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

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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 access to 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, and that banks use this information to allocate credit. Our findings show that banks' information production and monitoring create an information advantage over financial markets, even among publicly traded firms.

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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, classic theories of financial intermediation predict that banks act as "informed investors" relative to public markets.[1] Empirically testing these theories, however, is notoriously challenging,[2] as it requires simultaneously (i) observing banks' information, which is inherently unobservable; (ii) distinguishing banks' private information from information already present in broader financial markets; and (iii) identifying ex post outcomes that reveal whether informational differences are economically meaningful.[3]

In this paper, we use supervisory data on banks' private risk assessments for corporate loans in the US to address these challenges and directly test banks' role as informed finance. We show that changes in banks' internal risk assessments, which are not observable to other market participants, predict *future* stock returns, bond returns, and analyst earnings surprises. Intuitively, if banks had no information advantage over public markets, then changes in these risk assessments should not predict future asset prices, as current prices would already reflect banks' information. Therefore, our results provide direct evidence that banks possess valuable private information that broader financial markets do not. In addition to documenting the existence of asymmetric information, our data also allow us to answer other important questions that previous research has not been able to address. For instance, how valuable is this private information? How do banks actually obtain this information? For which types of firms is banks' information advantage strongest? The answers to these questions have vast implications for capital allocation across firms and can help guide policies meant to spur credit growth and maintain financial stability.

Our analysis uses the Federal Reserve's Y-14Q Schedule H.1 data, which include all corporate loans over one million dollars extended by large bank holding companies in the United States. These banks are required to report quarterly estimates 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 (EL = PD $\times$ LGD) variable for each bank-firm relationship, weighted by loan size. We first show that when a bank increases its assessed expected loss for a firm (i.e., becomes more pessimistic), this predicts underperformance of 77 and 20 basis points (bps) per quarter for stock

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

[2]This challenge extends to testing asymmetric information more generally; see Salanié (2017) for a discussion in the context of insurance markets.

[3]For example, a bank may assess a firm's credit risk differently from public markets due to subjective beliefs rather than superior private information.

and bond returns, respectively.[4] In contrast, we find no effect when banks adjust their expected losses downwards. This asymmetry is consistent with theories in which banks have stronger incentives to produce information when the firm is performing poorly.[5]

This underperformance is concentrated around earnings announcements. Upward adjustments in expected losses increase the likelihood of negative earnings surprises by about 2 percentage points (about 7% of its average), and 20bps of the 77bps of equity underperformance over the quarter occurs on the two days around the earnings announcement. The fact that annualized abnormal returns on earnings announcement days are close to 11 times higher than on non-earnings days (25.6% versus 2.4%) suggests that a large component of banks' private information over the previous quarter becomes public exactly on the earnings announcement date.

We next show that the return predictability is stronger among firms with lower market capitalizations (i.e., small firms) and lower book-to-market ratios (i.e., growth firms). These results are intuitive, as such firms are typically more opaque, making bank debt a more critical source of capital. Moreover, when we place firms into size quintiles, the smallest quintile underperforms by 174bps 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 risk assessments reflect banks' private information, 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 as in Khwaja and Mian (2008). These specifications allow us to isolate changes in lending behavior that arise from differences in bank-specific beliefs or private information. We find a negative relationship between banks' risk assessments and their committed loan volumes, suggesting that banks use this information to allocate credit to firms.

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 that predict the likelihood that banks update 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 more likely to update their internal risk assessments when their incentives to do so are stronger. For example, we find a positive relationship between banks' total loan exposure to a borrower and the likelihood of updating their risk assessments. We

[4]We stress that investors cannot follow this strategy without access to banks' *private* information. Moreover, banks themselves are unlikely to systematically profit from this information through proprietary trading, as they are legally prohibited from using lending information in their trading decisions.

[5]See Diamond (1984), Haubrich (1989), Besanko and Kanatas (1993), Rajan and Winton (1995), and Park (2000).

also show that banks are far more likely to update their risk assessments when they issue a new loan to that firm, consistent with active information production when new capital is at risk. Taken together, these results are consistent with theories in which banks are incentivized to 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, the bank immediately observes this information, but it is usually not immediately disclosed to public markets or other banks. We find that drawdowns significantly increase the likelihood that a bank increases its assessed expected losses and reduce the borrower's excess stock returns for the next quarter by -190bps. 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 suggest that credit line drawdowns are a source of private information for banks.[6] However, even when we include drawdowns as a control variable, changes in expected losses still have independent predictive power across all financial market outcomes.

A potential concern is that banks may misrepresent their risk assessments, perhaps to avoid higher capital requirements (e.g., Plosser and Santos (2018) and Behn, Haselmann, and Vig (2022)). To the extent that misreporting incentives are driven by concerns affecting the entire bank, they would not affect our results because we include bank-by-time fixed effects. To influence our results, banks would need to misrepresent differentially across loans; even if such systematic misreporting occurred, as long as these adjustments in ELs were not related to changes in firms' underlying credit quality, it would attenuate our results toward zero. Finally, risk-weighted capital requirements have been far from binding in the US during our sample period, reducing banks' incentives to manipulate their risk assessments.[7]

We view our results as a lower bound on the magnitude of banks' true information advantage over public markets for three reasons. First, we only observe banks' risk assessments at quarter-end. Hence, to the extent that banks' private information becomes public within the same quarter, our results will not capture these effects. Second, that we find stronger effects for smaller public firms suggests that bank information is likely to be even more important for *private* firms, which are not included in our sample due to the lack of publicly traded asset prices and earnings forecasts. In addition to being much smaller on average than publicly traded firms in our sample, private firms have much less public information, as they are exempt from most regulatory filings and usually lack equity research analyst coverage. Finally, our sample contains only the largest US banks,

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

[7] See Greenwood et al. (2017), Walz (2024) and Dubois and Rintamäki (2025) for evidence that other capital ratio constraints were more binding in the US in recent years.

which many have argued are less inclined to perform the traditional role of relationship banking.[8] 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.

2 Related Literature

Without access to banks' private information, past studies have relied on indirect evidence of banks' information advantage over financial markets. For example, James (1987) shows that stock prices respond positively to the announcement of new bank loans being granted and argues that this reaction is due to the market learning that the bank has certified the borrower. However, more recent work has called the robustness and interpretation of this result into question. For example, Preece and Mullineaux (1994) find no difference in stock price reaction across banks and non-banks after loans are granted, which is consistent with the stock price response being due to the signaling content of the loan contract itself rather than the information production of the bank.[9] Relatedly, Maskara and Mullineaux (2011) find no abnormal response once the selection bias in loan announcements is controlled for. Our empirical approach is not subject to these criticisms because we can directly observe banks' information and show that it preempts public financial markets. Moreover, whereas the idea behind James (1987) is that receiving a loan from a bank is positive news, which results in a positive stock price reaction, we find predictability only for negative news (i.e., risk assessments being adjusted upwards) among already established bank relationships.

Several papers analyze empirical proxies of bank monitoring over the life of loans, including 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. While these papers provide evidence that banks collect private information, they cannot determine how valuable it is without observing banks' actual assessments.[10] In contrast, we use banks' risk assessments to quantify how valuable this information is and

[8] 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)).

[9] 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.

[10] Relatedly, even if this information is valuable for banks, it could be that this information is not relevant for public equity or debt markets. Moreover, even when agents have private information, it can be fully imputed into market prices (e.g., Hayek (1945) and Grossman (1976)), perhaps through the actions of banks.

show that banks' information advantage is concentrated on the downside. Finally, we also show that banks use this information to allocate credit.

A 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. 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, banks may refrain from trading loans to keep information private (e.g., Dang et al. (2017)). Our sample also includes non-syndicated loans from these banks, which typically remain on their balance sheets. Moreover, loans with publicly available prices constitute a small share of our sample, and we show that our results hold when we exclude them, suggesting that our results are not driven by equity market inattention to loan markets.

In terms of empirical setting, the paper closest to ours is Plosser and Santos (2016). They use data from the Shared National Credit (SNC) program, which includes 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 a small part of their analysis, they also show that changes in banks' assessed PDs predict stock returns; however, their main focus is explaining when banks update their risk assessments, while ours is understanding the extent to which these updates preempt financial market outcomes and, therefore, reflect banks' private information. There are several other key differences between our papers. First, our sample is much larger because it includes all loans over $1 million and non-syndicated loans. Second, in addition to analyzing stock returns, we also analyze bond returns, earnings surprises, and earnings announcement returns. Third, we examine the cross-section of predictability and find that it is asymmetric (i.e., only negative information predicts future financial market outcomes) and concentrated among small and growth firms. Fourth, we show that banks allocate credit based on their private information. Finally, we provide evidence that banks obtain their information advantage from both receiving information before markets and actively producing it.

Our paper also relates to the growing literature analyzing how banks generate value (e.g., Begenau and Stafford (2019), Schwert (2020), Egan, Lewellen, and Sunderam (2022), and Flanagan (2025)). While these papers often measure value at a more aggregate level (e.g., how profitable their loan portfolios or deposits are)[11], our paper analyzes whether banks have an information advantage over public markets at the *asset* level. Moreover, our approaches are complementary: banks may have an informational advantage yet still earn average returns if screening and monitoring are costly. Indeed,

[11]One exception is Schwert (2020), who finds that the interest rates on bank loans are higher than that of bonds for the same firms, potentially indicating a benefit of borrowing from banks over public markets.

Flanagan (2025) finds that after incorporating the cost of bank staff, bank shareholders earn close to zero net risk-adjusted returns.

Finally, we contribute 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 (2022), Crawford, Pavanini, and Schivardi (2018), Darmouni (2020), Beyhaghi, Fracassi, and Weitzner (2025), Howes and Weitzner (Forthcoming) and Ioannidou, Pavanini, and Peng (2022)). The most common approach in this literature is to rely on proxies for asymmetric information or to assume that agents' decisions imply certain distributions of outcomes, and then test whether these outcomes are borne out in the data. In contrast, we can directly test for asymmetric information, without any structural assumptions, by analyzing the extent to which changes in banks' private information predict public financial market outcomes.[12]

3 Data

Our main source of data is Schedule H.1 of the Federal Reserve's Y-14Q data. The Federal Reserve began collecting these data in 2011 to support the Dodd-Frank mandated stress tests and the Comprehensive Capital Analysis and Review (CCAR). The data include corporate loans from all bank holding companies (BHCs) with total assets of $50bn or more, accounting for 85.9% of all assets in the US banking sector as of 2018Q4 (Frame, McLemore, and Mihov (2025)). Qualified BHCs are required to report detailed quarterly loan-level data on all corporate loans exceeding $1 million. 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, 2021).

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)."[13] Moreover, banks must update these regularly and immediately after any material changes: "Borrowers and facilities must have their rat-

[12] Beyhaghi, Fracassi, and Weitzner (2025) and Howes and Weitzner (Forthcoming) use the same data and show that banks' risk assessments predict loan performance even after conditioning on observable characteristics, suggesting that banks have private information not reflected in observables. In contrast to these papers, we directly show how banks' private information differs from that of public markets and quantify its actual value. Moreover, our approach allows us to analyze the types of informational advantage banks have and which types of firms they are most important for.

[13] The most recent instructions are available at Basel Committee on Banking Supervision (2023), 'Calculation of RWA for credit risk.'

ings 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 equals PD $\times$ LGD.

We also obtain stock returns from CRSP, bond returns from TRACE, analyst forecasts and earnings outcomes from IBES, and firm financials from Compustat. Because much of our analysis focuses on return predictability, we use the most recent publicly available financial ratios as of time t (from the WRDS Financial Ratios Suite based on Compustat). These ratios generally correspond to the previous quarter's data. We merge these data with the Y-14Q loan data using borrowers' tax IDs. To account for subsidiaries that report their parents' tax ID at the time of borrowing (Brown, Gustafson, and Ivanov, 2021), we keep only observations for which total assets reported in the Y-14Q data are within the 90% - 110% interval of total assets reported on Compustat in the same reporting quarter. We further restrict the sample to US public borrowers and exclude financial firms and utilities based on their Fama-French 30 industry classification.

Because banks often have multiple loans to the same borrower, we calculate, for each bank-firm quarter, the average PD, LGD, and expected loss, weighted by loan size. This approach yields a bank-firm-quarter panel with one observation per bank-firm relationship per quarter. After creating the panel, we drop firms with PDs or LGDs less than or equal to 0% or greater than 100%. To minimize reporting errors, we also drop observations in which the standard deviation of PD across a bank's loans within the same firm-quarter exceeds 0.50 percentage points or if the standard deviation of its LGDs exceeds 25 percentage points.[14] We also exclude likely data errors by requiring each borrower's total committed credit to be at least \$1 million and each borrower's utilized credit to be no more than its total committed credit. Together, these filters remove less than 3% of observations.[15]

Our final firm-bank-quarter panel contains 1,857 unique firms from 2014Q4 to 2019Q4, with an average of 1,306 unique firms per quarter.[16] Because the Y-14Q data include only outstanding loans, firms appear in our sample only when they have an active lending relationship with at least one Y-14 bank. Hence, the difference between the total number of unique firms and the per-quarter average reflects firms entering and exiting the sample when they no longer borrow from a Y-14 bank.[17] Appendix Table B1 compares our sample of firm-quarters to the standard CRSP-Compustat sample (3,296 unique non-financial, non-utility firms). Firms in our sample are larger and more highly levered,

[14] 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.

[15] See Online Appendix Table OA1 for details on the sample construction and data filters.

[16] The Y-14Q data begin in 2011; however, PDs and LGDs are not consistently reported until the end of 2014.

[17] This may occur because firms are acquired, delisted, default, or simply stop borrowing from one of these banks. Most of our analysis focuses on changes in risk assessments within an existing relationship, which mitigates selection concerns.

which is unsurprising given that they must have an outstanding bank loan.

Figure 1 plots the distribution of PD, LGD, and expected loss, and Figure 2 plots the distribution of non-zero changes in PD, LGD, and expected loss. We also plot the distribution of the number of banks per borrower and how the average number of banks varies across firm-size quintiles in Figure 3.

Because the relationship between expected losses and asset prices or earnings forecasts is likely to be highly non-linear, we construct dummy variables indicating whether expected losses increased (EL^+) or decreased (EL^-) relative to the previous quarter. We also follow the same naming convention when analyzing cases in which PD or LGD increase or decrease. Detailed variable descriptions can be found in Appendix A.

Table 1 includes summary statistics for the main variables in our firm-bank-quarter panel. The average PD, LGD, and expected loss are 1.01%, 38.97%, and 0.33%, respectively. Banks update their expected losses downward (become more optimistic) in 19% of quarters, whereas they adjust their expected losses upward (become more pessimistic) in 17% of quarters. The fact that banks update their expected losses downward more frequently is at least partially due to the fairly benign credit market conditions over our sample period.

The average firm has a market capitalization of about $18bn, with a median of just under $4bn. The firms in our sample are relatively highly levered, with average and median debt-to-capital ratios around 50%. Because these statistics inevitably overweight firms that borrow from multiple banks, Table 2 displays the same summary statistics aggregated to the firm-quarter level using volume-weighted averages for variables that differ across banks within a firm. In some specifications, we compare banks' risk assessments within firm-quarter; hence, for reference, Table 3 includes summary statistics of the cross-sectional standard deviation 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 tend to move in tandem, the correlation between their changes is fairly small (0.120 for increases in PD and LGD and 0.161 for decreases), suggesting that both measures contribute independently to changes in expected losses.

4 Empirical Analysis

In this section, we present our empirical analysis. We first present our main results on banks' information advantage over markets in Section 4.1, then demonstrate their robustness to alternative specifications in Section 4.2. In Section 4.3, we explore heterogeneity and dynamics of the return predictability. Section 4.4 shows that banks use their private information in credit allocation decisions, and Section 4.5 examines the sources of banks' information advantage.

4.1 The Information Advantage of Banks

In this section, we test whether banks possess information that public markets do not. Our empirical approach examines whether changes in banks' private information, as reflected in their risk assessments, predict public financial market outcomes. In our baseline specification, we use our firm-bank-quarter panel described in Section 3 to 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 a financial market outcome that occurs between quarter t and $t+1$. Specifically, we consider 1) quarterly equity return, 2) quarterly bond return, 3) a dummy variable that equals one if there is negative earnings surprise relative to analysts' earnings per share (EPS) estimates, and 4) the 2-day cumulative abnormal return (CAR), i.e., the individual stock return minus the value-weighted CRSP index return, around the earnings announcement date for firm i, all of which are measured in percentage points.[18] 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 publicly available 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.[19] Finally, we include bank-quarter fixed effects ($\delta_{b,t}$) to control for bank-specific factors that affect risk assessments, as well as industry-by-time fixed effects ($\gamma_{j,t}$). We cluster our standard errors by firm and bank-quarter. Intuitively, 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. 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 these regressions, firms appear more than once in a quarter if they borrow from multiple banks. This structure, which is similar to that of the credit rating literature (e.g., Kempf and Tsoutsoura (2021)) and the research analyst literature (e.g., Malmendier and Shanthikumar (2014)), means that there will be correlation in errors across banks within

[18] As is standard practice, we use a 2-day CAR since we do not know if the announcement was before the open or after the close of the stock market. Given the short horizon, it is common to use the raw excess return for the CAR (e.g., Kaniel et al. (2012)); however, as we discuss below, our results are robust to using standard factor models to calculate the CAR.

[19] Our timing convention means that $X_{i,t}$ reflects the most recent public observation as of time t. Since firms report financials with a lag, in practice, this will usually correspond to the realized values as of time $t-1$.

firm-quarters, which is why we cluster standard errors by firm.[20] This structure also places more weight on firms that borrow from more banks. However, as we show in Section 4.3, we find weaker effects among larger firms, which tend to borrow from more banks. Moreover, in Appendix Table B2, we find larger effects when we 1) reweight the observations inversely by the number of banks the firm borrows from at time t, and 2) aggregate bank risk assessments to the firm-quarter level.

The results of these regressions are displayed in Table 5. Column (1) shows that an increase in expected losses predicts a 77bp stock return underperformance in the next quarter. This suggests that if a bank raises its assessment of a firm's expected loss in a quarter, the firm's stock is expected to underperform by 77bps over the next quarter.[21] 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 2 percentage points more likely, which compares to the unconditional probability of 26.9%.[22] 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 -20bps two-day CAR around the earnings announcement date (-25.6% annualized).

Interestingly, the second row of Table 5 shows that reductions in expected losses do not predict returns or earnings surprises.[23] This result is 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 may be complementary. For example, if firms were more willing to reveal positive information about a loan's collateral value, this could incentivize banks to specifically focus on the production of negative information.

[20]Importantly, the cluster-robust variance estimator is agnostic to the source of correlation in errors (Liang and Zeger (1986)). Whether the correlation arises from a repeated outcome (as in our setting), a repeated regressor (as in the classic Moulton problem discussed in Angrist and Pischke (2009)), or unobserved cluster-level heterogeneity, the estimator remains valid.

[21]Though not completely comparable, James (1987), shows that stock prices increase by about 1.93% upon the announcement of a bank loan. Similarly, stock prices also drop by between 1.5 - 4% following credit rating and equity research analyst downgrades; however, recent studies find magnitudes close to zero when using intraday trading data (Altınkılıç and Hansen (2009) and Even-Tov and Ozel (2021)).

[22]We do not report positive earnings surprises separately because they are almost perfect complements of negative earnings surprises.

[23]There is a similar asymmetry in equity research analyst and credit rating downgrades (Womack (1996) and Brown, Wei, and Wermers (2014)).

4.2 Robustness Tests

In this section, we provide evidence that our main results—changes in banks' private information predict subsequent financial market outcomes—are not driven by 1) information that is public, but not reflected in equity markets, or 2) differences in risk premia across firms.

One concern is that, rather than capturing banks' private information, changes in banks' risk assessments simply reflect information in credit markets that is slow to be incorporated into equity prices.[24] We address this concern in several ways. First, Appendix Table B3 shows that our main results are robust to controlling for changes in Moody's EDF-X (formerly Moody's KMV EDF), which are one-year expected default frequencies.[25] This measure of default risk is commonly used by both academics and industry professionals (e.g., Duffie, Saita, and Wang (2007)), and according to Moody's, "signal credit distress well in advance of other credit measures" (Moody's Analytics, 2016).[26] Second, in Appendix Table B4, we show that our equity return predictability results hold when we exclude firms with traded loans, traded CDS, or traded bonds. Third, in Online Appendix Table OA4, we show that our results are robust to restricting the sample to firms whose stock is held by integrated funds, as defined in Addoum and Murfin (2020), which are more likely to use information available in debt markets to trade in equity markets. These tests help rule out the possibility that our results are driven by banks' risk assessments simply capturing publicly available information in credit markets.

Another concern is that the predictability arising from changes in banks' risk assessments reflects changes in risk premia, rather than private information, which our panel regression approach may not be able to distinguish. However, a large portion of the return predictability occurs right around the earnings announcement, making it highly unlikely that it is driven by risk premia or anomalies correlated with changes in banks' expected losses (Engelberg, McLean, and Pontiff, 2018).

Nonetheless, to further address this concern, we aggregate risk assessments across banks within each firm-quarter to conduct more standard asset pricing tests. First, in Appendix Table B5, we form equal-weighted stock portfolios based on whether or not firms' lagged loan volume-weighted average value of EL^{+} was greater than the corresponding average of EL^{-}, and estimate monthly alphas using the Fama-French three-factor

[24] For example, Acharya and Johnson (2007), Lee, Naranjo, and Velioglu (2018) and Addoum and Murfin (2020) provide evidence that credit markets incorporate information more quickly than equity markets.

[25] To calculate these expected default frequencies, Moody's first estimates Merton-style distance-to-default measures using equity market and liabilities data. This distance measure is then mapped to an empirical probability of default based on Moody's proprietary historical default database.

[26] Our results are also robust to 1) allowing for non-linear interactions between EDF-X and our control variables (Online Appendix Table OA2), and 2) controlling for an alternative public credit signal based on traded loan, CDS and bond prices when available, and EDF-X otherwise (See Online Appendix Table OA3 for more details).

and Carhart four-factor models. A long-short portfolio—going long upgraded firms and short downgraded firms—earns a statistically significant alpha of approximately 25bp per month. We also estimate Fama-MacBeth regressions (Fama and MacBeth (1973)) on a firm-quarter panel, with different aggregation methods, and obtain similar qualitative results (Appendix Table B6). Finally, our results are also robust to 1) using firm-level rolling three and four-factor alphas as the dependent variable in our baseline equity return and earnings announcement return predictability specifications (Appendix Table B7) and 2) controlling for three and four-factor loadings in our baseline regressions (Appendix Table B8).

4.3 Heterogeneity and Dynamics

In this section, we further analyze banks' information advantage over financial markets. Specifically, we 1) identify cross-sectionally where the predictability is strongest, 2) decompose the effect into its probability of default and loss given default components, 3) analyze its dynamics, and 4) further analyze its nonlinear structure.

First, we re-estimate Equation (1), but interact EL^+ with the main firm characteristics and controls. The results are displayed in Table 6. For stock returns and negative earnings surprises, the interaction between market capitalization and EL^+ is positive and statistically significant. These results suggest that the equity market predictability is lower for larger firms. The interaction terms for bond returns and earnings returns are positive but not statistically significant. The lack of statistical significance for bond returns is likely driven by the fact that roughly half of our observations do not have bonds, which not only leads to less precise estimates but also reduces the variation in firm size, given that the firms that do have bonds are much larger on average (see Online Appendix Table OA5). 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 both smaller and growth firms.

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 174bp quarterly underperformance in response to an increase in expected losses. The magnitude of the underperformance declines from quintile 1 to the middle three quintiles, though the effects remain statistically and economically significant. 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.

We next examine whether banks' information advantage stems from the probability of default, loss given default, or both by separately testing whether changes in PD and LGD predict quarter-ahead financial market outcomes in Table 8. As the main independent variables, we use PD^+ and LGD^+, which are dummy variables equal to 1 if PD or LGD increases from quarter $t-1$ to quarter t. In column 1, both PD^+ and LGD^+ have independent predictive power for stock returns. For bond returns, shown in column (2), the signs of the coefficients for PD^+ and LGD^+ are also negative and similar in magnitude, though the point estimates are noisier. 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.[27] In contrast, in columns (3) and (4), only the probability of default predicts earnings surprises and earnings returns. This result is consistent with short-term earnings predominantly affecting the likelihood that the firm can meet debt payments and avoid default, rather than the liquidation values of the firm's assets.

We next show that the predictability dissipates after one quarter. In Figure 4, we plot the coefficients of EL^+ estimated from (1) 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 negative and statistically significant coefficient is $t+1$, while the other coefficients are close to zero and statistically insignificant, suggesting that the return predictability occurs only in the first quarter after an increase in expected loss.

Finally, we investigate further the potentially nonlinear relationship between changes in expected losses and future financial market outcomes. In Online Appendix Table OA6, we report results using the raw change in expected loss as the independent variable. The results are directionally consistent with our main analysis, although not statistically significant. However, in Online Appendix Table OA7, we find a statistically significant relationship using the percentile change in expected losses among observations with nonzero changes. These results suggest a non-linear relationship between expected losses and asset returns. Online Appendix Figure OA1 illustrates this non-linearity, plotting changes in expected loss against subsequent stock returns. Notably, the figure shows a kink at zero: the slope is markedly steeper for positive than for negative changes in expected loss, providing visual confirmation of the asymmetry documented in our main analysis and validating our use of separate dummy variables for increases and decreases. Online Appendix Table OA8 further shows that our main equity market effects are concentrated in the top decile of expected loss increases.

[27]If lower LGDs are associated with liquidation values (e.g., Beyhaghi, Howes, and Weitzner (2025)), then higher LGDs can reduce the firm's debt capacity, which in turn can lower the value of equity.

4.4 Banks' Private Information and Lending Decisions

For banks, one of the primary benefits of producing information is to improve their allocation of credit. In this section, we show that banks' information affects their 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 driven solely by private information from those driven by 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:

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

where $Commitment_{i,b,t}$ is the log loan commitment amount (times 100) from bank b to firm i in quarter t, $EL_{i,b,t}$ is level of the expected loss, and $\delta_{b,t}$, $\alpha_{i,t}$ and $\sigma_{i,b}$ are bank-by-time, firm-by-time and firm-bank 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. We double-cluster our standard errors by firm and bank-quarter.

Beyond differences in information, differences in banks' risk assessments within firm-quarter may also reflect differences in banks' subjective beliefs.[28] However, we provide evidence in Section 4.5 that at least part of these differences stems from differences in private information.

The results are displayed in Table 9. In column (1), we estimate the regression without any fixed effects. The coefficient is negative and statistically significant with a point estimate of -18.07, which implies that a bank increasing its expected loss for a borrower by 0.28pp—the average standard deviation of expected losses across banks for a firm-quarter pair over our sample period reported in Table 3—is associated with an average decline in lending to that firm of just over 5%. The magnitude is little changed with the addition of bank-quarter fixed effects in column (2), but shrinks notably with the addition of firm-quarter fixed effects in column (3), as this specification relies on variation across different banks lending to the same firm at the same time. The addition of firm-bank fixed effects, which net out each bank's average lending to a firm, also leads to smaller estimates. However, even when including all three sets of fixed effects in

[28]For example, see Wang and Weitzner (2021) in the context of differences in subjective beliefs of credit rating agencies.

column (8), the coefficient remains statistically significant. Hence, these results suggest that banks use their information in their lending decisions.[29] Moreover, beyond adjusting lending volumes, we also find that changes in banks' risk assessments are associated with both contemporaneous (Online Appendix Table OA9) and future (Online Appendix Table OA10) loan modifications.

These results show that banks act on their private information when allocating credit. But why is it valuable for banks to have this information if it becomes public so soon afterwards? If a bank learns that a firm's creditworthiness is deteriorating, waiting for that information to be disclosed may worsen the bank's position. Before the information is revealed, the borrower can continue to draw on existing credit lines, reallocate collateral, or take on risky investments. Instead, acting immediately on its private information allows the bank to tighten terms, increase collateral, or renegotiate in anticipation of the deterioration, rather than waiting until it becomes publicly known and the borrower's financial condition has weakened further.[30]

Credit lines are a clear example of why the immediacy of information is valuable. In practice, firms often draw down credit lines after experiencing a negative shock; indeed, in Section 4.5, we show that banks increase their risk assessments when firms draw down their credit lines. Moreover, banks sometimes have the option to deny drawdown requests (Sufi (2009) and Acharya et al. (2014)). Hence, banks must quickly determine whether granting the borrower access to additional funds will help them recover or simply increase the bank's losses. Consistent with banks acting on their private information, Online Appendix Figure OA3 shows that banks reduce committed credit line exposure following increases in their risk assessments.

These results raise important questions about how banks' actions affect the returns we observe. On one hand, if banks became more pessimistic about firms for purely behavioral reasons, reduced lending could itself cause negative market reactions, even if that lending has nothing to do with banks' private information. On the other hand, if banks use their private information to conduct valuable monitoring, these actions may mitigate firms' losses, thereby attenuating the negative market reactions we observe relative to what would occur in the absence of such interventions. In either case, the abnormal returns we document reflect the net effect of banks' private information after any lending adjustments and monitoring interventions. However, we show that our main results are robust to excluding observations in which the bank gave the firm a new loan (Online Appendix Table OA11), if their total loan commitment to the firm changed by more than

[29] In Online Appendix Figure OA2, we also estimate dynamic responses and find that lending volume steadily falls following an increase in EL, with a statistically significant peak decline of almost 4% after two years.

[30] Consistent with this idea, Hertzberg, Liberti, and Paravisini (2011) use a natural experiment to show that banks cut lending in anticipation of bad news being revealed about firms. Being the first to act on deteriorating fundamentals allows the bank to secure collateral, seniority, or tighter covenants before other lenders respond.

1% from the previous quarter (Online Appendix Table OA12),[31], or if the interest rate or maturity changed on any loan within the firm-bank relationship (Online Appendix Table OA13). These results suggest that banks' information predicts financial market outcomes even when they do not act on that information.

4.5 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 determinants 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:

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

where the dependent variable $z_{i,b,t}$ is a dummy that equals one if either the PD, LGD, or expected loss increases or decreases from $t-1$ to t, i.e., PD^{+}, PD^{-}, etc. We include changes in the latest public firm financials and stock returns from $t-1$ to t, $\Delta X_{i,t}$, as independent variables to test when 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.[32] These results suggest that banks are indeed adjusting their PDs symmetrically in accordance with changes in firms' performance and characteristics.

In columns (3) and (4), we include LGD^{+} and LGD^{-} as dependent variables. Here, only changes in profitability affect the likelihood of banks raising LGDs, whereas higher contemporaneous stock returns reduce the likelihood that banks decrease their LGDs. These results suggest that LGDs are less tied to current public firm performance measures than PDs, which may also explain why changes in PDs predict earnings surprises, while changes in LGDs do not. Finally, Columns (5) and (6) show that changes in expected losses follow similar patterns to changes in PD, consistent with default probability being the primary driver of expected loss changes in response to public information.

The above tests provide a broad indication of when banks adjust their risk assessments, but they do not explain the actual sources of banks' private information, as all 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 at

[31]We choose a cutoff of 1% because some term loans are amortizing, which can mechanically change committed exposure even in the absence of any changes in lending decisions.

[32]Online Appendix Table OA14 repeats the same analysis but includes 4 lags of each variable.

producing (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 producing more information about smaller firms than public financial markets. Despite having the same disclosure requirements as large public firms, small public firms tend to be tracked by fewer equity research analysts, resulting in less publicly available analysis and information.

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}.[33] We include a vector of bank-firm level variables $X_{i,b,t}$, which include the bank's committed exposure amount (in logs times 100), 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 share of the committed loan amount allocated to term loans versus credit lines (in percentage points), and dummies variables equal to one if: 1) the bank specializes in the borrower's industry (from Paravisini, Rappoport, and Schnabl (2023)), 2) the bank granted a new loan from $t-1$ to t, 3) the firm draws down their credit lines, and 4) pays down their credit line. We also include firm-by-time fixed effects ($\alpha_{i,t}$) to control for information available to all banks simultaneously. Hence, this regression tests 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-quarter. The results are displayed in Table 11.

Across all specifications, we find that banks with larger commitments are more likely to update their PDs, LGDs, and expected losses. For example, a 10% increase in a bank's committed exposure makes it about 0.5 percentage point more likely to update its expected loss, compared to an unconditional likelihood of 36.0%. This result is consistent with information production having a fixed-cost component, a standard assumption in theories of financial intermediation (e.g., Boyd and Prescott (1986), Dang, Gorton, and Holmström (2012), Gorton and Ordonez (2014) and Weitzner (2020)). When information production involves fixed costs, the expected benefit of producing information increases with exposure, making banks more willing to incur these costs for larger loans.[34]

The coefficients for New Loan are also positive and statistically significant across all specifications. When a bank makes a new loan, it is 10.3 percentage points more

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

[34] Howes and Weitzner (Forthcoming) provide empirical evidence for this mechanism by showing that banks produce more information about larger loans and loans with higher potential losses.

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 are highest.[35] Taken together, these results provide support for the idea that banks' information advantage is at least partially due to incentive-driven information acquisition.

Table 11 also shows that banks are more likely to update their risk assessments when firms draw down or pay down their credit lines. This channel is a potentially important source of value-relevant information that banks receive prior to markets: if a firm draws down a credit line, this information is immediately known by the bank whose credit line is drawn, but is not usually immediately disclosed to public markets or other banks. We therefore test whether PDs, LGDs, and expected losses increase after firms draw down their credit lines by estimating 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 $Drawdown_{i,b,t}$, a dummy variable that equals one if the total utilization rate across all of a firm's credit lines from the same bank increases from quarter $t-1$ to t, and $\delta_{b,t}$ and $\alpha_{i,t}$ are bank-quarter and firm-quarter fixed effects.

The results are displayed in Table 12. Columns (1) - (3) exclude 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 that the bank increases the firm's expected loss by 4.0 percentage points compared to an unconditional mean of 16.9%. We find similar results in columns (4) - (6), which include firm-quarter fixed effects to see how differential drawdowns affect expected losses across banks for a firm borrowing from multiple banks. 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), and suggest that drawdowns are a source of private information for banks.

If a credit line is syndicated, drawdowns are typically made pro rata across syndicate members. Hence, members of the same syndicate are likely to observe the same information regarding the credit line drawdown. While we cannot reliably determine whether loans are part of the same syndicate, approximately half of the firm-bank-quarters in our sample report having no syndicated loans (Table 1), and in Online Appendix Table

[35] Banks may also be more likely to demand more information when granting a new loan. While we cannot fully quantify this channel, the regression controls for the time since the last audit and financial statement.

OA15, we find similar results when we restrict the sample to this set of observations. Additionally, almost half of our firm-quarters report multiple credit lines with interest rate differences of more than 25bps, and about one-fourth of firm-quarters have multiple credit lines with differences in maturity of more than one month, suggesting that many firms obtain credit lines through multiple syndicates. More broadly, neither the average dispersion in risk assessments across banks for the same firm (Appendix Table OA16) nor the intraclass correlation coefficients (Online Appendix Table OA17) suggests that syndication leads to stronger comovement in risk assessments across banks.[36]

If firms draw 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 (1) with both EL^+ and *Drawdown* as independent variables. The results are displayed in Table 13. Consistent with drawdowns containing private information about firms' prospects, drawdowns predict a 190bp quarterly negative stock return (column 1). In column (2), we include bond returns as the dependent variable; drawdowns do not appear to predict bond returns, whereas increases in expected losses continue to predict negative excess bond returns even after controlling for drawdowns. In columns (3) and (4), we observe a similar pattern for negative earnings surprises and earnings announcement returns as we do for stock returns.[37] Taken together, these results are consistent with banks' information advantage arising from both access to private information early and active information production. Of course, we cannot completely rule out the possibility that banks have access to other non-public information that could contribute to the predictability in changes to their credit assessments. However, we believe that these results, along with those presented in Table 11, suggest that at least a part of banks' advantage arises from information production.

5 Conclusion

Financial intermediation theory predicts that banks' information production and monitoring create 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

[36]While some information, such as financials, is shared across syndicate members, differences in information across banks are likely to remain for several reasons. For example, banks may have different incentives to collect information based on their level of exposure to the borrower (e.g., Table 9). Moreover, banks have heterogeneous exposures across industries and firm types in their portfolios, and as a result, may evaluate individual firms differently.

[37]Online Appendix Table OA18 shows that these results also hold when excluding firm-bank relationships with syndicated loans.

expected losses predict stock returns, bond returns, and analyst earnings surprises, and this advantage is stronger for smaller firms and growth firms. We 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. We also show that banks use their private information to allocate credit to firms.

Our findings likely represent a lower bound on banks' information advantage for three reasons. First, we only observe banks' risk assessments at the end of the quarter. Hence, we will not observe when banks update their risk assessments and preempt other financial market outcomes within the quarter. Second, our results are limited to public firms. In practice, we would expect banks' information advantage to be even stronger for smaller and more opaque firms that lack publicly traded equity or debt, consistent with our results showing that the advantage is stronger for smaller public firms. And third, our sample comprises only the largest US banks, which many argue are less likely to play the traditional role of relationship lending relative to smaller banks that are not included in our data (e.g., Berger et al. (2005)).

Our paper provides direct tests of banks as informed finance—one of the central tenets of financial intermediation theory. More broadly, our analysis provides direct evidence of asymmetric information in financial markets. Finally, we believe our paper validates the Y-14Q risk assessments as measures of banks' private information, thereby opening many avenues for future research to explore the determinants and implications of this information.

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Figure 1: Distributions of Risk Assessments

This figure plots the distribution of banks' internal risk assessments at the firm-bank-quarter level, where each observation represents a single bank's assessment of a specific firm in a given quarter. For readability, the PD and expected loss distributions are truncated at $\pm 5pp$ and $\pm 2.5pp$, respectively. The number of firm-bank-quarter observations shown in each panel are $N = 130{,}054$ for PD, $N = 135{,}214$ for LGD, and $N = 132{,}380$ for EL.

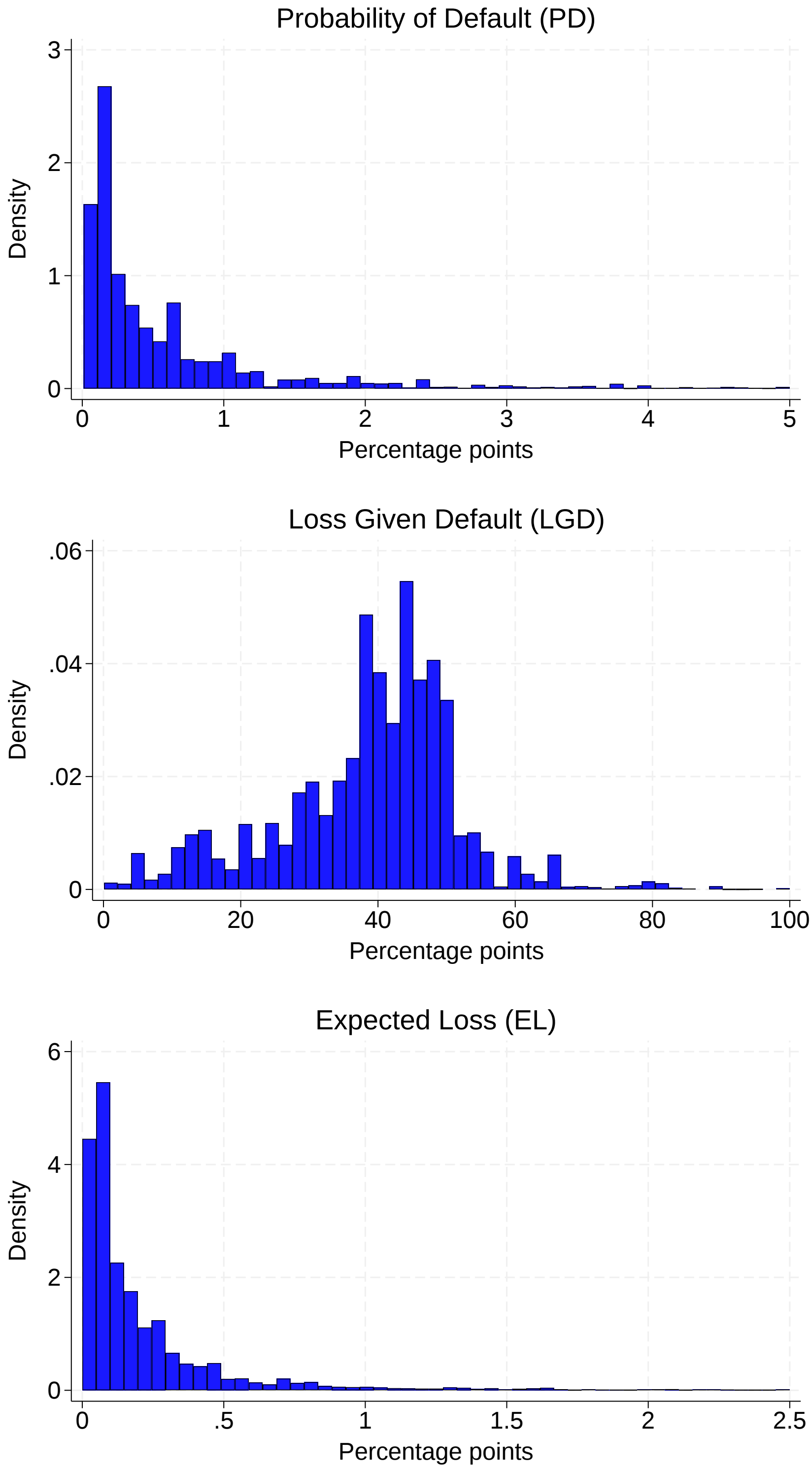


Figure 2: Distributions of Changes in Risk Assessments

This figure shows the distributions of nonzero changes in banks' internal risk assessments at the firm-bank-quarter level. For readability, the ΔPD, ΔLGD, and ΔEL distributions are truncated at $\pm 2pp$, $\pm 25pp$, and $\pm 0.25pp$, respectively. The number of firm-bank-quarter observations with nonzero changes shown in each panel are $N = 25{,}792$ for PD, $N = 28{,}971$ for LGD, and $N = 38{,}692$ for EL.

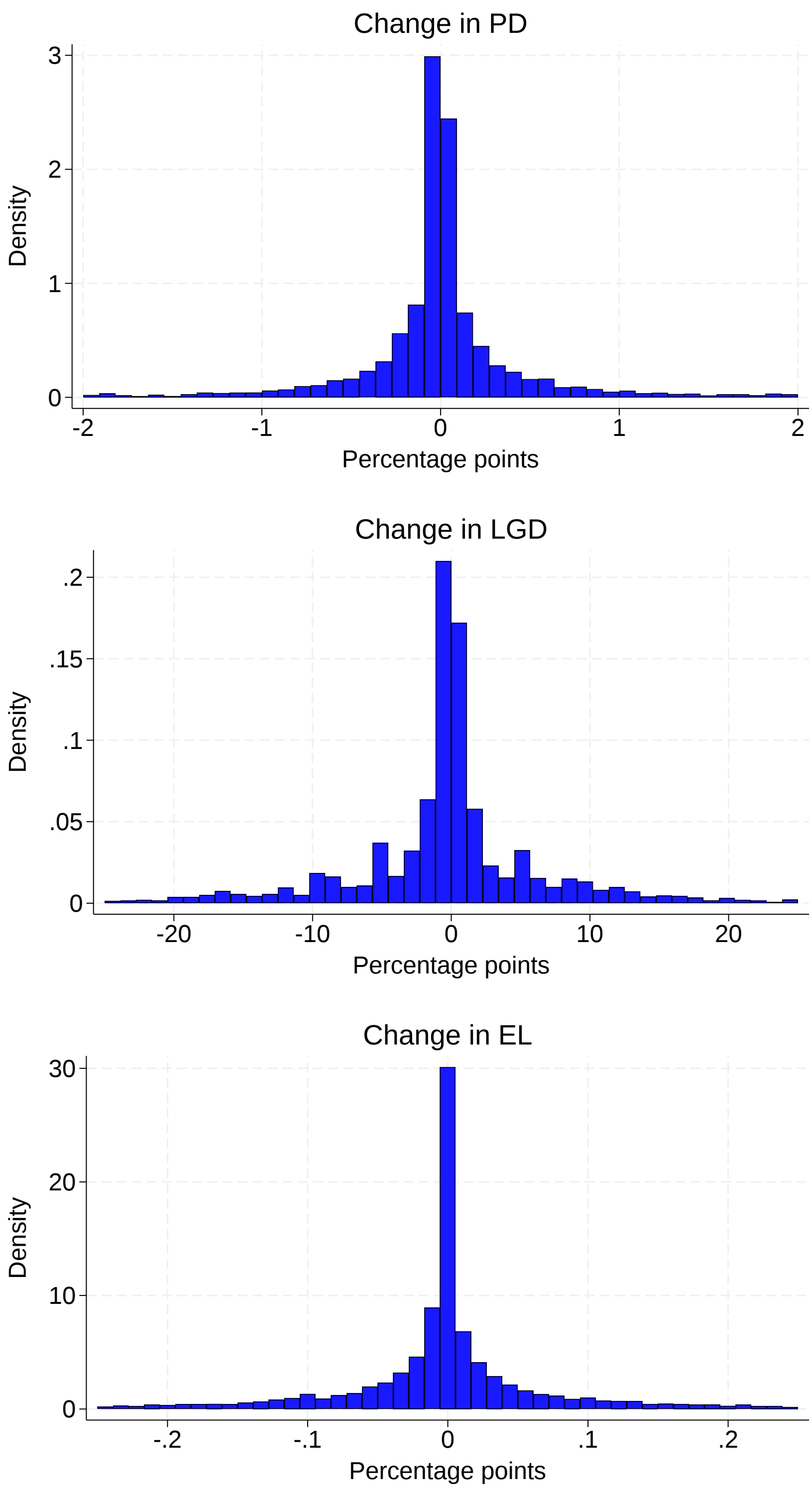
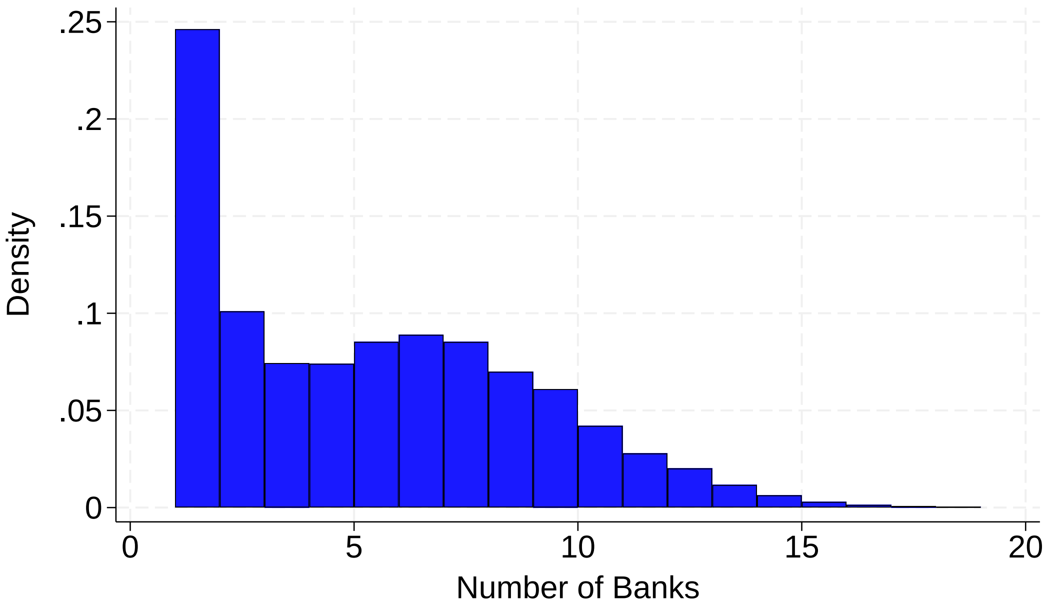


Figure 3: Distribution of Bank Relationships

This figure displays summary statistics of the number of bank relationships for firms in the sample. The top panel plots the distribution of the number of distinct bank relationships at the firm-quarter level. The bottom panel reports the average number of banks lending to each firm, split by quintile of the previous quarter's market capitalization. The total shown in the bottom row excludes observations for newly public firms for which lagged market capitalization data are unavailable.



Size Quintile	Avg. Number of Banks	Avg. Mkt. Cap. ($ bn)	Observations
1	2.16	0.22	11,741
2	3.98	0.90	21,656
3	5.18	2.17	28,132
4	6.11	5.97	33,192
5	7.29	56.04	39,595
Total	4.94	13.06	134,316

Figure 4: Equity Return Predictability Over Different Horizons

This figure examines stock return predictability following changes in banks' risk assessments at different horizons. The figure plots coefficient estimates of dummy variable equal to one if the bank's assessed expected loss for the firm increased between quarters $t-1$ and t (EL^{+}) from regression equation (1), where the dependent variable is quarterly stock returns (measured in percentage points) from quarter $t+h-1$ to quarter $t+h$ for horizons h=1 to h=9. All regressions include bank-by-time and industry-by-time fixed effects and firm-level controls (book-to-market, ROA, leverage, market capitalization, and lagged stock returns). Vertical lines indicate 95% confidence intervals calculated using standard errors that are double-clustered by firm and bank-quarter. Sample sizes for each coefficient range from $N = 117{,}622$ for horizon $t+1$ to $N = 53{,}649$ for horizon $t+9$.

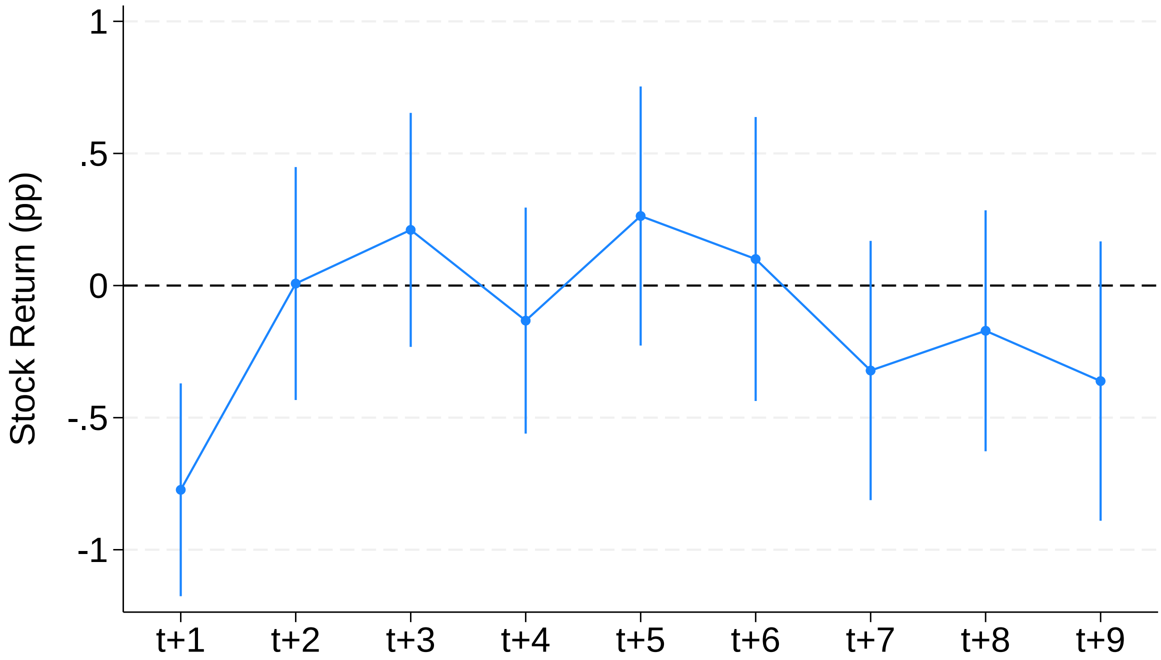


Table 1: Summary Statistics

This table presents summary statistics for the main variables used in the analysis. The sample includes all corporate loans exceeding $1 million extended by large U.S. bank holding companies to publicly traded non-financial, non-utility firms from 2014Q4 to 2019Q4. Observations are at the firm-bank-quarter level. Appendix Section A contains all variable definitions.

	Mean	SD	10%	Median	90%	N
PD (pp)	1.009	2.782	0.070	0.300	1.910	135,214
LGD (pp)	38.966	13.210	20.000	41.000	51.000	135,214
Expected Loss (pp)	0.326	0.900	0.029	0.102	0.594	135,214
PD^+	0.108	0.311	0.000	0.000	1.000	122,400
PD^-	0.120	0.325	0.000	0.000	1.000	122,400
LGD^+	0.113	0.316	0.000	0.000	1.000	122,400
LGD^-	0.131	0.337	0.000	0.000	1.000	122,400
EL^+	0.169	0.375	0.000	0.000	1.000	122,400
EL^-	0.191	0.393	0.000	0.000	1.000	122,400
Drawdown	0.259	0.438	0.000	0.000	1.000	122,400
Stock Return (pp)	0.834	19.735	-21.331	1.658	20.897	135,214
Bond Return (pp)	0.989	5.258	-2.570	1.133	4.384	63,685
Negative Surprise (pp)	26.891	44.340	0.000	0.000	100.000	123,943
Book-to-Market	0.482	0.378	0.119	0.383	0.945	130,132
ROA	0.138	0.074	0.064	0.131	0.231	134,583
Leverage	0.501	0.226	0.212	0.488	0.809	134,758
Market Cap ($ bn)	18.440	51.493	0.526	3.811	42.040	135,214
Maturity (months)	40.028	14.241	19.529	41.933	57.420	133,206
Term Loan (% of total)	17.389	30.150	0.000	0.000	67.056	135,214
Loan Volume ($ mn)	98.194	166.933	18.750	61.752	191.429	135,214
Syndicated Loan	0.485	0.500	0.000	0.000	1.000	135,214

Table 2: Summary Statistics at the Firm-Quarter Level

This table presents summary statistics for the main variables used in the analysis, aggregated to the firm-quarter level. All variables are loan-volume weighted averages across all banks lending to each firm in each quarter, except for Loan Volume, which is the total committed amount across all banks, and Number of Banks, which is the number of unique banks lending to the firm. Appendix Section A contains all variable definitions.

	Mean	SD	10%	Median	90%	N
PD (pp)	1.397	3.135	0.110	0.408	3.190	27,417
LGD (pp)	36.533	12.270	16.199	40.424	47.490	27,417
Expected Loss (pp)	0.418	1.020	0.041	0.140	0.850	27,417
PD^+	0.122	0.238	0.000	0.000	0.405	25,293
PD^-	0.135	0.241	0.000	0.000	0.425	25,293
LGD^+	0.124	0.228	0.000	0.000	0.388	25,293
LGD^-	0.143	0.239	0.000	0.000	0.443	25,293
EL^+	0.184	0.276	0.000	0.000	0.570	25,293
EL^-	0.206	0.279	0.000	0.090	0.598	25,293
Drawdown	0.267	0.390	0.000	0.000	1.000	25,293
Stock Return (pp)	0.944	22.567	-23.134	1.236	23.166	27,417
Bond Return (pp)	1.031	5.825	-2.598	1.178	4.525	8,937
Negative Surprise (pp)	29.363	45.543	0.000	0.000	100.000	23,322
Book-to-Market	0.515	0.414	0.122	0.404	1.030	26,343
ROA	0.129	0.086	0.040	0.126	0.232	27,278
Leverage	0.449	0.251	0.107	0.439	0.795	27,298
Market Cap ($ bn)	12.975	47.352	0.187	2.053	25.082	27,417
Maturity (months)	37.411	15.244	14.404	39.433	56.046	26,921
Term Loan (% of total)	19.299	29.386	0.000	3.554	65.909	27,417
Loan Volume ($ mn)	674.471	1,755.624	14.727	269.932	1,510.756	27,417
Syndicated Loan	0.432	0.435	0.000	0.471	1.000	27,417
Number of Banks	4.932	3.494	1.000	5.000	10.000	27,417

Table 3: Cross-Sectional Dispersion in Risk Assessments

This table presents summary statistics on the cross-sectional standard deviation of risk assessments and loan commitment amounts across banks at the firm-quarter level. Appendix Section A contains all variable definitions.

	Mean	10%	Median	90%	N
PD (pp)	0.776	0.047	0.257	1.655	20,666
LGD (pp)	8.965	3.663	8.133	15.100	20,666
EL (pp)	0.276	0.019	0.101	0.550	20,666
Committed ($ mn)	50.666	7.278	28.799	96.369	20,666
ΔPD (pp)	0.304	0.000	0.027	0.520	19,093
ΔLGD (pp)	2.319	0.000	0.757	6.571	19,093
ΔEL (pp)	0.120	0.000	0.016	0.211	19,093

Table 4: Correlations in Changes in Risk Assessments

This table presents correlation matrices for changes in banks' risk assessments at the firm-bank-quarter level. Panel A shows correlations among upward adjustments in risk assessments, where PD$^+$, LGD$^+$, and EL$^+$ are dummy variables equal to one if the bank increases its assessed probability of default, loss given default, or expected loss, respectively, from quarter $t-1$ to quarter t. Panel B shows correlations among downward adjustments, where PD$^-$, LGD$^-$, and EL$^-$ indicate decreases in these assessments. Both panels include correlations with one-quarter lagged values (subscript $t-1$) to examine persistence in changes in risk assessments. Appendix Section A contains all variable definitions.

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^+	0.120	1.000				
EL_t^+	0.720	0.605	1.000			
PD_{t-1}^+	0.036	0.023	0.037	1.000		
LGD_{t-1}^+	0.006	0.110	0.077	0.124	1.000	
EL_{t-1}^+	0.025	0.080	0.070	0.725	0.604	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^-	0.161	1.000				
EL_t^-	0.707	0.650	1.000			
PD_{t-1}^-	0.008	0.008	0.012	1.000		
LGD_{t-1}^-	0.001	0.102	0.075	0.160	1.000	
EL_{t-1}^-	-0.000	0.074	0.055	0.722	0.637	1.000

Table 5: Changes in Expected Losses Predict Financial Market Outcomes

This table examines whether changes in banks' internal risk assessments predict next-quarter financial market outcomes, using a firm-bank-quarter panel. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The main independent variables are EL^+ and EL^-, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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^+	−0.773***	−0.202**	1.960***	−0.203**
	(3.771)	(2.038)	(3.790)	(2.513)
EL^-	−0.226	0.097	0.449	0.077
	(1.267)	(1.463)	(1.073)	(1.162)
Book-to-Market	−0.103	0.284	4.344**	0.750***
	(0.167)	(0.741)	(2.395)	(3.428)
ROA	0.817	0.774	−3.080	0.911
	(0.410)	(0.758)	(0.459)	(1.026)
Leverage	−0.550	0.061	2.711	0.434
	(0.718)	(0.183)	(1.164)	(1.521)
Log(Market Cap)	0.200*	0.017	−3.722***	−0.058
	(1.744)	(0.315)	(10.528)	(1.504)
Lagged Stock Return	−0.014		−0.164***	0.312***
	(1.047)		(6.261)	(34.263)
Lagged Bond Return		−0.086**		
		(1.985)		
Mean of DV	0.83	0.99	26.89	0.14
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	117,622	54,075	107,899	115,084
R-squared	0.37	0.49	0.08	0.33

Table 6: Cross-Sectional Heterogeneity in Predictability

This table examines cross-sectional heterogeneity in how changes in banks' internal risk assessments predict next-quarter financial market outcomes, using a firm-bank-quarter panel. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The specification includes interactions between EL^+ (a dummy variable that equals one if the expected loss increases from quarter $t-1$ to quarter t) and firm characteristics (book-to-market ratio, ROA, leverage, market capitalization, and lagged returns). Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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^+	−5.918***	−2.087	13.368**	−0.774
	(2.672)	(1.561)	(2.567)	(0.907)
EL^+ × Book/Market	1.401**	−0.242	−3.153**	−0.095
	(2.001)	(0.479)	(2.124)	(0.372)
EL^+ × ROA	3.378	1.425	−4.742	−0.661
	(1.150)	(0.759)	(0.710)	(0.519)
EL^+ × Leverage	0.152	−0.262	2.180	−0.047
	(0.153)	(0.469)	(1.034)	(0.123)
EL^+ × Log(Market Cap)	0.265**	0.114	−0.686**	0.046
	(2.068)	(1.506)	(2.189)	(0.921)
EL^+ × Lagged Stock Return	−0.008		0.002	0.008
	(0.639)		(0.066)	(0.930)
EL^+ × Lagged Bond Return		0.092**		
		(2.107)		
Book-to-Market	−0.393	0.361	4.995***	0.775***
	(0.628)	(0.980)	(2.736)	(3.677)
ROA	0.205	0.595	−2.207	1.026
	(0.101)	(0.707)	(0.330)	(1.184)
Leverage	−0.600	0.134	2.406	0.451
	(0.771)	(0.446)	(1.030)	(1.623)
Log(Market Cap)	0.156	−0.006	−3.612***	−0.068*
	(1.355)	(0.109)	(10.209)	(1.774)
Lagged Stock Return	−0.012		−0.164***	0.310***
	(0.885)		(6.165)	(34.692)
Lagged Bond Return		−0.115***		
		(2.812)		
Mean of DV	0.83	0.99	26.89	0.14
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	117,622	54,075	107,899	115,084
R-squared	0.37	0.49	0.08	0.33

Table 7: Stock Return Predictability by Firm Size

This table examines how the predictability of banks' internal risk assessments for future stock returns varies across firm-size quintiles, using a firm-bank-quarter panel. The dependent variable is the quarterly stock return in quarter $t+1$ (in percentage points). Each column presents results for subsamples of different firm-size quintile based on lagged market capitalization, with Quintile 1 containing the smallest firms and Quintile 5 the largest. The main independent variable is EL^{+}, an indicator equal to one if the bank's assessed expected loss for the firm increased from quarter $t-1$ to quarter t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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^{+}	−1.744**	−0.771*	−0.843***	−0.522**	0.080
	(2.295)	(1.923)	(3.048)	(2.026)	(0.363)
Book-to-Market	3.504**	−1.773	−0.513	−2.277***	−1.606
	(2.553)	(1.485)	(0.446)	(2.623)	(1.352)
ROA	10.668	−2.932	−0.109	−5.147	−0.121
	(1.345)	(0.636)	(0.022)	(1.609)	(0.047)
Leverage	4.460	−2.734*	−1.687	−1.037	−0.554
	(1.576)	(1.696)	(1.216)	(0.984)	(0.555)
Log(Market Cap)	1.183*	−0.420	−1.982*	1.610***	0.462**
	(1.931)	(0.415)	(1.941)	(2.842)	(2.526)
Lagged Stock Return	−0.033	−0.017	0.001	−0.027	0.000
	(1.225)	(0.869)	(0.062)	(1.631)	(0.001)
Mean of DV	0.43	0.40	0.43	0.71	1.58
Bank-Quarter FE	YES	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES	YES
Observations	10,069	18,702	24,675	29,534	34,536
R-squared	0.39	0.48	0.48	0.53	0.51

Table 8: Decomposition of Predictability: PD vs. LGD

This table tests whether the predictive power of bank assessments stems from changes in the Probability of Default (PD), Loss Given Default (LGD), or both, using a firm-bank-quarter panel. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The main independent variables are PD^{+} and LGD^{+}, which are dummy variables equal to one if the bank's assessed probability of default or loss given default increased, respectively, from quarter $t-1$ to quarter t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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+	−0.418*	−0.177	1.968***	−0.269**
	(1.673)	(1.392)	(3.161)	(2.407)
LGD+	−0.626**	−0.198*	0.573	−0.038
	(2.479)	(1.790)	(0.984)	(0.462)
Book-to-Market	−0.109	0.283	4.316**	0.753***
	(0.176)	(0.738)	(2.378)	(3.442)
ROA	0.859	0.766	−3.176	0.907
	(0.431)	(0.750)	(0.473)	(1.022)
Leverage	−0.567	0.068	2.732	0.438
	(0.738)	(0.205)	(1.174)	(1.537)
Log(Market Cap)	0.203*	0.016	−3.728***	−0.059
	(1.761)	(0.291)	(10.537)	(1.530)
Lagged Stock Return	−0.014		−0.164***	0.312***
	(1.041)		(6.246)	(34.253)
Lagged Bond Return		−0.086**		
		(1.985)		
Mean of DV	0.83	0.99	26.89	0.14
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	117,622	54,075	107,899	115,084
R-squared	0.37	0.49	0.08	0.33

Table 9: Bank Information and Credit Allocation

This table examines whether banks use their private information to allocate credit, using a firm-bank-quarter panel. The dependent variable is the log of a bank's committed loan exposure to a borrower, multiplied by 100. The main independent variable is the bank's assessed expected loss (EL) for the firm, expressed in percentage points. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EL	−18.072***	−17.539***	−6.683***	−3.091***	−1.350***	−3.542***	−4.663***	−1.299***
	(9.442)	(9.163)	(6.152)	(6.463)	(3.342)	(6.671)	(4.755)	(3.156)
Mean of DV	1,788.08	1,788.08	1,788.08	1,788.08	1,788.08	1,788.08	1,788.08	1,788.08
Bank-Quarter FE	NO	YES	NO	NO	NO	YES	YES	YES
Firm-Quarter FE	NO	NO	YES	NO	YES	NO	YES	YES
Bank-Firm FE	NO	NO	NO	YES	YES	YES	NO	YES
Observations	135,214	135,195	128,463	134,531	127,786	134,512	128,444	127,767
R-squared	0.02	0.11	0.52	0.88	0.93	0.89	0.62	0.93

Table 10: Public Information and Changes in Banks' Risk Assessments

This table examines how changes in publicly available firm-level characteristics affect the likelihood that banks update their internal risk assessments, using a firm-bank-quarter panel. The dependent variables are dummy variables measured in percentage points, indicating if the bank's assessed PD, LGD, or expected loss increased (columns 1, 3, 5) or decreased (columns 2, 4, 6) from quarter $t-1$ to quarter t. The independent variables are lagged changes in firm characteristics (book-to-market ratio, ROA, leverage) and lagged stock returns, all measured from quarter $t-1$ to quarter t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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)
Lagged Change in Book/Market	0.101***	−0.050***	0.008	−0.011	0.092***	−0.057***
	(7.128)	(5.216)	(0.737)	(1.016)	(5.939)	(4.737)
Lagged Change in ROA	−1.246***	0.722***	−0.113*	0.018	−1.262***	0.805***
	(11.660)	(8.211)	(1.776)	(0.287)	(11.419)	(8.721)
Lagged Change in Leverage	0.183***	−0.159***	−0.033	0.024	0.167***	−0.123***
	(5.076)	(5.099)	(1.320)	(0.937)	(4.153)	(3.631)
Lagged Stock Return	−0.063***	0.019**	0.001	−0.014	−0.048***	0.007
	(5.835)	(2.510)	(0.100)	(1.559)	(4.160)	(0.727)
Mean of DV	10.82	11.96	11.27	13.05	16.88	19.08
Bank-Quarter FE	YES	YES	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES	YES	YES
Observations	116,985	116,985	116,985	116,985	116,985	116,985
R-squared	0.19	0.26	0.28	0.28	0.17	0.23

Table 11: Relationship-Level Drivers of Risk Assessment Updates

This table examines how bank-specific factors affect the likelihood that banks update their internal risk assessments, using a firm-bank-quarter panel. The dependent variables are dummy variables measured in percentage points indicating whether the bank's assessed PD, LGD, or expected loss changed (either increased or decreased) from quarter $t-1$ to quarter t. Log(Committed) is in log dollars times 100; Term Loan is in percentage points; and Specialize, New Loan, Drawdown, and Paydown are dummy variables that equal one or zero. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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)
Log(Committed)	0.020***	0.053***	0.052***
	(4.915)	(8.515)	(9.488)
Months Since Financial Statement	−0.167***	−0.027	−0.132**
	(3.707)	(0.446)	(2.245)
Months Since Audit	−0.043	−0.050	−0.087*
	(1.547)	(0.900)	(1.950)
Maturity (months)	−0.014	−0.094**	−0.068*
	(0.548)	(2.280)	(1.848)
Term Loan (% of total)	0.033**	0.106***	0.105***
	(2.543)	(4.918)	(5.133)
Specialize	−0.214	−0.552	−0.735
	(0.305)	(0.514)	(0.692)
New Loan	3.734***	9.577***	10.327***
	(4.319)	(8.868)	(9.852)
Drawdown	2.011***	12.415***	12.018***
	(2.850)	(9.893)	(9.799)
Paydown	2.540***	10.271***	10.445***
	(3.958)	(8.990)	(9.310)
Mean of DV	22.78	24.32	35.96
Bank-Quarter FE	YES	YES	YES
Firm-Quarter FE	YES	YES	YES
Observations	92,361	92,361	92,361
R-squared	0.48	0.55	0.49

Table 12: Credit Line Drawdowns and Bank Risk Assessments

This table examines whether credit line drawdowns predict changes in banks' risk assessments, using a firm-bank-quarter panel. The dependent variables are dummy variables measured in percentage points indicating whether the bank's assessed PD, LGD, or expected loss increased from quarter $t-1$ to quarter t. The main independent variable, Drawdown, is a dummy variable that equals one if the total utilization rate across all of a firm's credit lines from the same bank increases from quarter $t-1$ to t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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	2.269***	2.626***	3.965***	0.012	3.490***	2.462***
	(7.952)	(8.641)	(11.403)	(0.028)	(6.462)	(4.310)
Mean of DV	10.82	11.27	16.88	10.82	11.27	16.88
Bank-Quarter FE	YES	YES	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES	YES	YES
Firm-Quarter FE	NO	NO	NO	YES	YES	YES
Observations	114,836	114,836	114,836	109,476	109,476	109,476
R-squared	0.18	0.28	0.17	0.40	0.42	0.36

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

This table examines whether credit line drawdowns and changes in banks' internal risk assessments separately predict next-quarter financial market outcomes, using a firm-bank-quarter panel. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement EPS is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The main independent variables are Drawdown, a dummy variable that equals one if the total utilization rate across all of a firm's credit lines from the same bank increases from quarter $t-1$ to t, and EL^+, a dummy variable equal to one if the bank's assessed expected loss increases from quarter $t-1$ to quarter t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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)
Drawdown	-1.898^{***}	0.039	2.548^{***}	-0.227^{*}
	(7.412)	(0.293)	(3.169)	(1.934)
EL^+	-0.610^{***}	-0.254^{**}	1.655^{***}	-0.198^{**}
	(2.953)	(2.359)	(3.351)	(2.528)
Book-to-Market	-0.109	0.266	4.879^{**}	0.715^{***}
	(0.171)	(0.669)	(2.583)	(3.133)
ROA	2.155	0.796	-0.557	0.853
	(1.034)	(0.759)	(0.079)	(0.907)
Leverage	-0.307	0.035	2.781	0.428
	(0.386)	(0.101)	(1.152)	(1.428)
Log(Market Cap)	0.137	0.021	-3.644^{***}	-0.070^{*}
	(1.137)	(0.365)	(10.048)	(1.728)
Lagged Stock Return	-0.017		-0.168^{***}	0.313^{***}
	(1.184)		(6.104)	(32.443)
Lagged Bond Return		-0.089^{*}		
		(1.962)		
Mean of DV	0.83	0.99	26.89	0.14
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	110,450	51,415	101,377	108,095
R-squared	0.39	0.49	0.09	0.33

Appendix A. Variable Definitions

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

Bond Return: Firm-level quarterly bond return (in percentage points), value-weighted by bond size, from Bond Returns by WRDS/TRACE.

Book-to-Market: Book value of equity divided by market value of equity, winsorized at [1%, 99%], from Compustat.

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

Drawdown: A dummy variable that equals one if the total utilization rate across all of a firm's credit lines from the same bank increased from the prior quarter, and zero otherwise, 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 (EL): Probability of default multiplied by loss given default, weighted by the committed dollar amount of each loan at the bank-firm-quarter level, from Y-14Q.

EDF-X$^+$: A dummy variable that equals one if Moody's EDF-X (formerly Moody's KMV EDF) increased from quarter $t-1$ to quarter t, from Moody's CreditEdge.

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

Leverage: Total debt divided by total capital, winsorized at [1%, 99%], from Compustat.

Loan Volume: Total committed loan amount in millions of dollars, aggregated at the bank-firm-quarter level, from Y-14Q.

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

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

Market Cap: Market capitalization in billions of dollars, from CRSP.

Maturity: Remaining average maturity in months, weighted 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 financial statements from the firm, from Y-14Q.

Negative Earnings Surprise: A dummy variable that equals one if the earnings announcement earnings per share (EPS) comes in below the consensus analyst estimate, and zero otherwise, from IBES.

New Loan: A dummy variable that equals one if the bank originates a new loan to the firm in the quarter, and zero otherwise, from Y-14Q.

Number of Banks: The number of unique banks lending to a given firm in each quarter, from Y-14Q.

Paydown: A dummy variable that equals one if the total utilization rate across all of a firm's credit lines from the same bank decreased from the prior quarter, and zero otherwise, from Y-14Q.

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

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

ROA: Operating income before depreciation divided by average total assets (based on the most recent two periods), winsorized at [1%, 99%], from Compustat.

Specialize: A dummy variable 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.

Syndicated Loan: A dummy variable equal to one if a bank-firm-quarter pair includes at least one syndicated loan, from Y-14Q.

Term Loan: The fraction of committed loan amount allocated to term loans (as opposed to credit lines) at the bank-firm-quarter level, expressed in percentage points, from Y-14Q.

Appendix B. Additional Summary Statistics and Analysis

Table B1: Sample Representativeness

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)	12.975	2.053	27,417	7.967	0.901	48,193	5.008***	1.152***
Book-to-Market	0.515	0.404	26,343	0.526	0.386	45,098	-0.011***	0.018***
ROA	0.129	0.126	27,278	0.013	0.099	47,383	0.116***	0.027***
Leverage	0.449	0.439	27,298	0.412	0.376	47,480	0.037***	0.063***

Table B2: Quarterly Stock Returns (Alternative Specifications)

This table examines the effects of changes in risk assessments on quarterly stock returns across alternative specifications. The dependent variable is the quarterly stock return in quarter $t+1$ (in percentage points). Column (1) shows our baseline quarterly return result using the firm-bank-quarter panel shown in Table 5. Column (2) shows our baseline firm-bank-quarter results when the regressions are weighted by $\frac{1}{N_{i,t}}$, where $N_{i,t}$ is the number of different banks lending to firm i at time t. Column (3) creates a panel by aggregating EL^+ and EL^- to the firm-quarter level using lagged loan volume-weighted averages across banks in each quarter. Column (4) aggregates EL^+ and EL^- to the firm-quarter level using simple averages across banks in each quarter. Column (5) uses the maximum of EL^+ and EL^- across banks in each quarter. Column (6) takes the risk assessments from the bank with the highest total loan volume to each firm in each quarter. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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.

	(1)	(2)	(3)	(4)	(5)	(6)
EL^+	−0.773***	−0.831**	−1.829***	−1.640***	−0.799***	−1.379***
	(3.771)	(2.491)	(3.305)	(2.840)	(3.420)	(3.724)
EL^-	−0.226	−0.130	−0.283	−0.089	0.063	−0.556
	(1.267)	(0.425)	(0.554)	(0.162)	(0.250)	(1.616)
Book-to-Market	−0.103	−0.226	−0.230	−0.234	−0.184	−0.037
	(0.167)	(0.359)	(0.442)	(0.448)	(0.350)	(0.070)
ROA	0.817	−0.098	−0.513	−0.511	−0.396	−0.301
	(0.410)	(0.039)	(0.269)	(0.269)	(0.209)	(0.161)
Leverage	−0.550	−0.538	−0.710	−0.750	−0.600	−0.465
	(0.718)	(0.743)	(1.185)	(1.252)	(0.983)	(0.746)
Log(Market Cap)	0.200*	0.200*	0.188**	0.190**	0.248***	0.258***
	(1.744)	(1.921)	(2.251)	(2.277)	(2.970)	(2.927)
Lagged Stock Return	−0.014	−0.011	−0.013	−0.013	−0.013	−0.014
	(1.047)	(0.897)	(1.173)	(1.166)	(1.185)	(1.269)
Mean of DV	0.83	0.83	0.87	0.94	0.94	0.94
Bank-Quarter FE	YES	YES	NO	NO	NO	YES
Industry-Quarter FE	YES	YES	YES	YES	YES	YES
Observations	117,622	117,622	24,307	24,307	24,307	24,301
R-squared	0.37	0.30	0.30	0.30	0.30	0.31

Table B3: Changes in Expected Losses Predict Financial Market Outcomes (Controlling for Public Risk Assessments)

This table tests whether changes in banks' expected losses predict next-quarter stock returns, bond returns, earnings surprises, and earnings announcement returns, using a firm-bank-quarter panel while controlling for EDF-X^{+}, an indicator equal to one if EDF-X, a one-year estimated default probability from Moody's, increased from the prior period. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement EPS is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The main independent variables are EL^{+} and EL^{-}, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. Appendix Section A contains all other variable definitions. T-statistics are shown below the parameter estimates in parentheses 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^{+}	−0.818***	−0.208**	1.940***	−0.213***
	(3.976)	(2.094)	(3.742)	(2.625)
EL^{-}	−0.238	0.092	0.534	0.068
	(1.348)	(1.376)	(1.279)	(1.033)
EDF-X^{+}	−0.049	−0.080	2.036***	−0.230*
	(0.200)	(1.064)	(2.704)	(1.832)
Book-to-Market	−0.135	0.281	4.609**	0.739***
	(0.217)	(0.729)	(2.488)	(3.368)
ROA	0.871	0.762	−2.613	0.707
	(0.432)	(0.741)	(0.387)	(0.801)
Leverage	−0.466	0.047	2.648	0.420
	(0.605)	(0.141)	(1.133)	(1.485)
Log(Market Cap)	0.191*	0.014	−3.692***	−0.071*
	(1.660)	(0.263)	(10.349)	(1.843)
Lagged Stock Return	−0.014		−0.150***	0.311***
	(0.995)		(5.523)	(32.395)
Lagged Bond Return		−0.086**		
		(1.972)		
Mean of DV	0.83	0.99	26.89	0.14
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	115,988	53,727	106,362	113,467
R-squared	0.37	0.49	0.09	0.34

Table B4: Changes in Expected Losses Predict Equity Returns (Excluding Firms with Traded Credit Instruments)

This table tests whether changes in banks' expected losses predict next-quarter stock returns (measured in percentage points) using a firm-bank-quarter panel. The main independent variables are EL^+ and EL^-, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. Column (1) reports our baseline results. Column (2) excludes firm-quarters that have a loan with an observable secondary market price. We obtain secondary market loan prices from LPC Loan Pricing by Refinitiv, which we merge into Dealscan, then merge Dealscan into Compustat using the Roberts Dealscan-Compustat Linking Database and the matching protocol from Cohen et al. (2021). Column (3) excludes firm-quarters with traded credit default swaps (CDS data from S&P Global). Column (4) excludes firm-quarters with traded bonds. Column (5) excludes firms with any traded loans, CDS, or bonds. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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.

	Baseline	No Traded Loans	No Traded CDS	No Traded Bonds	No Traded Credit
	(1)	(2)	(3)	(4)	(5)
EL^+	−0.773***	−0.734***	−0.842***	−1.135***	−1.143***
	(3.771)	(3.608)	(3.610)	(4.939)	(4.755)
EL^-	−0.226	−0.219	−0.224	−0.379	−0.346
	(1.267)	(1.216)	(1.106)	(1.583)	(1.380)
Book-to-Market	−0.103	−0.379	−0.326	−0.452	−0.683
	(0.167)	(0.598)	(0.524)	(0.668)	(0.959)
ROA	0.817	0.271	0.794	−0.608	−1.532
	(0.410)	(0.134)	(0.356)	(0.240)	(0.578)
Leverage	−0.550	−0.544	−0.527	−0.725	−0.608
	(0.718)	(0.716)	(0.649)	(0.790)	(0.658)
Log(Market Cap)	0.200*	0.194*	0.093	0.103	0.117
	(1.744)	(1.707)	(0.675)	(0.649)	(0.732)
Lagged Stock Return	−0.014	−0.010	−0.012	−0.027**	−0.018
	(1.047)	(0.692)	(0.827)	(2.347)	(1.511)
Mean of DV	0.83	0.88	0.82	0.85	0.94
Bank-Quarter FE	YES	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES	YES
Observations	117,622	112,302	89,628	62,697	56,795
R-squared	0.37	0.38	0.36	0.35	0.34

Table B5: Portfolio Sorts

This table tests whether changes in banks' expected losses predict future stock returns using portfolio sorts as an alternative to panel regressions. We first collapse our data into a firm-quarter panel, taking averages of EL^{+} and EL^{-} weighted by lagged loan volume (Panel A) or equal-weighted (Panel B), calculated across banks at each point in time. At the end of each quarter, we sort stocks into portfolios based on whether this weighted average change in expected loss was negative ("Upgrade") or positive ("Downgrade"). This table reports equal-weighted monthly stock returns of each portfolio in percentage points. Three-Factor is the alpha from the Fama-French three-factor model, and Four-Factor is the alpha from the Carhart four-factor model.

Panel A: Value Weighted EL

	Returns	3-Factor	4-Factor
Upgrade	0.3226	0.1492	0.1501
Downgrade	-0.0111	-0.0985	-0.0959
Upgrade - Downgrade	0.3337	0.2477	0.2460
(t-stat)	2.43	2.23	2.69
N	60	60	60

Panel B: Equal Weighted EL

	Returns	3-Factor	4-Factor
Upgrade	0.3098	0.1357	0.1367
Downgrade	0.0037	-0.1161	-0.1031
Upgrade - Downgrade	0.3061	0.2518	0.2398
(t-stat)	2.36	2.35	2.57
N	60	60	60

Table B6: Fama-MacBeth Regressions

This table tests whether changes in banks' expected losses predict next-quarter stock returns (measured in percentage points) using Fama-MacBeth regressions. Column (1) is estimated on the firm-bank-quarter panel shown in Table 5. In column (2), we create a panel by aggregating EL^+ and EL^- to the firm-quarter level using lagged loan volume-weighted averages across banks. In column (3), we aggregate EL^+ and EL^- at the firm-quarter level using simple averages across banks. Appendix Section A contains all variable definitions. We report the time-series mean of the parameter estimates with t-statistics, calculated using Newey-West (1987) standard errors with three lags, shown below in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
EL^+	-0.466^{***}	-1.429^{***}	-1.244^{**}
	(3.906)	(3.892)	(2.791)
EL^-	-0.062	-0.367	-0.201
	(0.664)	(0.934)	(0.457)
Book-to-Market	-0.316	-0.219	-0.240
	(0.275)	(0.321)	(0.351)
ROA	0.340	-0.101	-0.022
	(0.124)	(0.039)	(0.008)
Leverage	-0.839	-0.863	-0.922
	(0.639)	(0.697)	(0.739)
Log(Market Cap)	0.227	0.209	0.210
	(0.895)	(1.000)	(1.003)
Lagged Stock Return	-0.013	-0.009	-0.009
	(0.845)	(0.549)	(0.534)
Mean of DV	0.83	0.87	0.94
Industry FE	YES	YES	YES
Observations	117,650	24,317	24,317
R-squared	0.15	0.12	0.12

Table B7: Changes in Expected Losses Predict Equity Alphas

This table examines whether changes in banks' internal risk assessments predict quarterly equity alphas and abnormal returns around earnings announcements, using a firm-bank-quarter panel. Column (1) reports our baseline estimates of the effects of changes in risk assessments on quarterly stock returns. The dependent variables in columns (2) and (3) are the quarterly Fama-French three-factor and Carhart four-factor model alphas, estimated using a rolling 5-year window. Column (4) reports our baseline estimates of the effects of changes in banks' risk assessments on earnings returns. The dependent variables in columns (5) and (6) are the two-day cumulative abnormal returns, where daily abnormal returns are calculated as the residual from either the Fama-French three-factor model or the Carhart four-factor model, estimated using a rolling 252-trading-day window. All outcomes are measured in percentage points. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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	3F Quarterly α	4F Quarterly α	Earnings Return	2-Day 3F CAR	2-Day 4F CAR
	(1)	(2)	(3)	(4)	(5)	(6)
EL^{+}	-0.773^{***}	-0.635^{***}	-0.586^{**}	-0.203^{**}	-0.206^{**}	-0.194^{**}
	(3.771)	(2.657)	(2.412)	(2.513)	(2.576)	(2.432)
EL^{-}	-0.226	-0.024	0.200	0.077	0.083	0.088
	(1.267)	(0.141)	(1.097)	(1.162)	(1.268)	(1.336)
Lagged Stock Return	-0.014	0.031^{**}	0.038^{**}	0.312^{***}	0.310^{***}	0.309^{***}
	(1.047)	(1.993)	(2.417)	(34.263)	(33.860)	(33.706)
Book-to-Market	-0.103	0.741	0.541	0.750^{***}	0.708^{***}	0.716^{***}
	(0.167)	(0.992)	(0.721)	(3.428)	(3.291)	(3.281)
ROA	0.817	4.664^{*}	3.797	0.911	1.137	0.948
	(0.410)	(1.935)	(1.523)	(1.026)	(1.302)	(1.081)
Leverage	-0.550	-1.375	-1.471	0.434	0.436	0.501^{*}
	(0.718)	(1.549)	(1.601)	(1.521)	(1.525)	(1.765)
Log(Market Cap)	0.200^{*}	-0.191^{*}	-0.210^{*}	-0.058	-0.083^{**}	-0.090^{**}
	(1.744)	(1.775)	(1.885)	(1.504)	(2.125)	(2.350)
Mean of DV	0.83	-0.51	-0.53	0.14	0.14	0.16
Bank-Quarter FE	YES	YES	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES	YES	YES
Observations	117,622	106,991	106,991	115,084	115,076	115,076
R-squared	0.37	0.11	0.11	0.33	0.33	0.33

Table B8: Financial Market Outcomes Controlling for Market Betas

This table tests whether changes in banks' expected losses predict next quarter stock and bond returns, using a firm-bank-quarter panel and controlling for market betas, which come from regressing excess returns on the three Fama-French factors (β^{3F}) or the four Carhart factors (β^{4F}). The main independent variables are EL^{+} and EL^{-}, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. All outcomes are measured in percentage points. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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	
	(1)	(2)	(3)	(4)
EL^{+}	−0.778***	−0.775***	−0.230**	−0.230**
	(3.635)	(3.623)	(2.150)	(2.172)
EL^{-}	−0.259	−0.255	0.067	0.064
	(1.446)	(1.425)	(1.014)	(0.951)
Book-to-Market	0.507	0.551	0.299	0.307
	(0.755)	(0.815)	(0.686)	(0.700)
ROA	1.571	1.550	0.481	0.554
	(0.732)	(0.726)	(0.458)	(0.526)
Leverage	−0.354	−0.305	0.135	0.147
	(0.435)	(0.369)	(0.374)	(0.406)
Log(Market Cap)	0.219*	0.226*	0.004	0.014
	(1.852)	(1.895)	(0.075)	(0.249)
Lagged Stock Return	−0.016	−0.016		
	(1.099)	(1.092)		
Lagged Bond Return			−0.081*	−0.082*
			(1.776)	(1.783)
$\hat{\beta}^{3F}_{MKTRF}$	−0.283		−0.155*	
	(1.298)		(1.866)	
$\hat{\beta}^{3F}_{SMB}$	0.144		−0.055	
	(0.909)		(0.542)	
$\hat{\beta}^{3F}_{HML}$	−0.114		0.093	
	(0.749)		(1.452)	
$\hat{\beta}^{4F}_{MKTRF}$		−0.275		−0.101
		(1.373)		(1.461)
$\hat{\beta}^{4F}_{SMB}$		0.154		−0.001
		(1.033)		(0.010)
$\hat{\beta}^{4F}_{HML}$		−0.096		0.054
		(0.627)		(0.863)
$\hat{\beta}^{4F}_{MOM}$		0.312*		−0.011
		(1.880)		(0.170)
Mean of DV	0.83	0.83	0.99	0.99
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	106,991	106,991	51,059	51,059
R-squared	0.38	0.38	0.49	0.49

Internet Appendix

Figure OA1: Asymmetric Market Reaction to Changes in Expected Loss

This figure shows a binscatter plot comparing quarterly stock returns and percentage changes in expected loss. The vertical axis is quarterly returns from quarter t to quarter $t+1$ in percentage points. The horizontal axis is the percent change in expected loss between quarter $t-1$ and quarter t calculated at the firm-quarter level using a loan-volume weighted average of EL for each firm across all banks in each quarter. The sample includes percentage changes in EL with absolute values above 0.5%. The red lines represent separate regression lines fitted for observations with percentage changes in EL above or below zero (shown as the dashed vertical line). The figure includes $N = 20,691$ firm-quarter observations. All bins include data pooled from at least 11 banks.

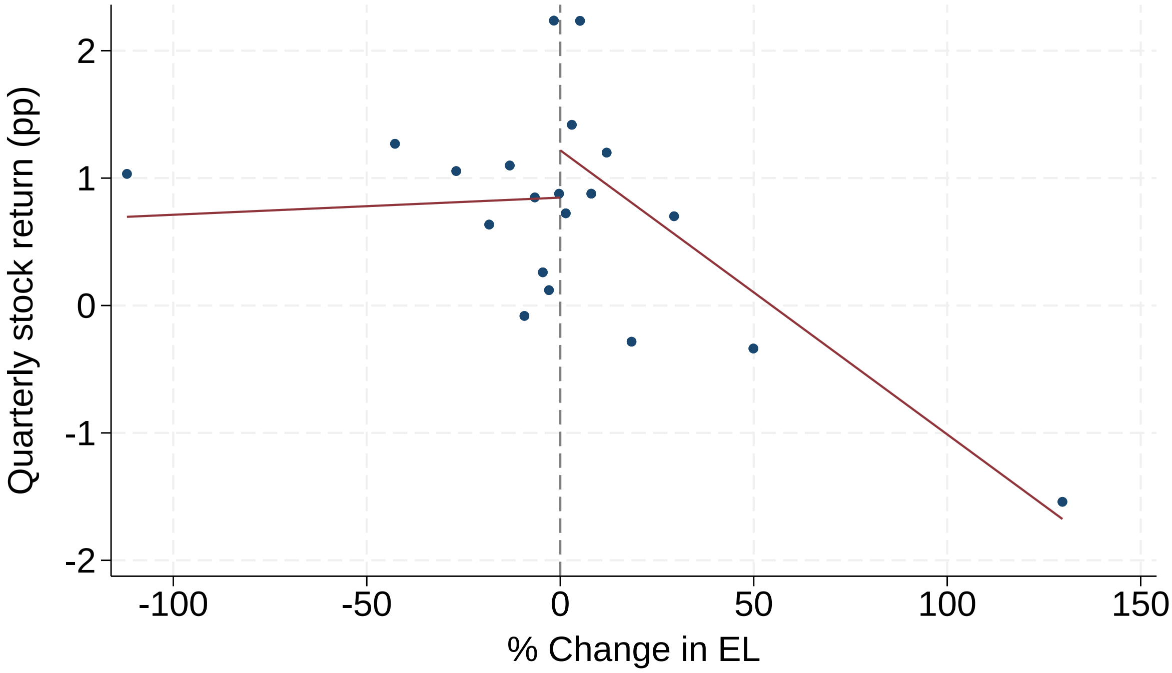


Figure OA2: Bank Information and Credit Allocation: Event Study

This figure shows the dynamic effects of changes in risk assessments on lending. For firm i borrowing from bank b at time t, we estimate the following regression: $\Delta y_{i,b,t+h} = \beta_1^h EL^+ + \beta_2^h EL^- + \alpha_{i,t}^h + \delta_{b,t}^h + \epsilon_{i,b,t+h}$ where $\Delta y_{i,b,t+h}$ is the percent change in committed exposure from bank b to firm i from quarter $t-1$ to quarter $t+h$, EL^+ and EL^- are indicators for whether expected losses increased or decreased between time t and time $t-1$, α are firm-quarter fixed effects, and δ are bank-quarter fixed effects. All regressions exclude firm-bank-quarter observations that recorded new loans at time t. The figure plots β_1^h for $h = 0$ to $h = 8$, with vertical lines indicating 95% confidence intervals calculated using standard errors double-clustered by firm and bank-quarter. The number of observations in each regression ranges from $N = 109,250$ for horizon $h = 0$ to $N = 49,179$ for horizon $h = 8$.

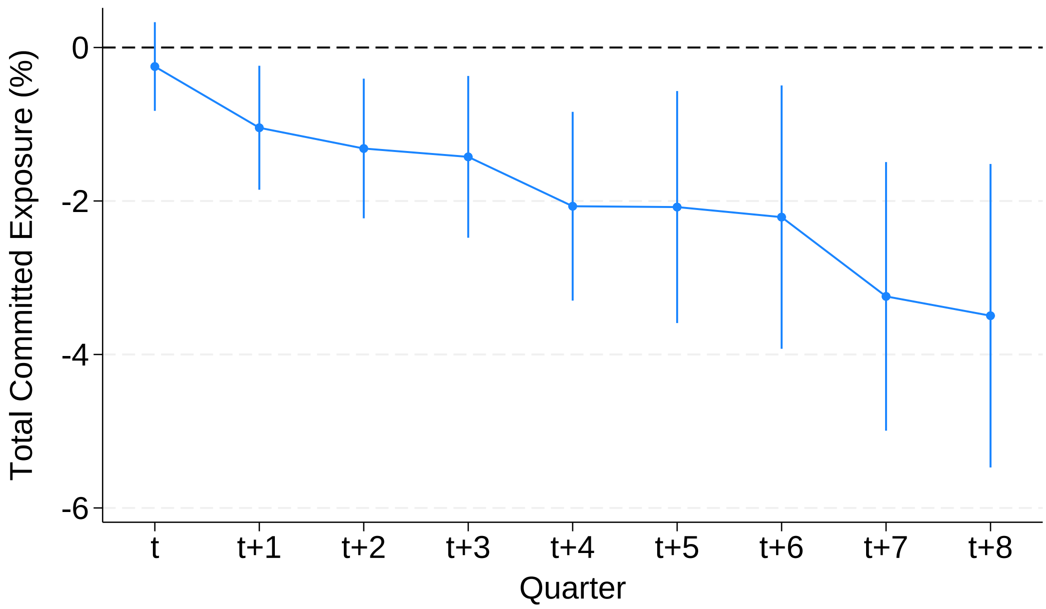


Figure OA3: Bank Information and Credit Allocation: Event Study (Credit Lines)

This figure shows the dynamic effects of changes in risk assessments on lending for credit lines. For firm i borrowing from bank b at time t, we estimate the following regression: $\Delta y_{i,b,t+h} = \beta_1^h EL^+ + \beta_2^h EL^- + \alpha_{i,t}^h + \delta_{b,t}^h + \epsilon_{i,b,t+h}$ where $\Delta y_{i,b,t+h}$ is the percent change in committed exposure across all revolving credit facilities from bank b to firm i from quarter $t-1$ to quarter $t+h$, EL^+ and EL^- are indicators for whether expected losses increased or decreased between time t and time $t-1$, α are firm-quarter fixed effects, and δ are bank-quarter fixed effects. All regressions exclude firm-bank-quarter observations that recorded new loans at time t. The figure plots β_1^h for $h = 0$ to $h = 8$, with vertical lines indicating 95% confidence intervals calculated using standard errors double-clustered by firm and bank-quarter. The number of observations in each regression ranges from $N = 102,370$ for horizon $h = 0$ to $N = 46,399$ for horizon $h = 8$.

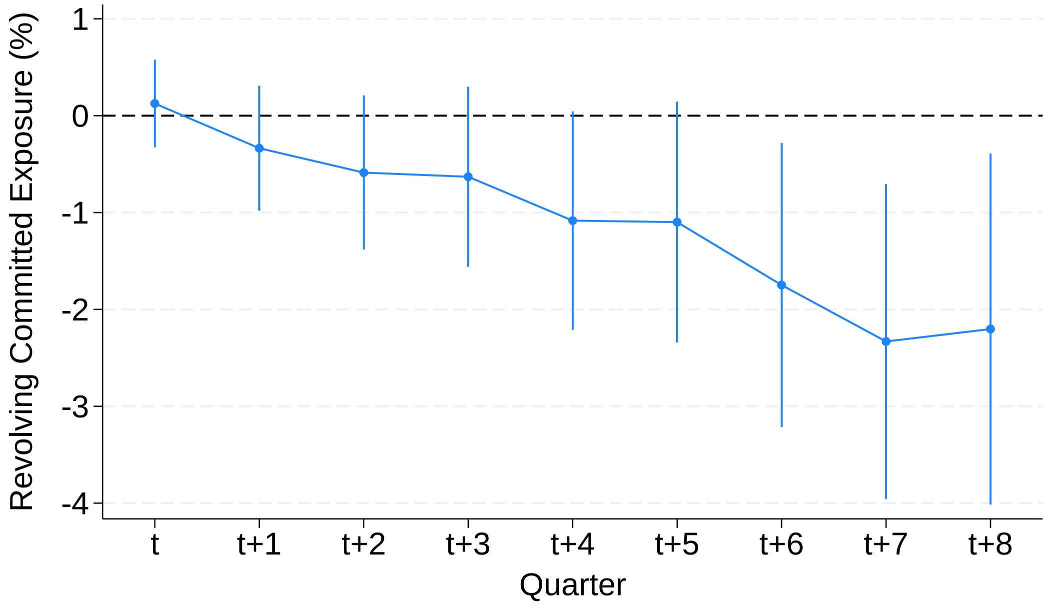


Table OA1: Sample Construction

This table describes the sequential construction of our main sample. The three columns display the number of unique firms, firm-quarters, and bank-firm-quarters remaining after each filter is applied. Panel A describes the matching process to CRSP and Compustat. After the initial merge, we retain observations where total assets reported in Y-14Q are within 90% to 110% of total assets reported in Compustat in the same quarter to account for subsidiaries reporting parent tax IDs. Panel B applies sample restrictions based on date range (2014Q4–2019Q4) and firm type (using the FF30 classification to exclude financials and utilities). Panel C applies the following data quality filters: (1) loans with total committed credit below \$1 million; (2) loans with utilized credit below zero or greater than committed credit; (3) loans with PD ≤ 0 or PD > 1; (4) loans with LGD ≤ 0; and (5) firm-quarters with cross-bank standard deviations of PD greater than 0.5 percentage points or cross-bank standard deviations of LGD greater than 25 percentage points.

	Firms	Firm-Quarters	Bank-Firm-Quarters
Panel A: Matching to Public Data			
After merging with CRSP/Compustat	2,476	42,781	210,864
Less: Assets outside 90%–110% range	2,213	41,442	201,248
Panel B: Sample Restrictions			
Less: Outside 2014Q4-2019Q4	1,940	29,006	147,033
Less: Financials and Utilities	1,865	27,639	138,263
Panel C: Additional Filters			
Less: Data quality filters	1,857	27,417	135,214
Final Sample	1,857	27,417	135,214

Table OA2: Changes in Expected Losses Predict Financial Market Outcomes (Controlling for Nonlinear Interactions of Public Risk Assessments)

This table tests whether changes in banks' expected losses predict next-quarter stock returns, bond returns, earnings surprises, and earnings announcement returns, using a firm-bank-quarter panel while controlling for nonlinear interactions between public credit risk signals and firm characteristics. Specifically, we include triple interaction terms between (1) EDF-X, an estimated one-year default probability from Moody's, (2) a dummy variable indicating whether EDF-X increased from the prior period, and (3) all control variables (book-to-market, ROA, leverage, log market capitalization, and lagged stock/bond returns). The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement EPS is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The main independent variables are EL^{+} and EL^{-}, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. Appendix Section A contains all other variable definitions. T-statistics are shown below the parameter estimates in parentheses 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^{+}	−0.887***	−0.236**	1.958***	−0.223***
	(4.263)	(2.368)	(3.807)	(2.740)
EL^{-}	−0.214	0.087	0.569	0.073
	(1.184)	(1.370)	(1.367)	(1.116)
Mean of DV	0.83	0.99	26.89	0.14
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	115,988	53,727	106,362	113,467
R-squared	0.38	0.51	0.09	0.34

Table OA3: Changes in Expected Losses Predict Financial Market Outcomes (Controlling for Public Credit Signals)

This table tests whether changes in banks' expected losses predict next-quarter stock returns, bond returns, earnings surprises, and earnings announcement returns, using a firm-bank-quarter panel while controlling for Public Credit Signal$^+$. Public Credit Signal$^+$ is constructed as follows: (1) If the firm has observed traded loans in the current and previous quarters, Public Credit Signal$^+$ equals one if the loan return (log change in average bid-ask midpoint) is negative and zero otherwise; (2) if the firm does not have traded loans but has traded CDS, Public Credit Signal$^+$ equals one if the quarterly change in XR14 5-year CDS spreads from S&P Global is positive and zero otherwise; (3) if the firm has neither traded loans nor traded CDS but has traded bonds, Public Credit Signal$^+$ equals one if the quarterly bond return is negative and zero otherwise; (4) and if the firm has no traded loans, CDS, or bonds, then Public Credit Signal$^+$ equals one if the firm's EDF-X, an estimated one-year default probability from Moody's, increased from the previous quarter and zero otherwise. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement EPS is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The main independent variables are EL$^+$ and EL$^-$, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. We obtain secondary market loan prices from LPC Loan Pricing by Refinitiv, merge them into Dealscan, and then link Dealscan to Compustat using the Roberts Dealscan-Compustat Linking Database and the matching protocol from Cohen et al. (2021). Appendix Section A contains all other variable definitions. T-statistics are shown below the parameter estimates in parentheses 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$^+$	-0.791^{***}	-0.203^{**}	1.953^{***}	-0.211^{***}
	(3.868)	(2.046)	(3.786)	(2.620)
EL$^-$	-0.229	0.099	0.531	0.071
	(1.302)	(1.499)	(1.275)	(1.081)
Public Credit Signal$^+$	-0.296	0.093	1.982^{***}	-0.117
	(1.150)	(0.930)	(2.622)	(0.944)
Book-to-Market	-0.118	0.278	4.591^{**}	0.757^{***}
	(0.189)	(0.732)	(2.489)	(3.434)
ROA	0.885	0.752	-2.529	0.833
	(0.438)	(0.738)	(0.375)	(0.941)
Leverage	-0.431	0.056	2.724	0.423
	(0.558)	(0.169)	(1.165)	(1.483)
Log(Market Cap)	0.184	0.014	-3.695^{***}	-0.071^{*}
	(1.601)	(0.266)	(10.370)	(1.844)
Lagged Stock Return	-0.016		-0.153^{***}	0.312^{***}
	(1.112)		(5.592)	(33.299)
Lagged Bond Return		-0.083^{*}		
		(1.899)		
Mean of DV	0.83	0.99	26.89	0.14
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	116,362	54,075	106,732	113,837
R-squared	0.37	0.49	0.09	0.34

Table OA4: Changes in Expected Losses Predict Financial Market Outcomes (Firms Held by Integrated Funds)

This table tests whether changes in banks' expected losses predict next-quarter stock returns, bond returns, earnings surprises, and earnings announcement returns using a firm-bank-quarter panel restricted to firms held by integrated funds. Following Addoum and Murfin (2020), we identify integrated funds as those holding both equities and syndicated loans in CRSP, then flag stocks owned by at least one such fund in the prior quarter. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement EPS is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The main independent variables are EL^{+} and EL^{-}, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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^{+}	−0.723***	−0.188**	1.949***	−0.166**
	(3.313)	(1.983)	(3.710)	(2.025)
EL^{-}	−0.262	0.059	0.289	0.096
	(1.476)	(0.897)	(0.682)	(1.397)
Book-to-Market	−0.041	0.376	3.899**	0.795***
	(0.060)	(0.967)	(2.111)	(3.303)
ROA	0.864	0.816	−5.215	1.380
	(0.417)	(0.928)	(0.758)	(1.489)
Leverage	−0.591	0.227	2.325	0.428
	(0.731)	(0.763)	(0.991)	(1.490)
Log(Market Cap)	0.242*	0.022	−3.653***	−0.048
	(1.875)	(0.437)	(10.001)	(1.138)
Lagged Stock Return	−0.009		−0.161***	0.316***
	(0.645)		(5.906)	(32.471)
Lagged Bond Return		−0.090**		
		(2.216)		
Mean of DV	0.83	0.99	26.89	0.14
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	111,089	53,030	103,745	108,913
R-squared	0.39	0.52	0.09	0.34

Table OA5: Share of Observations with Traded Credit Instruments

This table reports the availability of traded credit instruments across firm-size quintiles. Column (1) identifies the size quintile based on lagged market capitalization, and column (2) reports the total number of firm-bank-quarter observations. Columns (3)–(6) report the number of observations with traded loans, credit default swaps, bonds, or any of these instruments, respectively. We obtain secondary market loan prices from LPC Loan Pricing by Refinitiv, merge them into Dealscan, and then link Dealscan to Compustat using the Roberts Dealscan-Compustat Linking Database and the matching protocol from Cohen et al. (2021). CDS spreads are XR14 5-year tenor from S&P Global. The bottom row reports the average lagged market capitalization across all firm-bank-quarter observations with the traded instrument shown in the first row. Size quintiles are based on lagged market capitalization; therefore, the total in the bottom row excludes observations for newly public firms without lagged market capitalization data.

Size Quintile	**Observations**	**Traded Loan**	**Traded CDS**	**Traded Bond**	**Any Traded Credit Instrument**
1	11,741	494	242	1,575	1,925
2	21,656	1,354	949	4,437	5,556
3	28,132	1,745	2,823	7,785	9,788
4	33,192	2,261	6,375	16,432	19,032
5	39,595	667	22,143	33,215	34,120
Total	134,316	6,521	32,532	63,444	70,421
Average Market Cap ($ bn)		6.00	43.97	33.54	30.84

Table OA6: Changes in Expected Losses and Financial Market Outcomes (Linear Changes)

This table tests whether changes in banks' expected losses predict next-quarter stock returns, bond returns, earnings surprises, and earnings announcement returns, using a firm-bank-quarter panel and a continuous measure of changes in expected losses. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement EPS is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The main independent variable is Change in EL, the change in expected loss from quarter $t-1$ to quarter t, measured in percentage points. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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)
Change in EL	−0.062	−0.049	−0.158	−0.096
	(0.305)	(0.406)	(0.421)	(0.962)
Book-to-Market	−0.122	0.277	4.423**	0.746***
	(0.197)	(0.721)	(2.435)	(3.407)
ROA	0.942	0.786	−3.378	0.933
	(0.471)	(0.769)	(0.503)	(1.051)
Leverage	−0.598	0.057	2.824	0.429
	(0.779)	(0.172)	(1.212)	(1.501)
Log(Market Cap)	0.209*	0.018	−3.745***	−0.058
	(1.815)	(0.327)	(10.581)	(1.487)
Lagged Stock Return	−0.014		−0.165***	0.312***
	(1.027)		(6.301)	(34.272)
Lagged Bond Return		−0.086**		
		(1.974)		
Mean of DV	0.83	0.99	26.89	0.14
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	117,622	54,075	107,899	115,084
R-squared	0.37	0.49	0.08	0.33

Table OA7: Changes in Expected Losses and Financial Market Outcomes (Percentile Changes)

This table tests whether changes in banks' expected losses predict next quarter stock returns, bond returns, earnings surprises, and earnings announcement returns, using a firm-bank-quarter panel that includes only observations with nonzero changes in EL. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement EPS is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The main independent variable is EL Change Percentile, which ranks each nonzero change in EL by its position in the distribution of all nonzero changes across the entire sample, and ranges from 1 to 100. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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 Change Percentile	−0.011**	−0.007**	0.030***	−0.007***
	(2.198)	(2.127)	(2.891)	(3.654)
Book-to-Market	0.577	0.288	5.383***	0.732**
	(0.792)	(0.680)	(2.725)	(2.540)
ROA	2.974	1.505	−2.211	−0.084
	(1.211)	(0.982)	(0.289)	(0.070)
Leverage	0.317	0.059	4.168	0.647*
	(0.310)	(0.134)	(1.555)	(1.754)
Log(Market Cap)	0.263*	0.023	−3.684***	−0.083*
	(1.752)	(0.275)	(9.356)	(1.735)
Lagged Stock Return	−0.028**		−0.180***	0.315***
	(2.154)		(6.123)	(30.595)
Lagged Bond Return		−0.099		
		(1.517)		
Mean of DV	0.83	0.99	26.89	0.14
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	42,270	17,762	38,311	41,239
R-squared	0.40	0.53	0.10	0.35

Table OA8: Changes in Expected Losses and Financial Market Outcomes (Large Increases and Decreases)

This table examines how large and small changes in banks' expected losses predict next-quarter stock returns, bond returns, earnings surprises, and earnings announcement returns, using a firm-bank-quarter panel. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement EPS is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. We classify nonzero changes in expected loss into four categories: Large EL Increase (top 10% of changes), Small EL Increase (increases below the top 10%), Small EL Decrease (decreases above the bottom 10%), and Large EL Decrease (bottom 10% of changes), with observations showing no change as the omitted baseline category. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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)
Large EL Decrease	−0.371	0.499***	0.703	0.321*
	(0.872)	(3.332)	(0.773)	(1.921)
Small EL Decrease	−0.186	0.020	0.369	0.021
	(0.933)	(0.270)	(0.828)	(0.298)
Small EL Increase	−0.692***	−0.138**	1.511***	−0.120*
	(3.801)	(2.047)	(2.840)	(1.660)
Large EL Increase	−1.058**	−0.526	3.702***	−0.517**
	(2.087)	(1.260)	(3.330)	(2.338)
Book-to-Market	−0.094	0.297	4.281**	0.762***
	(0.151)	(0.773)	(2.355)	(3.494)
ROA	0.752	0.803	−2.825	0.909
	(0.380)	(0.784)	(0.420)	(1.024)
Leverage	−0.528	0.062	2.614	0.441
	(0.689)	(0.190)	(1.124)	(1.558)
Log(Market Cap)	0.194*	0.017	−3.696***	−0.059
	(1.696)	(0.325)	(10.499)	(1.549)
Lagged Stock Return	−0.014		−0.164***	0.312***
	(1.057)		(6.241)	(34.227)
Lagged Bond Return		−0.087**		
		(2.011)		
Mean of DV	0.83	0.99	26.89	0.14
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	117,622	54,075	107,899	115,084
R-squared	0.37	0.49	0.08	0.33

Table OA9: Changes in Expected Losses and Contemporaneous Loan Modifications

This table examines whether banks modify loan terms in the same quarter that they update risk assessments, using a firm-bank-quarter panel. The dependent variables are dummy variables (measured in percentage points) indicating whether loan terms changed from quarter $t-1$ to quarter t: Change in maturity equals one if the maturity of at least one loan in the firm-bank relationship changed; Change in IR equals one if the interest rate of at least one loan changed; and Any change equals one if either the maturity or interest rate of at least one loan changed. The main independent variables are EL^+ and EL^-, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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.

	Change in maturity				Change in IR				Any change			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
EL^+	8.062***	8.720***	7.018***	1.926***	6.932***	4.646***	1.098***	0.118	13.125***	11.523***	7.014***	2.138***
	(16.219)	(16.857)	(18.135)	(6.177)	(10.457)	(7.998)	(2.903)	(0.420)	(18.999)	(16.806)	(14.580)	(5.169)
EL^-	7.676***	8.059***	6.861***	2.138***	5.487***	3.605***	-0.034	-0.120	11.663***	10.315***	6.171***	2.147***
	(14.075)	(14.764)	(16.431)	(7.125)	(8.055)	(6.128)	(-0.094)	(-0.427)	(16.388)	(14.511)	(12.519)	(5.514)
Book-to-Market		-0.050	-1.889*			2.174	3.886**			2.177	2.497	
		(-0.073)	(-1.772)			(1.169)	(2.243)			(1.239)	(1.331)	
ROA		-7.071**	10.899**			10.151	-0.627			3.909	10.777	
		(-2.163)	(2.238)			(1.458)	(-0.074)			(0.558)	(1.208)	
Leverage		0.851	-2.669			22.481***	23.887***			20.816***	18.934***	
		(0.791)	(-1.186)			(8.982)	(6.521)			(8.585)	(4.890)	
Log(Market Cap)		1.898***	0.796			-4.991***	-0.725			-2.957***	-0.114	
		(9.141)	(1.286)			(-14.256)	(-0.679)			(-7.364)	(-0.103)	
Mean of DV	11.57	11.57	11.57	11.57	19.79	19.79	19.79	19.79	30.44	30.44	30.44	30.44
Controls	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y
Firm-bank FE	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Firm-quarter FE	N	N	N	Y	N	N	N	Y	N	N	N	Y
Bank-quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry-quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	116,823	112,260	111,743	105,798	121,673	116,938	116,436	110,534	116,824	112,261	111,744	105,799
R^2	0.070	0.078	0.257	0.641	0.121	0.168	0.487	0.745	0.089	0.107	0.387	0.693

Table OA10: Changes in Expected Losses and Future Loan Modifications

This table examines whether changes in risk assessments predict loan modifications in the subsequent quarter, using a firm-bank-quarter panel. The dependent variables are dummy variables (measured in percentage points) indicating whether loan terms changed from quarter t to quarter $t+1$: Change in maturity equals one if the maturity of at least one loan in the firm-bank relationship changed; Change in IR equals one if the interest rate of at least one loan changed; and Any change equals one if either the maturity or interest rate of at least one loan changed. The main independent variables are EL^{+} and EL^{-}, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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.

	Change in maturity				Change in IR				Any change			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
EL^{+}	3.432***	3.818***	1.137***	0.384	6.666***	4.528***	1.068***	0.283	8.649***	7.032***	1.637***	0.413
	(7.120)	(7.495)	(3.122)	(1.290)	(9.827)	(7.578)	(2.708)	(0.884)	(12.339)	(10.009)	(3.368)	(1.058)
EL^{-}	2.863***	3.219***	1.109***	0.430	5.298***	3.516***	0.124	0.332	6.703***	5.451***	0.550	0.422
	(6.296)	(6.985)	(3.452)	(1.609)	(8.344)	(6.590)	(0.344)	(1.097)	(10.099)	(8.493)	(1.294)	(1.155)
Book-to-Market		-0.097	-0.831			2.422	4.594**			2.346	3.845*	
		(-0.135)	(-0.742)			(1.229)	(2.461)			(1.247)	(1.911)	
ROA		-8.761***	11.630**			10.307	4.886			2.575	16.207*	
		(-2.589)	(2.037)			(1.403)	(0.563)			(0.349)	(1.846)	
Leverage		1.064	-4.550*			21.106***	15.754***			20.012***	11.373***	
		(0.937)	(-1.877)			(8.184)	(4.179)			(7.880)	(2.753)	
Log(Market Cap)		1.870***	0.465			-5.087***	-0.600			-3.081***	-0.255	
		(8.539)	(0.675)			(-13.968)	(-0.537)			(-7.284)	(-0.211)	
Mean of DV	11.35	11.35	11.35	11.35	20.46	20.46	20.46	20.46	30.34	30.34	30.34	30.34
Controls	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y
Firm-bank FE	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Firm-quarter FE	N	N	N	Y	N	N	N	Y	N	N	N	Y
Bank-quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry-quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	105,767	101,734	101,246	95,718	110,208	106,018	105,539	100,057	105,768	101,735	101,247	95,719
R^2	0.062	0.069	0.252	0.648	0.121	0.168	0.495	0.751	0.082	0.100	0.389	0.699

Table OA11: 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, using a firm-bank-quarter panel that excludes quarterly observations with at least one new loan origination for a given firm-bank pair. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement EPS is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The main independent variables are EL^{+} and EL^{-}, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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^{+}	−0.709***	−0.183*	1.676***	−0.182**
	(3.164)	(1.659)	(3.146)	(2.102)
EL^{-}	−0.175	0.115*	0.196	0.121*
	(0.976)	(1.673)	(0.466)	(1.787)
Book-to-Market	−0.180	0.316	4.245**	0.748***
	(0.290)	(0.795)	(2.346)	(3.451)
ROA	0.838	0.750	−2.305	0.876
	(0.414)	(0.712)	(0.340)	(0.974)
Leverage	−0.592	0.113	2.902	0.414
	(0.763)	(0.325)	(1.246)	(1.426)
Log(Market Cap)	0.189	0.015	−3.729***	−0.056
	(1.611)	(0.275)	(10.467)	(1.423)
Lagged Stock Return	−0.014		−0.166***	0.310***
	(1.033)		(6.216)	(33.873)
Lagged Bond Return		−0.089**		
		(2.018)		
Mean of DV	0.83	0.99	26.89	0.14
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	111,050	50,624	101,728	108,644
R-squared	0.37	0.49	0.08	0.33

Table OA12: 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 a firm-bank-quarter panel that includes 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. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement EPS is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The main independent variables are EL^+ and EL^-, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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^+	−0.586**	−0.154	1.831***	−0.260**
	(2.439)	(1.246)	(3.123)	(2.470)
EL^-	−0.174	0.020	0.351	0.079
	(0.780)	(0.266)	(0.698)	(0.840)
Book-to-Market	−0.504	0.236	4.028**	0.769***
	(0.726)	(0.549)	(2.136)	(3.452)
ROA	−0.376	0.430	1.288	1.392
	(0.171)	(0.443)	(0.178)	(1.476)
Leverage	−0.717	0.275	2.442	0.431
	(0.871)	(0.865)	(1.006)	(1.352)
Log(Market Cap)	0.189	0.015	−3.828***	−0.089*
	(1.574)	(0.270)	(10.200)	(1.944)
Lagged Stock Return	−0.005		−0.156***	0.309***
	(0.228)		(5.051)	(29.954)
Lagged Bond Return		−0.052		
		(0.977)		
Mean of DV	0.82	0.91	26.52	0.11
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	83,982	39,186	77,302	82,202
R-squared	0.39	0.53	0.09	0.33

Table OA13: Changes in Expected Losses Predict Financial Market Outcomes (No Loan Modifications)

This table tests whether changes in banks' expected losses predict next-quarter stock returns, bond returns, earnings surprises, and earnings announcement returns, using a firm-bank-quarter panel that includes only firm-bank relationships in which the interest rate spread and maturity date for all reported loans were unchanged from the previous quarter. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement EPS is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The main independent variables are EL^+ and EL^-, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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^+	−0.564**	−0.078	1.969***	−0.132
	(2.008)	(0.694)	(3.565)	(1.222)
EL^-	−0.052	0.148*	0.175	0.085
	(0.235)	(1.837)	(0.345)	(0.952)
Book-to-Market	−0.696	0.388	4.699**	0.543**
	(1.100)	(1.167)	(2.507)	(2.150)
ROA	−0.382	0.828	5.777	0.586
	(0.184)	(0.850)	(0.821)	(0.652)
Leverage	−1.068	0.166	2.288	0.390
	(1.232)	(0.496)	(0.982)	(1.206)
Log(Market Cap)	0.158	0.049	−3.763***	−0.065
	(1.262)	(0.831)	(10.321)	(1.468)
Lagged Stock Return	−0.019		−0.148***	0.303***
	(1.036)		(4.834)	(26.387)
Lagged Bond Return		−0.054		
		(1.114)		
Mean of DV	0.96	0.99	26.06	0.16
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	78,305	38,287	72,197	76,612
R-squared	0.39	0.51	0.09	0.33

Table OA14: Public Information and Changes in Banks' Risk Assessments (Additional Lags)

This table examines how changes in publicly available firm-level characteristics, lagged over four quarters, affect the likelihood that banks update their internal risk assessments, using a firm-bank-quarter panel. The dependent variables are dummy variables measured in percentage points indicating whether the bank's assessed PD, LGD, or expected loss increased (columns 1, 3, 5) or decreased (columns 2, 4, 6) from quarter $t-1$ to quarter t. The independent variables are lagged changes in firm characteristics (book-to-market ratio, ROA, leverage) and lagged stock returns. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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)
1Q Lagged Change in Book/Market	−0.004	0.006	0.020	−0.015	0.005	−0.002
	(0.169)	(0.417)	(1.199)	(1.050)	(0.205)	(0.144)
2Q Lagged Change in Book/Market	0.022	0.009	−0.011	0.001	0.026	−0.000
	(1.099)	(0.627)	(0.620)	(0.070)	(0.999)	(0.012)
3Q Lagged Change in Book/Market	0.044**	−0.013	0.014	−0.027*	0.061***	−0.041*
	(2.421)	(0.795)	(0.924)	(1.688)	(2.741)	(1.897)
4Q Lagged Change in Book/Market	0.088***	−0.042***	0.028*	0.007	0.104***	−0.035*
	(6.262)	(3.231)	(1.936)	(0.409)	(5.841)	(1.902)
1Q Lagged Change in ROA	−0.695***	0.470***	−0.165**	−0.005	−0.791***	0.523***
	(6.287)	(4.630)	(2.024)	(0.055)	(6.497)	(4.695)
2Q Lagged Change in ROA	−0.744***	0.600***	0.063	−0.121	−0.659***	0.452***
	(7.171)	(6.512)	(0.910)	(1.605)	(5.762)	(4.569)
3Q Lagged Change in ROA	−0.592***	0.314***	0.007	0.076	−0.583***	0.466***
	(6.097)	(3.484)	(0.104)	(1.004)	(5.450)	(4.426)
4Q Lagged Change in ROA	−0.424***	0.089	−0.000	−0.024	−0.448***	0.125
	(4.581)	(0.978)	(0.000)	(0.336)	(4.263)	(1.293)
1Q Lagged Change in Leverage	0.226***	−0.151***	−0.011	−0.022	0.208***	−0.147***
	(5.615)	(4.324)	(0.339)	(0.632)	(4.482)	(3.639)
2Q Lagged Change in Leverage	0.193***	−0.338***	0.030	−0.058	0.273***	−0.355***
	(4.416)	(7.931)	(0.915)	(1.469)	(5.504)	(7.089)
3Q Lagged Change in Leverage	0.114***	−0.120***	0.014	−0.011	0.124***	−0.120***
	(3.063)	(3.139)	(0.445)	(0.295)	(2.677)	(2.625)
4Q Lagged Change in Leverage	0.072**	−0.046	0.035	0.047*	0.092**	−0.035
	(2.052)	(1.373)	(1.213)	(1.655)	(2.274)	(0.908)
1Q Lagged Stock Return	−0.069***	0.026***	−0.003	−0.014	−0.060***	0.017
	(5.989)	(3.102)	(0.439)	(1.439)	(5.169)	(1.579)
2Q Lagged Stock Return	−0.119***	0.055***	0.004	−0.011	−0.106***	0.051***
	(7.865)	(4.801)	(0.332)	(0.902)	(6.075)	(3.652)
3Q Lagged Stock Return	−0.093***	0.060***	−0.014	−0.018	−0.086***	0.045***
	(7.057)	(5.378)	(1.114)	(1.298)	(5.225)	(3.215)
4Q Lagged Stock Return	−0.071***	0.052***	−0.001	−0.015	−0.058***	0.033**
	(6.137)	(4.428)	(0.136)	(1.399)	(4.162)	(2.427)
Mean of DV	10.82	11.96	11.27	13.05	16.88	19.08
Bank-Quarter FE	YES	YES	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES	YES	YES
Observations	85,448	85,448	85,448	85,448	85,448	85,448
R-squared	0.22	0.26	0.30	0.31	0.19	0.23

Table OA15: Credit Line Drawdowns and Bank Risk Assessments (No Syndicated Loans)

This table examines whether credit line drawdowns predict changes in banks' risk assessments, using a firm-bank-quarter panel that excludes all firm-bank relationships that report a syndicated loan in that quarter. The dependent variables are dummy variables measured in percentage points indicating whether the bank's assessed PD, LGD, or expected loss increased from quarter $t-1$ to quarter t. The main independent variable, Drawdown, is a dummy variable that equals one if the total utilization rate across all of a firm's credit lines from the same bank increases from quarter $t-1$ to t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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	2.385***	2.944***	4.090***	−0.004	3.638***	2.400***
	(5.972)	(6.444)	(7.887)	(0.005)	(4.889)	(2.751)
Mean of DV	10.84	11.13	16.71	10.84	11.13	16.71
Bank-Quarter FE	YES	YES	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES	YES	YES
Firm-Quarter FE	NO	NO	NO	YES	YES	YES
Observations	53,446	53,446	53,446	44,825	44,825	44,825
R-squared	0.16	0.31	0.18	0.44	0.50	0.44

Table OA16: Cross-Sectional Dispersion in Risk Assessments (No Syndicated Loans)

This table presents summary statistics on the cross-sectional standard deviation of risk assessments and loan commitment amounts across banks at the firm-quarter level for bank-firm relationships that do not report a syndicated loan in that quarter. Appendix Section A contains all variable definitions.

	Mean	10%	Median	90%	N
PD (pp)	0.764	0.042	0.231	1.636	7,566
LGD (pp)	9.173	3.200	7.952	16.340	7,566
EL (pp)	0.263	0.018	0.094	0.532	7,566
Committed ($ mn)	46.106	6.258	26.169	89.839	7,566
ΔPD (pp)	0.327	0.000	0.021	0.502	6,317
ΔLGD (pp)	1.951	0.000	0.158	5.933	6,317
ΔEL (pp)	0.117	0.000	0.012	0.192	6,317

Table OA17: Differences in Changes in Risk Assessments Across Banks

This table presents measures of differences in risk assessment changes across banks lending to the same firm in each quarter. The sample includes only firm-quarters with at least two different banks. For each risk assessment measure (PD, LGD, or EL), Disagreement (%) reports the percentage of firm-quarters where at least one bank increases its assessment and at least one bank decreases its assessment. The ICC^{+} column reports the intraclass correlation coefficient for upward changes in risk assessments, calculated as the R^2 from regressing an indicator for increases on firm-quarter fixed effects: $EL^{+}_{i,b,t} = \alpha_{i,t} + \epsilon_{i,b,t}$. Higher values indicate greater within-firm agreement across banks regarding changes in risk assessments. The ICC^{-} and $ICC^{\Delta=0}$ columns report the analogous measures for downward changes or no changes, respectively. The $ICC^{+|\Delta=1}$ column reports the intraclass correlation coefficient for upward changes in risk assessments conditional on having a nonzero change. The top panel includes all firms (N=116,634 firm-bank-quarter observations across $N = 19,527$ firm-quarters) and the bottom panel restricts to firm-bank relationships with no reported syndicated loans in that quarter (N=54,804 firm-bank-quarter observations across $N = 16,820$ firm-quarters). Appendix Section A contains all variable definitions.

Panel A: All Bank-Firm Relationships

	Disagreement (%)	ICC^{+}	ICC^{-}	$ICC^{\Delta=0}$	$ICC^{+\|\Delta=1}$
PD	18.8%	0.264	0.206	0.330	0.636
LGD	24.8%	0.186	0.190	0.302	0.529
EL	37.3%	0.234	0.198	0.280	0.463

Panel B: Bank-Firm Relationships without Syndicated Loans

	Disagreement (%)	ICC^{+}	ICC^{-}	$ICC^{\Delta=0}$	$ICC^{+\|\Delta=1}$
PD	20.1%	0.389	0.334	0.502	0.687
LGD	26.6%	0.324	0.348	0.489	0.597
EL	39.7%	0.372	0.341	0.445	0.669

Table OA18: Changes in Expected Losses, Financial Market Outcomes, and Credit Line Drawdowns (No Syndicated Loans)

This table tests whether both credit line drawdowns and changes in banks' expected losses separately predict next-quarter stock returns, bond returns, earnings surprises, and earnings announcement returns, using a firm-bank-quarter panel that excludes all firm-bank relationships that report a syndicated loan in that quarter. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The main independent variables are Drawdown, a dummy variable that equals one if the total utilization rate across all of a firm's credit lines from the same bank increases from quarter $t-1$ to t, and EL^+, a dummy variable equal to one if the bank's assessed expected loss increases from quarter $t-1$ to quarter t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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)
Drawdown	-2.055^{***}	-0.024	1.948^{*}	-0.294^{*}
	(5.979)	(0.101)	(1.934)	(1.904)
EL^+	-0.496	-0.346^{*}	1.443^{**}	-0.223^{**}
	(1.477)	(1.713)	(2.006)	(1.976)
Book-to-Market	0.186	0.557	8.029^{***}	0.965^{***}
	(0.238)	(1.243)	(3.518)	(3.086)
ROA	-1.238	1.234	6.167	0.034
	(0.437)	(0.708)	(0.713)	(0.027)
Leverage	0.139	-0.176	1.354	0.301
	(0.138)	(0.317)	(0.464)	(0.720)
Log(Market Cap)	0.017	-0.007	-3.195^{***}	-0.047
	(0.110)	(0.069)	(7.635)	(0.914)
Lagged Stock Return	-0.018		-0.148^{***}	0.301^{***}
	(0.822)		(4.526)	(27.185)
Lagged Bond Return		-0.112^{**}		
		(2.073)		
Mean of DV	1.17	1.29	27.25	0.22
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	51,348	23,210	46,419	50,132
R-squared	0.33	0.43	0.09	0.32

Table OA19: Changes in Expected Losses, Financial Market Outcomes, and Credit Line Drawdowns (Relationships with Syndicated Loans)

This table tests whether both credit line drawdowns and changes in banks' expected losses separately predict next-quarter stock returns, bond returns, earnings surprises, and earnings announcement returns, using a firm-bank-quarter panel that includes only firm-bank relationships that report a syndicated loan in that quarter. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The main independent variables are Drawdown, a dummy variable that equals one if the total utilization rate across all of a firm's credit lines from the same bank increases from quarter $t-1$ to t, and EL^+, a dummy variable equal to one if the bank's assessed expected loss increases from quarter $t-1$ to quarter t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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)
Drawdown	−1.629***	0.109	3.200***	−0.120
	(5.139)	(0.864)	(3.089)	(0.828)
EL^+	−0.676***	−0.187**	1.822***	−0.173*
	(2.775)	(2.063)	(2.865)	(1.671)
Book-to-Market	−1.255	−0.094	2.985	0.641**
	(1.370)	(0.154)	(1.315)	(2.103)
ROA	2.533	0.216	−2.515	1.807
	(0.870)	(0.196)	(0.264)	(1.506)
Leverage	−0.969	0.007	3.552	0.524
	(0.932)	(0.016)	(1.191)	(1.469)
Log(Market Cap)	0.393**	0.137**	−3.910***	−0.129**
	(2.425)	(1.997)	(8.526)	(2.339)
Lagged Stock Return	−0.016		−0.192***	0.328***
	(1.240)		(5.964)	(32.080)
Lagged Bond Return		−0.087		
		(1.606)		
Mean of DV	0.47	0.69	26.53	0.05
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	54,080	25,823	50,264	53,037
R-squared	0.45	0.59	0.10	0.35

Table OA20: Changes in Expected Losses and Other Financial Market Outcomes (Small Firms)

This table tests whether changes in banks' expected losses predict next-quarter loan returns (log change in bid-ask midpoint), changes in XR14 5-year CDS spreads from S&P Global, and changes in estimated one-year default probabilities from Moody's EDF-X, using a firm-bank-quarter panel, all measured in percentage points. The main independent variables are EL^+ and EL^-, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. The sample includes firms in the bottom three quintiles of market capitalization. We obtain secondary market loan prices from LPC Loan Pricing by Refinitiv. We merge the data into Dealscan, then merge Dealscan into Compustat using the Roberts Dealscan-Compustat Linking Database and the matching protocol from Cohen et al. (2021). Appendix Section A contains all other variable definitions. T-statistics are shown below the parameter estimates in parentheses 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.

	Loan Return		Change in CDS Spreads		Change in EDF-X	
	(1)	(2)	(3)	(4)	(5)	(6)
EL^+	−0.308*	−0.278*	0.075*	0.049	0.088***	0.085***
	(1.962)	(1.755)	(1.936)	(1.408)	(2.901)	(2.895)
EL^-	−0.276	−0.185	−0.040	−0.045	−0.043**	−0.034*
	(1.544)	(1.272)	(1.205)	(1.338)	(2.215)	(1.914)
Book-to-Market	1.282**	2.004***	−0.772***	−0.737**	−0.174**	−0.209**
	(2.373)	(2.764)	(2.715)	(2.235)	(2.313)	(2.515)
ROA	1.503	−2.119	−2.461*	−2.609*	−0.732***	−0.714***
	(0.402)	(0.500)	(1.803)	(1.996)	(2.620)	(2.680)
Leverage	2.214***	0.882	−0.024	−0.086	0.208***	0.185**
	(3.607)	(1.051)	(0.105)	(0.372)	(2.890)	(2.548)
Log(Market Cap)	0.311*	0.733**	0.106	0.097	−0.124***	−0.108***
	(1.918)	(2.047)	(1.228)	(1.155)	(5.723)	(5.206)
Lagged Loan Return	0.085	0.039				
	(1.002)	(0.323)				
Lagged Change in CDS Spread			−33.979***	−35.400***		
			(2.952)	(2.947)		
Lagged Change in EDF-X					−0.071**	−0.073**
					(2.426)	(2.329)
Mean of DV	-0.09	-0.09	0.00	0.00	0.10	0.10
Bank-Quarter FE	YES	YES	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES	YES	YES
Control for Factor Loadings	NO	YES	NO	YES	NO	YES
Observations	1,929	1,301	2,524	2,492	45,882	40,645
R-squared	0.68	0.75	0.83	0.70	0.14	0.16

Table OA21: Changes in Expected Losses Predict Financial Market Outcomes (Small Firms)

This table tests whether changes in banks' expected losses predict next-quarter stock returns, bond returns, earnings surprises, and earnings announcement returns using a firm-bank-quarter panel and including only firms in the bottom three quintiles of market capitalization. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t + 1$. The main independent variables are EL^+ and EL^-, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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^+	−1.115***	−0.534**	2.046**	−0.346***
	(3.646)	(2.339)	(2.575)	(2.660)
EL^-	−0.129	0.349*	0.254	0.109
	(0.496)	(1.793)	(0.401)	(0.999)
Book-to-Market	0.664	1.316*	5.214**	0.817***
	(0.864)	(1.788)	(2.351)	(2.879)
ROA	1.339	4.820	−11.664	1.415
	(0.422)	(1.359)	(1.177)	(0.935)
Leverage	−0.639	0.850	7.429**	0.712*
	(0.586)	(0.641)	(2.244)	(1.662)
Log(Market Cap)	0.040	−0.034	−5.850***	−0.067
	(0.157)	(0.105)	(6.239)	(0.692)
Lagged Stock Return	−0.013		−0.164***	0.320***
	(0.846)		(4.850)	(28.316)
Lagged Bond Return		−0.126**		
		(2.042)		
Mean of DV	0.42	1.00	33.14	-0.03
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	53,526	11,112	45,901	51,808
R-squared	0.36	0.57	0.10	0.36

Table OA22: Changes in Expected Losses Predict Financial Market Outcomes (No Syndicated Loans)

This table tests whether changes in banks' expected losses predict next-quarter stock returns, bond returns, earnings surprises, and earnings announcement returns, using a firm-bank-quarter panel that excludes all firm-bank relationships that report a syndicated loan in that quarter. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The main independent variables are EL^{+} and EL^{-}, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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^{+}	−0.704**	−0.252	1.784**	−0.247**
	(2.223)	(1.418)	(2.384)	(2.229)
EL^{-}	−0.173	0.294***	0.394	0.131
	(0.757)	(2.862)	(0.638)	(1.356)
Book-to-Market	0.313	0.563	6.963***	1.015***
	(0.433)	(1.323)	(3.303)	(3.562)
ROA	−2.600	1.214	1.042	0.152
	(1.037)	(0.739)	(0.134)	(0.136)
Leverage	−0.168	−0.112	1.020	0.326
	(0.185)	(0.225)	(0.376)	(0.861)
Log(Market Cap)	0.109	−0.003	−3.249***	−0.035
	(0.819)	(0.032)	(8.312)	(0.745)
Lagged Stock Return	−0.014		−0.141***	0.300***
	(0.728)		(4.786)	(29.943)
Lagged Bond Return		−0.105**		
		(2.055)		
Mean of DV	1.17	1.29	27.25	0.22
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	57,224	25,278	51,749	55,868
R-squared	0.31	0.43	0.09	0.32

Table OA23: Changes in Expected Losses Predict Financial Market Outcomes (Relationships with Syndicated Loans)

This table tests whether changes in banks' expected losses predict next-quarter stock returns, bond returns, earnings surprises, and earnings announcement returns, using a firm-bank-quarter panel that includes only firm-bank relationships that report a syndicated loan in that quarter. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The main independent variables are EL^{+} and EL^{-}, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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^{+}	−0.787***	−0.185**	2.109***	−0.162
	(3.093)	(2.225)	(3.162)	(1.482)
EL^{-}	−0.249	−0.033	0.517	0.053
	(0.982)	(0.393)	(0.896)	(0.542)
Book-to-Market	−1.317	−0.104	3.045	0.629**
	(1.445)	(0.171)	(1.349)	(2.060)
ROA	2.375	0.136	−1.971	1.730
	(0.822)	(0.124)	(0.208)	(1.454)
Leverage	−1.049	0.011	3.883	0.492
	(1.009)	(0.025)	(1.309)	(1.394)
Log(Market Cap)	0.445***	0.132**	−4.027***	−0.121**
	(2.808)	(1.988)	(8.878)	(2.218)
Lagged Stock Return	−0.016		−0.195***	0.328***
	(1.193)		(6.042)	(32.350)
Lagged Bond Return		−0.089*		
		(1.653)		
Mean of DV	0.47	0.69	26.53	0.05
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	55,048	26,286	51,165	53,974
R-squared	0.45	0.59	0.09	0.35

Table OA24: Changes in Expected Losses Predict Financial Market Outcomes (Excluding Bank-Quarter Fixed Effects)

This table tests whether changes in banks' expected losses predict next-quarter stock returns, bond returns, earnings surprises, and earnings announcement returns using a firm-bank-quarter panel and excluding bank-quarter fixed effects. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t + 1$. The main independent variables are EL^{+} and EL^{-}, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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^{+}	−0.566***	−0.177**	1.537***	−0.155**
	(3.411)	(2.164)	(3.729)	(2.287)
EL^{-}	−0.010	0.122**	0.294	0.118**
	(0.074)	(2.261)	(0.940)	(2.270)
Book-to-Market	−0.118	0.271	4.248**	0.754***
	(0.192)	(0.706)	(2.332)	(3.415)
ROA	0.825	0.757	−2.799	0.859
	(0.411)	(0.730)	(0.417)	(0.969)
Leverage	−0.637	0.049	2.699	0.452
	(0.836)	(0.145)	(1.155)	(1.581)
Log(Market Cap)	0.199*	0.010	−3.806***	−0.063*
	(1.805)	(0.185)	(10.773)	(1.658)
Lagged Stock Return	−0.014		−0.163***	0.312***
	(1.045)		(6.203)	(34.109)
Lagged Bond Return		−0.086*		
		(1.964)		
Mean of DV	0.83	0.99	26.89	0.14
Bank-Quarter FE	NO	NO	NO	NO
Industry-Quarter FE	YES	YES	YES	YES
Observations	117,641	54,095	107,919	115,103
R-squared	0.37	0.48	0.08	0.33

Table OA25: Fama-MacBeth Regressions (Firm-Bank-Quarter Panel)

This table tests whether changes in banks' expected losses predict next-quarter stock returns, bond returns and earnings surprises, by estimating Fama-MacBeth regressions on a firm-bank-quarter panel. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The main independent variables are EL^{+} and EL^{-}, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. Appendix Section A contains all variable definitions. We report the time-series mean of the parameter estimates with t-statistics, calculated using Newey-West (1987) standard errors with three lags, shown below in parentheses. *, **, 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^{+}	−0.466***	−0.136*	1.553***	−0.160***
	(3.906)	(1.993)	(5.182)	(2.919)
EL^{-}	−0.062	0.098	0.324	0.104***
	(0.664)	(1.543)	(1.526)	(2.896)
Book-to-Market	−0.316	−0.145	4.206**	0.935**
	(0.275)	(0.332)	(2.530)	(2.619)
ROA	0.340	−0.149	−3.721	1.164
	(0.124)	(0.210)	(0.674)	(1.149)
Leverage	−0.839	−0.332	2.802**	0.559*
	(0.639)	(0.618)	(2.534)	(1.854)
Log(Market Cap)	0.227	0.030	−3.796***	−0.087
	(0.895)	(0.196)	(15.208)	(1.206)
Lagged Stock Return	−0.013		−0.171***	0.320***
	(0.845)		(8.002)	(25.669)
Lagged Bond Return		−0.087*		
		(1.999)		
Mean of DV	0.83	0.99	26.89	0.14
Industry FE	YES	YES	YES	YES
Observations	117,650	54,104	107,928	115,112
R-squared	0.15	0.35	0.09	0.34

Table OA26: 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, using a firm-bank-quarter panel and excluding firm-quarters with a loan that has an observable secondary-market price. The dependent variables are quarterly stock returns (column 1), quarterly bond returns (column 2), a dummy variable that equals one if the earnings announcement is below the consensus analyst estimate (column 3), and two-day cumulative abnormal returns, i.e., the individual stock return minus the value-weighted CRSP index return, around earnings announcements (column 4), all measured in percentage points in quarter $t+1$. The main independent variables are EL^+ and EL^-, which are dummy variables equal to one if the bank's assessed expected loss for the firm increased or decreased, respectively, from quarter $t-1$ to quarter t. We obtain secondary market loan prices from LPC Loan Pricing by Refinitiv. We merge the data into Dealscan, then merge Dealscan into Compustat using the Roberts Dealscan-Compustat Linking Database and the matching protocol from Cohen et al. (2021). Appendix Section A contains all variable definitions. T-statistics are shown below the parameter estimates in parentheses 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^+	−0.610***	−0.172*	1.916***	−0.192**
	(2.911)	(1.716)	(3.611)	(2.253)
EL^-	−0.214	0.085	0.596	0.048
	(1.168)	(1.210)	(1.339)	(0.674)
Book-to-Market	−0.472	0.244	4.959**	0.745***
	(0.732)	(0.595)	(2.563)	(3.298)
ROA	−0.370	0.237	−2.781	1.008
	(0.175)	(0.222)	(0.383)	(1.177)
Leverage	−0.581	−0.042	1.438	0.479
	(0.740)	(0.121)	(0.562)	(1.619)
Log(Market Cap)	0.196*	0.041	−3.516***	−0.064
	(1.697)	(0.725)	(9.414)	(1.592)
Lagged Stock Return	−0.008		−0.158***	0.312***
	(0.581)		(5.597)	(30.857)
Lagged Bond Return		−0.077*		
		(1.683)		
Mean of DV	0.83	0.99	26.89	0.14
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	105,802	50,314	96,763	103,659
R-squared	0.38	0.50	0.09	0.34

Table OA27: Credit Line Drawdowns and Bank Risk Assessments (Relationships with Syndicated Loans)

This table examines whether credit line drawdowns predict changes in banks' risk assessments, using a firm-bank-quarter panel that includes only firm-bank relationships that report a syndicated loan in that quarter. The dependent variables are dummy variables, measured in percentage points, indicating whether the bank's assessed PD, LGD, or expected loss increased from quarter $t-1$ to quarter t. The main independent variable, Drawdown, is a dummy variable that equals one if the total utilization rate across all of a firm's credit lines from the same bank increases from quarter $t-1$ to t. Appendix Section A contains all other variable definitions. T-statistics are shown below the parameter estimates in parentheses 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	2.204***	2.420***	3.926***	0.320	3.580***	2.801***
	(6.066)	(6.554)	(9.127)	(0.606)	(5.213)	(3.877)
Mean of DV	10.79	11.41	17.04	10.79	11.41	17.04
Bank-Quarter FE	YES	YES	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES	YES	YES
Firm-Quarter FE	NO	NO	NO	YES	YES	YES
Observations	61,355	61,355	61,355	59,738	59,738	59,738
R-squared	0.21	0.26	0.17	0.43	0.43	0.38