Are Banks Really Informed? Evidence From Their Private Information*

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March 2023

Abstract

Yes. We exploit confidential regulatory data containing banks' *private* assessments of their loans' expected losses. We show that changes in expected losses predict firms' next quarter stock returns, bond returns and earnings surprises. The predictability is concentrated among small firms and growth firms and only occurs when banks adjust their risk assessments downwards, consistent with banks monitoring firms for negative information. Using within firm variation in borrowing across banks, we find that credit line drawdowns are an important source of private information for banks. Overall, our findings are consistent with banks engaging in information production and monitoring, even among publicly traded firms.

*We thank Jan Ericsson, Thomas Philippon, Malcom Wardlaw and conference and seminar participants at the Corporate Finance Conference at WashU, McGill, Notre Dame and the UT Austin PhD Alumni Conference for the helpful comments and discussions. Special thanks to Adolfo De Motta for the many extensive conversations about this paper. We thank Tianshi Yuan for excellent research assistance. The views expressed in this paper are solely those of the authors. They do not necessarily reflect the views of the Federal Reserve Bank of Richmond or the Federal Reserve System.

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1 Introduction

A fundamental role of banks is to collect and process information about borrowers. Traditional theories of financial intermediation posit that banks can better economize on the costs of information production and monitoring than financial markets.[1] Accordingly, bank debt is thought to be a critical source of capital for certain firms. However, recent trends call the traditional view of banks as informed financiers into question. Over the past twenty years, hedge funds and other non-bank investors have substantially increased their direct lending to firms.[2] Moreoever, rapid advances in financial technology have dramatically altered key banking functions.

Understanding if and when banks are informed is not just a theoretical curiosity, but is critical to designing policies to stabilize the financial system and spur economic growth. For example, if bank financing is the only source of capital for certain firms, policymakers should focus on stimulating bank lending to supply capital to those firms.[3] On the other hand, if bank financing is merely a substitute for other forms of capital then policies need not involve the banking sector at all. Despite the fundamental nature of this question, testing whether banks are informed is extremely challenging because banks' information is intrinsically private, and therefore unobservable to other market participants and the econometrician. Because of this data limitation, many papers have attempted to study this problem using indirect evidence. However, without access to banks' private information, researchers are severely limited in their potential inference.

In this paper, we address this problem by exploiting confidential regulatory data which contains banks' risk assessments for corporate loans in the US. These assessments are not observable to other market participants and hence reflect banks' private information. We show that changes in banks' assessments of their loans' expected losses predict *future* changes in public stock/bond prices and analyst earnings surprises. Our effects are con-

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

[2]See Chernenko et al. (2019), Gopal and Schnabl (2020), Irani et al. (2021), Why Direct Lending Is a Booming Part of Private Debt and Bank Said No? Hedge Funds Fill a Void in Lending.

[3]See for example the Paycheck Protection Program implemented in the US in 2020

centrated among small and growth firms. Moreover, the predictability only occurs when banks become more negative about firms' prospects. Finally, we provide evidence that banks information advantage arises from both receiving private information and processing information. Overall, our results i) support the traditional view of banks as informed finance, ii) directly show that banks' specialize in collecting negative information and iii) highlight for which types of firms banks relationships are most important.

Our analysis uses Federal Reserve's Y-14Q Schedule H.1 data that includes all corporate loans over one million dollars extended by large bank holding companies (BHCs) in the United States. BHCs are required to report quarterly internal measures of probability of default (PD) and loss given default (LGD) for each of these loans on their balance sheets. We use these measures to create a quarterly expected loss (PD $\times$ LGD) variable for each bank/firm relationship. In order to test banks' role as informed financiers, we examine whether banks' estimates of expected loss predict future asset prices as well as analyst earnings surprises. Intuitively, if banks have no informational advantage over public markets, then changes in expected losses should have no relationship with future asset prices or earnings surprises as banks' information would already be incorporated into asset prices and current analyst forecasts.

We first test whether increases or decreases in expected losses predict future realized stock and bond returns as well as earnings surprises. We find that when banks adjust their expected losses up, firms' stock and bond prices drop, while negative (positive) earnings surprises become more (less) likely. In particular, an upward adjustment in banks' expected losses leads to an 80bp and 20bps per quarter underperformance in stocks and bonds, respectively.[4] Interestingly, we find no effect when banks adjust their expected losses downwards. This asymmetry suggests that banks focus on collecting negative information and is consistent with theories in which banks' have higher incentives to learn when the firm is performing poorly, i.e., when agency problems are highest (e.g., Diamond (1984), Haubrich (1989), Besanko and Kanatas (1993)), or when firms are close to violating a covenant (Rajan and Winton (1995) and Park (2000)).

[4]It is worth stressing that the return predictability we document is not a strategy that investors can follow because it is based on banks' *private* information.

Next, we explore the cross-sectional variation in return predictability across firms. We find that the return predictability is stronger among smaller firms (firms with lower market capitalizations) and growth firms (firms with lower book-to-markets). We believe this is intuitive as these types of firms are typically more opaque, making bank debt a more critical source of capital for them. In fact, when we place firms into size quintiles, there is no stock return predictability in the largest size quintile, with a steady increase up to the smallest quintile, which exhibits 1.7% per quarter underperformance. These results suggest that banks' private information is particularly important for smaller, publicly traded firms, but not for the largest.

Is banks information coming from assessments of the likelihood of default or the expected recovery in default? To answer this question, we decompose changes in expected losses into changes in probability of default and loss given default. We find that stock and bond returns are driven by both PD and LGD, which is consistent with banks both focusing on firms' abilities to stay solvent as well as the liquidation value in the case of default.[5] In contrast, we find that only the probability of default predicts earnings surprises, which is consistent with short-term earnings affecting the likelihood the firm can meet debt payments and avoid default, but affecting less liquidation values.

We next explore the timing of the predictability of banks' private information. We show that both the stock and bond return predictability is concentrated in the first two months of the following quarter after the change in expected loss and dissipates two quarters ahead.[6]

What drives changes in banks' private information? Banks could have a superior ability to process publicly available information. In contrast, banks may simply have access to private information before markets (e.g., Wight et al. (2009) and Minnis and Sutherland (2017)). One source of private information stems from bank credit lines. If a firm draws down a credit line, this information is immediately known by the bank, but is not immediately disclosed to other banks. We therefore test whether firms' expected

[5]This is also consistent with collateral creating an incentive to monitor (e.g., Rajan and Winton (1995)).

[6]We do find that changes in expected losses predict earnings surprises two quarters out. However, this could be due to analysts underreacting to bad news (Abarbanell and Bernard (1992)).

losses increase after drawing down their credit lines. In our specifications, we include firm by time fixed effects to compare expected losses across banks for a firm borrowing from multiple banks at once (e.g., Khwaja and Mian (2008)). We find that drawdowns dramatically increase the likelihood of banks increasing their assessed expected losses and also negatively predict future financial outcomes. For example, excess stock returns in the next quarter are -1.8% following a drawdown. These results are consistent with firms drawing down credit lines following a negative shock (e.g., Shockley and Thakor (1997) and Holmström and Tirole (1998)) and show that credit line drawdowns are a source of private information for banks.[7] However, even when we include drawdowns as a control variable, changes in expected losses still have independent predictive power across all financial market outcomes. Hence, while banks have access to valuable information prior to other market participants, they still seem to have an advantage in processing information through their credit assessments.

In our data we only observe banks' expected losses at quarter end; however, banks may have updated the expected loss earlier, prior to information being released within that quarter. For this reason, we view the magnitude of our results as a lower bound on the true information advantage of banks. Moreoever, the size relationship we find suggests that bank information is even more important for smaller private firms, which are not included in our sample because of lack of publicly traded asset prices and earnings forecasts.

Our results support the traditional view of banks as informed financiers. What is perhaps surprising is that banks' have an informational advantage even among large publicly traded firms.[8] Moroever, our sample comprises the largest US banks, which many have argued are less inclined to perform the traditional roles of relationship banking.[9] Taken together, our results i) shed light on what types of information banks' specialize in

[7]This is also consistent with the empirical findings of Mester, Nakamura, and Renault (2007), Jiménez, Lopez, and Saurina (2009) and Berrospide and Meisenzahl (2015).

[8]When we say large we mean relative to smaller, non-publicly traded firms. As mentioned earlier, we find no effects in the largest quintile of publicly traded firms in our sample.

[9]For instance, larger banks are thought to focus more on transactional loans rather than relationship ones (Berger and Udell (2002)) and have less personal relationships (Berger et al. (2005)). They are also often more hierarchal which prevents them from using their soft information (Stein (2002) Liberti and Mian (2008)).

and ii) can help policymakers and researcher identify firms for which bank relationships are most important.

2 Related Literature

Our paper builds on the literature testing the role of bank debt as informed finance. Perhaps the first to do this was James (1987) who analyzes stock price responses after banks are granted loans. Intuitively, if banks have private information about borrowers, the fact that a firm receives a loan is a positive signal to the market implying a positive stock price reaction, which is exactly what James (1987) finds.[10] Other papers analyze information production/screening in the primary market (e.g., Liberti and Mian (2008), Keys et al. (2010), Agarwal and Hauswald (2010), Keys, Seru, and Vig (2012), Iyer et al. (2016), Lisowsky, Minnis, and Sutherland (2017), Hertzberg, Liberman, and Paravisini (2018), Bedayo et al. (2020) and Weitzner and Howes (2021)). A critical difference in our approach is that we directly see how banks' private information evolves over the life of the loan and how this compares to the evolution of public information. This allows us to i) directly test banks' roles as informed financiers and ii) shed light on the information collection process over the life of the loan.

Another subset of the literature focuses on banks' monitoring over the life of loans (e.g., Ono and Uesugi (2009), Cerqueiro, Ongena, and Roszbach (2016), Gustafson, Ivanov, and Meisenzahl (2021) and Heitz, Martin, and Ufier (2022)). Gustafson, Ivanov, and Meisenzahl (2021) and Heitz, Martin, and Ufier (2022) create direct measures of bank monitoring based on the number of visits banks make to the firm. However, they do not observe how banks' information changes following these visits and how banks' information compares to public information. Moreoever, we specifically show for which type of information banks specialize in (i.e., negative information).

The closest paper to us is Plosser and Santos (2016). They use data from the Shared

[10]Subsequent papers have questioned the interpretation of this result. For example, Preece and Mullineaux (1994) finds no difference in stock price reaction across banks and non-banks after loans are granted. Maskara and Mullineaux (2011) finds no abnormal response once the selection of announcing the loan is controlled for. Finally, De Marco and Petriconi (2020) find a positive reaction in more recent data; however, it is smaller in magnitude than what James (1987) finds.

National Credit (SNC) program which include banks' risk assessments for syndicated loans for which the aggregate commitment is at least \$20 million and which is held by two or more federally supervised institutions that are unaffiliated with the agent bank. As 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 to understand to what extent these updates preempt financial market outcomes and therefore reflect banks' private information.[11] There are a few other key differences between our paper. First, because our sample includes all loans over \$1mm and non-syndicated loans, our sample of loans is larger. Second, beyond analyzing stock returns, we also analyze bond returns and earnings surprises. Third, we explore the cross-section of predictability and find that the predictability is asymmetric and concentrated on smaller and growth firms. Finally, we show how credit line drawdowns are an important source of private information for banks.

Another related paper is Addoum and Murfin (2020) who find that changes in publicly observable syndicated loan prices predict future equity returns.[12] 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.[13] We also show that banks specialize in information regarding firms downsides and this informational advantage is concentrated among small and growth firms. Finally, because our data is at the bank level, rather than just at the loan level, we are also able to i) test which type of information is important for market outcomes and ii) explore the sources of banks' private information.

Finally, our paper also contributes to the broader literature examining asymmetric information in credit markets (e.g., Kurlat and Stroebel (2015), Stroebel (2016), Botsch and Vanasco (2019), DeFusco, Tang, and Yannelis (2021), Crawford, Pavanini, and Schivardi (2018), Darmouni (2020), Beyhaghi, Fracassi, and Weitzner (2020) and Ioannidou, Pa-

[11] As we show in our analysis, banks may update their risk assessments not because of private information but purely in response to changes in publicly available information. Therefore, we view it as critical that changes in these risk assessments indeed predict returns in order for them to be considered private information.

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

[13] Many of the loans in our sample are not syndicated or traded. Moreover, banks may refrain from trading to keep information private (e.g., Dang et al. (2017)).

vanini, and Peng (2022)). The most common approach in this literature is to rely on either proxies of asymmetric information or assume agents' decisions imply certain distributions of outcomes and test whether these outcomes bear out in the data. We do not need make these assumptions because we arguably have direct access to banks' private information and can thus directly test the degree of asymmetric information between banks and public markets.[14]

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

3 Data

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

The data include detailed loan characteristics as well as firm financials (balance sheet

[14]For this reason, our paper also contributes to the broader literature on testing information asymmetries in economics (e.g., Chiappori and Salanie (2000), Finkelstein and Poterba (2004), Cohen and Siegelman (2010), and Hendren (2013)).

and income statement). Importantly for our analysis, banks are also required to report their internal estimates of probability of default (PD) and loss given default (LGD) for each loan to the Federal Reserve on their Y-14Q filings. According to the Basel Committee on Banking Supervision, internal estimates of PD and LGD "must incorporate all relevant, material and available data, information and methods. A bank may utilize internal data and data from external sources (including pooled data)."[15] Our main variable of focus is the loan's expected loss which is equal to PD times LGD.

We also obtain stock returns from CRSP, bond returns from TRACE, firm financials from Compustat and analyst forecast and earnings outcomes from IBES. We merge these data with loan data based on borrowers' tax ID. To account for subsidiaries that report their parents' tax ID at the time of borrowing (Brown, Gustafson, and Ivanov (2021)) we keep only the observations for which total assets reported in the Y-14Q data is within (90%, 110%) interval of total assets reported on Compustat in the same reporting quarter. Moreover, we restrict the sample to US borrowers and exclude financial firms and utilities based on their Fama-French 30 industry classification. Our final sample contains 1,854 unique firms from 2014Q4 to 2019Q4. Appendix Table B1 compares our sample to the standard CRSP/Compustat sample (3,296 unique non-financial non-utilities firms). Given that firms in our sample must have a bank loan, it is perhaps unsurprising that firms in our sample tend to be larger, more profitable and are more highly levered.

Because banks often have multiple loans to the same borrower we create a weighted average PD, LGD and Expected Loss based on the size of the loan. This allows us to create a bank-firm panel where in each quarter we will have one observation per bank-firm relationship. After creating the panel, we drop firms with PDs of 0 or 1. To avoid reporting errors, we also drop firm quarter observations in which the standard deviation of PD is greater than 0.50pp.[16] We also exclude likely data errors by requiring the following data conditions: 1) total banks' commitment to a borrower does not fall below $1 million, 2) total borrowers' utilized amount does not exceed total commitment amount, and 3)

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

[16] The probability of default should be the same across all loans since default is measured at the borrower level.

LGD not equal to 0 or 1. These filters, overall, remove less than 1% of the data. If a firm borrows from multiple banks, it will have repeat observations in the sample; however, to avoid inflated standard errors, we cluster our standard errors by firm.[17]

Because the relationship between expected losses and asset prices/earnings forecasts is unknown and likely to be highly non-linear, in our main specifications we focus on simply analyzing cases in which the expected loss goes up or down, which we call EL^{+} and EL^{-}, respectively. In some specifications we also follow the same naming convention when we analyze cases in which PD and LGD go up or down. Detailed variable descriptions can be found in Appendix A.

Table 1 includes summary statistics for the main variables used in the analysis. The average PD, LGD and expected loss are about 1pp, 39pp and 0.33pp, respectively. Banks update their expected losses fairly frequently (33% of quarters), where they adjust the expected loss down (19% of quarters) more often than they update it upwards (17% of quarters). The average firm size is quite large at just over $18bn whereas the median firm size is just under $4bn. The firms in our sample are fairly highly levered with the average and median debt to capital ratio being around 50%. In Table 2 we also display correlations between the main variables as well as their lagged values. As expected, PD and LGD do seem to go up and down at the same time; however, the correlation is fairly small (0.119 for increases in PD and LGD and 0.159 for decreases). In our analysis we will separately analyze the relevance of PD and LGD in banks' private information.

4 Empirical Analysis

4.1 Are Banks Informed?

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

[17] Larger firms that borrow from several banks are also over-represented in the sample. However, if anything as we show later this should dampen our results as we find that bank information is more important for smaller firms.

More specifically, we first estimate the following regression:

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

where $y_{i,t+1}$ is the $t+1$ quarterly equity return, bond return or a dummy variable that equals one if there is negative or positive earnings surprise in that quarter for firm i. Our main independent variables of interest are $EL^{+}_{i,b,t}$ and $EL^{-}_{i,b,t}$, which dummy variables that equal one if bank b's assessment of firm i's expected loss increases or decreases from quarter $t-1$ to quarter t. We also include a vector of firm-level controls $X_{i,t}$, which include book-to-market, return on assets, leverage (debt to capital), market capitalization as well as the lagged stock or bond returns. Finally, we include bank by time ($\delta_{b,t}$) and industry by time fixed effects ($\gamma_{j,t}$) throughout the specifications and cluster our standard errors by firm and bank-quarter.[18]

The results of these regressions are displayed in Table 3. In column 1 an increase in expected losses predicts a 80bp per quarter underperformance in the stock market. In column 2 we find a similar pattern for bond returns but with a smaller magnitude of 20bps. Finally, in columns 3 and 4 negative earnings surprises are 1.8pp more likely and positive earnings surprises are 1.7pp less likely (compared to unconditonal likelihoods of 26.9pp and 72.6pp, respectively). Interestingly, reductions in expected losses do not predict returns or analyst forecasts.[19] This result is consistent with banks specializing in information production and monitoring firms for negative information (e.g., Rajan and Winton (1995)). More generally, debt investors should be more focused on producing negative information (e.g., Yang (2020)).

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

[18]Our results are robust to excluding bank by time fixed effects as shown in Appendix Table B3.

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

positive stock and bond returns.

An alternative approach more standard in the asset pricing literature is to estimate Fama-Macbeth regressions. However, given the unbalanced nature of our panel this puts additional weight on observations in quarters with more bank loans to more firms (Petersen (2009)). Moreoever, it limits our ability to mitigate correlation in residuals within quarter, i.e., via clustering. Nonetheless, we find fairly similar results in Fama-Macbeth regressions which are displayed in Appendix Table B2. We also find similar magnitudes in stock return predictability when we use portfolio sorts in Appendix Table B4.

Next, we explore the cross-sectional variation in return predictability across firms. To do so, we reestimate (2), but we interact EL^+ with the main firm characteristics/controls. The results are displayed in Table 4. Across all outcome variables the interaction between both book-to-market and market capitalization are positive and statistically significant. This suggests that banks' information advantage is stronger among smaller firms as well as growth firms. Building off these results, in Table 5 we split the the sample into size quintiles and separately reestimate the stock return regressions for each quintile.[20] In column 5, EL^+ exhibits no return predictability among the largest size quintile. Moreoever, the return predictability begins in the second largest size quintile and steadily increases to the smallest quintile (column 1), which exhibits a 1.7% quarterly underperformance.

Banks' informational advantage could be about borrowers' likelihood of default or expected recovery in default. To better understand the source of banks' informational advantage, we separately test whether changes in PD and LGD predict next quarter financial market outcomes. As the main independent variables, we use PD^+ and LGD^+, which are dummy variables that equal one if the PD or LGD increases in from quarter $t-1$ to quarter t. The results are displayed in Table 8. In column 1 both PD and LGD seem to have independent predictive power for stock returns. A similar pattern emerges in column 2 for bond returns; however while the signs of the coefficients for PD and LGD are similar in magnitude, neither are quite statistically significant on their own. These

[20] Most smaller firms do not have bonds so we are unable to meaningfully do this for bond returns.

results are consistent with Chousakos, Gorton, and Ordoñez (2020) who show that both PD and LGD affect the value of both debt and equity securities.[21] In contrast, in columns 5 - 6, only the probability of default predicts earnings surprises. This result is consistent with short-term earnings predominantly affecting the likelihood the firm can meet debt payments and avoid default, rather than the liquidation values of the firms' assets.

We next explore the timing of the predictability of banks' private information. In Table 6 we use monthly returns to breakdown the stock and bond return predictability by month. For both stock and bonds, the return predictability is concentrated in the first two months of the quarter after the change in expected loss. In Table 7 we reestimate our main regression (2), but use financial market outcomes from two quarters ahead. Both stock and bond returns do not appear to exhibit any return predictability two quarters ahead. However, changes in expected losses do seem to predict earnings surprises two quarters out. This result can be rationalized by analysts underreacting to bad news (e.g., Abarbanell and Bernard (1992)). It may seem at first surprising that the return predictability only lasts for two months. However, as we discuss in further detail below, the risk assessments banks report are as of the end of the quarter. Hence, we do not know if changes in these assessments already preempted financial market outcomes in the previous quarter. Thus, we view two months as the absolute minimum horizon in which we would expect to see effects.

4.2 Determinants of Banks' Private Information

After having established that banks' private information preempts financial market outcomes, we next explore what drives changes in banks' private information. First we examine scenarios under which banks are more likely to revise their PDs, LGDs and expected losses. To do so, we estimate the following regression:

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

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

where the dependent variable $z_{i,t}$ is the contemporaneous change in PD, LGD, or expected loss, i.e., PD^{+}, PD^{-}, etc. We also include changes in firm financials and stock returns, $\Delta X_{i,t}$ to test under which firm conditions these updates are more likely to occur. Once again, we cluster our standard errors by firm and bank/quarter. The results are displayed in Table 9. In column 1, banks appear to increase their PDs following increases in book-to-market and leverage and following decrease in profitability and lower recent returns. Moreoever, the coefficient sign flips for all variables in column 2, when we include PD^{-} as the dependent variable. These results suggests that banks are indeed adjusting their PDs in accordance with changes in firms' performances and characteristics. In columns 3 and 4 we include LGD^{+} and LGD^{-} as dependent variables. Only the change in profitability seems to affect the likelihood of raising LGDs. These results seem to suggest that LGDs are less tied to current firm performance, which may reflect the idea that changes in the liquidation values of firms are slow moving and do not necessarily reflect recent developments in the firm. This rationale can also explain why changes in LGD do not seem to predict earnings surprises.

It is also worth mentioning that although decreases in PD do not predict *future* financial market outcomes, they are positively associated with changes in *contemporaneous* equity returns. Hence, banks are likely either receiving information at the same time as markets or simply adjusting their risk metrics based on what they observe in the market when they reduce their PDs.

The above tests tell us broadly when banks adjust their risk assessments, but do not explain the actual source of banks' private information because all of the predictors are publicly available to market participants. We next attempt to better understand the sources of banks' informational advantage. There are multiple reasons banks could have superior information than financial markets. On the one hand, banks may be better at processing publicly available information. On the other hand, banks may simply have access to private information before markets (Wight et al. (2009)).[22] We believe our results regarding firm size likely reflect banks' information processing advantage being higher

[22]Another way to think about this is "soft" versus "hard" information (e.g., Liberti and Petersen (2019)).

for smaller firms. For large firms there are much more research analysts and competition among informed investors. In contrast, the disclosure requirements are typically quite similar across publicly traded firms. While we view this as less likely, it is still possible that banks receive more information prior to markets for smaller firms and this is driving the predictability of changes in banks' risk assessments.

In order to better understand the sources of banks' private information, we analyze a specific source of early access to information for banks: credit lines. If a firm draws down a credit line, this information is immediately known by the bank, but is not disclosed until the firm's next public filing. Hence, we next test whether PDs, LGDs, and expected losses increase after firms draw down their credit lines. Specifically we estimate the following regressions:

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

where our dependent variables are PD^{+}, LGD^{+} and EL^{+}. Our main independent variable is $Drawdown_{i,b,t}$, which is a dummy variable that equals one if the utilization rate increases. We also include firm by time fixed effects to see how differential drawdowns affect expected losses across banks for a firm borrowing from multiple banks at once (e.g., Khwaja and Mian (2008)). The results are displayed in Table 10. We find that bank drawdowns dramatically increase the likelihood of banks increasing their assessed PDs, LGDs and expected losses. For instance, in column 3 a drawdown raises the probability of the bank increases the firm's expected loss by 4.7pp compared to an unconditional mean of 17.2pp. This is consistent with firms drawing down credit lines following a negative shock (e.g., Shockley and Thakor (1997) and Holmström and Tirole (1998)).[23]

If firms are indeed drawing down their credit lines in bad times we would expect that drawdowns negatively predict future stock returns. Moreover, it is possible that the entirety of banks' information advantage that we document in this paper arises from their access to the information regarding credit line drawdowns. To answer these questions,

[23] This is also consistent with the empirical findings of Mester, Nakamura, and Renault (2007), Jiménez, Lopez, and Saurina (2009) and Berg, Saunders, and Steffen (2016).

we reestimate a version of (2) with both EL^+ and $Drawdown$ as independent variables. The results are displayed in Table 11. Consistent with drawdowns containing private information about firms' prospects, drawdowns predict a -1.8% quarterly negative excess stock return (column 1). However, EL^+ still strongly predicts negative stock returns on its own. In column 3, we include bond returns as the dependent variable and drawdowns do not appear to predict bond returns, while increases in expected losses still predict negative excess bond returns even after controlling for drawdowns. In columns 5 and 7, we see a similar pattern for earnings surprises as we do for stock returns. Taken together, these results are consistent with banks having both access to private information early while still having an information processing advantage through their risk assessments. Of course we cannot completely rule out that banks have access to other non-public information that is driving all of the predictability in the changes in their credit assessments. However, we believe the results presented in Table 11 together with the results on firm size suggest that at least a part of their advantage is from information processing.

5 Discussion

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

A potential concern with the risk assessments we use is that banks may misrepresent them (e.g., Plosser and Santos (2018) and Behn, Haselmann, and Vig (2022)). The fact we use bank by quarter fixed effects throughout somewhat alleviates this concern because we would absorb any aggregate bank-level effects. Hence, banks would need to have an incentive to lie differentially across loans. Nonetheless, if banks are indeed misrepresenting their risk measures, this would bias our results to zero.

One question could be whether banks' information is about cash flows or discount rates. First, because our results are not very long-lasting, it is unlikely discount rates would change so dramatically for just one quarter. Second, the fact that returns predict the level of earnings surprises seems most consistent with the information being about cash flows. Finally, banks are specifically asked to report physical default probabilities and recoveries, not risk-neutral ones. Hence, the changes in information we identify are much more likely about the expected cash flows of the firm, not changes in discount rates.

6 Conclusion

One of the central tenets of financial intermediation is the role of banks as informed finance. Despite the appeal of this class of theories, testing the presence of information asymmetries is extremely challenging because agents' private information is inherently unobservable. In this paper we address this challenge by using a unique dataset that provides direct access to banks' private information. We show that changes in banks' private information predict stock returns, bond returns and analyst earnings surprises. Consistent with theory, we show that banks' specialize in collecting negative information. Moreoever, banks' information advantage is stronger for smaller firms and growth firms. Because of this, we conjecture that banks' informational advantage is even stronger for smaller, more opaque, non-publicly traded firms. Despite recent trends questioning the traditional view of banks, our evidence strongly supports banks as informed financiers. More broadly, our work highlights the importance of information asymmetries in financial markets.

We also view a key contribution of this paper is validating banks' risk assessments as actual sources of banks' private information. This opens up many avenues of future research to explore the determinants of implications of banks' private information.

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Table 1: Summary Statistics

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

	Mean	SD	10%	Median	90%	N
PD (%)	1.012	2.784	0.070	0.300	1.910	136,882
LGD (%)	38.945	13.213	20.000	41.000	51.000	136,882
Expected Loss (%)	0.326	0.901	0.029	0.102	0.600	136,882
PD^{+}	0.110	0.312	0.000	0.000	1.000	124,506
PD^{-}	0.121	0.326	0.000	0.000	1.000	124,506
LGD^{+}	0.116	0.320	0.000	0.000	1.000	124,506
LGD^{-}	0.134	0.340	0.000	0.000	1.000	124,506
EL^{+}	0.172	0.377	0.000	0.000	1.000	124,506
EL^{-}	0.194	0.395	0.000	0.000	1.000	124,506
Drawdown	0.262	0.440	0.000	0.000	1.000	124,506
Stock Return	0.008	0.197	-0.213	0.016	0.209	136,882
Bond Return	0.010	0.053	-0.026	0.011	0.044	64,533
Negative Surprise	0.269	0.443	0.000	0.000	1.000	125,493
Positive Surprise	0.726	0.446	0.000	1.000	1.000	125,493
Book-to-Market	0.482	0.377	0.119	0.384	0.946	131,731
ROA	0.138	0.074	0.064	0.131	0.231	136,240
Leverage	0.501	0.226	0.213	0.488	0.809	136,417
Market Cap ($bn)	18.436	51.537	0.526	3.814	42.036	136,882

Table 2: Correlations Across Risk Assessment Adjustments

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

Panel A: Upward Estimates

	PD_t^+	LGD_t^+	EL_t^+	PD_{t-1}^+	LGD_{t-1}^+	EL_{t-1}^+
PD_t^+	1.000					
LGD_t^+	0.119	1.000				
EL_t^+	0.717	0.607	1.000			
PD_{t-1}^+	0.040	0.023	0.040	1.000		
LGD_{t-1}^+	0.007	0.115	0.079	0.124	1.000	
EL_{t-1}^+	0.028	0.082	0.073	0.721	0.607	1.000

Panel B: Downward Estimates

	PD_t^-	LGD_t^-	EL_t^-	PD_{t-1}^-	LGD_{t-1}^-	EL_{t-1}^-
PD_t^-	1.000					
LGD_t^-	0.159	1.000				
EL_t^-	0.703	0.652	1.000			
PD_{t-1}^-	0.012	0.010	0.015	1.000		
LGD_{t-1}^-	0.002	0.104	0.076	0.158	1.000	
EL_{t-1}^-	0.002	0.075	0.057	0.717	0.639	1.000

Table 3: Do Changes in Expected Losses Predict Financial Market Outcomes?

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

	Stock Return	Bond Return	Negative Surprise	Positive Surprise
	(1)	(2)	(3)	(4)
EL^+	−0.008***	−0.002*	0.018***	−0.017***
	(3.910)	(1.942)	(3.673)	(3.471)
EL^-	−0.002	0.001	0.003	−0.002
	(1.392)	(1.262)	(0.714)	(0.441)
Book-to-Market	−0.001	0.003	0.044**	−0.040**
	(0.106)	(0.728)	(2.429)	(2.207)
ROA	0.007	0.008	−0.027	0.030
	(0.363)	(0.741)	(0.412)	(0.457)
Leverage	−0.006	0.001	0.026	−0.019
	(0.738)	(0.198)	(1.146)	(0.805)
Log(Market Cap)	0.002*	0.000	−0.037***	0.040***
	(1.815)	(0.401)	(10.518)	(11.284)
Lagged Stock Return	−0.014		−0.163***	0.165***
	(1.090)		(6.262)	(6.316)
Lagged Bond Return		−0.086**		
		(2.015)		
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	119,649	55,097	109,772	109,772
R-squared	0.37	0.49	0.08	0.09

Table 4: Cross-Sectional Variation in Predictability

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

	Stock Return	Bond Return	Negative Surprise	Positive Surprise
	(1)	(2)	(3)	(4)
EL^+	-0.059^{***}	-0.011	0.134^{***}	-0.128^{**}
	(2.733)	(0.932)	(2.660)	(2.524)
Book-to-Market	-0.004	0.002	0.050^{***}	-0.047^{***}
	(0.598)	(0.628)	(2.779)	(2.590)
ROA	0.000	0.004	-0.019	0.021
	(0.015)	(0.472)	(0.280)	(0.315)
Leverage	-0.007	0.001	0.023	-0.015
	(0.846)	(0.331)	(1.001)	(0.626)
Log(Market Cap)	0.002	-0.000	-0.036^{***}	0.039^{***}
	(1.435)	(0.361)	(10.167)	(10.934)
Lagged Stock Return	-0.013	0.011^{**}	-0.163^{***}	0.166^{***}
	(0.954)	(2.117)	(6.185)	(6.230)
EL^+ × Book-to-Market	0.015^{**}	-0.002	-0.032^{**}	0.034^{**}
	(2.104)	(0.510)	(2.170)	(2.300)
EL^+ × ROA	0.038	0.010	-0.045	0.048
	(1.296)	(0.577)	(0.694)	(0.741)
EL^+ × Leverage	0.004	-0.003	0.022	-0.027
	(0.405)	(0.519)	(1.065)	(1.300)
EL^+ × Log(Market Cap)	0.003^{**}	0.001	-0.007^{**}	0.007^{**}
	(2.030)	(0.966)	(2.285)	(2.162)
EL^+ × Lagged Stock Return	-0.006	0.011	0.004	-0.005
	(0.510)	(1.526)	(0.157)	(0.187)
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	119,649	55,963	109,772	109,772
R-squared	0.37	0.49	0.08	0.09

Table 5: Stock Return Predictability Across Size Quintiles

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

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
	(1)	(2)	(3)	(4)	(5)
EL^+	-0.017^{**}	-0.008^{**}	-0.008^{***}	-0.006^{**}	0.001
	(2.280)	(2.153)	(2.898)	(2.171)	(0.257)
Book-to-Market	0.033^{**}	-0.007	-0.009	-0.026^{***}	-0.013
	(2.375)	(0.572)	(0.792)	(3.027)	(1.130)
ROA	0.093	-0.016	-0.017	-0.048	-0.001
	(1.260)	(0.351)	(0.356)	(1.598)	(0.028)
Leverage	0.042	-0.019	-0.024^{*}	-0.008	-0.001
	(1.473)	(1.138)	(1.686)	(0.794)	(0.106)
Log(Market Cap)	0.011^{*}	0.008	-0.013	0.013^{**}	0.004^{**}
	(1.716)	(0.689)	(1.266)	(2.185)	(2.182)
Lagged Stock Return	-0.037	-0.020	0.003	-0.027	-0.005
	(1.387)	(0.986)	(0.162)	(1.571)	(0.254)
Bank-Quarter FE	YES	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES	YES
Observations	10,227	18,779	24,553	29,551	33,983
R-squared	0.38	0.48	0.49	0.53	0.51

Table 6: The Timing of the Return Predictability

This table tests the timing of the stock and return predictability. These regressions use one month returns rather than quarterly returns. T-statistics are shown below the parameter estimates in parenthesis and are calculated using robust standard errors clustered by firm and bank/quarter. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Stock Return			Bond Return		
	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3
	(1)	(2)	(3)	(4)	(5)	(6)
EL^{+}	−0.002*	−0.004***	−0.001	−0.001**	−0.001**	0.000
	(1.684)	(3.252)	(1.360)	(2.376)	(2.362)	(0.900)
Book-to-Market	−0.003	−0.006*	0.007*	0.002	−0.003**	0.004*
	(0.934)	(1.875)	(1.787)	(0.796)	(2.482)	(1.789)
ROA	−0.010	−0.012	0.027**	−0.002	−0.000	0.009
	(0.930)	(0.990)	(2.462)	(0.355)	(0.053)	(1.169)
Leverage	0.001	−0.006	−0.003	0.003	−0.003*	0.001
	(0.366)	(1.390)	(0.673)	(1.459)	(1.806)	(0.463)
Log(Market Cap)	0.003***	−0.000	−0.000	−0.001***	0.000	0.001
	(5.234)	(0.363)	(0.439)	(3.038)	(0.970)	(1.586)
Lagged Stock Return	−0.033***	0.019***	−0.010			
	(5.121)	(2.768)	(1.521)			
Lagged Bond Return				−0.021	−0.008	−0.091*
				(0.435)	(0.367)	(1.852)
Bank-Quarter FE	YES	YES	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES	YES	YES
Observations	119,649	119,649	119,649	55,103	55,109	55,210
R-squared	0.33	0.27	0.44	0.35	0.31	0.54

Table 7: Two Quarter Ahead Predictability

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

	Stock Return	Bond Return	Negative Surprise	Positive Surprise
	(1)	(2)	(3)	(4)
EL^+	0.000	0.001	0.014**	−0.013**
	(0.027)	(1.553)	(2.538)	(2.466)
Book-to-Market	−0.006	0.000	0.038**	−0.034*
	(0.980)	(0.052)	(2.004)	(1.793)
ROA	−0.002	−0.008	0.000	0.011
	(0.107)	(0.828)	(0.000)	(0.156)
Leverage	−0.009	0.002	0.026	−0.019
	(1.132)	(0.849)	(1.093)	(0.790)
Log(Market Cap)	0.003**	0.000	−0.038***	0.041***
	(2.163)	(0.484)	(10.564)	(11.276)
Lagged Stock Return	−0.028**		−0.101***	0.101***
	(2.310)		(3.957)	(3.860)
Lagged Bond Return		−0.024		
		(0.421)		
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	108,890	50,070	99,988	99,988
R-squared	0.38	0.47	0.08	0.09

Table 8: Is PD or LGD Driving the Predictability?

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

	Stock Return	Bond Return	Negative Surprise	Positive Surprise
	(1)	(2)	(3)	(4)
PD^+	−0.004*	−0.002	0.019***	−0.018***
	(1.782)	(1.431)	(3.181)	(2.987)
LGD^+	−0.006***	−0.002	0.005	−0.006
	(2.604)	(1.600)	(0.969)	(1.032)
Book-to-Market	−0.001	0.003	0.044**	−0.040**
	(0.115)	(0.727)	(2.414)	(2.195)
ROA	0.008	0.007	−0.028	0.031
	(0.384)	(0.735)	(0.423)	(0.466)
Leverage	−0.006	0.001	0.027	−0.019
	(0.760)	(0.218)	(1.153)	(0.809)
Log(Market Cap)	0.002*	0.000	−0.037***	0.040***
	(1.833)	(0.381)	(10.521)	(11.284)
Lagged Stock Return	−0.014		−0.163***	0.165***
	(1.085)		(6.247)	(6.303)
Lagged Bond Return		−0.086**		
		(2.017)		
Bank-Quarter FE	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES
Observations	119,649	55,097	109,772	109,772
R-squared	0.37	0.49	0.08	0.09

Table 9: Contemporaneous Changes in Banks' Risk Assessments and Firm Performance

This table tests whether changes in firm performance predict contemporaneous changes in bank risk assessments. Variables with Δ in front are changes from $t-1$ to t, stock returns are from $t-1$ to t and outcomes variables are measured at time t. T-statistics are shown below the parameter estimates in parenthesis and are calculated using robust standard errors clustered by firm and bank/quarter. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	PD^{+}	PD^{-}	LGD^{+}	LGD^{-}	EL^{+}	EL^{-}
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Book-to-Market	0.099***	−0.051***	0.009	−0.012	0.091***	−0.057***
	(7.009)	(5.310)	(0.805)	(1.066)	(5.942)	(4.734)
Δ ROA	−1.252***	0.742***	−0.117*	0.024	−1.272***	0.823***
	(11.716)	(8.521)	(1.814)	(0.384)	(11.453)	(9.062)
Δ Leverage	0.178***	−0.158***	−0.038	0.035	0.166***	−0.117***
	(4.994)	(5.124)	(1.474)	(1.343)	(4.191)	(3.432)
Stock Return	−0.062***	0.018**	−0.000	−0.015	−0.049***	0.006
	(5.879)	(2.426)	(0.061)	(1.638)	(4.243)	(0.664)
Bank-Quarter FE	YES	YES	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES	YES	YES
Observations	118,997	118,997	118,997	118,997	118,997	118,997
R-squared	0.18	0.26	0.27	0.28	0.16	0.22

Table 10: Credit Line Drawdowns and Bank Risk Assessments

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

	PD^+	LGD^+	EL^+
	(1)	(2)	(3)
Drawdown	0.018***	0.048***	0.047***
	(4.006)	(5.850)	(6.825)
Firm-Quarter FE	YES	YES	YES
Bank-Quarter FE	YES	YES	YES
Observations	118,287	118,287	118,287
R-squared	0.26	0.18	0.23

Table 11: Do Changes in Expected Losses Predict Financial Market Outcomes Beyond Credit Line Drawdowns?

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

	Quarterly Stock Return		Quarterly Bond Return		Negative Surprise		Positive Surprise	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Drawdown	−0.018***	−0.017***	0.001	0.001	0.023***	0.022***	−0.023***	−0.023***
	(7.456)	(6.924)	(0.532)	(0.928)	(3.275)	(3.119)	(3.290)	(3.113)
EL^{+}	−0.006***	−0.004*	−0.002**	−0.002*	0.016***	0.016***	−0.015***	−0.015***
	(3.093)	(1.766)	(2.158)	(1.671)	(3.417)	(2.979)	(3.262)	(2.768)
Drawdown $\times$ EL^{+}		−0.006*		−0.002		0.001		−0.002
		(1.725)		(0.651)		(0.120)		(0.227)
Book-to-Market	−0.001	−0.001	0.003	0.003	0.044**	0.044**	−0.040**	−0.040**
	(0.144)	(0.143)	(0.730)	(0.733)	(2.444)	(2.444)	(2.223)	(2.223)
ROA	0.011	0.011	0.007	0.007	−0.032	−0.032	0.035	0.035
	(0.534)	(0.532)	(0.735)	(0.739)	(0.477)	(0.477)	(0.522)	(0.522)
Leverage	−0.003	−0.003	0.001	0.001	0.024	0.024	−0.016	−0.016
	(0.435)	(0.438)	(0.196)	(0.196)	(1.047)	(1.047)	(0.701)	(0.701)
Log(Market Cap)	0.001	0.001	0.000	0.000	−0.036***	−0.036***	0.039***	0.039***
	(1.259)	(1.266)	(0.425)	(0.431)	(10.256)	(10.255)	(11.014)	(11.014)
Lagged Stock Return	−0.015	−0.015			−0.162***	−0.162***	0.164***	0.164***
	(1.161)	(1.166)			(6.218)	(6.216)	(6.271)	(6.269)
Lagged Bond Return			−0.086**	−0.086**				
			(2.012)	(2.021)				
Bank-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	119,649	119,649	55,097	55,097	109,772	109,772	109,772	109,772
R-squared	0.37	0.37	0.49	0.49	0.08	0.08	0.09	0.09

Appendix A. Variable Definitions

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

Drawdown: A dummy variable that equals one if the utilization rate increases, from Y-14Q.

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

EL^+: A dummy variable that equals one if Expected Loss increases from previous quarter and equals zero otherwise, from Y-14Q.

EL^-: A dummy variable that equals one if Expected Loss decreases from the previous quarter and equals zero otherwise, from Y-14Q.

Market Cap: market capitalization, from CRSP.

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

LGD^+: A dummy variable that equals one if LGD increases from previous quarter and equals zero otherwise, from Y-14Q.

LGD^-: A dummy variable that equals one if LGD decreases from the previous quarter and equals zero otherwise, from Y-14Q.

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

PD^+: A dummy variable that equals one if PD increases from previous quarter and equals zero otherwise, from Y-14Q.

PD^-: A dummy variable that equals one if PD decreases from the previous quarter and equals zero otherwise, from Y-14Q.

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

ROA: Operating income before depreciation as a fraction of average total assets based on most recent two periods, winsorized at [1%, 99%], from Compustat.

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

Stock Return: quarterly stock return, from CRSP.

Utilization Rate: utilization amount divided by committed amount, value weighted by the size of the loan, from Y-14Q.

Appendix B. Additional Tests

Table B1: Sample Comparison

This table compares our final sample with a standard CRSP/Compustat merged sample. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively based on a t-test.

	Sample			CRSP/Compustat			Difference	
	Mean	Median	N	Mean	Median	N	Mean	Median
Market Cap ($bn)	12.946	2.050	27,491	7.967	0.901	48,193	4.979***	1.149***
Book-to-Market	0.515	0.404	26,412	0.526	0.386	45,098	-0.011***	0.018***
ROA	0.129	0.126	27,351	0.013	0.099	47,383	0.116***	0.027***
Leverage	0.448	0.439	27,371	0.412	0.376	47,480	0.036***	0.063***

Table B2: Fama-Macbeth Regressions

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

	Stock Return	Bond Return	Negative Surprise	Positive Surprise
	(1)	(2)	(3)	(4)
EL^{+}	-0.007^{***}	-0.001^{*}	0.017^{***}	-0.016^{***}
	(4.466)	(1.825)	(3.413)	(3.181)
EL^{-}	-0.002	0.001	0.003	-0.002
	(1.254)	(1.379)	(1.171)	(0.703)
Book-to-Market	-0.003	-0.001	0.043^{**}	-0.039^{**}
	(0.234)	(0.256)	(2.437)	(2.166)
ROA	0.003	-0.001	-0.037	0.041
	(0.079)	(0.132)	(0.644)	(0.738)
Leverage	-0.008	-0.003	0.027	-0.019
	(0.581)	(0.551)	(1.430)	(1.066)
Log(Market Cap)	0.002	0.000	-0.037^{***}	0.040^{***}
	(0.917)	(0.255)	(18.467)	(19.582)
Lagged Stock Return	-0.013		-0.171^{***}	0.172^{***}
	(0.579)		(7.021)	(7.186)
Lagged Bond Return		-0.089		
		(1.229)		
Bank FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	119,677	55,126	109,801	109,801
R-squared	0.15	0.36	0.09	0.09

Table B3: Predictability Excluding Bank-Quarter Fixed Effects

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

	Stock Return	Bond Return	Negative Surprise	Positive Surprise
	(1)	(2)	(3)	(4)
EL^+	−0.006***	−0.002**	0.015***	−0.014***
	(3.438)	(2.030)	(3.653)	(3.498)
EL^-	−0.000	0.001**	0.002	−0.001
	(0.108)	(2.060)	(0.582)	(0.290)
Book-to-Market	−0.001	0.003	0.043**	−0.039**
	(0.130)	(0.696)	(2.367)	(2.152)
ROA	0.007	0.007	−0.025	0.028
	(0.366)	(0.716)	(0.369)	(0.414)
Leverage	−0.006	0.001	0.026	−0.018
	(0.837)	(0.171)	(1.132)	(0.792)
Log(Market Cap)	0.002*	0.000	−0.038***	0.040***
	(1.897)	(0.267)	(10.764)	(11.497)
Lagged Stock Return	−0.014		−0.162***	0.164***
	(1.092)		(6.199)	(6.262)
Lagged Bond Return		−0.086**		
		(1.995)		
Industry-Quarter FE	YES	YES	YES	YES
Observations	119,668	55,117	109,792	109,792
R-squared	0.37	0.48	0.08	0.08

Table B4: Portfolio Sorts

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

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