markets, then changes in expected losses should have no relationship with future asset prices or earnings surprises, as banks' information would already be incorporated into asset prices and current analyst forecasts.

We find that when a bank increases its assessed expected loss for a firm (i.e., becomes more pessimistic), on average, that firm experiences negative excess stock and bond returns over the next quarter. In particular, an increase in banks' expected losses leads to an 79bp and 20bp per quarter underperformance in stock and bond returns, respectively. In contrast, we find no effect when banks adjust their expected losses downwards. This asymmetry is consistent with i) theories in which banks' have higher incentives to learn when the firm is performing poorly, i.e., when agency problems are highest (e.g., Diamond (1984), Haubrich (1989), Besanko and Kanatas (1993)), or when firms are close to violating a covenant (Rajan and Winton (1995) and Park (2000)) and ii) firms releasing positive news much more quickly than negative news.[3]

We next show that this underperformance is concentrated around earnings announcements. First, upward adjustments in expected losses increase the likelihood of negative earnings surprises by 7%. Second, 22bps of the 79bps of equity underperformance over the quarter occurs on the two days around the earnings announcement, meaning the annualized abnormal returns on earnings announcement days are over 12 times higher than on non-earnings days (27.7% versus 2.3%).[4] We again find no effect when banks reduce their expected losses. This result suggests that a large component of banks' private information over the previous quarter becomes public exactly on the earnings announcement date. Moreover, the difference in predictability on earnings announcement and non-earnings days makes it highly unlikely that the return predictability is driven by risk premia or anomalies correlated with changes in banks' expected losses. Finally, it is worth stressing that the return predictability we document is not a strategy that investors can follow because they do not have access to banks' *private* information.

Next, we explore the cross-sectional variation in return predictability to understand the types of firms for which banks' information advantage is strongest. We

[3]We cannot directly test the latter channel because we only observe banks' risk assessments at quarter-end, not at the exact moment they update them. For theoretical and empirical evidence that firms release good news earlier see Dye (1990) and Miller (2002), respectively.

[4]This a lower bound since we inevitably the majority of abnormal returns happen on the first trading day after the earnings announcement is made. As is standard practice, we use a 2-day cumulative abnormal return since we do not know if the announcement was before the open or after the close of the stock market.

find that the return predictability is stronger among smaller firms (firms with lower market capitalizations) and growth firms (firms with lower book-to-markets). We believe this is intuitive as these types of firms are typically more opaque, making bank debt a more critical source of capital for them. In fact, when we place firms into size quintiles, the smallest quintile underperforms by 187bps per quarter, with a steady decrease in magnitude up to the largest quintile, which exhibits no underperformance at all. These results suggest that bank relationships remain important for most publicly traded firms, though not necessarily for the very largest firms.

If the risk assessments reflect banks' private information, theory would predict that banks should use this information in their credit allocation decisions. To test this hypothesis, we exploit the fact that many firms borrow from multiple banks at the same time. We regress banks' loan commitment amounts on their expected losses, controlling for firm-by-time fixed effects (e.g., Khwaja and Mian (2008)). These specifications allow us to isolate changes in lending that specifically come from differences in bank-specific beliefs/private information. Consistent with banks using their information to allocate credit to firms, we find a negative relationship between banks' assessed expected losses and their loan commitment amounts.

How do banks' obtain their information advantage over markets? One possibility is that this advantage arises from active information production (e.g., Diamond (1984) and Boyd and Prescott (1986)). To test this channel, we estimate regressions in which we predict the likelihood of banks' updating their risk assessments. We again include firm-by-time fixed effects to compare risk assessments across banks for a given firm at a given time. We find that banks are far more likely to update their internal risk assessments when their incentives to do so are higher. For example, we find a positive relationship between banks' total loan exposure to a borrower and the likelihood of updating their risk assessments. This result is consistent with banks actively monitoring firms over the life of the loan when their incentives to do so are higher. We also show that banks are far more likely to update their risk assessments when they issue a new loan to that firm, suggesting active information production when new capital is at risk. Taken together, these results are consistent with theories in which banks are incentivized to actively produce information about borrowers.

A second, non-mutually exclusive channel is that banks simply have access to non-public information before it reaches financial markets (e.g., Wight et al. (2009) and Minnis and Sutherland (2017)). One source of such information stems from bank credit lines. If a firm draws down a credit line, this information is immediately known by the bank (or banks in case of a syndicate), but is not immediately disclosed to public markets or other banks. We therefore test whether banks increase their assessed expected losses relative to other banks after firms draw down their credit lines. We find that drawdowns dramatically increase the likelihood of banks increasing their assessed expected losses and also predict negative future financial outcomes. For example, excess stock returns in the next quarter are -188bps following a drawdown. These results are consistent with firms drawing down credit lines following a negative shock (e.g., Shockley and Thakor (1997) and Holmström and Tirole (1998)) and show that credit line drawdowns are a source of private information for banks.[5] However, even when we include drawdowns as a control variable, changes in expected losses still have independent predictive power across all financial market outcomes. These and the previous results, suggest that banks' benefit from access to information before it reaches public markets, but also actively produce information when their incentives to do so are higher.

We view our results as a lower bound on the magnitude of banks' true information advantage over public markets for three reasons. First, in our data we only observe banks' expected losses at quarter end; however, in practice banks can update their expected losses throughout the quarter. To the extent that banks' private information becomes public within the same quarter, our results will not capture these effects. Second, the fact that we find stronger effects for smaller public firms suggests that bank information is even more important for *private* firms, which are not included in our sample due to a lack of publicly traded asset prices and earnings forecasts. In addition to being on average much smaller than the publicly traded firms in our sample, there is much less public information regarding private firms, such as regulatory filings or analyst coverage. Consistent with this, Beyhaghi, Fracassi, and Weitzner (2020) and Weitzner and Howes (2021) show that among private firms, PDs strongly predict default even after controlling for many loan and firm characteristics. Finally, our sample contains only the largest US banks, which many have argued are less inclined to perform the traditional roles of relationship banking. For instance, larger banks tend to focus more on transactional loans rather than relationship loans (Berger and Udell (2002)), have fewer personal relationships (Berger et al. (2005)), and are often more hierarchical, which prevents them from using their soft information (Stein (2002), Liberti and Mian (2008)). That we find economically significant evidence of banks' information advantage despite these caveats only reinforces the importance of banks' role as informed financiers in broader credit markets.

[5] This is also consistent with the empirical findings of Mester, Nakamura, and Renault (2007), Jiménez, Lopez, and Saurina (2009) and Berrospide and Meisenzahl (2022).

2 Related Literature

To our knowledge, this is the first paper to directly test for banks' information advantage over financial markets. To this point, the existing literature typically relies on indirect evidence. For example, James (1987) analyzes stock price responses after firms are granted bank loans. Intuitively, if banks have private information about borrowers, the fact that a firm receives a loan is a positive signal to the market implying a positive stock price reaction, which is exactly what James (1987) finds. However, subsequent papers have raised questions about the interpretation of this result. For example, Preece and Mullineaux (1994) find no difference in stock price reaction across banks and non-banks after loans are granted which could mean the stock price response is due to the signaling content of the loan contract itself rather than the information of the bank.[6] A critical difference in our approach is that we observe banks' information and how it evolves over the life of the loan, allowing us to avoid having to infer banks' information indirectly.

Because we observe how banks' private information evolves over time, our paper provides direct insights on the monitoring role of banks. Several papers use empirical proxies of bank monitoring over the life of loans (e.g., Cerqueiro, Ongena, and Roszbach (2016), Gustafson, Ivanov, and Meisenzahl (2021), Heitz, Martin, and Ufier (2022) and Haque, Mayer, and Wang (2023)). For example, Gustafson, Ivanov, and Meisenzahl (2021) and Heitz, Martin, and Ufier (2022) create measures of bank monitoring based on the number of visits banks make to the firm. However, they do not observe banks' actual information to see how it changes following these visits and how it compares to public information. Without access to banks' private information it is unclear whether banks visit the firms to collect private information, or in response to receiving private information (or both). In contrast, because we are able to directly observe banks' information, we can analyze what causes banks' information to change and the extent to which bank and public market information differ.

In terms of empirical settings, the closest paper to us is Plosser and Santos (2016). They use data from the Shared National Credit (SNC) program, which include banks' risk assessments for syndicated loans for which the aggregate commitment is at least $20 million and which is shared by, or sold to, three or more federally supervised institutions. As part of their analysis, they also show that changes in banks' assessed PDs predict stock returns; however, their main focus is

[6]For instance, the use of collateral (Chan and Kanatas (1985)) and covenants (Manso, Strulovici, and Tchistyi (2010)) can signal information about the firm's credit quality. Relatedly, Maskara and Mullineaux (2011) find no abnormal response once the selection of announcing the loan is controlled for. Finally, De Marco and Petriconi (2020) find a positive reaction in more recent data; however, it is smaller in magnitude than what James (1987) finds.

explaining when banks update their risk assessments, while ours is to understand to what extent these updates preempt financial market outcomes and therefore reflect banks' private information. There are a few other key differences between our paper. First, because our sample includes all loans over $1mm and non-syndicated loans, our sample of loans is larger. Second, beyond analyzing stock returns, we also analyze bond returns and earnings surprises/earnings announcement returns. Third, we explore the cross-section of predictability and find that the predictability is asymmetric and concentrated in smaller and growth firms. Fourth, we show that banks allocate credit based on their private information. Finally, we show how credit line drawdowns are an important source of private information for banks.[7]

Another related paper is Addoum and Murfin (2020) who find that changes in publicly observable syndicated loan prices predict future equity returns and argue that this is due to equity market inattention to loan markets.[8] The key difference between their paper and ours is that we have direct access to banks' *private* information, which may not necessarily be reflected in public prices. For instance, even among traded loans, banks may refrain from trading to keep information private (e.g., Dang et al. (2017)). Moreoever, loans that have publicly available prices make up a small portion of our sample and we show that our results hold when we exclude them. This suggests that our results are not driven by equity market inattention to loan markets. Finally, because we observe banks' actual information, we are able to explore determinants of this information and understand how it makes its way into financial markets.

Our paper also contributes to the literature testing for asymmetric information in credit markets (e.g., Kurlat and Stroebel (2015), Stroebel (2016), Botsch and Vanasco (2019), DeFusco, Tang, and Yannelis (2021), Crawford, Pavanini, and Schivardi (2018), Darmouni (2020), Beyhaghi, Fracassi, and Weitzner (2020), Weitzner and Howes (2021) and Ioannidou, Pavanini, and Peng (2022)). The most common approach in this literature is to rely on either proxies of asymmetric information or assume agents' decisions imply certain distributions of outcomes and test whether these outcomes bear out in the data. We do not need to make these assumptions because we can observe banks' private information.

[7]Our paper also relates to the broader literature analyzing bank internal risk-measures (e.g., Agarwal and Hauswald (2010), Qian, Strahan, and Yang (2015), Berg and Koziol (2017), Behn, Haselmann, and Vig (2022), Dell'Ariccia, Laeven, and Suarez (2017), Plosser and Santos (2018), Nakamura and Roszbach (2018), Becker, Bos, and Roszbach (2018), Adelino, Ivanov, and Smolyansky (2019), Beyhaghi, Fracassi, and Weitzner (2020) and Weitzner and Howes (2021)). In contrast to these papers, our focus is on using this data to test if and when banks have an informational advantage over public markets.

[8]Relatedly, Altman, Gande, and Saunders (2010) finds that loan prices are more informationally efficient that bond prices.

Finally, because our paper shows the existence of asymmetric information between banks and public markets, our paper also contributes to the broader literature on testing information asymmetries in economics (e.g., Chiappori and Salanie (2000), Finkelstein and Poterba (2004), Finkelstein and McGarry (2006), Cohen and Siegelman (2010), Hendren (2013) and Finkelstein and Poterba (2014)). One challenge in this literature is a lack of data on the private beliefs of agents.[9] We address this challenge by using data on banks' beliefs regarding firms' creditworthiness to directly test for asymmetric information.

3 Data

Our main source of data is Schedule H.1 of the Federal Reserve's Y-14Q data. The Federal Reserve began collecting this data in 2011 to support the Dodd-Frank mandated stress tests and the Comprehensive Capital Analysis and Review (CCAR). The sample includes corporate loans from all bank holding companies (BHCs) with \$50bn or more in total assets, accounting for 85.9% of all assets in the US banking sector as of 2018:Q4 (Frame, McLemore, and Mihov (2020)). Qualified BHCs are required to report detailed quarterly loan level data on all corporate loans that exceed one million dollars in size. These loans constitute over 97% of these BHCs' corporate exposure (Beyhaghi (2022)) and represent about 70% of all commercial and industrial loan volume in the US extended by BHCs that file a FR Y-9C (Y9) report (Bidder, Krainer, and Shapiro (2020)).

The data include detailed loan characteristics as well as firm balance sheet and income statement information. Banks are also required to report their internal estimates of probability of default (PD) and loss given default (LGD) for each loan to the Federal Reserve on their Y-14Q filings. According to the Basel Committee on Banking Supervision, internal estimates of PD and LGD "must incorporate all relevant, material and available data, information and methods. A bank may utilize internal data and data from external sources (including pooled data)."[10] Moreover, banks must update these regularly and immediately after any material changes: "Borrowers and facilities must have their ratings refreshed at least on an annual basis... In addition, banks must initiate a new rating if material information on the borrower or facility comes to light." Our main variable of focus is the loan's expected loss (EL) which is equal to PD $\times$ LGD.

We also obtain stock returns from CRSP, bond returns from TRACE, firm financials from Compustat and analyst forecast and earnings outcomes from IBES. We merge these data with the Y-14Q loan data based on borrowers' tax ID. To

[9] One exception to this is Finkelstein and McGarry (2006) who use patient survey data.

[10] The most recent instructions are available at Calculation of RWA for credit risk.

account for subsidiaries that report their parents' tax ID at the time of borrowing (Brown, Gustafson, and Ivanov (2021)) we keep only the observations for which total assets reported in the Y-14Q data is within (90%, 110%) interval of total assets reported on Compustat in the same reporting quarter. Moreover, we restrict the sample to US borrowers and exclude financial firms and utilities based on their Fama-French 30 industry classification. Our final sample contains 1,854 unique firms from 2014Q4 to 2019Q4. Table 1 compares our sample of firm/quarters to the standard CRSP/Compustat sample (3,296 unique non-financial, non-utility firms). Given that firms in our sample must have a bank loan, it is unsurprising that firms in our sample tend to be larger and more highly levered.

Because banks often have multiple loans to the same borrower, for each bank/firm quarter, we create an average PD, LGD and expected loss weighted by the size of the loan. This approach allows us to create a bank-firm panel with one observation per bank-firm relationship in each quarter. After creating the panel, we drop firms with PDs of 0 or 1. To avoid reporting errors, we also drop observations in which the standard deviation of PD across a bank's loans within the same firm-quarter is greater than 0.50pp.[11] We also exclude likely data errors by requiring the following data conditions: 1) total banks' commitment to a borrower does not fall below \$1 million, 2) total borrowers' utilized credit does not exceed the total committed amount, and 3) LGD values fall strictly between 0 and 1. Together, these filters remove less than 1% of the data. If a firm borrows from multiple banks, it will have repeat observations in the sample; however, to avoid inflated standard errors, we double cluster our standard errors by firm and bank-time.[12] Figure 1 plots the distribution of PD, LGD and expected loss and Figure 2 plots the distribution of changes in PD, LGD and expected loss. We also plot the distribution of number of banks per borrower in Figure 3.

Because the relationship between expected losses and asset prices/earnings forecasts is unknown and likely to be highly non-linear, in our main specifications we simply use dummy variables indicating whether expected losses increased, EL^{+}, or decreased, EL^{-}, relative to the previous quarter. In some specifications we also follow the same naming convention when we analyze cases in which PD and LGD go up or down. Detailed variable descriptions can be found in Appendix A.

Table 2 includes summary statistics for the main variables used in the analysis. The average PD, LGD and expected loss are 1.01%, 38.94% and 0.33%, respectively. Banks update their expected losses downward, i.e., become more

[11] The probability of default should in principle be the same across all of a bank's loans to the same borrower since default is measured at the borrower level.

[12] Larger firms that borrow from several banks are also over-represented in the sample. However, if anything this should weaken our results, because as we show later, we find larger effects for smaller firms.

optimistic, in 19% of quarters, whereas they adjust their expected losses upward, i.e., become more pessimistic in 17% of quarters. The fact that banks update the expected losses downward more frequently is at least partially due to the fact that credit market conditions were fairly benign over our sample period.

The average firm size is just over $18bn, with a median size of just under $4bn. The firms in our sample are fairly highly levered with the average and median debt-to-capital ratio being around 50%. In some specifications we compare banks' risk assessments within firm/time, hence for reference, Table 3 includes summary statistics of the cross-sectional standard deviation, i.e. dispersion, in risk assessments and lending amounts. In Table 4 we also display correlations between the risk assessment variables as well as their lagged values. While PD and LGD do tend to go up and down at the same time, the correlation is fairly small (0.119 for increases in PD and LGD and 0.160 for decreases), suggesting that both measures contribute independently to changes in expected losses.

4 Empirical Analysis

4.1 The Information Advantage of Banks

Our empirical approach centers on testing whether changes in banks' private information, in the form of their assessed expected losses, predict public financial market outcomes. We first estimate the following regression:

$$y_{i,t+1} = \beta_1 EL^{+}_{i,b,t} + \beta_2 EL^{-}_{i,b,t} + \Gamma X_{i,t} + \delta_{b,t} + \gamma_{j,t} + \epsilon_{i,b,t}, \tag{1}$$

where $y_{i,t+1}$ is the $t+1$ quarterly equity return, bond return, a dummy variable that equals one if there is negative earnings surprise relative to analysts' EPS estimates, or the cumulative abnormal return (CAR) on the earnings announcement date for firm i, all of of which are multipled by 100. Our main independent variables of interest are $EL^{+}_{i,b,t}$ and $EL^{-}_{i,b,t}$, which are dummy variables that equal one if bank b's assessment of firm i's expected loss increases or decreases from quarter $t-1$ to quarter t. We also include a vector of firm-level controls $X_{i,t}$, which include book-to-market, return on assets, leverage (debt to capital), market capitalization and lagged stock or bond returns. Finally, we include bank-by-time ($\delta_{b,t}$) and industry-by-time fixed effects ($\gamma_{j,t}$) throughout the specifications and cluster our standard errors by firm and bank-time.[13] Intuitively, if banks have no informational advantage over public markets, then changes in expected losses should have

[13]Our results are robust to excluding bank-by-time fixed effects as shown in Appendix Table OA2.

no relationship with future asset prices or earnings surprises, as banks' information would already be incorporated into asset prices and current analyst forecasts. In contrast, if banks do have an information advantage over public markets, we would expect changes in expected losses to predict future market outcomes as this information ultimately becomes public. In this specification we analyze one quarter ahead outcomes; however, we also analyze longer horizons below.

The results of these regressions are displayed in Table 5. In column 1, an increase in expected losses predicts an 79bp per quarter stock return underperformance in the next quarter. In column 2 we find a similar directional pattern for bond returns but with an underperformance of 20bps. In column 3, we find that negative earnings surprises are 1.8pp more likely compared to an unconditional likelihoods of 26.9pp.[14] If increases in expected losses predict future negative earnings surprises, we would expect these firms to experience negative abnormal returns around the earnings announcement. Consistent with this hypothesis, column 4 shows that increases in expected losses predict firms experiencing a 22bps two-day CAR around the earnings announcement date (27.7% annualized).

Interestingly, reductions in expected losses do not predict returns or earnings surprises.[15] This result could be consistent with banks specializing in information production and monitoring firms for negative information (e.g., Rajan and Winton (1995)). However, because we only see banks' risk assessments at quarter-end, it could also be that firms release positive information more quickly than negative information (e.g., Dye (1990) and Miller (2002)), and we are not able to observe the predictability if banks updated their assessments earlier in the quarter. These channels are not mutually exclusive, however. If firms are more willing to release positive information, this can cause banks to have increased incentives to specifically collect negative information. For example, firms are likely very willing to reveal good information about a loan's collateral value, but less willing to reveal negative information. This could incentivize banks to specifically focus on collecting negative information about collateral values.

That decreases in expected losses do not predict financial outcomes does not imply that banks' expected losses are "incorrect." It only implies that banks do not appear to have an informational advantage over public markets regarding positive news. Indeed, as shown below, *contemporaneous* drops in expected loss are strongly associated with positive stock and bond returns.

[14]Positive earnings surprises are also less likely to occur following increases in expected losses; however, we do not report these regressions since negative and positive surprises are effectively complements of one another.

[15]There is a similar asymmetry in research analyst reports (Womack (1996) and Brown, Wei, and Wermers (2014)). However, research analysts are much more often positive than negative, which does not appear to be the case for banks in this sample.

As robustness tests, we also find similar magnitudes to the main analysis when we estimate Fama-Macbeth regressions (Online Appendix Table OA1) and portfolio sorts in (Online Appendix Table OA3).[16]

Next, we explore the cross-sectional variation in return predictability across firms. To do so, we re-estimate Equation (2), but we interact EL^+ with the main firm characteristics/controls. The results are displayed in Table 6. For stock returns, negative earnings surprises and earnings returns, the interaction between market capitalization and EL^+ are positive and statistically significant besides earnings returns which is just below the threshold for statistical significance. These results suggest that the equity market predictability is lower for larger firms. The interaction term for bond returns is positive but not statistically significant. This could be for two reasons: first, the sample size is about half as large given many publicly traded firms do not have bonds and second, because they have traded bonds, these are already larger firms to begin with.

We also find that the interaction between book-to-market and EL^+ is statistically significant for stock returns and negative earnings surprises, but not for bond returns and earnings announcement returns. Taken together, these results suggest that banks' information advantage is stronger among smaller firms as well as growth firms.[17]

In Table 7, we expand on these results by splitting the sample into size quintiles and separately re-estimate the stock return regressions for each quintile. The smallest firms, shown in column 1, exhibit a statistically significant 187bp quarterly underperformance in response to an increase in expected losses. This effect decreases from quintile 1 to 2, remains stable from quintile 2 to 3 then decreases again from quintile 3 to 4 and 4 to 5. The point estimates are all statistically and economically significant for all but the top size quintile. Indeed, column 5 shows that EL^+ exhibits no return predictability for the very largest firms, suggesting that banks do not have an information advantage for these firms.

To see whether banks' information advantage comes from the likelihood of default, expected recovery in default, or both, we separately test whether changes in PD and LGD predict quarter ahead financial market outcomes. As the main independent variables, we use PD^+ and LGD^+, which are dummy variables that equal one if PD or LGD increases in from quarter $t-1$ to quarter t. The results

[16] We stick to panel regressions as our preferred approach for a few reasons. First, given the unbalanced nature of our panel, a Fama-Macbeth would put additional weight on observations in quarters with more bank loans to more firms (Petersen (2009)). Second, given the structure of our data, Fama-Macbeth limits our ability to mitigate correlation in residuals within quarter, i.e., via clustering.

[17] The former result is consistent with Bharath et al. (2011) who argue that bank relationships are only important for smaller borrowers, but measure the value of a relationship based on changes in lending rates over time within bank/firm relationship.

are displayed in Table 8. In column 1, both PD^+ and LGD^+ have independent predictive power for stock returns. A similar pattern emerges in column 2 for bond returns; however, while the signs of the coefficients for PD^+ and LGD^+ are similar in magnitude, both are just below the threshold of statistical significance. These results are consistent with Chousakos, Gorton, and Ordoñez (2020), who show that both PD and LGD affect the value of both debt and equity securities.[18] In contrast, in columns 3 - 4, only the probability of default predicts earnings surprises and earnings returns. This result is consistent with short-term earnings predominantly affecting the likelihood the firm can meet debt payments and avoid default, rather than the liquidation values of the firms' assets.

We next show that the predictability dissipates after one quarter. In Figure 4, we plot the coefficients of EL^+ estimated from (2) with one quarter stock return as the dependent variable, but with horizons of one quarter ahead up to eight quarters ahead (i.e, returns from t to $t+1$, $t+1$ to $t+2$, etc.). The only coefficient that is negative and statistically significant is $t+1$, while the other coefficients are close to zero and statistically insignificant, suggesting that the return predictability only occurs in the first quarter after the increase in expected loss.

4.2 Banks' Private Information and Lending Decisions

For banks, one of primary benefits of producing information is to improve their allocation of credit. In this section, we show that the information advantage documented in the previous section translates to changes in lending behavior. There are two key challenges to identifying the effect of banks' information on their credit allocation decisions. First, it is difficult to isolate changes in lending coming from purely private information versus public information. Second, changes in banks' risk assessments could be correlated with changes in loan demand unrelated to banks' private information. For example, when firms have attractive investment opportunities, this could reduce their credit risk while simultaneously increasing their demand for credit. To alleviate these concerns, we exploit the fact that firms often borrow from multiple banks at once, allowing us to estimate regressions with firm-by-time fixed effects to control for information available to all banks and firm-level loan demand as in Khwaja and Mian (2008). Specifically, we estimate the following regressions:

$$Commitment_{i,b,t} = \beta EL_{i,b,t} + \delta_{b,t} + \alpha_{i,t} + \epsilon_{i,b,t},$$

[18]If LGD affects liquidation values then LGD increases the potential debt capacity of a firm which in turn can raise the value of the equity.

where $Commitment_{i,b,t+k}$ is the loan commitment amount (in logs) from bank b to firm i in quarter t, $EL_{i,b,t}$ is level of the expected loss, and $\delta_{b,t}$ and $\alpha_{i,t}$ are bank-by-time and firm-by-time fixed effects. The coefficient of interest is β which represents how an increase in one bank's assessed expected loss affects its loan commitment amount, compared to other banks lending to the same firm at the same time. The results are displayed in Table 9 where we again double cluster our standard errors by firm and bank-time. In column 1, we estimate the regression without any of the fixed effects. The coefficient is negative and statistically significant with a point estimate of -17.97. We find a similar effect in column (2) when we add bank-by-time fixed effects. In column (3) we include the firm-by-time fixed effects and the coefficient remains negative and statistically significant, but smaller (-6.41). This coefficient implies that an increase in the average cross-sectional dispersion in expected loss (0.28pp) decreases a bank's log commitment amount by 1.77 which is about equal to the average cross-sectional dispersion in log commitment amounts.[19] In column (4), the coefficient is -4.34 and remains statistically significant when we include both firm-by-time and bank-by-time fixed effects. Hence, these results suggests that banks use their information in their lending decisions.

We use firm-time fixed effects to help identify differences in information across banks; however, this means that our results will not capture any information advantage over public markets that is common across banks. We thus view our results as a lower bound on the true effects of bank private information on credit allocation.

These results raise a potential concern that the return predictability we document in Section 4.1 is driven purely by banks' lending decisions. For example, if banks became more pessimistic about firms for purely behavioral reasons, this could result in less lending to those firms, which could then cause the negative stock and bond returns. We address this concern by showing that our main results remain unchanged when we exclude observations in which the bank gave the firm a new loan (Online Appendix Table OA4) or when their loan commitment amounts change by less than 1% from the previous quarter (Online Appendix Table OA5).[20]

4.3 Determinants of Banks' Private Information

Thus far we have taken banks' risk assessments as given. We next explore what factors drive changes in these risk assessments to better understand the determi-

[19] Table 3 contains summary statistics on the cross-sectional dispersion of the risk assessments and commitment amounts.

[20] We choose this latter cutoff because many term loans are amortizing, which can mechanically change committed exposure even in the absence of any changes in lending decisions.

nants of banks' private information. First we examine situations in which banks are more likely to revise their PDs, LGDs and expected losses. To do so, we estimate the following regression:

$$z_{i,b,t} = \Gamma \Delta X_{i,t} + \delta_{b,t} + \gamma_{j,t} + \epsilon_{i,b,t}, \tag{2}$$

where the dependent variable $z_{i,t}$ is a dummy that equals one if either the PD, LGD, or expected loss increase or decrease from $t-1$ to t, i.e., PD^{+}, PD^{-}, etc. We also include changes in firm financials and stock returns from $t-1$ to t, $\Delta X_{i,t}$ to test under which firm conditions these updates are more likely to occur. Once again, we cluster our standard errors by firm and bank/quarter. The results are displayed in Table 10. Column 1 shows that banks increase their PDs following increases in book-to-market and leverage, and following decreases in profitability and stock returns. The coefficient sign flips for all variables in column 2, when we consider PD^{-} as the dependent variable. These results suggests that banks are indeed adjusting their PDs symmetrically in accordance with changes in firms' performances and characteristics. In columns 3 and 4 we include LGD^{+} and LGD^{-} as dependent variables. Here, only the change in profitability seems to affect the likelihood of banks raising LGDs, while higher contemporaneous stock returns reduce the likelihood of banks decreasing LGDs. These results suggest that LGDs are less tied to current firm performance, which may reflect the idea that changes in the liquidation values of firms are slow moving and do not necessarily reflect the most recent developments in the firm. This rationale can also explain why changes in LGD do not seem to predict earnings surprises.

Although decreases in PD do not predict *future* financial market outcomes, they are positively associated with changes in *contemporaneous* equity returns. Hence, when banks reduce their PDs, banks are either receiving positive information at the same time as markets or adjusting their risk metrics in response to the positive news they observe in the markets.

The above tests tell us broadly when banks adjust their risk assessments, but do not explain the actual source of banks' private information because all of the predictors are publicly available to market participants. We next attempt to better understand the sources of banks' informational advantage. On the one hand, banks may be better, or have increased incentives to actively produce information. On the other hand, banks may simply have access to valuable information before markets (Wight et al. (2009)). We believe our results regarding firm size likely reflect banks' information production being higher than the market for smaller firms. Large firms are tracked by many more research analysts and attract greater competition among informed investors. In contrast, the disclosure requirements are typically quite similar across publicly traded firms.

To provide further evidence for this channel, we analyze differences in the adjustment rates of risk assessments across banks. Specifically, we estimate the following regression:

$$z_{i,b,t} = \Gamma X_{i,b,t} + \delta_{b,t} + \alpha_{i,t} + \epsilon_{i,b,t},$$

where the dependent variable $z_{i,b,t}$ is a dummy variable that equals one if the corresponding risk assessment changes and equals zero otherwise, where we refer to these variables as PD^{Δ}, LGD^{Δ} and EL^{Δ}.[21] We include a vector of bank/firm level variables $X_{i,b,t}$, which include the bank's committed exposure amount (in logs), the time since the bank last collected financials from the firm (in months), the time since the bank last audited the firm (in months), the maturity of the loan (in months), the percent of the committed loan amount allocated to term loans versus credit lines, whether the bank specializes in the borrower's industry (from Paravisini, Rappoport, and Schnabl (2023)), whether the bank granted a new loan from $t-1$ to t and dummies that equal one if the whether the firm draws down or pays down their credit lines. We also include firm-by-time fixed effects ($\alpha_{i,t}$) to absorb any information that is available to all banks at the same time. Hence, this regression asks how differences in bank/firm specific factors affect the likelihood of banks updating their risk assessments. We again cluster our standard errors by firm and bank-time. The results are displayed in Table 11.

Across all specifications we find that banks are more likely to update their PDs, LGDs and expected losses when their commitment amount is higher. This result is intuitive, as banks should have a higher incentive to monitor and produce information over the life of the relationship when they have more capital at risk. For example, a 10% increase in the committed amount of a bank, makes it 6pp more likely to update its expected loss, which compares to an unconditional likelihood of updating its expected loss of 36.5%. The coefficients for New Loan are also positive and statistically significant across all specifications. When a bank gives a new loan it is 11.5pp more likely to update its expected loss assessment (column 3). This result is consistent with banks collecting more information when they are putting new capital at stake and hence their incentives to collect information is highest.[22] Finally, when banks are are likely to update their risk assessments whenever firms drawdown or paydown their credit lines. This result points to the possibility of banks also receiving private information before others, which we explore below. Taken together, these results provide support for the idea that banks' information

[21] For example, $PD^{\Delta} = PD^{+} + PD^{-}$.

[22] See also Weitzner and Howes (2021) who show that banks information production incentives are particularly high for new loans and loans in which the bank faces higher potential losses.

advantage is at least partially due to incentive-driven information acquisition.

We next explore the second channel of banks' information advantage, i.e., whether they have access to value-relevant information prior to markets. To do so, we analyze a specific source of early access to information for banks: credit lines. If a firm draws down a credit line, this information is immediately known by the bank whose credit line is drawn, but is not immediately known by other banks or disclosed until the firm's next public filing.[23] Hence, we next test whether PDs, LGDs, and expected losses increase after firms draw down their credit lines. Specifically, we estimate the following regressions:

$$z_{i,b,t} = \beta Drawdown_{i,b,t} + \delta_{b,t} + \alpha_{i,t} + \epsilon_{i,b,t},$$

where our dependent variables are PD^+, LGD^+ and EL^+. Our main independent variable is $Drawdown_{i,b,t}$, which is a dummy variable that equals one if the utilization rate on firms' credit lines increases. We also include firm-by-time fixed effects to see how differential drawdowns affect expected losses across banks for a firm borrowing from multiple banks. The results are displayed in Table 12. In columns 1 - 3, we show the results without firm-quarter fixed effects. In each case, bank drawdowns increase the likelihood of banks increasing their assessed PDs, LGDs and expected losses. For instance, in column 3 a drawdown raises the probability of the bank increases the firm's expected loss by 4.0pp compared to an unconditional mean of 17.2pp. We find similar results in columns 4 - 6, in which we include firm-by-time fixed effects. Hence, these results are consistent with models in which firms draw down credit lines following a negative shock (e.g., Shockley and Thakor (1997) and Holmström and Tirole (1998)), as well as the empirical findings of Mester, Nakamura, and Renault (2007), Jiménez, Lopez, and Saurina (2009), Norden and Weber (2010), Berg, Saunders, and Steffen (2016) and Brown, Gustafson, and Ivanov (2021). Moreoever, these results also show that drawdowns are a source of private information for banks.

If firms are drawing down their credit lines in bad times, we would expect that drawdowns negatively predict future stock returns. To test this, we reestimate a version of (2) with both EL^+ and $Drawdown$ as independent variables. The results are displayed in Table 13. Consistent with drawdowns containing private

[23] If the credit line is syndicated, the firm will typically inform the lead bank that it is drawing the credit line down. The lead bank then communicates this information to other banks in the syndicate, after which the credit line is drawn pro-rata across syndicate members. In our sample, however, a large portion of our firms appear to borrow using multiple different credit lines. We do not observe the syndicate structure in the Y-14Q data; however, we find that in almost half of our firm/quarters, firms borrow from credit lines with interest rate differences of more than 25bps, and about a quarter of firm/quarters have multiple credit lines with differences of maturity of over one month. This suggests that firms are indeed borrowing using different credit lines not part of the same syndicate.

information about firms' prospects, drawdowns predict a 188bp quarterly negative excess stock return (column 1). However, EL^+ still strongly predicts negative stock returns on its own. In column 2, we find that EL^+ still strongly predicts stock returns on its own if we also include an interaction term between EL^+ and $Drawdown$. In column 3, we include bond returns as the dependent variable and drawdowns do not appear to predict bond returns, while increases in expected losses still predict negative excess bond returns even after controlling for drawdowns. In columns 5 and 7, we see a similar pattern for negative earnings surprises and earnings announcement returns as we do for stock returns. Taken together, these results are consistent with banks having both access to private information early while still having an information processing advantage through their risk assessments. Of course we cannot completely rule out that banks have access to other non-public information that is driving all of the predictability in the changes in their credit assessments. However, we believe that these results along with results presented in Table 11 suggest that at least a part of banks' advantage is from information processing.

5 Discussion

Our findings likely represent a lower bound on the true predictability of banks' private risk assessments for several reasons. First, banks only report their risk assessments at quarter end. Therefore, banks may have updated their risk assessments earlier in the quarter and preempted other financial market outcomes; however, the data do not allow us to see this. Second, as mentioned earlier, our main measures of changes in risk assessments are simply dummy variables which equal one if the expected loss increases or decreases. While we believe this is the most straightforward approach given the complexity in estimating the relationship between expected losses and market outcomes, we inevitably lose information from these risk assessments by using this approach. Finally, for more opaque firms that do not have publicly traded equity or debt, we would expect banks' informational advantage to be even stronger.

A potential concern with the risk assessments we use is that banks may misrepresent them (e.g., Plosser and Santos (2018) and Behn, Haselmann, and Vig (2022)). The fact we use bank-by-time fixed effects throughout should alleviate this concern because we would absorb any aggregate bank-level incentives to misreport. To influence our results, banks would need to have an incentive to misrepresent differentially across loans; and even in the event such systematic misreporting occurred, it would bias our results toward zero.

6 Conclusion

Financial intermediation theory predicts that banks' information production and monitoring creates asymmetric information between banks and broader financial markets. Despite the importance of this class of theories, testing for asymmetric information is extremely challenging because banks' private information is unobservable.

In this paper we address this challenge by using a unique dataset that provides direct access to banks' private credit assessments. We show that changes in banks' assessed expected losses predict stock returns, bond returns and analyst earnings surprises. Consistent with theory, we show that banks' specialize in collecting negative information. Moreover, banks' information advantage is stronger for smaller firms and growth firms. Because of this, we conjecture that banks' informational advantage is even stronger for smaller, more opaque, non-publicly traded firms. We also identify sources of private information for banks and argue that these arise from both active information production and having access to non-public information prior to markets. Finally, we show that banks use their private information to allocate credit to firms.

The evidence in this paper provides strong support for one of the central tenets of financial intermediation theory in which banks act as informed finance. More broadly, we provide direct evidence of information asymmetries in financial markets.

Finally, we believe our paper validates the Y-14Q reported risk assessments as measures of banks' private information, which opens up many avenues of future research to explore the determinants and implications of banks' private information.

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Figure 1: Distributions of Risk Assessments

This figure plots the distribution of risk assessments, i.e., PD, LGD and expected loss, aggregated to the firm-bank-quarter level. For readability, the PD and expected loss distributions are truncated at ±5% and ±2.5%, respectively.

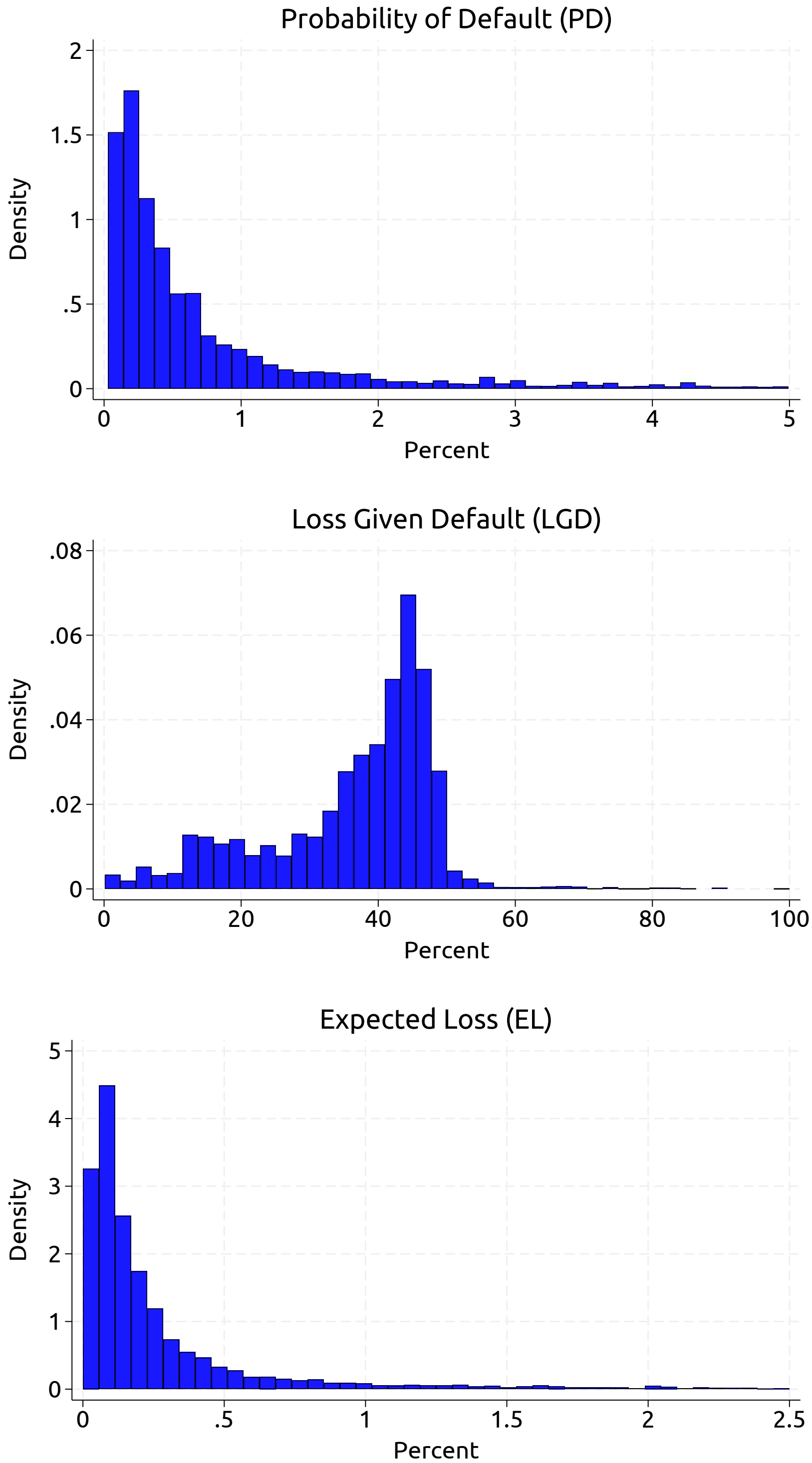

Figure 2: Distributions of Changes in Risk Assessments

This figure shows histograms of nonzero values of changes in PD, LGD and expected losses, i.e., ΔPD, ΔLGD, and ΔEL, aggregated to the firm-bank-quarter level. For readability, the ΔPD, ΔEL, and ΔLGD distributions are truncated at ±2%, ±25%, and ±0.25%, respectively.

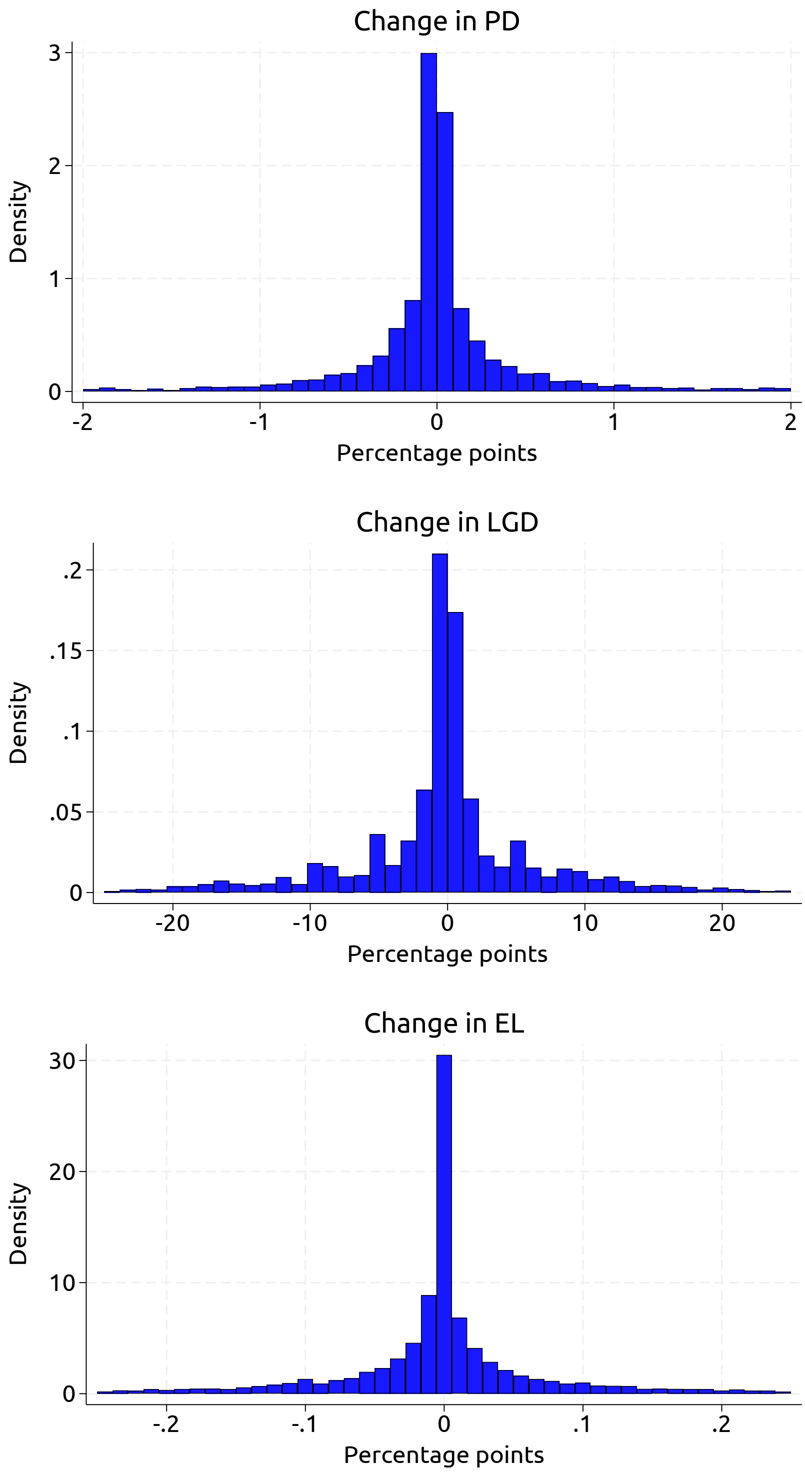

Figure 3: Distribution of Bank Relationships

This figure plots the distribution of the number of banks per firm collapsed to the firm-quarter level.

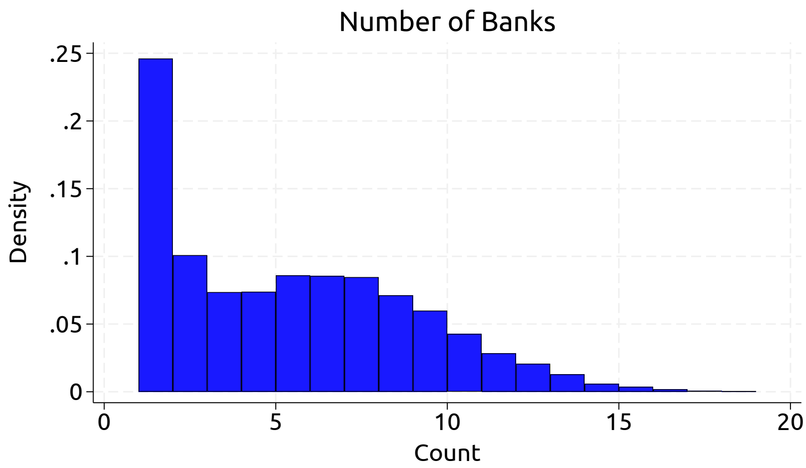

Figure 4: Equity Return Predictability Over Different Horizons

This figure tests how long the stock return predictability of changes in banks' risk assessments lasts. Specifically, it plots the coefficient estimates of EL^+ from the regression equation (1), with quarterly equity returns of different horizons as dependent variables (i.e., one quarter ahead, two quarters ahead, etc). Vertical lines indicate 95% confidence intervals calculated using standard errors that are double clustered by firm and bank-time.

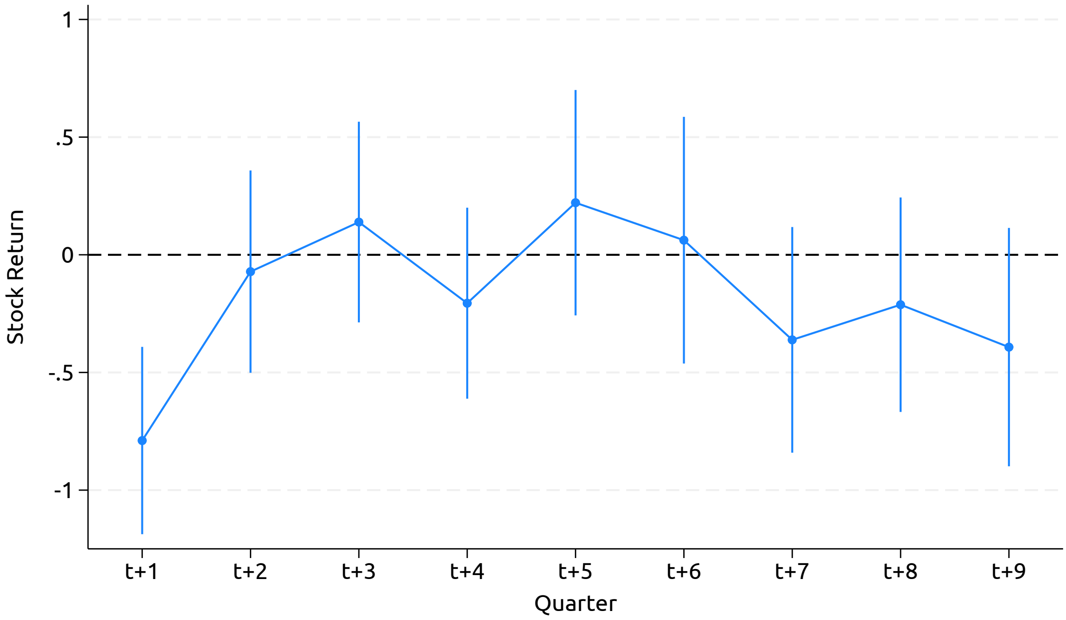

Table 1: Sample Comparison to CRSP/Compustat

This table compares our final sample, collapsed to the firm/quarter level, with a standard CRSP/Compustat merged sample. Appendix Section A contains all variable definitions. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively based on a t-test.

	Sample			CRSP/Compustat			Difference	
	Mean	Median	N	Mean	Median	N	Mean	Median
Market Cap ($bn)	12.952	2.050	27,478	7.967	0.901	48,193	4.985***	1.149***
Book-to-Market	0.515	0.404	26,399	0.526	0.386	45,098	-0.011***	0.018***
ROA	0.129	0.126	27,338	0.013	0.099	47,383	0.116***	0.027***
Leverage	0.449	0.439	27,358	0.412	0.376	47,480	0.037***	0.063***

Table 2: Summary Statistics

This table contains summary statistics. Section A of the Appendix includes detailed definitions of all of our variables and Section 3 explains our data filters.

	Mean	SD	10%	Median	90%	N
PD (pp)	1.013	2.789	0.070	0.300	1.910	136,279
LGD (pp)	38.941	13.208	20.000	41.000	51.000	136,279
Expected Loss (pp)	0.327	0.902	0.029	0.102	0.600	136,279
ΔPD (pp)	0.030	1.362	-0.020	0.000	0.010	123,731
PD^+	0.109	0.312	0.000	0.000	1.000	123,731
PD^-	0.120	0.325	0.000	0.000	1.000	123,731
ΔLGD (pp)	-0.078	4.373	-0.310	0.000	0.036	123,731
LGD^+	0.116	0.320	0.000	0.000	1.000	123,731
LGD^-	0.133	0.340	0.000	0.000	1.000	123,731
ΔEL (pp)	0.009	0.497	-0.018	0.000	0.015	123,731
EL^+	0.172	0.377	0.000	0.000	1.000	123,731
EL^-	0.193	0.395	0.000	0.000	1.000	123,731
Drawdown	0.261	0.439	0.000	0.000	1.000	123,731
Stock Return (pp)	0.812	19.743	-21.361	1.637	20.897	136,279
Bond Return (pp)	0.984	5.257	-2.570	1.135	4.379	64,263
Earnings Return (pp)	0.128	8.351	-9.210	0.188	9.208	133,164
Negative Surprise	0.269	0.443	0.000	0.000	1.000	124,912
Positive Surprise	0.725	0.446	0.000	1.000	1.000	124,912
Book-to-Market	0.482	0.377	0.119	0.384	0.945	131,149
ROA	0.138	0.074	0.064	0.131	0.231	135,639
Leverage	0.501	0.226	0.212	0.488	0.809	135,816
Months Since Financial Statement	7.536	7.144	3.000	6.000	15.000	133,390
Months Since Audit	12.552	27.857	3.000	9.000	15.000	115,867
Market Cap ($bn)	18.460	51.623	0.526	3.815	42.077	136,279

Table 3: Cross-Sectional Dispersion in Risk Assessments

This table shows summary statistics for the dispersion, i.e., cross-sectional standard deviation, of risk assessments and loan commitment amounts at the firm-quarter level across banks. Appendix Section A contains all variable definitions.

	Mean	10%	Median	90%	N
PD (pp)	0.777	0.047	0.256	1.655	20,714
LGD (pp)	8.984	3.670	8.170	15.127	20,714
EL (pp)	0.276	0.019	0.101	0.552	20,714
Committed ($ mil)	50.914	7.352	28.896	97.706	20,714
ΔPD (pp)	0.303	0.000	0.027	0.521	19,150
ΔLGD (pp)	2.379	0.000	0.809	6.731	19,150
ΔEL (pp)	0.120	0.000	0.016	0.215	19,150

Table 4: Correlations Across Risk Assessment Adjustments

This table contains correlation matrices containing changes in banks' risk assessments. Panel A includes upwards estimates, i.e., PD^+ , LGD^+ and EL^+, while Panel B includes downward estimates.

Panel A: Upward Adjustments

Variables	PD_t^+	LGD_t^+	EL_t^+	PD_{t-1}^+	LGD_{t-1}^+	EL_{t-1}^+
PD_t^+	1.000					
LGD_t^+	0.119	1.000				
EL_t^+	0.715	0.609	1.000			
PD_{t-1}^+	0.039	0.022	0.038	1.000		
LGD_{t-1}^+	0.007	0.114	0.079	0.124	1.000	
EL_{t-1}^+	0.027	0.081	0.072	0.720	0.609	1.000

Panel B: Downward Adjustments

Variables	PD_t^-	LGD_t^-	EL_t^-	PD_{t-1}^-	LGD_{t-1}^-	EL_{t-1}^{--}
PD_t^-	1.000					
LGD_t^-	0.160	1.000				
EL_t^-	0.702	0.654	1.000			
PD_{t-1}^-	0.008	0.009	0.012	1.000		
LGD_{t-1}^-	0.001	0.102	0.075	0.159	1.000	
EL_{t-1}^-	-0.001	0.074	0.055	0.716	0.641	1.000

Table 5: Changes in Expected Losses Predict Financial Market Outcomes

This table tests whether changes in banks' expected losses predict next quarter stock returns, bond returns, earnings surprises, and earnings announcement returns. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parenthesis and are calculated using robust standard errors clustered by firm and bank/quarter. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Stock Return	Bond Return	Negative Surprise	Earnings Return
	(1)	(2)	(3)	(4)
EL^{+}	-0.789***	-0.198**	1.832***	-0.222***
	(3.896)	(2.024)	(3.654)	(2.734)
EL^{-}	-0.233	0.088	0.266	0.073
	(1.343)	(1.342)	(0.634)	(1.067)
Book-to-Market	-0.073	0.283	4.112**	0.755***
	(0.118)	(0.737)	(2.326)	(3.449)
ROA	0.709	0.790	-3.489	0.936
	(0.358)	(0.773)	(0.526)	(1.048)
Leverage	-0.585	0.073	2.402	0.434
	(0.766)	(0.223)	(1.052)	(1.528)
Log(Market Cap)	0.209*	0.022	-3.711***	-0.055
	(1.819)	(0.407)	(10.564)	(1.427)
Lagged Stock Return	-0.014		-0.163***	0.313***
	(1.093)		(6.215)	(34.449)
Lagged Bond Return		-0.085**		
		(1.999)		
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	118,901	54,741	109,051	116,340
R-squared	0.37	0.49	0.08	0.33

Table 6: Cross-Sectional Variation in Predictability

This table tests cross-sectional differences in the predictability of changes in banks' expected losses. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parenthesis and are calculated using robust standard errors clustered by firm and bank/quarter. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Stock Return	Bond Return	Negative Surprise	Earnings Return
	(1)	(2)	(3)	(4)
EL^+	-5.988***	-2.005	13.896***	-1.080
	(2.728)	(1.547)	(2.727)	(1.279)
EL^+ × Book/Market	1.522**	-0.233	-3.605**	-0.082
	(2.189)	(0.471)	(2.492)	(0.321)
EL^+ × ROA	3.821	1.273	-4.924	-0.461
	(1.292)	(0.709)	(0.758)	(0.374)
EL^+ × Leverage	0.361	-0.202	1.864	-0.105
	(0.373)	(0.370)	(0.908)	(0.286)
EL^+ × Log(Market Cap)	0.254**	0.108	-0.698**	0.065
	(2.023)	(1.464)	(2.264)	(1.327)
EL^+ × Lagged Stock Return	-0.005		-0.002	0.009
	(0.419)		(0.091)	(1.066)
EL^+ × Lagged Bond Return		0.090**		
		(2.031)		
Book-to-Market	-0.395	0.359	4.878***	0.779***
	(0.632)	(0.974)	(2.714)	(3.698)
ROA	0.006	0.630	-2.518	1.024
	(0.003)	(0.743)	(0.379)	(1.178)
Leverage	-0.673	0.137	2.141	0.461*
	(0.864)	(0.460)	(0.930)	(1.669)
Log(Market Cap)	0.166	0.000	-3.594***	-0.068*
	(1.436)	(0.002)	(10.206)	(1.789)
Lagged Stock Return	-0.013		-0.162***	0.311***
	(0.976)		(6.108)	(34.815)
Lagged Bond Return		-0.114***		
		(2.825)		
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	118,901	54,741	109,051	116,340
R-squared	0.37	0.49	0.08	0.33

Table 7: Stock Return Predictability Across Size Quintiles

This table tests the next quarter stock return predictability across firm size quintiles. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parenthesis and are calculated using robust standard errors clustered by firm and bank/quarter. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
	(1)	(2)	(3)	(4)	(5)
EL^+	-1.870**	-0.849**	-0.856***	-0.599**	0.090
	(2.425)	(2.076)	(3.039)	(2.260)	(0.389)
Book-to-Market	3.342**	-0.622	-0.666	-2.665***	-1.371
	(2.387)	(0.481)	(0.605)	(3.111)	(1.148)
ROA	8.473	-1.268	-1.115	-4.808	-0.329
	(1.158)	(0.277)	(0.230)	(1.605)	(0.122)
Leverage	4.246	-2.055	-2.261	-0.762	-0.191
	(1.446)	(1.209)	(1.608)	(0.720)	(0.189)
Log(Market Cap)	1.185*	0.418	-1.500	1.329**	0.407**
	(1.894)	(0.381)	(1.462)	(2.246)	(2.191)
Lagged Stock Return	-0.039	-0.020	0.005	-0.025	-0.006
	(1.458)	(0.965)	(0.264)	(1.480)	(0.329)
Bank-Quarter FE	YES	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES	YES
Observations	10,145	18,642	24,379	29,354	33,728
R-squared	0.38	0.48	0.49	0.53	0.51

Table 8: Is PD or LGD Driving the Predictability?

This table tests whether changes in banks' PDs, LGDs or both predict next quarter stock returns, bond returns, earnings surprises and earnings announcement returns. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parenthesis and are calculated using robust standard errors clustered by firm and bank/quarter. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Stock Return	Bond Return	Negative Surprise	Earnings Return
	(1)	(2)	(3)	(4)
PD^+	-0.469*	-0.181	1.940***	-0.272**
	(1.905)	(1.480)	(3.207)	(2.389)
LGD^+	-0.604**	-0.171	0.513	-0.069
	(2.567)	(1.612)	(0.921)	(0.849)
Book-to-Market	-0.077	0.282	4.087**	0.757***
	(0.126)	(0.736)	(2.310)	(3.462)
ROA	0.750	0.786	-3.565	0.934
	(0.378)	(0.768)	(0.537)	(1.046)
Leverage	-0.603	0.080	2.414	0.438
	(0.787)	(0.244)	(1.058)	(1.544)
Log(Market Cap)	0.211*	0.021	-3.714***	-0.056
	(1.836)	(0.387)	(10.564)	(1.453)
Lagged Stock Return	-0.014		-0.162***	0.313***
	(1.088)		(6.200)	(34.436)
Lagged Bond Return		-0.085**		
		(2.000)		
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	118,901	54,741	109,051	116,340
R-squared	0.37	0.49	0.08	0.33

Table 9: Do Banks Use Their Information to Allocate Credit?

This table shows the relationship between banks' risk assessments and their committed exposure. The dependent variable in each regression is the log of a bank's committed exposure to a borrower. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parenthesis and are calculated using robust standard errors clustered by firm and bank/quarter. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Committed			
	(1)	(2)	(3)	(4)
Expected Loss	-17.968***	-17.453***	-6.414***	-4.342***
	(9.234)	(8.938)	(5.705)	(4.290)
Bank-Quarter FE	NO	YES	NO	YES
Firm-Quarter FE	NO	NO	YES	YES
Observations	136,279	136,260	129,515	129,496
R-squared	0.02	0.11	0 .51	0.62

Table 10: Firm Performance and Contemporaneous Changes in Banks' Risk Assessments

This table tests whether changes in firm performance are related to contemporaneous changes in bank risk assessments. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parenthesis and are calculated using robust standard errors clustered by firm and bank/quarter. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	PD^{+}	PD^{-}	LGD^{+}	LGD^{-}	EL^{+}	EL^{-}
	(1)	(2)	(3)	(4)	(5)	(6)
Change in Book/Market	0.099***	-0.051***	0.008	-0.013	0.091***	-0.058***
	(7.034)	(5.327)	(0.709)	(1.137)	(5.958)	(4.762)
Change in ROA	-1.242***	0.732***	-0.122*	0.022	-1.269***	0.816***
	(11.576)	(8.412)	(1.874)	(0.345)	(11.315)	(8.950)
Change in Leverage	0.182***	-0.154***	-0.039	0.037	0.163***	-0.111***
	(5.106)	(5.014)	(1.540)	(1.413)	(4.118)	(3.261)
Lagged Stock Return	-0.001***	0.000**	0.000	-0.000*	-0.001***	0.000
	(6.124)	(2.480)	(0.006)	(1.742)	(4.425)	(0.718)
Bank-Quarter FE	YES	YES	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES	YES	YES
Observations	118,251	118,251	118,251	118,251	118,251	118,251
R-squared	0.19	0.26	0.27	0.28	0.16	0.23

Table 11: Bank-Level Factors Affecting the Likelihood of Banks' Adjusting Their Risk Assessments

This table tests how various bank-level factors affect the likelihood of banks updating their internal risk assessments. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parenthesis and are calculated using robust standard errors clustered by firm and bank/quarter. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	PD^{Δ}	LGD^{Δ}	EL^{Δ}
	(1)	(2)	(3)
Committed	0.021***	0.059***	0.060***
	(5.073)	(9.539)	(10.695)
Months Since Financial Statement	-0.002***	-0.000	-0.001**
	(3.638)	(0.374)	(2.168)
Months Since Audit	-0.000	-0.000	-0.001*
	(1.576)	(0.834)	(1.884)
Maturity (months)	-0.000	-0.001***	-0.001**
	(0.874)	(2.972)	(2.505)
Term Loan (% of Total $)	0.020	0.047**	0.037*
	(1.466)	(2.112)	(1.823)
Specialize	-0.005	-0.007	-0.008
	(0.739)	(0.636)	(0.781)
New Loan	0.044***	0.103***	0.115***
	(4.795)	(9.778)	(10.816)
Drawdown	0.025***	0.120***	0.120***
	(3.337)	(9.708)	(9.813)
Paydown	0.025***	0.097***	0.098***
	(3.721)	(8.511)	(8.871)
Bank-Quarter FE	YES	YES	YES
Firm-Quarter FE	YES	YES	YES
Observations	93,163	93,163	93,163
R-squared	0.48	0.54	0.49

Table 12: Credit Line Drawdowns and Bank Risk Assessments

This table tests whether credit line drawdowns predict changes in banks' risk assessments. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parenthesis and are calculated using robust standard errors clustered by firm and bank/quarter. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	PD^+	LGD^+	EL^+	PD^+	LGD^+	EL^+
	(1)	(2)	(3)	(4)	(5)	(6)
Drawdown	0.000***	0.027***	0.040***	0.009	0.039***	0.033***
	(2.983)	(9.134)	(11.208)	(1.615)	(5.927)	(4.779)
Bank-Quarter FE	YES	YES	YES	YES	YES	YES
Firm-Quarter FE	NO	NO	NO	YES	YES	YES
Observations	115,814	115,814	115,814	110,446	110,446	110,446
R-squared	0.03	0.27	0.16	0.26	0.18	0.23

Table 13: Changes in Expected Losses, Financial Market Outcomes and Credit Line Drawdowns

This table tests whether both credit line drawdowns and changes in expected losses separately predict next quarter stock returns, bond returns, earnings surprises and earnings announcement returns. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parenthesis and are calculated using robust standard errors clustered by firm and bank/quarter. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Stock Return		Bond Return		Negative Surprise		Earnings Return	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Drawdown	-1.881***	-1.740***	0.041	0.057	2.513***	2.430***	-0.219*	-0.211*
	(7.453)	(6.894)	(0.318)	(0.500)	(3.160)	(2.994)	(1.884)	(1.868)
EL^{+}	-0.595***	-0.319	-0.231**	-0.203*	1.618***	1.454***	-0.199**	-0.182**
	(3.000)	(1.377)	(2.253)	(1.948)	(3.368)	(2.701)	(2.529)	(1.990)
Drawdown × EL^{+}		-0.847**		-0.097		0.507		-0.052
		(2.509)		(0.401)		(0.578)		(0.355)
Book-to-Market	-0.075	-0.076	0.266	0.267	4.651**	4.652**	0.715***	0.715***
	(0.117)	(0.120)	(0.669)	(0.670)	(2.523)	(2.523)	(3.116)	(3.115)
ROA	2.026	2.022	0.794	0.796	-0.898	-0.895	0.897	0.897
	(0.974)	(0.972)	(0.756)	(0.758)	(0.128)	(0.127)	(0.951)	(0.951)
Leverage	-0.380	-0.380	0.056	0.056	2.481	2.481	0.437	0.437
	(0.482)	(0.482)	(0.162)	(0.164)	(1.048)	(1.048)	(1.464)	(1.464)
Log(Market Cap)	0.151	0.153	0.028	0.028	-3.631***	-3.632***	-0.067*	-0.067*
	(1.256)	(1.266)	(0.472)	(0.475)	(10.076)	(10.078)	(1.656)	(1.654)
Lagged Stock Return	-0.017	-0.017			-0.166***	-0.166***	0.314***	0.314***
	(1.235)	(1.242)			(6.066)	(6.063)	(32.573)	(32.564)
Lagged Bond Return			-0.089**	-0.089**				
			(1.994)	(2.001)				
Bank-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	111,384	111,384	51,977	51,977	102,196	102,196	109,009	109,009
R-squared	0.39	0.39	0.49	0.49	0.09	0.09	0.33	0.33

Appendix A. Variable Definitions

ΔEL: The change in Expected Loss from $t-1$ to t, from Y-14,

Bond Return: firm-level quarterly bond return (in pp), value weighted by the size of the bond, from Bond Returns by WRDS/TRACE.

Book-to-market: book value of equity as a fraction of market value of equity, winsorized at [1%, 99%], from Compustat.

Committed: Total loan commitment amount, in logs, aggregated at the bank/firm level, from Y-14.

Drawdown: A dummy variable that equals one if the utilization rate on a firms' credit lines increases, from Y-14Q.

Earnings Return: Cumulative abnormal return (in percentage points) during the [0,1] window around the earnings announcement date calculated using the CRSP value-weighted market return, from CRSP.

Expected Loss: Probability of default times loss given default weight by the committed dollar amount of each loan at the bank/firm/quarter level, from Y-14Q.

EL^{+}: A dummy variable that equals one if Expected Loss increases from previous quarter and equals zero otherwise, from Y-14Q. If the superscript is $-$ or δ instead, the variable is a dummy that equals one if EL decreases or changes, respectively.

Market Cap: Market capitalization in billions, from CRSP.

New Loan: A dummy variable that equals one if the bank gives the firm a new loan in the quarter, from Y-14.

Leverage: debt/capital, winsorized at [1%, 99%], from Compustat.

LGD^{+}: A dummy variable that equals one if LGD increases from previous quarter and equals zero otherwise, from Y-14Q. If the superscript is $-$ or δ instead, the variable is a dummy that equals one if LGD decreases or changes, respectively.

Loss Given Default (LGD): The bank's estimated loss given default per unit of loan weight by the committed dollar amount of each loan at the bank/firm/quarter level, from Y-14Q.

Maturity: Remaining maturity in months weight by the committed dollar amount of each loan at the bank/firm/quarter level, from Y-14Q.

Months Since Audit: The number of months since the bank last audited the firm, from Y-14Q.

Months Since Financial Statement: The number of months since the bank last collected financials, from Y-14Q.

Negative Earnings Surprise: Dummy that equals one if the earnings announcement comes in below consensus estimates, from IBES.

Paydown: A dummy variable that equals one if the utilization rate on a firms' credit lines decreases, from Y-14Q.

PD^{+}: A dummy variable that equals one if PD increases from previous quarter and equals zero otherwise, from Y-14Q. If the superscript is $-$ or δ instead, the variable is a dummy that equals one if PD decreases or changes, respectively.

Probability of Default (PD): The bank's expected annual default rate over the life of the loan weight by the committed dollar amount of each loan at the bank/firm/quarter level, trimmed if $PD = 0$ or $PD = 1$, from Y-14Q.

ROA: Operating Income Before Depreciation as a fraction of average Total Assets based on most recent two periods, winsorized at [1%, 99%], from Compustat.

Specialize: Dummy that equals one if the bank specializes in the industry of the borrower as defined by Paravisini, Rappoport, and Schnabl (2023), from Y-14Q.

Stock Return: Quarterly stock return (in percentage points), from CRSP.

Term Loan: The fraction of committed loan amount allocated to term loans relative to credit lines at the bank/firm/quarter level, from Y-14Q.

Online Appendix

Table OA1: Fama-Macbeth Regressions

This table tests whether changes in banks' PDs, LGDs or both predict next quarter stock returns, bond returns and earnings surprises using Fama-Macbeth regressions. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Stock Return	Bond Return	Negative Surprise	Earnings Return
	(1)	(2)	(3)	(4)
EL^{+}	−0.370	−0.092	1.532***	−0.189*
	(1.622)	(0.742)	(3.659)	(1.953)
EL^{-}	−0.151	0.064	0.501*	0.135**
	(0.879)	(0.866)	(1.739)	(2.765)
Book-to-Market	−1.590	−0.616	7.606***	1.136***
	(1.067)	(0.751)	(5.569)	(3.226)
ROA	−4.165	−1.622	0.633	1.447
	(0.975)	(1.109)	(0.109)	(1.352)
Leverage	−1.190	−0.184	6.891***	0.477
	(0.914)	(0.399)	(3.042)	(1.594)
Log(Market Cap)	0.200	0.044	−3.650***	−0.068
	(0.825)	(0.341)	(16.127)	(0.859)
Lagged Stock Return	0.002		−0.187***	0.305***
	(0.104)		(6.570)	(29.565)
Lagged Bond Return		−0.041		
		(0.552)		
Bank FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	115,364	54,746	106,258	112,911
R-squared	0.06	0.23	0.04	0.31

Table OA2: Predictability Excluding Bank-Quarter Fixed Effects

This table tests whether changes in banks' expected losses predict next quarter stock returns, bond returns and earnings surprises, excluding bank-quarter fixed effects. T-statistics are shown below the parameter estimates in parenthesis and are calculated using robust standard errors clustered by firm and bank/quarter. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Stock Return	Bond Return	Negative Surprise	Earnings Return
	(1)	(2)	(3)	(4)
EL^+	-0.562^{***}	-0.169^{**}	1.461^{***}	-0.168^{**}
	(3.392)	(2.105)	(3.656)	(2.447)
EL^-	-0.003	0.114^{**}	0.157	0.118^{**}
	(0.024)	(2.147)	(0.497)	(2.212)
Book-to-Market	-0.085	0.271	4.022^{**}	0.757^{***}
	(0.138)	(0.703)	(2.264)	(3.433)
ROA	0.728	0.772	-3.238	0.889
	(0.364)	(0.744)	(0.488)	(0.996)
Leverage	-0.654	0.065	2.393	0.450
	(0.860)	(0.195)	(1.043)	(1.584)
Log(Market Cap)	0.210^{*}	0.014	-3.795^{***}	-0.060
	(1.903)	(0.270)	(10.805)	(1.597)
Lagged Stock Return	-0.014		-0.161^{***}	0.312^{***}
	(1.096)		(6.153)	(34.291)
Lagged Bond Return		-0.086^{**}		
		(1.978)		
Industry-Quarter FE	YES	YES	YES	YES
Observations	118,920	54,761	109,071	116,359
R-squared	0.37	0.48	0.08	0.33

Table OA3: Portfolio Sorts

At the end of each quarter we sort stocks into portfolios based on whether their expected loss increases (EL^+), decreases (EL^-) or remains the same (EL^{NC}). Because stocks may lend to multiple banks there can be multiple observations of the same firm in different portfolios. This table reports equal weighted monthly stock returns of each portfolio. 3-Factor is the Fama-French three-factor model and 4-Factor is the Carhart four-factor model.

	Returns	3-Factor	4-Factor
EL^+	0.0000	0.0012	0.0012
EL^{NC}	0.0026	0.0036	0.0036
EL^-	0.0020	0.0032	0.0032
$EL^+ - EL^{NC}$	-0.0026	-0.0024	-0.0024
(t-stat)	-2.90	-2.76	-2.70
$EL^+ - EL^-$	-0.0020	-0.0020	-0.0019
(t-stat)	-3.01	-3.03	-2.98
N	60	60	60

Table OA4: Do Changes in Expected Losses Predict Financial Market Outcomes? (Excluding New Loans)

This table tests whether changes in banks' expected losses predict next quarter stock returns, bond returns, earnings surprises and earnings announcement returns excluding quarterly observations which recorded at least one new loan for a given firm-bank pair. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parenthesis and are calculated using robust standard errors clustered by firm and bank/quarter. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Stock Return	Bond Return	Negative Surprise	Earnings Return
	(1)	(2)	(3)	(4)
EL^{+}	-0.732***	-0.180*	1.592***	-0.202**
	(3.306)	(1.661)	(3.079)	(2.330)
EL^{-}	-0.183	0.106	0.068	0.114*
	(1.040)	(1.557)	(0.162)	(1.661)
Book-to-Market	-0.150	0.314	4.000**	0.764***
	(0.242)	(0.792)	(2.275)	(3.523)
ROA	0.807	0.773	-2.832	0.925
	(0.402)	(0.731)	(0.423)	(1.020)
Leverage	-0.634	0.130	2.585	0.409
	(0.818)	(0.380)	(1.134)	(1.415)
Log(Market Cap)	0.197*	0.020	-3.722***	-0.053
	(1.681)	(0.359)	(10.494)	(1.352)
Lagged Stock Return	-0.015		-0.164***	0.311***
	(1.101)		(6.164)	(34.031)
Lagged Bond Return		-0.089**		
		(2.038)		
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	112,120	51,177	102,685	109,695
R-squared	0.37	0.49	0.08	0.33

Table OA5: Do Changes in Expected Losses Predict Financial Market Outcomes? (Unchanged Commitments)

This table tests whether changes in banks' expected losses predict next quarter stock returns, bond returns, earnings surprises and earnings announcement returns using only observations in which the quarterly total committed loan volume for a given firm-bank pair was within 1% of its previous quarter's value. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parenthesis and are calculated using robust standard errors clustered by firm and bank/quarter. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Stock Return	Bond Return	Negative Surprise	Earnings Return
	(1)	(2)	(3)	(4)
EL^{+}	-0.605**	-0.145	1.692***	-0.271**
	(2.550)	(1.213)	(2.922)	(2.580)
EL^{-}	-0.178	0.018	0.191	0.074
	(0.825)	(0.240)	(0.382)	(0.792)
Book-to-Market	-0.507	0.229	3.846**	0.770***
	(0.726)	(0.535)	(2.098)	(3.453)
ROA	-0.518	0.435	0.991	1.364
	(0.237)	(0.443)	(0.139)	(1.431)
Leverage	-0.735	0.290	2.146	0.415
	(0.896)	(0.918)	(0.903)	(1.306)
Log(Market Cap)	0.191	0.017	-3.831***	-0.085*
	(1.588)	(0.307)	(10.233)	(1.881)
Lagged Stock Return	-0.005		-0.156***	0.308***
	(0.222)		(5.070)	(30.038)
Lagged Bond Return		-0.054		
		(1.012)		
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	84,134	39,336	77,426	82,356
R-squared	0.39	0.53	0.09	0.33

Table OA6: Do Changes in Expected Losses Predict Financial Market Outcomes? (Excluding Firms with Observable Loan Prices)

This table tests whether changes in banks' expected losses predict next quarter stock returns, bond returns, earnings surprises and earnings announcement returns excluding all firms that have a loan with an observable secondary market price at any point in the sample. We obtain secondary market loan prices from the LPC Loan Pricing by Refinitiv. We merge the data to Dealscan and then merge Dealscan to Compustat using the Roberts Dealscan-Compustat Linking Database as well as the matching protocol from Cohen et al. (2021). Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parenthesis and are calculated using robust standard errors clustered by firm and bank/quarter. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Stock Return	Bond Return	Negative Surprise	Earnings Return
	(1)	(2)	(3)	(4)
EL^{+}	-0.661***	-0.168*	1.866***	-0.203**
	(3.218)	(1.720)	(3.647)	(2.381)
EL^{-}	-0.216	0.075	0.455	0.047
	(1.213)	(1.089)	(1.025)	(0.654)
Book-to-Market	-0.462	0.241	4.702**	0.758***
	(0.721)	(0.589)	(2.495)	(3.358)
ROA	-0.588	0.245	-3.292	1.048
	(0.280)	(0.230)	(0.459)	(1.212)
Leverage	-0.630	-0.032	1.036	0.496*
	(0.802)	(0.094)	(0.413)	(1.682)
Log(Market Cap)	0.206*	0.047	-3.505***	-0.062
	(1.788)	(0.822)	(9.444)	(1.558)
Lagged Stock Return	-0.009		-0.158***	0.313***
	(0.627)		(5.584)	(31.052)
Lagged Bond Return		-0.076*		
		(1.683)		
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	106,869	50,916	97,712	104,705
R-squared	0.39	0.50	0.09	0.34