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, testing these theories is difficult due to the lack of access to banks' private information. In this paper, we use supervisory data containing banks' *private* assessments of their loans' expected losses. We show that increases in expected losses predict firms' future stock returns, bond returns, and earnings surprises. Our findings support theories in which banks' information production and monitoring generate an information advantage over financial markets.

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1 Introduction

A fundamental role of banks is to collect and process information about borrowers. Because banks can 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 private; (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.

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 other market participants cannot observe, predict *future* stock returns, bond returns, and analyst earnings surprises. Intuitively, if banks had no information advantage over public markets, changes in these risk assessments should not predict future asset prices, as current prices would already reflect banks' information.[3] Therefore, our results provide direct evidence that banks possess valuable private information that broader financial markets do not. Beyond documenting asymmetric information, our data also let us answer other important questions that previous research could not 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 the committed loan exposure. 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

[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] Public information can also predict returns through variation in risk premia. We therefore control for public credit signals and adjust returns for standard risk factors, as discussed in more detail below.

quarter for stock and bond returns, respectively.[4] The predictability of bond returns helps rule out the possibility that our findings merely reflect credit-market information reaching equity markets slowly. Interestingly, we find no effect when banks lower their expected losses. 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 quarterly equity underperformance 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 the magnitude decreasing up to the largest quintile, which exhibits no underperformance.

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 predicting the likelihood that banks update their risk assessments. We include firm-quarter 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 for borrowers with greater total loan exposure. This result is consistent with banks' endogenously producing information when their incentives to do so are higher.

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 is 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 stock returns for the next quarter by 190bps. These results are consistent with firms drawing down credit lines following a negative

[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). As we discuss below, banks' reporting incentives could also contribute to this asymmetry.

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.

If risk assessments reflect banks' private information, banks should use this information in their credit allocation decisions. To test this, we exploit the fact that many firms borrow from several banks at once and estimate event studies of a bank's committed exposure around changes in its assessment of a borrower's existing loans, including firm-quarter fixed effects as in Khwaja and Mian (2008). Because these fixed effects absorb the borrower's credit demand and any information available to all of its lenders, identification comes from one bank revising its assessment relative to the other banks lending to the same firm in the same quarter. We find that when a bank raises its assessed expected loss on a borrower's existing loans, its committed exposure to that borrower drops in the same quarter relative to the firm's other lenders, with no pre-trend. This difference persists into the following quarter before dissipating, and we find no response to decreases in expected losses. While we emphasize, and discuss in more detail below, that identifying the causal effects of bank information on lending outcomes is extremely challenging, the timing and direction of banks' lending responses following risk assessment updates are consistent with banks using their information to allocate credit to firms.[7]

A potential concern is that banks may misreport their risk assessments, for example to improve their reported position in regulatory stress tests (Plosser and Santos (2018), Begley, Purnanandam, and Zheng (2017) and Behn, Haselmann, and Vig (2022)). In Section 3 we describe how these assessments are produced and used, and the incentives banks face in reporting them. Because our treatment variables are *changes* in a bank's assessment, misreporting that is stable within a bank-firm relationship is differenced out, and bank-quarter fixed effects absorb reporting shifts common to all of a bank's loans in a given quarter. Misreporting that varies across loans, such as a bank's reluctance to recognize deterioration, would if anything attenuate the predictability of EL^+. Hence, although the predictability we document for increases in expected losses cannot be explained by misreporting, we cannot rule out reporting incentives, such as uninformative reductions that improve a bank's reported risk profile, as contributing to the absence of predictability for decreases.[8] We discuss these issues, including how selective misreporting could affect our cross-sectional results, in Sections 4.1 and 4.3.

We view our results as a lower bound on the magnitude of banks' true information

[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]In particular, differences in risk assessments across banks lending to the same firm may partly reflect differences in subjective beliefs rather than private information. We discuss this and other issues in Section 4.5.

[8]That said, as we discuss in Section 4.3, it is not obvious that banks would prefer this particular form of misreporting over others that would not generate the asymmetry.

advantage over public markets for three reasons. First, we only observe banks' risk assessments at quarter-end. Hence, if 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 in our sample. 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, which many have argued are less inclined to perform the traditional role of relationship banking.[9] 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 announcements of new bank loans and argues that this reaction reflects 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 reactions between banks and non-banks after loans are granted, consistent with the stock price response reflecting the signaling content of the loan contract rather than the bank's information production.[10] Relatedly, Maskara and Mullineaux (2011) find no abnormal response once the selection bias in loan announcements is controlled for. Our empirical approach avoids 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 upward) 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)

[9]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) and Liberti and Mian (2008)).

[10]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.

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 its value without observing banks' actual assessments.[11] In contrast, we use banks' risk assessments to quantify how valuable this information is and show that banks' information advantage is concentrated on the downside.

A related paper is Addoum and Murfin (2020), which finds that changes in publicly observable syndicated loan prices predict future equity returns and argues 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 nonsyndicated 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 closest paper 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 are 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. Our papers also differ in several other important ways. First, our sample is much larger because it includes all loans over $1 million and nonsyndicated loans. Second, in addition to analyzing stock returns, we also analyze bond returns, earnings surprises, and earnings announcement returns. Finally, 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.

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)[12], our paper analyzes whether banks have an information advantage over public markets at the *asset* level. Moreover,

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

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

our approaches are complementary: banks may have an information advantage yet still earn average returns if screening and monitoring are costly. Indeed, 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 (2026) 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.[13]

3 Data

Our main data source 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 an 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. Under the advanced approaches to regulatory capital, these estimates are inputs into the calculation of credit-risk-weighted assets, which determine risk-based capital requirements. 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

[13]Beyhaghi, Fracassi, and Weitzner (2025) and Howes and Weitzner (2026) 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, we directly show how banks' private information differs from that of public markets and quantify its actual value.

from external sources (including pooled data)."[14] Moreover, banks must update these regularly and immediately after any material changes: "Borrowers and facilities must have their ratings refreshed at least on an annual basis... In addition, banks must initiate a new rating if material information on the borrower or facility comes to light." Our main variable is the loan's expected loss (EL), which equals PD $\times$ LGD.

Banks are also required to use these assessments in their own internal decisions. According to the Basel Committee's Internal Ratings-Based (IRB) approach,[15]

> "Internal ratings and default and loss estimates must play an essential role in the credit approval, risk management, internal capital allocations, and corporate governance functions of banks using the IRB approach. Ratings systems and estimates designed and implemented exclusively for the purpose of qualifying for the IRB approach and used only to provide IRB inputs are not acceptable."

Banks therefore have incentives to assess borrower risk accurately for their own lending and risk-management decisions, independently of regulatory constraints. Even absent regulations, banks typically maintain risk measures for their borrowers (Treacy and Carey, 1998). Because banks already calculate these measures for their own use, the burden of reproducing them for regulators is likely limited.

At the same time, banks may have incentives to report their risk assessments strategically. Lower PDs and LGDs reduce risk-weighted assets under the advanced approaches,[16] and the Y-14Q data support supervisory stress tests whose results constrain banks' capital distributions. Because a bank's capital plan is evaluated against its projected losses under the adverse scenario, the latter incentive can operate even when the bank's current capital ratios exceed regulatory minima. Supervisors regularly review banks' risk management systems, so persistent deviations between the assessments banks report and those they use internally would risk running afoul of regulators and incurring penalties. Nonetheless, Begley, Purnanandam, and Zheng (2017), Plosser and Santos (2018) and Behn, Haselmann, and Vig (2022) provide evidence that banks understate risk, particularly for capital-constrained banks and during periods of stress. We discuss how incentives to misreport could affect the interpretation of our results in Section 4.1.

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

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

[15] See Section 6 here.

[16] In practice, the standardized approach has typically been the binding risk-based constraint for large US banks during our sample period (Greenwood et al. (2017), Walz (2024) and Dubois and Rintamäki (2025)) since required capital is based on the higher of standardized and advanced-approaches risk-weighted assets. Even when the advanced approaches do not bind, internal PD and LGD estimates feed into loan-loss allowances, internal capital allocation, and banks' own stress projections.

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 in which total assets reported in the Y-14Q data fall within the 90%-110% interval of total assets reported in 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 across outstanding loans, weighted by each loan's total committed exposure in that quarter.[17] Changes in this average can reflect both revisions to individual loan assessments and changes in the composition or committed amounts of outstanding loans. To isolate reassessments, we also construct a measure based on changes in expected losses for loans outstanding in both consecutive quarters, weighted by their lagged committed exposure. We use this alternative measure in our lending analysis to mitigate mechanical relationships between independent and outcome variables; however, we also show that our return predictability results are robust to using indicators based on this measure (Online Appendix Table OA28).

Aggregating the data results in a panel with one observation per bank-firm relationship per quarter. After creating the panel, we drop loans with PDs or LGDs less than or equal to 0% or PDs 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 in which the standard deviation of its LGDs exceeds 25 percentage points.[18] We also exclude likely data errors by requiring each loan's total committed credit to be at least $1 million and each loan's utilized credit to be no more than its total committed credit. Together, these filters remove less than 3% of observations.[19]

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.[20] 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

[17]Using committed rather than utilized exposure avoids mechanical changes in weights due to credit line drawdowns.

[18]PD is measured at the borrower level and should therefore be identical across a bank's loans to the same borrower. In our data, PDs are identical across loans in more than 90% of bank-firm-quarter cells. LGDs, which can differ across loans because of differences in collateral and seniority, are identical in just over 75% of cells.

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

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

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.[21] 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, 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 nonzero changes in PD, LGD, and expected loss. Figure 3 also plots the distribution of the number of banks per borrower and how the average number of banks varies across firm-size quintiles.

Because the relationship between expected losses and asset prices or earnings forecasts is likely to be highly nonlinear, 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. Appendix A provides detailed variable descriptions.

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, while they adjust them upward (become more pessimistic) in 17% of quarters. 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 report correlations between the risk assessment variables and their lagged values. The correlation between changes in PD and LGD 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.

[21] This may occur because firms are acquired or 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.

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 examines the sources of banks' information advantage, and Section 4.5 examines how banks' lending changes around revisions to their risk assessments.

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 a 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.[22] 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.[23] Finally, we include bank-quarter fixed effects ($\delta_{b,t}$) to control for bank-specific factors that affect risk assessments, as well as industry-quarter fixed effects ($\gamma_{j,t}$). We cluster standard errors at the firm and bank-quarter level. Intuitively, if banks have no information advantage over public markets, changes in expected losses should not be related to future asset prices or earnings surprises, as banks' information would already be incorporated into asset prices and current

[22] 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.

[23] 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 usually corresponds to realized values as of time $t-1$.

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 firm-quarters, which is why we cluster standard errors by firm.[24] 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.

Table 5 reports these results. 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.[25] In column (2), we find a similar directional pattern for bond returns but with an underperformance of 20bps. That banks' information advantage also shows up in publicly traded credit markets suggests our results are not driven purely by market segmentation.

In column (3), we find that negative earnings surprises are 2 percentage points more likely, compared with an unconditional probability of 26.9%.[26] 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.[27] 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

[24]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.

[25]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 drop by between 1.5% and 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)).

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

[27]There is a similar asymmetry in equity research analyst and credit rating downgrades (Womack (1996) and Holthausen and Leftwich (1986)).

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 would not 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 focus on producing negative information.

Banks' reporting incentives could also contribute to this asymmetry. As discussed in Section 3, banks may have incentives to understate expected losses. Reductions that reflect such incentives rather than new information would have no predictive content and would weaken any predictability from EL^-, so we cannot rule out that misreporting contributes to the absence of predictability for decreases in expected losses. Importantly, however, our conclusions do not require that banks report truthfully. Because our independent variables are changes in assessments and we include bank-quarter fixed effects, misreporting that is stable within a bank-firm relationship, or common across a bank's loans in a given quarter, does not affect our estimates. Similarly, banks could assign a lower expected loss at origination rather than misreporting changes in expected losses of existing loans over time; however, this type of bias would not affect our results as long as it is constant within the loan over time. Misreporting that varies across a bank's loans cannot generate the predictability we find for EL^+: a bank reluctant to recognize deterioration reports fewer or later increases, which attenuates the coefficient, and increases unrelated to borrowers' prospects would only add noise. Moreover, it is not obvious that banks would have stronger incentives to actively lower expected losses than to refrain from raising them, since the latter requires no action and is easier to explain to supervisors.[28] If banks respond to reporting incentives in this way, the decreases we observe reflect genuine improvements and would, if anything, be *more* informative than increases, which is the opposite of what we find.

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) differences in risk premia across firms or 2) information that is public, but not reflected in equity markets.

One concern is that predictability from changes in banks' risk assessments reflects changes in risk premia rather than private information, which our panel regression approach may not distinguish. Much of the return predictability occurs right around the

[28]Consistent with this idea, the disclosure literature typically treats withholding information as feasible while outright misstatement is either infeasible or costly (e.g., Dye (1985), Kartik, Ottaviani, and Squintani (2007) and Kartik (2009)), and there is experimental evidence that individuals are more willing to lie by omission than by commission (Pittarello, Rubaltelli, and Motro (2016)).

earnings announcement, making it highly unlikely that it is driven purely by risk premia correlated with changes in banks' expected losses (Engelberg, McLean, and Pontiff, 2018). Nonetheless, to address this concern further, we aggregate risk assessments across banks within each firm-quarter to run more standard asset pricing tests.

First, in Table 6, we form equal-weighted stock portfolios based on whether the average change in expected loss across firms' banks, weighted by lagged loan volume, was positive or not, and estimate monthly alphas using the Fama-French three-factor 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. Results are similar when we instead weight changes in expected loss equally across banks (Panel B). 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 B3). Second, Table 7 shows that our results are also robust to using firm-level rolling three- and four-factor alphas as the dependent variable in our baseline equity return and earnings announcement return predictability specifications. Additionally, Appendix Table B4 shows that our results are robust to controlling for three- and four-factor loadings in our baseline regressions.

Another 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.[29] The bond-return predictability we document in Table 5 helps assuage this concern because it suggests that banks' information advantage extends to public debt markets, rather than simply reflecting credit-market information that has not yet reached equity markets. Nonetheless, we further address this concern in three ways.

First, Appendix Table B5 shows that our main results are robust to controlling for changes in the firm's probability of default as estimated using a Merton distance-to-default model based on publicly available equity prices and accounting information, following Vassalou and Xing (2004), as explained in more detail in Online Appendix Section C. Specifically, we control for an indicator equal to one if this Merton PD increased from the prior quarter.[30] Our results are also robust to controlling for Moody's EDF-X (formerly Moody's KMV EDF), a proprietary forecast of one-year expected default frequency

[29]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.

[30]Unlike banks' risk assessments, which change only when banks make discrete updates, Merton PDs and EDF-X are recalculated from equity prices and therefore change in virtually every quarter. An indicator for a decrease would thus be nearly perfectly collinear with the indicator for an increase, so we include only the latter.

that is commonly used by both academics and industry professionals.[31] In addition, they are robust to 1) allowing for nonlinear interactions between Merton PDs 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 Merton PDs otherwise (see Online Appendix Table OA3 for more details).

Second, in Appendix Table B6, we show that our equity return predictability results hold when we exclude firms with traded loans, traded CDS, or traded bonds. The predictability is in fact concentrated among firms with no traded credit instruments (column 5) and is statistically insignificant among firms with at least one (column 6), which are considerably larger.[32] Third, in Online Appendix Table OA7, 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.

4.3 Heterogeneity and Dynamics

In this section, we 1) analyze the cross-section of return predictability across firms, 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. Table 8 reports the results. For stock returns and negative earnings surprises, the interaction between market capitalization and EL^+ is positive for stock returns and negative for negative earnings surprises, and statistically significant in both cases. 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 OA8). We also find that the interaction between book-to-market and EL^+ is statistically significant

[31] See Online Appendix Tables OA4, OA5 and OA6. 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. According to Moody's, EDF-X measures "signal credit distress well in advance of other credit measures" (Moody's Analytics, 2016). Because EDF-X must be purchased from Moody's and its methodology and default database are proprietary, it is not fully transparent, which is why we use Merton PDs as our main control for public information.

[32] Among firms with at least one traded credit instrument, additionally controlling for a signal based solely on traded loan, CDS, and bond prices leaves the coefficient on EL^+ essentially unchanged (Online Appendix Table OA9).

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 9, we expand on these results by splitting the sample into size quintiles and separately re-estimating 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^+ has no return predictability for the very largest firms.

Reporting incentives could also vary across a bank's loans, which has implications for both our baseline and cross-sectional estimates. In particular, banks may be more reluctant to recognize deterioration on their largest exposures, which contribute the most to risk-weighted assets and projected stress losses. If so, the increases in expected losses we observe would underweight the most informative changes in expected losses, attenuating our estimates. As shown below in Table 12, banks update their assessments more, not less, frequently on larger exposures, which suggests that large exposures are not systematically absent from our sample of changes. Nonetheless, because we do not observe which loans banks would choose to misreport, we cannot sign the potential bias in our cross-sectional estimates. The weaker predictability we find among larger and value firms is intuitive and naturally predicted by theory; however, we cannot rule out selective misreporting as a contributor.

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 10. 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^+ independently predict 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.[33] 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.

To assess whether banks' PD revisions contain information beyond publicly observable default risk, we repeat the above analysis while controlling for increases in publicly observable Merton PD. Online Appendix Table OA10 shows that the results are basi-

[33]If lower LGDs are associated with higher 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.

cally unchanged, suggesting that PD's predictive content is not subsumed by this public default-risk measure. The t-statistic for stock returns does fall slightly (from 1.67 to 1.45), so that this coefficient is no longer statistically significant at conventional levels, though the point estimate is barely changed.

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 nine quarters ahead (i.e., returns from t to $t+1$, $t+1$ to $t+2$, etc.). The only negative and statistically significant coefficient is for $t+1$, 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 OA11, 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 OA12, we find a statistically significant relationship using the percentile change in expected losses among observations with nonzero changes. These results suggest a nonlinear relationship between expected losses and asset returns. Online Appendix Figure OA1 illustrates this nonlinearity, 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 negative changes in expected loss, visually confirming the asymmetry documented in our main analysis and validating our use of separate dummy variables for increases and decreases. Online Appendix Table OA13 further shows that our main equity market effects are larger for the top decile of expected loss increases.

4.4 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 by estimating 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.

Table 11 reports the results. 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.[34] 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, and none of these variables significantly predicts LGD decreases. 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.

These 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' information advantage. On the one hand, banks may be better at 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)).

To test whether banks actively produce information, 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 either PD^Δ, LGD^Δ, or EL^Δ, which are indicators that equal one if the corresponding risk assessment changes and equal zero otherwise. 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 firm's last audit (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 dummy 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 its credit lines, and 4) the firm pays down its credit lines. We also include firm-quarter fixed effects ($\alpha_{i,t}$) to control for information available to all banks simultaneously. Hence, this regression tests

[34] Online Appendix Table OA17 repeats the same analysis but includes 4 lags of each variable.

how differences in bank-firm-specific factors relate to the likelihood of banks updating their risk assessments. We again cluster our standard errors at the firm and bank-quarter level. Table 12 reports the results.

Across all specifications, 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 points more likely to update its expected loss, compared to an unconditional likelihood of 36%. This result is consistent with information production having a fixed-cost component, a feature of many models 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.[35]

At first blush, this result may seem surprising given that we see less return predictability for large firms, which tend to receive larger loans.[36] However, weaker return predictability does not necessarily imply reduced information production for three reasons.

First, while our results in Table 5 show that the information contained within banks' risk assessments is valuable to equity markets *on average*, this information can be valuable to a bank without necessarily affecting the value of the borrower's publicly traded securities. For example, information about collateral securing a particular loan or the likely effectiveness of contractual protections may inform the bank's lending, monitoring, or renegotiation decisions while being less relevant to equity holders or other creditors. Hence, predictability in equity or public debt returns need not capture the full benefit of information acquisition to the bank.

Second, quarter-ahead return predictability depends on how quickly banks' information becomes incorporated into market prices. Banks could acquire valuable information about larger firms that becomes reflected in prices within the quarter—a reasonable assumption given that these firms are more likely to receive media or financial analyst coverage—leaving less predictability at the horizon we examine.

Third, banks' incentives depend on the total benefit of information across their exposure. The same improvement in a lending or monitoring decision should be worth more to a bank with a larger exposure. Consequently, even information associated with a smaller subsequent stock return response could be more valuable for that bank to acquire. Similarly, banks may optimally update assessments more frequently for some borrowers, with each update containing less incremental information.

Nonetheless, more frequent updating may not be driven purely by increased informa-

[35]Howes and Weitzner (2026) provide empirical evidence for this mechanism by showing that banks produce more information about larger loans and loans with higher potential losses.

[36]Because larger firms often borrow from multiple banks, firm size need not translate one-for-one into any individual bank's exposure.

tion production. We therefore view these results as consistent with theories of endogenous information production rather than as direct evidence of it.

Beyond the incentives to produce information, banks are also uniquely positioned to obtain information about borrowers before it becomes public through credit lines. If a firm draws down a credit line, this information is immediately known by the bank whose credit line is drawn, but is not usually immediately disclosed to public markets or other banks.[37] Table 12 confirms that banks are more likely to update their risk assessments when firms draw down or pay down their credit lines. We therefore test whether PDs, LGDs, and expected losses increase when 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 13. Columns (1)–(3) replace firm-quarter fixed effects with industry-quarter fixed effects. In each case, credit-line drawdowns are associated with a higher likelihood of banks increasing their assessed PDs, LGDs, and expected losses. For instance, in column (3), a drawdown is associated with a 4 percentage point higher probability that the bank increases its expected loss assessment, 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 are consistent with drawdowns being 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

[37] Beyond conveying information about the firm's fundamentals, a drawdown may also reveal an increase in the borrower's debt and associated interest expense before these changes appear in public financial statements. Thus, banks may learn about changes in leverage and their implications for future earnings through their lending relationships, without actively acquiring additional information.

OA18, 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 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 (Online Appendix Table OA20) nor the intraclass correlation coefficients (Online Appendix Table OA21) suggest that syndication leads to stronger comovement in risk assessments across banks.[38]

If credit-line drawdowns reveal adverse information that is not yet fully reflected in market prices, they should predict negative subsequent stock returns. To examine this, we re-estimate a version of (1) with both EL^{+} and *Drawdown* as independent variables. Table 14 reports the results. 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 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.[39]

4.5 Banks' Private Information and Lending Decisions

For banks, the primary benefit of producing information is to improve credit allocation. In this section, we examine how banks adjust their lending around revisions to their assessments of borrowers' credit risk. Precisely identifying the role of private information in these decisions is challenging for several reasons. First, changes in risk assessments may coincide with changes in borrowers' demand for credit. For example, attractive investment opportunities could reduce a firm's credit risk while increasing its demand for credit. Second, changes in banks' risk assessments and lending may both reflect public information. Third, changes in risk assessments could be the result of, rather than the cause of, changes in credit allocation. Finally, lending outcomes may be insensitive to small changes in risk assessments because of adjustment costs, inertia, or the timing of renegotiation opportunities.

Our empirical approach to determining how banks adjust lending in response to private information is designed to mitigate these four challenges as much as possible. Be-

[38]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 12). Moreover, banks have heterogeneous exposures across industries and firm types in their portfolios, and as a result, may evaluate individual firms differently.

[39]Online Appendix Table OA22 shows that these results also hold when excluding firm-bank relationships with syndicated loans.

cause the timing of these effects is crucial to understanding how long public markets take to incorporate this information, we use the distributed lead-lag approach of Sachdeva et al. (2025) and trace committed exposure from four quarters before to eight quarters after increases and decreases in assessed expected losses. This approach lets us examine whether lending changes precede reassessments, occur contemporaneously, or emerge only afterward, while accounting for other reassessments within the event window.

To address the first two concerns about credit demand and public information, we exploit the fact that firms often borrow from multiple banks simultaneously and include firm-quarter fixed effects, following Khwaja and Mian (2008). These fixed effects absorb borrower-level factors common to the borrower's lenders, including public information and common changes in credit demand, allowing us to compare lending and assessment revisions across banks lending to the same firm in the same quarter.

To mitigate concerns about mechanical changes in risk assessments that can accompany changes in lending, we calculate the average change in expected loss across loans outstanding in both quarters $t-1$ and t, weighted by committed exposure at $t-1$. For example, when a bank issues a new unsecured loan alongside an existing secured loan, average expected loss can increase even if neither loan's assessment changes. We define $\widetilde{EL}^{+}_{i,b,t}$ and $\widetilde{EL}^{-}_{i,b,t}$ as indicators for whether this weighted average change is more than 0.01 percentage points or less than -0.01 percentage points, respectively. Unlike our baseline return-predictability indicators, these indicators focus on larger revisions: small changes in assessed risk may contain information without being large enough to warrant an adjustment in lending. Focusing on changes above these thresholds lets us analyze the most consequential information changes likely to drive credit allocation.

Formally, we estimate the following Poisson regression:

$$\mathbb{E}\left[Y_{i,b,t} \mid \cdot\right] = \exp\left(\alpha_{i,t} + \gamma_{b,t} + \delta_{i,b} + \sum_{\substack{k=-4 \\ k\neq -1}}^{8} \beta_k^{+} \widetilde{EL}^{+}_{i,b,t-k} + \sum_{\substack{k=-4 \\ k\neq -1}}^{8} \beta_k^{-} \widetilde{EL}^{-}_{i,b,t-k}\right). \tag{2}$$

We estimate (2) by Poisson pseudo-maximum likelihood (Correia, Guimarães, and Zylkin, 2020), with total committed exposure from bank b to firm i in quarter t, measured in dollars, as the dependent variable $Y_{i,b,t}$. This approach models lending in levels rather than logs and accommodates a continuous, nonnegative outcome (Cohn, Liu, and Wardlaw (2022) and Chen and Roth (2024)).[40] In addition to firm-quarter fixed effects

[40] Although Poisson estimation allows for zero committed exposures, our specification requires observing leads and lags of changes in risk assessments, which are unavailable when a bank-firm relationship is no longer reported and cannot be meaningfully imputed following the separation of a relationship. Therefore, our results are based only on a selected sample of firm-bank-quarters with an ongoing lending relationship. If banks are more likely to end a relationship after becoming more pessimistic about a borrower, excluding these exits leads us to understate, rather than overstate, the lending response to an increase in expected losses.

$\alpha_{i,t}$, we include bank-quarter fixed effects $\gamma_{b,t}$ and firm-bank fixed effects $\delta_{i,b}$, which absorb bank-wide changes in credit supply and persistent differences across lending relationships. Standard errors are clustered by firm and bank-quarter.

Unlike a setting with a single event per unit, banks in our sample may revise their assessments several times within the event window. The distributed lead-lag specification accounts for these overlapping reassessments by including them jointly (Schmidheiny and Siegloch, 2023). The coefficients β_k^+ and β_k^- trace the conditional relationship between committed exposure and large increases and decreases in assessed expected losses, respectively. Negative values of k correspond to quarters before the reassessment, $k = 0$ captures the contemporaneous relationship, and positive values correspond to subsequent quarters. We plot coefficients multiplied by 100, which can be interpreted as approximate percentage differences in committed exposure relative to the last quarter before the risk assessment changed.

Figure 5 presents the results, with the top panel plotting the coefficients for increases in expected losses (β_k^+) and the bottom panel plotting those for decreases (β_k^-). An increase in a bank's assessed expected loss on existing loans is associated with approximately 4% lower committed exposure in the same quarter, relative to other banks lending to the same borrower. We find no evidence of a pre-trend, and the estimated relationship persists into the following quarter before dissipating. In contrast, decreases in assessed expected losses are not associated with a statistically significant change in committed exposure. We also find similar results when we instead use changes in PDs, which are set at the borrower level and are therefore not affected by the composition of a bank's loans to the firm (Online Appendix Figure OA5). These results are consistent with banks incorporating their information into lending decisions before it is reflected in the subsequent quarter's market outcomes and are consistent with the stock return predictability dynamics we report in Figure 4, which fade after one quarter. Because the specification includes firm-quarter fixed effects, these estimates capture differences across lenders to the same borrower rather than changes in the borrower's aggregate credit availability. Accordingly, the disappearance of the estimated relationship at subsequent horizons need not imply that the reassessing bank reverts to its previous lending volume; it could also reflect adjustments by other lenders. Relatedly, because the firm-quarter fixed effects absorb any information that is common to a firm's lenders, these estimates likely capture only part of the relationship between banks' private information and lending.

Beyond differences in information, differences in banks' risk assessments within firm-quarter may also reflect differences in banks' subjective beliefs.[41] Our empirical design cannot separate these two sources of variation, and we therefore do not claim that the lending responses we document are driven entirely by private information. That said, in

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

Section 4.4 we show that credit line drawdowns, which the lending bank observes before markets or other banks, predict both increases in risk assessments and subsequent stock returns, suggesting that at least part of the variation in assessments across banks reflects information rather than beliefs alone.

Beyond lending volumes, we also consider changes in loan terms. Here we follow Bidder et al. (2023), who track loan-level modifications using the same data and focus on the differences in modification rates across syndicated and nonsyndicated loans. Because we are ultimately interested in loan modifications to the extent that they provide evidence about the channels that make banks' private information useful to equity markets, we adopt their definition of a modification as a change in a loan's maturity date or interest rate from the previous quarter and aggregate modifications up to the firm-bank-quarter level. Directionally consistent with their results, Online Appendix Figure OA2 shows that both increases and decreases in assessed expected losses are associated with a higher probability of contemporaneous loan modification, although these estimates are not statistically significant. We also find similar patterns using changes in borrower-level PDs (Online Appendix Figure OA6).

Interpreting these results requires caution because modifications can themselves change assessed risk. For example, changing a loan's collateral can directly affect LGD. For this reason, we focus on lending volumes as our main evidence that banks act on their information.

Why is it valuable for banks to have this information if it becomes public so soon afterward? 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.[42]

Credit lines illustrate why the immediacy of information matters. In practice, firms often draw down credit lines after experiencing a negative shock; indeed, in Section 4.4, 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 the borrower recover or simply increase the bank's losses.

These results raise important questions about how banks' actions affect the return

[42]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. Acting first on deteriorating fundamentals allows the bank to secure collateral, seniority, or tighter covenants before other lenders respond.

predictability we observe. On the 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 without 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 OA14), in which its total loan commitment to the firm changed by more than 1% from the previous quarter (Online Appendix Table OA15)[43], or in which the interest rate or maturity changed on any loan within the firm-bank relationship (Online Appendix Table OA16). These results suggest that banks' information predicts financial market outcomes even when they do not immediately act on that information through changes in lending volumes or loan terms.

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 increases in banks' assessed expected losses predict stock returns, bond returns, and analyst earnings surprises, and this predictability is stronger for smaller firms and growth firms. We identify sources of private information for banks and find evidence consistent with both active information production and access to non-public information before markets. We also find evidence consistent with banks using 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 expect banks' information advantage to be even stronger for smaller, more opaque firms that lack publicly traded equity or debt, consistent with our results showing a stronger advantage for smaller public firms. Third, our sample comprises only the largest US banks, which many argue are less likely to play the traditional role of

[43]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.

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 financiers — 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, opening many avenues for future research on 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. The vertical axes are scaled so that each figure integrates to one. For readability, the PD and expected loss distributions are truncated at 5pp and 2.5pp, respectively. The number of firm-bank-quarter observations shown in each panel is $N = 130{,}054$ for PD, $N = 135{,}214$ for LGD, and $N = 132{,}380$ for EL.

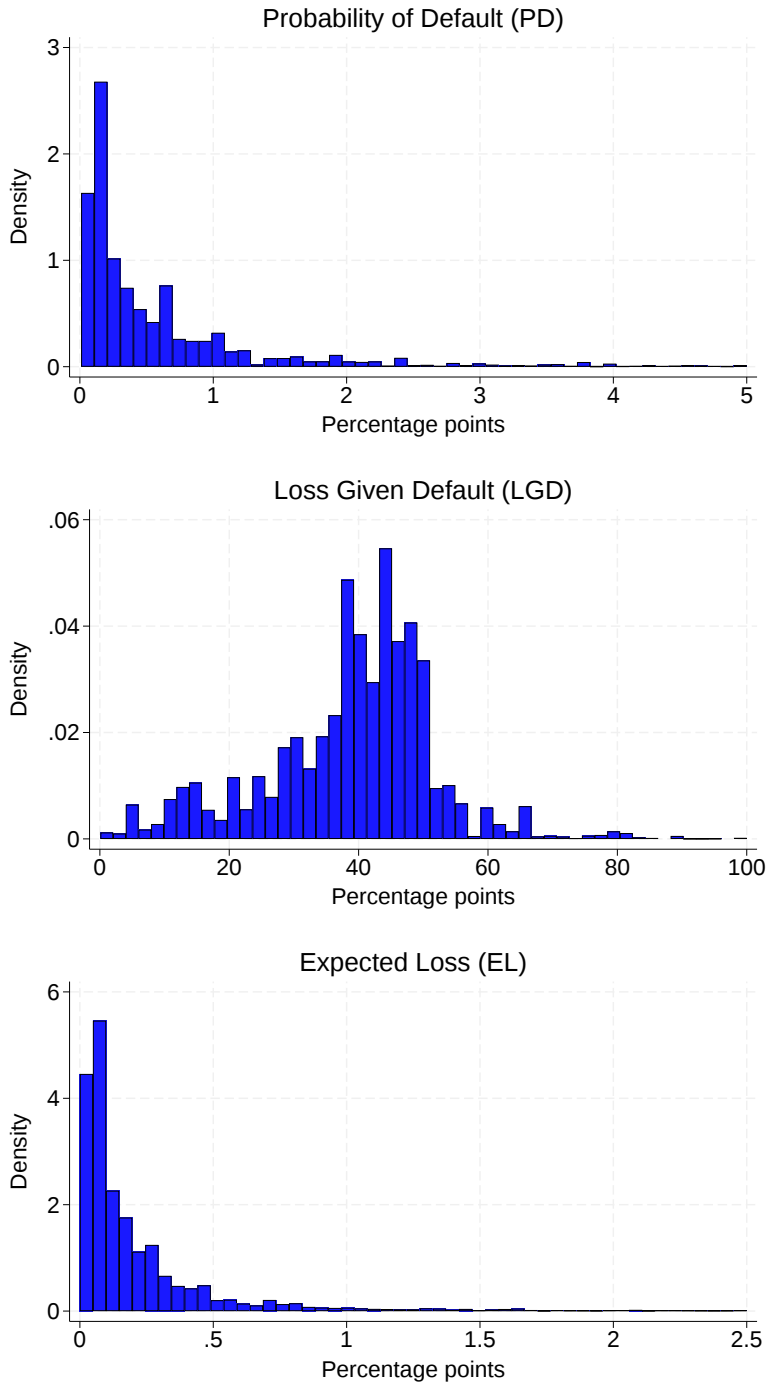


Figure 2: Distributions of Changes in Risk Assessments

This figure shows the distributions of nonzero changes in banks' internal risk assessments at the firm-bank-quarter level. The vertical axes are scaled so that each figure integrates to one. For readability, the ΔPD, ΔLGD, and ΔEL distributions are truncated at ±2pp, ±25pp, and ±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.

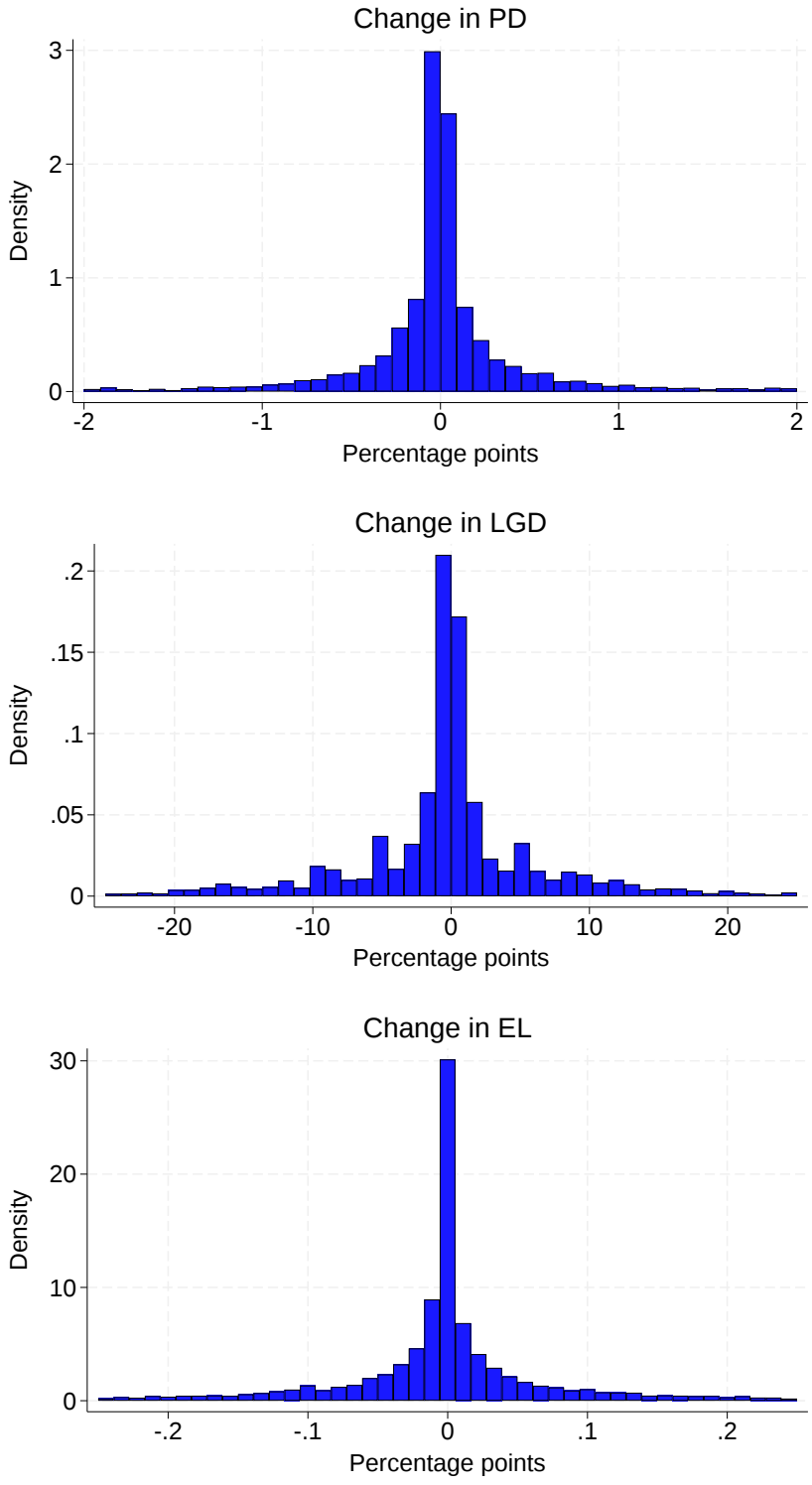
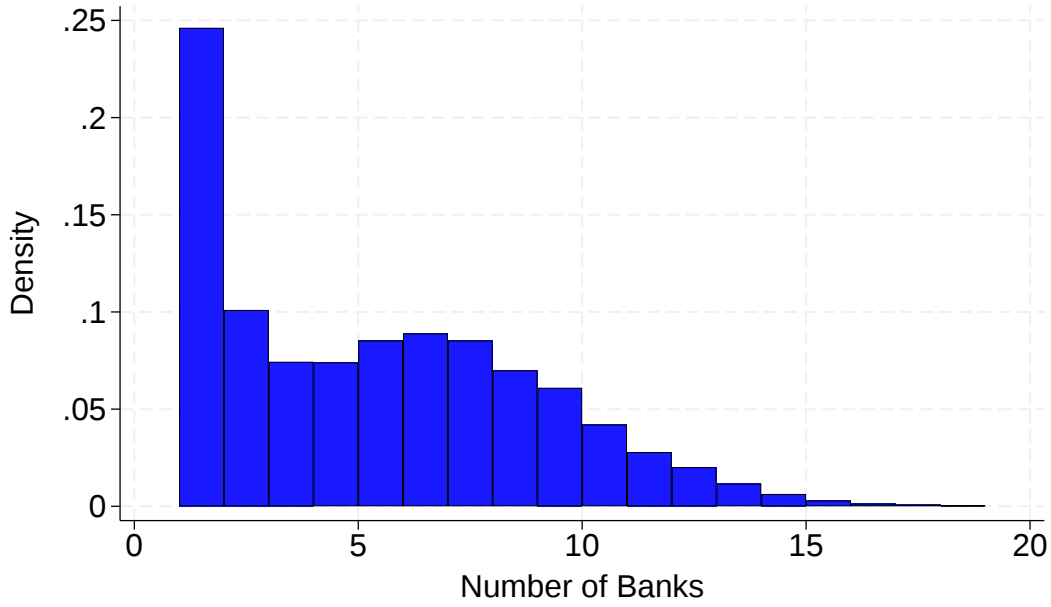


Figure 3: Distribution of Bank Relationships

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 vertical axis is scaled so that the figure integrates to one. 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	13.04	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 a 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-quarter and industry-quarter 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 $t+9$.

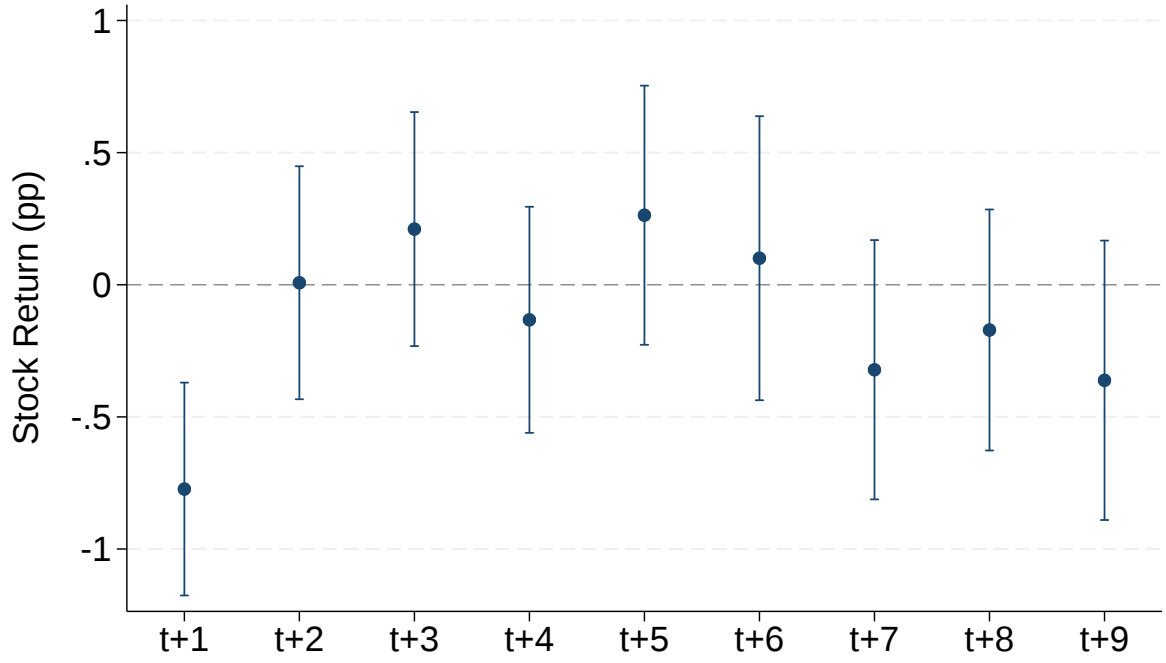


Figure 5: Changes in Expected Loss and Lending Volume

This figure shows how changes in banks' risk assessments affect their subsequent lending volume. The top (bottom) figure plots the coefficient estimates β_k^+ (β_k^-) from Equation 2, which is estimated using Poisson pseudo-maximum likelihood. The dependent variable is total relationship-level committed exposure in dollars. These coefficients represent the marginal effects of $\widetilde{EL}^+_{i,b,t-k}$ ($\widetilde{EL}^-_{i,b,t-k}$), which is an indicator equal to one if the average of all within-loan changes in expected loss between time $t-1$ and time t weighted by committed exposure at time $t-1$ increased (decreased) by more than 0.01pp. These coefficients are scaled by 100 and can be interpreted as approximate percentage differences in committed exposure relative to the last quarter before the risk assessment changed ($t-1$). Vertical lines indicate 95% confidence intervals calculated using standard errors that are double clustered by firm and bank-quarter. The sample size is $N = 30,512$ firm-bank-quarter observations. Appendix Section A contains all variable definitions.

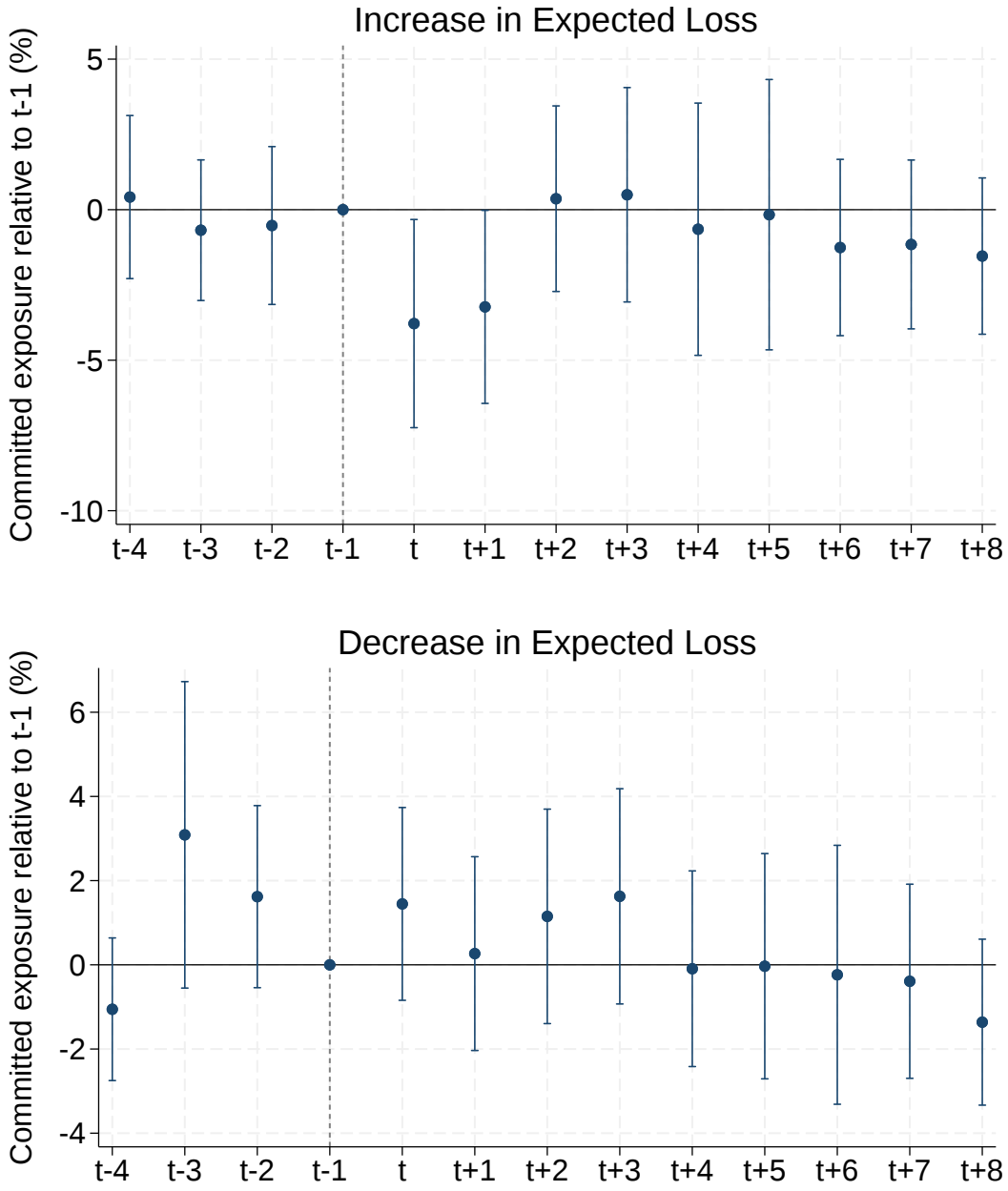


Table 1: Summary Statistics

This table presents summary statistics for the main variables used in the analysis. The sample includes all corporate loans of at least $1 million extended by large US 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	0.311	0.463	0.000	0.000	1.000	126,167
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
Syndicated Loan	0.485	0.500	0.000	0.000	1.000	135,214
Loan Volume ($ mn)	98.194	166.933	18.750	61.752	191.429	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	0.323	0.418	0.000	0.022	1.000	25,431
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
Syndicated Loan	0.432	0.435	0.000	0.471	1.000	27,417
Loan Volume ($ mn)	484.269	822.529	14.000	230.500	1,159.402	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 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^+	-0.773^{***}	-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: 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 the average change in expected loss 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 positive ("Downgrade") or not ("Upgrade"). 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	0.3228	0.0586	0.0595
Downgrade	-0.0387	-0.1973	-0.1945
Upgrade - Downgrade	0.3615	0.2559	0.2540
(t-stat)	2.22	2.01	2.39
N	60	60	60
Panel B: Equal Weighted EL			
	Returns	3-Factor	4-Factor
Upgrade	0.3066	0.0507	0.0515
Downgrade	-0.0111	-0.1884	-0.1856
Upgrade - Downgrade	0.3176	0.2391	0.2371
(t-stat)	2.07	1.96	2.41
N	60	60	60

Table 7: 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 8: 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 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 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 stock (bond) 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 9: 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 quintiles 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 10: 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 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 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 11: 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 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 changes in firm characteristics (book-to-market ratio, ROA, leverage) based on the latest publicly available financials, and 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 12: Relationship-Level Drivers of Risk Assessment Updates

This table examines how relationship-level 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 13: 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 14: 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.

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.

$\widetilde{EL}^{+}$: A dummy variable that equals one if the average change in Expected Loss across all existing loans in a bank-firm relationship (weighted by total committed exposure at $t-1$) increased by more than 0.01pp between $t-1$ and t, from Y-14Q. If the superscript is $-$, the variable equals one if the weighted average change in EL decreased by more than 0.01pp.

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.

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.

Merton PD^{+}: A dummy variable that equals one if the firm's iterative distance-to-default-based Merton PD increased from the prior period and zero otherwise. Details on the construction of this measure are in Online Appendix C.

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 long-run annual default rate, weighted by the committed dollar amount of each loan at the bank-firm-quarter level, excluding loans with $PD \leq 0$ 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 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 (for means) and a Wilcoxon rank-sum Mann-Whitney test (for medians).

	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 quarter columns (3) - (5), and by firm and bank-quarter in all other columns. *, **, 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**	−1.014***
	(3.771)	(2.491)	(3.006)	(2.496)	(2.544)	(2.785)
EL^-	−0.226	−0.130	−0.283	−0.089	0.063	−0.300
	(1.267)	(0.425)	(0.496)	(0.138)	(0.229)	(0.789)
Book-to-Market	−0.103	−0.226	−0.230	−0.234	−0.184	−0.238
	(0.167)	(0.359)	(0.193)	(0.196)	(0.155)	(0.344)
ROA	0.817	−0.098	−0.513	−0.511	−0.396	−0.700
	(0.410)	(0.039)	(0.116)	(0.116)	(0.090)	(0.269)
Leverage	−0.550	−0.538	−0.710	−0.750	−0.600	−0.320
	(0.718)	(0.743)	(0.530)	(0.556)	(0.449)	(0.392)
Log(Market Cap)	0.200*	0.200*	0.188	0.190	0.248	0.196
	(1.744)	(1.921)	(0.958)	(0.975)	(1.215)	(1.509)
Lagged Stock Return	−0.014	−0.011	−0.013	−0.013	−0.013	−0.012
	(1.047)	(0.897)	(0.751)	(0.746)	(0.761)	(0.952)
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	23,749
R-squared	0.37	0.30	0.30	0.30	0.30	0.31

Table B3: 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 B4: 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

Table B5: Changes in Expected Losses Predict Financial Market Outcomes (Controlling for Merton PDs)

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 Merton PD^+, an indicator equal to one if the probability of default estimated from a Merton model increased from the prior period. Online Appendix C details this methodology. 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^+	−0.751***	−0.198**	2.007***	−0.178**
	(3.576)	(1.998)	(3.855)	(2.168)
EL^-	−0.239	0.093	0.469	0.084
	(1.331)	(1.402)	(1.109)	(1.253)
Merton PD^+	−0.118	−0.199**	−0.398	−0.737***
	(0.349)	(2.020)	(0.443)	(4.186)
Book-to-Market	−0.066	0.271	4.247**	0.760***
	(0.104)	(0.705)	(2.258)	(3.393)
ROA	1.252	0.805	−6.379	1.248
	(0.606)	(0.788)	(0.914)	(1.351)
Leverage	−0.485	0.032	3.369	0.390
	(0.593)	(0.098)	(1.355)	(1.293)
Log(Market Cap)	0.186	0.012	−3.657***	−0.059
	(1.585)	(0.227)	(10.131)	(1.487)
Lagged Stock Return	−0.016		−0.166***	0.303***
	(0.971)		(5.396)	(28.482)
Lagged Bond Return		−0.089**		
		(2.037)		
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	113,635	54,013	104,647	111,210
R-squared	0.38	0.49	0.09	0.34

Table B6: 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. Column (6) includes only firms with at least one traded loan, CDS, or bond. 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	Any Traded Credit
	(1)	(2)	(3)	(4)	(5)	(6)
EL^+	−0.773***	−0.734***	−0.842***	−1.135***	−1.143***	−0.357
	(3.771)	(3.608)	(3.610)	(4.939)	(4.755)	(1.130)
EL^-	−0.226	−0.219	−0.224	−0.379	−0.346	−0.082
	(1.267)	(1.216)	(1.106)	(1.583)	(1.380)	(0.377)
Book-to-Market	−0.103	−0.379	−0.326	−0.452	−0.683	0.826
	(0.167)	(0.598)	(0.524)	(0.668)	(0.959)	(0.846)
ROA	0.817	0.271	0.794	−0.608	−1.532	3.287
	(0.410)	(0.134)	(0.356)	(0.240)	(0.578)	(1.134)
Leverage	−0.550	−0.544	−0.527	−0.725	−0.608	0.429
	(0.718)	(0.716)	(0.649)	(0.790)	(0.658)	(0.347)
Log(Market Cap)	0.200*	0.194*	0.093	0.103	0.117	0.390**
	(1.744)	(1.707)	(0.675)	(0.649)	(0.732)	(2.149)
Lagged Stock Return	−0.014	−0.010	−0.012	−0.027**	−0.018	−0.008
	(1.047)	(0.692)	(0.827)	(2.347)	(1.511)	(0.286)
Mean of DV	0.83	0.88	0.82	0.85	0.94	0.74
Bank-Quarter FE	YES	YES	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES	YES	YES
Observations	117,622	112,302	89,628	62,697	56,795	60,823
R-squared	0.37	0.38	0.36	0.35	0.34	0.45

Online 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 across at least 11 banks.

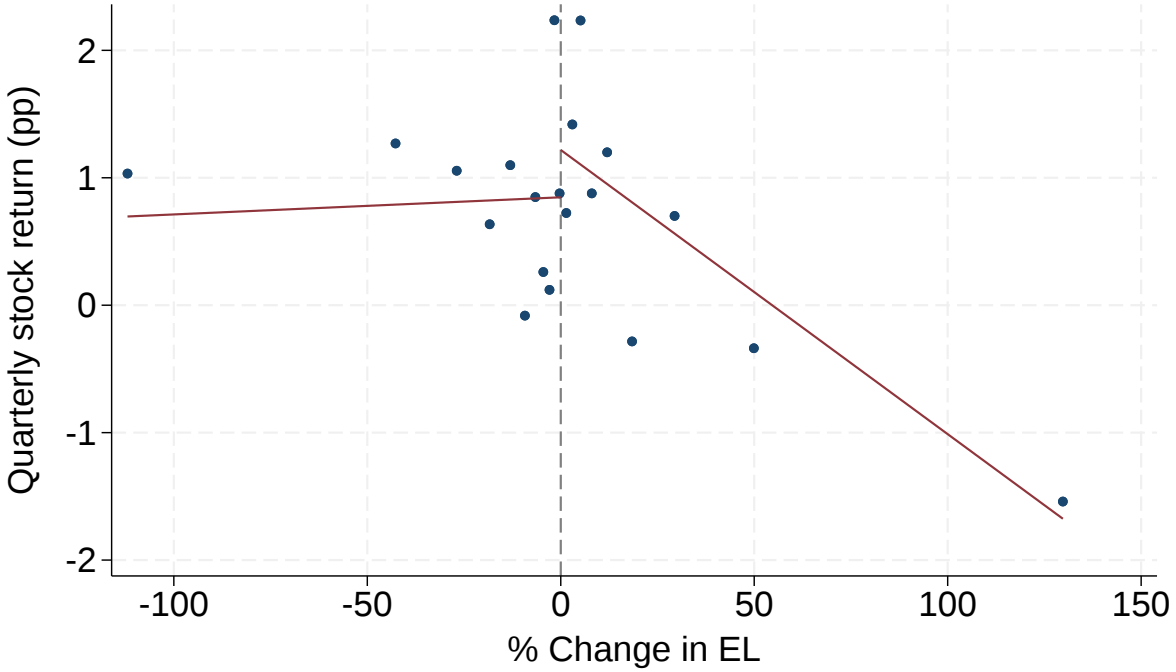
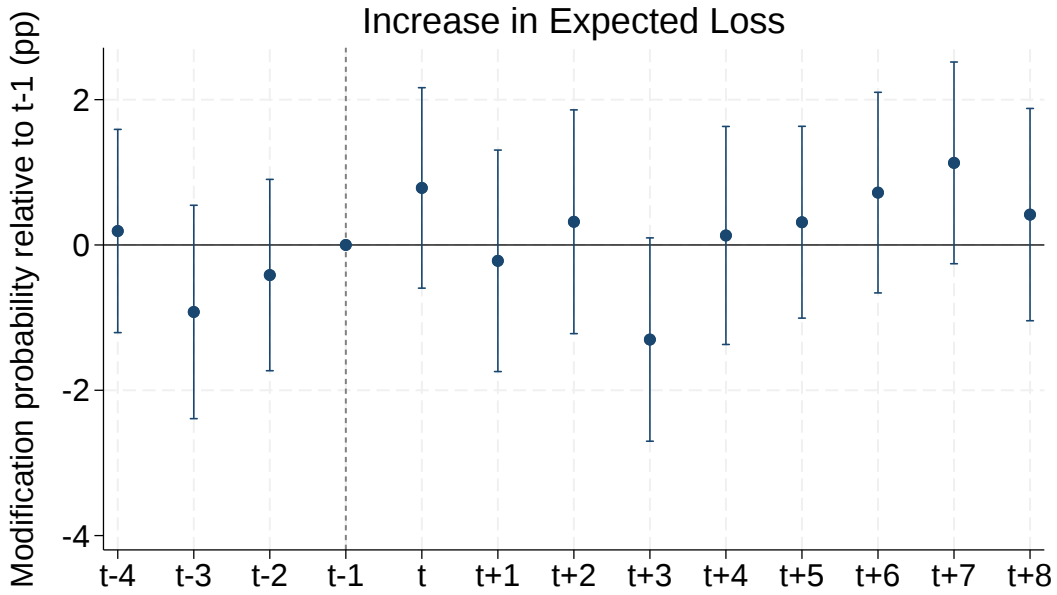


Figure OA2: Changes in Expected Loss and Loan Modifications

This figure shows how changes in banks' risk assessments affect their subsequent probability of loan modifications. The top (bottom) figure plots the coefficient estimates β_k^+ (β_k^-) from the OLS version of Equation 2. The dependent variable is an indicator equal to one if the interest rate or maturity date of any loan in the bank-firm relationship changed between time $t-1$ and time t. These coefficients represent the marginal effects of $\widetilde{EL}_{i,b,t-k}^{+}$ ($\widetilde{EL}_{i,b,t-k}^{-}$), which is an indicator equal to one if the average of within-loan changes in expected loss between time $t-1$ and time t weighted by committed exposure at time $t-1$ increased (decreased) by more than 0.01pp. These coefficients represent percentage point changes in the probability of loan modification relative to the last quarter before the risk assessment changed ($t-1$). Vertical lines indicate 95% confidence intervals calculated using standard errors that are double clustered by firm and bank-quarter. The sample size is $N = 29,705$ firm-bank-quarter observations. Appendix Section A contains all variable definitions.



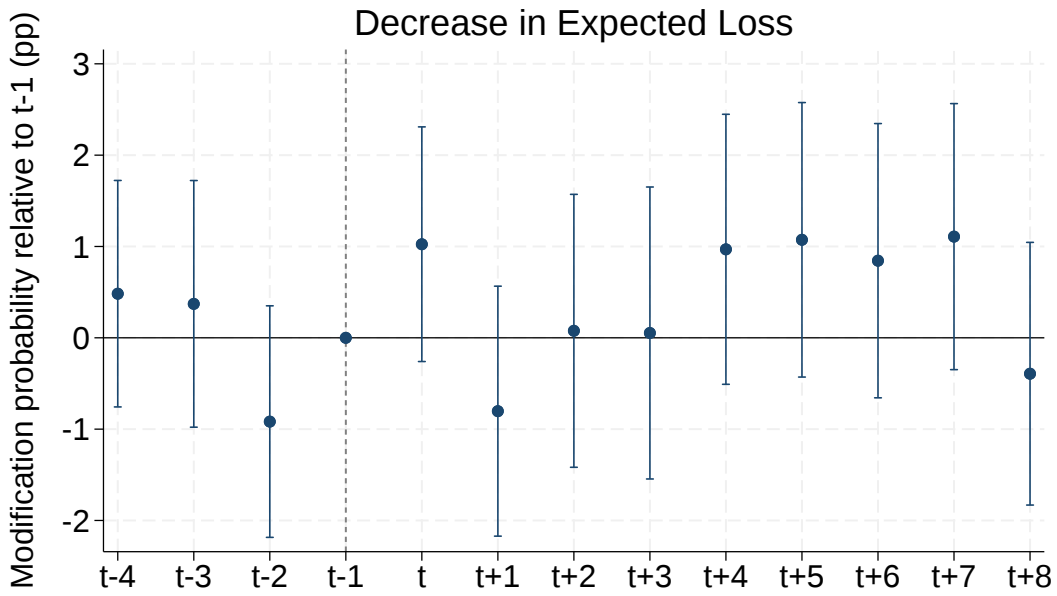


Figure OA3: Changes in Expected Loss and Maturity

This figure shows how changes in banks' risk assessments affect borrowers' subsequent loan maturity. The top (bottom) figure plots the coefficient estimates β_k^+ (β_k^-) from the OLS version of Equation 2. The dependent variable is the loan volume-weighted average maturity (in months) of a borrower's loans from a bank at time t. These coefficients represent the marginal effects of $\widetilde{EL}_{i,b,t-k}^{+}$ ($\widetilde{EL}_{i,b,t-k}^{-}$), which is an indicator equal to one if the average of within-loan changes in expected loss between time $t-1$ and time t weighted by committed exposure at time $t-1$ increased (decreased) by more than 0.01pp. These coefficients represent changes in loan maturity (in months) relative to the last quarter before the risk assessment changed ($t-1$). Vertical lines indicate 95% confidence intervals calculated using standard errors that are double clustered by firm and bank-quarter. The sample size is $N = 30,290$ firm-bank-quarter observations. Appendix Section A contains all variable definitions.

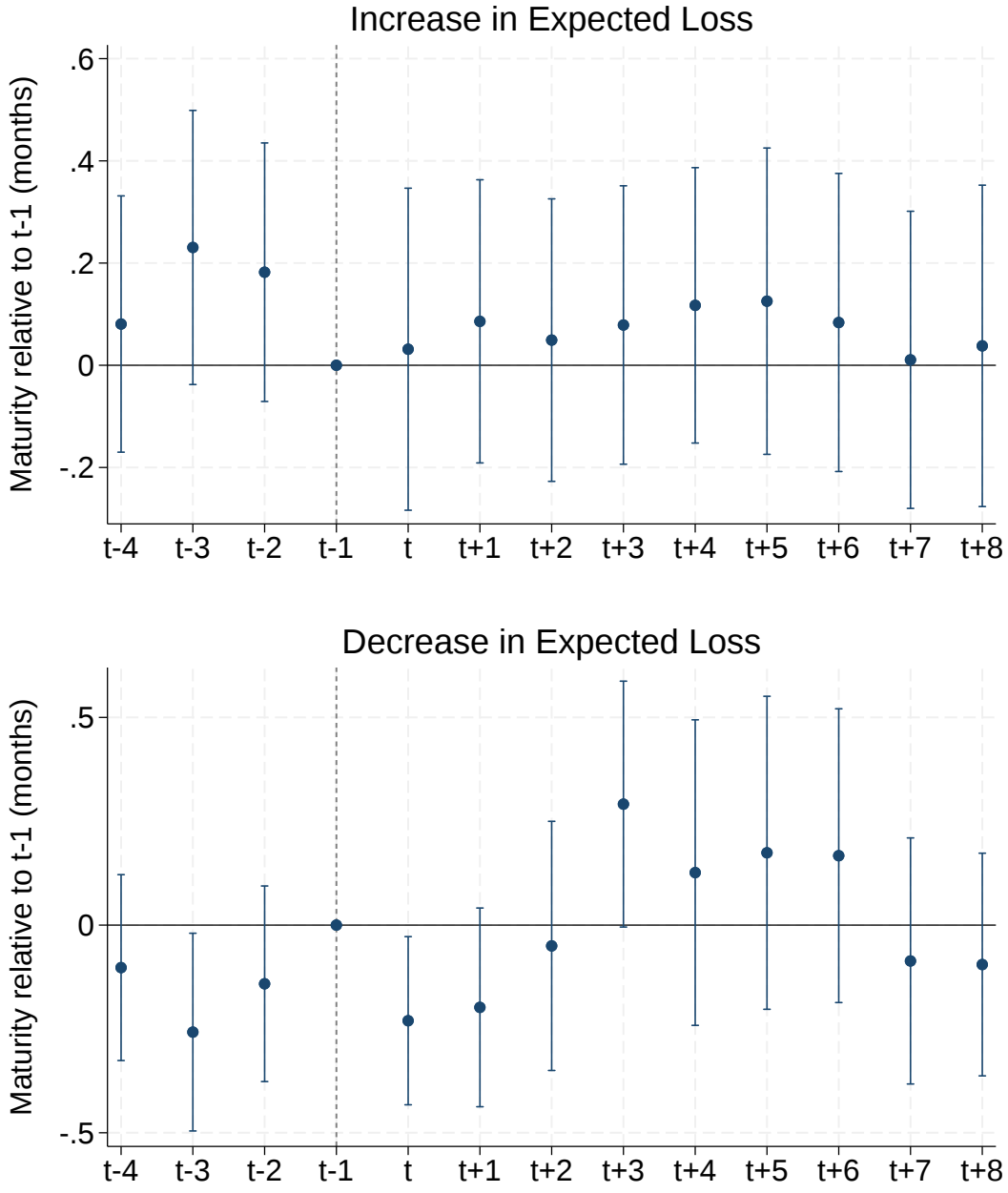


Figure OA4: Changes in Expected Loss and Interest Rates

This figure shows how changes in banks' risk assessments affect borrowers' subsequent interest rate. The top (bottom) figure plots the coefficient estimates β_k^+ (β_k^-) from the OLS version of Equation 2. The dependent variable is the loan volume-weighted average interest rate (in percentage points) of a borrower's loans from a bank at time t. These coefficients represent the marginal effects of $\widetilde{EL}^+_{i,b,t-k}$ ($\widetilde{EL}^-_{i,b,t-k}$), which is an indicator equal to one if the average of within-loan changes in expected loss between time $t-1$ and time t weighted by committed exposure at time $t-1$ increased (decreased) by more than 0.01pp. These coefficients represent percentage point changes in the interest rate relative to the last quarter before the risk assessment changed ($t-1$). Vertical lines indicate 95% confidence intervals calculated using standard errors that are double clustered by firm and bank-quarter. The sample size is $N = 30,440$ firm-bank-quarter observations. Appendix Section A contains all variable definitions.

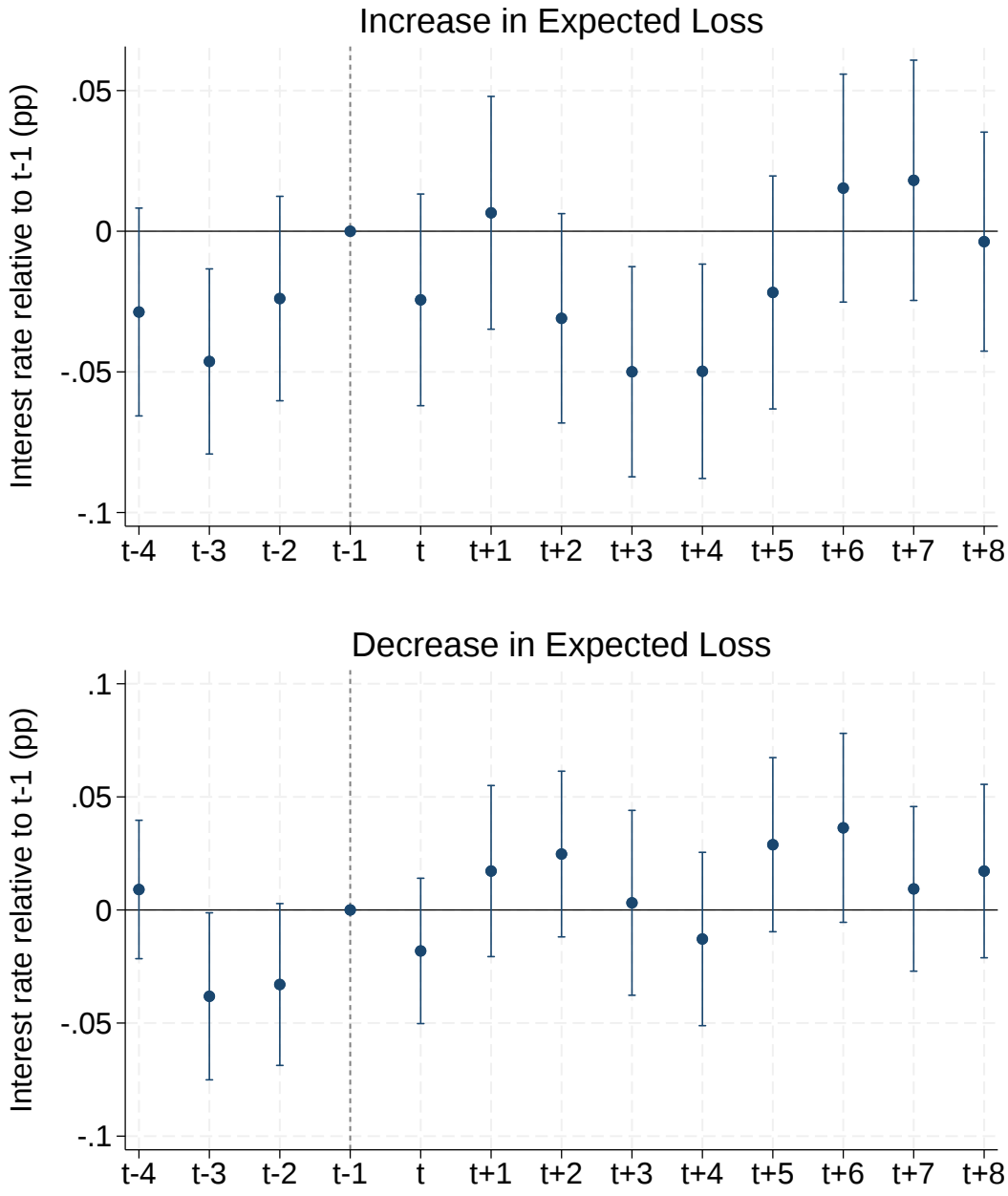
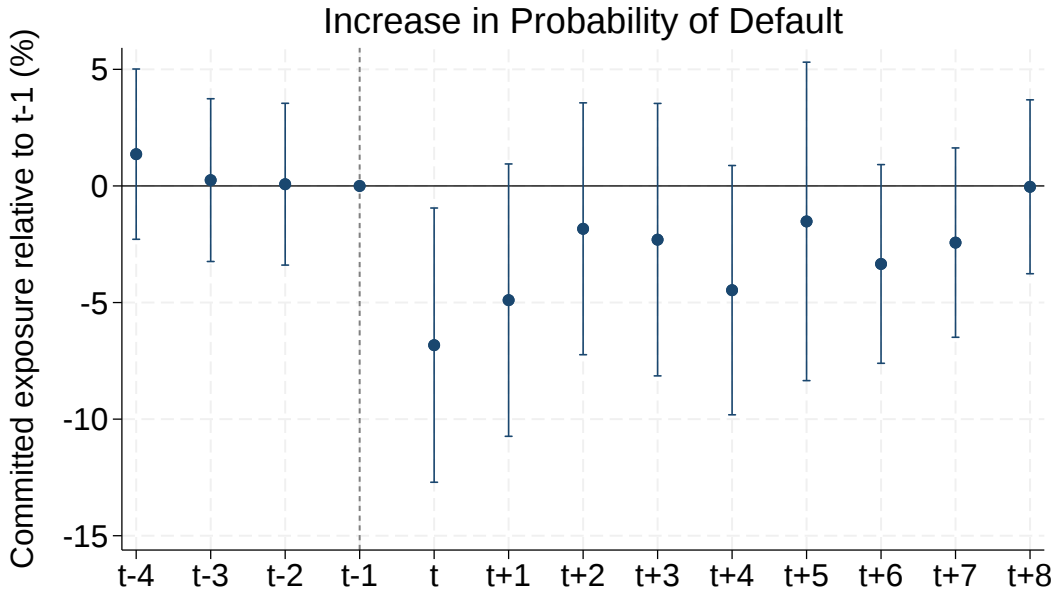


Figure OA5: Changes in Probability of Default and Lending Volume

This figure shows how changes in banks' risk assessments affect their subsequent lending volume. The top (bottom) figure plots the coefficient estimates β_k^+ (β_k^-) from a modified version of Equation 2 that uses probability of default instead of expected losses and is estimated using Poisson pseudo-maximum likelihood. The dependent variable is total relationship-level committed exposure in dollars. These coefficients represent the marginal effects of $\widetilde{PD}_{i,b,t-k}^{+}$ ($\widetilde{PD}_{i,b,t-k}^{-}$), which is an indicator equal to one if the average of all within-loan changes in probability of default between time $t-1$ and time t weighted by committed exposure at time $t-1$ increased (decreased) by more than 0.1pp. These coefficients are scaled by 100 and can be interpreted as approximate percentage differences in committed exposure relative to the last quarter before the risk assessment changed ($t-1$). Vertical lines indicate 95% confidence intervals calculated using standard errors that are double clustered by firm and bank-quarter. The sample size is $N = 30,512$ firm-bank-quarter observations. Appendix Section A contains all variable definitions.



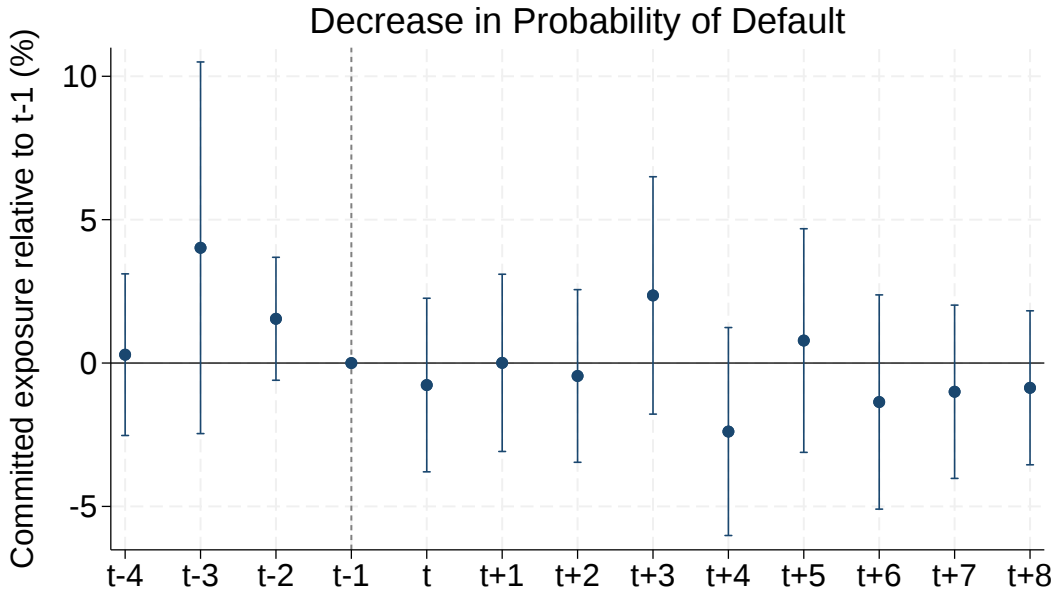
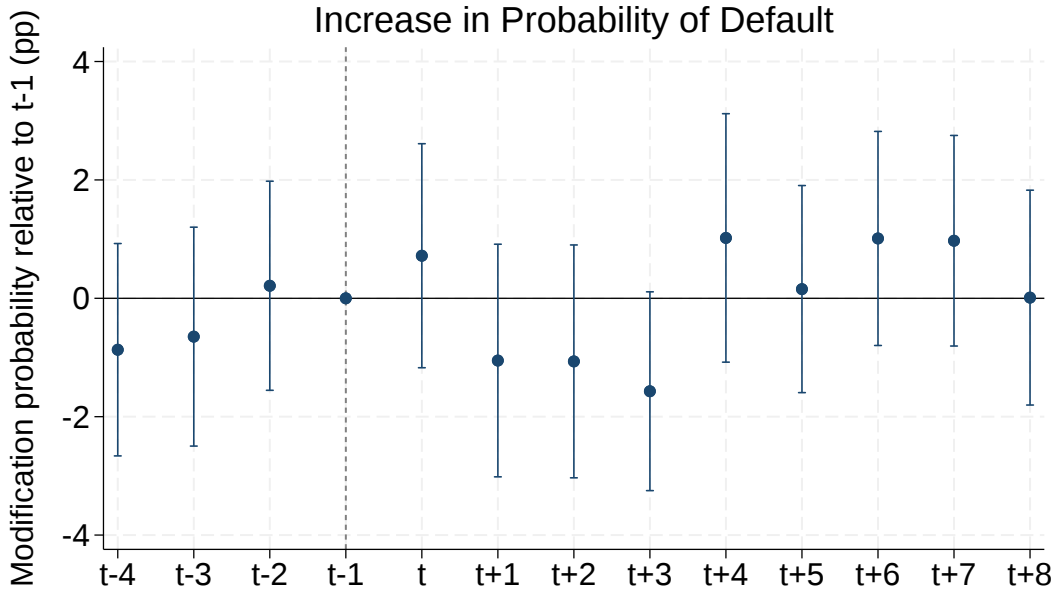


Figure OA6: Changes in Probability of Default and Loan Modifications

This figure shows how changes in banks' risk assessments affect their subsequent probability of loan modifications. The top (bottom) figure plots the coefficient estimates β_k^+ (β_k^-) from a modified OLS version of Equation 2 that uses probability of default instead of expected losses. The dependent variable is an indicator equal to one if the interest rate or maturity date of any loan in the bank-firm relationship changed between time $t-1$ and time t. These coefficients represent the marginal effects of $\widetilde{PD}^+_{i,b,t-k}$ ($\widetilde{PD}^-_{i,b,t-k}$), which is an indicator equal to one if the average of within-loan changes in probability of default between time $t-1$ and time t weighted by committed exposure at time $t-1$ increased (decreased) by more than 0.1pp. These coefficients represent percentage point changes in the probability of loan modification relative to the last quarter before the risk assessment changed ($t-1$). Vertical lines indicate 95% confidence intervals calculated using standard errors that are double clustered by firm and bank-quarter. The sample size is $N = 29,705$ firm-bank-quarter observations. Appendix Section A contains all variable definitions.



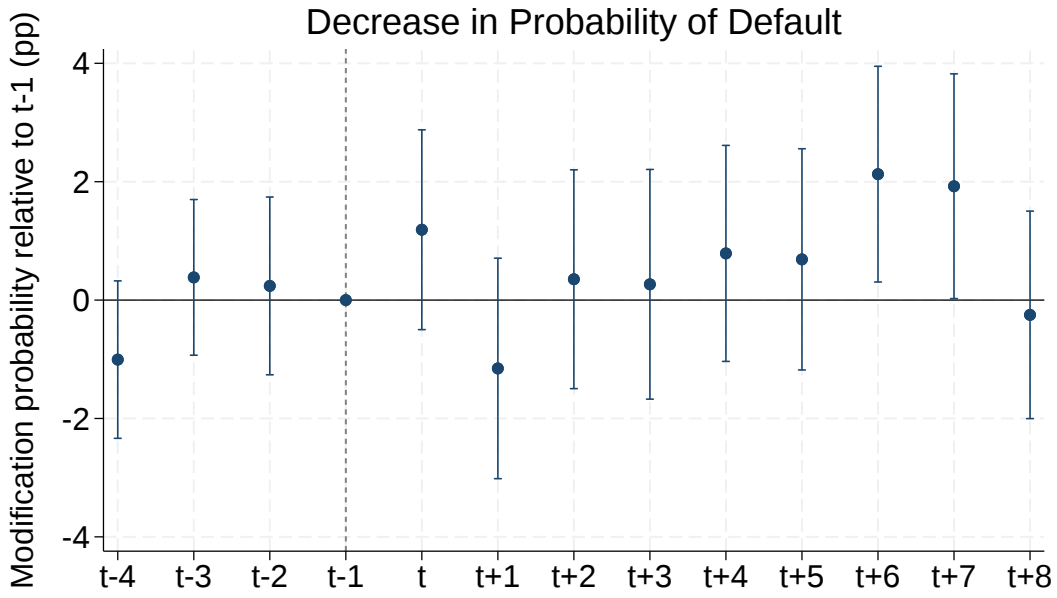


Figure OA7: Changes in Probability of Default and Maturity

This figure shows how changes in banks' risk assessments affect borrowers' subsequent loan maturity. The top (bottom) figure plots the coefficient estimates β_k^+ (β_k^-) from a modified OLS version of Equation 2 that uses probability of default instead of expected losses. The dependent variable is the loan volume-weighted average maturity (in months) of a borrower's loans from a bank at time t. These coefficients represent the marginal effects of $\widetilde{PD}^+_{i,b,t-k}$ ($\widetilde{PD}^-_{i,b,t-k}$), which is an indicator equal to one if the average of within-loan changes in probability of default between time $t-1$ and time t weighted by committed exposure at time $t-1$ increased (decreased) by more than 0.1pp. These coefficients represent changes in loan maturity (in months) relative to the last quarter before the risk assessment changed ($t-1$). Vertical lines indicate 95% confidence intervals calculated using standard errors that are double clustered by firm and bank-quarter. The sample size is $N = 30,290$ firm-bank-quarter observations. Appendix Section A contains all variable definitions.

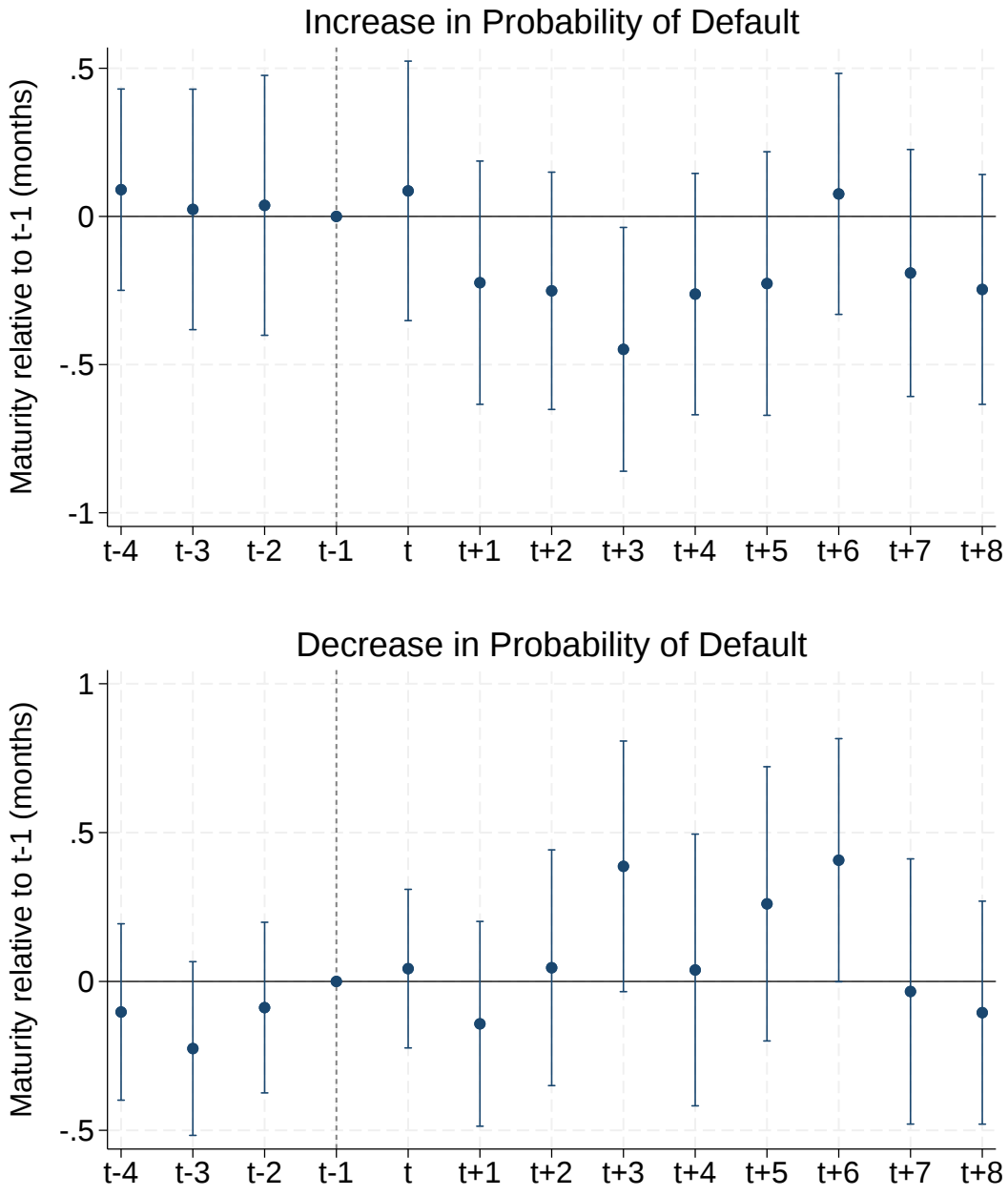


Figure OA8: Changes in Probability of Default and Interest Rates

This figure shows how changes in banks' risk assessments affect borrowers' subsequent interest rate. The top (bottom) figure plots the coefficient estimates β_k^+ (β_k^-) from a modified OLS version of Equation 2 that uses probability of default instead of expected losses. The dependent variable is the loan volume-weighted average interest rate (in percentage points) of a borrower's loans from a bank at time t. These coefficients represent the marginal effects of $\widetilde{PD}_{i,b,t-k}^+$ ($\widetilde{PD}_{i,b,t-k}^-$), which is an indicator equal to one if the average of within-loan changes in probability of default between time $t-1$ and time t weighted by committed exposure at time $t-1$ increased (decreased) by more than 0.1pp. These coefficients represent percentage point changes in the interest rate relative to the last quarter before the risk assessment changed ($t-1$). Vertical lines indicate 95% confidence intervals calculated using standard errors that are double clustered by firm and bank-quarter. The sample size is $N = 30,440$ firm-bank-quarter observations. Appendix Section A contains all variable definitions.

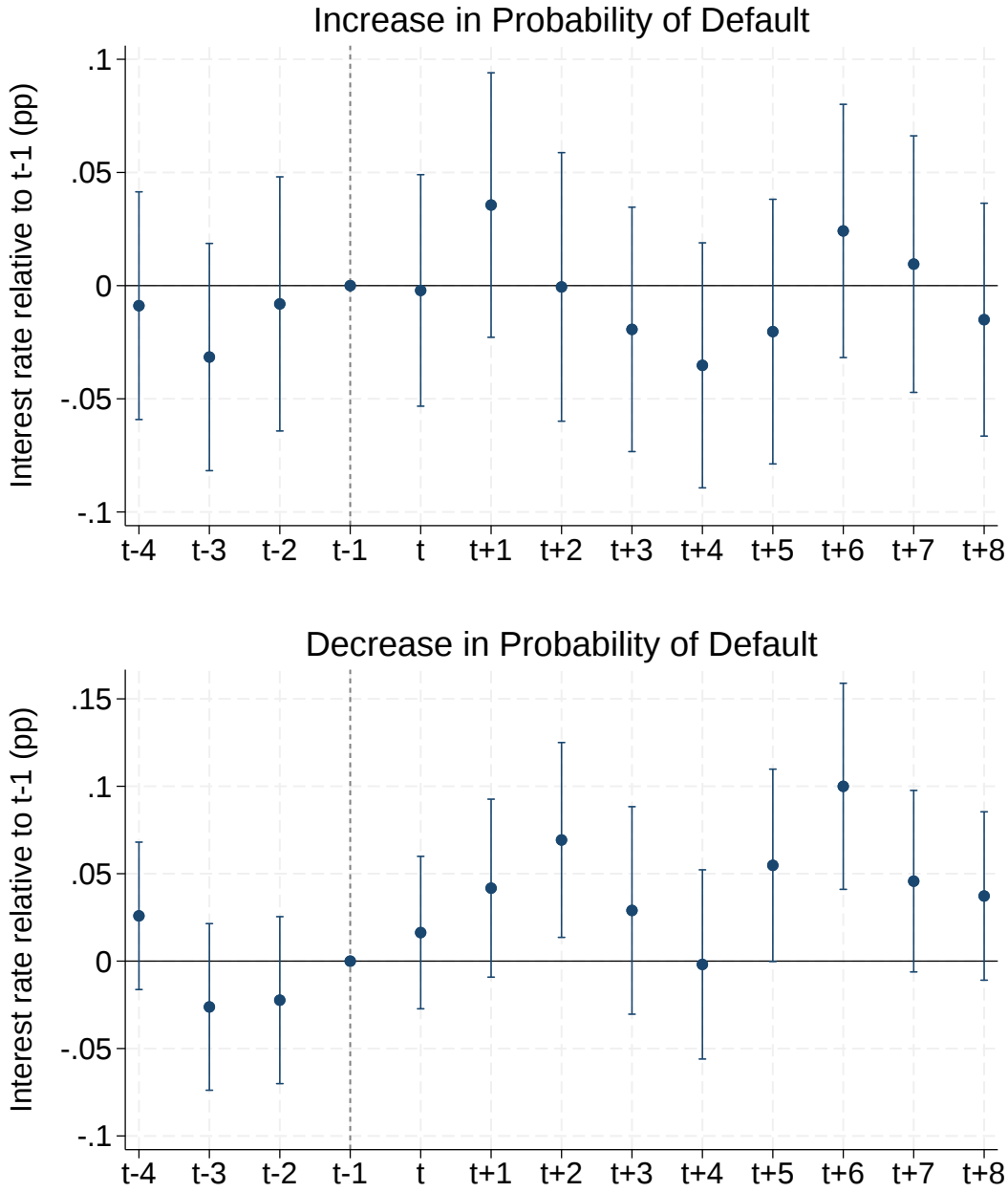


Table OA1: Sample Construction

This table describes the sequential construction of our main sample. The three columns display the number of unique firms, firm-quarters, and firm-bank-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-bank-quarters in which the standard deviation of PD across the bank's loans exceeds 0.5 percentage points or the standard deviation of LGD exceeds 25 percentage points.

	Firms	Firm-Quarters	Firm-Bank-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 with Merton PDs)

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) Merton PD, a probability of default estimated based on a Merton model whose construction is described in Online Appendix C, (2) a dummy variable indicating whether the Merton PD 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. For brevity, we report only the coefficients on EL^+ and EL^-. 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^+	-0.842^{***}	-0.212^{**}	2.030^{***}	-0.148^{*}
	(3.771)	(2.316)	(3.921)	(1.853)
EL^-	-0.228	0.088	0.478	0.115^{*}
	(1.044)	(1.393)	(1.132)	(1.713)
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	113,635	54,013	104,647	111,210
R-squared	0.39	0.51	0.09	0.35

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

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 Merton Credit Signal$^+$, which is constructed as follows: (1) If the firm has observed traded loans in the current and previous quarters, Public Merton 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 Merton 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 Merton Credit Signal$^+$ equals one if the quarterly bond return is negative and zero otherwise; and (4) if the firm has no traded loans, CDS, or bonds, then Public Merton Credit Signal$^+$ equals one if the firm's Merton PD (described in Online Appendix C) 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$^+$	−0.750***	−0.203**	1.991***	−0.185**
	(3.583)	(2.046)	(3.817)	(2.267)
EL$^-$	−0.222	0.099	0.413	0.083
	(1.235)	(1.499)	(0.976)	(1.227)
Public Merton Credit Signal$^+$	−0.271	0.093	0.264	−0.362**
	(0.904)	(0.930)	(0.322)	(2.451)
Book-to-Market	−0.077	0.278	4.237**	0.763***
	(0.121)	(0.732)	(2.260)	(3.377)
ROA	1.091	0.752	−6.020	1.214
	(0.528)	(0.738)	(0.863)	(1.307)
Leverage	−0.469	0.056	3.199	0.332
	(0.568)	(0.169)	(1.289)	(1.089)
Log(Market Cap)	0.188	0.014	−3.674***	−0.064
	(1.604)	(0.266)	(10.170)	(1.631)
Lagged Stock Return	−0.016		−0.158***	0.309***
	(1.085)		(5.521)	(31.407)
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	113,802	54,075	104,811	111,373
R-squared	0.38	0.49	0.09	0.33

Table OA4: Changes in Expected Losses Predict Financial Market Outcomes (Controlling for EDF-X)

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$^+$	−0.820***	−0.207**	1.992***	−0.218***
	(3.987)	(2.100)	(3.845)	(2.687)
EL$^-$	−0.237	0.091	0.529	0.069
	(1.339)	(1.371)	(1.267)	(1.051)
EDF-X$^+$	0.066	−0.102	0.276	−0.052
	(0.276)	(1.388)	(0.360)	(0.434)
Book-to-Market	−0.148	0.281	4.698**	0.729***
	(0.237)	(0.731)	(2.528)	(3.329)
ROA	0.862	0.757	−2.652	0.716
	(0.428)	(0.737)	(0.393)	(0.811)
Leverage	−0.470	0.051	2.787	0.407
	(0.610)	(0.153)	(1.191)	(1.436)
Log(Market Cap)	0.193*	0.014	−3.715***	−0.069*
	(1.677)	(0.250)	(10.400)	(1.788)
Lagged Stock Return	−0.013		−0.166***	0.313***
	(0.946)		(5.988)	(32.692)
Lagged Bond Return		−0.086**		
		(1.978)		
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	115,993	53,727	106,362	113,472
R-squared	0.37	0.49	0.09	0.34

Table OA5: Changes in Expected Losses Predict Financial Market Outcomes (Controlling for Nonlinear Interactions with EDF-X)

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. For brevity, we report only the coefficients on EL^+ and EL^-. 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^+	-0.868^{***}	-0.224^{**}	1.994^{***}	-0.229^{***}
	(4.232)	(2.329)	(3.879)	(2.795)
EL^-	-0.215	0.109^{*}	0.556	0.082
	(1.201)	(1.705)	(1.331)	(1.243)
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	115,993	53,727	106,362	113,472
R-squared	0.38	0.52	0.09	0.35

Table OA6: Changes in Expected Losses Predict Financial Market Outcomes (Controlling for Public Credit Signals Based on EDF-X)

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; and (4) 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$^+$	−0.788***	−0.203**	1.966***	−0.216***
	(3.849)	(2.046)	(3.811)	(2.669)
EL$^-$	−0.228	0.099	0.519	0.073
	(1.295)	(1.499)	(1.247)	(1.110)
Public Credit Signal$^+$	−0.339	0.093	1.237	0.023
	(1.349)	(0.930)	(1.609)	(0.178)
Book-to-Market	−0.119	0.278	4.571**	0.754***
	(0.190)	(0.732)	(2.474)	(3.432)
ROA	0.902	0.752	−2.666	0.840
	(0.447)	(0.738)	(0.395)	(0.949)
Leverage	−0.429	0.056	2.709	0.429
	(0.555)	(0.169)	(1.157)	(1.503)
Log(Market Cap)	0.185	0.014	−3.702***	−0.070*
	(1.604)	(0.266)	(10.397)	(1.806)
Lagged Stock Return	−0.016		−0.158***	0.313***
	(1.131)		(5.772)	(33.253)
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	116,367	54,075	106,732	113,842
R-squared	0.37	0.49	0.09	0.34

Table OA7: 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	0.79	0.96	26.50	0.12
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 OA8: Number 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 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	43.98	33.54	30.84

Table OA9: Changes in Expected Losses Predict Financial Market Outcomes (Controlling for Traded 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 Traded Credit Signal$^+$. Traded Credit Signal$^+$ is constructed as follows: (1) If the firm has observed traded loans in the current and previous quarters, Traded 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, Traded 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, Traded Credit Signal$^+$ equals one if the quarterly bond return is negative and zero otherwise. The sample is limited to firms with traded loans, CDS, or bonds. 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$^+$	−0.346	−0.203**	0.791	−0.205**
	(1.118)	(2.046)	(1.097)	(2.082)
EL$^-$	0.009	0.099	0.535	0.018
	(0.041)	(1.499)	(0.848)	(0.214)
Traded Credit Signal$^+$	−0.266	0.093	0.660	−0.203
	(0.653)	(0.930)	(0.565)	(1.070)
Book-to-Market	0.854	0.278	2.858	0.851***
	(0.883)	(0.732)	(1.043)	(2.613)
ROA	3.401	0.752	2.678	0.779
	(1.161)	(0.738)	(0.269)	(0.525)
Leverage	0.006	0.056	−0.918	0.707
	(0.005)	(0.169)	(0.243)	(1.459)
Log(Market Cap)	0.431**	0.014	−3.693***	−0.024
	(2.361)	(0.266)	(6.207)	(0.358)
Lagged Stock Return	−0.006		−0.103**	0.286***
	(0.213)		(2.342)	(17.248)
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	60,480	54,075	57,469	59,357
R-squared	0.45	0.49	0.12	0.35

Table OA10: Predictability across PD, Merton PD, and LGD

This table tests whether changes in banks' assessed Probability of Default (PD) and Loss Given Default (LGD) predict financial market outcomes after controlling for changes in the probability of default estimated from a Merton model (Merton PD), 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 PD^+, LGD^+, and Merton PD^+, which are dummy variables equal to one if the bank's assessed probability of default, the bank's assessed loss given default, or the Merton PD (described in Online Appendix C) 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^+	−0.371	−0.172	2.112***	−0.244**
	(1.453)	(1.353)	(3.384)	(2.174)
LGD^+	−0.663***	−0.195*	0.471	−0.028
	(2.656)	(1.765)	(0.791)	(0.337)
Merton PD^+	−0.120	−0.200**	−0.389	−0.738***
	(0.356)	(2.030)	(0.433)	(4.189)
Book-to-Market	−0.072	0.270	4.212**	0.762***
	(0.114)	(0.702)	(2.237)	(3.404)
ROA	1.298	0.798	−6.486	1.242
	(0.628)	(0.782)	(0.929)	(1.346)
Leverage	−0.500	0.039	3.388	0.394
	(0.610)	(0.118)	(1.364)	(1.307)
Log(Market Cap)	0.189	0.011	−3.664***	−0.060
	(1.604)	(0.204)	(10.143)	(1.515)
Lagged Stock Return	−0.016		−0.165***	0.302***
	(0.968)		(5.375)	(28.470)
Lagged Bond Return		−0.089**		
		(2.038)		
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	113,635	54,013	104,647	111,210
R-squared	0.38	0.49	0.09	0.34

Table OA11: 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 OA12: 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	0.68	1.17	28.60	0.10
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 OA13: 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 Decrease (bottom 10% of changes), Small EL Decrease (decreases above the bottom 10%), Small EL Increase (increases below the top 10%), and Large EL Increase (top 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 OA14: 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	0.86	0.99	27.00	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 OA15: 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 OA16: 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 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^+	-0.824^{**}	-0.130	1.690^{**}	-0.224^{*}
	(2.052)	(0.950)	(2.212)	(1.714)
EL^-	-0.366	0.113	0.639	0.084
	(1.307)	(1.157)	(0.913)	(0.692)
Book-to-Market	-0.684	0.460	3.542	0.168
	(0.915)	(1.348)	(1.645)	(0.585)
ROA	-0.499	1.577	9.815	-0.119
	(0.204)	(1.427)	(1.276)	(0.117)
Leverage	-0.912	0.112	-0.101	0.184
	(0.784)	(0.246)	(0.038)	(0.464)
Log(Market Cap)	0.191	0.060	-3.970^{***}	-0.081
	(1.178)	(0.784)	(9.253)	(1.499)
Lagged Stock Return	-0.016		-0.124^{***}	0.288^{***}
	(0.660)		(3.217)	(19.848)
Lagged Bond Return		-0.097^{**}		
		(2.156)		
Mean of DV	0.90	0.95	25.22	0.20
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	47,782	28,035	44,342	46,808
R-squared	0.40	0.55	0.12	0.33

Table OA17: 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 OA18: 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 OA19: 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

Table OA20: 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 OA21: 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 $\text{ICC}^{\Delta=0}$ columns report the analogous measures for downward changes or no changes, respectively. The $\text{ICC}^{+|\Delta=1}$ 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^{-}	$\text{ICC}^{\Delta=0}$	$\text{ICC}^{+\|\Delta=1}$
PD	18.8%	0.264	0.206	0.225	0.636
LGD	24.8%	0.186	0.190	0.194	0.529
EL	37.4%	0.234	0.198	0.216	0.463

Panel B: Bank-Firm Relationships without Syndicated Loans

	Disagreement (%)	ICC^{+}	ICC^{-}	$\text{ICC}^{\Delta=0}$	$\text{ICC}^{+\|\Delta=1}$
PD	20.1%	0.337	0.270	0.301	0.548
LGD	26.6%	0.263	0.271	0.269	0.457
EL	39.7%	0.313	0.272	0.293	0.447

Table OA22: 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 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	−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 OA23: 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 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	−1.629***	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 OA24: 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. Columns (2), (4), and (6) additionally control for factor loadings. 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	0.102***	0.102***
	(1.962)	(1.755)	(1.936)	(1.408)	(3.625)	(3.743)
EL^-	−0.276	−0.185	−0.040	−0.045	−0.027	−0.023
	(1.544)	(1.272)	(1.205)	(1.338)	(1.570)	(1.295)
Book-to-Market	1.282**	2.004***	−0.772***	−0.737**	−0.131*	−0.123
	(2.373)	(2.764)	(2.715)	(2.235)	(1.732)	(1.414)
ROA	1.503	−2.119	−2.461*	−2.609*	−0.623**	−0.501*
	(0.402)	(0.500)	(1.803)	(1.996)	(2.541)	(1.891)
Leverage	2.214***	0.882	−0.024	−0.086	0.287***	0.260***
	(3.607)	(1.051)	(0.105)	(0.372)	(3.668)	(3.159)
Log(Market Cap)	0.311*	0.733**	0.106	0.097	−0.129***	−0.112***
	(1.918)	(2.047)	(1.228)	(1.155)	(5.913)	(5.118)
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					−0.032	−0.008
					(0.938)	(0.185)
Mean of DV	-0.09	-0.09	0.00	0.00	0.11	0.11
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	45,887	40,645
R-squared	0.68	0.75	0.83	0.70	0.13	0.14

Table OA25: 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 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^+	−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 OA26: 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 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^+	−0.704**	−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 OA27: 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 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^+	−0.787***	−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 OA28: Within-Loan Changes in Expected Losses Predict Financial Market Outcomes

This table tests whether changes in banks' expected losses predict next-quarter stock returns, bond returns, earnings surprises, and earnings announcement returns using within-loan changes in risk assessments. 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 $\widetilde{EL}^{+}$ and $\widetilde{EL}^{-}$, which are dummy variables equal to one if the lagged loan volume-weighted average change in loan-level expected loss increased or decreased by more than 0.01 percentage points, 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)
$\widetilde{EL}^{+}$	−0.683**	−0.244	2.268***	−0.239**
	(2.511)	(1.592)	(3.780)	(2.061)
$\widetilde{EL}^{-}$	−0.110	0.155	−0.019	0.199**
	(0.577)	(1.492)	(0.039)	(2.395)
Book-to-Market	−0.100	0.286	4.312**	0.754***
	(0.163)	(0.748)	(2.375)	(3.448)
ROA	0.815	0.776	−3.040	0.922
	(0.409)	(0.759)	(0.452)	(1.038)
Leverage	−0.556	0.065	2.704	0.432
	(0.725)	(0.198)	(1.161)	(1.516)
Log(Market Cap)	0.197*	0.017	−3.709***	−0.058
	(1.716)	(0.307)	(10.512)	(1.491)
Lagged Stock Return	−0.014		−0.164***	0.312***
	(1.049)		(6.248)	(34.262)
Lagged Bond Return		−0.086**		
		(1.992)		
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 OA29: 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 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^+	−0.566***	−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 OA30: Fama-MacBeth Regressions (Firm-Bank-Quarter Panel)

This table tests whether changes in banks' expected losses predict next-quarter stock returns, bond returns, earnings surprises, and earnings announcement returns, 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 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. 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 OA31: Relationship-Level Drivers of Risk Assessment Updates for Smallest Firms

This table examines how relationship-level factors affect the likelihood that banks update their internal risk assessments, using a firm-bank-quarter panel of observations in the bottom quintile of firm market capitalization. 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)	0.022*	0.097***	0.076***
	(1.859)	(4.773)	(4.590)
Months Since Financial Statement	−0.582***	−0.074	−0.450*
	(2.619)	(0.288)	(1.653)
Months Since Audit	0.009	0.090	0.067
	(0.049)	(0.530)	(0.360)
Maturity (months)	−0.106	−0.148	−0.085
	(0.787)	(1.021)	(0.570)
Term Loan (% of total)	−0.035	−0.152*	−0.133
	(0.613)	(1.870)	(1.571)
Specialize	−1.153	14.380***	8.052*
	(0.313)	(3.263)	(1.905)
New Loan	9.231**	25.358***	25.978***
	(2.246)	(6.058)	(6.510)
Drawdown	−2.337	0.642	2.483
	(0.730)	(0.154)	(0.676)
Paydown	2.053	1.810	4.155
	(0.664)	(0.484)	(1.241)
Mean of DV	31.07	29.29	45.29
Bank-Quarter FE	YES	YES	YES
Firm-Quarter FE	YES	YES	YES
Observations	5,862	5,862	5,862
R-squared	0.57	0.58	0.56

Table OA32: Relationship-Level Drivers of Risk Assessment Updates for Largest Firms

This table examines how relationship-level factors affect the likelihood that banks update their internal risk assessments, using a firm-bank-quarter panel of observations in the top quintile of firm market capitalization. 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)	0.015**	0.026***	0.031***
	(2.445)	(3.426)	(4.018)
Months Since Financial Statement	−0.007	0.121	0.100
	(0.152)	(1.202)	(1.360)
Months Since Audit	−0.017	−0.042	−0.079
	(0.448)	(0.351)	(0.968)
Maturity (months)	−0.019	−0.137***	−0.113**
	(0.545)	(2.764)	(2.234)
Term Loan (% of total)	0.076***	0.141***	0.180***
	(3.083)	(4.747)	(5.231)
Specialize	0.455	−2.181*	−1.400
	(0.480)	(1.730)	(0.919)
New Loan	3.395***	7.516***	8.793***
	(2.968)	(4.954)	(5.415)
Drawdown	3.057***	15.984***	16.508***
	(2.675)	(7.636)	(8.241)
Paydown	2.251**	14.439***	15.026***
	(2.060)	(7.502)	(7.820)
Mean of DV	17.62	20.36	29.59
Bank-Quarter FE	YES	YES	YES
Firm-Quarter FE	YES	YES	YES
Observations	29,305	29,305	29,305
R-squared	0.48	0.61	0.52

Appendix C. Construction of the Merton Distance-to-Default Measure

This appendix describes how we construct the distance-to-default and default probability measures used as public-information controls. We follow the standard academic implementation of the Merton (1974) structural credit model, and we report results using the iterative Black-Scholes inversion of Vassalou and Xing (2004). Our results are very similar and available upon request for the naive closed-form measure of Bharath and Shumway (2008).

C.1. The model

The Merton model treats the equity of a firm as a call option on the firm's assets, struck at the face value of its debt. Let V denote the market value of the firm's assets, σ_V their volatility, E the market value of equity, F the face value of debt, r the risk-free rate, and T the forecast horizon. Under the model's assumptions, equity satisfies the Black-Scholes formula,

$$E = V\,\Phi(d_1) - F e^{-rT}\Phi(d_2), \qquad d_1 = \frac{\ln(V/F) + \left(r + \frac{1}{2}\sigma_V^2\right)T}{\sigma_V\sqrt{T}}, \qquad d_2 = d_1 - \sigma_V\sqrt{T}, \tag{3}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function. The distance to default is the number of standard deviations by which the expected asset value at the horizon exceeds the default point,

$$DD = \frac{\ln(V/F) + \left(\mu - \frac{1}{2}\sigma_V^2\right)T}{\sigma_V\sqrt{T}}, \tag{4}$$

where μ is the expected return on assets. The corresponding default probability is the standard normal transform

$$PD = \Phi(-DD). \tag{5}$$

C.2. Inputs

We set the horizon to $T = 1$ year throughout, the standard convention in this literature. The remaining inputs are constructed as follows, for each firm at the end of each calendar quarter.

Market value of equity (E): CRSP market capitalization on the last trading day of the quarter, equal to shares outstanding times the absolute value of the closing price.

Equity volatility (σ_E): the annualized standard deviation of daily log equity returns over the 252 trading days ending on the quarter-end date, requiring at least 126 non-missing daily returns.

Face value of debt (F): debt in current liabilities plus one-half of long-term debt, $DLCQ + 0.5 \times DLTTQ$, from the most recent Compustat quarterly filing that was publicly available as of the quarter-end date. This is the convention of Crosbie and Bohn (2003), also adopted by Vassalou and Xing (2004) and Bharath and Shumway (2008). Section C.4 below describes the availability requirement in detail.

Risk-free rate (r): the one-year constant-maturity Treasury yield on the quarter-end date, from the Federal Reserve's H.15 release (FRED series DGS1).

Expected asset return (μ): the firm's equity log return over the prior year, as in the naive measure of Bharath and Shumway (2008), floored at the risk-free rate as in Hillegeist et al. (2004).

The sample is the intersection of CRSP and Compustat, restricted to U.S. common stocks (share codes 10 and 11) listed on the NYSE, AMEX, or NASDAQ, linked using the CRSP/Compustat Merged linking table with primary links only.

C.3. The two measures

Naive distance to default. Bharath and Shumway (2008) show that a simple closed-form approximation forecasts default at least as well as the full structural solution. Their naive measure approximates asset volatility as a weighted average of equity volatility and an assumed debt volatility,

$$\sigma_V^{\text{naive}} = \frac{E}{E+F}\,\sigma_E + \frac{F}{E+F}\,(0.05 + 0.25\,\sigma_E)\,,$$

and replaces the unobserved asset value with $V = E + F$. Substituting into (4) and (5) gives DD^{naive} and PD^{naive}.

Iterative distance to default. Our main measure uses the iterative procedure of Vassalou and Xing (2004). Starting from an initial guess $\sigma_V = \sigma_E\,E/(E+F)$, we invert (3) numerically on each of the preceding 252 trading days to recover a daily series of implied asset values, compute the annualized standard deviation of the daily log asset returns, and use that as the updated σ_V. We repeat until successive values of σ_V differ by less than 10^{-4}. The converged σ_V and the implied asset value on the quarter-end date are then substituted into (4) and (5) to give DD^{iter} and PD^{iter}. The procedure converges for every firm-quarter in our sample, and the two distance-to-default measures are highly correlated ($\rho = 0.91$), consistent with the finding in Bharath and Shumway (2008) that the naive measure captures most of the information in the full solution.

C.4. Timing: ensuring the measure is public

Because we use this measure as a benchmark for the information already available to public markets, and because we use it to predict returns in the *following* quarter, it is essential that no input be drawn from data that had not yet been disclosed as of the measurement date.

The market-based inputs pose no difficulty: equity value, equity volatility, the expected asset return, and the risk-free rate are all measured on or before the last trading day of the quarter. The accounting input requires more care. Compustat's *datadate* is the end of the firm's fiscal quarter, not the date on which the corresponding filing became public, and firms typically file their quarterly reports several weeks after the fiscal quarter ends. Selecting the most recent filing by *datadate* would therefore incorporate a balance sheet that had not yet been disclosed.

We accordingly require two conditions for a filing to enter the calculation at quarter-end t. First, following Campbell, Hilscher, and Szilagyi (2008), we lag quarterly accounting data by two months. Second, we require that Compustat's report date of quarterly

earnings (RDQ) precede the measurement date, so that no filing enters the measure before it was publicly reported. We then use the most recent filing satisfying both conditions. This ensures, as in Vassalou and Xing (2004), that all information used to calculate the measure was available to investors at the time of the calculation.