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No News is Bad News: Monitoring, Risk, and Stale Financial Performance in Commercial Real Estate*

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Abstract

As financial intermediaries, banks have a key role in producing information and managing the risks on diverse loan portfolios. An important input into this process is ongoing collection of financial performance from borrowers. Using supervisory data on commercial real estate loans (CRE), this paper studies relationships between the content and timeliness of borrower-reported performance, internal bank risk ratings, and subsequent loan performance. Banks heavily rely on borrower reporting when setting risk ratings, despite the fact that borrowers with stale financials are more likely to default. Although banks can generally be slow to update their ratings as information becomes more stale on average, we find causal evidence that they do monitor more intensively in response to loan, location and portfolio risks.

Keywords: bank monitoring, risk management, commercial real estate mortgages, financial performance reporting

JEL Classification: G14, G21, G32, R33

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1 Introduction

Banks have a key role in the financial system as intermediaries. Their role includes screening and subsequently monitoring the creditworthiness of borrowers. Monitoring is essential for promptly identifying and managing risks and vulnerabilities as they emerge when the underlying collateral for loans is very sensitive to shifts in economic conditions (Weil 2024), as is the case with commercial real estate (CRE) loans. Monitoring is partly based on acquiring regular reports on collateral performance from borrowers and producing internal credit risk assessments.[1] But the monitoring is not free, banks face both direct costs in terms of labor hours for loan officers and risk managers and indirect costs, including imposing higher reporting requirements from borrowers which could affect future bank-client relationships. Studying how banks optimize their monitoring given these costs is essential to understanding how systemically important banks learn about and manage risks during times of rising financial stress.

This paper aims to study borrower reporting of financial performance and how that reporting is used in banks' ongoing monitoring of CRE loans. The paper has three main findings: first, banks heavily rely on borrowers' performance reporting in their risk assessments; second, banks respond relatively slowly to stale or delayed reporting despite a positive correlation between stale performance and default risk; and third, banks adjust their information acquisition in response to loan- or portfolio-level shocks, demanding more timely reports when the banks are more concerned about losses on CRE loans. This paper uses a loan-level dataset of commercial real estate mortgages from large U.S. banks that tracks the performance of the loans, property-level financials, and the banks' estimate of the loans' probability of default.

The main findings are consistent with theories of financial intermediation in which banks' comparative advantage over atomized investors is their ability to monitor loan performance (e.g., Diamond 1984; Boyd and Prescott 1986). Large banks maintain significant research, servicing, and risk management departments consistent with theory, all of which represents a direct cost of monitoring. Given banks' growing analytical capacity and access to information, it is somewhat surprising how much banks still seem to rely on the traditional monitoring process of borrowers reporting their performance directly to the bank. These reporting requirements represent an indirect cost to the bank, as more onerous reporting requirements might encourage borrowers to consider lenders with more relaxed monitoring. The information banks receive about performance appears to be valuable to them when assessing default risk, but how do they balance this benefit against both the direct and indirect costs of producing it? Empirical results on adjustments in monitoring and information production provide support for the view that acquiring more information is costly. Slow adjustments in bank risk ratings may be efficient given the need to trade off costs and benefits of monitoring on the margin. Banks adjust their acquisition of information as risk exposures change, allowing them to hedge against losses or build up reserves in response to economic or financial shocks.

The first finding documented in this paper is that when borrowers report an update to their net

[1] Risk assessments or risk ratings can have regulatory implications for risk-based capital (affecting Basel II risk weights on commercial real estate based on loan-to-value ratios or obligor risk weights) and loan loss reserves or provisioning (as of December 2019, some banks are required to maintain allowances for losses based on Current Expected Credit Losses, a form of rating the probability of default at the loan level).

operating income (NOI) or occupancy rate, banks are 50% more likely to change their estimate of the loans' probability of default (PD). This effect on internal PDs, which map onto banks' internal risk rating, is shown in generalized event studies around the quarter that a performance update shows up in the bank's internal system. Once the bank receives a performance update, the size of the change in NOI or occupancy flows through to upgrades and downgrades in risk assessments. A 10 percent decline in NOI increases the PD by 6.9 basis points (and a 10 percent occupancy decline increases PD by 16.7 basis points) on a sample average PD of 1.1 percent.

The next main finding is that outdated financial reporting is positively related to default probability, but negatively correlated with banks' internal credit ratings. The paper documents this by constructing a loan-level measure referred to as the "staleness" of banks' information on performance (also referred to as "outdated" information or the "age" of reported data).[2] Staleness is defined as the number of quarters between the current quarter and the date attached to the most recent performance update. Figure 1 previews these results in two binned scatter plots for the relationship between the staleness measure of NOI with default probability in the left panel and the probability of a downgrade in banks' internal estimate of PD in the right panel.[3] Increasingly stale information is strongly positively correlated with default but has little impact on the propensity for banks to downgrade the loan. If anything, banks are less likely to downgrade loans with stale information even as default risk rises, suggesting they often employ a "wait-and-see" approach to reporting.

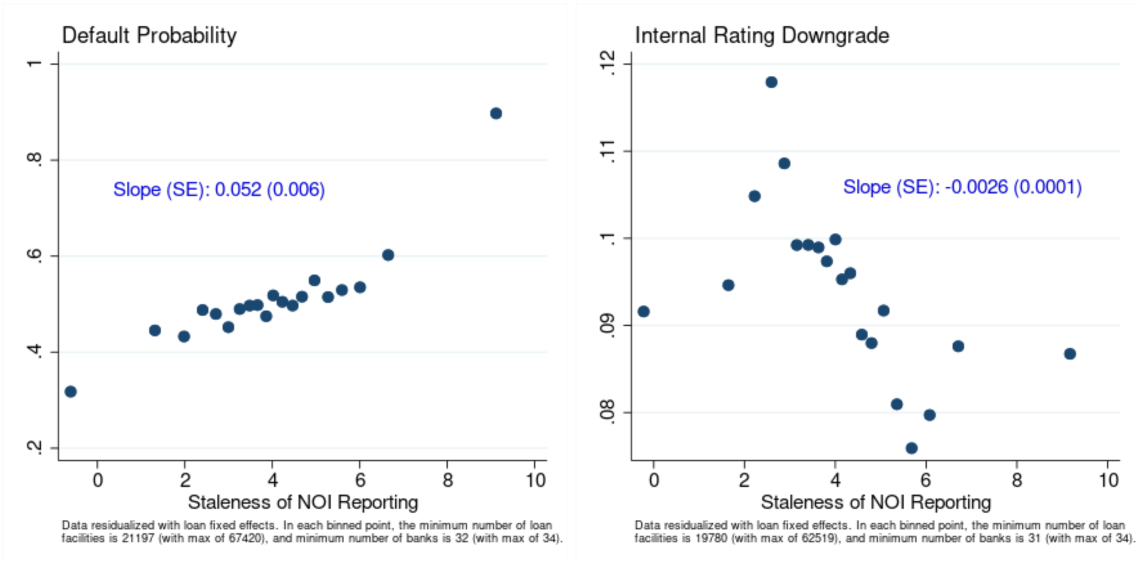
Having shown that performance reporting is an essential component of bank monitoring for CRE mortgages, the final portion of the paper analyzes two empirical exercises that elucidate sources of endogenous adjustment in bank monitoring activity. In particular, we argue that banks are willing to incur more costs when the benefits of more timely credit risk information is greater. Increasing monitoring likely involves both direct costs in terms of prioritizing the work of credit risk monitoring staff, and indirect costs where loan officers may demand more timely reporting from borrowers, potentially imposing hassle costs on borrowers and affecting relationship capital. These exercises support the final finding in this paper that banks monitor more intensively when they observe shocks to loan-specific risks, location-specific risks, or risks on the bank's overall portfolio.

The first empirical exercise uses variation from a sharp oil price decline of more than 50% in late 2014, which we treat as an exogenous shock in a triple difference-style regression framework. Relative to cities with little or no employment in oil and gas-related industries, banks increase monitoring of CRE loans in highly exposed cities. Monitoring of CRE appears to decline, on average, in cities with only small or moderate levels of oil and gas industry activity. These effects using across-city variation are decomposed using within-city variation by measuring how exposed individual banks are to oil and gas lending on their commercial and industrial (C&I) loan portfolios. Banks that are heavily exposed appear to increase monitoring of CRE mortgages across all types of cities, regardless of whether the city is exposed to oil and gas employment. In contrast, banks with minimal C&I loan exposure to oil and gas firms increase their CRE monitoring activity in cities heavily exposed to oil and gas but decrease monitoring for loans secured by property in less-exposed cities. These

[2]See e.g., Bernhardt and Miao (2004) for a description of stale information in a numerical and theoretical framework.

[3]The binned scatter plots of each variable residualize the quarterly data with loan fixed effects. One additional quarter of stale information is correlated with 5 basis points higher default risk.

Figure 1: Impact of Staleness of NOI On Default and Ratings Downgrades



Notes: Figures show a binned scatterplot of loan-by-quarter observations of the probability of default, probability of a downgrade in bank internal ratings of default risk, and financial reporting staleness (current reporting quarter minus quarter that the most recent financials were reported 'as of'). The figure plots residuals from a regression removing loan fixed effects to isolate within-loan variation in staleness and default risk ratings. Among these figures, the minimum number of loans in the smallest binned point on the scatter plot is 19,780, and the minimum number of banks summarized by any binned point is 31.
Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

results complement existing evidence on de-risking and re-balancing by exposed banks (e.g., Wang 2021; Bidder et al. 2021).

The second empirical exercise isolates variation in loan-specific risk by studying the relative effect of shifts in interest rates on information production for floating-rate mortgages versus fixed-rate mortgages. Difference-in-difference regressions with heterogeneous treatment variation coming from interest rate changes show the causal effects of within-loan changes in credit risk on bank monitoring behavior. Banks increase monitoring activity on floating rate loans relative to fixed-rate loans in response to rising interest rates and decrease information acquisition as rates decline. One consequence of this behavior is that banks are relatively more likely to both downgrade and upgrade their internal risk ratings on floating-rate CRE mortgages as interest rates rise. This evidence on monitoring implies that a previously unidentified channel exists by which interest rates can affect bank behavior (e.g., Ippolito et al. 2018) and relates to discontinuous changes in behavior after mortgage rate resets, which has been analyzed most closely in the residential homeowner context (Di Maggio et al. 2017).

The following section contains a discussion of the theory and practice of loan monitoring with a summary of related literature. Section 3 then discusses the data used in our analysis and how we measure the staleness of performance, which is the primary measure of monitoring activity. Section 4 establishes the extent to which banks use performance updates to inform their internal risk assessments. Section 5 provides evidence that "stale" property financials indicate subsequent loan distress, and banks appear slow to catch that distress early. Section 6 studies loan monitoring in two empirical settings: response to the 2014 oil and gas shock, and exposure to interest rates on floating rate loans. The paper closes with a short discussion of potential implications for improving credit risk monitoring and the status of CRE.

2 Bank Monitoring Discussion and Literature Review

For CRE mortgages, loan contracts specify a reporting schedule for borrower financials. This is a core piece of loan monitoring, where borrowers report financials approximately once per year.[4] Financial reporting is often treated as a CRE loan covenant, similar to the commercial loan context—if borrowers do not report on time, the lender should have the ability to enact some penalties or classify the loan as in technical default. For loans in commercial mortgage-backed securities (CMBS), the standard process based on the CRE Finance Council's Investor Reporting Package specifies that if borrowers fail to report after multiple (usually four) consecutive quarters, they are placed on a servicer watchlist and eventually sent to a special servicer.[5]

Multiple channels of servicer communication are essential to loan monitoring. Banks collect both soft and hard information about borrower performance. However, we only observe the outcome of this communication and monitoring—hard information on when borrower financials show up in bank databases. Communications may include calling, emailing, sending formal 'delinquent financial reporting' letters, and eventually showing up at the building or office of the borrower. Gustafson et al. (2021) uses the text-based servicer commentary summarizing these communications in the syndicated loan market. The securitized CRE mortgage market has some of this style of commentary, but the CCAR Y-14Q supevisory data collection does not include servicer commentary.

By our understanding, banks have significant discretion in these communications and in how they respond to delayed reporting. Some industry discussion about the monitoring process points to potential carrots and sticks by which banks can influence borrowers to report: banks may be able to impose or waive monetary penalties or assume some operational control, for example through something like a springing lockbox (or a "cash flow sweep"); alternatively, for faithfully reporting and well-performing borrowers, banks may be able to release additional reserves or tenant improvement funds. Likely the ultimate disciplining factor in achieving good behavior is maintaining borrower-lender relationships and obtaining repeat business. Chodorow-Reich (2014) suggests that these relationships are quite valuable, so this is a particularly important mechanism for borrowers who value the ability to rollover debt with the same lender.

In banking and financial intermediation theory, banks play a dual role of assembling capital to lend and resolving a principal-agent problem between investors and firm operators by specializing in information acquisition and performance monitoring. Diamond (1984) and Boyd and Prescott (1986) theorize that banks' role as a diversified financial intermediary with a comparative advantage in collecting information and monitoring borrower performance can resolve the problem that without a specialized intermediary, all investors (i.e., depositors) would have to engage in duplicative

[4]Appendix Figures A.2 & A.4 indicate that 25% of loans report financials in the average quarter.
[5]See e.g., https://www.crefc.org/irp.

monitoring of borrowers or no investors would engage in costly monitoring because of a free rider problem. In the context of commercial real estate, we might expect that banks would have departments specializing in CRE, using their scale to acquire and use market activity and performance data while monitoring their lending portfolio.

Theoretical work on banks' information and screening behavior often focuses on loan origination with less emphasis on monitoring or information gathering during the life of the loan. The optimal information production behavior for banks is not entirely clear. Some research suggests that decaying information quality contributes to credit booms and busts (e.g., Gorton and Ordonez 2014), while other work argues that more opacity in information about collateral quality can help stave off financial crises driven by short-term debt markets (e.g., Dang et al. 2020).[6] CRE may be important to study in the context of this macro and credit research because it is considered cyclically sensitive and has a relatively high risk for lenders.

Empirical work on information production has also focused on loans at origination in the same vein——the role of information and misreporting was a core area of study in residential mortgage markets and housing construction leading up to the Great Financial Crisis (see e.g., Keys, Mukherjee, et al. 2010; Keys, Piskorski, et al. 2012; Lisowsky et al. 2017).[7] Aiello (2016) and Munneke and Smith (2023) analyze residential mortgage servicers' use of payment behavior as predictive information about future performance. In CRE-related settings similar to this paper, Garmaise (2015), Kruger and Maturana (2021), and Griffin and Priest (2023) show that intermediary or borrower misreporting is predictive of default and relatively common in residential mortgage and CMBS 2.0 markets, respectively.[8]

Exposure to real estate appears to be quite important to the banking system's functioning, and bank monitoring adjusts strongly over the business cycle. Most research on real estate monitoring over recent business cycles highlights the role of construction lending (Heitz et al. 2023). Banks decreased collection of audited financial statements on construction companies during the boom and sharply increased collection during the bust around the Great Financial Crisis, contributing to larger loan losses and bank stress (Lisowsky et al. 2017).

Because of the recent availability of quality supervisory data on bank balance sheet lending, a growing research literature documents lenders' lending, monitoring, and risk management behavior in the commercial lending market. There is evidence that banks endogenously adjust monitoring activity,[9] and that the anticipated costs of active monitoring influence loan contract terms at origi-

[6]Gorton and Ordonez (2014) study endogenous credit booms and financial crisis risk in the context of information about collateral that decays over time. Dang et al. (2020) argue that the increased opacity of collateral quality can be beneficial for short-term debt markets, at least in terms of preventing financial crises. Ahnert and Kakhbod (2017) make similar theoretical points about when investors make information acquisition choices—they argue that optimal policy around information acquisition depends on the collateral quality or solvency of borrowers. Asriyan et al. (2022) study the mix of collateral and costly screening that lenders use to mitigate moral hazard by borrowers, and argue that in a credit boom, costly information is underprovided (due to increasing collateral values).

[7]Suggestive of limitations in the use or production of quality information on newly originated loans, Tzioumis (2017) points out that co-borrowing affects mortgage performance, but banks appear to fail to price interest rates based on number of borrowers; Aiello (2016) shows that MBS investors and rating agencies appear not to incorporate information about borrowers' mortgage performance prior to securitization into their pricing at issuance.

[8]Ambrose et al. (2024) show that CMBS Pooling and Servicing Agreements, which provide information about mortgage collateral and convey information about servicing and monitoring behavior, are meaningfully correlated with ex post default and loan performance.

[9]Cerqueiro et al. 2016; Minnis and Sutherland 2017; Becker et al. 2020; Gustafson et al. 2021; Branzoli and

nation.[10] Among the commercial lending research, Cerqueiro et al. (2016) constructs a measure of information quite similar to the measure of stale information used in this paper. That measure is calculated as the time between bank employees' reviews of borrowers or collateral. The time between reviews is used as a proxy for monitoring in an empirical setting that analyzes a Swedish legal reform that caused a decline in loan collateral values and resulted in a decline in bank monitoring intensity.

This paper contributes to the broad literature on information and the narrow literature on monitoring and risk management in the real estate sector at large banks. Our focus on measuring specific pieces of information, how that information is transmitted to the bank, and how banks use that information advances this literature. We use variation at the loan, location, and bank level to study information production to test and validate a new and potentially useful measure of information available to regulators through existing supervisory data collection.[11]

3 Data on Monitoring of Property Financials and Bank Internal Credit Ratings

This paper uses data in the Federal Reserve's Form Y-14Q Schedule H.2 Commercial Real Estate loan-level reporting.[12] This reporting is part of the Federal Reserve's annual Comprehensive Capital Analysis and Review (CCAR) process for evaluating whether the largest banks operating in the U.S. are well-capitalized and able to meet their obligations in the event of economic stress.[13] This paper uses loan facilities classified as retail, industrial (and warehouse), multifamily, and office property types.[14] Banks report current net operating income and occupancy for properties with loans on their balance sheets. Each current NOI observation is reported with an "as of" date. The NOI reported by the banks in a given CCAR reporting quarter are based on the most recently reported values the bank has received from the borrower.[15] Generally, there is a several-quarter lag between the "as of"

Fringuellotti 2022; Howes and Weitzner 2023; Claessens et al. 2023; Haque et al. 2024.

[10]See Chodorow-Reich et al. 2022; Jiang et al. 2024. A connected literature on information production in the context of bank lending studies the consequences of information on asset markets and trading. See Beyhaghi et al. 2023; Haselmann et al. 2022. Information disclosure behavior can also be strategic. Borrowers choose to disclose or fail to disclose information in the process of searching for or negotiating financing. See Bird, Karolyi, and Ruchti 2019; Bird, Ertan, et al. 2020; Gustafson et al. 2021; Jiang et al. 2024; Back et al. 2023. Strategic incentives in information disclosure are important in other contexts as well: T. Gormley et al. (2019) and T. A. Gormley et al. (2022) show that firms internalize how stock market participants will respond to financial information. Information provision and processing also appears to be important for participants in public markets and for credit rating agencies (Gredil et al. 2022). There may be reason for caution in relying too heavily on one source of risk assessment given the role of credit rating agencies in the Great Financial Crisis (Freixas and Laux 2011).

[11]Connected to the empirical setting in this paper on bank exposure to oil and gas industry lending, prior work highlighted bank specialization or lending concentration as determinants of bank information production (Berger et al. 2017).

[12]The data is Schedule H.2 of the FR-Y14Q data collection and is actually collected at the credit facility level. Given that most credit facilities have a single loan, we treat it as loan-level.

[13]Appendix A contains additional information about the Y-14Q CRE dataset, performance reporting, and internal risk ratings.

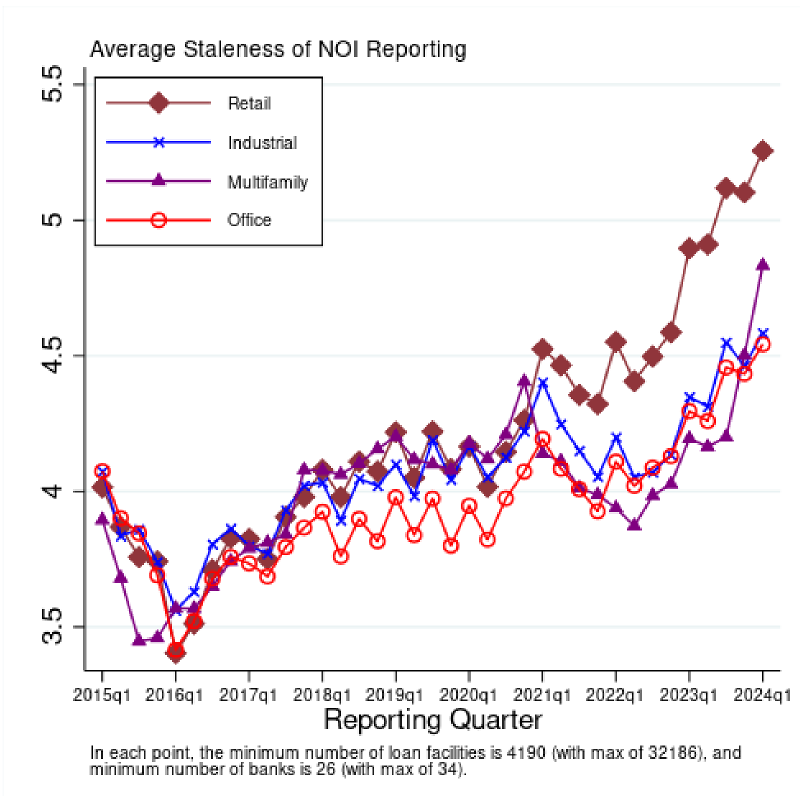
[14]Owner-occupied properties are not collected in the FR Y-14Q, Schedule H.2. We drop from our analysis construction loans and loans secured by other property types as the focus of this paper is the ongoing monitoring on the investment class income-generating properties with comparable leasing behavior and similar tenant relationships (e.g. hotels effectively have one night leases and significantly different market dynamics).

[15]The structure of this performance reporting is similar to the reporting for securitized loans where borrowers report to servicers for commercial mortgage-backed securities (CMBS) using the CRE Finance Council's Investor Reporting Package, though only a small amount of information is available in the CCAR supervisory data.

date and the date that the borrower sends the bank their performance update—for example, NOI for fiscal year 2017 will be listed "as of" Q4 2017 (Dec. 31, 2017), and will often be reported in Q2 2018 (e.g., by June 30, 2018).

We construct a measure of the "staleness" of borrowers' performance reporting as the current reporting quarter minus the currently reported "as of" quarter of NOI. In the example discussed above with Q4 2017 financials reported in Q2 2018 would have a staleness measure of two quarters, the staleness measure would increase to three quarters in Q3 2018, and 4 quarters in Q4 2018. This measure is distinct from a measure of reporting delay or lag—it combines how long it takes to send a performance update initially and how long it has been since the last update in performance. If borrowers were immediately sending banks their performance annually and those updates were immediately reflected on banks internal systems (i.e., the Q4 2017 financials are sent to the bank in Q4 2017), then the average staleness measure should be around 2, depending on seasonality in lending and reporting.

Figure 2: Average Staleness of Performance Reporting



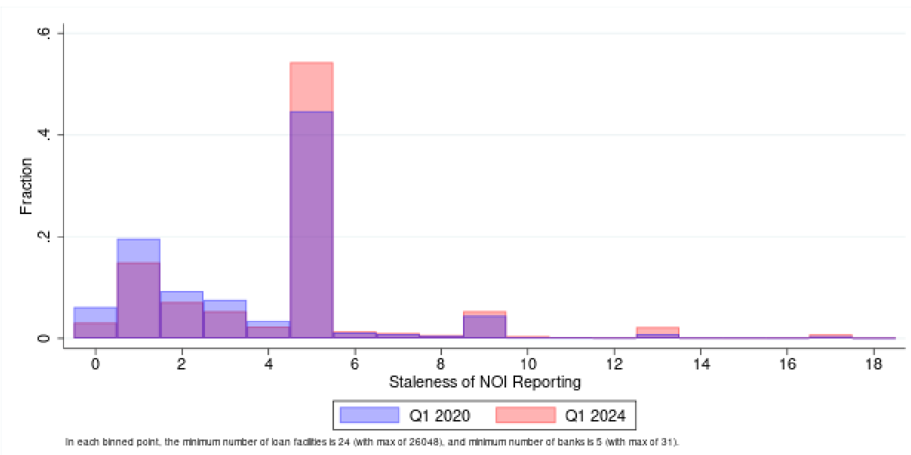
Notes: Figures show times series average of reporting information 'staleness' for all mortgages of each type. Staleness is defined as the number of quarters between the current quarter and the most recent reported 'as of' date on borrower's financial reporting information. Acquired loans are excluded. Among these figures the minimum number of loans in the smallest bin on the histogram is 4,190 and the minimum number of banks (RSSDs) summarized by any bin is 26.

Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Figure 2 shows the average staleness of reporting NOI over time in the CCAR data.[16] On average, pre-Covid (2015-2019) reporting was approximately four quarters outdated on portfolio loans with some variation across property types. There has been an increase in the staleness of performance reporting in 2020 and sharp increases in the prevalence of stale performance on banks' portfolio CRE mortgages. The 2020 increase was 0.25 to 0.5 quarters (with a larger increase for retail properties), suggesting that the average borrower delayed performance reporting for an additional 1 or 2 months. By 2022, the increase in outdated information had returned to the pre-pandemic level. The increases in outdated performance data after 2022 are larger, with nearly one quarter more outdated reporting relative to 2019. In general, banks' information appears to be relatively outdated, and their information quality has degraded in recent years.

Given that most financial reporting is based on annual financials, it makes sense that the staleness measure constructed at a quarterly frequency has a lumpy distribution at any given time. Figure 3 overlays the distribution of the measure for Q1 2020 (in blue), and Q1 2024 (in red) to show how the staleness of performance reporting has shifted from pre-pandemic to the post-rate hike period. At the beginning of each calendar year, banks generally have performance information from 5 quarters prior for financials. Descriptively, reporting in 2024 is noticeably more outdated. The distribution for NOI has more loans with five quarters outdated financials and somewhat more with 9 or 13 quarters-old financial performance.

Figure 3: Histogram of Staleness of Performance Reporting

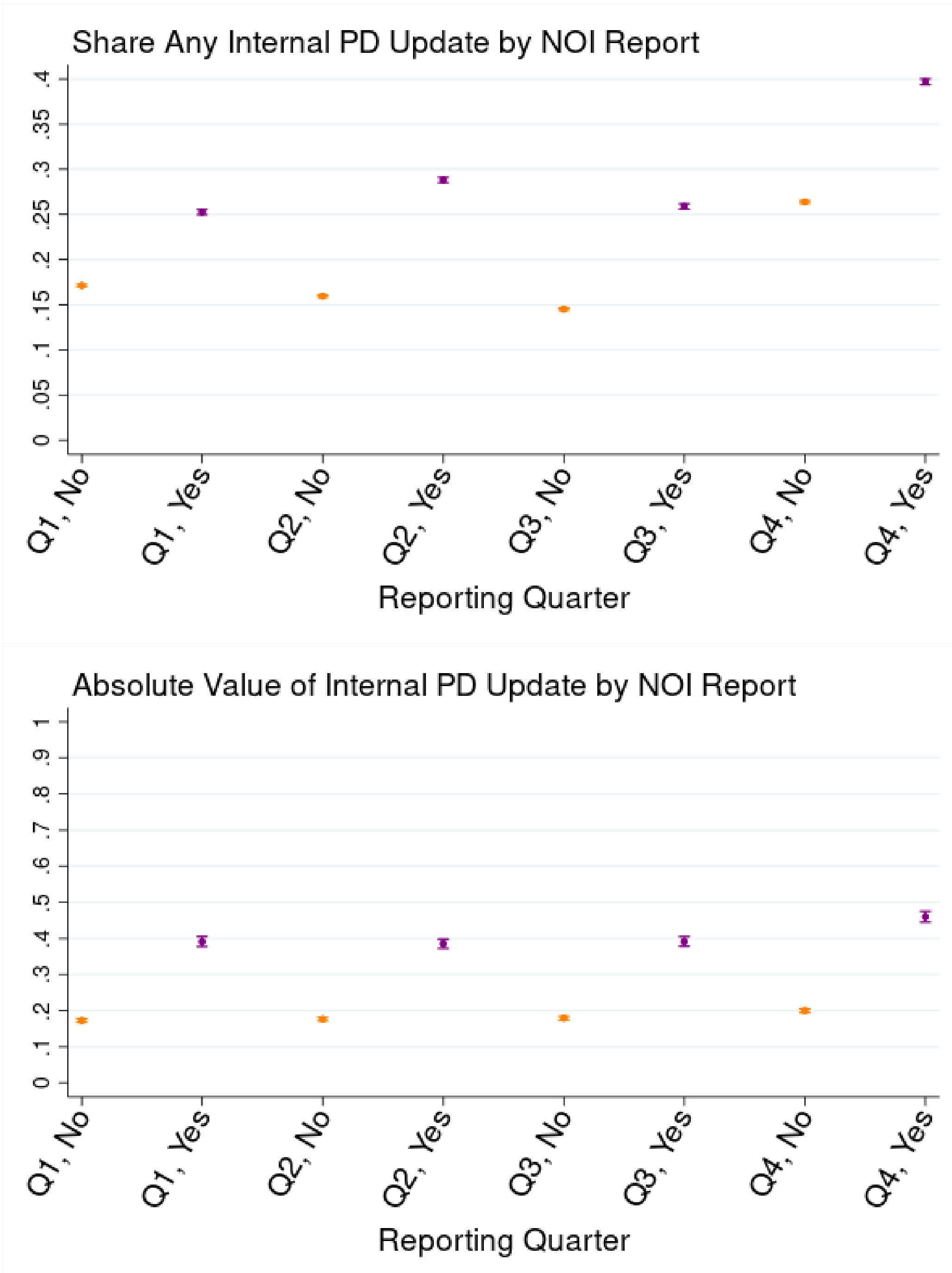


Notes: Histogram shows the distribution of reporting information 'staleness' for mortgages in Q1 2020 (blue) and Q1 2024 (red). Overlaps in the Q1 2020 and Q1 2024 distribution are displayed in a purple shade. Staleness is defined as the number of quarters between the current quarter and the most recent reported 'as of' date on borrower's financial reporting information. Acquired loans are excluded; only first liens originated after 2010 are included. Among these figures the minimum number of loans in the smallest bin on the histogram is 24 and the minimum number of banks (RSSDs) summarized by any bin is 5.
Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

How does borrower performance reporting relate to banks' internal risk ratings? Figure 4 shows the probability of banks updating their PDs and the absolute value of those updates in quarters

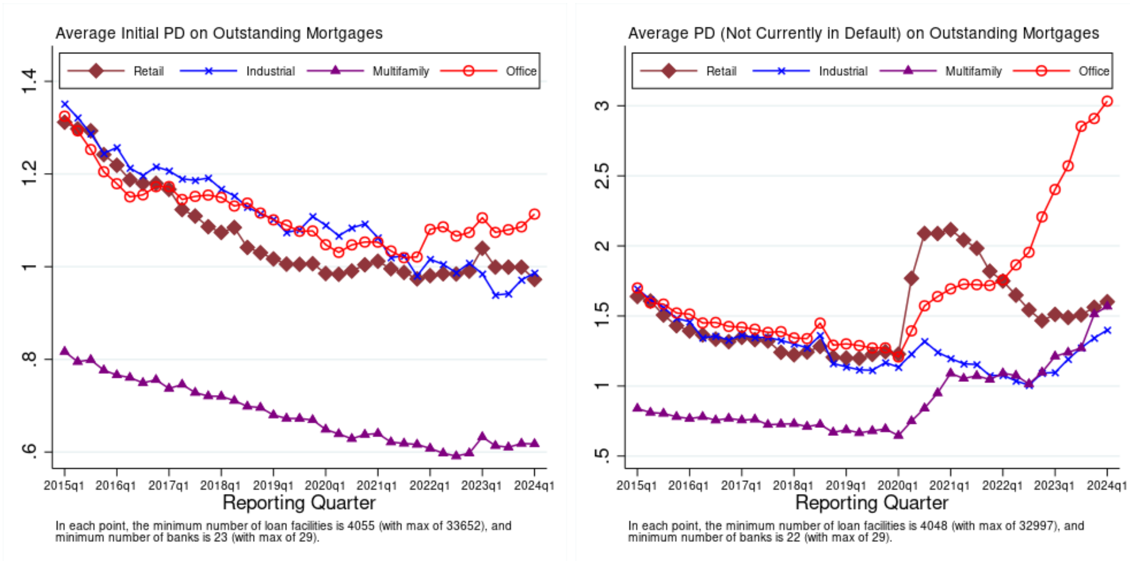
[16] See Appendix Figure A1 for corresponding measures for occupancy.

Figure 4: Probability of Banks Updating PD by Whether Borrower Reported Financial Performance



Notes: Figures show the regression output showing the share of loans with a PD update and the size of the change in internal bank PD for all mortgages by calendar reporting quarter (reporting 95% confidence intervals in the figure). The averages are split into two categories in each quarter: "No" indicates that the borrower did not submit an update to their financial data reporting, and "Yes" indicates that they did submit an update in the quarter.
Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Figure 5: Trends in Bank PD Estimates at Origination and Contemporaneously



Notes: Figures show times series average of initial or origination PD (left-hand) and current PD (right-hand) for all mortgages of each type on the bank's balance sheet in each reporting quarter. The right-hand graph excludes loans currently in default (defined as loans with PD equal to 100). Acquired loans are excluded. Among these figures the minimum number of loans in the smallest point is 4,048 and the minimum number of banks (RSSDs) summarized by any point is 22.

Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

when the borrower sends an update on their reported financial performance (NOI) in that quarter versus those that do not send an update. By breaking down the average PD updates by calendar quarter, we highlight that banks are more likely to change PDs in the fourth quarter. Loans where the borrower updates their performance are 50-100% more likely to experience a PD update and the content of those updates is significantly larger (on average, double the size in absolute terms from 20 to 40 basis points).

The data discussion ends here with a summary of banks internal credit ratings. In the CCAR Y-14Q CRE reporting, large banks report their internal credit ratings for loan facilities and borrowers. This includes a PD, which can be described as a probability of default over a given year.[17] Figure 5 shows summary statistics on aggregate trends in banks' internal PDs over time. The left panel of Figure 5 shows the trends for bank PD estimates at origination or when the loan first enters the CCAR dataset for all loans currently on bank balance sheets in each quarter. Note that these ratings are conditional on the new loan being made by the bank. When there is an aggregate increase in credit risk in the economy, well-run banks will tighten underwriting. This results in fewer loans being made, but the tighter underwriting may offset the higher aggregate risk, keeping average risk of accepted loans steady. The right panel shows the average of contemporaneous PDs for loans in bank portfolios. The gap between the left and right panel reflects how PDs have changed since origination in response to changes in credit risk conditions since origination. Multifamily loans have

[17]For banks subject to advanced approaches for regulatory capital, this may use a more sophisticated estimate of probability of default, while for other banks this may map directly onto the bank's system of internal credit ratings.

significantly lower PDs at origination than the other property types. We also observe that banks express concerns about default risk for retail and office mortgages with rising initial PDs during the COVID-19 pandemic. This pattern is even more pronounced for contemporaneous PD estimates for retail and office properties early in the pandemic. Retail CRE loan risk ratings have decreased as consumer spending rebounded in 2021-2022. In contrast, the estimated PDs for office loans have continued to increase. This analysis helps establish descriptively that bank PDs change over time, responding to aggregate changes in risk.

4 Banks Heavily Rely on Performance Information to Assess Risk

4.1 Banks Update Risk Ratings When They Receive Borrower Performance

We might expect that large banks with sophisticated research and risk management departments produce loan monitoring analysis that makes annual reporting of financial performance duplicative. Private sector data analysis companies track neighborhood and even property-level rents, leasing, and property valuation data. Many of these firms have large banks as their clients, so updates to loan- or property-level performance could have only small effects on banks internal risk ratings. This section studies when and how much banks change their risk ratings in the quarters around receiving a performance update from their borrower.

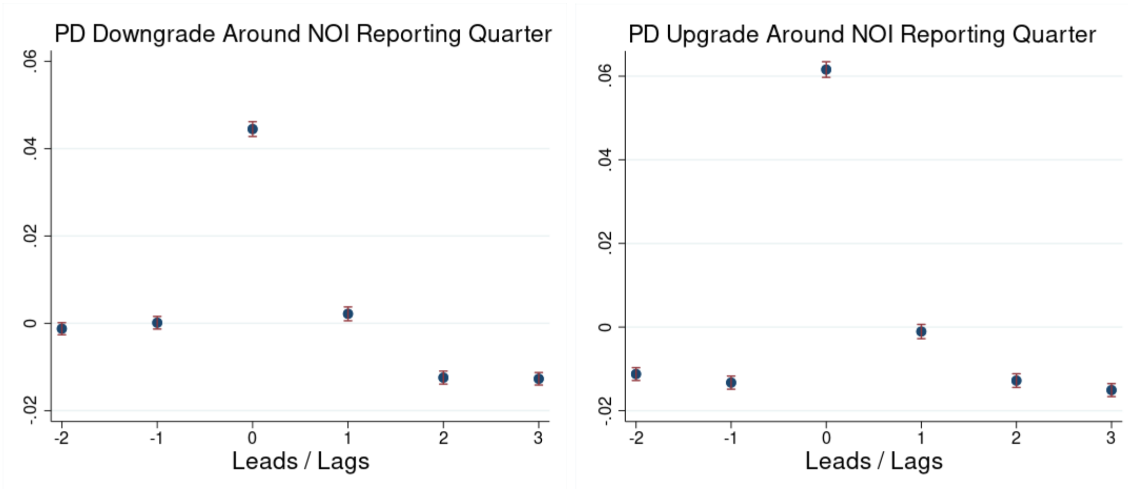
This section uses a generalized event study approach to study the effect of a performance update on the bank's propensity to update its internal risk ratings. This regression can have one of two outcome variables, represented as $1(PD\ Update_{it})$.[18] A PD downgrade is defined as a binary variable for any quarter-over-quarter increase in the PD. The PD upgrade binary variable is any instance of a decline in the PD. An upgrade or downgrade event is regressed on a binary variable for whether or not there is a change in the borrower's recorded NOI in the quarter, $1(Performance\ Update_{it})$. Two leads and three lags of the performance update variable are included. The regression equation includes fixed effects for the reporting quarter, loan, calendar quarter, and loan seasoning. Standard errors are clustered by loan.

$$1(PD\ Update_{it}) = \sum_{k=-2}^{3} \beta_k\ 1(Performance\ Update_{it;k}) + \alpha_i + \alpha_t + \alpha_q + \alpha_s + \nu_{it} \qquad (1)$$

The coefficients of interest are β_k representing the marginal relationship between a bank changing risk ratings and the timing around a borrower reporting new information about the collateral's performance. The leads indicate the propensity for banks to change PDs just prior to a performance update, while the lags represent the extent to which banks update their risk evaluation following new performance data.

[18]Unconditional PD Update probability by calendar quarter is shown in Appendix Figure A8.

Figure 6: Timing of Up and Downgrades Around Reported NOI



Notes: Figures show coefficients and 95% confidence intervals from regressions of a binary variable for an update to banks internal PD (either a downgrade or upgrade) on leads and lags of a binary variable for whether the borrower reported new financial information, covering data on all mortgages of each type.
Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Figure 6 shows that the probability of downgrade rises 4 percentage points and the probability of upgrade rises just over 6 percentage points in exactly the quarter when a borrower updates their financials with the bank.[19] These regression coefficients are reported in Appendix Table B6. Two quarters before an NOI update, lenders are 1.5 ppt less likely to update the loans PD, and the quarter of the NOI update, the probability of PD update is 9.8 ppt higher. Appendix Figure A9 shows the absolute value of the PD change, illustrating that the quarter of performance updating has a 15-18 percentage point larger PD change than the average quarter without a performance update. These results establish that updates to property financials trigger significant re-evaluations of the credit risk of the loan by the banks.

This evidence suggests that banks respond strongly to performance information provided directly by the borrower. The base probability of banks downgrading a loan in the average quarter is 13 percent, and the probability of upgrading a loan is 12 percent. Given these estimates, an update on the financial performance increases downgrades by approximately 30% and upgrades by 50%.

4.2 Banks' Risk Ratings Change with the Size and Direction of Updated Performance

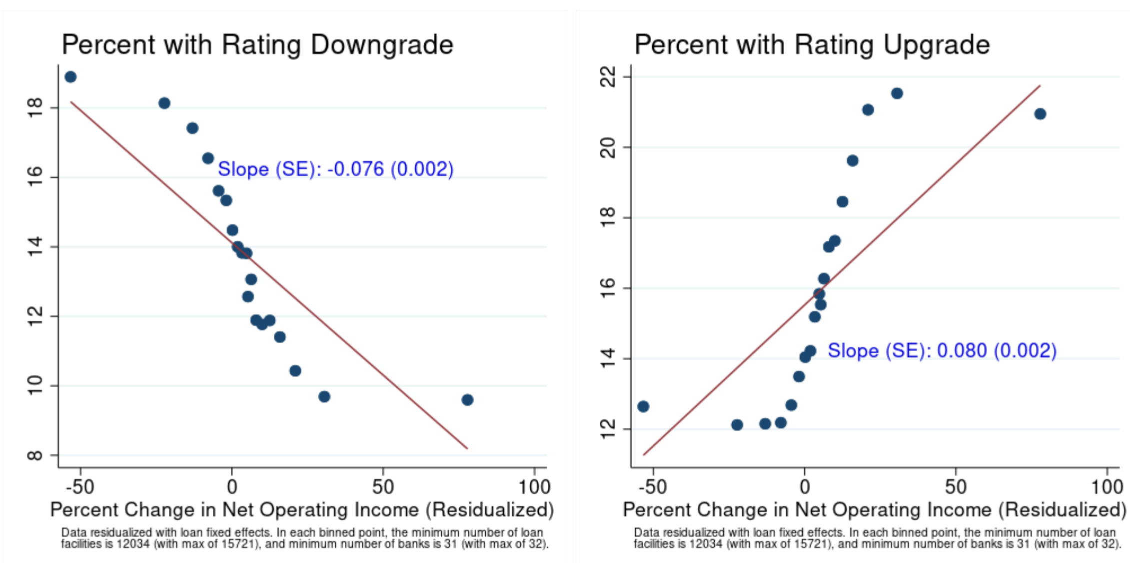
Banks update internal risk ratings in the same quarter that borrowers provide performance updates. This section emphasizes that those performance updates feed directly into banks' internal PDs. To visualize and measure this relationship in this section, the analysis shows the relationship between

[19] Appendix Figures A6 through A9 also confirm that adding together the downgrade and upgrade events, there is a 10-12 percentage point relative increase in the probability of any PD update around an NOI update. The size of this up- and downgrade probability is similar across property types, as shown in Appendix Figure A7.

quarterly changes in internal PDs and the percent change in performance in the quarter in which the loan experiences an update to the NOI.

Figure 7 shows the relationship between change in financial performance and change in internal PDs during the quarter in which the borrower's performance is updated. The binned scatter plots are grouped residuals from a regression with loan fixed effects. The graphs show the percent of loans that receive a downgrade or an upgrade in the banks' internal risk ratings system, conditional on a performance update in the quarter. Properties reporting a decline in NOI are significantly more likely to be downgraded and less likely to be upgraded. The reverse is true for loans reporting higher NOI. The graphs report the linear OLS slope, which suggests that a 10 percent higher NOI leads to a 0.76 percent lower likelihood of downgrade and a 0.8 percent higher likelihood of upgrade. Visually, these relationships appear to be non-linear. This is likely because risk ratings are bounded below by 0 and above by 100%, with a median rating of 0.41%.[20] This means that at some point, an upgrade cannot provide much information about the loan becoming safer if the probability of default is already at or near zero.

Figure 7: Changes in Performance Feed into Internal Risk Downgrades and Upgrades



Notes: Figures show binned scatter plots of the relationship between the actual average percent change in net operating income on the x-axis, and the percent of loans with a rating downgrade (left) or upgrade (right) on the y-axis. Observations included any quarter in which the borrower's financial performance is updated. Percent change in NOI truncated above at 290% and below at -90% (1st and 99th percentile). Each variable is residualized with loan fixed effects. Linear OLS slope and standard error, clustered by loan, reported in the graph. Among these figures the minimum number of loans in the smallest binned point on the scatter plot is 12,034 and the minimum number of banks summarized by any binned point is 31.

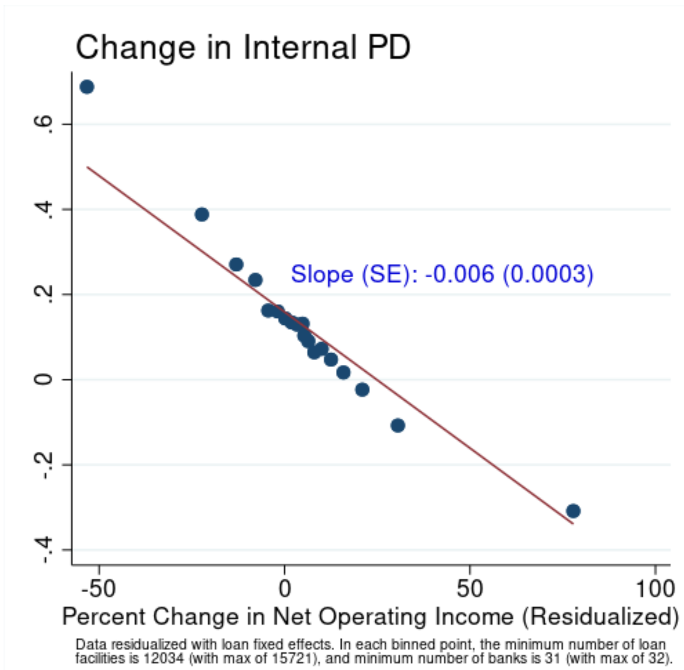
Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

This relationship holds not just for updates to both financial performance, as measured by NOI,

[20] Appendix Figures A9 and A10 show a non-linear relationship between change in NOI and the probability of any change in PDs. Appendix Figure A11 repeats this analysis looking at updates to the occupancy performance of the property.

but also leasing performance, as measured by the occupancy rate. The performance change passes through to PDs at a rate of 0.06 or 0.17 from a ten percent change in net income or occupancy, respectively. Figure 8 displays this relationship repeating the exercise of showing within loan changes in performance and PD downgrades or upgrades. Figure A12 in the appendix shows the analogous results for changes in occupancy. In contrast to Figure 7 where the outcome is a binary variable for any downgrade, which had a non-linear slope, the magnitude of the change in the numerical PDs is nearly linear in the change in performance. The strength of the relationship is suggestive of how responsive banks are to borrowers providing private information on their property-specific performance.

Figure 8: Changes in Financial and Leasing Performance Feed into Internal PDs



Notes: Figure shows binned scatter plot of the relationship between the actual average percent change in net operating income on the x-axis, and internal PD ratings on the y-axis. Observations included any quarter in which the borrower's financial performance is updated. Percent change in NOI truncated above at 290% and below at -90% (1st and 99th percentile). Each variable is residualized with loan fixed effects. Linear OLS slope and standard error, clustered by loan, reported in the graph. Among these figures the minimum number of loans in the smallest binned point on the scatter plot is 12,034 and the minimum number of banks summarized by any binned point is 31.

Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

These regression results are formalized in Table 1 with a similar specification as above. We regress the quarter-over-quarter change in PD on the change in performance during the quarter of a performance update. This likely underestimates the total effect of a performance update because this regression only includes the quarter in which a performance update occurs, not including any quarters afterwards where some banks may continue to update internal risk ratings. In this model, one concern is about local demand shocks affecting both property performance and bank PD updates.

To deal with this concern we control for CBSA-by-reporting quarter fixed effects to absorb any variation related to city- and time-specific factors. The regression equation is specified as

$$\Delta rating_{it} = \beta\ \Delta performance_{it} + \alpha_i + \alpha_{ct} + \alpha_q + \alpha_s + \nu_{it} \tag{2}$$

On average, one percent additional net operating income growth corresponds to 0.0069 percentage point lower internal rating of probability of default. Additionally, we interact the performance change with indicators for each property type. The specification includes property type by quarter fixed effects to control for shocks specific to property types. The multifamily sector appears to be more responsive to financial performance updates, declining 0.0121 percentage points. This may be somewhat surprising given that anecdotally there is more granular and accessible private sector analysis of the rental housing market compared with other CRE sectors. Columns (3) and (5) show the corresponding relationships for ratings downgrades and upgrades. The coefficients imply that 10 percent NOI growth corresponds to 0.829 percent decline in PD downgrade and 0.850 percent increase in probability of PD upgrade. Appendix Table B3 shows the analogous regressions for the effect of change in occupancy performance on internal PDs. The results are similar to NOI: an increase in an occupancy rate of 1 percentage point leads to a 0.0167 percentage point decline in the internal rating of the probability of default. Appendix Table B4 shows the results of a spline regression of a binary variable for any change in PD on change in performance, allowing the effect of a performance update to have a different slope above and below zero. This allows us to formally test the results of the figures showing the probability of any change in PD. Banks are less likely to update PDs when there is no change or a smaller change in performance.

The combination of these results shows that banks increase PDs when performance declines, and decrease PDs when performance improves exactly in the quarter that the borrower sends new information about performance. We argue that the measurement of these relationships is informative about how banks use new information and how heavily banks rely on loan-specific performance updated through this part of the monitoring process.

5 Banks Are Slow to Respond to Stale Borrower Performance, Even Though Default Risk Rises

5.1 Stale Borrower Performance is Related to Mortgage Distress

This section studies the relationship between reporting behavior and loan performance. It could be the case that borrowers occasionally make mistakes—either by forgetting or failing to send lenders their performance updates. In this case, stale performance for lenders would be essentially random, providing no additional information about credit risk or probability of default. Given the average staleness and non-reporting propensity, this might also imply that it is costless (or very low cost) for borrowers to fail to report NOI updates to bank lenders. On the other hand, if outdated information or non-reporting does predict default or delinquency, it provides evidence that non-reporting is meaningful information about credit risk.

Table 1: Change in Internal Risk Ratings and Change in NOI at Performance Update

Outcome:	Change in Internal PD		1(PD Downgrade)		1(PD Upgrade)	
	(1)	(2)	(3)	(4)	(5)	(6)
Percent Change in NOI	-0.00693***		-0.0829***		0.0850***	
	(0.000285)		(0.00250)		(0.00257)	
Percent Change in NOI X Retail		-0.00332***		-0.0471***		0.0483***
		(0.000466)		(0.00463)		(0.00507)
Percent Change in NOI X Industrial		-0.00228***		-0.0342***		0.0361***
		(0.000594)		(0.00717)		(0.00776)
Percent Change in NOI X Multifamily		-0.0121***		-0.133***		0.140***
		(0.000546)		(0.00403)		(0.00418)
Percent Change in NOI X Office		-0.00253***		-0.0420***		0.0375***
		(0.000401)		(0.00515)		(0.00495)
Observations	313,995	313,995	313,995	313,995	313,995	313,995
R-squared	0.204	0.209	0.325	0.337	0.324	0.329
Dep Var Mean	0.122	0.122	13.64	13.64	15.91	15.91
Reporting Quarter-by-CBSA FE	Y	Y	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y	Y	Y
Quarter of Year FE	Y	Y	Y	Y	Y	Y
Quarters Since Orig	Y	Y	Y	Y	Y	Y
Property Type-by-Quarter FE	N	Y	N	Y	N	Y

Note: Observations included any quarter in which the borrower's financial performance is updated. Independent variable is the percent change in NOI. NOI changes are censored around the 1st and 99th percentiles at -99% and 290%. The dependent variables are: the change in internal PD, excluding instances where PD is equal to 100% (currently in default); a PD downgrade, where PD increases quarter over quarter; and a PD upgrade, where PD declines. Standard errors are clustered by loan.

Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

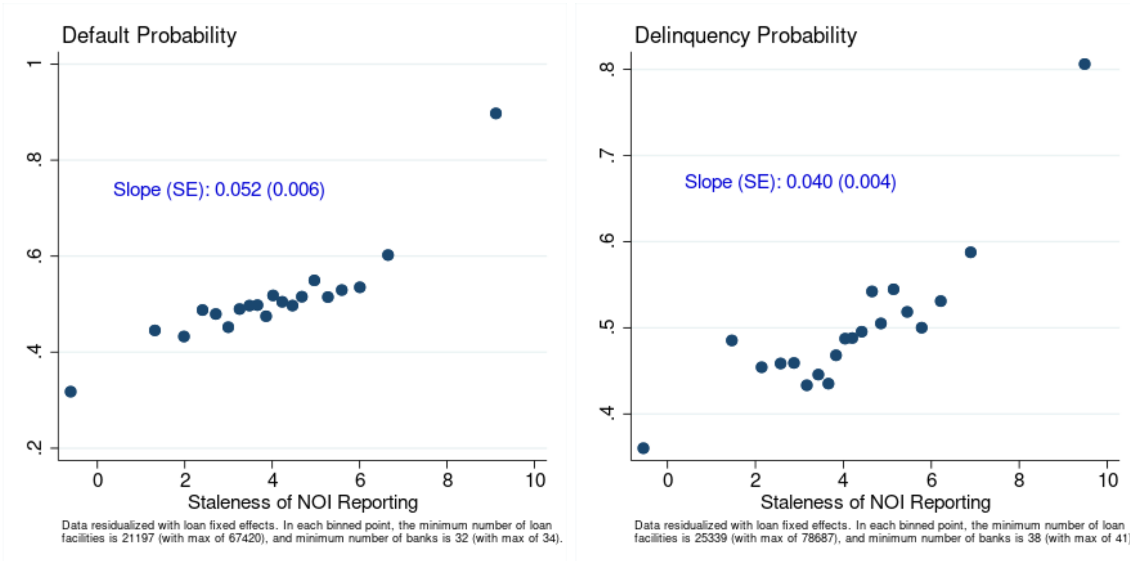
As an initial exploration of the relationship between financial reporting and loan performance, Figure 9 shows the relationship between default probability and stale information. The plot is a binned scatter of the residuals from removing loan fixed effects, reflecting for an average loan, as its financial reporting becomes more outdated, the probability of a realized negative loan outcome changes. There are two outcome variables reflecting adverse loan outcomes, (a) default, which is identified as times when the lender's internal probability of default is 100% (coded in FR Y-14Q for loans currently in default), and (b) delinquency, which is identified as any loan with a non-zero past due balance. We emphasize the usefulness of studying both an indicator for default and delinquency because a lender can trigger a technical default, specifically because a borrower has failed to report their financials for several consecutive quarters.[21]

There is a strong positive correlation between increasingly outdated financial data and adverse loan performance. As the NOI reported by the borrower ages and fails to be updated, borrowers appear significantly more likely to default or become delinquent. There may be some non-linearity to this relationship. It appears that consistently non-reporting borrowers are systematically more likely to default. Most of the distribution is approximately linear, with increasing default risk as staleness rises.

The main regression specification is a linear probability model that isolates within-loan variation

[21] See the servicer's watchlist section of the CRE Finance Council Investor Reporting Package Version 8.3; Adopted October 2, 2023, Effective October 31, 2023, and March 2024: https://www.crefc.org/cre/learn/irp/cre/content/learn/irp/irp-home.aspx.

Figure 9: Default and Delinquency Rate by Staleness of NOI Reporting



Notes: Figures show binned scatterplot of loan-by-quarter observations of probability of default, probability of delinquency, and financial reporting staleness (current reporting quarter minus quarter that the most recent financials were reported 'as of'). Average default and delinquency are both around 0.5% in the Y-14Q dataset. The figure plot residuals from a regression removing loan fixed effects (then adding the sample constant of the dependent and independent variable back into the graphed observations) to isolate within-loan facility variation in staleness and default risk ratings. Among these figures the minimum number of loans in the smallest binned point on the scatter plot is 21,197 and the minimum number of banks summarized by any binned point is 32.

Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

in reporting and loan performance. The regressions include loan fixed effects and fixed effects for the time period (reporting quarter) and city, calendar quarter, and quarters since origination. These fixed effects should absorb variation coming from seasonality in reporting or monitoring activity and any systematic variation between older financial reporting, default risk, and seasoning of the loan. The main sample only includes loans originated and serviced by the bank.[22] The regression is clustered by loan. The variables are indexed as loan i, city c, time period t, calendar quarter q, and time since origination s.

$$default_{it} = \beta \; staleness_{it} + \alpha_i + \alpha_{ct} + \alpha_q + \alpha_s + \nu_{it} \tag{3}$$

We include four lags for reporting staleness to show the dynamics of the reporting behavior and loan performance relationship. This allows us to address the question: does stale information on a loan today (or last quarter) predict mortgage delinquency next quarter? The main regressions report the contemporaneous measure of stale reporting to speak to the issue of whether stale reporting is

[22] In other words, the main regression excludes loans identified as "acquired" loans. In Appendix tables, we include robustness to show the effects are consistent even including acquired loans, and we test whether the predictive value of reporting staleness is independent of local economic conditions by including leads and lads of city-level unemployment rates instead of city-by-quarter fixed effects. Additional tables show staleness effects broken down by property type.

a valuable predictor of default or delinquency. The cumulative lagged measure suggests that failure to update borrower performance over multiple consecutive quarters can predict a larger probability of mortgage distress. The outcome variable is a binary variable for whether a loan is classified as in default based on the internal bank PD. These results are consistent using an alternative measure of mortgage distress based on mortgage delinquency—a binary variable for having any past due payments. Reporting both of these effects may be important because banks have some discretion about whether to classify a loan as 'in default,' while delinquency should be a fairly objective and consistent definition across banks.

Table 2: Default and Delinquency Probability and Staleness of Financial Reporting

Outcome:	Default		Delinquency	
	(1)	(2)	(3)	(4)
Staleness NOI	0.0377***	0.0226***	0.0120**	-0.000968
	(0.00892)	(0.00610)	(0.00551)	(0.00476)
L1.Staleness NOI		0.0161***		0.0178***
		(0.00340)		(0.00403)
L2.Staleness NOI		0.0161***		0.00633
		(0.00369)		(0.00388)
L3.Staleness NOI		0.00481		0.00192
		(0.00395)		(0.00405)
L4.Staleness NOI		0.000777		-9.36e-05
		(0.00630)		(0.00500)
Cumulative Effect		0.060		0.025
P-Value (Cumulative Effect = 0)		0.000		0.010
Observations	1,145,002	1,145,002	1,276,059	1,276,059
R-squared	0.509	0.509	0.308	0.308
Dep Var Mean	0.396	0.396	0.445	0.445
Reporting Quarter-CBSA FE	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y
Quarter of Year FE	Y	Y	Y	Y
Quarters Since Orig	Y	Y	Y	Y

Note: Default is defined as where current PD is equal to 1 (when the obligor is currently in default). Delinquency is defined as where past due payments is greater than 0 and non-missing. The independent variables are calculated as the number of quarters between the "as of" date of the current reported NOI and the reporting date (where reporting and as of dates are quarterly).

Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Results are reported in Table 2. Conditional on time, location, and loan controls, stale financial performance reporting is significantly positively correlated with default and delinquency probability. Reported performance being one quarter more outdated is correlated with 3.77 basis points higher default probability, which is 9.5% higher default relative to the average population default probability of 0.396%. Including a series of lags in this regression indicates that delayed reporting has cumulative effects on mortgage distress. Adding these lagged coefficients together suggests that default probability rises over five quarters by 6 basis points, or a 15.15% increase in default probability.[23] These results are broadly consistent, though somewhat attenuated, when studying the relationship with delinquency. This may be because banks maintain discretion in reporting a loan as "in default" through a technical default on mortgage contract terms without having late payments, which is more strongly correlated with failure to report performance in a timely manner.

The results in this section indicate that financial performance reporting behavior contains meaningful information about subsequent mortgage performance. This information could be useful to incorporate into credit risk modeling in a systematic fashion. While this section focused on the relationship between stale financials and mortgage performance, in the next section we show the logical channel by which outdated information predicts worse mortgage performance: through declining property performance as information becomes more and more outdated, in other words, "no news" is "bad news". We intend for the combination of these sections to provide estimates for future credit risk modeling as an alternative to a common practice of "walking forward" stale financials. Anecdotally, many applications in credit risk modeling walk forward outdated financials to estimate credit risk, either by taking the old NOI directly or inflating it based on some market rent measure (or changes in national inflation). The evidence in this section and the next section suggests this approach may be missing relatively poor performance for non-reporting properties.

5.2 No News Is Generally Bad News

In this section, we study the relationship between the timing of borrower performance reporting and the actual content of those performance updates. To do this, the analysis focuses on loan-by-reporting quarter observations where borrowers updated the financial performance observed by the bank. For each property with an updated performance metric, we construct a variable representing the time since the prior reporting update, calculated as the number of quarters between the current reporting quarter and the last quarter in which the borrower updated their performance. Below, this variable is labeled $\textit{time since prior}_{i,t-j\rightarrow t}$. The primary exercise in this section is to look at the time since the prior performance update and the actual content of that performance. The content of the performance update is measured as either the percent change in net operating income on currently reported financials relative to the previously reported financials—in the equation below, this is Δy_{it}.

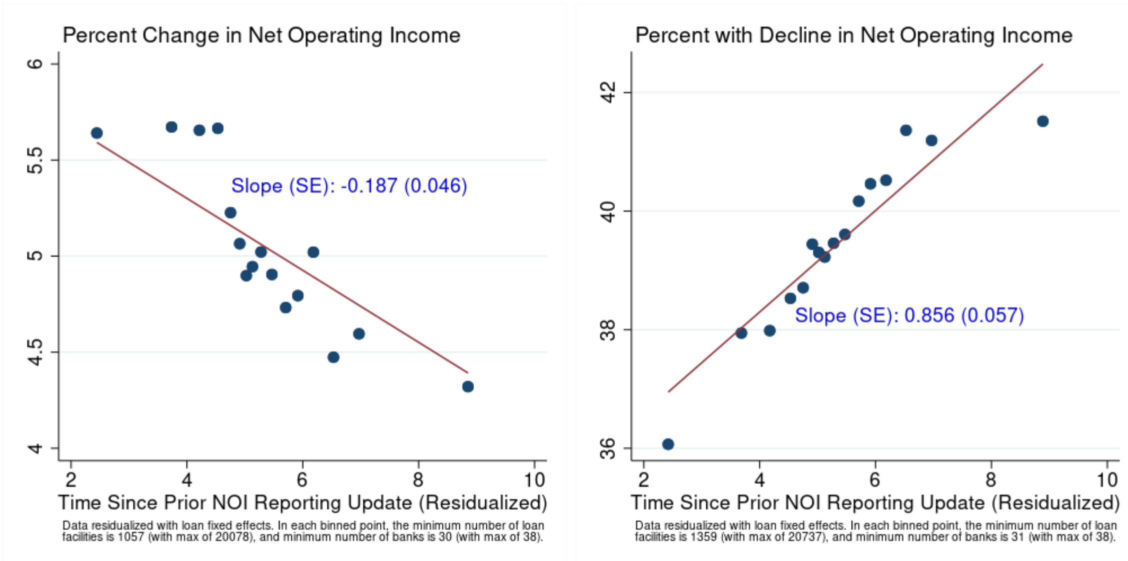
Figure 10 contains a binned scatter plot where we have residualized both the time since prior update variable and the reported change in performance using loan fixed effects.[24] This graph looks at within-loan variation in relatively early or late performance reporting. Because of the controls for loan fixed effects, the graph focuses exclusively on loans that report performance more than once over the mortgage term.

Figure 10 shows that loans that have taken a longer time to report an update to performance have, on average, lower net operating income and lower occupancy rates (shown in Figure A13). The

[23] Appendix Tables B8 and B9 show additional specifications, and robustness checks. The appendix specifications also include all loans (including acquired loans) in the estimation sample. They also report effects of stale occupancy performance. The financial performance in NOI reporting appears to have a stronger relationship with mortgage distress.

[24] See Appendix Figure A13 for corresponding results on occupancy reporting.

Figure 10: Actual Change in Performance by Time to Performance Update



Notes: Figures show binned scatter plots of the relationship between the time since a loan's previous reporting quarter and the new reporting quarter on the x-axis, and the actual average percent change in net operating income on the y-axis. Percent change in NOI truncated above at 290% and below at -90% (1st and 99th percentile). Each variable is residualized with loan fixed effects. Linear OLS slope and standard error, clustered by loan, reported in the graph. Among these figures the minimum number of loans in the smallest binned point on the scatter plot is 1,057 and the minimum number of banks summarized by any binned point is 30.

Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

slope of these relationships is negative and statistically significant, indicating that one additional quarter of delay has 0.187 percent lower income and 0.057 ppt lower occupancy. Note that even in severely delayed reporting, NOI grows on average. To study indicators of the risk distribution or tail risk, rather than the average performance change, the right-hand side figures look at the percent of performance updates that report a decline in NOI or in occupancy. One additional quarter of delayed reporting is related to 0.856 percent higher probability of a decline in NOI and 0.430 percent higher probability of a decline in occupancy.

This relationship is formalized in a regression specification that studies the reporting timing and performance using within-city, within-loan variation. Loan fixed effects, as well as fixed effects for the time period (reporting quarter)-by-city, calendar quarter, and quarters since origination are included in the regression. These fixed effects should absorb variation coming from seasonality in reporting, and any systematic variation between time since previous instances of financial reporting and seasoning of the loan (i.e., how long ago the loan was originated). The variables are indexed as loan i, city c, time period t, calendar quarter q, and time since origination s.

$$\Delta y_{it} = \beta \; time\ since\ prior_{i,t-j\to t} + \alpha_i + \alpha_{ct} + \alpha_q + \alpha_s + \nu_{it} \tag{4}$$

The results of this regression are reported in Table 3. The coefficients match those reported in

Table 3: Change in Performance and the Length of Time Between Reporting Updates

Outcome:	Percent Change in NOI		1(Decline in NOI)		Change in Occupancy		1(Decline in Occupancy)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time Since Prior Reporting Quarter	-0.201***		0.836***		-0.0636***		0.433***	
	(0.0509)		(0.0623)		(0.00658)		(0.0340)	
Time Since Prior Reporting X Retail		-0.124		0.777***		-0.0555***		0.489***
		(0.122)		(0.140)		(0.0143)		(0.0708)
Time Since Prior Reporting X Industrial		0.304		0.506**		-0.0252		0.158
		(0.193)		(0.222)		(0.0215)		(0.101)
Time Since Prior Reporting X Multifamily		-0.384***		1.046***		-0.0688***		0.393***
		(0.0605)		(0.0820)		(0.00846)		(0.0468)
Time Since Prior Reporting X Office		0.0718		0.483***		-0.0698***		0.635***
		(0.148)		(0.151)		(0.0188)		(0.0818)
Observations	339,974	339,974	349,845	349,845	340,722	340,722	344,315	344,315
R-squared	0.238	0.239	0.253	0.255	0.223	0.223	0.306	0.306
Dep Var Mean	5.016	5.016	39.40	39.40	0.0848	0.0848	24.55	24.55
Reporting Quarter-by-CBSA FE	Y	Y	Y	Y	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter of Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarters Since Orig	Y	Y	Y	Y	Y	Y	Y	Y
Property Type-by-Quarter FE	N	Y	N	Y	N	Y	N	Y

Note: Observations included any quarter in which the borrower's performance is updated. Dependent variable is the percent change in NOI, a binary variable for NOI decline, change in occupancy rate, or a binary variable for occupancy rate decline. NOI changes are censored around the 1st and 99th percentiles at -99% and 290%, and occupancy rate changes are censored above and below at 50%. The independent variables are calculated as the number of quarters since the previous reporting quarter of either performance metric (NOI or occupancy). Standard errors are clustered by loan.

Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

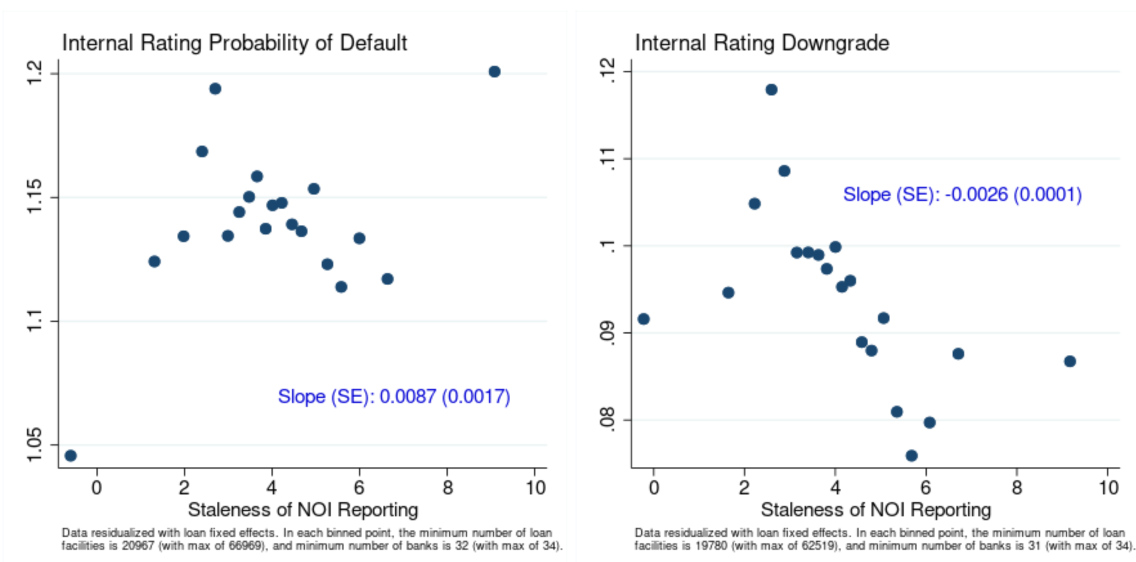
the binned scatter plot. The results also report the time since last reporting interacted with property type indicators. This shows that the negative coefficient for financial reporting is entirely driven by a negative relationship between time since prior reporting and NOI growth for multifamily properties. However, delayed reporting is positively correlated with the probability of income decline across all property types. The non-significant and positive coefficients in column (2) could be consistent with a 'gambling for resurrection' dynamic where borrowers delay reporting and engage in the more strategically risky behavior to avoid default. On average, it appears delayed reporters are more likely to end up with NOI declines, but there is a long right-tailed distribution of NOI growth. For occupancy reporting, the length of time between reports is related to consistently negative occupancy outcomes, though the relationship is not statistically significant in the industrial sector. One additional quarter of delayed reporting has an average relationship suggesting an additional 0.836 percent probability of NOI decline and 0.433 percent probability of occupancy decline.

5.3 On Average, Banks Are Slow to Downgrade (or Upgrade) Due to Stale Performance

It could be the case that because independent monitoring is costly, on the margin, banks rely heavily on borrower performance reporting. Monitoring costs could rely on 'lumpy' investments (e.g., in data, IT, analysis, or physical visits to borrower locations)—banks face a dynamic choice of whether to discontinuously increase effort and resources spent on monitoring. Banks may 'miss' increases in default risk if they fail to update internal risk assessments for non-reporting or late-reporting borrowers. In part, this section studies the extent to which banks follow a "wait-and-see" approach to borrower performance, compared to an approach with quickly escalating risk ratings when their information on the borrower degrades.

To explore the monitoring-risk rating relationship, Figure 11 shows a binned scatterplot of the relationship between reporting staleness and internal probability of default, representing banks' internal risk rating for each loan facility. The binned data is residualized by loan fixed effects to isolate within-loan changes in PDs. The figure shows that while the average loan with recently updated data has relatively lower-rated risk, while exceptionally stale financial data has higher risk ratings. There is a negative relationship between reporting staleness and PDs through most of the distribution. This slope is a marked contrast to the prior sections, which showed a near-monotonic positive relationship between realized distress and reporting staleness, and a consistent negative relationship between time to update and ex post performance. The right-hand figure isolates quarter over quarter changes in PDs, identifying rating downgrades as a greater than one basis point increase in the bank's internal PD. The probability of downgrades is declining with the age of financial performance data, suggesting that lenders are not systematically increasing PDs (i.e., downgrading loan-specific risk ratings) continuously as the existing financial data in the bank's records becomes more and more outdated.

Figure 11: Relationship between Internal PD or Downgrade on Stale Reporting



Notes: Figures show binned scatterplot of loan-by-quarter observations of banks internal ratings of probability of default, probability of a downgrade (where PD increases), and financial reporting staleness (current reporting quarter minus quarter that the most recent financials were reported 'as of'). The figure plot residuals from a regression removing loan fixed effects to isolate within-loan facility variation in staleness and default risk ratings. Among these figures the minimum number of loans in the smallest binned point on the scatter plot is 19,780 and the minimum number of banks summarized by any binned point is 31.
Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

The main specification used to study this setting regresses an indicator variable for any instance of a lender rating update, upgrade, or downgrade on the continuous staleness measure for the reported financial data. The regressions control for loan, reporting quarter-by-CBSA, calendar quarter, and loan seasoning fixed effects. This set of fixed effects should absorb several sources of variation that could confound the relationship between bank's risk rating decisions and the contemporaneous staleness of the information available to them. Because this analysis is focusing on marginal changes in bank's risk rating behavior in advance of a loan entering default or delinquency, the estimation sample removes any observations where a loan is classified as in default in the current quarter or the previous quarter.

Table 4: Lenders' Internal PD Updating Behavior and Stale Financial Performance Reporting

Outcome:	Current Internal PD		1(PD Update)		1(Downgrade PD)		1(Upgrade PD)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Staleness NOI	-0.0404***	-0.0389***	-0.0145***	-0.0271***	-0.00612***	-0.0114***	-0.00837***	-0.0157***
	(0.00288)	(0.00248)	(0.000260)	(0.000301)	(0.000161)	(0.000208)	(0.000181)	(0.000227)
L1.Staleness NOI		-0.00868***		0.0219***		0.00883***		0.0131***
		(0.00145)		(0.000319)		(0.000226)		(0.000253)
L2.Staleness NOI		0.00485***		0.00596***		0.00372***		0.00224***
		(0.00139)		(0.000264)		(0.000192)		(0.000217)
L3.Staleness NOI		0.00499***		0.000906***		-0.000516***		0.00142***
		(0.00149)		(0.000257)		(0.000189)		(0.000214)
L4.Staleness NOI		0.00340		-0.00554***		-0.00235***		-0.00319***
		(0.00231)		(0.000249)		(0.000180)		(0.000196)
Cumulative Effect		-0.034		-0.004		-0.002		-0.002
P-Value (Cumulative Effect = 0)		0.000		0.000		0.000		0.000
Observations	1,069,901	1,069,901	1,069,901	1,069,901	1,069,901	1,069,901	1,069,901	1,069,901
R-squared	0.533	0.533	0.235	0.244	0.199	0.202	0.159	0.164
Dep Var Mean	1.112	1.112	0.209	0.209	0.0977	0.0977	0.111	0.111
Reporting Quarter-CBSA FE	Y	Y	Y	Y	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter of Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarters Since Orig	Y	Y	Y	Y	Y	Y	Y	Y

Note: Current Internal PD is the numeric value of the reported PD by the bank with any instances that the loan is in default excluded from the regression. 1(PD Update) is any change in the bank internal PD for a loan of more than one basis point. A downgrade is any increase in the PD, and an upgrade is any decline in the PD. Loans in default this quarter or last quarter are excluded from the regression sample. The independent variables are calculated as the number of quarters between the "as of" date of the current reported NOI or occupancy and the reporting date (where reporting and as of dates are quarterly). The Cumulative Effect in the middle rows reports the sum of all five coefficients with a P-Value reported for a test that the sum of coefficients is equal to zero.

Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Table 4 displays the results of these regressions. One quarter more outdated financial performance is correlated with 1.45 percentage points lower probability of any change in the bank's internal risk rating. The dynamic specification with lags of the staleness measure suggests that the cumulative effect is only 0.4 percentage points because banks change PDs over the two quarters following an increase in the outdatedness of financial performance. Those lagged changes in risk ratings do not appear to accumulate, given that the probability of updating PDs is negative in the fourth lag coefficient, showing the effect a year after a marginal increase in stale NOI reporting.

The results on the probability of updating internal risk ratings are consistently in the same direction for both upgrades and downgrades, which is quite surprising. One might expect that increasingly stale financial performance would lead almost uniformly to downgraded risk ratings, given that delayed reporting is a negative signal on average. Instead, the lagged effect of stale performance appears to be weighted towards slightly more upgrades in loan quality than downgrades.

Consistent with this net effect on the probability of changing risk ratings, columns (1) and (2) (also see Appendix Table B9) show that the average level of PDs declines in response to increasingly stale financial performance. This net negative effect on PD levels runs counter to the earlier results indicating that delayed performance is correlated with worse eventual news about financial performance, which is also correlated with higher default probability. However, one potential implication of this result on bank risk rating behavior is that banks are likely monitoring CRE through multiple channels, not just through borrower-reported performance. A rational bank should observe local employment and real estate data by city or neighborhood (or for comparable properties) to incorporate into risk ratings, even without performance updates for each specific property. Prior research (e.g., Lisowsky et al. 2017; Gustafson et al. 2021) suggests that banks acquire soft information through site visits. Anecdotally, banks also collect soft information through conversations via phone calls, emails, or other meetings. While the bank may view these alternative sources of information as substitutable with hard information, the hard information provided through reporting financial or leasing performance seems significantly more valuable credit risk management perspective.

6 Banks Endogenously Shift Monitoring Effort

We have established that stale reporting is correlated with declines in both property and loan performance. We have also shown that banks are very dependent on receiving these reports before reviewing and updating their views on the credit risk of their loans. This raises a key question: given the value of this information, why do banks tolerate stale financial reporting? One possible explanation is that improving the timeliness of the financial reporting is costly, both directly and indirectly. Direct costs include the staffing and hours of loan officers, credit risk analysts, or special distressed asset work-out staff at the bank, including via reaching out to borrowers to request information or visiting their properties or offices directly. This outreach no doubt would include local loan officers who approved the loans, and have an ongoing relationship with the borrower. Monitoring and information acquisition necessarily involves trade-offs: for loan officers, alienating borrowers by persistently requesting information, imposing hassle costs on them or even threatening them with audits or penalties may cause the bank to lose future business. These dynamics likely create indirect costs to bank-client relationships. We propose to study these trade-offs in this section. If cost is indeed a factor, we would expect banks to be more willing to pay said costs if the potential value of the more timely information increases. This section studies two such shocks to the marginal value of information.

6.1 Bank Monitoring Responds to Local Shocks, and to Indirect Stress in Their Loan Portfolio

Our first test uses a plausibly exogenous shock that affected local economic conditions in a set of U.S. cities to disentangle potential borrower-specific and lender-specific forces that affect performance reporting and loan monitoring behavior. The shock also had differential effects on banks based on their pre-existing balance sheet exposure—this source of bank-level variation is used to disentangle the bank's monitoring motives from the effect of the shock on borrower reporting behavior.

The shock studied in this section is the sharp oil price decline in late 2014 (between Q3 2014 and Q1 2015). Bidder et al. (2021) and Wang (2021) both study different consequences of this shock for banks' risk management and new lending behavior. Prior research found substantial bank-level risk-shifting behavior in response to the oil price shock. This is consistent with banks engaging in new lending or loan sales to raise cash reserves or capital when hit by a large asset shock. This section uses the oil price decline to show how banks engage in costly monitoring activity when hit by an adverse event. The costly monitoring activity could partially be in service to banks evaluating their available assets to sell or refinance in anticipation of a funding shock. Unfortunately, before 2016, there is very little information on asset or loan-level disposition reported in the Y-14 CRE schedule, so we cannot study loan sales, refinance, or REO outcomes around the oil shock.

Bank-level exposure is measured based on the oil and gas industry share of committed loan balances in each bank's commercial and industrial lending portfolio ("C&I lending"). The measure is based on the Q4 2013 C&I lending data, where oil and gas exposure is determined based on industry codes (NAICS, SIC, or GICS), similarly constructed to Bidder et al. (2021).[25] An exposed bank is defined as one with higher-than-average oil and gas exposure, which approximately corresponds to the top quartile of CCAR reporting banks (because the C&I lending-based O&G exposure has a long right-tail).

City-level exposure to the oil and gas industry is defined using the share of payrolls from industries classified as oil and gas related, using data based on Wang (2021). The geographic unit of interest is core-based metropolitan statistical areas (CBSAs), which we aggregate using the County Business Patterns data with six-digit NAICS codes. The average city or region has relatively little oil and gas payroll employment, with an average of nearly 0.1%. There is a long right tail in local oil and gas exposure. We define the top quartile of CBSAs as moderately exposed if they have more than 0.36% of payrolls in those industries, and further define a very heavily exposed city as one with greater than 5% of payrolls in oil and gas.

We hypothesize that (a) all banks should engage in more intensive monitoring in heavily hit regions; (b) heavily exposed banks should engage in more intensive monitoring in most regions, but especially those hit by the shock; and (c) it is unclear whether non-exposed banks will engage in more or less intensive monitoring in areas "moderately" hit by the shock.

The analysis splits the dataset into six groups of loans: (1) loans in areas not affected by oil price declines with lenders not very exposed to the oil and gas industry; (2) loans in areas moderately affected by oil price declines with lenders not very exposed to the oil and gas industry; (3) loans in areas heavily affected by oil price declines with lenders not very exposed to the oil and gas industry; (4) loans in areas not affected by oil price declines with lenders very exposed to the oil and gas industry; (5) loans in areas moderately affected by oil price declines with lenders very exposed to the oil and gas industry; and (6) loans in areas heavily affected by oil price declines with lenders very exposed to the oil and gas industry. The overall CRE loan share at the beginning of 2014 in these six groups is presented in Table 5.

[25] This paper uses just Q4 2013 rather than 2012-2013 averages. The bank-level average oil and gas exposure is 5.4%, slightly below the Bidder et al. (2021) calculation of 5.9%.

Table 5: CRE Exposure to the 2014 Oil Price Shock by City & by Bank

	Banks Exposed (>5.4%)	Banks Not Exposed (<5.4%)
City Not Exposed (<0.36%)	14.4	52.8
Moderately Exposed (0.36-5%)	3.9	26.4
Heavily Exposed (>5%)	0.9	1.6

Note: City exposure is defined as a percent of payroll employment in oil & gas industries; bank exposure is defined as a percent of C&I lending to oil & gas industries, see more in text. Contains 1,135,927 observations (141,423 loan facilities over 28 banks; 11 banks in the exposed group and 17 in the non-exposed group).
Source: U.S. Census Bureau County Business Patterns data. Federal Reserve Form Y-14Q Schedule H.1 and H.2, Authors' analysis.

By breaking down the lending and monitoring activity into these groups, we can measure the extent to which borrowers exposed to the local economic shock changed their financial performance reporting behavior. The breakdown by bank allows us to infer whether banks heavily exposed to the oil price decline engaged in more active monitoring activity of loans and whether that monitoring activity spilled over into geographic markets that were not particularly affected by the oil price shock.

To study the evolution of reporting and monitoring in each of these groups, we run regressions with time-fixed and city-fixed effects. For clarity of presentation and to match the timing of the oil shock, we include quarter-by-loan level data but include time-fixed effects at the half-year level (combining Q1 & Q2 into H1 and Q3 & Q4 into H2). Loans are indexed by i, time is indexed by t, cities are indexed by c, and banks are indexed by b. Additional controls include loan, calendar quarter, and quarters since origination fixed effects. We study the dynamics of these effects by interacting the city and bank-level exposure measures with time-specific coefficients.

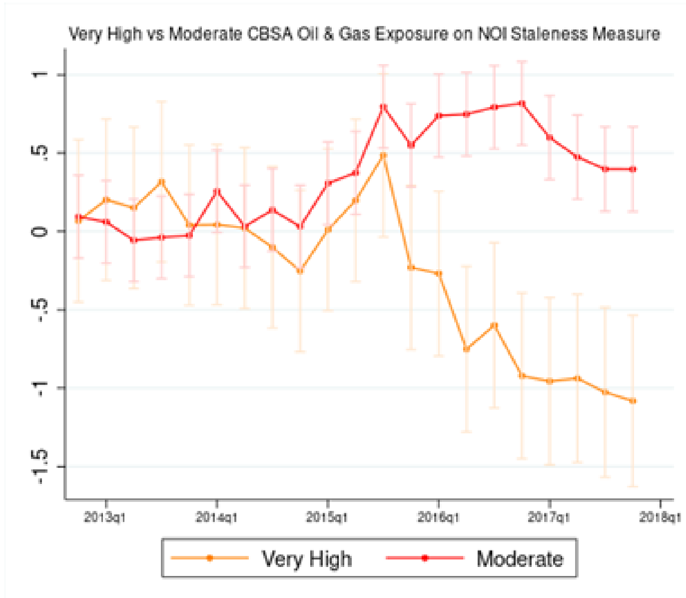
$$staleness_{it} = \beta_{gt}\ I(loan_i \in group_{g(cb)}) + \alpha_i + \alpha_t + \alpha_q + \alpha_s + \alpha_c + \nu_{it} \tag{5}$$

In the regression, the excluded group is loans in regions not hit by the oil shock and whose lenders are not heavily exposed to the shock. This is the majority of the sample (52.8% shown in the table above). The excluded time period is H1 2014, the half-year just before the oil price shock.

Before turning to the regression with the interaction of both bank-specific groupings, we study the effect of the oil shock on loan performance reporting and monitoring using the city-level variation. We show results from a regression with only three city groups: loans in cities heavily exposed to oil and gas ("Very High"), loans in cities moderately exposed ("Moderate," as defined above), and cities not exposed to the shock. The excluded group is loans in cities not exposed to the oil and gas shock based on their 2013 employment-industry structure, so differential borrower-reporting changes can be interpreted as causal effects of the oil shock on loan monitoring relative to loans in non-exposed cities.

Figure 12 shows the coefficients with 95% confidence intervals using all CRE loans in multifamily, office, industrial, and retail. The "Moderate" and "Very High" exposure coefficients are all estimated relative to the average values of non-exposed CBSAs. Loans in highly exposed cities experience an

Figure 12: Dynamic Effects of Oil Price Shock on Financial Performance Staleness for Moderately Exposed and Heavily Exposed CBSAs (Relative to Excluded Group of Non-Exposed CBSAs)



Notes: Regression coefficients plotted for moderately exposed and very high exposure cities (defined using core-based statistical areas). City exposure is defined as a percent of payroll employment in oil & gas industries, see more in text. Excluded group is loans in cities with less than 0.36% of payroll employment in oil and gas industries.

Source: U.S. Census Bureau County Business Patterns data. Federal Reserve Form Y-14Q Schedule H.1 and H.2, Authors' analysis.

increase in the staleness of financial performance in the quarters just following the oil shock (Q1-Q3 2015), then a sharp and sustained decline in the performance staleness of CRE loans on their books. In contrast, loans in moderately exposed cities experience a sharp and persistent increase in stale performance data because of changes in monitoring and reporting to the banks. Internal PDs increased in late 2015 and early 2016, and a subsequent increase in realized delinquency rates in late 2016 and early 2017 in Appendix Figure D15. Banks intensify monitoring and, at least at an aggregate level, correctly anticipate an increase in mortgage distress. These differential trends in monitoring and risk management outcomes help motivate the analysis, breaking down both city exposure and bank exposure.[26]

Figure 13 reports the main regression output, with loans held by non-exposed banks in non-exposed CBSAs being the excluded comparison group.[27] The main effects on the staleness measure are shown in the three figures. The measure of stale information for exposed banks in non-exposed cities declines by 23% by early 2016 relative to the pre-oil shock average. We interpret these effects on exposed banks in non-exposed cities as proximate causal effects of the oil price shock on bank

[26] In Appendix D, we report results broken down by property type. The results indicate that effects are stronger for multifamily apartment buildings, but generally consistent for office, retail, and industrial properties where banks in very high exposed cities intensify monitoring activity. The increase in stale performance in cities that are only moderately exposed to the oil price shock is primarily present in the multifamily sector.

[27] The results of the event study coefficients are reproduced in table format in Appendix Table D16.

monitoring for banks whose balance sheets are most heavily exposed to the oil and gas industry. This set of non-exposed cities should experience no direct effect of a decline in oil prices on mortgage performance (if anything, the decline in input prices could have an indirect positive effect on supply-side costs for some industries). Any oil and gas-related effects should not differentially affect loans based on whether their lenders are exposed to the shock except through a bank-funding shock channel. Because of the limitations of the supervisory data in this early period, this paper cannot address exactly what banks do with this improved information. The bank's incentive for seeking out better information about their loan assets could be in anticipation of the need to sell loans to investors or other commercial banks if they experience a funding stress event, a run on their deposits (which may also be exposed to oil and gas firms), or a need to raise capital or cash reserves to deal with distressed loans.

The differential response to the oil and gas shock by bank-level exposure to the oil and gas industry is very clear when considering cities that are moderately exposed to the oil and gas industry. In moderately exposed cities, the exposed banks decrease the staleness of performance information by around 24%. However, non-exposed banks in moderately exposed cities experience an increase in stale reporting by 11%. This increase in stale performance matches the results in the city-level analysis in Figure 12. These differences between banks suggest that monitoring of CRE loans involves "active monitoring", so banks exposed to the shock engage in more intensive monitoring across cities, but non-exposed banks appear to allow for more lax monitoring of their CRE loans. The average delinquency rates in Appendix Figure D15 suggest that this reduction in monitoring intensity for non-exposed banks has few observable negative consequences given that delinquency rates in moderately exposed cities do not significantly rise through 2017.

Finally, the most exposed cities see a delayed response in reporting for all types of banks. There are significant declines in stale information by mid-2016, nearly two years after the oil price shock. Both types of banks end up with a decline in stale performance information of 25-27% by the end of 2016. These results help suggest that banks intensify monitoring when they know where to look geographically. Interestingly, banks do not appear to acquire fresh information in the highest-risk areas immediately, given that it can take a year or more to significantly decrease the average age of loan monitoring data. Both the most and least exposed banks behave in surprisingly similar ways, producing improved information in the most-affected geographic areas with a lag.

6.2 Banks Intensify or Relax Monitoring Due to Loan-Specific Risks

In prior sections, we study the dynamics of lender demand for and use of performance information on CRE assets. Exposure to oil price shocks affects local collateral performance and bank monitoring activity through their exposure to other parts of their loan portfolio.

The empirical exercise in this section exploits loan-specific shocks that affect borrower solvency and are transmitted through the lender. For floating-rate mortgages, changes in interest rates directly affect the borrower's cash flows, and the lender directly observes and transmits the change in those mortgage payments. The bank observes distress (or alleviation of distress) coming through changes in mortgage payments. This allows us to test whether a negative loan-specific shock (from higher

Figure 13: Regression Results of Oil Price Shock on Monitoring by CBSA-level Exposure & Bank-Specific Exposure (Comparing to Non-O&G Exposed CBSA & Bank; Base Period H1 2014)

Notes: City exposure is defined as a percent of payroll employment in oil & gas industries, see more in text. Excluded group is loans in cities with less than 0.36% of payroll employment in oil and gas industries, and base period H1 2014.

Source: U.S. Census Bureau County Business Patterns data. Federal Reserve Form Y-14Q Schedule H.1 and H.2, Authors' analysis.

rates) causes an increase or decrease in information production. Borrowers may have an incentive to report positive performance more promptly to head off costly bank monitoring activities (e.g., an audit) when interest rates increase; banks may also have an incentive to increase monitoring activity when they transmit increases in mortgage payments. In the case of a positive rate shock, we may see an increase in reporting for both better-performing, lower-risk collateral and poor-performing, high-risk collateral. This also provides an opportunity to test for symmetry: does reporting activity decline in response to positive shocks (from declining rates)?

To study this setting, we construct national interest rate shifts using 10-year Treasury yields and interact those shifts with a binary variable for floating rate loans. The set of floating rate loans are those with rates that report resets on a monthly frequency. Many of these loans are pegged to SOFR or another specific index. Treasuries yields are used in this analysis for simplicity and clarity. The main results provide direct evidence of the relevance of this measure: Treasury yields pass through strongly to mortgage rates on floating-rate loans. The comparison group of fixed-rate loans is those classified as fixed the first time they enter the Y-14Q dataset. This paper does not use any variation in changes in the rate status of the loan or options to float or fix the rate. Additionally, because quarterly reporting updates are observed in the Y-14Q dataset and do not contain any contract specifics about when rates versus payments change, we calculate interest rate shifts as changes over the past three quarters.

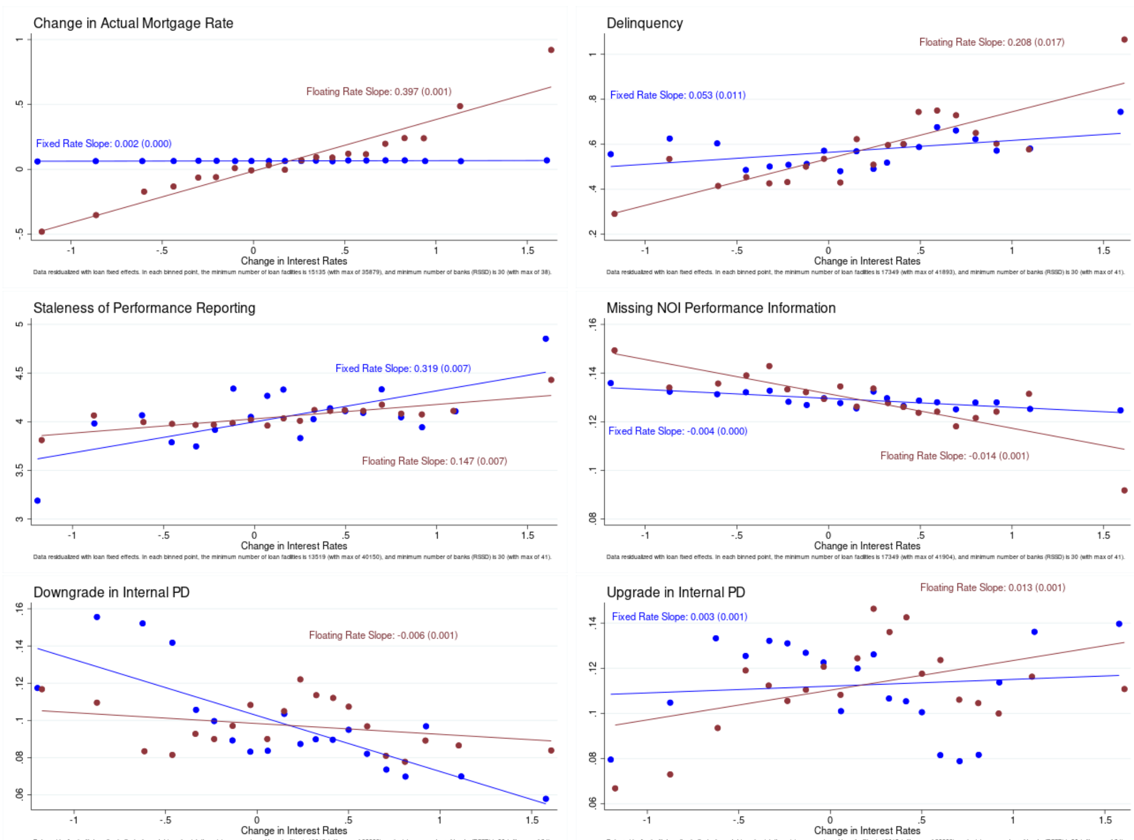
Before turning to regression specifications, binned scatterplots are shown in Figure 14, comparing interest rate shifts with loan-level outcomes for fixed-rate loans versus floating-rate loans. These binned plots control for loan fixed effects to isolate the within-loan variation in rates and loan-level outcomes. A 100 basis point change in Treasury yields shifts loans classified initially as floating rate mortgages by 39.7 basis points and fixed rate loans by just 0.2 basis points. The relationship between rates and delinquency suggests the same rate shock is correlated with 5.3 basis points higher delinquency for fixed-rate loans, and 20.8 basis points higher delinquency for floating-rate loans. The main regressions control for location and time-specific sources of variation to absorb any confounding variation that could contribute to the positive coefficients for fixed rate loans.

Consistent with the discussion of motives for performance reporting, large rate increases lead to relatively less stale reporting for floating rate loans with a significant decrease in missing NOI performance data for floating rate loans exposed to large mortgage rate increases. This effect appears to be symmetric: rate declines (improving the credit quality of the loan) lead to relatively more outdated financial reporting and relatively more missing financial data. Finally, rate increases are correlated with both a higher probability of downgrades and upgrades in banks' internal risk ratings, while rate decreases lead to both fewer downgrades and upgrades.

This analysis is performed with a regression specification comparing the effect of rate shocks by using the relative slopes for floating- and fixed-rate loans with a common component of rate variation absorbed by reporting quarter fixed effects. In the most parsimonious specifications, the regression absorbs quarter-by-city fixed effects (α_{ct}), as well as loan fixed effects (α_i), calendar quarter fixed effects (α_q), and loan seasoning fixed effects (α_s).

$$staleness_{it} = \beta \ \times I(floating_i) \ \times \Delta rates_t + \alpha_i + \alpha_{ct} + \alpha_q + \alpha_s + \nu_{it} \tag{6}$$

Figure 14: Effect of Rate Changes on Actual Mortgage Rates, Mortgage Distress, Staleness of Performance Reporting, and Banks' Internal Risk Ratings for Floating Rate Loans Relative to Fixed Rate Loans



Notes: Change in Interest Rates captures 3-quarter change in average Treasury yields. Floating versus fixed rate loans are identified in the initial quarter the loan enters the dataset. Among these figures the minimum number of loans in the smallest binned point on the scatter plot is 13,615 and the minimum number of banks summarized by any binned point is 26.

Source: U.S. Census Bureau County Business Patterns data. Federal Reserve Form Y-14Q Schedule H.2. Federal Reserve Bank of St. Louis, FRED (Federal Reserve Economic Data), Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis (DGS10), Authors' analysis.

The first set of results in Table 6 shows the effect of rates on the current mortgage rate of the loan, the delinquency probability, and the loan default probability. The Treasury yield-to-mortgage rate relationship is around 0.4, as shown in the graphs above. In the cross-section, delinquency and default increased by 0.244 and 0.254 percentage points in response to interest rate changes. That relationship is attenuated by exploiting within-loan and within-city variation, though still economically and statistically significant. Delinquency increases by 0.134 ppt and default by 0.106 ppt.

Table 6: Effect of Rate Changes on Actual Mortgage Rates and Mortgage Distress for Floating Rate Loans Relative to Fixed Rate Loans

Outcome:	Δ(Mortgage Rate)			Delinquency			Default		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Floating X ΔTreasury Rates	0.433***	0.407***	0.402***	0.244***	0.125***	0.134***	0.254***	0.0963***	0.106***
	(0.000889)	(0.00105)	(0.00118)	(0.0202)	(0.0213)	(0.0250)	(0.0260)	(0.0246)	(0.0293)
Δ UER (t+2,t+1)		-0.00840***			-0.0154*			-0.0115*	
		(0.000386)			(0.00791)			(0.00623)	
Δ UER (t+1,t)		0.00284***			-0.00894			-0.0167**	
		(0.000464)			(0.00911)			(0.00709)	
Δ UER (t,t-1)		0.00173***			-0.0186**			-0.0172**	
		(0.000517)			(0.00949)			(0.00803)	
Δ UER (t-1,t-2)		-0.00719***			-0.000409			-0.0208***	
		(0.000419)			(0.00881)			(0.00755)	
Δ UER (t-2,t-3)		0.000288			0.0242***			-0.00780	
		(0.000394)			(0.00880)			(0.00684)	
Observations	1,593,880	1,455,061	1,525,656	1,799,495	1,649,438	1,741,074	1,543,477	1,422,271	1,490,181
R-squared	0.472	0.550	0.563	0.000	0.324	0.344	0.001	0.588	0.587
Dep Var Mean	0.0645	0.0658	0.0645	0.582	0.520	0.547	0.541	0.469	0.504
Reporting Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan FE	N	Y	Y	N	Y	Y	N	Y	Y
Quarter of Year FE	N	Y	Y	N	Y	Y	N	Y	Y
Quarters Since Orig	N	Y	Y	N	Y	Y	N	Y	Y
CBSA-Quarter FE	N	N	Y	N	N	Y	N	N	Y

Note: Dependent variable is either the change in actual, current mortgage rates reported on the loan over the past quarter, a binary variable for whether the loan was delinquent on any payments, or a binary variable for whether the bank classified the loan as in default. The independent variables are calculated as the interaction between a loan being floating rate when first entering the Y-14Q dataset interacted with the change in Treasury yields over the past 3 quarters. Additional controls include quarter-over-quarter changes in CBSA unemployment rates. These unemployment rates are absorbed when including CBSA-by-year fixed effects.

Source: Bureau of Labor Statistics, Local Area Unemployment Statistics. Federal Reserve Form Y-14Q Schedule H.2. Federal Reserve Bank of St. Louis, FRED (Federal Reserve Economic Data), Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis (DGS10), Authors' analysis.

The next results show the effect of rate changes on performance reporting behavior. Table 7 shows that rate increases reduce the staleness of financial data observed by the banks, increases the propensity for reporting, and reduces the probability of leaving the financial fields missing in banks internal systems. A 100 basis point rate shock transmits to 0.138 quarters less outdated financial reporting, a 0.9 percent higher probability of updating financials, and a 1.1 percent lower probability of the bank leaving the financial reporting fields empty. Considering the baseline 12.9% of loans with missing financial data in any given month, the decline in missing performance information declines by a non-trivial 8.5%. In Appendix Table D23, we show very similar results for occupancy performance reporting probability. The caveat for occupancy performance is that in the cross-section, occupancy information is more outdated for floating rate loans, but controlling for year-by-CBSA fixed effects returns a negative effect on occupancy staleness consistent with the increased probability of updating occupancy reported to the bank and reduction in missing occupancy data observed in columns (4)-(6) and (7)-(9).

Table 7: Effect of Rate Changes on Loan Reporting and Monitoring for Floating Rate Loans Relative to Fixed Rate Loans

Outcome:	Staleness NOI			1(Update NOI)			1(NOI Performance Missing)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Floating X ΔTreasury Rates	-0.152***	-0.132***	-0.138***	0.0194***	0.00967***	0.00901***	0.0504***	-0.0124***	-0.0114***
	(0.0114)	(0.00934)	(0.0104)	(0.000839)	(0.000771)	(0.000834)	(0.00119)	(0.000597)	(0.000647)
Δ UER (t+2,t+1)		0.00754***			-0.00183***			0.000337**	
		(0.00269)			(0.000501)			(0.000168)	
Δ UER (t+1,t)		0.0181***			-0.00153***			0.000640***	
		(0.00310)			(0.000496)			(0.000189)	
Δ UER (t,t-1)		0.0219***			-0.00205***			0.00100***	
		(0.00337)			(0.000518)			(0.000204)	
Δ UER (t-1,t-2)		0.0415***			-0.00727***			0.00109***	
		(0.00330)			(0.000504)			(0.000196)	
Δ UER (t-2,t-3)		0.0322***			-0.000808*			0.00108***	
		(0.00290)			(0.000490)			(0.000176)	
Observations	1,576,123	1,443,348	1,523,085	1,799,716	1,649,692	1,741,326	1,799,716	1,649,692	1,741,326
R-squared	0.024	0.642	0.695	0.007	0.268	0.288	0.004	0.858	0.863
Dep Var Mean	4.050	3.965	4.078	0.271	0.265	0.265	0.129	0.129	0.129
Reporting Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan FE	N	Y	Y	N	Y	Y	N	Y	Y
Quarter of Year FE	N	Y	Y	N	Y	Y	N	Y	Y
Quarters Since Orig	N	Y	Y	N	Y	Y	N	Y	Y
CBSA-Quarter FE	N	N	Y	N	N	Y	N	N	Y

Note: Dependent variable is either the NOI staleness measure, a binary variable for whether there was any update to the NOI reporting, or a binary variable for whether the NOI performance reporting was missing or a non-applicable value. The independent variables are calculated as the interaction between a loan being floating rate when first entering the Y-14Q dataset interacted with the change in Treasury yields over the past 3 quarters. Additional controls include quarter-over-quarter changes in CBSA unemployment rates. These unemployment rates are absorbed when including CBSA-by-year fixed effects.

Source: Bureau of Labor Statistics, Local Area Unemployment Statistics. Federal Reserve Form Y-14Q Schedule H.2. Federal Reserve Bank of St. Louis, FRED (Federal Reserve Economic Data), Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis (DGS10), Authors' analysis.

The final set of results in this section show the effect of rate shocks on banks internal risk rating behavior. Because on average floating rate loans become more risky as rates rise, we should observe an increase in the PD ratings in the cross-section. However, consistent with the binned scatterplots above and the evidence on commercial & industrial lending in Howes and Weitzner (2023), banks may engage in more intensive monitoring activity to identify riskier versus safer loans when they observe a shock to loan-level risks. Table 8 shows these results. In the cross-section, internal PDs increase by 22.5 basis points, matching almost exactly the cross-sectional increase in observed delinquency (24.4 basis points). However, controlling for loan fixed effects and year-by-CBSA fixed effects reduces this average increase in PDs to a coefficient that is economically near and statistically indistinguishable from zero in Columns (2)-(3). The next columns show that floating rate loans are more likely to have internal PD updates, increasing 3.45 in Column (5) and 3.35 percentage points in Column (6) in response to a 100 basis point increase in interest rates. Finally, Columns (7)-(9) show that there is a 2 percentage point increase in PD downgrades. Given the base level of downgrade probability of 9.7%, this increase in downgrades amounts to a change of 20%. Columns (11) and (12) show that controlling for loan fixed effects and local conditions suggests that there is also a relative increase in upgrades: banks can observe performing loans and upgrade their internal PDs by 1.4 percentage points (12% of the sample average rate of upgrades).

Table 8: Effect of Rate Changes on Bank Risk Rating Updates for Floating Rate Loans Relative to Fixed Rate Loans

Outcome:	Current Internal PD			1(PD Update)			1(PD Downgrade)			1(PD Upgrade)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Floating X ΔTreasury Rates	0.225***	-0.0118	0.00673	0.0212***	0.0345***	0.0335***	0.0193***	0.0212***	0.0197***	0.00194***	0.0133***	0.0138***
	(0.0118)	(0.0110)	(0.0124)	(0.000902)	(0.00103)	(0.00108)	(0.000614)	(0.000737)	(0.000791)	(0.000665)	(0.000777)	(0.000803)
Δ UER (t+2,t+1)		-0.0366***			0.0242***			0.0143***			0.00994***	
		(0.00304)			(0.000681)			(0.000541)			(0.000460)	
Δ UER (t+1,t)		-0.0424***			0.00830***			0.00253***			0.00576***	
		(0.00345)			(0.000586)			(0.000421)			(0.000448)	
Δ UER (t,t-1)		-0.0431***			0.00648***			0.00329***			0.00318***	
		(0.00390)			(0.000620)			(0.000507)			(0.000429)	
Δ UER (t-1,t-2)		-0.0350***			0.00481***			0.00291***			0.00191***	
		(0.00373)			(0.000560)			(0.000409)			(0.000422)	
Δ UER (t-2,t-3)		-0.0110***			-0.00425***			-0.00102**			-0.00323***	
		(0.00326)			(0.000586)			(0.000404)			(0.000473)	
Observations	1,535,121	1,415,520	1,482,556	1,413,249	1,295,210	1,356,706	1,413,249	1,295,210	1,356,706	1,413,249	1,295,210	1,356,706
R-squared	0.003	0.552	0.568	0.030	0.160	0.207	0.027	0.124	0.165	0.018	0.111	0.152
Dep Var Mean	1.293	1.258	1.279	0.208	0.212	0.210	0.0965	0.0972	0.0972	0.112	0.114	0.113
Reporting Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan FE	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Quarter of Year FE	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Quarters Since Orig	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
CBSA-Quarter FE	N	N	Y	N	N	Y	N	N	Y	N	N	Y

Note: Dependent variable is either the current internal PD (excluding currently-in-default loans), a binary variable for whether the internal PD was updated over the last quarter, a binary variable for whether the PD increased (indicating a downgrade in the credit risk), or a binary variable for whether the PD declined (indicating an upgrade in the loan risk). The independent variables are calculated as the interaction between a loan being floating rate when first entering the Y-14Q dataset interacted with the change in Treasury yields over the past 3 quarters. Additional controls include quarter-over-quarter changes in CBSA unemployment rates. These unemployment rates are absorbed when including CBSA-by-year fixed effects.

Source: Bureau of Labor Statistics, Local Area Unemployment Statistics. Federal Reserve Form Y-14Q Schedule H.2. Federal Reserve Bank of St. Louis, FRED (Federal Reserve Economic Data), Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis (DGS10), Authors' analysis.

Between the causal effects of interest rate shocks on mortgage distress, the effects on monitoring behavior, and the effects on banks' internal risk ratings, this section provides strong evidence that lenders endogenously adjust loan monitoring behavior in response to loan-specific shocks. Conditional on a loan not already being in default, we surprisingly find that rate shocks cause both downgrades in loan risk rating and upgrades in loan risk rating. One reason that banks may have an incentive to offset higher risks for loan already on banks' balance sheets because of their capital reserve of loan loss reserve requirements. For example, Current Expected Credit Losses (CECL) rules post-2019 require banks to book loan loss reserves based on internal PD levels representing the lifetime expected losses for individual loans. In this CECL framework, banks may have an incentive to offset higher loan loss reserves for floating rate loans at higher risk due to rate shocks with lowering PDs for some loans that appear relatively safe despite interest rate increases. It could also be the case that similar to the oil price shock, banks have an incentive to intensify monitoring in anticipation of potential loan distress. The bank may need to deal with distress by selling loans off their balance sheet or swapping loans for cash in the event of a funding shock. These are potential channels that increase the marginal value of loan performance information if banks engage in advantageous selection (or "cream-skimming") in debt rollover decisions or in adverse selection (or simply accurate marketing and due diligence) in loan sales to other banks or investors.

7 Conclusion

This paper studies how banks monitor loan performance, use the information they collect to develop their internal risk ratings, how banks balance the benefits of more timely information against the costs of acquiring the more timely data, and how shocks to loan- or bank-specific exposures affect bank monitoring behavior. Banks appear to rely heavily on borrower-reported performance. Such heavy reliance might be rational given the potential costs of independent monitoring on every loan. However, this paper documents that a particular piece of information—stale, outdated, or delayed borrower performance—has likely not been fully incorporated into bank risk management. This finding is relevant to improving loan credit risk models.

We document that internal measures of loan risk are sensitive to information on property financials. In two settings, including a national oil price shock and interest rate shocks through floating rate mortgages, we show that banks' monitoring behavior responds endogenously to their incentives. This "endogenous" monitoring response is in contrast to some theoretical treatments of monitoring as an exogenous or fixed cost of lending. Potential stress increases monitoring, especially when the bank directly observes the shock.

Our paper also provides several important insights to anyone modeling commercial real estate credit risk. First we demonstrate that information on the quality of data, in this paper the staleness of financial reports, can help predict future loan distress. Second, we document the endogeneity of the staleness, showing that, on average, no news is in fact bad news. This generates a bias if modelers simply walked forward property financials from the last reported date using market averages, artificially smoothing out property-level performance. Both academic researchers and industry analysts should account for the endogeneity of reported property financials in their analysis of commercial real estate credit risk.

Potential extensions of this research could examine and model more formally the balance between supply and demand in information. Appendix C, which analyzes responses to labor market shocks, notes that the data collected by banks is an equilibrium outcome affected both by banks monitoring (information demand) and borrowers reporting incentives (information supply). In the appendix, we note that average information staleness rises after unemployment rises. The rise in stale information indicating that negative economic shocks reduce information quality reported by borrowers, is suggestive of a decline in information supply from borrowers. This makes it important to distinguish information demand versus supply shocks, as the main analysis in this paper highlights by looking at lender-oriented shocks (affecting information demand).

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A Additional Data Discussion and Descriptive Analysis

The required reporting of current NOI began by 2011-2012, and occupancy began reporting consistently in 2014. Most of the analyses in this paper use data only starting in Q1 2015. The exception is the oil and gas analysis, which focuses on NOI performance reporting starting in 2013.

Several categories of CRE loans are exempt or not required to report current income or occupancy in the CCAR Y-14Q instructions. Following Figure 2 and 3, Appendix Figure A1 and A2 shows average staleness for occupancy. These include construction or land development loans, any loans not currently generating income, and some participated or cross-collateralized loans have different performance reporting requirements. In Figure A3, we show the share of current NOI and occupancy with missing, 'NA', or inconsistent values over time (where inconsistent includes values 1 year in the future or 40 years in the past). Between 8 and 20% of loans report missing or inconsistent values at any given time. Industrial properties appear to have systematically higher incidence of missing observations, while retail properties have relatively few missing observations. This share has changed relatively little over the past 8 years, and if anything declined slightly post-Covid with the exception of late 2022 and early 2023 where every segment reported more missing data.

In Appendix Figure A4, we create descriptive figures showing the share of loans reporting an NOI update by quarter, the share reporting an occupancy update, the share of loans with a change in the banks' internal risk rating (a quarter-over-quarter change in PD of more than 1 basis point), and the average PD by property type in the CCAR reporting (for loans that are not classified as 'in default' in every quarter). Appendix Figure A5 displays the overall distribution of the staleness measures for NOI and occupancy across all quarters (in contrast to Figure 3 which focuses on Q1 of 2020 and 2024). These distributions are smoother and evenly distributed than the distribution for any one quarter because borrowers appear to be on different accounting schedules and reporting schedules with their lender.

As a descriptive exercise, we explore how banks use the self-reported borrower financials to determine the credit quality of the loans at issuance. Appendix Table A1 reports a regression on the initial PD estimate for a loan based on a range of observable loan characteristics. The first two columns include all property types, with CBSA fixed effects in column 2. The remaining columns repeat the regression separately for each property type. The results are consistent with our expectations: longer term loans have lower PDs and higher leveraged loans have higher PDs. There is a systematic positive relationship between mortgage rates and risk ratings, though the mortgage's rate does not fully explain the variation between risk ratings and other loan- and property-level characteristics. We also see some significant differences across property type. The primary goal of this analysis is to simply establish that the PDs do vary based on observable loan characteristics that are correlated with potential default risk.

It is also relevant to establish that the bank risk rating estimates of default probability evolve over time, both in general and specifically in response to changes in self-reported property financials. Appendix Table A2 below shows the transition matrix between initial levels of PDs and the ongoing performance of PDs in our data. We see a large concentration in loans that have initial PDs between 0 and 0.5 which do not shift to a different segment, though over 10 percent of these loans see downgrades (i.e., bank PD estimates increase). We see more movement in loans starting with PDs between 0.5 and 1, with about half of these loans having changes in bank PD estimates, roughly evenly split between up- and downgrades.

Appendix Figure A6 shows seasonality in the share of borrowers reporting updates to their financial performance. In each quarter, 20-30% of borrowers update their NOI or occupancy. Those updates are most common in Q2 and Q3.

Appendix Figure A7 shows the generalized event study for upgrading or downgrading PDs around the quarter of new performance updates by property type.

Appendix Figure A8 shows seasonality in banks PD updating behavior. In general, banks update risk ratings 50% more in the last quarter of the year. We note in the bottom figure that even though banks are more likely to update PDs in Q4, those updates do not appear to be much larger, in average. The figure shows the absolute value of the change in PDs—this value fluctuates around 20 basis points and appears to be 2-3 basis points higher in Q4.

Appendix Figure A9 shows the time dynamics of these updates, displaying a generalized event study regression of a binary variable for a PD update (or the absolute value of the change in PDs) on leads and lags of a binary variable for whether the NOI was updated in the quarter.

In Appendix Figures A10 and A11, we repeat the analysis studying the change in performance on banks PD updating behavior. In the bottom figures, we allow the slope of an OLS regression line to vary above and below zero on the x-axis. The non-parametric binned scatter plot shows a 'cursive v' shaped relationship where negative NOI updates lead to PD updates (i.e., higher probability of downgrade). The probability of any update declines as NOI growth approaches zero. Past zero with positive values of NOI growth, the probability of any change in internal PD rises, likely capturing an increasing probability of rating upgrade. The final graph shows the relationship between change in NOI and change in PD. The slope indicates that 10 percent higher NOI growth results in 0.06 percent lower probability of default based on the bank's internal risk rating.

In Appendix Figure A11, we repeat the exercise analyzing change PDs and change in performance using occupancy reporting updates. If anything, the relationship is stronger for occupancy updates. One percentage point higher occupancy leads to 0.192 percent lower probability of downgrade, 0.185 percent higher probability of upgrade, and 0.017 percent lower PD. There is a similar non-linear, nearly v-shaped relationship between occupancy change and the probability of any change in PD.

Table A1: Determinants Initial PD Estimates

	Initial Rating of Probability of Default (X 100)					
Property Type:	All		Retail	Industrial	Multifamily	Office
	(1)	(2)	(3)	(4)	(5)	(6)
Initial Rate	0.516***	0.524***	1.024***	0.369***	0.272***	0.625***
	(0.0709)	(0.0707)	(0.190)	(0.101)	(0.0674)	(0.125)
Log Initial Term	-0.611***	-0.614***	-1.184***	-0.675***	-0.309***	-1.465***
	(0.0729)	(0.0889)	(0.249)	(0.204)	(0.0444)	(0.295)
1(Floating)	-0.0205	-0.0617	0.124	-0.324	0.201**	-0.228
	(0.0863)	(0.1000)	(0.181)	(0.287)	(0.0797)	(0.182)
Log Property Size	0.0453***	0.0409***	0.0122	-0.140**	-0.0300**	-0.0544
	(0.0113)	(0.0125)	(0.0631)	(0.0686)	(0.0141)	(0.0937)
1(Recourse)	-0.0299	0.00878	0.0769	-0.0677	-0.138**	0.00314
	(0.0503)	(0.0584)	(0.140)	(0.150)	(0.0569)	(0.127)
Log Property Value	0.415***	0.401***	1.177***	1.067**	0.129	0.246
	(0.120)	(0.120)	(0.362)	(0.524)	(0.0844)	(0.205)
Log Loan Amount	-0.297***	-0.274***	-0.528**	-0.753	-0.0860	-0.107
	(0.0957)	(0.0955)	(0.241)	(0.484)	(0.0632)	(0.175)
Initial LTV	0.0140***	0.0137***	0.0264***	0.0186*	0.00754***	0.0177***
	(0.00244)	(0.00241)	(0.00690)	(0.0104)	(0.00218)	(0.00606)
Initial Occupancy Rate	-0.0270***	-0.0272***	-0.0471***	-0.0155**	-0.0106***	-0.0365***
	(0.00326)	(0.00332)	(0.00980)	(0.00657)	(0.00264)	(0.00701)
Log Initial NOI	-0.257***	-0.266***	-0.693***	-0.244*	-0.0838	-0.279***
	(0.0566)	(0.0565)	(0.163)	(0.127)	(0.0540)	(0.103)
Observations	132,117	132,004	22,551	10,861	78,970	19,252
R-squared	0.033	0.044	0.086	0.113	0.034	0.075
Dependent Variable Mean	1.117	1.117	1.729	1.528	0.717	1.802
Orig Quarter FE	Y	Y	Y	Y	Y	Y
CBSA FE	N	Y	Y	Y	Y	Y

Note: Initial PD is the reported PD at origination or in the reporting quarter closest to the recorded origination date. Observations include all loans originated that have initial PDs and are observed starting in Q1 2015. Loan characteristics are also all taken as the initial observation of the loan, closest to the origination quarter for each variable.

Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

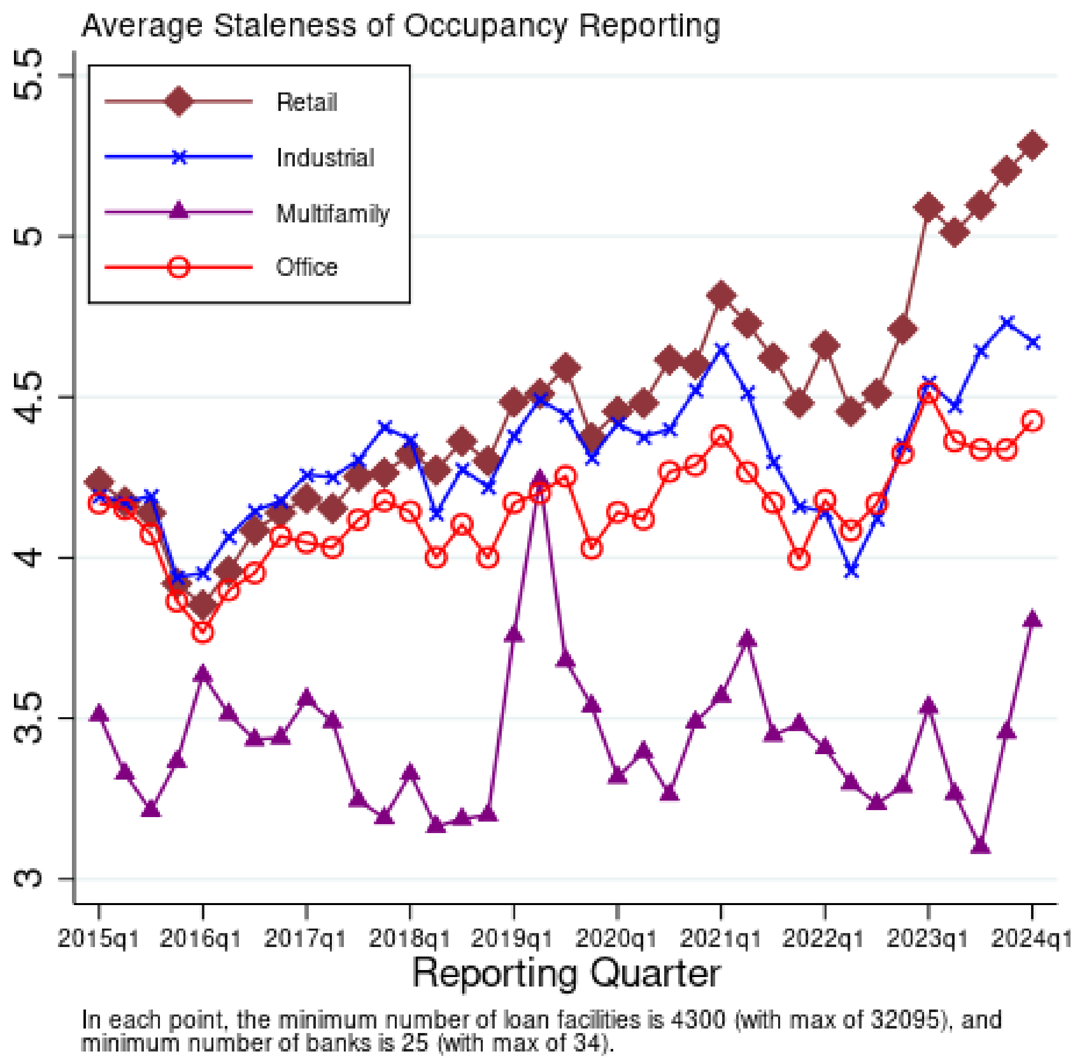
Table A2: PD Transition Matrix

		Contemporaneous PD (Reported any quarter after origination)								
		PD = 0%	PD in (0,0.5]	PD in (0.5,1]	PD in (1,2.5]	PD in (2.5,5]	PD in (5,10]	PD in (10,20]	20%<PD	Share of Total
Initial PD (Reported at or near origination date)	PD = 0%		3.34%	0.97%	0.85%	0.17%	0.22%	0.09%	0.16%	5.82%
	PD in (0,0.5]	0.08%	41.19%	3.43%	1.50%	0.33%	0.29%	0.26%	0.36%	47.44%
	PD in (0.5,1]		6.46%	13.75%	2.82%	0.52%	0.35%	0.27%	0.19%	24.36%
	PD in (1,2.5]		2.47%	3.21%	9.97%	1.03%	0.50%	0.29%	0.20%	17.66%
	PD in (2.5,5]		0.32%	0.39%	0.58%	1.25%	0.16%	0.09%	0.05%	2.83%
	PD in (5,10]		0.14%	0.11%	0.18%	0.11%	0.39%	0.04%	0.04%	1.01%
	PD in (10,20]		0.04%	0.02%	0.04%	0.03%	0.02%	0.15%	0.03%	0.33%
	20%<PD		0.04%	0.03%	0.04%	0.02%	0.03%	0.03%	0.31%	0.51%
	Share of Total	0.12%	54.01%	21.92%	15.98%	3.45%	1.96%	1.22%	1.34%	100.00%

Note: Table shows PD distribution as a share of all loan-by-reporting quarter observations. There are 2,049,832 observations with PDs for both variables for reporting quarters starting in Q1 2015. Each cell represents the share of those total observations. Cells with fewer than 5 distinct loans or with loans from fewer than 5 banks are left blank. The minimum number of banks in any populated cell is 5 (average of 23.4), and the minimum number of loans in any cell is 108 (average of 5,051.9). The rows represent categories of PD reported at origination or in the reporting quarter closest to the recorded origination date. Columns represent current (or 'contemporaneous') PDs in any reporting quarter observed in the Y-14Q CRE dataset. In this table, PD greater than 20% includes all loans with PDs of 100%, which according to the FR Y-14Q Reporting Form indicates a currently-in-default loan facility. In other results, currently-in-default loans are either used as an outcome for probability of default or omitted when studying bank current PDs.

Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

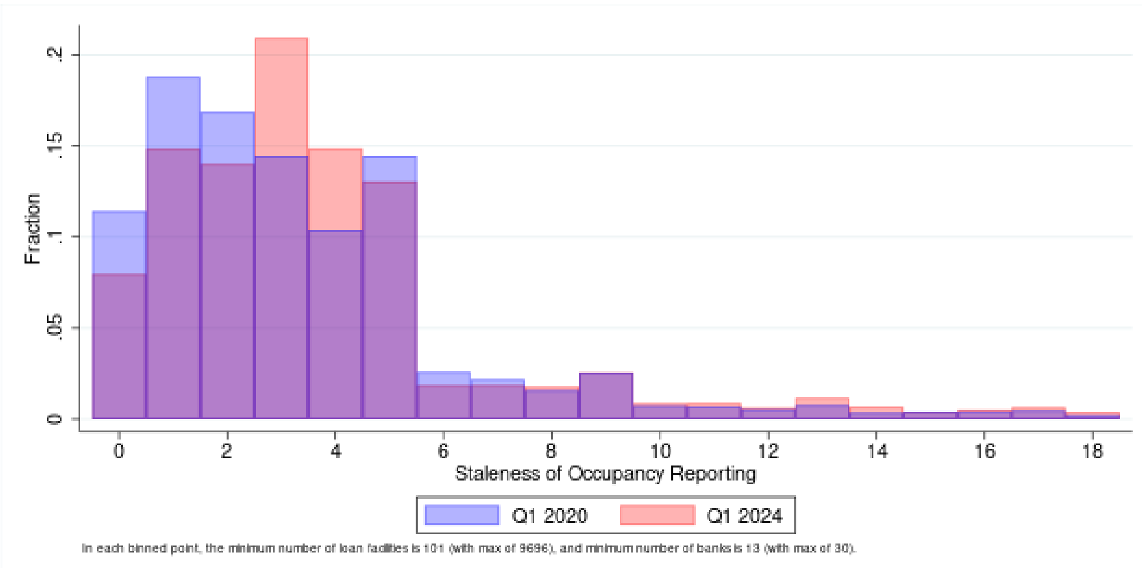
Figure A1: Average Staleness of Occupancy Reporting



Notes: Figures show times series average of reporting information 'staleness' for all mortgages of each type. Staleness is defined as the number of quarters between the current quarter and the most recent reported 'as of' date on borrower's financial reporting information. Acquired loans are excluded. Among these figures the minimum number of loans in the smallest bin on the histogram is 4,300 and the minimum number of banks (RSSDs) summarized by any bin is 25.

Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

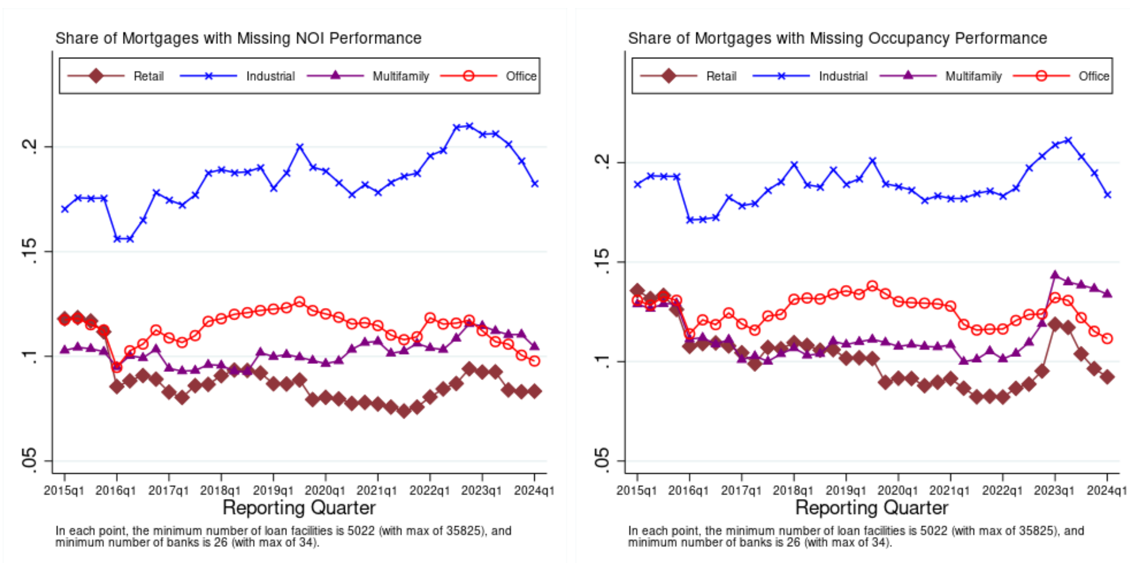
Figure A2: Histogram of Staleness of Occupancy Reporting



Notes: Histogram shows the distribution of reporting information 'staleness' for mortgages in Q1 2020 (blue) and Q1 2024 (red). Overlaps in the Q1 2020 and Q1 2024 distribution are displayed in a purple shade. Staleness is defined as the number of quarters between the current quarter and the most recent reported 'as of' date on borrower's financial reporting information. Acquired loans are excluded; only first liens originated after 2010 are included. Among these figures the minimum number of loans in the smallest bin on the histogram is 24 and the minimum number of banks (RSSDs) summarized by any bin is 5.

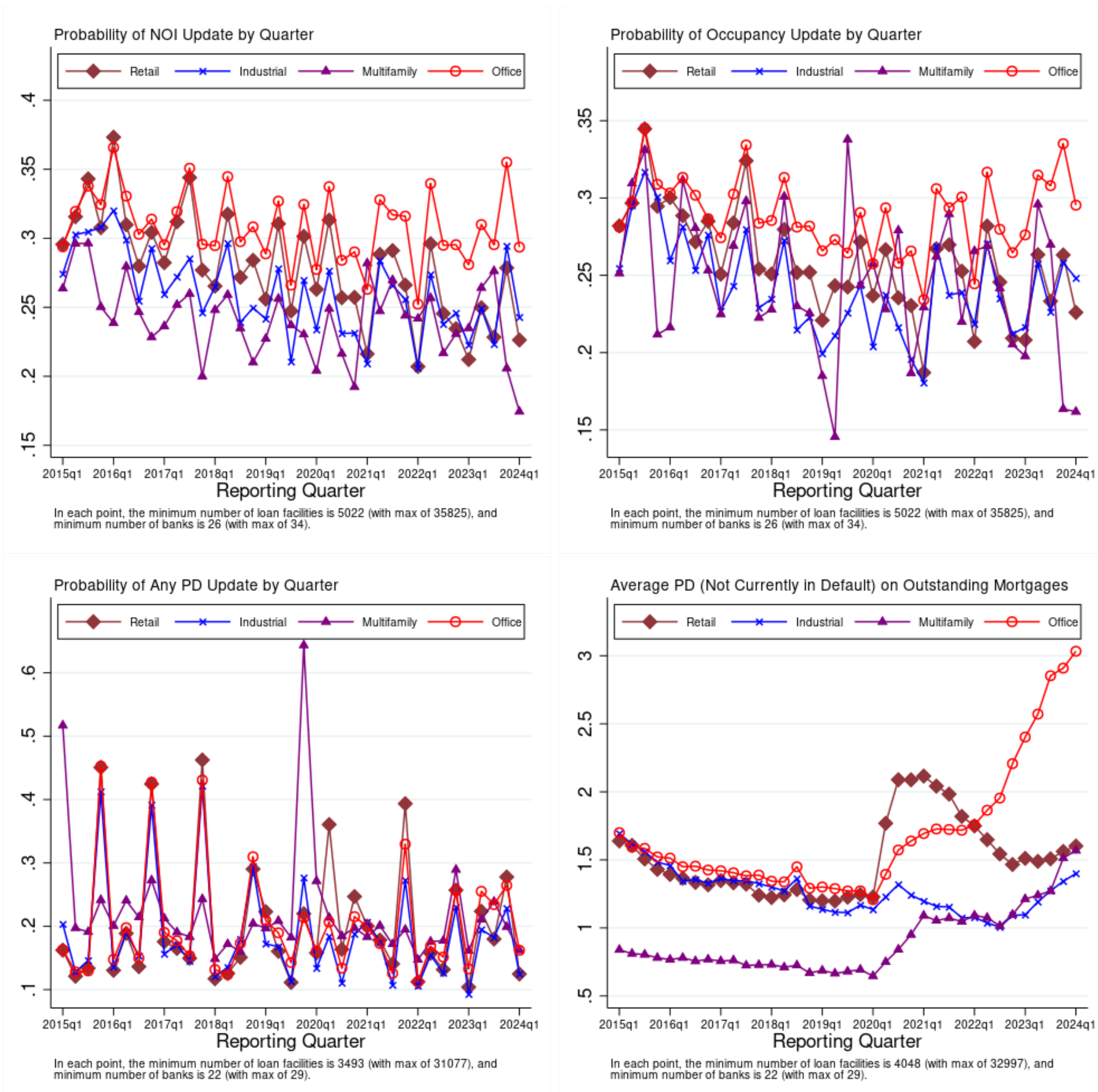
Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Figure A3: Reporting of CRE Borrower Operating Performance



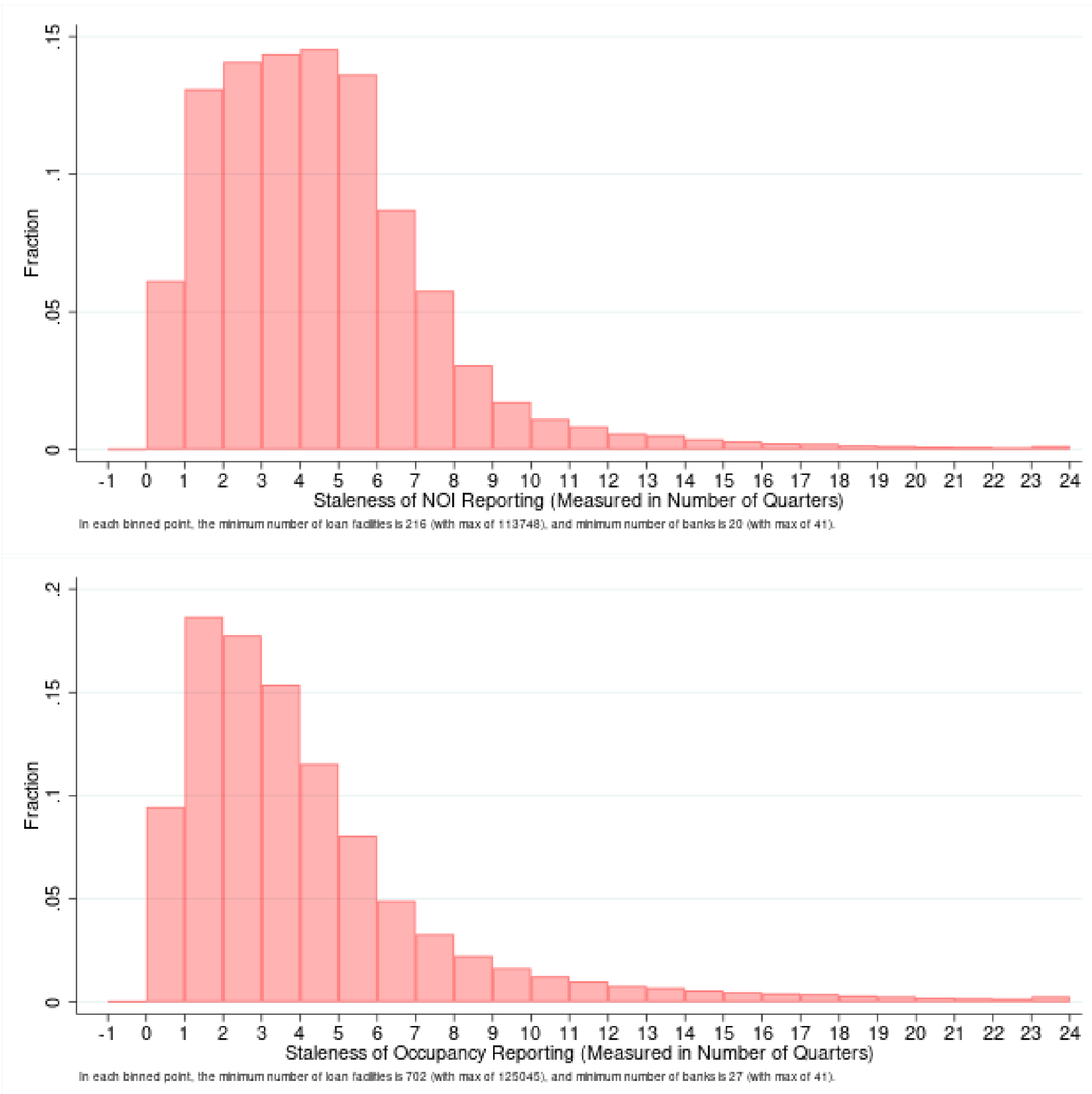
Notes: Figures show times series average of missing financial reporting information for all Retail, Industrial, Multifamily and Office mortgages. Acquired loans are excluded. Missing is defined as cases where the NOI or occupancy is missing, the date as of is missing, greater than one year in the future, or greater than 40 years in the past. Among these figures the minimum number of loans in the smallest point is 5,022 and the minimum number of banks (RSSDs) summarized by any point is 26.
Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Figure A4: Time Series of NOI and Occupancy Updates & PD Updating



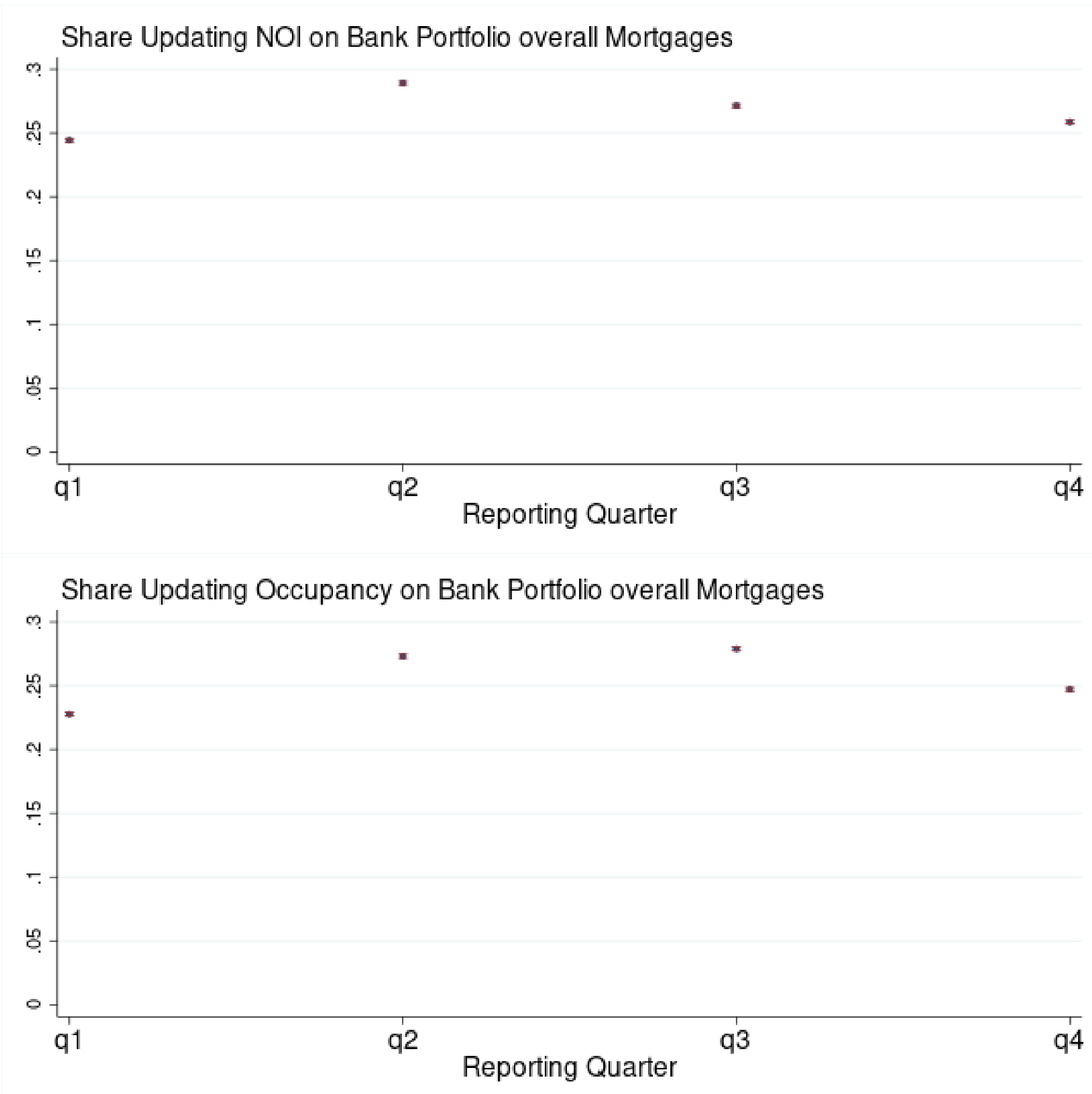
Notes: Figures show times series average of reporting information or all mortgages of each type. Acquired loans are excluded. Among these figures the minimum number of loans in the smallest point is 3,493 and the minimum number of banks (RSSDs) summarized by any point is 22.
Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Figure A5: Histogram of Staleness Measure Across All Quarters and Property Types



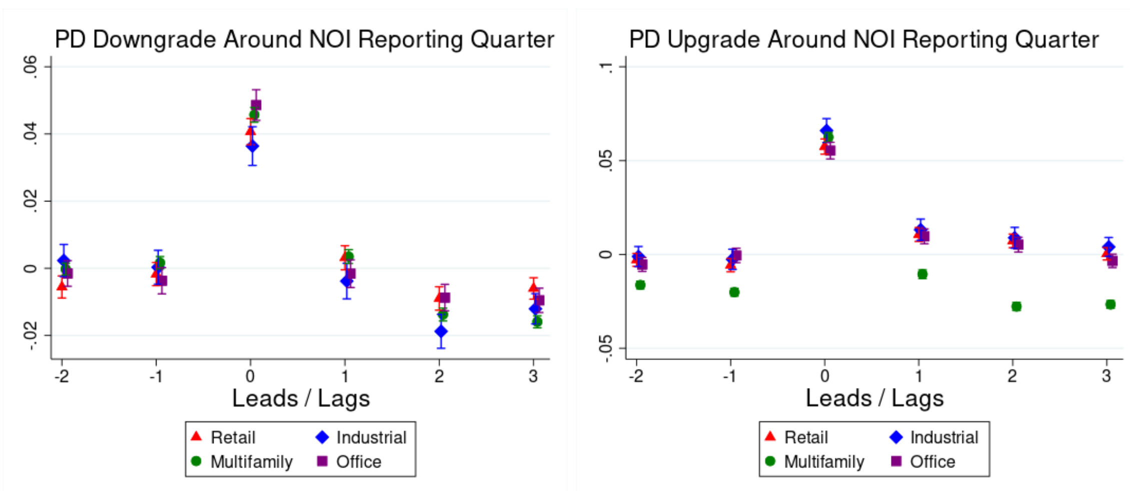
Notes: Figures show histogram of distribution of staleness measure for all mortgages of each type. Acquired loans are excluded; only first liens originated after 2010 are included. Among these figures the minimum number of loans in the smallest bin on the histogram is 216 and the minimum number of banks (RSSDs) summarized by any bin is 20.
Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Figure A6: Seasonality in Performance Reporting



Notes: Figures show the regression output showing the average of the share of borrowers reporting new occupancy or NOI across calendar quarters for all mortgages of each type (coefficients recovered by excluding constant term; 95% confidence intervals).
Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Figure A7: Timing of Up and Downgrades Around Reported NOI by Property Type

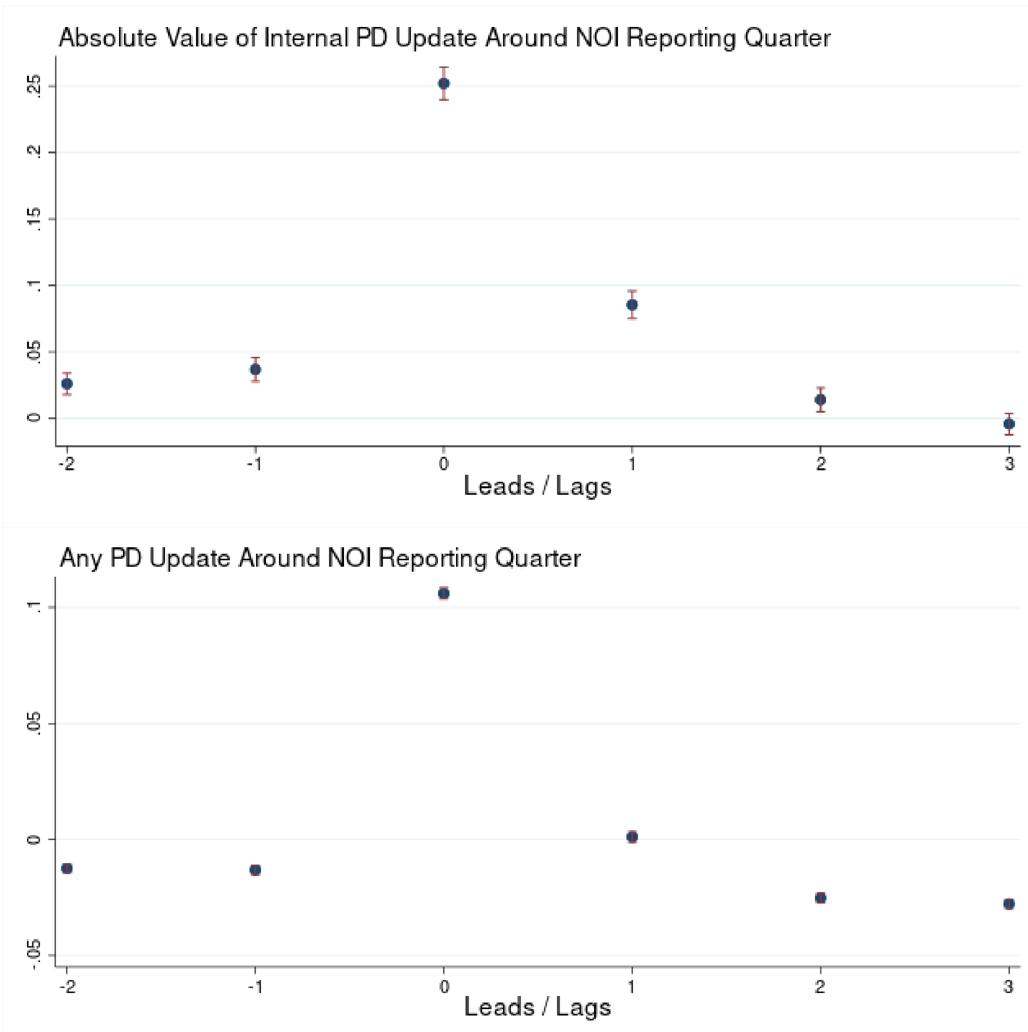


Notes: Figures show coefficients and 95% confidence intervals from regressions of a binary variable for an update to banks internal PD (either a downgrade or upgrade) on leads and lags of a binary variable for whether the borrower reported new financial information, covering data on all mortgages of each type.
Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Figure A8: Seasonality in Internal PD Updating

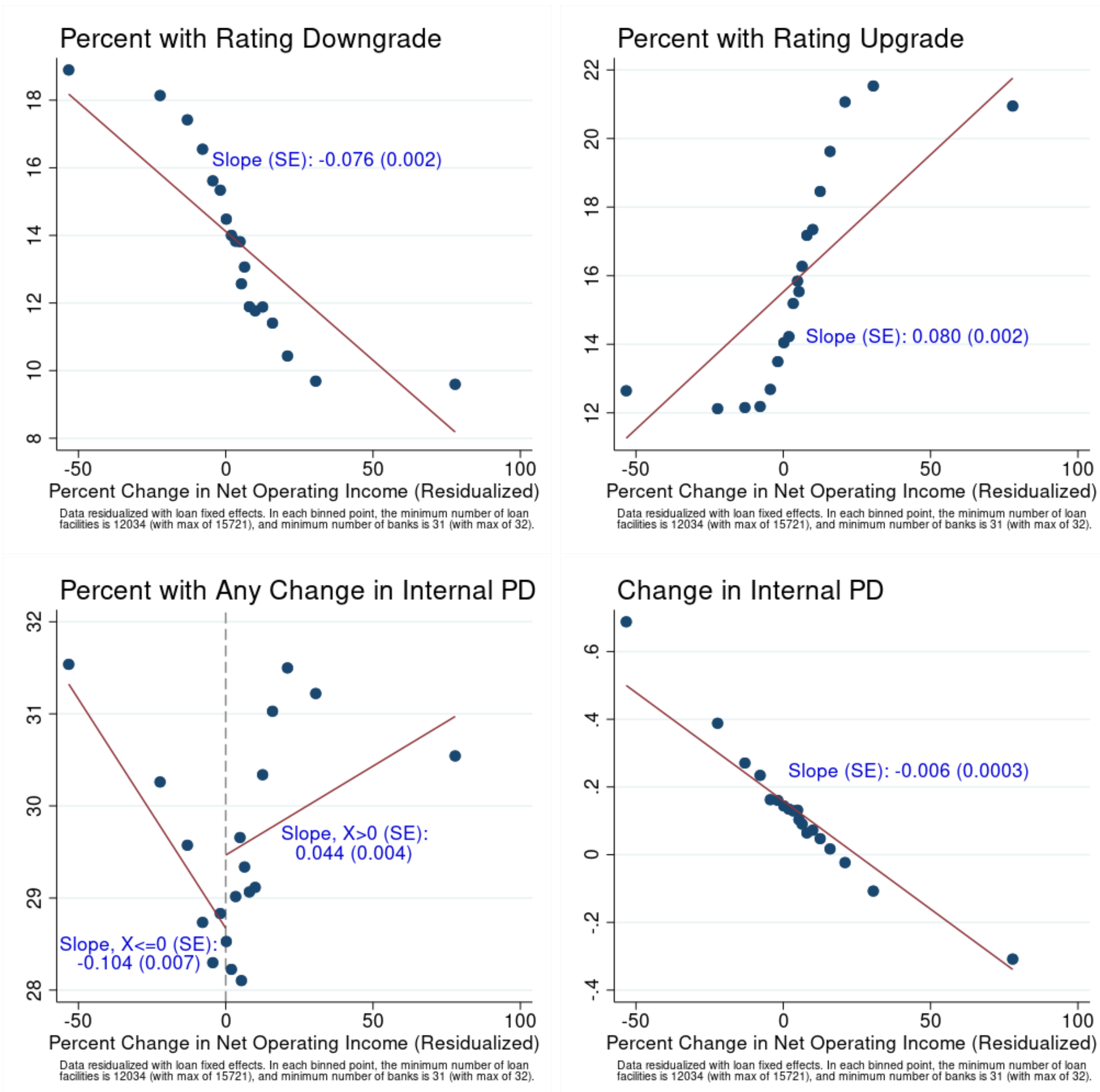
Notes: Figures show the regression output showing the share of loans with a PD update and the average absolute value of the size of the change in internal bank PD for all mortgages by calendar quarter (coefficients recovered by excluding constant term; 95% confidence intervals).
Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Figure A9: Dynamics of PD Updating around Quarter of NOI Update



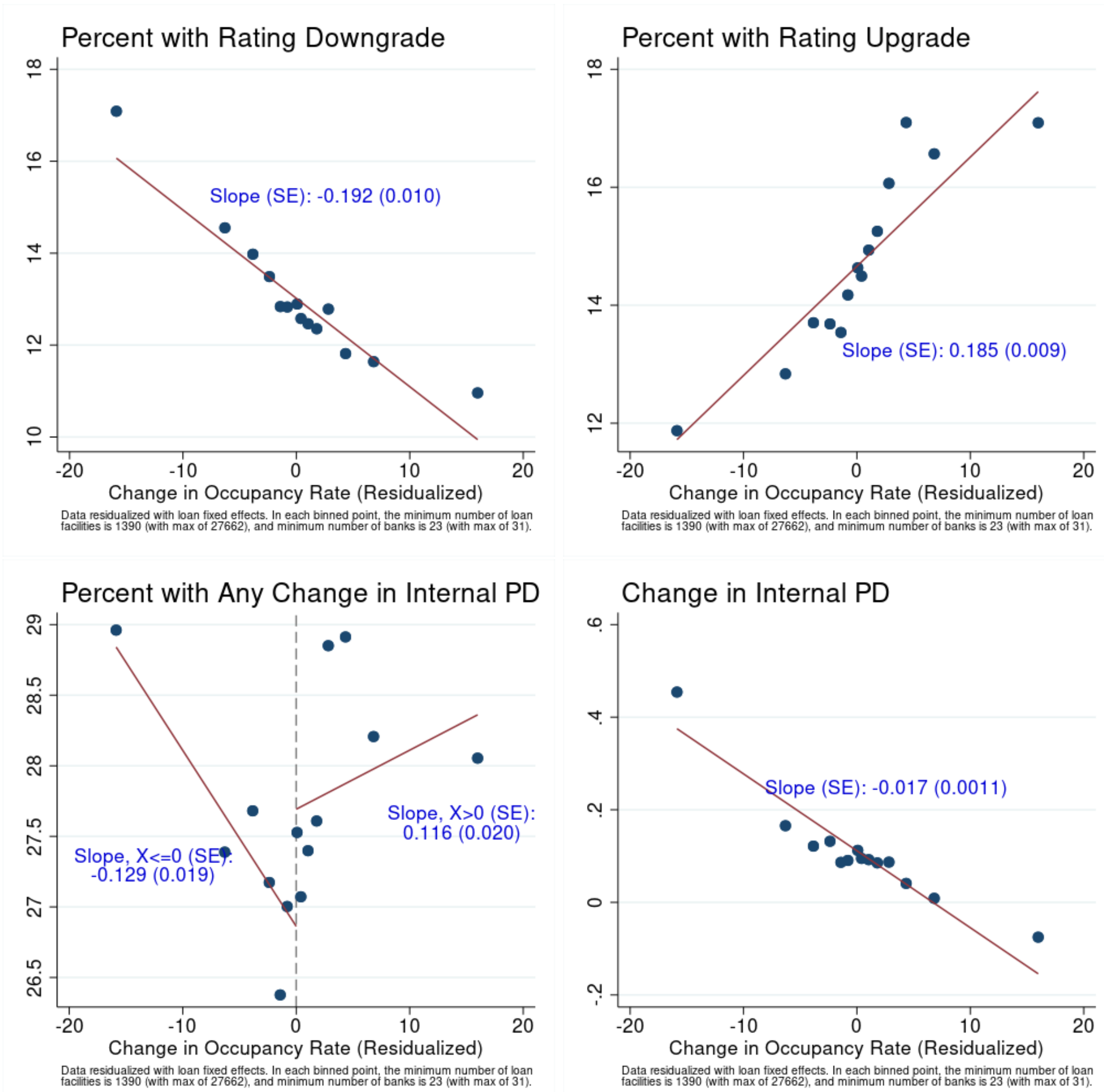
Notes: Figures show coefficients and 95% confidence intervals from regressions of a binary variable for an update to banks internal PD (including either a downgrade or upgrade) and the absolute value of the change in PD on leads and lags of a binary variable for whether the borrower reported new financial information, covering data on all mortgages of each type.
Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Figure A10: Changes in Financial Performance Feed into Internal PDs



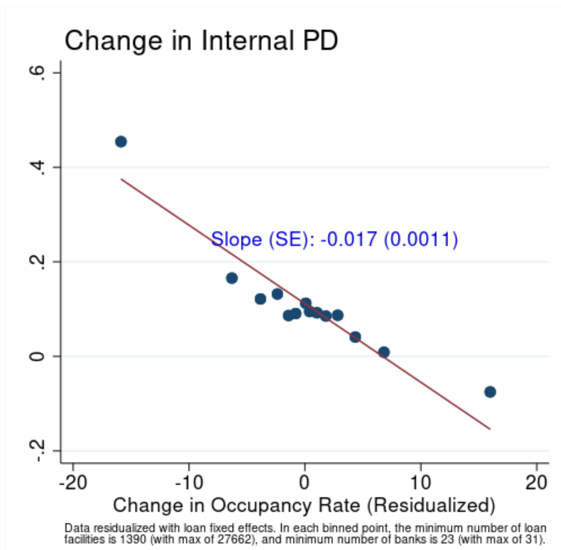
Notes: Figures show binned scatter plots of the relationship between the time since a loan's previous reporting quarter and the new reporting quarter on the x-axis, and the actual average percent change in net operating income on the y-axis. Percent change in NOI truncated above at 290% and below at -90% (1st and 99th percentile). Each variable is residualized with loan fixed effects. Linear OLS slope and standard error, clustered by loan, reported in the graph. Among these figures the minimum number of loans in the smallest binned point on the scatter plot is 12,034 and the minimum number of banks summarized by any binned point is 31.
Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Figure A11: Changes in Leasing Performance Feed into Internal PDs



Notes: Figures show binned scatter plots of the relationship between the time since a loan's previous reporting quarter and the new reporting quarter on the x-axis, and the actual percentage point change in occupancy rate on the y-axis. Change in occupancy truncated at -50 and 50 percent. Each variable is residualized with loan fixed effects. Linear OLS slope and standard error, clustered by loan, reported in the graph. Among these figures the minimum number of loans in the smallest binned point on the scatter plot is 1,393 and the minimum number of banks summarized by any binned point is 22.
Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

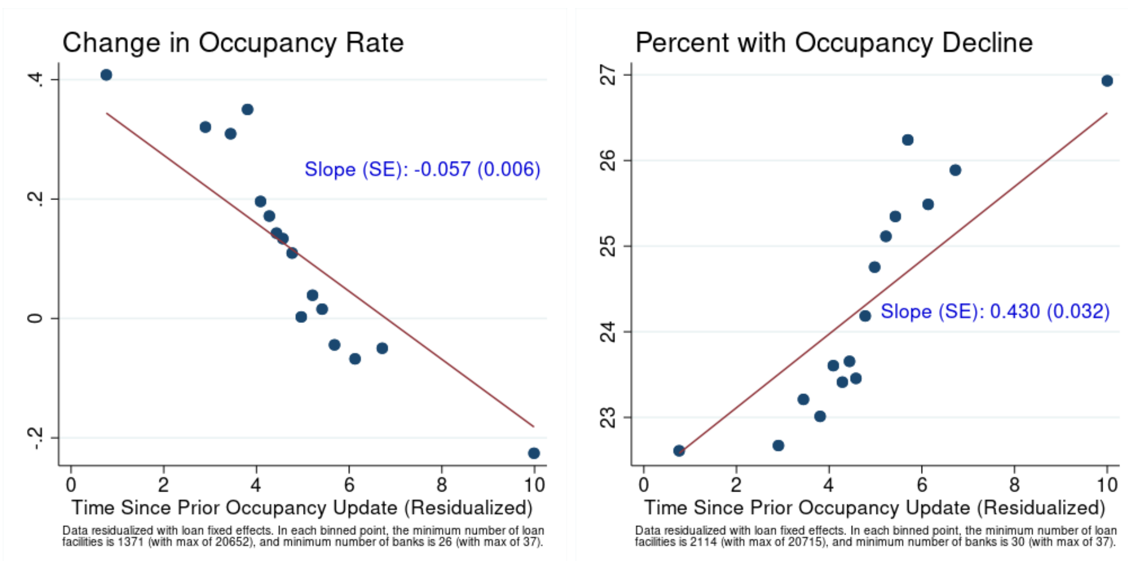
Figure A12: Changes in Leasing Performance Feed into Internal PDs



Notes: Figure shows binned scatter plot of the relationship between the actual average percent change in and occupancy rate on the x-axis, and internal PD ratings on the y-axis. Observations included any quarter in which the borrower's performance is updated. Change in occupancy truncated at -50 and 50 percent. Each variable is residualized with loan fixed effects. Linear OLS slope and standard error, clustered by loan, reported in the graph. Among these figures the minimum number of loans in the smallest binned point on the scatter plot is 1,390 and the minimum number of banks summarized by any binned point is 23.

Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Figure A13: Actual Change in Occupancy by Time to Performance Update



Notes: Figures show binned scatter plots of the relationship between the time since a loan's previous reporting quarter and the new reporting quarter on the x-axis, and the actual average percentage point change in occupancy rate on the y-axis. Percent change in occupancy truncated at -50 and 50 percent. Each variable is residualized with loan fixed effects. Linear OLS slope and standard error, clustered by loan, reported in the graph. Among these figures the minimum number of loans in the smallest binned point on the scatter plot is 1,371 and the minimum number of banks summarized by any binned point is 26.

Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

B Additional Empirical Results and Robustness

Appendix Table B3 shows the results from regressions the change in leasing performance—calculated as the change in occupancy rates—on the change in internal PDs and the probability of either downgrading or updating the risk rating. The table also reports the effects broken down by property type segment. The effects are in the same direction across property types, and indicate that banks update risk ratings consistently in response to changes in reported occupancy rates exactly when the borrower reports the updated occupancy. Appendix Table B4 performs a similar analysis by regressing a binary variable for any change in internal PDs on the change in performance. The regression flexibly allows for a nonlinear relationship by interacting a binary variable for performance improving versus performance declining in the newly updated performance measure for both occupancy and NOI. The results indicate that banks are more likely to change the internal PD in general, the larger the change in performance. To restate the result, small changes in reported performance are less likely to result in a change in the risk rating.

Appendix Table B5 interacts a set of loan characteristics with the staleness measure to identify the extent to which delinquency or default probability is differentially likely for larger, higher LTV, or loans with other characteristics at origination.

Appendix Table B6 reports the generalized event study estimates of the probability of changing PDs including upgrades or downgrades around the timing of the quarter of an update to the borrower's performance.

Appendix Table B7 displays regression results from a linear probability model of mortgage default on the continuous measure of performance reporting staleness (defined for each loan-quarter as the difference between current quarter and 'as of' quarter of NOI or occupancy). Default is measured for loans with internal PDs, defined as PD equal to 100 (currently in default), which can include loans in default on payments or in violation of loan terms and covenants. In the Columns 1 and 4, we show the cross-sectional relationship, controlling for reporting quarter fixed effects. Stale NOI and occupancy reporting is positively correlated with default probability. We then control for loan facility fixed effects, calendar quarter fixed effects, and quarters since origination fixed effects. This isolates within-loan variation in reporting and default, accounting for both seasonality of reporting and seasoning of the loan (given that older loans may be more likely to default and may be correlated with having older reporting information). We find that age of NOI and occupancy data are each positively related to default. These relationships are statistically significant above the 99% confidence level. The dynamic specification implies that current and lagged NOI staleness have a strong positive relationship with default. A marginal increase in the stale information appears to be associated with increasing loan distress over the next three quarters.

Appendix Table B8 repeats this exercise for delinquency probability, which is a subtle but useful distinction. The delinquency definition used here is agnostic to loan terms and is only defined as loans reported as being behind on mortgage payments. We perform this exercise because (a) it includes all loans, not just those with lenders' reporting PDs; and (b) we are concerned that the above default definition includes loans that are in default because the obligor has not promptly reported NOI or occupancy performance. Table 5 shows that the positive cross-sectional (Columns

1 and 4) and positive conditional relationship between staleness of NOI reporting (Columns 2 and 5) are very similar to the default specification. The main difference is that 1-2 quarter lagged NOI staleness is most strongly correlated with delinquency (Columns 3 and 7).

We find that our measure of delayed reporting or non-reporting is positively associated with default and delinquency. The effect sizes suggest that a one quarter increase in outdated financial data is associated with a 0.02 to 0.03 percentage point increase in delinquency or default probability. Scaling by the dependent variable mean, this represents a 6 to 7 percent increase in the rate of distress.

Appendix Table B9 uses as the dependent variable the current PD of the loan. This specification should be informative about whether lenders incorporate the staleness of obligor performance reporting behavior into their internal risk assessments. If they incorporated it to reflect higher default risk to non-reporting borrowers, we would expect a positive relationship between staleness and PDs, controlling for loan, quarter, and seasoning fixed effects. I find a positive cross-sectional relationship between staleness of reporting and current PD in Columns 1 and 4. However, conditioning on fixed effects to analyze within-loan variation implies that banks are systematically giving stale loans lower PDs (Columns 2 and 5). Somewhat reassuringly, the total effects do not appear to be persistent. As a loan's financial reporting becomes more outdated, PDs decline for two quarters, then increase somewhat over the next three quarters. The total effect is still negative; each additional quarter of staleness in the financial data is associated with a 2 to 3 basis point decline in PD. Appendix Table B.9 presents evidence that the one quarter lag of unemployment rates strongly increases banks' assessment of default probability on average, suggesting that banks ratings directly incorporate county or state-level unemployment rates. Including these effects does not explain their PD updating behavior in response to borrower financial reporting.

Appendix Table B10 regresses the binary variable for whether the bank updates the internal probability of default on staleness in NOI and occupancy reporting. This specification is informative about the dynamics of banks internal responsiveness to delayed, stale, and failures to report financials, including the dynamics over five lagged quarters. In the cross-section, there is a negative correlation between the probability of updating the internal PD and the staleness of NOI performance. This relationship is stronger conditioning on loan, quarter, and seasoning fixed effects, indicating 1 quarter older NOI information is related to 1.2% lower probability of PD updating. In a specification with lags of the staleness measure, the first lag is positively correlated with PD updating, but adding up the lags still indicates that 1 quarter more outdated information about NOI is correlated with 0.9% lower probability of a PD update over 5 quarters. This relationship is similar, though slightly smaller for outdated occupancy reporting. The combination of this table with the prior set of results suggest that banks are systematically waiting to update internal risk metrics when borrowers fail to update their performance reporting. When lenders eventually do update their internal PD, they appear to be systematically under-estimating the risk of distress among tardy borrowers.

Having analyzed the level of PDs and the probability of updating those PDs, agnostic to the direction of the update, we turn to measuring the probability of upgrade versus downgrade. We measure upgrade as a decline in the current PD relative to the prior reporting quarter, and measure a downgrade as an increase in the PD over the past quarter. We only require that the change be one basis point or greater, and exclude loans that enter or leave default.

Appendix Table B11 shows the CRE sector-specific staleness' relationship with level of current PD and probability of updating in Columns 1-4, and the probability of downgrade or upgrade in Columns 5-8. We observe that the effects on the level of PD and the probability of updating are significantly negative for all property types. In Column 5 and 7, we observe that a marginal increase in the staleness of reporting information is negatively associated with both the probability of upgrading and downgrading the loans internal risk rating. We include the local unemployment rates as a benchmark that these PD updates are consistent with banks meaningfully updating default risk. We observe that the probability of downgrade increases and the probability of upgrade decreases in response to higher unemployment rates in the prior quarter. This is suggestive of banks using lagged local labor market data as an input to their risk modeling.

Appendix Table B12 shows heterogeneity in the staleness relationship with lender PD updating by loan-level characteristics. We z-score each characteristic to allow for easier interpretation of the average effect of stale information. Current PDs and PD updating probability are both lower for high ex ante PD loans that have stale NOI reporting, as well as for larger loans. Columns 5-8 show analogous effects for the probability of downgrading or upgrading the lender's internal PD. The probability of upgrading and downgrading both decline with more outdated financial reporting. The main notable difference in effect direction is that recourse loans with more outdated NOI reporting are marginally more likely to receive a downgrade (though interpretation of the coefficients implies the total effect is still negative ($-0.00615 + 0.00158 = -0.00457$). It also appears that higher LTV and smaller loans are more likely to be downgraded when their performance is more outdated.

Table B3: Change in Internal Risk Ratings and Change in Occupancy at Performance Update

Outcome:	Change in Internal PD		1(PD Downgrade)		1(PD Upgrade)	
	(1)	(2)	(3)	(4)	(5)	(6)
Change in Occupancy Rate	-0.0167***		-0.180***		0.161***	
	(0.00118)		(0.0103)		(0.00965)	
Change in Occupancy X Retail		-0.0127***		-0.186***		0.113***
		(0.00249)		(0.0247)		(0.0214)
Change in Occupancy X Industrial		-0.00843***		-0.110***		0.192***
		(0.00237)		(0.0352)		(0.0375)
Change in Occupancy X Multifamily		-0.0181***		-0.155***		0.175***
		(0.00172)		(0.0136)		(0.0133)
Change in Occupancy X Office		-0.0180***		-0.257***		0.130***
		(0.00244)		(0.0243)		(0.0208)
Observations	314,950	314,950	314,950	314,950	314,950	314,950
R-squared	0.212	0.214	0.331	0.342	0.315	0.318
Dep Var Mean	0.105	0.105	12.95	12.95	14.56	14.56
Reporting Quarter-by-CBSA FE	Y	Y	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y	Y	Y
Quarter of Year FE	Y	Y	Y	Y	Y	Y
Quarters Since Orig	Y	Y	Y	Y	Y	Y
Property Type-by-Quarter FE	N	Y	N	Y	N	Y

Note: Observations included any quarter in which the borrower's financial performance is updated. Independent variable is the change in occupancy rate. Occupancy changes are censored at -50% and 50%. The dependent variables are: the change in internal PD, excluding instances where PD is equal to 100% (currently in default); a PD downgrade, where PD increases quarter over quarter; and a PD upgrade, where PD declines. Standard errors are clustered by loan.

Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Table B4: Spline for Any Change in Internal Risk Ratings and Change in Performance

Outcome:	1(Any Change in PD)			
	NOI Performance		Occupancy Performance	
	(1)	(2)	(3)	(4)
Change in Performance X 1(Negative)	-0.125***		-0.156***	
	(0.00789)		(0.0198)	
Change in Performance X 1(Positive)	0.0490***		0.117***	
	(0.00404)		(0.0202)	
Change in Performance X 1(Negative) X Retail		-0.0438***		-0.166***
		(0.0159)		(0.0434)
Change in Performance X 1(Positive) X Retail		0.0185**		0.0284
		(0.00832)		(0.0471)
Change in Performance X 1(Negative) X Industrial		-0.0977***		-0.0190
		(0.0256)		(0.0746)
Change in Performance X 1(Positive) X Industrial		0.0345***		0.162**
		(0.0113)		(0.0683)
Change in Performance X 1(Negative) X Multifamily		-0.205***		-0.103***
		(0.0122)		(0.0273)
Change in Performance X 1(Positive) X Multifamily		0.0832***		0.138***
		(0.00624)		(0.0273)
Change in Performance X 1(Negative) X Office		-0.0759***		-0.308***
		(0.0154)		(0.0436)
Change in Performance X 1(Positive) X Office		0.0234***		0.0858*
		(0.00833)		(0.0461)
Observations	313,995	313,995	314,950	314,950
R-squared	0.384	0.393	0.381	0.389
Dep Var Mean	29.54	29.54	27.51	27.51
Reporting Quarter-by-CBSA FE	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y
Quarter of Year FE	Y	Y	Y	Y
Quarters Since Orig	Y	Y	Y	Y
Property Type-by-Quarter FE	N	Y	N	Y

Note: Observations included any quarter in which the borrower's financial performance is updated. Independent variable is the change in performance quarter-over-quarter (either percent change in NOI in Columns (1)-(2) or change in occupancy rate in Columns (3)-(4)). The change in performance is interacted with a binary variable for whether the performance change is positive (or equal to zero), or binary variable for whether the performance change is negative. NOI changes are censored around the 1st and 99th percentiles at -99% and 290%, and occupancy changes are censored at -50% and 50%. The dependent variable is a binary variable for any change in internal PD, excluding instances where PD is equal to 100% (currently in default). Standard errors are clustered by loan.

Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Table B5: Loan Performance and Staleness of Financial Reporting by Loan Characteristics

Outcome:	Delinquency		Default	
	(1)	(2)	(3)	(4)
Staleness NOI	0.00806***	0.00503*	0.0232***	0.0349***
	(0.00216)	(0.00278)	(0.00171)	(0.00221)
Staleness NOI X Z(Initial PD)		-0.0236**		0.0923***
		(0.0108)		(0.00849)
Staleness NOI X Z(Orig LTV)		-0.00135		0.00118
		(0.00237)		(0.00190)
Staleness NOI X Z(Participation)		-0.000365		-0.0151***
		(0.00470)		(0.00377)
Staleness NOI X Z(Any Recourse)		0.00410		-0.00547***
		(0.00261)		(0.00209)
Staleness NOI X Z(Log Orig Amount)		0.000790		0.00726***
		(0.00336)		(0.00268)
Staleness NOI X Z(Log Orig Sq. Ft.)		0.00359		-0.00314
		(0.00243)		(0.00194)
F1.Unemployment Rate	0.00443	0.00987	0.00164	-0.00284
	(0.00788)	(0.00824)	(0.00631)	(0.00665)
Unemployment Rate	-0.00400	-0.00924	-0.00888	-0.00675
	(0.00961)	(0.0101)	(0.00768)	(0.00812)
L1.Unemployment Rate	0.0225***	0.0186**	0.00869	0.00472
	(0.00791)	(0.00829)	(0.00632)	(0.00667)
Observations	1,784,970	1,500,955	1,750,713	1,468,224
R-squared	0.266	0.266	0.446	0.441
Dependent Variable Mean	0.408	0.400	0.324	0.320
Reporting Quarter FE	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y
Quarter of Year FE	Y	Y	Y	Y
Quarters Since Orig	Y	Y	Y	Y

Note: Observations included any quarter in which the borrower's financial performance is updated. Independent variable is the change in performance quarter-over-quarter (either percent change in NOI in Columns (1)-(2) or change in occupancy rate in Columns (3)-(4)). The change in performance is interacted with a binary variable for whether the performance change is positive (or equal to zero), or binary variable for whether the performance change is negative. NOI changes are censored around the 1st and 99th percentiles at -99% and 290%, and occupancy changes are censored at -50% and 50%. The dependent variable is a binary variable for any change in internal PD, excluding instances where PD is equal to 100% (currently in default). Standard errors are clustered by loan.

Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Table B6: Generalized Event Study Estimates of Bank Risk Rating Response to Average Update to Financial Performance

Outcome:	1(Update PD)	1(Downgrade PD)	1(Upgrade PD)	Abs(Change in PD)
	(1)	(2)	(3)	(4)
F2.1(NOI Update)	-0.0155***	-0.00231**	-0.0132***	0.0444***
	(0.00129)	(0.000952)	(0.00104)	(0.00611)
F1.1(NOI Update)	-0.0203***	-0.00288***	-0.0174***	0.0616***
	(0.00138)	(0.00103)	(0.00110)	(0.00680)
1(NOI Update)	0.105***	0.0453***	0.0595***	0.291***
	(0.00166)	(0.00121)	(0.00129)	(0.00908)
L1.1(NOI Update)	0.00562***	0.00416***	0.00146	0.125***
	(0.00152)	(0.00112)	(0.00121)	(0.00786)
L2.1(NOI Update)	-0.0259***	-0.0140***	-0.0119***	0.0200***
	(0.00139)	(0.00103)	(0.00112)	(0.00645)
L3.1(NOI Update)	-0.0321***	-0.0121***	-0.0200***	-0.0130**
	(0.00132)	(0.000979)	(0.00106)	(0.00588)
Initial Update Effect	0.125	0.0480	0.0770	0.230
P-Value of Initial Effect	0.0000	0.0000	0.0000	0.0000
Observations	670,227	670,227	670,227	670,227
R-squared	0.268	0.227	0.187	0.195
Dependent Variable Mean	0.223	0.102	0.120	0.238
Reporting Quarter-CBSA FE	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y
Quarter of Year FE	Y	Y	Y	Y
Quarters Since Orig	Y	Y	Y	Y

Note: The independent variable is an indicator for whether or not the loan observation experiences an update to their financial performance, represented by 1(NOI Update). The regression includes two leads and three lags of this variable. Controls for reporting quarter-by-CBSA, loan, calendar quarter, and quarters since origination fixed effects. The outcome variables are either an indicator for any update to the bank's internal risk rating, a downgrade in the PD risk rating, an upgrade in the risk rating, or the absolute value of the quarter-over-quarter change in the bank's internal PD. The middle panel reports the difference between the first lead, 'F1.1(NOI Update)', and contemporaneous update variable '1(NOI Update)' to measure the immediate effect of a change in reported performance on bank's risk evaluation. The P-Value a test that this difference is zero is also reported in the row below.

Source: Federal Reserve Form Y-14Q Schedule H.2, Authors' analysis.

Table B7: Default Probability and Staleness of Financial Reporting

Outcome:	Default X 100						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Staleness NOI			0.0197***				0.0198***
			(0.00256)				(0.00318)
L1.Staleness NOI	0.0856***	0.0285***	0.0121***				0.0122***
	(0.00164)	(0.00184)	(0.00292)				(0.00361)
L2.Staleness NOI			0.0160***				0.0166***
			(0.00296)				(0.00365)
L3.Staleness NOI			0.00312				0.00334
			(0.00302)				(0.00370)
L4.Staleness NOI			-0.00271				0.000862
			(0.00269)				(0.00332)
Staleness Occ						0.00727***	0.000746
						(0.00213)	(0.00254)
L1.Staleness Occ				0.0602***	0.0162***	0.00354	-0.000734
				(0.00131)	(0.00143)	(0.00250)	(0.00296)
L2.Staleness Occ						0.00598**	-0.000717
						(0.00254)	(0.00301)
L3.Staleness Occ						0.00231	0.00113
						(0.00262)	(0.00310)
L4.Staleness Occ						0.000332	-0.00236
						(0.00230)	(0.00273)
F1.Unemployment Rate	0.0226**	0.00781	0.00327	0.0235***	0.00937	0.00519	0.00332
	(0.00907)	(0.00677)	(0.00778)	(0.00899)	(0.00674)	(0.00780)	(0.00787)
Unemployment Rate	-0.00618	-0.0111	-0.00907	-0.00618	-0.00784	-0.00573	-0.00771
	(0.0120)	(0.00821)	(0.00940)	(0.0118)	(0.00817)	(0.00946)	(0.00954)
L1.Unemployment Rate	0.0215**	0.00876	0.0105	0.0208**	0.0148**	0.0134*	0.0116
	(0.00901)	(0.00676)	(0.00773)	(0.00892)	(0.00672)	(0.00777)	(0.00783)
Observations	1,654,650	1,637,627	1,342,295	1,637,868	1,620,749	1,241,868	1,225,072
R-squared	0.003	0.571	0.582	0.002	0.568	0.557	0.555
Default Mean	0.461	0.456	0.500	0.446	0.441	0.454	0.455
Reporting Quarter FE	Y	Y	Y	Y	Y	Y	Y
Loan FE	N	Y	Y	N	Y	Y	Y
Quarter of Year FE	N	Y	Y	N	Y	Y	Y
Quarters Since Orig	N	Y	Y	N	Y	Y	Y

Note: Default is defined as where current PD is equal to 1 (when the obligor is currently in default). The independent variables are calculated as the number of quarters between the "as of" date of the current reported NOI or occupancy and the reporting date (where reporting and as of dates are quarterly).

Source: Federal Reserve Form Y-14Q Schedule H.2. Bureau of Labor Statistics, Local Area Unemployment Statistics, Authors' analysis.

Table B8: Delinquency Probability and Staleness of Financial Reporting

Outcome:	Delinquency X 100						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Staleness NOI			0.000240				0.00840**
			(0.00299)				(0.00368)
L1.Staleness NOI	0.0620***	0.0209***	0.0159***				0.0117***
	(0.00146)	(0.00211)	(0.00345)				(0.00421)
L2.Staleness NOI			0.00801**				0.0125***
			(0.00349)				(0.00424)
L3.Staleness NOI			0.00211				-0.00330
			(0.00356)				(0.00430)
L4.Staleness NOI			-0.00263				-0.00493
			(0.00316)				(0.00383)
Staleness Occ						-0.00839***	-0.0101***
						(0.00248)	(0.00290)
L1.Staleness Occ				0.0411***	0.0134***	0.0124***	0.00816**
				(0.00109)	(0.00162)	(0.00295)	(0.00343)
L2.Staleness Occ						-0.000813	-0.00555
						(0.00300)	(0.00349)
L3.Staleness Occ						0.00702**	0.00755**
						(0.00309)	(0.00359)
L4.Staleness Occ						0.00426	0.00524*
						(0.00269)	(0.00313)
F1.Unemployment Rate	0.00272	0.00719	0.00712	0.00422	0.00681	0.00382	0.00237
	(0.00834)	(0.00784)	(0.00901)	(0.00830)	(0.00781)	(0.00907)	(0.00914)
Unemployment Rate	0.00105	-0.00668	-0.0106	0.00113	-0.00543	-0.0101	-0.0108
	(0.0110)	(0.00952)	(0.0109)	(0.0109)	(0.00948)	(0.0110)	(0.0111)
L1.Unemployment Rate	0.0285***	0.0306***	0.0337***	0.0292***	0.0382***	0.0383***	0.0375***
	(0.00831)	(0.00784)	(0.00897)	(0.00825)	(0.00780)	(0.00905)	(0.00912)
Observations	1,874,692	1,848,132	1,494,540	1,860,059	1,833,342	1,384,419	1,360,437
R-squared	0.001	0.319	0.325	0.001	0.317	0.316	0.311
Delinquent Mean	0.460	0.452	0.485	0.449	0.442	0.467	0.464
Reporting Quarter FE	Y	Y	Y	Y	Y	Y	Y
Loan FE	N	Y	Y	N	Y	Y	Y
Quarter of Year FE	N	Y	Y	N	Y	Y	Y
Quarters Since Orig	N	Y	Y	N	Y	Y	Y

Note: Delinquency is defined as where past due payments is greater than 0 and non-missing. The independent variables are calculated as the number of quarters between the "as of" date of the current reported NOI or occupancy and the reporting date (where reporting and as of dates are quarterly).

Source: Federal Reserve Form Y-14Q Schedule H.2. Bureau of Labor Statistics, Local Area Unemployment Statistics, Authors' analysis.

Table B9: Lenders' Internal PD and Stale Financial Reporting

Outcome:	Current PD X 100						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Staleness NOI			-0.0296***				-0.0259***
			(0.00124)				(0.00158)
L1.Staleness NOI	0.0139***	-0.0232***	-0.00712***				-0.00580***
	(0.000763)	(0.000901)	(0.00142)				(0.00179)
L2.Staleness NOI			0.00317**				0.00330*
			(0.00144)				(0.00181)
L3.Staleness NOI			0.00271*				0.00263
			(0.00147)				(0.00183)
L4.Staleness NOI			0.00340***				0.00221
			(0.00130)				(0.00165)
Staleness Occ						-0.0227***	-0.0130***
						(0.00106)	(0.00126)
L1.Staleness Occ				0.0304***	-0.0160***	-0.00598***	-0.00297**
				(0.000617)	(0.000713)	(0.00125)	(0.00147)
L2.Staleness Occ						0.00196	0.000350
						(0.00127)	(0.00149)
L3.Staleness Occ						0.00484***	0.00301**
						(0.00131)	(0.00153)
L4.Staleness Occ						0.00413***	0.00508***
						(0.00115)	(0.00135)
F1.Unemployment Rate	-0.0301***	0.0134***	0.0115***	-0.0287***	0.0122***	0.00679*	0.00846**
	(0.00420)	(0.00330)	(0.00376)	(0.00421)	(0.00334)	(0.00388)	(0.00389)
Unemployment Rate	-0.00234	-0.00140	-0.000342	-0.00157	-0.000427	0.00111	0.000583
	(0.00553)	(0.00401)	(0.00455)	(0.00554)	(0.00404)	(0.00470)	(0.00472)
L1.Unemployment Rate	0.0235***	0.0612***	0.0610***	0.0205***	0.0607***	0.0618***	0.0621***
	(0.00417)	(0.00330)	(0.00374)	(0.00418)	(0.00333)	(0.00386)	(0.00387)
Observations	1,647,027	1,630,083	1,335,520	1,630,563	1,613,530	1,236,175	1,219,449
R-squared	0.006	0.526	0.549	0.007	0.521	0.534	0.534
PD Mean	1.123	1.118	1.154	1.112	1.107	1.135	1.122
Reporting Quarter FE	Y	Y	Y	Y	Y	Y	Y
Loan FE	N	Y	Y	N	Y	Y	Y
Quarter of Year FE	N	Y	Y	N	Y	Y	Y
Quarters Since Orig	N	Y	Y	N	Y	Y	Y

Note: Dependent variable is the current PD excluding observations when PD is equal to 1 (when the obligor is currently in default). The independent variables are calculated as the number of quarters between the "as of" date of the current reported NOI or occupancy and the reporting date (where reporting and as of dates are quarterly).

Source: Federal Reserve Form Y-14Q Schedule H.2. Bureau of Labor Statistics, Local Area Unemployment Statistics, Authors' analysis.

Table B10: Lenders' Internal PD Updating Probability and Stale Borrower Reporting

Outcome:	1(PD Update)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Staleness NOI	-0.00436***	-0.0121***	-0.0260***				-0.0238***
	(9.80e-05)	(0.000156)	(0.000213)				(0.000266)
L1.Staleness NOI			0.0203***				0.0192***
			(0.000243)				(0.000302)
L2.Staleness NOI			0.00422***				0.000271
			(0.000246)				(0.000305)
L3.Staleness NOI			-0.00112***				0.00143***
			(0.000251)				(0.000310)
L4.Staleness NOI			-0.00621***				-0.00535***
			(0.000224)				(0.000278)
Staleness Occ				-0.00208***	-0.00604***	-0.0149***	-0.00444***
				(7.81e-05)	(0.000122)	(0.000180)	(0.000212)
L1.Staleness Occ						0.00976***	0.00215***
						(0.000211)	(0.000247)
L2.Staleness Occ						0.00864***	0.00713***
						(0.000214)	(0.000252)
L3.Staleness Occ						0.000857***	0.000216
						(0.000221)	(0.000259)
L4.Staleness Occ						-0.00443***	-0.000977***
						(0.000194)	(0.000229)
F1.Unemployment Rate	0.00913***	0.00633***	0.00428***	0.00872***	0.00557***	0.00286***	0.00299***
	(0.000540)	(0.000576)	(0.000645)	(0.000543)	(0.000581)	(0.000656)	(0.000656)
Unemployment Rate	-0.00428***	-0.00459***	-0.00495***	-0.00405***	-0.00428***	-0.00392***	-0.00411***
	(0.000712)	(0.000699)	(0.000779)	(0.000716)	(0.000704)	(0.000795)	(0.000796)
L1.Unemployment Rate	0.000574	-0.00246***	-0.00440***	-0.000109	-0.00288***	-0.00765***	-0.00739***
	(0.000536)	(0.000575)	(0.000641)	(0.000539)	(0.000579)	(0.000653)	(0.000653)
Observations	1,650,752	1,634,189	1,332,936	1,634,664	1,618,111	1,233,667	1,216,952
R-squared	0.035	0.165	0.184	0.036	0.164	0.183	0.190
Update Mean	0.213	0.214	0.224	0.214	0.214	0.221	0.220
Reporting Quarter FE	Y	Y	Y	Y	Y	Y	Y
Loan FE	N	Y	Y	N	Y	Y	Y
Quarter of Year FE	N	Y	Y	N	Y	Y	Y
Quarters Since Orig	N	Y	Y	N	Y	Y	Y

Note: Dependent variable is a binary variable for whether current PD changed since past quarter (specifically when the difference is greater than 0.01 ppt), excluding observations when PD is equal to 1 in either quarter (i.e., when the obligor is currently in default). The independent variables are calculated as the number of quarters between the "as of" date of the current reported NOI or occupancy and the reporting date (where reporting and as of dates are quarterly).

Source: Federal Reserve Form Y-14Q Schedule H.2. Bureau of Labor Statistics, Local Area Unemployment Statistics, Authors' analysis.

Table B11: Loan Performance and Staleness of Financial Reporting by Property Type

Outcome:	Current PD		1(Update PD)		1(Downgrade PD)		1(Upgrade PD)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Staleness NOI	-0.0321***		-0.0121***		-0.00408***		-0.00802***	
	(0.000860)		(0.000156)		(0.000113)		(0.000127)	
Staleness NOI X Retail		-0.00438**		-0.0114***		-0.00515***		-0.00629***
		(0.00194)		(0.000358)		(0.000260)		(0.000291)
Staleness NOI X Industrial/Warehouse		-0.0300***		-0.0117***		-0.00416***		-0.00753***
		(0.00294)		(0.000548)		(0.000399)		(0.000445)
Staleness NOI X Multifamily		-0.0421***		-0.0120***		-0.00328***		-0.00876***
		(0.00107)		(0.000196)		(0.000143)		(0.000160)
Staleness NOI X Office		-0.0249***		-0.0134***		-0.00614***		-0.00727***
		(0.00220)		(0.000405)		(0.000295)		(0.000329)
F1.Unemployment Rate	0.0138***	0.0142***	0.00632***	0.00631***	0.00202***	0.00199***	0.00430***	0.00433***
	(0.00317)	(0.00317)	(0.000577)	(0.000577)	(0.000420)	(0.000420)	(0.000469)	(0.000469)
Unemployment Rate	-0.00141	-0.00117	-0.00456***	-0.00455***	-0.00147***	-0.00148***	-0.00308***	-0.00307***
	(0.00385)	(0.00385)	(0.000699)	(0.000699)	(0.000509)	(0.000509)	(0.000568)	(0.000568)
L1.Unemployment Rate	0.0602***	0.0606***	-0.00250***	-0.00250***	0.00138***	0.00135***	-0.00388***	-0.00385***
	(0.00317)	(0.00317)	(0.000575)	(0.000576)	(0.000419)	(0.000419)	(0.000468)	(0.000468)
Observations	1,744,964	1,744,964	1,632,812	1,632,812	1,632,812	1,632,812	1,632,812	1,632,812
R-squared	0.516	0.516	0.165	0.165	0.128	0.128	0.119	0.119
Dependent Variable Mean	1.106	1.106	0.214	0.214	0.0945	0.0945	0.120	0.120
Reporting Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter of Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarters Since Orig	Y	Y	Y	Y	Y	Y	Y	Y

Note: Staleness is defined as the difference between the reporting quarter and the 'as of' quarter for the NOI reporting. Staleness measure interacted with property type indicator variables. Controls for reporting quarter, loan, calendar quarter, and quarters since origination fixed effects. The other independent variables are one lead and lag of the CBSA-level unemployment rate (from county-level LAUS BLS data, weighted by county labor force to calculate CBSA averages).

Source: Federal Reserve Form Y-14Q Schedule H.2. Bureau of Labor Statistics, Local Area Unemployment Statistics, Authors' analysis.

Table B12: Lender PD Updating and Staleness of Financial Reporting by Loan Characteristics

Outcome:	Current PD		1(Update PD)		1(Downgrade PD)		1(Upgrade PD)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Staleness NOI	-0.0321***	-0.0386***	-0.0121***	-0.0154***	-0.00408***	-0.00615***	-0.00802***	-0.00923***
	(0.000860)	(0.00115)	(0.000156)	(0.000202)	(0.000113)	(0.000149)	(0.000127)	(0.000163)
Staleness NOI X Z(Initial PD)		-0.0252***		-0.00682***		-0.000590		-0.00623***
		(0.00453)		(0.000806)		(0.000594)		(0.000652)
Staleness NOI X Z(Orig LTV)		0.00319***		0.00110***		0.000739***		0.000361**
		(0.000976)		(0.000175)		(0.000129)		(0.000141)
Staleness NOI X Z(Participation)		-0.00516***		-0.000818**		0.000140		-0.000958***
		(0.00196)		(0.000352)		(0.000259)		(0.000284)
Staleness NOI X Z(Any Recourse)		-0.00300***		0.00119***		0.00158***		-0.000397**
		(0.00107)		(0.000195)		(0.000143)		(0.000157)
Staleness NOI X Z(Log Orig Amount)		-0.00937***		-0.00819***		-0.00390***		-0.00429***
		(0.00138)		(0.000250)		(0.000184)		(0.000202)
Staleness NOI X Z(Log Orig Sq. Ft.)		0.0115***		-0.000285		-0.000842***		0.000557***
		(0.00100)		(0.000181)		(0.000133)		(0.000146)
F1.Unemployment Rate	0.0138***	0.0124***	0.00632***	0.00508***	0.00202***	0.00152***	0.00430***	0.00356***
	(0.00317)	(0.00342)	(0.000577)	(0.000601)	(0.000420)	(0.000442)	(0.000469)	(0.000486)
Unemployment Rate	-0.00141	-0.000194	-0.00456***	-0.00468***	-0.00147***	-0.00200***	-0.00308***	-0.00267***
	(0.00385)	(0.00417)	(0.000699)	(0.000732)	(0.000509)	(0.000539)	(0.000568)	(0.000592)
L1.Unemployment Rate	0.0602***	0.0554***	-0.00250***	-0.00594***	0.00138***	0.000212	-0.00388***	-0.00615***
	(0.00317)	(0.00343)	(0.000575)	(0.000602)	(0.000419)	(0.000443)	(0.000468)	(0.000486)
Observations	1,744,964	1,463,485	1,632,812	1,376,634	1,632,812	1,376,634	1,632,812	1,376,634
R-squared	0.516	0.492	0.165	0.170	0.128	0.138	0.119	0.109
Dependent Variable Mean	1.106	1.070	0.214	0.209	0.0945	0.0955	0.120	0.114
Reporting Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter of Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarters Since Orig	Y	Y	Y	Y	Y	Y	Y	Y

Note: Staleness is defined as the difference between the reporting quarter and the 'as of' quarter for the NOI reporting. Staleness variable is interacted with a z-scored measure of loan facility characteristics defined at origination or the initial value when the loan enters the Y-14Q dataset. Interacted variables include initial PD, origination LTV, initial participation interest of the bank, an indicator for whether the loan includes a partial or full recourse term, log of the total origination amount, and log of the total property square footage. The other independent variables are one lead and lag of the CBSA-level unemployment rate (from county-level LAUS BLS data, weighted by county labor force to calculate CBSA averages).

Source: Federal Reserve Form Y-14Q Schedule H.2. Bureau of Labor Statistics, Local Area Unemployment Statistics, Authors' analysis.

C Additional Analysis on Impact of Local Labor Market Conditions on "Stale" Reporting

In this section, we consider the effect of local economic conditions on borrower reporting behavior. There are two useful insights to be gained from this analysis. First, if borrowers are less likely to report negative financial outcomes, then negative shocks should lead to more non-reporting and more outdated financial data on bank balance sheets. Second, this analysis should provide an initial indication about whether borrower reporting is primarily driven by local conditions. In other words, it could be the case that reporting behavior is driven by observable economic conditions, so borrower non-reporting does not provide idiosyncratic, valuable information about predicting borrower default risk. We study the usefulness of reporting behavior for predicting this default risk in the next section.

The primary measure of local economic conditions used in this section is the change in city-level unemployment rates. In constructing this regression specification, we consider that there may be a systematic correlation between the quality of borrowers or properties and the level of local unemployment rates. High risk borrowers who are systematically late in reporting may be selected into riskier cities.

The main regression specification isolates within-city, within-loan variation in reporting and local economic shocks. We include loan fixed effects, as well as fixed effects for the time period (reporting quarter), calendar quarter, and quarters since origination. These fixed effects should absorb variation coming from seasonality in reporting or monitoring activity, and any systematic variation between staleness of financial reporting and seasoning of the loan (i.e., how long ago the loan was originated). Well-performing, more seasoned loans may receive less monitoring attention and may therefore have more outdated financial reports. We index these effects: loan i, city c, time period t, calendar quarter q, and time since origination s.

$$staleness_{it} = \sum_{k=-3}^{3} \beta_k \Delta uer_{c,t+k-1\rightarrow t+k} + \alpha_i + \alpha_t + \alpha_q + \alpha_s + \nu_{it} \qquad (7)$$

To show the dynamics of the effects of local unemployment shocks on reporting behavior, we include two leads and two lags for unemployment rate changes. This allows us to test whether changes in reporting occur before changes in unemployment—an indication that we may not be measuring the effects of local economic shocks, but some omitted variable affecting both unemployment and reporting. The lagged values allow us to measure whether reporting propensity changes in the same quarter as an employment shock, or whether effects accumulate or lag over the quarters follow an economic shock.

We study two different outcomes in this regression: the first is the continuous measure for reporting staleness (current reporting quarter minus the 'as of' quarter for the financials contemporaneously recorded by the bank); the second is a binary indicator for any update the financial reports. The binary variable is an interesting complement because it considers any time the borrower provides more recent financials (even if the newly reported financials are 'stale') and it includes any observations with a missing or non-applicable value for the reporting 'as of' date as a zero. The missing or non-applicable values would be excluded from the regression on stale information because they do not allow a clean calculation of the staleness measure.

Appendix Table C13 shows the results of these regressions, separately showing effects for retail (Columns 1-2), industrial and warehouse (Columns 3-4), multifamily (Columns 5-6), and office properties (Columns 7-8). The dependent variable mean for each estimation sample is reported in the row below the number observations and R-squared. For retail and industrial mortgages, there is a decline in the probability of reporting updated financials 1-2 quarters after a change in unemployment rates (Columns 2 and 4), significantly different from zero at the 95% confidence level. There is similar evidence of an increase in staleness 2-3 quarters after an increase in unemployment (Columns 1 and 3). For industrial properties, the positive leading coefficients may be evidence of some systematic positive correlation between rising unemployment and increasingly stale financial reporting for industrial properties.

For multifamily mortgages, while there may be some systematic positive correlation between stale NOI reporting and rising unemployment, there is a clear trend break where reporting staleness and probability of reporting change in response to an unemployment change in period t to t-1. A one percentage point rise in unemployment is associated with 0.036 quarters more outdated financial data (comparing the leading coefficients to the lagged coefficients in Column 5), which is 0.9% of the dependent variable mean. Corresponding to this increase in aged data, there is a half percentage point decrease in the probability of a borrower sending any NOI update in the three quarters following a change in unemployment (Column 6). This effect appears to deepen one to two quarters after a shock, then attenuate in the third lagging quarter. To interpret, we can scale this coefficient by the dependent variable mean, which suggests an average effect over three quarters of 2.6% more outdated NOI reporting from a one percentage point unemployment shock.

In the office sector, there is a sharp and significant increase in financial data staleness around a change in unemployment. The average staleness of office NOI data increases by 0.0281 quarters from a one percentage point increase in unemployment rates, representing a 0.7% increase on the average staleness in the data (Column 7). Corresponding to the increase in stale information, the probability of a borrower updating their NOI reporting decreases by 0.37 percentage points, or 1.2% of the dependent variable mean (Column 8).

The combination of these results suggests: (1) on average, unemployment rate shocks are negatively correlated with the quality of current financial reporting data; (2) these effects are heterogeneous across CRE asset classes, with multifamily and office mortgages particularly sensitive to local economic conditions; and (3) while local conditions significantly affect reporting behavior, they do not appear to explain much of the aggregate movements in outdated data and leave significant room for other factors to influence reporting. In Appendix Table C14, we report analogous results analyzing the reporting behavior of borrowers' occupancy rates. We find broadly similar effects for multifamily properties, less statistically significantly strong effects on reporting for office and industrial properties, and some evidence that occupancy reporting rises for retail properties in the quarter a city experiences an unemployment shock.

Table C13: Local Economic Conditions and Financial Reporting Behavior

Property Type:	Retail		Industrial		Multifamily		Office	
Outcome:	Staleness (NOI)	1(Update NOI)	Staleness (NOI)	1(Update NOI)	Staleness (NOI)	1(Update NOI)	Staleness (NOI)	1(Update NOI)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ UER (t+2,t+1)	0.00375	0.000556	0.0214***	-0.000740	0.0206***	0.00160**	0.00177	-0.000332
	(0.00542)	(0.00100)	(0.00804)	(0.00143)	(0.00399)	(0.000685)	(0.00637)	(0.00117)
Δ UER (t+1,t)	0.00526	0.00129	0.0314***	0.000146	0.0255***	0.00128*	0.00869	-0.00145
	(0.00554)	(0.00102)	(0.00819)	(0.00146)	(0.00399)	(0.000686)	(0.00655)	(0.00120)
Δ UER (t,t-1)	-0.00221	0.00185*	0.0230***	-0.000934	0.0544***	-0.00366***	0.0130*	-0.00159
	(0.00572)	(0.00106)	(0.00848)	(0.00151)	(0.00417)	(0.000716)	(0.00683)	(0.00125)
Δ UER (t-1,t-2)	0.00786	-0.00283***	0.0340***	-0.00392***	0.0738***	-0.00780***	0.0281***	-0.00373***
	(0.00556)	(0.00103)	(0.00824)	(0.00147)	(0.00402)	(0.000690)	(0.00667)	(0.00122)
Δ UER (t-2,t-3)	0.0120**	9.95e-05	0.0156*	-3.33e-05	0.0536***	-0.000581	0.0171***	0.00235*
	(0.00549)	(0.00101)	(0.00810)	(0.00144)	(0.00405)	(0.000692)	(0.00661)	(0.00121)
Observations	364,977	400,731	168,623	205,592	1,108,369	1,227,257	294,390	332,571
R-squared	0.630	0.236	0.642	0.248	0.657	0.242	0.643	0.284
Dependent Variable Mean	4.332	0.274	4.244	0.247	4.096	0.240	4.060	0.300
Reporting Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter of Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarters Since Orig	Y	Y	Y	Y	Y	Y	Y	Y

Note: Staleness is defined as the difference between the reporting quarter and the 'as of' quarter for the NOI or occupancy reporting. The binary variable for an NOI or occupancy update is simply a decline in the staleness measure relative to last quarter. This is agnostic to the direction or the exact timing of the newly reported performance, only capturing that it is more recent than the prior quarter. The independent variables are differences in the CBSA-level unemployment rate (from county-level LAUS BLS data, weighted by county labor force to calculate CBSA averages). To study the dynamics of these effects, 2 leads and 2 lags are included, capturing the change in unemployment rates 1 to 2 quarters before and 2 to 3 quarters after the quarter denoted t.

Source: Federal Reserve Form Y-14Q Schedule H.2. Bureau of Labor Statistics, Local Area Unemployment Statistics, Authors' analysis.

Table C14: Local Economic Conditions and Occupancy Reporting Behavior

Property Type:	Retail		Industrial		Multifamily		Office	
Outcome:	Staleness (Occ)	1(Update Occ)	Staleness (Occ)	1(Update Occ)	Staleness (Occ)	1(Update Occ)	Staleness (Occ)	1(Update Occ)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ UER (t+2,t+1)	-0.00853	0.00132	0.0116	0.000509	0.0178***	0.00381***	-0.00898	-0.000282
	(0.00753)	(0.000962)	(0.0109)	(0.00137)	(0.00514)	(0.000689)	(0.00854)	(0.00113)
Δ UER (t+1,t)	-0.0208***	0.00118	0.00560	0.000490	-0.00650	0.00228***	-0.00683	-0.00149
	(0.00769)	(0.000982)	(0.0111)	(0.00140)	(0.00513)	(0.000690)	(0.00877)	(0.00116)
Δ UER (t,t-1)	-0.0279***	0.00303***	0.00425	0.000390	0.0188***	-0.00293***	-0.00424	-0.000952
	(0.00794)	(0.00102)	(0.0114)	(0.00145)	(0.00536)	(0.000720)	(0.00914)	(0.00121)
Δ UER (t-1,t-2)	-0.0177**	-0.000828	-0.00456	-0.00101	0.00919*	-0.00284***	0.00435	-0.00184
	(0.00771)	(0.000986)	(0.0111)	(0.00141)	(0.00515)	(0.000694)	(0.00892)	(0.00118)
Δ UER (t-2,t-3)	-0.00848	0.000232	-0.0107	-0.00249*	0.00689	-0.00422***	-0.000355	0.00280**
	(0.00761)	(0.000972)	(0.0109)	(0.00138)	(0.00519)	(0.000696)	(0.00882)	(0.00117)
Observations	361,621	400,731	168,386	205,592	1,098,856	1,227,257	292,190	332,571
R-squared	0.684	0.262	0.703	0.273	0.636	0.241	0.683	0.306
Dependent Variable Mean	4.573	0.254	4.461	0.230	3.548	0.244	4.260	0.282
Reporting Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter of Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarters Since Orig	Y	Y	Y	Y	Y	Y	Y	Y

Note: Staleness is defined as the difference between the reporting quarter and the 'as of' quarter for the NOI or occupancy reporting. The binary variable for an NOI or occupancy update is simply a decline in the staleness measure relative to last quarter. This is agnostic to the direction or the exact timing of the newly reported performance, only capturing that it is more recent than the prior quarter. The independent variables are differences in the CBSA-level unemployment rate (from county-level LAUS BLS data, weighted by county labor force to calculate CBSA averages). To study the dynamics of these effects, 2 leads and 2 lags are included, capturing the change in unemployment rates 1 to 2 quarters prior and 2 to 3 quarters after the quarter denoted t.

Source: Federal Reserve Form Y-14Q Schedule H.2. Bureau of Labor Statistics, Local Area Unemployment Statistics, Authors' analysis.

D Additional Results on Endogenous Bank Monitoring

The four-panel graphs in Appendix Figure D14 below show the effects of the oil price shock on moderate or very high exposure cities by property type. The trends are similar across property types with declines in staleness measures for loans in areas with very high oil and gas exposure approximately a year after the oil shock. Moderately affected regions experience an increase in performance staleness for multifamily properties, but little or no evidence of changes for office, industrial, or retail properties.

Having looked at the measure of staleness of financial performance in the main text, we also analyze the realization of delinquency, the banks' internal rating of the probability of default, and the probability of updating NOI performance in Appendix Figure D15. There is some evidence of an increase in delinquency (late payments) in mid-2016 among loans in the most-exposed cities. Banks appear to anticipate this shock on average: internal PD ratings increase in the most exposed areas in mid-2015. The timing indicates that banks did not update PDs in Q4 2014 when the initial oil shock hit, but did begin to update PDs the next year (around Q4 2015). Their average risk updating appears to have finished by Q1 2017. The bottom panel shows that the most-exposed cities may have experienced an initial relative decline in financial performance update probability in late 2014 or early 2015, but by mid-2015 there was a significant increase in reporting in the hardest hit CBSAs. In moderately-exposed CBSAs, there was little or no evidence of an increase in updating probability.

In the following graphs, we show regression output comparing loan performance data for exposed and non-exposed banks within each different group of cities. The first set of graphs, Appendix Figure D16, shows the average values for each outcome within each group of banks and cities. These graphs help summarize the levels and trends of our main outcomes around the timing of the oil price shock. The output is also summarized in Appendix Table D16 showing these average values by bank-by-CBSA grouping over time.

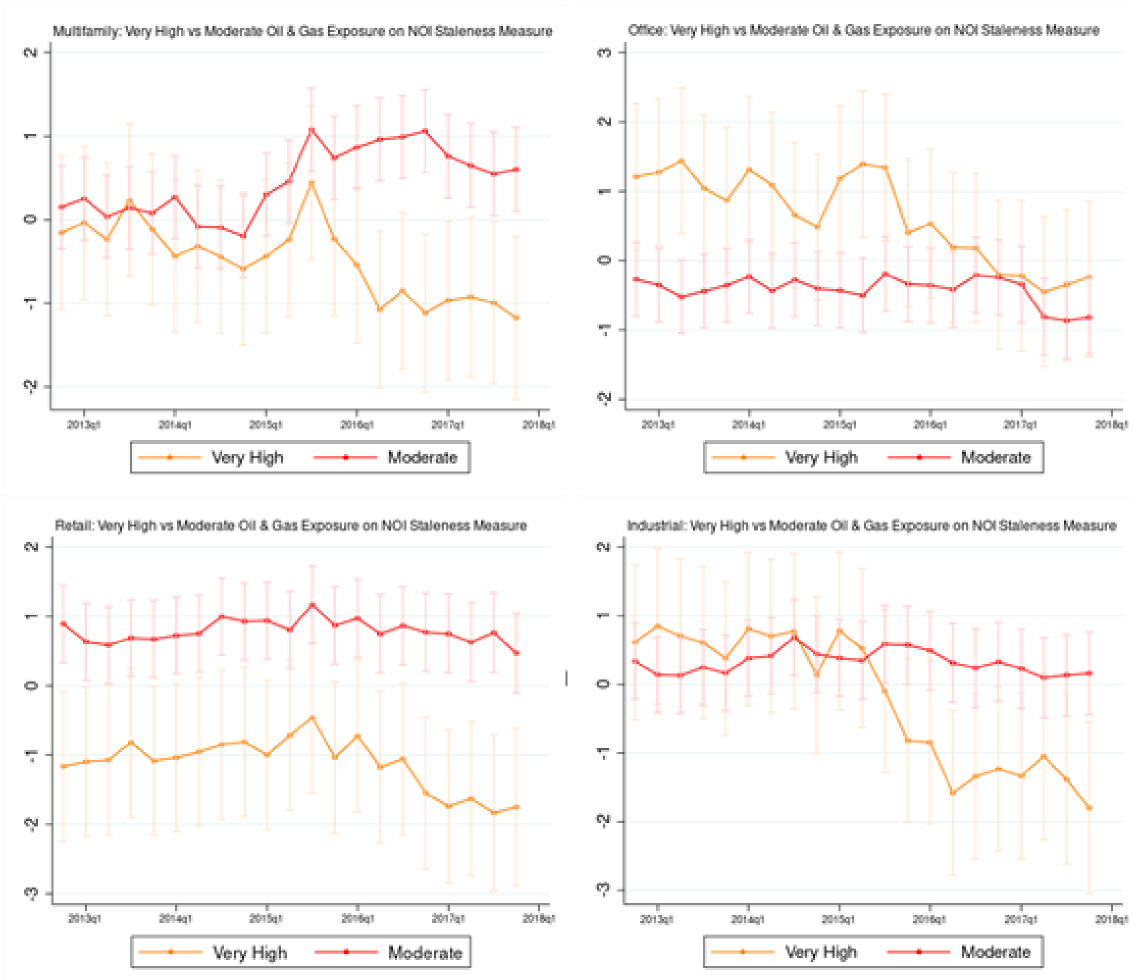
Prior to the oil shock, CRE loans in non-exposed CBSAs for exposed banks had more outdated performance data compared to non-exposed banks. We do not have a strong interpretation of this descriptive statistic, and it does not appear to be related to a difference in bank-specific strategy because in the moderately and heavily exposed CBSAs, the exposed banks actually had less-stale performance data. The updating probability is more noisy for the exposed bank, which makes sense given that there are fewer of them (the top quartile of banks by C&I exposure). The trends in 2013 look reasonably similar. We do not think noise in these variables is a large problem given that this period was part of the introduction of Y-14 data collection through the FRB's CCAR framework.

The regression output is reported in Appendix Figure D.4 and Table D.2, where loans held by non-exposed banks in non-exposed CBSAs are the excluded, comparison group. We show the effects on our staleness measure in the top panel. The amount of stale information for exposed banks in non-exposed cities declines by 23% by early 2016 relative to the pre-oil shock average. In moderately exposed cities, we observe that exposed banks also see a decline in outdated performance by around 24%. However, non-exposed banks in moderately exposed cities experience an increase in stale reporting by 11%. The most exposed cities see a delayed response in their reporting for all types of banks. Non-exposed banks see performance updates earlier, while exposed banks only see large changes by mid-2016. Both types of banks end up with a decline in performance staleness of 25-27% by the end of 2016.

In the bottom panel of Appendix Figure D17 and in Appendix Table D17, we observe the changes in probability of updating financial performance where the regression takes the form of a linear probability model. Consistent with the results on stale information, in non-exposed cities, loans held by the most exposed banks see a relative increase in updating of financial performance. In moderately exposed CBSAs, there is a short-lived increase in updating, especially for exposed banks. In the most heavily exposed cities, both types of banks experience increases in the probability of updating financial performance, but given that it takes several quarters to decrease the age of reporting data, it may be the case that right after the oil shock, some borrowers increased reporting of stale, relatively outdated financial performance. In Appendix Table D19 and D20 on performance staleness and Appendix Table D21 and D22 on updating probability, we repeat this exercise for a subset of loans that were originated in the two years leading up to the oil price shock from Q1 2012 to Q1 2014. We acknowledge that this dataset might be preferable given potential for endogenous selection on survival of older loans and origination of newer loans on balance sheets around the time of the oil price shock. The FRB's Y14Q CCAR reporting framework did not include detail on loan disposition until well after the oil price shock (around 2017).

Appendix Table D23 presents additional results on how loan monitoring changes on floating rate loans for occupancy performance. Conditional on loan fixed effects and controlling for location and time-related factors, higher interest rates lead to more intensive monitoring and reporting behavior.

Figure D14: By Property Type: Quarterly Dynamics of Staleness Measure for Moderately Exposed and Heavily Exposed CBSAs (Relative to Excluded Group of Non-Exposed CBSAs)



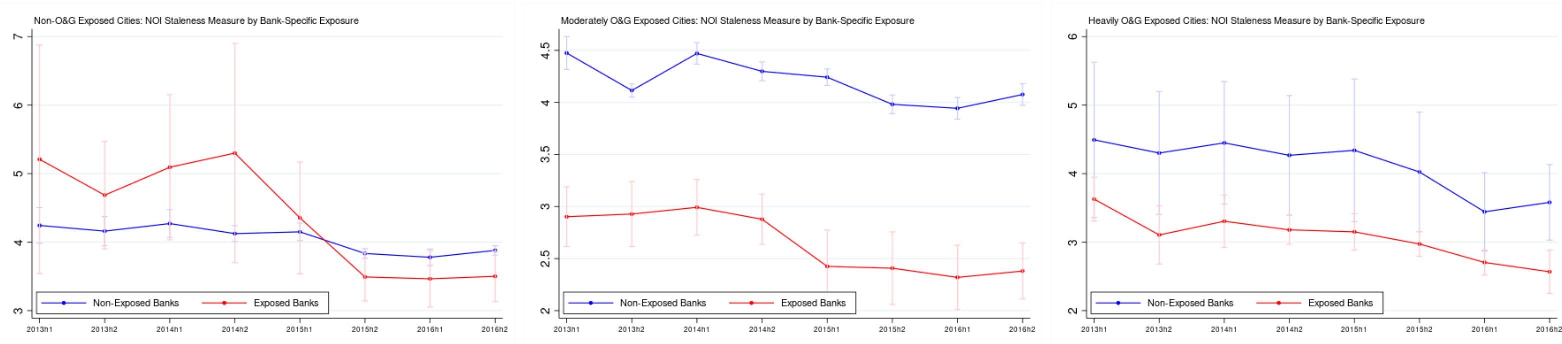
Notes: City exposure is defined as a percent of payroll employment in oil & gas industries, see more in text. Excluded group is loans in cities with less than 0.36% of payroll employment in oil and gas industries, and base period H1 2014.
Source: U.S. Census Bureau County Business Patterns. Federal Reserve Form Y-14Q Schedule H.1 and H.2, Authors' analysis.

Figure D15: Quarterly Dynamics of Delinquency, Internal PDs, and Probability of NOI Updating for Moderately Exposed and Heavily Exposed CBSAs (Relative to Excluded Group of Non-Exposed CBSAs)

Notes: City exposure is defined as a percent of payroll employment in oil & gas industries, see more in text. Excluded group is loans in cities with less than 0.36% of payroll employment in oil and gas industries, and base period H1 2014.
Source: U.S. Census Bureau County Business Patterns. Federal Reserve Form Y-14Q Schedule H.1 and H.2, Authors' analysis.

Figure D16: Summary by CBSA-level Exposure & Bank-level Exposure

(a) Staleness of NOI Reporting

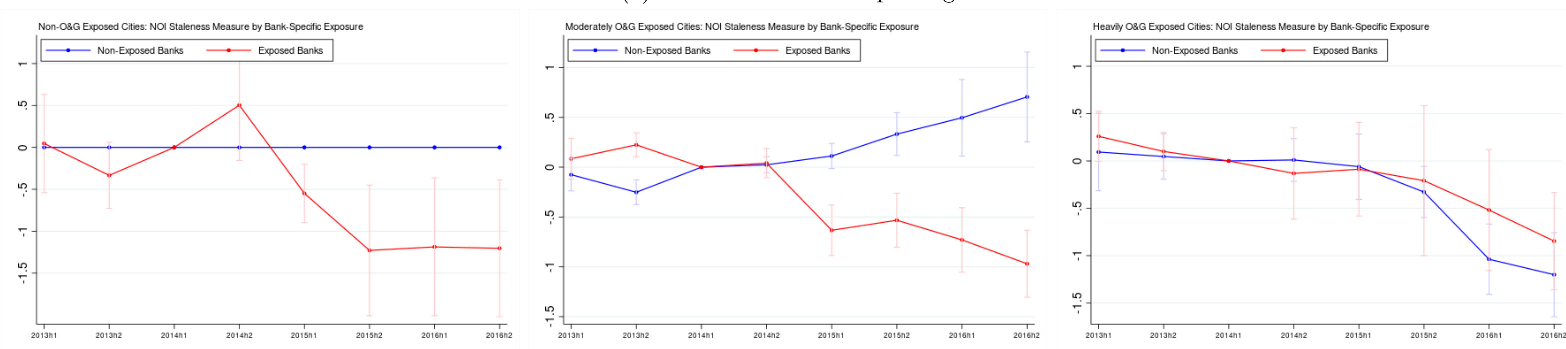


(b) Probability of NOI Updating

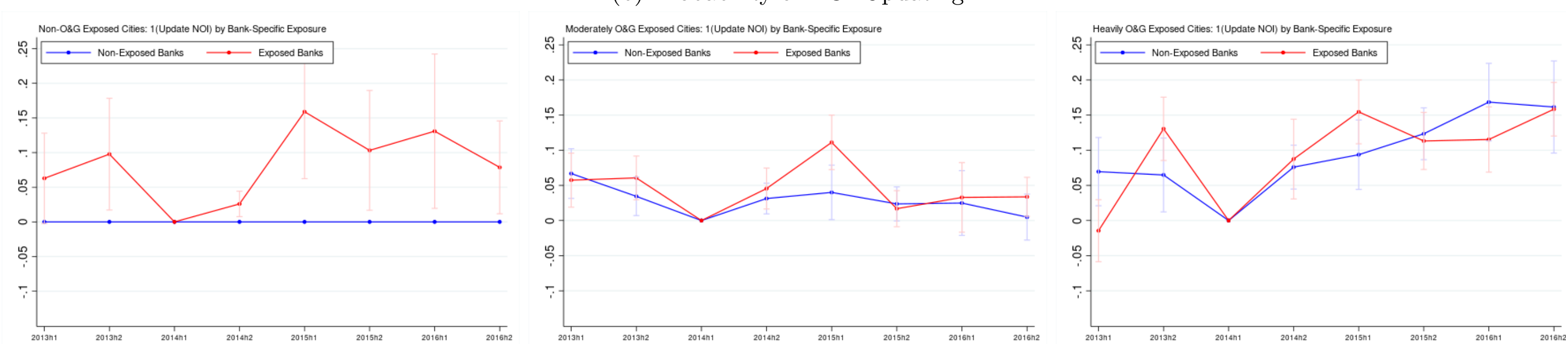
Notes: City exposure is defined as a percent of payroll employment in oil & gas industries, see more in text.
Source: U.S. Census Bureau County Business Patterns. Federal Reserve Form Y-14Q Schedule H.1 and H.2, Authors' analysis.

Figure D17: Regression Results by CBSA-level Exposure & Bank-level Exposure (Comparing to Non-O&G Exposed CBSA & Bank; Base Period H1 2014)

(a) Staleness of NOI Reporting



(b) Probability of NOI Updating



Notes: City exposure is defined as a percent of payroll employment in oil & gas industries, see more in text. Excluded group is loans in cities with less than 0.36% of payroll employment in oil and gas industries, and base period H1 2014.
Source: U.S. Census Bureau County Business Patterns. Federal Reserve Form Y-14Q Schedule H.1 and H.2, Authors' analysis.

Table D15: Staleness of NOI Reporting: OLS Regression by CBSA-level Exposure & Bank-level Exposure

Outcome:	Staleness NOI					
	Non-O&G Exposed CBSA		Moderately O&G Exposed CBSA		Very Heavily Exposed CBSA	
	Exposed Banks	Non-Exp. Banks	Exposed Banks	Non-Exp. Banks	Exposed Banks	Non-Exp. Banks
	(1)	(2)	(3)	(4)	(5)	(6)
H1 2013	5.208***	4.243***	2.902***	4.475***	3.628***	4.493***
	(0.849)	(0.133)	(0.146)	(0.0802)	(0.163)	(0.577)
H2 2013	4.686***	4.161***	2.928***	4.115***	3.105***	4.301***
	(0.400)	(0.108)	(0.159)	(0.0320)	(0.217)	(0.457)
H1 2014	5.093***	4.272***	2.992***	4.471***	3.305***	4.449***
	(0.539)	(0.103)	(0.136)	(0.0528)	(0.195)	(0.456)
H2 2014	5.299***	4.125***	2.878***	4.299***	3.179***	4.267***
	(0.815)	(0.0591)	(0.123)	(0.0462)	(0.107)	(0.445)
H1 2015	4.354***	4.151***	2.425***	4.243***	3.150***	4.340***
	(0.416)	(0.0652)	(0.178)	(0.0404)	(0.135)	(0.530)
H2 2015	3.492***	3.835***	2.408***	3.982***	2.973***	4.024***
	(0.178)	(0.0356)	(0.178)	(0.0456)	(0.0923)	(0.445)
H1 2016	3.465***	3.780***	2.320***	3.944***	2.703***	3.443***
	(0.210)	(0.0615)	(0.157)	(0.0528)	(0.0935)	(0.291)
H2 2016	3.501***	3.879***	2.380***	4.077***	2.567***	3.582***
	(0.188)	(0.0345)	(0.137)	(0.0526)	(0.160)	(0.280)
Observations	733,469	733,469	733,469	733,469	733,469	733,469
R-squared	0.552	0.552	0.552	0.552	0.552	0.552
Dependent Variable Mean	4.075	4.075	4.075	4.075	4.075	4.075
Reporting Quarter FE	N	N	N	N	N	N
Loan FE	N	N	N	N	N	N
CBSA FE	N	N	N	N	N	N
Quarter of Year FE	N	N	N	N	N	N
Quarters Since Orig	N	N	N	N	N	N

Note: Columns report results from the same regression, where loans from all categories are pooled (by level of CBSA exposure, then by bank-level exposure to corporate & industrial loans in the O&G industry). Staleness is defined as the difference between the reporting quarter and the 'as of' quarter for the NOI or occupancy reporting.

Source: U.S. Census Bureau County Business Patterns. Federal Reserve Form Y-14Q Schedule H.1 and H.2, Authors' analysis.

Table D16: Staleness of NOI Reporting: Fixed Effects Regression by CBSA-level Exposure & Bank-level Exposure

Outcome:	Staleness NOI					
	Non-O&G Exposed CBSA		Moderately O&G Exposed CBSA		Very Heavily Exposed CBSA	
	Exposed Banks	Non-Exp. Banks	Exposed Banks	Non-Exp. Banks	Exposed Banks	Non-Exp. Banks
	(1)	(2)	(3)	(4)	(5)	(6)
H1 2013	0.0478		0.0850	-0.0750	0.261*	0.0953
	(0.298)		(0.104)	(0.0824)	(0.135)	(0.208)
H2 2013	-0.334*		0.224***	-0.252***	0.100	0.0474
	(0.201)		(0.0614)	(0.0632)	(0.103)	(0.122)
H1 2014						
H2 2014	0.504		0.0410	0.0237	-0.131	0.0108
	(0.336)		(0.0748)	(0.0410)	(0.246)	(0.115)
H1 2015	-0.549***		-0.633***	0.112*	-0.0874	-0.0602
	(0.178)		(0.129)	(0.0642)	(0.252)	(0.176)
H2 2015	-1.228***		-0.532***	0.332***	-0.208	-0.328**
	(0.397)		(0.138)	(0.109)	(0.403)	(0.137)
H1 2016	-1.187***		-0.730***	0.496**	-0.519	-1.038***
	(0.418)		(0.165)	(0.196)	(0.325)	(0.189)
H2 2016	-1.204***		-0.970***	0.705***	-0.847***	-1.201***
	(0.415)		(0.171)	(0.230)	(0.261)	(0.226)
Observations	721,176	721,176	721,176	721,176	721,176	721,176
R-squared	0.715	0.715	0.715	0.715	0.715	0.715
Dependent Variable Mean	4.101	4.101	4.101	4.101	4.101	4.101
Reporting Quarter FE	Y	Y	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y	Y	Y
CBSA FE	Y	Y	Y	Y	Y	Y
Quarter of Year FE	Y	Y	Y	Y	Y	Y
Quarters Since Orig	Y	Y	Y	Y	Y	Y

Note: Columns report results from the same regression, where loans from all categories are pooled (by level of CBSA exposure, then by bank-level exposure to corporate & industrial loans in the O&G industry). Staleness is defined as the difference between the reporting quarter and the 'as of' quarter for the NOI or occupancy reporting. The regression specification includes quarter, loan, city, quarter of year, and time since origination fixed effects. Accordingly, the excluded category in the regression is loans in non-O&G exposed cities held by non-exposed banks. The excluded time period is the first half of 2014 (just prior to the sharp oil price decline).

Source: U.S. Census Bureau County Business Patterns. Federal Reserve Form Y-14Q Schedule H.1 and H.2, Authors' analysis.

Table D17: Probability of NOI Updating: OLS Regression by CBSA-level Exposure & Bank-level Exposure

Outcome:	1(NOI Update)					
	Non-O&G Exposed CBSA		Moderately O&G Exposed CBSA		Very Heavily Exposed CBSA	
	Exposed Banks	Non-Exp. Banks	Exposed Banks	Non-Exp. Banks	Exposed Banks	Non-Exp. Banks
	(1)	(2)	(3)	(4)	(5)	(6)
H1 2013	0.241***	0.286***	0.329***	0.281***	0.219***	0.314***
	(0.0251)	(0.0108)	(0.0165)	(0.00694)	(0.0157)	(0.0405)
H2 2013	0.282***	0.282***	0.335***	0.243***	0.362***	0.302***
	(0.0145)	(0.00766)	(0.00771)	(0.00908)	(0.0121)	(0.0143)
H1 2014	0.215***	0.305***	0.298***	0.234***	0.230***	0.250***
	(0.0395)	(0.0113)	(0.0113)	(0.00659)	(0.00835)	(0.0204)
H2 2014	0.221***	0.277***	0.342***	0.242***	0.284***	0.299***
	(0.0489)	(0.00520)	(0.00817)	(0.00727)	(0.0214)	(0.0188)
H1 2015	0.353***	0.279***	0.404***	0.263***	0.337***	0.282***
	(0.0146)	(0.00929)	(0.0223)	(0.00652)	(0.0134)	(0.0247)
H2 2015	0.308***	0.295***	0.328***	0.256***	0.324***	0.308***
	(0.0113)	(0.00534)	(0.0158)	(0.00661)	(0.0122)	(0.0181)
H1 2016	0.329***	0.275***	0.333***	0.243***	0.301***	0.334***
	(0.00968)	(0.00879)	(0.0124)	(0.00895)	(0.0101)	(0.0176)
H2 2016	0.259***	0.261***	0.300***	0.226***	0.311***	0.306***
	(0.0156)	(0.00489)	(0.0192)	(0.00727)	(0.0123)	(0.0203)
Observations	812,681	812,681	812,681	812,681	812,681	812,681
R-squared	0.278	0.278	0.278	0.278	0.278	0.278
Dependent Variable Mean	0.274	0.274	0.274	0.274	0.274	0.274
Reporting Quarter FE	N	N	N	N	N	N
Loan FE	N	N	N	N	N	N
CBSA FE	N	N	N	N	N	N
Quarter of Year FE	N	N	N	N	N	N
Quarters Since Orig	N	N	N	N	N	N

Note: Columns report results from the same regression, where loans from all categories are pooled (by level of CBSA exposure, then by bank-level exposure to corporate & industrial loans in the O&G industry). Staleness is defined as the difference between the reporting quarter and the 'as of' quarter for the NOI or occupancy reporting.

Source: U.S. Census Bureau County Business Patterns. Federal Reserve Form Y-14Q Schedule H.1 and H.2, Authors' analysis.

Table D18: Probability of NOI Updating: Fixed Effects Regression by CBSA-level Exposure & Bank-level Exposure

Outcome:	1(NOI Update)					
	Non-O&G Exposed CBSA		Moderately O&G Exposed CBSA		Very Heavily Exposed CBSA	
	Exposed Banks	Non-Exp. Banks	Exposed Banks	Non-Exp. Banks	Exposed Banks	Non-Exp. Banks
	(1)	(2)	(3)	(4)	(5)	(6)
H1 2013	0.0629*		0.0574***	0.0669***	-0.0145	0.0696***
	(0.0332)		(0.0196)	(0.0180)	(0.0225)	(0.0247)
H2 2013	0.0978**		0.0606***	0.0346**	0.131***	0.0648**
	(0.0411)		(0.0158)	(0.0140)	(0.0229)	(0.0268)
H1 2014						
H2 2014	0.0259***		0.0455***	0.0315***	0.0875***	0.0760***
	(0.00936)		(0.0148)	(0.0111)	(0.0289)	(0.0159)
H1 2015	0.159***		0.111***	0.0400**	0.155***	0.0937***
	(0.0492)		(0.0198)	(0.0198)	(0.0231)	(0.0252)
H2 2015	0.103**		0.0168	0.0238*	0.113***	0.123***
	(0.0440)		(0.0131)	(0.0123)	(0.0207)	(0.0188)
H1 2016	0.131**		0.0328	0.0249	0.115***	0.169***
	(0.0567)		(0.0252)	(0.0235)	(0.0237)	(0.0281)
H2 2016	0.0787**		0.0337**	0.00503	0.158***	0.162***
	(0.0341)		(0.0141)	(0.0167)	(0.0194)	(0.0334)
Observations	799,298	799,298	799,298	799,298	799,298	799,298
R-squared	0.280	0.280	0.280	0.280	0.280	0.280
Dependent Variable Mean	0.268	0.268	0.268	0.268	0.268	0.268
Reporting Quarter FE	Y	Y	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y	Y	Y
CBSA FE	Y	Y	Y	Y	Y	Y
Quarter of Year FE	Y	Y	Y	Y	Y	Y
Quarters Since Orig	Y	Y	Y	Y	Y	Y

Note: Columns report results from the same regression, where loans from all categories are pooled (by level of CBSA exposure, then by bank-level exposure to corporate & industrial loans in the O&G industry). 1(NOI Update) is defined as a binary variable equal to 1 when there is a decline in the staleness measure relative to last quarter. This is agnostic to the direction or the exact timing of the newly reported performance, only capturing that it is more recent than the prior quarter. The regression specification includes quarter, loan, city, quarter of year, and time since origination fixed effects. Accordingly, the excluded category in the regression is loans in non-O&G exposed cities held by non-exposed banks. The excluded time period is the first half of 2014 (just prior to the sharp oil price decline).

Source: U.S. Census Bureau County Business Patterns. Federal Reserve Form Y-14Q Schedule H.1 and H.2, Authors' analysis.

Table D19: Staleness of NOI Reporting: OLS Regression by CBSA-level Exposure & Bank-level Exposure Including Only Loans Originated from Q1 2012 to Q1 2014

Outcome:	Staleness NOI					
	Non-O&G Exposed CBSA		Moderately O&G Exposed CBSA		Very Heavily Exposed CBSA	
	Exposed Banks	Non-Exp. Banks	Exposed Banks	Non-Exp. Banks	Exposed Banks	Non-Exp. Banks
	(1)	(2)	(3)	(4)	(5)	(6)
H1 2013	2.914***	2.504***	2.298***	2.259***	2.532***	2.648***
	(0.228)	(0.0417)	(0.0843)	(0.0469)	(0.0886)	(0.255)
H2 2013	3.107***	2.974***	2.403***	2.907***	1.993***	2.933***
	(0.246)	(0.0585)	(0.0763)	(0.0369)	(0.0952)	(0.245)
H1 2014	3.563***	3.458***	2.554***	3.672***	2.634***	3.311***
	(0.322)	(0.0737)	(0.0655)	(0.0320)	(0.0616)	(0.245)
H2 2014	4.394***	3.924***	2.694***	4.266***	2.831***	3.759***
	(0.574)	(0.0750)	(0.0924)	(0.0429)	(0.0864)	(0.269)
H1 2015	4.102***	4.316***	2.311***	4.866***	3.062***	4.155***
	(0.320)	(0.124)	(0.236)	(0.0888)	(0.159)	(0.417)
H2 2015	3.685***	4.170***	2.562***	4.758***	3.335***	3.943***
	(0.165)	(0.0821)	(0.189)	(0.0958)	(0.193)	(0.409)
H1 2016	3.641***	4.253***	2.288***	4.871***	3***	3.167***
	(0.239)	(0.155)	(0.244)	(0.119)	(0.154)	(0.273)
H2 2016	3.839***	4.410***	2.445***	5.203***	2.887***	3.264***
	(0.257)	(0.119)	(0.213)	(0.152)	(0.194)	(0.223)
Observations	278,205	278,205	278,205	278,205	278,205	278,205
R-squared	0.717	0.717	0.717	0.717	0.717	0.717
Dependent Variable Mean	3.791	3.791	3.791	3.791	3.791	3.791
Reporting Quarter FE	N	N	N	N	N	N
Loan FE	N	N	N	N	N	N
CBSA FE	N	N	N	N	N	N
Quarter of Year FE	N	N	N	N	N	N
Quarters Since Orig	N	N	N	N	N	N

Note: Columns report results from the same regression, where loans from all categories are pooled (by level of CBSA exposure, then by bank-level exposure to corporate & industrial loans in the O&G industry). Staleness is defined as the difference between the reporting quarter and the 'as of' quarter for the NOI or occupancy reporting. Sample includes only loans that were originated between Q1 2012 and Q1 2014.

Source: U.S. Census Bureau County Business Patterns. Federal Reserve Form Y-14Q Schedule H.1 and H.2, Authors' analysis.

Table D20: Staleness of NOI Reporting: Fixed Effects Regression by CBSA-level Exposure & Bank-level Exposure Including Only Loans Originated from Q1 2012 to Q1 2014

Outcome:	Staleness NOI					
	Non-O&G Exposed CBSA		Moderately O&G Exposed CBSA		Very Heavily Exposed CBSA	
	Exposed Banks	Non-Exp. Banks	Exposed Banks	Non-Exp. Banks	Exposed Banks	Non-Exp. Banks
	(1)	(2)	(3)	(4)	(5)	(6)
H1 2013	0.162		0.946***	-0.578***	0.678**	0.513**
	(0.204)		(0.148)	(0.152)	(0.270)	(0.221)
H2 2013	0.0984		0.510***	-0.278***	0.144	0.216
	(0.133)		(0.108)	(0.0796)	(0.111)	(0.146)
H1 2014						
H2 2014	0.425		-0.305***	0.128***	-0.405***	-0.0399
	(0.260)		(0.0771)	(0.0439)	(0.134)	(0.103)
H1 2015	-0.405*		-1.122***	0.354***	-0.533**	-0.00175
	(0.230)		(0.208)	(0.119)	(0.246)	(0.274)
H2 2015	-0.728***		-0.772***	0.398***	-0.293	-0.154
	(0.279)		(0.157)	(0.116)	(0.360)	(0.266)
H1 2016	-0.837***		-1.130***	0.439**	-0.622**	-0.915***
	(0.313)		(0.237)	(0.196)	(0.267)	(0.226)
H2 2016	-0.784***		-1.154***	0.611***	-0.853***	-0.993***
	(0.277)		(0.184)	(0.203)	(0.211)	(0.212)
Observations	275,805	275,805	275,805	275,805	275,805	275,805
R-squared	0.602	0.602	0.602	0.602	0.602	0.602
Dependent Variable Mean	3.806	3.806	3.806	3.806	3.806	3.806
Reporting Quarter FE	Y	Y	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y	Y	Y
CBSA FE	Y	Y	Y	Y	Y	Y
Quarter of Year FE	Y	Y	Y	Y	Y	Y
Quarters Since Orig	Y	Y	Y	Y	Y	Y

Note: Columns report results from the same regression, where loans from all categories are pooled (by level of CBSA exposure, then by bank-level exposure to corporate & industrial loans in the O&G industry). 1(NOI Update) is defined as a binary variable equal to 1 when there is a decline in the staleness measure relative to last quarter. This is agnostic to the direction or the exact timing of the newly reported performance, only capturing that it is more recent than the prior quarter. Sample includes only loans that were originated between Q1 2012 and Q1 2014.

Source: U.S. Census Bureau County Business Patterns. Federal Reserve Form Y-14Q Schedule H.1 and H.2, Authors' analysis.

Table D21: Probability of NOI Updating: OLS Regression by CBSA-level Exposure & Bank-level Exposure Including Only Loans Originated from Q1 2012 to Q1 2014

Outcome:	1(NOI Update)					
	Non-O&G Exposed CBSA		Moderately O&G Exposed CBSA		Very Heavily Exposed CBSA	
	Exposed Banks	Non-Exp. Banks	Exposed Banks	Non-Exp. Banks	Exposed Banks	Non-Exp. Banks
	(1)	(2)	(3)	(4)	(5)	(6)
H1 2013	0.258***	0.313***	0.344***	0.291***	0.164***	0.310***
	(0.0186)	(0.0108)	(0.0168)	(0.00465)	(0.0246)	(0.0223)
H2 2013	0.298***	0.284***	0.344***	0.229***	0.357***	0.298***
	(0.0200)	(0.00939)	(0.0107)	(0.00810)	(0.0163)	(0.0160)
H1 2014	0.238***	0.275***	0.293***	0.205***	0.182***	0.222***
	(0.0242)	(0.00969)	(0.0187)	(0.00602)	(0.00568)	(0.0174)
H2 2014	0.206***	0.246***	0.269***	0.194***	0.229***	0.282***
	(0.0466)	(0.00736)	(0.00707)	(0.0103)	(0.0169)	(0.0215)
H1 2015	0.342***	0.258***	0.364***	0.215***	0.312***	0.298***
	(0.0153)	(0.0141)	(0.0203)	(0.0107)	(0.0124)	(0.0193)
H2 2015	0.292***	0.308***	0.271***	0.275***	0.300***	0.335***
	(0.0165)	(0.00597)	(0.00854)	(0.00570)	(0.0206)	(0.0125)
H1 2016	0.346***	0.267***	0.335***	0.219***	0.353***	0.387***
	(0.0197)	(0.0175)	(0.00897)	(0.0127)	(0.0195)	(0.0118)
H2 2016	0.268***	0.268***	0.282***	0.215***	0.320***	0.340***
	(0.0180)	(0.00799)	(0.0136)	(0.0108)	(0.0185)	(0.0242)
Observations	309,662	309,662	309,662	309,662	309,662	309,662
R-squared	0.269	0.269	0.269	0.269	0.269	0.269
Dependent Variable Mean	0.264	0.264	0.264	0.264	0.264	0.264
Reporting Quarter FE	N	N	N	N	N	N
Loan FE	N	N	N	N	N	N
CBSA FE	N	N	N	N	N	N
Quarter of Year FE	N	N	N	N	N	N
Quarters Since Orig	N	N	N	N	N	N

Note: Columns report results from the same regression, where loans from all categories are pooled (by level of CBSA exposure, then by bank-level exposure to corporate & industrial loans in the O&G industry). 1(NOI Update) is defined as a binary variable equal to 1 when there is a decline in the staleness measure relative to last quarter. This is agnostic to the direction or the exact timing of the newly reported performance, only capturing that it is more recent than the prior quarter. Sample includes only loans that were originated between Q1 2012 and Q1 2014.

Source: U.S. Census Bureau County Business Patterns. Federal Reserve Form Y-14Q Schedule H.1 and H.2, Authors' analysis.

Table D22: Probability of NOI Updating: Fixed Effects Regression by CBSA-level Exposure & Bank-level Exposure Including Only Loans Originated from Q1 2012 to Q1 2014

Outcome:	1(NOI Update)					
	Non-O&G Exposed CBSA		Moderately O&G Exposed CBSA		Very Heavily Exposed CBSA	
	Exposed Banks	Non-Exp. Banks	Exposed Banks	Non-Exp. Banks	Exposed Banks	Non-Exp. Banks
	(1)	(2)	(3)	(4)	(5)	(6)
H1 2013	0.0352		0.0167	0.0669***	-0.0918***	0.0231
	(0.0299)		(0.0168)	(0.0140)	(0.0198)	(0.0174)
H2 2013	0.0640***		0.0486***	0.0267**	0.117***	0.0390*
	(0.0206)		(0.0148)	(0.0110)	(0.0169)	(0.0205)
H1 2014						
H2 2014	-0.00827		-0.00582	0.0156	0.0757***	0.0872***
	(0.0215)		(0.0190)	(0.0107)	(0.0190)	(0.0211)
H1 2015	0.120***		0.0717***	0.0305*	0.133***	0.0928***
	(0.0382)		(0.0179)	(0.0170)	(0.0232)	(0.0261)
H2 2015	0.0235		-0.0721***	0.0451***	0.0854***	0.107***
	(0.0219)		(0.0141)	(0.0118)	(0.0262)	(0.0201)
H1 2016	0.118***		0.0375	0.0301	0.179***	0.195***
	(0.0384)		(0.0229)	(0.0201)	(0.0271)	(0.0246)
H2 2016	0.0468**		-0.0104	0.0321***	0.153***	0.153***
	(0.0210)		(0.0128)	(0.0105)	(0.0207)	(0.0361)
Observations	307,162	307,162	307,162	307,162	307,162	307,162
R-squared	0.248	0.248	0.248	0.248	0.248	0.248
Dependent Variable Mean	0.261	0.261	0.261	0.261	0.261	0.261
Reporting Quarter FE	Y	Y	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y	Y	Y
CBSA FE	Y	Y	Y	Y	Y	Y
Quarter of Year FE	Y	Y	Y	Y	Y	Y
Quarters Since Orig	Y	Y	Y	Y	Y	Y

Note: Columns report results from the same regression, where loans from all categories are pooled (by level of CBSA exposure, then by bank-level exposure to corporate & industrial loans in the O&G industry). 1(NOI Update) is defined as a binary variable equal to 1 when there is a decline in the staleness measure relative to last quarter. This is agnostic to the direction or the exact timing of the newly reported performance, only capturing that it is more recent than the prior quarter. The regression specification includes quarter, loan, city, quarter of year, and time since origination fixed effects. Accordingly, the excluded category in the regression is loans in non-O&G exposed cities held by non-exposed banks. The excluded time period is the first half of 2014 (just prior to the sharp oil price decline). Sample includes only loans that were originated between Q1 2012 and Q1 2014.

Source: U.S. Census Bureau County Business Patterns. Federal Reserve Form Y-14Q Schedule H.1 and H.2, Authors' analysis.

Table D23: Effect of Rate Changes on Loan Reporting and Monitoring for Occupancy Performance for Floating Rate Loans Relative to Fixed Rate Loans

Outcome:	Staleness Occupancy			1(Update Occupancy)			1(Occupancy Performance Missing)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Floating X ΔTreasury Rates	0.161***	-0.00318	-0.0512***	0.0233***	0.0240***	0.0223***	0.0486***	-0.0124***	-0.0118***
	(0.0155)	(0.0132)	(0.0149)	(0.000861)	(0.000793)	(0.000861)	(0.00120)	(0.000596)	(0.000639)
Δ UER (t+2,t+1)		-0.00449			0.000606			0.000304*	
		(0.00356)			(0.000494)			(0.000174)	
Δ UER (t+1,t)		-0.0259***			0.000449			0.000371*	
		(0.00402)			(0.000484)			(0.000196)	
Δ UER (t,t-1)		-0.0241***			-0.00115**			0.00106***	
		(0.00448)			(0.000506)			(0.000216)	
Δ UER (t-1,t-2)		-0.0251***			-0.00262***			0.00100***	
		(0.00429)			(0.000493)			(0.000198)	
Δ UER (t-2,t-3)		-0.0197***			-0.00269***			0.000506***	
		(0.00377)			(0.000482)			(0.000174)	
Observations	1,562,981	1,432,439	1,511,300	1,799,716	1,649,692	1,741,326	1,799,716	1,649,692	1,741,326
R-squared	0.008	0.664	0.700	0.007	0.280	0.300	0.004	0.860	0.865
Dep Var Mean	4.005	3.906	4.020	0.262	0.258	0.258	0.140	0.139	0.138
Reporting Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan FE	N	Y	Y	N	Y	Y	N	Y	Y
Quarter of Year FE	N	Y	Y	N	Y	Y	N	Y	Y
Quarters Since Orig	N	Y	Y	N	Y	Y	N	Y	Y
CBSA-Quarter FE	N	N	Y	N	N	Y	N	N	Y

Note: Dependent variable is either the Occupancy staleness measure, a binary variable for whether there was any update to the Occupancy reporting, or a binary variable for whether the Occupancy performance reporting was missing or a non-applicable value. The independent variables are calculated as the interaction between a loan being floating rate when first entering the Y-14Q dataset interacted with the change in Treasury yields over the past 3 quarters. Additional controls include quarter-over-quarter changes in CBSA unemployment rates. These unemployment rates are absorbed when including CBSA-by-year fixed effects.
Source: U.S. Census Bureau County Business Patterns. Federal Reserve Form Y-14Q Schedule H.2. Federal Reserve Bank of St. Louis, FRED (Federal Reserve Economic Data), Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis (DGS10), Authors' analysis.