Bank Information Production Over the Business Cycle*

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Abstract

The information banks have about borrowers drives their lending decisions and macroeconomic outcomes, but this information is inherently difficult to analyze because it is private. We construct a novel measure of bank information quality from confidential regulatory data that include banks' private risk assessments for US corporate loans. We show that our measure of information quality improves as local economic conditions deteriorate, particularly for newly originated loans and loans with greater information sensitivity. Our results provide empirical support for theories of countercyclical information production in credit markets, and suggest that policies designed to stimulate macroeconomic activity through the banking sector may be less effective in recessions.

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1 Introduction

A key role of banks is to produce information about prospective borrowers.[1] Because banks' information influences both the recipients and terms of financing, their information production decisions can affect real economic activity and financial stability through the supply of credit to firms. Moreover, banks' incentives to produce information may vary over the business cycle (e.g., Dang, Gorton, and Holmström (2012)). Despite policymaker interest and an extensive theoretical literature[2] emphasizing the importance of bank information, there is little evidence of its empirical properties.

In this paper, we create a new measure of bank information quality using confidential loan-level regulatory data for corporate bank loans in the US. Exploiting variation in county-level unemployment rates, we show that banks' information quality improves as local economic conditions worsen. Consistent with banks actively producing more information when their incentives to do so are higher, we find that the sensitivity of information production to the business cycle is concentrated in: i) newly issued loans, and ii) loans that theory predicts to be more information sensitive. Overall, our results provide empirical support for theories in which banks' information production decisions hinge on economic conditions. Our results also can also provide insights to policymakers and regulators about how banks respond to policy interventions meant to stimulate lending, as these types of policies may be less effective in recessions when banks screen their borrowers more intensively.

The main empirical challenge to testing theories of information production is that lenders' information is generally private and unobservable. We overcome this hurdle by using banks' risk assessments from Y-14Q regulatory filings that they report to the Federal Reserve. This dataset includes the universe of corporate loans over $1 million on the balance sheets of US bank holding companies (BHCs) with at least $50 billion in total assets. In addition to detailed loan and borrower characteristics, qualified BHCs are

[1] e.g., Leland and Pyle (1977) and Diamond (1984).

[2] A non-exhaustive list of theoretical analyses of information production in credit markets includes: Gorton and Pennacchi (1990), Thakor (1996), Fulghieri and Lukin (2001), Dang, Gorton, and Holmström (2012), Chemla and Hennessy (2014), Yang and Zeng (2019), Yang (2020) and Weitzner (2019).

required to report their internal estimate of the borrower's probability of default (PD).

We first establish that banks' PD estimates are statistically and economically significant predictors of realized default even after controlling for a rich set of loan and firm-level controls. This result suggests that banks' risk assessments contain private information that is both: 1) relevant for predicting default, and 2) not captured by other observables.[3] We create a measure of information quality based on the size of the PD coefficient in OLS regressions predicting realized default at origination. We then use this approach to show that information quality improves as local economic conditions deteriorate. In particular, we estimate that a one percentage point increase in the local unemployment rate increases the sensitivity of realized default to PD by roughly 50% of its average level. This result provides support for theories in which banks produce more information when economic conditions weaken as the returns to distinguishing between different borrower types increase.[4]

While our empirical results are consistent with banks producing more information about borrowers during downturns, there are other potential channels that can explain our main result. One possibility is banks' information quality changes exogenously over the business cycle. We develop several tests to provide further evidence for the endogenous information production mechanism. First, we analyze how the R^2 obtained from regressing default on PD and firm/loan characteristics change over the business cycle. During periods of elevated unemployment, we find that the total R^2 is lower, but the marginal contribution of PD to the regression's R^2 is higher. This result is consistent with the idea that observable characteristics do a worse job at predicting default in bad times. This in turn incentivizes banks to produce more private information, resulting in PD having a larger marginal impact on the explanatory power of the regression in periods of high unemployment.

Next, we show that the cyclical sensitivity of information is almost entirely driven

[3]This result is consistent with the literature using the Y-14Q data to analyze the predictability of banks' PDs for default (Adelino, Ivanov, and Smolyansky (2019) and Beyhaghi, Fracassi, and Weitzner (2020)).

[4]See Ruckes (2004), Dell'Ariccia and Marquez (2006), Dang, Gorton, and Holmström (2012) and Gorton and Ordonez (2014).

by newly issued loans to firms in nontradeable industries. Intuitively, banks' information production incentives should be more sensitive to the business cycle for new loans because they are risking additional capital, while for already issued loans that capital is already sunk. The effects should also be larger for nontradeable producers, as these firms will be more sensitive to changes in local economic conditions. We argue that both of these results are difficult to rationalize via an exogenous information mechanism.

Finally, we analyze how bank information quality varies across different proxies for the information sensitivity of a loan (Dang, Gorton, and Holmström (2012)). Specifically, we hypothesize that banks will produce more information about loans with larger potential losses. Hence, we expect information quality to be higher for larger loans as well as loans to more highly levered borrowers.[5] We also expect the information asymmetry problem to be more severe for smaller firms, which incentivizes more information production by banks. To test these hypotheses, we estimate regressions that include interactions between PD and these characteristics. Consistent with our hypotheses, we find positive interaction coefficients with loan size and leverage, and a negative interaction coefficient with firm size. We also show that the relationship between information quality and loan/firm characteristics are amplified when the unemployment rate is high. This is consistent with Dang, Gorton, and Holmström (2012), who show that information production decisions become more sensitive to loan features following negative aggregate shocks. Overall, these results provide additional support for the information production channel, and to our knowledge, are the first in the literature highlighting how the business cycle can affect the information sensitivity of loans.

One concern is that our results could be driven by selection effects. For example, banks may be lending to fundamentally different borrowers in downturns. To address this concern, we regress various loan characteristics on the local unemployment rate and show that they do not vary meaningfully over the local business cycle. While the number of loans and loan volume drop, realized default rates do not appear to change, which we interpret as banks maintaining their credit standards as economic conditions deteriorate.

[5] This is a direct implication of Dang, Gorton, and Holmström (2012) who show that lower expected recovery values increase lenders' information production incentives.

Our findings have important consequences for policymakers because a bank's lending response to policy interventions may vary depending on the information production incentives that bank faces. One policy-relevant example is that interventions meant to stimulate bank lending, including monetary policy, may become less effective in downturns. During periods of high unemployment, banks will screen their potential borrowers more thoroughly, which can alter the pool of loan recipients. This can help explain why some research has found modest effects of stimulus policies enacted in the wake of the Great Recession, particularly for the riskiest firms.[6] Ultimately, the empirical properties of bank information production are crucial for understanding the link between bank lending and real economic activity, as well as how this link changes over the business cycle. We view this paper as an important step in analyzing these properties.

Literature review. Our paper relates to the empirical literature on bank information production. A subset of this 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 (2020)). Gustafson, Ivanov, and Meisenzahl (2020) create a measure of monitoring based on the number of visits banks take to firms. In contrast, we are focused on banks' information about borrower risk at loan origination by directly using banks' information they report to the Federal Reserve.

Other papers analyze information production in the primary market. For example, Keys et al. (2010) and Keys, Seru, and Vig (2012) analyze screening in the consumer loan market, while Iyer et al. (2016) analyze information production in an online peer lending platform. Lisowsky, Minnis, and Sutherland (2017) show that banks collected less information from construction firms in the run-up to the 2008/2009 financial crisis. 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), Behn, Haselmann, and Vig (2016), Dell'Ariccia, Laeven, and Suarez (2017), Plosser and Santos (2018), Nakamura and Roszbach (2018), Becker, Bos, and Roszbach (2020), Adelino, Ivanov,

[6]For example, Andrade et al. (2019) analyze the bank lending response to the Eurosystem's LTRO program and find an increase in overall lending but no increase in lending to riskier firms. In the case of QE, Butt et al. (2014) find no evidence that it stimulated bank lending in the UK.

and Smolyansky (2019) and Beyhaghi, Fracassi, and Weitzner (2020)).

The paper whose empirical approach is closest to ours is Becker, Bos, and Roszbach (2020), who find that bank credit ratings perform better at predicting default in bad economic times. There are several key differences in both our analysis and the interpretation of our results. First, their data are restricted to a single Swedish bank. Because of this, they rely on a single time series measure of aggregate economic conditions. In contrast, our paper exploits variation in economic conditions across the US at each point in time. This allows us to rule out supply-side effects at the bank level because we can compare information quality across loans in different regions given by the same bank. Second, their data are at the firm level rather than the loan level. This difference allows us to explore the relationship between loan/firm characteristics and information production and how the intensity of this relationship varies over the business cycle. Finally, they argue that the cyclicality of information quality is exogenous; however, we show that it almost entirely driven by new loans, which we argue is difficult to explain via exogenous changes in information over the business cycle.

While we focus on information production, our work also relates to the empirical literature on the cyclicality of lending standards (e.g., Asea and Blomberg (1998), Lown and Morgan (2006), Dell'Ariccia, Igan, and Laeven (2012), Jiménez et al. (2014), Bassett et al. (2014), Dell'Ariccia, Laeven, and Suarez (2017), Maddaloni and Peydró (2011), Rodano, Serrano-Velarde, and Tarantino (2018), Mariathasan and Zhuk (2018), and Dempsey, Ionescu et al. (2019)). For the most part, existing studies find that lending standards are countercyclical. Our results compliment this finding by suggesting banks are producing more information when economic conditions deteriorate. While we do not observe the composition of loan applicants and thus cannot directly analyze lending standards, the theoretical channels we use to interpret our results are consistent with countercyclical lending standards.

Our paper also relates to work analyzing the cyclicality of information production in credit markets. This includes an extensive theoretical literature in which information production is countercyclical (e.g., Ruckes (2004), Gorton and He (2008), Gorton and Ordonez (2014) Gorton and Ordonez (2020), Fishman, Parker, and Straub (2020) Dell'Ariccia and Marquez (2006), Petriconi (2015) Farboodi and Kondor (2020)). Several of our tests also appeal to predictions in the theoretical literature relating security design and information production such as Boot and Thakor (1993), Gorton and Pennacchi (1990), Fulghieri and Lukin (2001), Dang, Gorton, and Holmström (2012), Gorton and Ordonez (2014), Dang, Gorton, and Holmstrom (2019), Yang and Zeng (2019), Yang (2020), and Weitzner (2019).

Finally, our work complements research analyzing the cyclicality of attention in macroeconomic settings more broadly. Coibion and Gorodnichenko (2015) show that forecast quality for macroeconomic aggregates such as inflation is countercyclial, while Song and Stern (2021) and Flynn and Sastry (2021) provide empirical that firm attention to macroeconomic news is countercyclical. Theoretical analysis of the drivers of information production decisions include Mäkinen and Ohl (2015), Benhabib, Liu, and Wang (2016), and Chiang (2021). Our work connects these research agendas to those from the finance literature by providing empirical evidence that attention allocation decisions in the banking sector can affect macroeconomic outcomes.

The paper is structured as follows. Section 2 describes our data. Section 3 presents empirical evidence that information quality is countercyclical as well as evidence on potential mechanisms. Section 4 discusses implications for policymakers. Section 5 concludes.

2 Data

Our main source of data is Schedule H.1 of the Federal Reserve's Y-14Q data. The Federal Reserve began collecting these data in June 2012 to support the Dodd-Frank mandated stress tests and the Comprehensive Capital Analysis and Review (CCAR). The sample includes commercial and industrial (C&I) loans from banks with \$50bn or more in total assets, accounting for 85.9% of all assets in the banking sector (Frame, McLemore, and Mihov (2020)).[7] Qualified banks are required to report detailed quarterly loan level data on corporate loans that exceed \$1mm. The universe of loans we analyze is large: Bidder,

[7] In 2019, this threshold was increased to \$100bn.

Krainer, and Shapiro (2020) show that the Y-14Q data cover 70% of all commercial and industrial loan volume. The data include detailed loan characteristics (such as interest rates, maturity, amount, collateral, and purpose) and performance measures (defaults, past-due payments, non-accruals, and charge-offs). They also include income, balance sheet, and geographic information about borrowers. Crucially, banks are also required to report their internal estimates of probability of default (PD) for each loan to the Federal Reserve on their Y-14Q filings.

Because we are focused on banks' information production incentives at loan origination, our baseline results only include newly originated loans. We exclude "demand loans," which can be recalled by the borrower at any time, as well as loans with government guarantees, tax-exempt loans, loans to foreign borrowers and loans to firms in the finance, insurance, and real estate (FIRE) sectors. We drop loans with negative interest rates, or interest rates over 100%, as well as those with missing company identifiers, PD, or loan amount at origination. We follow Brown, Gustafson, and Ivanov (2021) and exclude loans to companies with under $100k in reported assets at origination; given that the minimum reporting thresholds for loans is $1 million, these observations are likely reporting errors. We also drop loans with PDs that are above the 99th percentile at origination to minimize the effects of outliers and reporting errors. Finally, we drop firms with assets above the 99th percentile and publicly traded firms, as these firms are likely to be more geographically diverse and thus less sensitive to changes in local economic conditions. Our sample period starts in 2014Q4, which is when the PD variable first becomes well populated, and extends through 2019Q1 to allow at least one year for loans to default (our sample ends in 2020Q1).

We define the following firm-level financial variables: profitability (EBITDA/assets), size (log assets), tangibility (tangible assets/assets), and leverage (debt/assets), which we winsorize at the 1% and 99% level. Our main measure of loan performance is default, which is a dummy variable that equals 1 if the borrower defaults within two years after origination. Focusing on a two-year default window strikes a balance between the limited time series dimension of our data and the fact that the median loan maturity is close to five years. The full details of the variable construction as well as the sources, purpose, and properties of the PD estimates are described in Appendix A.

Table 1 includes summary statistics for these measures. The average and median loan size is approximately \$12.9mm and \$3.5mm, respectively, and over 90% of loans are less than \$30mm. The median firm has \$47.4mm in assets and a leverage ratio of 0.31. These loan and firm sizes are small relative to other sources of loan data such as DealScan, reflecting the fact that our sample contains many more small and nonpublic firms. The loan sample is approximately evenly split among credit lines and term loans and the median interest rate is 3.25%. The rightmost column of Table 1 shows summary statistics for the PD estimates in our sample. Over our sample period, 0.41% of firms default within the first two years after loan origination. This compares to an average ex-ante expected PD of 1.47%, suggesting that economic conditions were relatively benign during this period relative to banks' expectations.

Overall, this dataset is uniquely suited to analyze the dynamics of banks' information quality over the business cycle for several reasons. First, as mentioned earlier, it covers the vast majority of commercial bank loans in the US. Second, it includes both realized and predicted default at the loan level, which allows us to create an empirical measure of bank information quality and analyze its properties over the business cycle.

Figure 1 shows the distributions of both PD and log(PD). If PD contains information useful for predicting default, than there should be a positive correlation between PD and future realized default. A simple graphical illustration of this is shown in Figure 2. Figure 3 shows the relationship between PD and realized default in our data. Each column corresponds to a PD quintile, with the number below the column representing the average level of PD for that bucket of loans, while the vertical axis represents the average realized default rate for loans in that bucket. There is a clear positive relationship between PDs and realized defaults, suggesting that PD has useful information for predicting default. In the next section, we show this formally in regressions and implement our approach to measuring bank information quality.

3 Empirical Results

This section contains our main empirical results. We first justify our approach to measuring information quality by showing that PD is a statistically and economically significant predictor of realized default in Section 3.1. In Section 3.2, we show that PD becomes a better predictor of default as the unemployment rate increases. In Section 3.3 we conduct several tests which suggest that the cyclicality of banks' information quality is driven by endogenous information production. Finally, we analyze how the composition of loans and the characteristics of the firms that receive them change across the business cycle in Section 3.4.

3.1 Predicting Default

We first confirm that banks' PD estimates predict default. To do so we estimate the following linear regression:

$$Default_i = \beta PD_i + \Omega X_i + \delta_{b,t} + \gamma_{j,t} + \sigma_{b,c} + \epsilon_i, \tag{1}$$

where i, t, b, c, and j index loan, quarter, bank, county, and industry, respectively. $Default_i$ is a dummy variable that equals 1 if loan i defaults within eight quarters following origination. PD_i is the percentile rank (scaled to $(0, 100]$) within each bank and quarter of the PD for loan i at origination. We use this measure rather than the raw PD level for several reasons. First, the distribution of PD has a very large number of very small observations with a long right tail, leading to a potential outsized influence of outliers (see Figure 1). Second, ranking each PD within a given bank-quarter also ensures that all comparisons are between loans issued by the same group of bank decisionmakers. Third, the ranked approach avoids potential biases in the level of PD that might change over the business cycle. As a robustness check, we show very similar results using both the level of PD and log(PD) in Appendix Tables D.1 and D.2.

X_i is a vector of firm and loan characteristics which include size (log of total assets), leverage ratio (total debt to total assets), profitability ratio (EBITDA to total assets), and tangibility ratio (tangible assets to total assets), log loan size, the log of the original loan maturity in months, the loan's interest rate, the bank's estimate of loss given default (LGD), as well as loan type fixed effects. We include bank-quarter fixed effects ($\delta_{b,t}$) to absorb any differences in banks' risk assessment models and cost of capital, industry-quarter fixed effects ($\gamma_{j,t}$) to absorb variation in average loan performance across industries, and bank-county fixed effects ($\sigma_{b,c}$) to absorb persistent differences in risk assessment models or credit analysts across geographies. Throughout all of our regressions we cluster standard errors at the county level.

The results are shown in Table 2. The primary coefficient of interest is β, which represents the expected increase in realized default (measured in percentage points) from a one unit increase in a loan's PD percentile rank. For the same reason that measurement error will lead to attenuation bias when estimating a coefficient, a higher value of β can be interpreted as banks having more precise information about their borrowers. For example, in Column (1) the coefficient estimate is 0.0105, which means that, holding all else equal, going from the 25th percentile of PD to the 75th percentile will increase the probability of realized default by about $0.0105 \times (75 - 25) = 0.525$ percentage points. This effect is both statistically and economically significant considering the unconditional default rate in our sample is 0.4%. In Column (2), we display the results with firm and loan characteristics, and in Column (3) we include the credit spread as an additional regressor. These specifications show similar results, suggesting that PD captures information that is useful for predicting default even after controlling for the credit spread and other observable characteristics.[8]

[8]These results are consistent with Adelino, Ivanov, and Smolyansky (2019) and Beyhaghi, Fracassi, and Weitzner (2020) who also show PDs predict loan performance even after controlling for interest rates.

3.2 Information Quality Over the Business Cycle

3.2.1 Local Unemployment Rates and Information Quality

In this section, we test the cyclicality of bank information quality by asking how changes in local economic conditions affect PD's regression coefficient and R^2 when predicting default. Our measure of county-level economic conditions is the unemployment rate from the BLS.[9]

To test whether the ability of PD to predict default changes across different economic conditions, we first estimate the regressions from the previous section separately based on whether the county-level unemployment rate is above or below that county's median during our sample. The first two columns of Table 3 show the results of regressing default on PD without including any controls or fixed effects. While the coefficient on PD is statistically significant for both high and low unemployment periods, it is about three times as large during periods of high unemployment. Furthermore, the R^2 is higher for the high-unemployment observations. These results suggest PD becomes a better predictor of default as local economic conditions deteriorate.

The third and fourth columns of Table 3 show the same exercise, but with the inclusion of the bank-by-time, industry-by-time, and bank-by-county fixed effects that we use in our main specification. The coefficient on PD remains much higher during periods of high unemployment. The inclusion of these fixed effects unsurprisingly increases the R^2 of these regressions, though unlike the specification including only PD, the total R^2 is actually *lower* during periods of high unemployment. This is consistent with the idea that observable firm and loan characteristics become *less* useful for predicting default even as PD becomes *more* useful.

To further test this idea, we consider predictions of default using controls and fixed effects but excluding PD as an independent variable. These results are shown in the first

[9]The Y-14Q data use ZIP codes as geographical identifiers, so we first use the ZIP-to-county crosswalks from the Department of Housing and Urban Development to assign a county to each zip code before merging it with the unemployment rate data. Figure 6 shows a time series plot of the dispersion of county-level unemployment rates used in our analysis over time. In addition, Appendix Figure D.1 shows that defaults occur across a wide range of unemployment rates in our data, while Appendix Table D.12 shows that most counties experienced meaningful variation in the unemployment rate during our sample period.

two columns of Table 4 and suggest the R^2 is higher during periods of low unemployment when PD is excluded. For comparison, the third and fourth columns predict default using both PD and controls. While the changes are relatively small, including PD in the regression increases the R^2 more during periods of high unemployment (going from 0.264 to 0.267) than during periods of low unemployment (going from 0.311 to 0.312). Taken together, these results suggest that PD becomes a more useful predictor of default during periods of high unemployment, while other firm and loan characteristics collectively become worse at predicting default during periods of high unemployment. These results are consistent with information frictions being more severe in bad times, which results in a lower R^2. In turn, banks invest more in their PD calculations in bad times which leads to a higher marginal impact of PD on the total R^2.

Next, we directly test whether the sensitivity of realized default to PD varies over the business cycle by estimating the following regression:

$$Default_i = \beta_0 PD_i + \beta_1 UR_{c,t} + \beta_2 (PD_i \times UR_{c,t}) + \Omega X_i + \delta_{b,t} + \gamma_{j,t} + \sigma_{b,c} + \epsilon_i. \qquad (2)$$

This regression is similar to Equation (1) with the addition of an interaction term between predicted default and the county-level unemployment rate ($PD_i \times UR_{c,t}$). The coefficient of interest is β_2, which represents the change in the sensitivity of actual to predicted default given a one percentage point increase in the unemployment rate.[10] Our use of bank-by-quarter fixed effects means that our results will not be driven by supply-side factors affecting lending decisions at the bank level, such as changes in a bank's cost of capital or bank-level risk appetite.

The results are displayed in Table 5. The first two columns show the results with and without the inclusion of controls. Across both of these specifications, we find a positive and statistically significant coefficient for β_2, which suggests that banks' PDs are better at predicting default in bad times. Column (1) shows a 1pp increase in the unemployment rate increases the default sensitivity by about 0.5 basis points; this is

[10] Appendix Table D.6 shows very similar results using the lagged, rather than the contemporaneous, unemployment rate.

statistically significant and represents about 46% of the average effect of PD estimated in Section 3.1. Column (2) adds interactions between the employment rate and other firm and loan controls and shows that the estimates become slightly larger in magnitude and remain statistically significant. Columns (3) and (4) add county-quarter fixed effects, which absorb level differences in activity across different counties in each quarter, and show very similar coefficient estimates.

One concern is that, because our measure of PD is ordinal, this relationship could be mechanical if PDs become more dispersed in bad times. Figure A.1 in the Appendix shows that the distributions of PD are fairly stable over time, particularly when we include the fixed effects from our baseline regressions, suggesting this is not a concern. However, our results are also robust to using the level of PD (Appendix Table D.4) and the log of PD (Appendix Table D.5), which are not be subject to this critique.

Overall, these results suggest that increases in unemployment have a statistically and economically significant relationship with improvements in bank information quality. Hence, we conclude that bank information quality is countercyclical.

On its own, our approach cannot tell us whether higher unemployment rates cause banks to have higher information quality. The evidence we provide is consistent with theories predicting that information production is an endogenous response to changes in economic conditions. However, if improvements in bank information quality lead to higher screening, reduced loan volumes, and thus higher unemployment, then our evidence may be misinterpreting the direction of causality. To address this issue, we show in Section C of the Appendix that exogenous shocks to local economic conditions caused by abnormally high snowfall cause both an increase in local unemployment rates and higher information quality. In the next section, we provide further evidence for the mechanisms driving our results.

3.3 Mechanisms

While our empirical results are consistent with banks producing more information about borrowers during downturns, we cannot directly observe banks' information production decisions, only the ultimate quality of their information. Hence, our empirical results could simply be driven by exogenous variation in information quality. We next develop additional tests in order to distinguish between these channels.

First, we compare the cyclicality of bank information quality for newly issued loans to those which were issued in prior quarters. Intuitively, if banks are producing more information about their loans in bad times, we would expect these effects to be largest for newly originated loans, as the marginal value of information falls sharply after the bank's capital has already been committed. As a result, banks will have more incentives to produce information for new loans than for loans which are already outstanding.

To test this hypothesis, we extend our sample to include all observations of each loan, rather than focusing exclusively on the quarter of origination as we have throughout the rest of our analysis. We then estimate a modified version of (2) that includes interactions with $NewLoan$, which is a dummy variable that equals one if the loan is originated in that quarter.

The results are shown in Table 6. First, note that the interaction term between PD and the new loan indicator is negative and statistically significant. This result suggests that PD becomes a better predictor of default after origination, which is not surprising given that the bank likely learns more about the borrower's risk over time. However, the triple interaction term between PD, the new loan indicator, and the unemployment rate is positive and statistically significant across all specifications, which implies that information quality is more sensitive to economic conditions for new loans as compared to loans issued in prior quarters. In addition, PD interacted with the unemployment rate on its own is economically small and not statistically significant in any of the specifications, suggesting there is minimal cyclicality of information quality among previously issued loans. This result provides support for endogenous information production as a driving force behind the cyclicality of information quality we see in the data.

We also plot how both the sensitivity of PD to realized default and its cyclicality evolve over the life of the loan in Figures 4 and 5. We create dummy variables for each year of the age of the loan including including origination (year zero). As seen in Figure

4, the sensitivity of realized default increases over the life of the loan. In contrast, the cyclicality of the sensitivity of realized default, displayed in Figure 5 decreases by over 0.1 in the year after origination and continues to decrease over life of the loan. The fact that bank information quality simultaneously improves and becomes less cyclical over the life of a loan is difficult to reconcile with theories in which information quality is independent of bank screening intensity.

We next test whether banks' information quality is higher among loans for which their incentives to produce information are higher, i.e., loans that are more information sensitive (Dang, Gorton, and Holmström (2012)). Specifically, we first predict that banks will have higher quality information about larger loans. As the size of a loan increases, banks face larger potential losses and thus gain more from learning more about the borrower's type. The cost of producing information, however, should not vary with the loan size.[11] In addition, we expect that banks should produce more information about more highly levered borrowers. Intuitively, the asymmetric information problem becomes exacerbated by increasing the sensitivity of a security's payoff to firm quality e.g., (Heider (2003)).[12] Finally, we also predict that banks will have greater incentives to produce information about smaller firms because the asymmetric information problem is more severe (e.g., Chae (2005)).

These predictions imply particular signs of the interaction coefficients between PD and firm or loan characteristics. For instance, a positive coefficient estimate for the interaction between PD and a characteristic implies that PD does a better job predicting realized default for larger values of that characteristic, or equivalently, banks have more precise information about loans with higher values of that characteristic. We estimate a modified version of Equation (1) once again using only new loans that includes these interactions:

$$Default_i = \beta PD_i + \Omega X_i + \rho \left(X_i \times PD_i \right) + \delta_{b,t} + \gamma_{j,t} + \sigma_{b,c} + \epsilon_i. \tag{3}$$

[11] See Dang, Gorton, and Holmström (2012) and Weitzner (2019).

[12] Moreover, higher leverage means lower recovery values in the event of default, so banks will have a stronger incentive to avoid losses for these types of firms (e.g., Dang, Gorton, and Holmström (2012)).

The results are shown in Table 7. The first row shows the interaction between PD and loan size, the latter of which is measured in standard deviations after taking logs. This coefficient suggests that a one standard deviation increase in the log loan size increases the sensitivity of realized default to PD by 0.005, or about half of the unconditional effect shown in Table 2. The second row displays the interaction between PD and firm size and shows that a one standard deviation decrease in a firm's log assets increases the PD coefficient by approximately 15%.[13] Finally, the third row shows the interaction coefficient between PD and leverage. This coefficient is positive, though it is not statistically significant; however, as we show later, the coefficient is statistically significant in periods of high unemployment. Overall, these results are consistent with banks producing more information about loans in which their incentives to produce information are higher.

For further evidence of the endogenous information production channel, we examine how the sensitivity of information quality to these firm and loan characteristics evolves over the business cycle. Dang, Gorton, and Holmström (2012) show that lenders' incentives to produce information about loans are more sensitive to the size of the loan following negative aggregate shocks. Although, they do not specifically analyze this, a direct implication of their theory is that the relationship between leverage and information production will become stronger in bad times. We test these hypotheses by estimating a modified version of Equation 2 that also includes triple interaction terms between PD, the unemployment rate, and firm/loan characteristics. Following the predictions of Dang, Gorton, and Holmström (2012), we expect the triple interaction coefficients should have the same sign as the interaction coefficients shown in Table 7 as banks respond more strongly to these characteristics in downturns.

The results are shown in Table 8. Consistent with our hypothesis, we find that the triple interaction coefficients for loan size, leverage, and firm size all have the same sign as the interactions with predicted default in Table 7. The coefficients are positive for

[13] The fact the size interaction is negative may be puzzling at first blush because there is likely more public information about larger firms. However, this result can be rationalized if the asymmetric information problem is more severe for smaller firms, which could induce banks to produce more information. For instance, this might occur if the distribution of cash flows across smaller firms has a higher variance than larger firms, increasing the returns to distinguishing between borrowers.

loan size and leverage, suggesting that bank information quality is more sensitive to the business cycle for large loans and loans to highly leveraged companies. The interaction coefficient for firm size is negative, which is consistent with our predictions, though it is not statistically significant.

We also split the sample into periods of high and low unemployment based on whether the local unemployment rate is above its median level and re-estimate Equation 3 in Table 9. The first two columns only interact PD with the unemployment rate, while the third and fourth columns also interact PD with the firm and loan controls. While the interaction coefficient between PD and UR is positive across both high- and low-unemployment samples, it becomes larger and displays greater statistical significance during periods of low unemployment. On the other hand, interactions between the controls and PD are only statistically and economically significant during periods when the local unemployment rate is above its median. Taken together, these results provide support for the theoretical framework of Dang, Gorton, and Holmström (2012), in which the information sensitivity of certain types of loans increases during downturns.

Finally, we expect that the cyclicality of information production will be greater for industries whose cash flows are more sensitive to local economic conditions. We test this by comparing firms in tradeable and nontradeable industries. Because firms in nontradeable industries are restricted to local markets, the same change in local economic conditions should have a larger effect on their likelihood of default, and as a result we would expect banks to produce more information about these firms as local conditions worsen. In Table 10, we test this prediction using regressions that interact PD and the local unemployment rate with dummy variables if the firm is a nontradeable industry.[14] Consistent with our hypothesis, the cyclical sensitivity of PD to default is only statistically significant for nontradable firms.

In the absence of direct evidence of increased banks' increasing their information production in downturns, we cannot entirely rule out the possibility that banks exogenously receive more precise information about their borrowers in bad times, as argued in Becker,

[14]The list of nontradable industries includes utilities, construction, wholesale trade, retail trade, transportation, accommodation, food services, information and communication, and professional services.

Bos, and Roszbach (2020). However, it is difficult for this channel to jointly rationalize that: i) information quality exogenously improves more for new loans versus old loans during downturns, ii) information quality is higher for larger loans, smaller firms and more highly levered firms, iii) the sensitivity of information quality to these characteristics increases in downturns, and iv) this information sensitivity is highest for firms in nontradeable industries. Overall, we believe our results are consistent the framework of Dang, Gorton, and Holmström (2012) and other models in which the endogenous information production decisions of financiers varies over the business cycle and across different types of securities.

3.4 Composition Effects

Thus far we have provided evidence that banks endogenously produce more information when their incentives to do so are greater. However, our results cannot yet speak to whether this has a direct effect on which types of firms ultimately receive credit and the aggregate supply of credit. We next analyze how the business cycle affects the types of loans that are granted credit over the business cycle. We first estimate the following regression across different outcomes variables y_i:

$$y_i = \beta UR_{c,t} + \Omega X_i + \delta_{b,t} + \gamma_{j,t} + \sigma_{b,c} + \epsilon_i. \quad (4)$$

This regression includes the same loan and firm-level characteristics in X_i that we use in our baseline specification, as well as the same set of fixed effects. However, we exclude loan characteristics as controls when we include loan characteristics as dependent variables. The coefficient β describes how the characteristic in question changes over local business cycles.

We first consider the effect of the local unemployment rate on loan characteristics. Tables 11 shows that average loan size, interest rate, loss given default, and maturity do not appear to meaningfully vary with local economic conditions. This suggests that our results are not being driven by changes in the characteristics of loans over the business cycle. Most interestingly, the interest rate on loans does not vary across local business cycles. While the pool of potential borrowers is likely to be riskier in downturns, the pool of loans actually granted does not seem riskier. Consistent with this idea, we show below that loans do not default more often and only have marginally higher PDs when the unemployment rate is high.

The sixth column of Table 11 shows the results of estimating Equation 4 for realized default rates. The coefficient is positive, suggesting that default becomes more likely as the local unemployment rate increases, but the effect is not statistically significant. Finally, we consider the response of PDs to local economic conditions. Here we use the level of the PD rather than the percentile rank. The last column shows that a one percentage point increase in the unemployment rate leads to an estimated increase in PD of about three basis points that is statistically significant at the 10% level. Taken together, these results suggest that the composition and risk profile of borrowers exhibit minimal, if any, variation across local business cycles, suggesting that our results are unlikely to be driven by selection effects in banks' loan portfolios. In the next section, we discuss the implications of our findings for policy makers.

4 Policy Implications

The evidence we provide in this paper suggests that countercyclical information quality is driven by endogenous information production by banks. In this section we consider the implications of this mechanism for policies designed to stimulate bank lending. Many governments and central banks around the world responded to the global financial crisis by implementing monetary or fiscal stimulus measures. These measures included policies explicitly focused on promoting bank lending, such as the U.K.'s Funding for Lending program (see Churm et al. (2012)). Supporting credit markets was also often mentioned as a motivation behind more other policy instruments such as interest rate cuts, liquidity facilities, and asset purchases.[15]

Because economic conditions affect banks' screening efforts, they will also impact the

[15]See https://www.federalreserve.gov/newsevents/speech/bernanke20090113a.htm.

transmission of these policies. As bank screening intensity increases during downturns, some firms which would have been able to receive credit in good times might suddenly find themselves excluded from borrowing. This means the marginal borrowers in recessions and expansions—and thus the ultimate beneficiaries of policies designed to stimulate lending—will be different. In other words, recessions will be periods in which fewer but higher quality firms receive credit. This mirrors the findings of Ates and Saffie (2021), who show that financial factors can explain why fewer firms enter during periods of financial distress, but the firms that do enter are more productive.

More generally, these results can also shed light on the potential underlying mechanisms in research analyzing the state dependent effects of monetary policy. Past work such as Gertler and Gilchrist (1994), Bernanke and Gertler (1995), and Bernanke, Gertler, and Gilchrist (1999) has argued that bank lending is an important transmission channel for monetary policy. Separate and more recent work including Tenreyro and Thwaites (2016) has showed that monetary policy is less effective in recessions. Our results suggest that changes in banks' information production incentives can lead to changes in the number and composition of firms that receive financing following changes in monetary policy, and thus help explain the state dependence observed in the data. This is also consistent the findings of Wieland and Yang (2020), who show that loan retrenchment by bank holding companies during downturns diminishes the efficacy of monetary policy.

5 Conclusion

Information plays a crucial role in banks' lending decisions and in turn macroeconomic outcomes, but it is difficult to analyze empirically. In this paper, we construct a novel measure of bank information quality from confidential regulatory data and analyze its properties. Using county-level variation in unemployment rates, we find that information quality improves as local economic conditions worsen. We argue that these results are consistent with theories of endogenous information production by showing that our results are driven by newly originated loans and more information-sensitive loans. To our knowledge our findings are the first in the empirical banking literature showing that countercyclical bank information quality is driven by endogenous information production. These findings have important implications for policymakers because banks' information production decisions affect the volume of credit available to firms, and thus the efficacy of many policy tools may critically depend on aggregate economic conditions.

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6 Figures

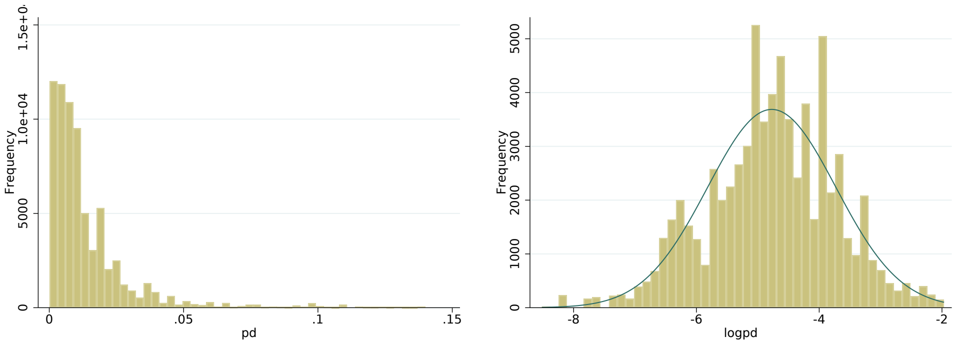

Figure 1: Frequency distributions of PD (left) and log(PD) (right)

This figure shows the frequency distributions of PD (left) and log(PD) (right) at origination for our sample. The sample construction is described in Section 2.

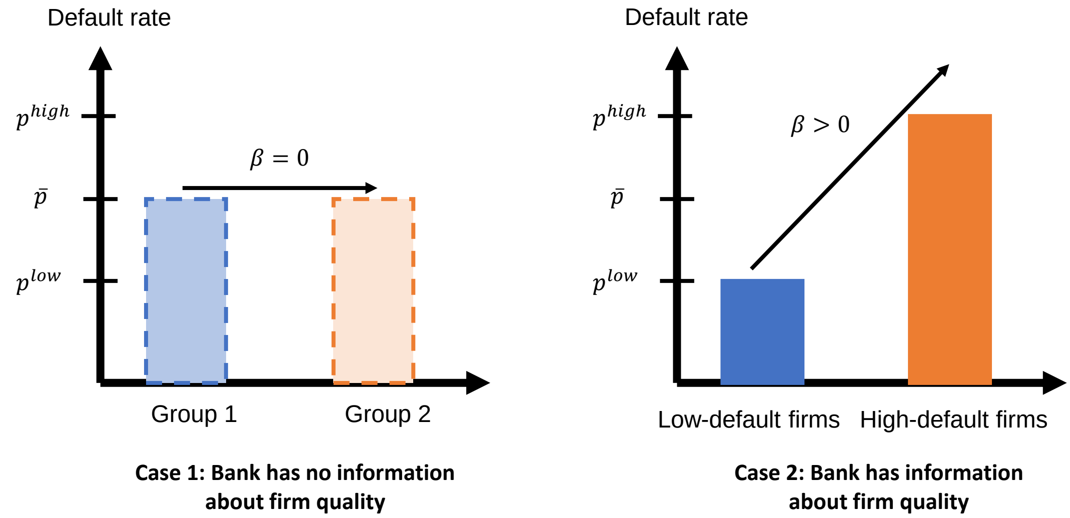

Figure 2: Information Quality

This figure illustrates our empirical approach to measuring information quality. The left panel shows a bank which has no information about firm quality, which means their default rates for each group of firms will simply be the unconditional average default rate $\bar{p}$. The right panel shows a bank with information about firm quality. Because the bank is able to identify which firms have ex-ante higher or lower default rates, the sensitivity of actual to predicted default will be positive.

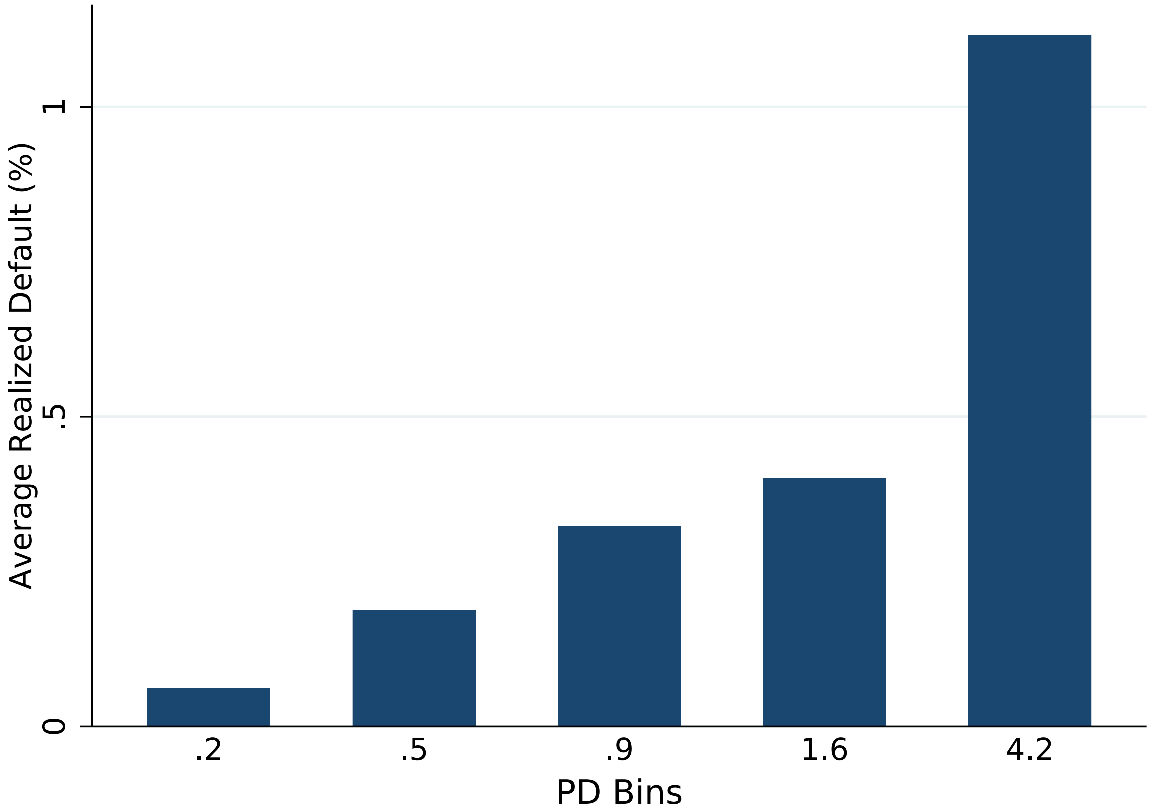

Figure 3: Realized Default Rates Across Risk Quintiles

This figure shows default rates by quintiles of PD. The y-axis shows the realized default rate for each bucket while the numbers on the x-axis underneath each bar correspond to the average value included in the bucket (rounded to the nearest 0.1pp). All variables are measured in percentage points.

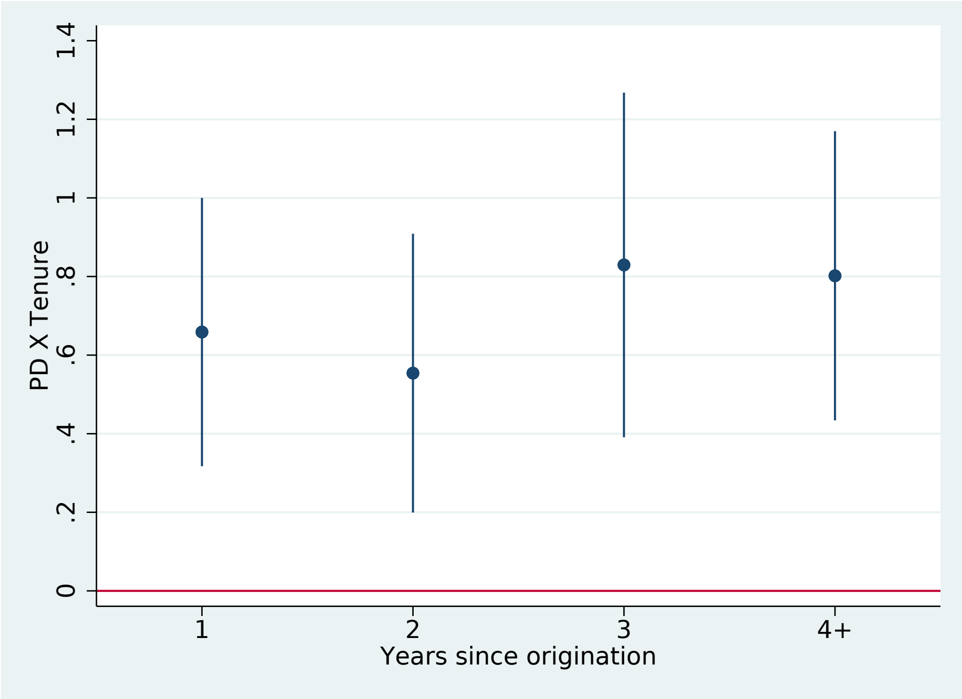

Figure 4: Information quality over the life of a loan

This figure shows estimates of the coefficient on PD x Tenure from a modified version of Equation 2 that includes an additional interaction between PD, UR, and an indicator capturing how long its been since a loan was issued. PD is in levels and multiplied by 100. The dependent variable in each regression is a dummy variable indicating whether each loan defaults within the subsequent eight quarters Coefficient estimates show effects relative to the excluded group, which is comprised of new loans issued in that quarter. Vertical bars represent 95% confidence intervals from standard errors clustered by county.

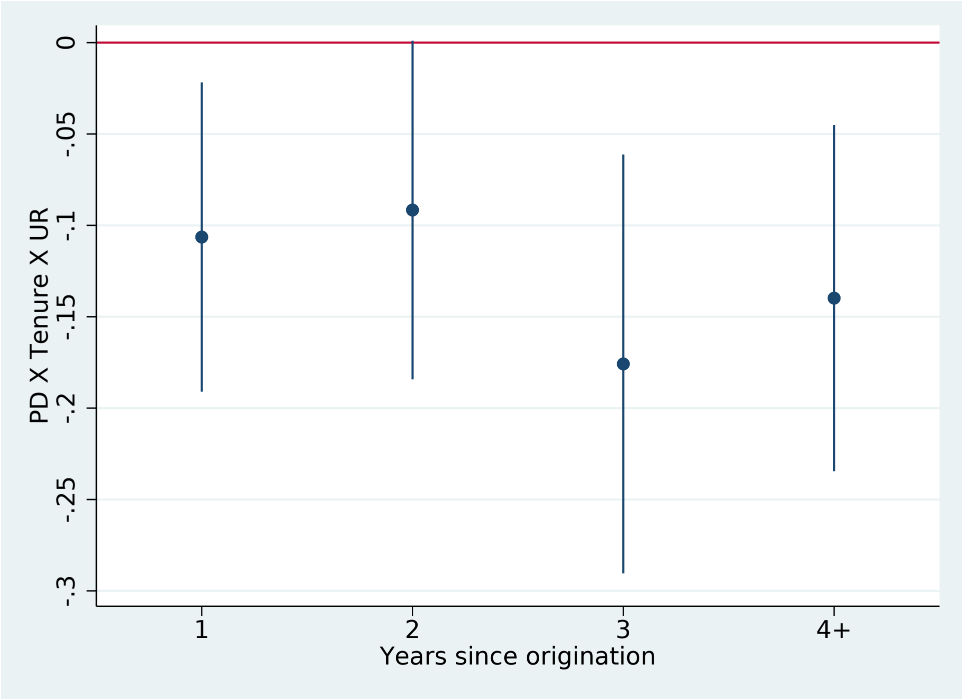

Figure 5: Information sensitivity over the life of a loan

This figure shows estimates of the coefficient on PD x Tenure x UR from a modified version of Equation 2 that includes an additional interaction between PD, UR, and an indicator capturing how long its been since a loan was issued. PD is in levels and multiplied by 100. The dependent variable in each regression is a dummy variable indicating whether each loan defaults within the subsequent eight quarters Coefficient estimates show effects relative to the excluded group, which is comprised of new loans issued in that quarter. Vertical bars represent 95% confidence intervals from standard errors clustered by county.

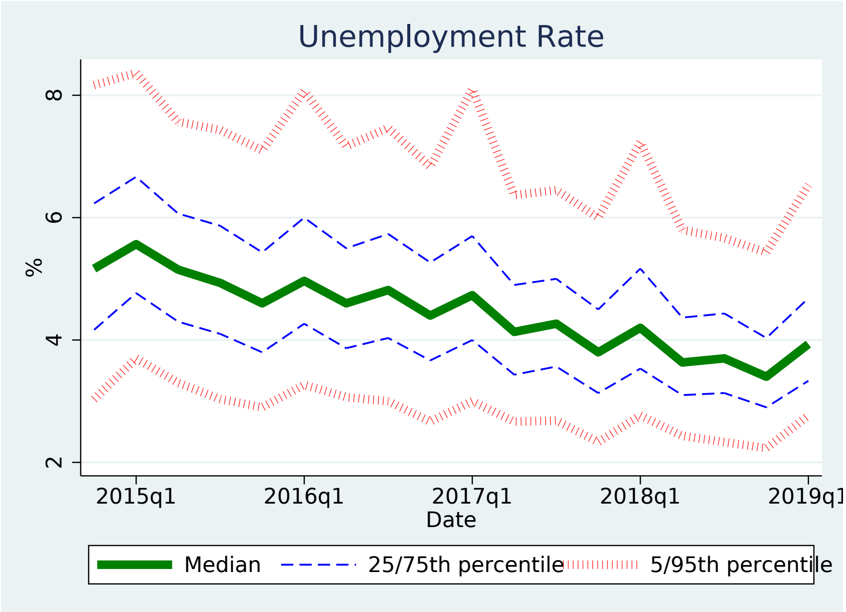

Figure 6: Unemployment rate dispersion over time

This figure displays the range of the county-level unemployment rates in our analysis.

7 Tables

Table 1: Summary Statistics

This table contains summary statistics for our sample. Section 2 describes our sample and Appendix A describes how the variables are constructed.

	Sales ($mm)	Assets ($mm)	Leverage	Maturity (m)	Loan ($mm)	PD (%)
Mean	2,293.0	3,928.3	0.34	47.4	12.9	1.40
Median	76.8	47.2	0.31	58.0	3.5	0.91
5th pct	2.7	1.8	0.00	7.0	1.0	0.15
95th pct	4,234.5	4,771.9	0.80	89.0	50.0	4.41
SD	38,289.7	81,914.7	0.26	30.5	38.7	1.67
N	58,235	58,221	57,111	70,863	70,863	70,863

Table 2: Predicting Realized Default

This table tests whether PD predicts realized default beyond other loan and firm characteristics (Equation 1). The dependent variable in each regression is $Default$, an indicator for whether each loan defaults within eight quarters after origination and then multiplied by 100 so that coefficients are interpreted in percentage points. PD represents the percentile rank within a bank-quarter pair for each PD and takes values in $(0, 100]$. Section 2 describes our sample. Standard errors are clustered at the county level and shown in parentheses.

	(1)	(2)	(3)
PD	0.0105***	0.0121***	0.0144***
	(0.00126)	(0.00201)	(0.00279)
Interest rate spread			0.128**
			(0.0493)
Controls	N	Y	Y
Observations	67,578	52,967	32,175
R^2	0.194	0.214	0.268

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Splits Across Business Cycles Excluding Controls

This table shows the results of estimating Equation 3 across separate samples depending on whether the unemployment rate in the county of issuance was above or below its median value for that county over the sample (2014Q4 through 2019Q1) at the time the loan was issued. The unemployment rate is measured in percentage points. PD represents the percentile rank within a bank-quarter pair for each PD and takes values in $(0, 100]$. Loan and firm sizes are in logs and leverage is a ratio. Appendix A describes how the variables are constructed and Section 2 describes our sample. Standard errors are clustered at the county level and shown in parentheses.

	UR above median	UR below median	UR above median	UR below median
PD	0.0155***	0.00502***	0.0161***	0.00538**
	(0.00192)	(0.00156)	(0.00227)	(0.00192)
FE	N	N	Y	Y
Observations	35,647	34,940	33,069	32,410
R^2	0.004	0.001	0.245	0.264

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Splits Across Business Cycles Including Controls

This table shows the results of estimating Equation 3 across separate samples depending on whether the unemployment rate in the county of issuance was above or below its median value for that county over the sample (2014Q4 through 2019Q1) at the time the loan was issued. The unemployment rate is measured in percentage points. PD represents the percentile rank within a bank-quarter pair for each PD and takes values in $(0, 100]$. Loan and firm sizes are in logs and leverage is a ratio. Appendix A describes how the variables are constructed and Section 2 describes our sample. Standard errors are clustered at the county level and shown in parentheses.

	UR above median	UR below median	UR above median	UR below median
PD			0.0173***	0.00822**
			(0.00275)	(0.00351)
FE	Y	Y	Y	Y
Observations	25,739	25,390	25,739	25,390
R^2	0.264	0.311	0.267	0.312

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Information Quality Over the Business Cycle

This table tests whether the local unemployment rate affects the sensitivity of realized default to PD (Equation 2). The dependent variable in each regression is $Default$, an indicator for whether each loan defaults within eight quarters after origination expressed in percentage points. The unemployment rate is measured in percentage points. PD represents the percentile rank within a bank-quarter pair for each PD and takes values in $(0, 100]$. The "Control interactions" means that interaction terms between the controls and unemployment rate are included in the regression. Appendix A describes how the variables are constructed and Section 2 describes our sample. Standard errors are clustered at the county level and shown in parentheses.

	(1)	(2)	(3)	(4)
PD	-0.011^{***}	-0.062^{**}	-0.007	-0.046
	(0.0042)	(0.0268)	(0.0048)	(0.0319)
UR	-0.176	-0.218		
	(0.160)	(0.176)		
PD × UR	0.0048^{***}	0.0054^{***}	0.0042^{***}	0.0047^{***}
	(0.0010)	(0.0013)	(0.0011)	(0.0015)
Control interactions	N	Y	N	Y
County-quarter FE	N	N	Y	Y
Observations	67,587	52,967	63,414	49,151
R^2	0.194	0.215	0.281	0.328

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Information Quality Over the Business Cycle: New Versus Old Loans

This table tests whether firm and loan characteristics increase the sensitivity of realized default to PD when economic conditions deteriorate. The regression is estimated using a modified version of Equation 2 that also includes triple interaction terms between PD, the unemployment rate, and an indicator representing whether the loan was issued in that quarter. PD is in levels and multiplied by 100. The dependent variable in each regression is a dummy variable indicating whether each loan defaults within the next eight quarters and then multiplied by 100 so that coefficients are interpreted in percentage points. Appendix A describes how the variables are constructed and Section 2 describes our sample. Standard errors are clustered at the county level and shown in parentheses.

	(1)	(2)	(3)	(4)
PD	0.442***	0.436***	0.405***	0.400***
	(0.064)	(0.069)	(0.066)	(0.072)
New loan	0.730***	1.711	0.765***	2.694
	(0.256)	(3.081)	(0.270)	(3.286)
PD × (New loan)	-0.666***	-0.699***	-0.658***	-0.708***
	(0.148)	(0.167)	(0.162)	(0.189)
PD × UR	0.0292	0.0322*	0.0429**	0.0453**
	(0.0181)	(0.0195)	(0.0181)	(0.0197)
PD × (New loan) × UR	0.103***	0.121***	0.0962**	0.117**
	(0.0400)	(0.0443)	(0.0436)	(0.0506)
Control interactions	N	Y	N	Y
County-time FE	N	N	Y	Y
Observations	714,933	608,276	708,434	601,954
R^2	0.379	0.377	0.398	0.397

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Information Quality Across Loan and Firm Characteristics

This table tests whether certain firm and loan characteristics affect the sensitivity of realized default to PD (Equation 3). PD represents the percentile rank within a bank-quarter pair for each PD and takes values in $(0, 100]$. The dependent variable in each regression is a dummy variable indicating whether each loan defaults within eight quarters after origination and then multiplied by 100 so that coefficients are interpreted in percentage points. Firm size and loan size are measured in standard deviations of logs while leverage is a ratio. Appendix A describes how the variables are constructed and Section 2 describes our sample. Standard errors are clustered at the county level and shown in parentheses.

PD × (Loan size)	0.0050***
	(0.0014)
PD × (Firm size)	−0.0016*
	(0.0008)
PD × Leverage	0.0061
	(0.0044)
Observations	52,967
R^2	0.214

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Information Sensitivity of Firm and Loan Characteristics Over the Business Cycle

This table tests whether firm and loan characteristics increase the sensitivity of realized default to PD when economic conditions deteriorate. The regression is estimated using a modified version of Equation 2 that also includes triple interaction terms between PD, the unemployment rate, and firm/loan characteristics. PD represents the percentile rank within a bank-quarter pair for each PD and takes values in $(0, 100]$. The dependent variable in each regression is a dummy variable indicating whether each loan defaults within eight quarters after origination and then multiplied by 100 so that coefficients are interpreted in percentage points. Appendix A describes how the variables are constructed and Section 2 describes our sample. Standard errors are clustered at the county level and shown in parentheses.

PD × UR × (Loan size)	0.0034***
	(0.0011)
PD × UR × (Firm size)	-0.0009
	(0.0010)
PD × UR × Leverage	0.0136**
	(0.0068)
Observations	52,967
R^2	0.216

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Splits Across Business Cycles Using Interactions

This table shows the results of estimating Equation 3 across separate samples depending on whether the unemployment rate in the county of issuance was above or below its median value for that county over the sample (2014Q4 through 2019Q1) at the time the loan was issued. The unemployment rate is measured in percentage points. PD represents the percentile rank within a bank-quarter pair for each PD and takes values in $(0, 100]$. Loan and firm sizes are in logs and leverage is a ratio. Appendix A describes how the variables are constructed and Section 2 describes our sample. Standard errors are clustered at the county level and shown in parentheses.

	UR above median	UR below median	UR above median	UR below median
PD	0.000583	-0.0192*	-0.104**	-0.0581
	(0.00945)	(0.0106)	(0.0423)	(0.0506)
UR	0.167	-0.296	0.164	-0.306
	(0.291)	(0.274)	(0.291)	(0.274)
PD × UR	0.00341*	0.00712**	0.00347*	0.00733**
	(0.00199)	(0.00323)	(0.00196)	(0.00324)
PD × (Loan size)			0.00958***	0.00149
			(0.00235)	(0.00241)
PD × (Firm size)			-0.00232*	0.000548
			(0.00137)	(0.000767)
PD × Leverage			0.0165**	-0.00696
			(0.00794)	(0.00532)
Control interactions	N	N	Y	Y
Observations	25,739	25,390	25,739	25,390
R^2	0.267	0.313	0.269	0.313

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Information quality and tradability

This table estimates triple interaction terms between PD, the unemployment rate, and indicators representing whether the loans are made to firms in nontradable industries. Industry classification is based on two-digit NAICS codes; nontradables include firms in utilities, construction, wholesale trade, retail trade, transportation, accommodation, food services, information and communication, and professional services (NAICS codes 22-23, 42, 44-45, 48-49, 51, 54, and 72). The dependent variable in each regression is an indicator for whether each loan defaults within eight quarters and then multiplied by 100 so that coefficients are interpreted in percentage points. PD represents the percentile rank within a bank-quarter pair for reach PD and takes values in (0,100]. Standard errors are clustered at the county level and shown in parentheses.

PD	-0.0952*
	(0.0500)
UR	-0.0698
	(0.205)
PD × UR	0.0015
	(0.0020)
PD × Nontradable	0.0546
	(0.0565)
PD × UR × Nontradable	0.0069**
	(0.0034)
Observations	52,967
R^2	0.216

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Loan Characteristics Over the Business Cycle

This table shows the estimated effect of the unemployment rate on loan characteristics. The dependent variable in each regression is shown at the top of each column. Loan size is measured in logs. The unemployment rate and interest rate are measured in percentage points. Maturity is measured in log months. All regressions control for the firm characteristics we use in our baseline results. Appendix A describes how the variables are constructed and Section 2 describes our sample. Standard errors are clustered at the county level and shown in parentheses.

	Loan size	Interest rate	Spread	Maturity	Default	PD
UR	-0.00999	0.000278	-0.000136	0.0122	0.0713	0.0320*
	(0.0120)	(0.000177)	(0.000185)	(0.0111)	(0.183)	(0.0182)
Observations	54,239	54,242	43,088	54,227	52,967	52,967
R^2	0.551	0.629	0.586	0.424	0.212	0.365

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix A. Data Description

A.1. Probability of Default Estimates

This section describes in more detail the probability of default (PD) estimates that we use in our analysis. The primary purposes of these estimates are stress testing and capital risk weight calculations. According to the Basel Committee on Banking Supervision, internal estimates of PD "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)." This instruction suggests that banks must report their best estimates of PD based on any information they have. Moreover, the instructions also state "PD estimates must be a long-run average of one-year default rates for borrowers in the grade'.[16]

Banks have strong incentives to ensure that these estimates are accurate. Consistently underestimating default rates will attract regulatory scrutiny and can lead to additional restrictions on banks' activities.[17] Following supervisory exams, for example, a bank's models can be flagged by regulators as falling under Matters Requiring Attention (MRAs) or Matters Requiring Immediate Attention (MRIAs). While not as severe as other enforecment penalties, if left unresolved they can escalate into more severe penalties. Inadequate models can also be used by regulators as justification to force banks to recognize (or provision for) additional losses, which can lead to embarrassment and financial losses for the bank. Regulators can also prevent the banks which are unable to accurately model their losses from paying dividends.

Evaluating these estimates is complicated by the fact they are driven in part by other factors that may affect all other loans at the bank, county, or time level. For example, some counties might contain more small firms throughout our sample period; some banks may systematically focus on lending to less risky borrowers; and a nationwide recession means that all defaults may be higher in some quarters. These factors will all affect the average *level* of defaults for a county, bank, or quarter, respectively, without necessarily affecting the *relative* risk between loans within each of these groups. Given this issue, the models producing these default forecasts are often evaluated by both banks and regulators in relative (rather than absolute) terms. This aligns closely with our empirical approach where we use a rich set of fixed effects, which tells us *given the same loan, borrower and lender characteristics* whether loans that have higher PDs are more likely to default. Our approach will thus be unaffected by systematic misestimation of the *level* of the default

[16] In our main analysis we include a default horizon of two years to capture as many defaults as possible. Our results are robust to alternative default horizons and definitions.

[17] For more details regarding the regulatory approach to model evaluation, see the Federal Reserve Board's Bank Holding Company Supervision Manual (https://www.federalreserve.gov/publications/files/bhc.pdf) and the Basel II framework (https://www.govinfo.gov/content/pkg/FR-2007-12-07/pdf/07-5729.pdf).

rate.

Figure A.1 shows the dispersion of both PD and log(PD) over time in our sample. The left panel shows that the median values are quite stable. This is consistent with the instructions given to banks that ask for "through-the-cycle" estimates that ask for default forecasts averaged across a range of potential future business cycle conditions. This interpretation is supported by Ma, Paligorova, and Peydro (2021), who show that banks with more pessimistic forecasts of economic conditions do not necessarily have higher PDs. The rightmost columns show residuals from regressing each measure on the set of fixed effects used in our main specification. This suggests that our empirical approach, which we describe in the next section, is driven by cross-sectional variation in the ability of PD to predict default.

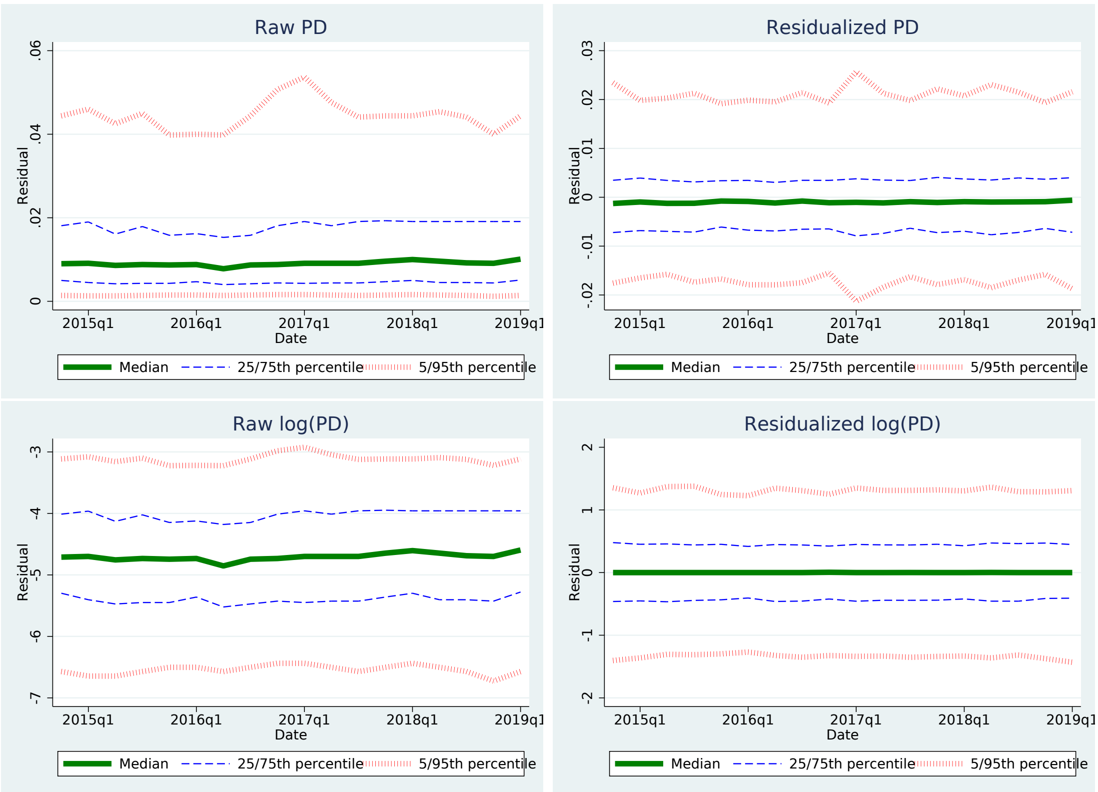

Figure A.1: PD dispersion over time

This figure shows the ranges of PD over our sample. The top row uses the standard PD, while the bottom row uses log(PD). The left column shows the raw series, while the right column shows the residuals after regressing each PD measure on bank-time, county-time, bank-county, industry-time, and loan type fixed effects.

A.2. Variable Definitions

Firm Size: log(assets) trimmed at the 99th percentile, from Y-14Q.

Total Debt: The sum of long-term debt and short-term debt, from Y-14Q.

Leverage: total debt/total assets measured in percentage points, winsorized at [1%, 99%], from Y-14Q.

Tangibility: tangible assets/total assets, winsorized at [1%, 99%], from Y-14Q.

Profitability: EBITDA/assets measured in percentage points, winsorized at [1%, 99%], from Y-14Q.

Collateral: Dummy variable that equals one if the loan is collateralized, from Y-14Q.

Interest Rate: Loan interest rate measured in percentage points, trimmed at [0,1), from Y-14Q.

Credit Spread:

Maturity: Log of loan maturity in months, from Y-14Q.

Default: Dummy variable that equals one if the firm defaults within the first 8 quarters following the origination of the loan multiplied by 100, from Y-14Q.

PD: The bank's expected annual average default rate over the life of the loan, trimmed if equals zero or above the 99th percentile from Y-14Q. Throughout the majroity of the paper, our default measure of PD is obtained by calculating the percentile rank within a bank-quarter pair for each PD so that it takes values in $(0, 100]$, unless we explicitly state we are using the level. In the Appendix, we also consider alternative measures of PD, including in levels and logs.

LGD: The log of the bank's estimated loss given default in percentage points, from Y-14Q.

NewLoan: Dummy variable that equals one if the loan is newly originated in the quarter, from Y-14Q.

UR: The county-level quarterly unemployment rate in percentage points from BLS.

Appendix B. Evaluating Information Quality

This section describes our approach to evaluating bank information quality in more detail. Our measure is based on the idea that after controlling for observables, the predicted probability of default (PD) will have higher correlation with realized default for banks with better information. We provide some theoretical intuition for this approach and show that it can be calculated empirically as the coefficient on PD in regressions with default as the dependent variable. Higher coefficients on PD in these regressions imply a greater sensitivity of realized default to predicted default and thus more precise information.

To provide a more general illustration of this concept, consider a simple model of forecasters trying to predict the likelihood that a loan will default. The default probability p is drawn from a known distribution $F(p)$. Forecasters do not observe p, but instead receive a signal $s = p + \epsilon$, where ϵ is a conditionally independent noise term with mean zero and variance σ^2. Default probability forecasts will be weighted averages of the signal and the unconditional default probability: $\hat{p} = \alpha s + (1-\alpha)\bar{p}$, where α is the weight banks place on their signal. The optimal weight α^* will be decreasing in σ^2. If $\sigma^2 = 0$, the optimal forecast will be the signal realization, so $\hat{p} = s = p$. In the extreme case in which σ^2 is infinite, the signal s_i provides no information and the optimal forecast is simply the unconditional average $\bar{p}$.

These weights can be estimated empirically using a linear regression of default on PD. Figure B.1 shows this approach graphically using simulated data for three different signal qualities. The left panel shows a high-precision signal, the middle panel shows a low-precision signal, and the right panel shows a signal that has zero correlation with p. The vertical axes correspond to bins of realized default probabilities, with the red dotted line representing the unconditional average default rate, while the horizontal axes correspond to bins of predicted default probabilities. For example, the point (0.20,0.25) would mean that the set of all loans classified by forecasters as having a default probability of 20% actually defaulted 25% of the time.

The slope of the solid black regression line through these points represents the sensitivity of realized default to predicted default. This line can be thought of as the optimal default forecast as a function of PD. A steeper slope means that predicted and realized default will have a stronger correlation, and therefore that more weight should be put on PD. When the variance of the noise surrounding the signal is low as in the left panel, the information contained in PD will be more precise and the regression line will be steeper. In this case, a 1 percentage point increase in predicted default corresponds to an increase of around 0.74 percentage points in realized default.

As the variance of the noise term increases, the signal becomes less precise and the estimated coefficient attenuates. This can be seen in the middle panel, where a noisier signal leads to a flatter slope and the same 1 percentage point increase in predicted default leads to an increase of just 0.26 percentage points in realized default. Finally, in the extreme case in which the signal provides no useful information, the sensitivity of realized default to predicted default will be zero and the optimal forecast of default probability will simply correspond to the unconditional average default rate regardless of the signal's realization. Together, these images provide graphical intuition for why larger regression coefficients on PD correspond to more precise information.

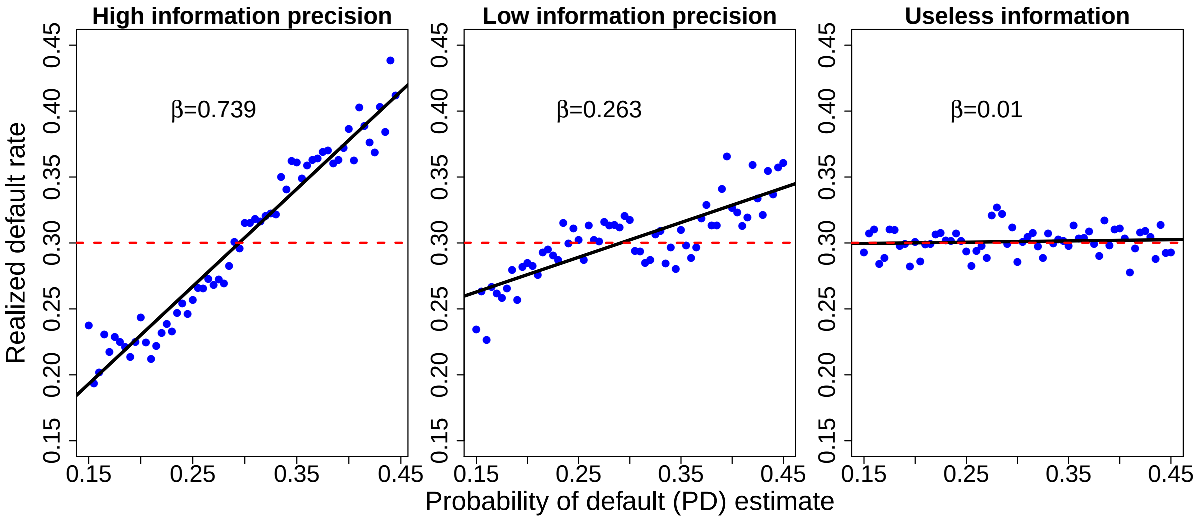

Figure B.1: Simulated Information Quality

This simple illustration is most easily interpreted as a single bank making a large number of loans to a fixed distribution of borrowers. In practice, heterogeneity across firms, banks, and economic conditions can lead to differences across these groups that can complicate the process of estimating the relationship between expected and realized defaults. This could occur, for example, if one bank consistently over-estimated its default probabilities. In that case, a naive approach which pooled all observations together would not accurately estimate the correct sensitivity between predicted and realized default.

This can be seen graphically in Figure B.2. The left panel shows a similar exercise to the one shown in Figure B.1, but for two banks. Bank 1 (shown as the orange circles) has estimates which are on average equal to the true underlying default rate. Bank two (shown as the purple squares) has default estimates which are consistently too conservative. Despite this bias in the *level* of its default estimates, the sensitivity of realized default to predicted default is still positive for Bank 2. Both banks have the same signal variance, so in the limit the estimates of β should both be equal to one. When the elasticities are estimated separately for each bank, the estimates are similar to those of the high-information case shown previously ($\beta^1 = 0.63$ and $\beta^2 = 0.75$).

When all of the estimates are pooled, however, the coefficient attenuates to $\beta = 0.22$. This is shown in the middle panel and occurs because many of the predicted default rates with the same level correspond to different portions of the distribution of each bank's estimates: a PD of 0.4 is on the low end of what Bank 2 forecasts, but on the high end of what Bank 1 forecasts. Not accounting for this leads to a deterioration in the relationship between predicted and realized default and lowers the coefficient estimate relative to the true marginal effect.

The use of fixed effects allow accurate estimation of the average sensitivity of actual to predicted default in the presence of this type of persistent heterogeneity. An illustration of this approach is shown in the right panel of Figure B.2. In this figure both the dependent and independent variables are de-meaned within each bank, so that positive values of the x-axis correspond to above-average predicted default rates. Using this approach, the estimated sensitivity is the average of the elasticities obtained from the separate approach in the left panel and confirms that bank default forecasts are useful for predicting realized default. This approach is equivalent to evaluating banks' PD forecasts on a relative (rather than absolute) basis.[18]

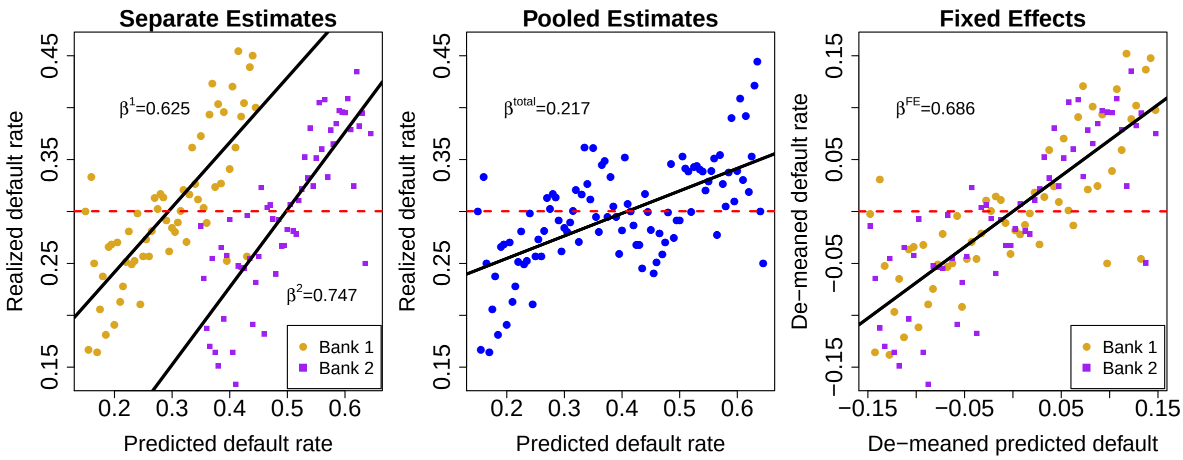

Figure B.2: Simulated Information Quality with Bank Heterogeneity

In summary, the sensitivity of realized default to PD is a useful measure of the underlying quality of bank information, and the use of fixed effects for different groups of loans allows us to estimate changes in information quality even in the presence of persistent biases in the *level* of default forecasts.

[18] As discussed in Appendix A.1, this approach is consistent with how regulators evaluate banks' risk models.

Appendix C. Abnormal Snowfall and Information Quality

In this section, we exploit abnormal snowfall as an exogenous shock to economic conditions in order to address potential concerns that our results are capturing reverse causality between the business cycle and information quality. To construct the abnormal snow series, we follow the approach of Brown, Gustafson, and Ivanov (2021). We first obtain data on daily snow cover from the National Oceanic and Atmospheric Administration website and calculate the average value of snow cover across weather stations for each day and county pair. Next, we calculate the average snow cover in each county-quarter from 2000-2020. We create a rolling 10-year average snowfall cover measure for each county-quarter and create a variable *AbnormalSnow* which is the difference between the current county-quarter average snowfall and the trailing 10-year average.[19] To minimize the impact of extreme outliers, we winsorize the top and bottom 1% of observations across the entire sample period. For these tests, we only use data in the first and fourth quarter of the calendar year because there is rarely any snowfall outside of these periods.

We begin by showing that excess snowfall leads to an increase in a county's unemployment rate. To do so we estimate the following regression at the county-quarter level:

$$UR_{c,t} = \beta AbormalSnow_{c,t} + \alpha_c + \delta_t + \epsilon_{c,t}, \tag{5}$$

where α_c are county fixed effects and δ_t are quarter fixed effects. The results are displayed in Table C.1, with and without county fixed-effects. For instance, without county fixed effects an additional inch of snow leads to a statistically significant 0.005pp increase in that county's unemployment rate. The standard deviation of *AbnormalSnow* is 3.1 inches and the average unemployment rate of 4.8%. Hence, a one standard deviation increase in abnormal snowfall leads to a 32bp increase in the unemployment rate. This result is consistent with the main findings in Brown, Gustafson, and Ivanov (2021), who show that abnormal snowfall leads to decreases in firms' cash flows.

After establishing that abnormal snowfall leads to increases in unemployment, we estimate a modified version of Equation (2) where the unemployment rate is replaced with this measure of abnormal snowfall.[20] These results are shown in Table C.2. We estimate that an additional inch of abnormal snow increases the sensitivity of realized to predicted default by 0.18bp. This measure is both statistically and economically significant; as an additional inch of abnormal snow increases the sensitivity of realized default to PD by approximately 15% of the unconditional estimate shown in Table 2. This is consistent with our unemployment results in the main text and suggests that the direction of

[19] The trailing average only considers snowfall in the calendar quarter of interest, so in Q1 of each year snowfall is compared to the average over the previous ten Q1s.

[20] One might consider a two-stage least squares specification given that abnormal snow is likely exogenous; however, we do not because it is unlikely abnormal snow only affects information quality through the unemployment rate.

causality for our main findings flows from changes in economic conditions to changes in information quality.

Table C.1: The Effect of Abnormal Snowfall on Unemployment

This table tests whether abnormal snowfall leads to higher local unemployment rates. The The construction of *AbnormalSnow* is described in Section C. Standard errors are clustered at the county level and shown in parentheses.

	ΔUR	UR
AbnormalSnow	0.0047**	0.013***
	(0.0019)	(0.0021)
Quarter FE	Y	Y
County FE	N	Y
Observations	30,957	30,939
R^2	0.535	0.885

Table C.2: The Effect of Abnormal Snowfall on Information Quality

This table tests whether abnormal snowfall affects the sensitivity of realized default to PD. The estimated regression is a modified version of Equation 2 in which the unemployment rate is replaced with *AbnormalSnow* which is measured in inches. The dependent variable is a dummy indicating whether each loan defaults within eight quarters after origination expressed in percentage points. PD represents the percentile rank within a bank-quarter pair for each PD and takes values in $(0, 100]$. Standard errors clustered by county are shown in parentheses.

PD	-0.0840^{*}
	(0.0477)
AbnormalSnow	-0.0896^{***}
	(0.0378)
PD × AbnormalSnow	0.00155^{*}
	(0.000799)
Observations	27,370
R^2	0.242

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix D. Extensions and Robustness Checks

Table D.1: Predicting Default: PD Level

This table shows the results of estimating Equation 1. The dependent variable in each regression is a dummy variable indicating whether each loan defaults within eight quarters after origination and then multiplied by 100 so that coefficients are interpreted in percentage points. Interest rates and interest rate spreads are measured in percentage points. PD is reported in levels and is in percentage points. Section 2 describes the sample construction. Standard errors are clustered at the county level and shown in parentheses.

	(1)	(2)	(3)	(4)
PD	0.245***	0.307***	0.309***	0.379***
	(0.0402)	(0.0616)	(0.0683)	(0.0838)
Interest rate			0.083*	
			(0.0429)	
Interest rate spread				0.127***
				(0.0448)
Controls	N	Y	Y	Y
Observations	67,578	52,967	42,407	32,175
R^2	0.195	0.215	0.254	0.270

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.2: Predicting Default: Log(PD)

This table shows the results of estimating Equation 1. The dependent variable in each regression is a dummy variable indicating whether each loan defaults within eight quarters after origination and then multiplied by 100 so that coefficients are interpreted in percentage points. PD is reported in logs and multiplied by 100. Interest rates and interest rate spreads are measured in percentage points. Appendix A describes how the variables are constructed and Section 2 describes our sample. Standard errors are clustered at the county level and shown in parentheses.

	(1)	(2)	(3)	(4)
log(PD)	0.319***	0.387***	0.401***	0.496***
	(0.0393)	(0.0650)	(0.0734)	(0.0960)
Interest rate			0.0898**	
			(0.0432)	
Interest rate spread				0.129***
				(0.0445)
Controls	N	Y	Y	Y
Observations	67,578	52,967	42,407	32,175
R^2	0.194	0.214	0.253	0.268

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.3: Alternate Loan Performance Measures

This table shows the results of estimating Equation 1 with alternative measures of loan performance. The dependent variable in each regression is a dummy variable corresponding to the column heading and then multiplied by 100 so that coefficients are interpreted in percentage points. "Any Default" measures whether a loan is recorded as defaulting at any point in our sample period. "Average Default" divides the "Any Default" measure by the number of years in which the loan is observed to generate an annual average; if a loan defaults within one quarter after origination, this variable will take on a value of 2, while if the loan defaults eight quarters after origination, this variable will take on a value of 0.5. "1Y Default" is an indicator for whether the loan defaults within four quarters of origination. "Delinquency" is an indicator for whether the loan is reported as delinquent within eight quarters after origination. "Chargeoff" is an indicator representing whether a bank records a chargeoff for that loan within eight quarters after origination. PD represents the percentile rank within a bank-quarter pair for each PD and takes values in $(0, 100]$. Standard errors are clustered at the county level and shown in parentheses.

	Any Default	Average Default	1Y Default	Delinquency	Chargeoff
PD	0.0186***	0.0115***	0.00336***	0.00653***	0.00317***
	(0.00290)	(0.00186)	(0.000891)	(0.00125)	(0.000917)
Observations	52,967	52,967	52,967	52,967	52,967
R^2	0.222	0.239	0.214	0.146	0.194

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.4: Information Quality over the Business Cycle: PD Level

This table shows coefficient estimates from Equation 2 with and without interactions between PD and the firm- and loan-level controls. The dependent variable in each regression is a dummy variable indicating whether each loan defaults within eight quarters after origination expressed in percentage points. The unemployment rate is measured in percent. log(PD) is measured measured in standard deviations calculated across our entire sample. Appendix A describes how the variables are constructed and Section 2 describes our sample. Standard errors are clustered at the county level and shown in parentheses.

	(1)	(2)	(3)	(4)
PD	-0.112	-1.464*	-0.0961	-1.035
	(0.121)	(0.792)	(0.138)	(0.848)
UR	-0.0401	-0.0644		
	(0.172)	(0.189)		
PD × UR	0.0799***	0.0931***	0.0782**	0.0752*
	(0.0277)	(0.0352)	(0.0312)	(0.0394)
Control interactions	N	Y	N	Y
County-quarter FE	N	N	Y	Y
Observations	67,578	52,967	63,414	49,151
R^2	0.195	0.217	0.282	0.330

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.5: Information Quality over the Business Cycle: Log(PD)

This table shows coefficient estimates from Equation 2 with and without interactions between PD and the firm- and loan-level controls. The dependent variable in each regression is a dummy variable indicating whether each loan defaults within eight quarters after origination expressed in percentage points. The unemployment rate is measured in percent. log(PD) is measured measured in standard deviations calculated across our entire sample. Appendix A describes how the variables are constructed and Section 2 describes our sample. Standard errors are clustered at the county level and shown in parentheses.

	(1)	(2)	(3)	(4)
log(PD)	-0.00259^{**}	-0.0163^{**}	-0.00187	-0.0125
	(0.00124)	(0.00773)	(0.00143)	(0.00903)
UR	0.695^{***}	0.813^{***}		
	(0.239)	(0.293)		
log(PD) × UR	0.00131^{***}	0.00158^{***}	0.00119^{***}	0.00134^{***}
	(0.000282)	(0.000364)	(0.000328)	(0.000424)
Control interactions	N	Y	N	Y
County-quarter FE	N	N	Y	Y
Observations	67,578	52,967	63,414	49,151
R^2	0.194	0.215	0.281	0.328

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.6: Information Quality over the Business Cycle Using Lagged Unemployment Rate

This table shows coefficient estimates from a modified version of Equation 2 that uses the unemployment rate lagged by one quarter with and without interactions between PD and the firm- and loan-level controls. The dependent variable in each regression is a dummy variable indicating whether each loan defaults within eight quarters after origination expressed in percentage points. UR_{t-1} corresponds to the previous quarter's unemployment rate and is measured in percent. PD represents the percentile rank within a bank-quarter pair for each PD and takes values in $(0, 100]$. Appendix A describes how the variables are constructed and Section 2 describes our sample. Standard errors are clustered at the county level and shown in parentheses.

	(1)	(2)	(3)	(4)
PD	-0.00715**	-0.0570**	-0.00427	-0.0424
	(0.00364)	(0.0269)	(0.00425)	(0.0320)
UR_{t-1}	-0.135	-0.122		
	(0.150)	(0.169)		
PD $\times \text{UR}_{t-1}$	0.00388***	0.00425***	0.00340***	0.00392***
	(0.000845)	(0.00111)	(0.000991)	(0.00133)
Control interactions	N	Y	N	Y
County-quarter FE	N	N	Y	Y
Observations	67,578	52,967	63,414	49,151
R^2	0.194	0.215	0.281	0.328

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.7: Number and Volume of New Loans Over the Business Cycle

This table shows how county-level lending patterns evolve over the business cycle. All regressions include the county-level unemployment rate (UR) and county fixed effects, and columns (2), (4), and (6) additionally include the US aggregate unemployment rate. Columns Columns (1) and (2) show the response of the log total number of new loans at the county level (in log points), columns (3) and (4) show the log total volume of new loans at the county level (in log points), and columns (5) and (6) show the response of the standard deviation of PD for new loans at the county level (in percentage points). Standard errors are clustered at the county level and shown in parentheses.

	Loan count		Loan volume		PD Dispersion	
	(1)	(2)	(3)	(4)	(5)	(6)
UR	-0.012*	-0.027***	-0.042***	-0.058***	0.039*	0.014
	(0.0065)	(0.0088)	(0.0144)	(0.0201)	(0.0207)	(0.0279)
Aggregate UR		0.032***		0.034		0.042
		(0.0118)		(0.0273)		(0.0327)
Observations	11,845	11,845	11,845	11,845	7,044	7,044
R^2	0.773	0.773	0.615	0.615	0.220	0.220

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.8: County Loan Count Over the Business Cycle

This table estimates triple interaction terms between PD, a new loan indicator, and firm/loan characteristics. In contrast to our main results, which focus on origination, these results use all observations. The dependent variable in each regression is an indicator for whether each loan defaults within eight quarters and then multiplied by 100 so that coefficients are interpreted in percentage points. PD here is reported in levels multiplied by 100 so that it takes values in $(0, 100]$. We use levels instead of percentiles in this exercise because a loan's percentile rank can change even if the PD remains constant. The Appendix describes the sample construction and reports all variable definitions. Standard errors are clustered at the county level and shown in parentheses.

PD × (New loan) × (Loan size)	-0.059
	(0.046)
PD × (New loan) × (Firm size)	-0.048**
	(0.022)
PD × (New loan) × Leverage	0.480*
	(0.267)
Observations	608,281
R^2	0.381

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

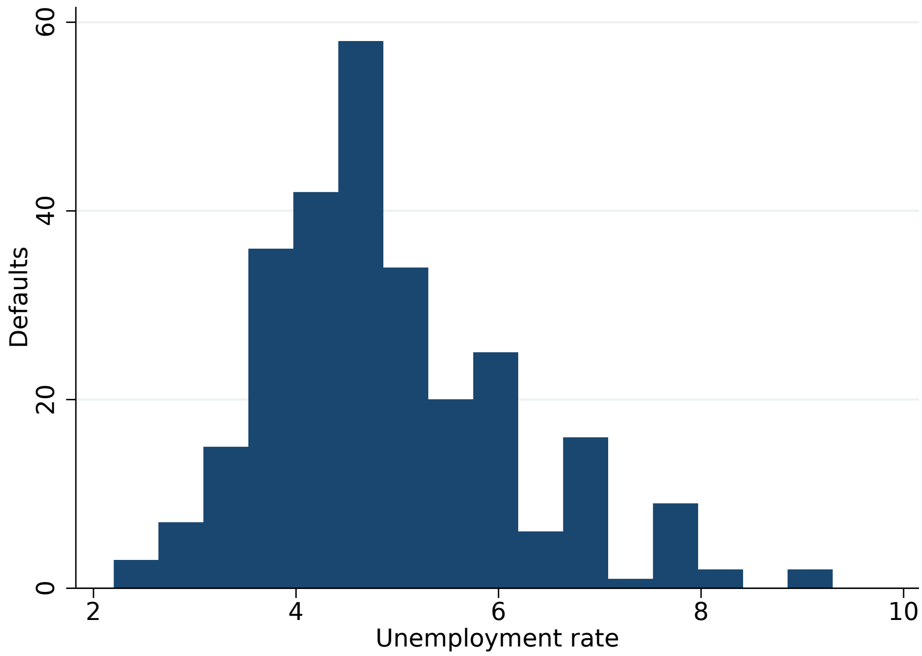

Figure D.1: Default frequency across unemployment rates

This figure shows the frequency distribution of defaults within two years of origination in our sample based on the county-level unemployment rate at origination. For readability, the figure excludes a single default for a loan issued in a county with an unemployment rate of more than 15%.

Table D.9: Information quality excluding oil and gas firms

This table shows estimates from Equation 2 that exclude all loans to companies in mining, quarrying, and oil and gas extraction (NAICS sector 21). The dependent variable in each regression is an indicator for whether each loan defaults within eight quarters and then multiplied by 100 so that coefficients are interpreted in percentage points. PD represents the percentile rank within a bank-quarter pair for reach PD and takes values in (0,100]. Standard errors are clustered at the county level and shown in parentheses.

	(1)	(2)
PD	-0.010***	-0.016
	(0.0036)	(0.0211)
UR	-0.245**	-0.255**
	(0.106)	(0.107)
PD × UR	0.0043***	0.00486***
	(0.00087)	(0.0011)
Control interactions	N	Y
Observations	65,287	51,422
R^2	0.188	0.206

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.10: Information quality excluding high-PD loans

This table shows estimates from Equation 2 that exclude all loans with PDs above the 90th percentile in a given bank-quarter. The dependent variable in each regression is an indicator for whether each loan defaults within eight quarters and then multiplied by 100 so that coefficients are interpreted in percentage points. PD represents the percentile rank within a bank-quarter pair for reach PD and takes values in (0,100]. Standard errors are clustered at the county level and shown in parentheses.

	(1) Baseline	(2) Control Interactions
PD	-0.0119**	-0.0541**
	(0.00560)	(0.0248)
UR	-0.196	-0.186
	(0.167)	(0.177)
PD × UR	0.00452***	0.00450***
	(0.00137)	(0.00169)
Control interactions	N	Y
Observations	60,887	48,000
R^2	0.189	0.207

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.11: Information quality excluding syndicated loans

This table shows estimates from Equation 2 that exclude all syndicated loans. The dependent variable in each regression is an indicator for whether each loan defaults within eight quarters and then multiplied by 100 so that coefficients are interpreted in percentage points. PD represents the percentile rank within a bank-quarter pair for reach PD and takes values in (0,100]. Standard errors are clustered at the county level and shown in parentheses.

	(1)	(2)
PD	-0.00984**	-0.0241
	(0.00430)	(0.0321)
UR	-0.252**	-0.252*
	(0.127)	(0.129)
PD × UR	0.00364***	0.00371***
	(0.00100)	(0.00133)
Control interactions	N	Y
Observations	45,053	34,507
R^2	0.214	0.236

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.12: Unemployment variation within counties

This table shows measures of variation in the unemployment rate within counties over our sample period (2014Q4 through 2019Q1). Columns under the "Range" heading show the difference between the highest and lowest unemployment rates observed within each county. Columns under the "Standard deviation" heading show the standard deviation for the unemployment rate within each county. Results are split based on how many observations of the unemployment rate each county had during the sample period: the "$\geq 2/4$" columns show results for all counties that had at least two/four observations of the unemployment rate, respectively, while the "All" column restricts the results to only counties which have observed unemployment rates in every quarter throughout the sample. The last row shows the number of counties used in each calculation.

	Range			**Standard deviation**		
County-quarters observed	≥ 2	≥ 4	All	≥ 2	≥ 4	All
5th percentile	0.37	0.83	1.13	0.19	0.27	0.29
25th percentile	1.17	1.50	1.70	0.44	0.48	0.46
Median	1.87	2.07	2.25	0.66	0.67	0.6
Mean	1.97	2.20	2.26	0.74	0.72	0.63
75th percentile	2.53	2.67	2.80	0.90	0.87	0.78
95th percentile	5.93	3.90	3.47	1.51	1.32	0.99
Number of counties	1,417	1,035	186	1,417	1,035	186

Appendix E. Simple Theoretical Framework

In this section we present a simple model that highlights how the business cycle can affect bank information production incentives.

There is a single borrower seeking funds from a bank at $t = 0$ for a project that pays off at $t = 1$. The borrower and bank are risk neutral and there is no discounting. There are two types of borrowers $\theta \in \{G, B\}$ (Good, Bad) where θ is initially unknown to all and the prior probability of the borrower being good is λ.[21] The borrower has an investment opportunity that requires an initial investment of I at $t = 0$ and yields a cash flow at $t = 1$ of $R > I$ with probability π_θ and 0 otherwise where $\pi_G > \pi_B$. Although the borrower's type θ is initially unknown, the bank can pay a cost $c > 0$ to learn θ before committing funds at $t = 0$. The borrower offers the bank a loan contract that raises I at $t = 0$ and promises to repay D at $t = 1$. To simplify the analysis, we take the terms of the contract, i.e., D, as given.[22]

We assume the average project is NPV positive, i.e., $(\lambda\pi_G + (1-\lambda)\pi_B)R > I$, while the bad project is NPV negative, i.e., $\pi_B R < I$. Moreoever, we make the following assumptions so that the bank's participation constraint always holds

$$\lambda\pi_G D + (1-\lambda)\pi_B D - I \geq 0 \tag{6}$$

$$\lambda(\pi_G D - I) \geq c \tag{7}$$

The bank then decides whether to produce information based on the following inequality

$$\lambda(\pi_G D - I) - c \geq \lambda\pi_G D + (1-\lambda)\pi_B D - I, \quad \implies \underbrace{(1-\lambda)(I - \pi_B D)}_{\text{Value of Information}} \geq c. \tag{8}$$

Intuitively, (8) says that the bank's profits from producing information and only financing the good borrower must be higher than the profits from not producing information and financing the borrower regardless of its type. We interpret a recession as either a decrease in the probability of the project being good λ or a decrease in the expected cash flow of bad borrowers, i.e., a decrease in π_B. For both of these cases, the value of information in (8) increases, thereby increasing the incentives of the bank to produce information.

[21] The borrower can know its type and the results would not change as there is no potential for signaling and the borrower's outside option is 0 so there is no adverse selection problem on the borrower side.

[22] This allows us to abstract away from the bargaining process. See Dang, Gorton, and Holmström (2012) and Weitzner (2019) for cases in which the face value of debt is endogenous.