Expected Liquidation Values*

Mehdi Beyhaghi[†] Cooper Howes[‡] Gregory Weitzner[§]

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Abstract

We use supervisory commercial real estate data to create the first forward-looking measure of expected liquidation values in default. Loans secured by collateral with higher liquidation values, relative to their current market values, are larger, have longer maturities and are less likely to be renegotiated. In the time series, there is a strong relationship between industry-level stock returns and changes in liquidation values, even after controlling for contemporaneous changes in current property values. Finally, the pass-through of industry shocks is amplified among property types with more correlated default rates. Our results provide support for incomplete contracting theory and industry-driven fire sales. Finally, our new measure of expected liquidation costs can be used by policymakers to monitor fire sale risk in real time.

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[†]Board of Governors of the Federal Reserve System. Email: mehdi.beyhaghi@frb.gov.

[‡]Board of Governors of the Federal Reserve System. Email: cooper.a.howes@frb.gov.

[§]McGill University. Email: gregory.weitzner@mcgill.ca.

1 Introduction

The expected liquidation value of an asset is a central object in finance and economics. In contract theory, liquidation values affect the terms of debt contracts, such as their size, maturity and interest rates (e.g., Hart and Moore (1994)). In macroeconomics, industry-level distress can lead to fire sales (Shleifer and Vishny (1992)) and shocks to liquidation values can feed back into investment decisions through borrowing constraints (Kiyotaki and Moore (1997)). Despite their importance, there is little direct empirical evidence on the properties of expected liquidation values, given that they are typically not observable to researchers. For this reason, most existing empirical research uses proxies for expected liquidation values or attempts to measure them ex-post in bankruptcy. However, these approaches suffer from measurement error and selection issues, limiting researchers' ability to test these theories.

In this paper, we create a new measure of banks' expected liquidation values using a supervisory dataset of commercial real estate loans. Our measure has five important features: it is i) forward-looking, ii) available outside of default, iii) asset-specific, iv) observed over the entire life of the loan, and v) can be compared to the current value of the same asset outside of distress. We use our measure to conduct two main exercises. First, we test the relationship between expected liquidation values and contract terms, and find results consistent with incomplete contracting models in which expected liquidation values drive the design of debt contracts. Second, we examine how liquidation values evolve over the life of the loan and respond to industry-level shocks, and find evidence that fire sales depress liquidation values.

Our analysis uses Schedule H.2 of the Federal Reserve's Y-14Q, which includes all commercial real estate loans exceeding one million dollars extended by large bank holding companies (BHCs) in the United States. These loans finance the construction or acquisition of a variety of property types, such as retail, industrial, multi-family and office buildings. In addition to detailed loan and property characteristics, BHCs are required to report quarterly estimates of the probability of default (PD), loss given default (LGD), and exposure at default (EAD) for each loan on their balance sheets. Importantly, they also report the current estimated value of the property collateralizing the loan.

To isolate the expected liquidation value of an individual property, we restrict the sample to non-recourse loans, i.e., project finance loans, secured by a single property.[1] We then define the expected liquidation value as follows:

$$\text{Expected Liquidation Value} = (1 - \text{LGD}) \times \text{EAD},$$

where $1-\text{LGD}$ is the expected recovery rate per dollar of exposure in default, and EAD is the expected loan exposure in the case of default.[2] Intuitively, for non-recourse loans, the recovery rate given default should depend solely on the value of the collateral since lenders have no claim on the borrower's other assets. Hence, restricting our analysis to non-recourse loans collateralized by a single asset allows us to isolate the liquidation values of those assets from the borrowers' other assets, which may affect recovery rates in recourse loans. We also define the expected liquidation cost, conditional on default, as a percentage of the current property value as follows:[3]

$$\text{Expected Liquidation Cost} = 1 - \frac{\text{Expected Liquidation Value}}{\text{Current Property Value}}.$$

We verify that these measures accurately reflect banks' expectations through several tests. First, banks' estimated losses are consistent with their loan loss allowances.[4] Second, ex-ante EADs predict future realized exposures with extremely high accuracy. Third, banks' current property valuations are correlated with local house price growth.[5]

[1] We also remove loans in which the collateral is pledged to multiple loans.

[2] Because LGD and EAD are both expectations, in principle, the correlation between the two realizations should affect the expected liquidation value; however, as we discuss in more detail in Section 3.1, banks and regulators do not seem to consider this correlation particularly important in practice. Moreover, we find no correlation between the two risk assessments in our sample.

[3] As we discuss in further detail later, this measure encompasses both the costs of liquidating the asset in default and the expected change in its value prior to default.

[4] Loan loss allowances (also called loan loss reserves or provisions) are funds that banks set aside to cover expected losses on their loan portfolios. If our measures of PD, LGD, and EAD accurately reflect banks' expectations, then the product PD $\times$ LGD $\times$ EAD should closely align with the allowances banks report for these loans.

[5] Although not directly used in our measures of liquidation values and costs, we also show that PDs are strong predictors of future realized default.

We next examine the relationship between ex-ante liquidation costs and loan contract terms at origination. In several incomplete contracting models (e.g., Williamson (1988), Shleifer and Vishny (1992), Harris and Raviv (1990), and Hart and Moore (1994)) debt is enforced through the threat of liquidation. Hence, when the liquidation value is higher, the lender's outside option is higher, making it willing to lend more and over a longer horizon. Additionally, fixing the size of the loan, a higher liquidation value should reduce interest rates (e.g., Harris and Raviv (1990)). Benmelech, Garmaise, and Moskowitz (2005) test these predictions empirically using zoning regulations as a proxy for liquidation values and find results consistent with the theory. Motivated by their analysis, we conduct similar tests but use our direct measure of expected liquidation values and costs rather than a proxy.

Consistent with these predictions, we find that loans with higher liquidation costs have lower loan-to-value ratios, shorter maturities, and higher interest rates. Importantly, when we examine the liquidation value and current property value separately, we find that the liquidation value has a stronger relationship with these contract terms.[6] This finding suggests that liquidation values, rather than current values, are a more important determinant of contract terms in these markets.

Our initial results are consistent with the predictions from incomplete contracting models such as Hart and Moore (1994). In Hart and Moore (1994), borrowers, who have better expertise than lenders in operating projects, can threaten to walk away from the projects to renegotiate more favorable debt terms. This threat becomes stronger when the amount lenders expect to recover in default, i.e., the liquidation value, is lower. We test this prediction by examining the relationship between ex-ante liquidation values and subsequent loan renegotiations. In our sample, about 26% of loans are renegotiated at least once over their lives. Moreover, we find that a 10 percent increase in the ex-ante expected liquidation value is associated with a decrease of about one percentage point in the probability of loan renegotiation. This result provides direct evidence that lower liquidation values strengthen borrowers' bargaining power in renegotiations, consistent

[6] In the case of loan amounts, we use the log of the loan size as the dependent variable rather than the loan-to-value ratio.

with incomplete contracting theory.

After analyzing how liquidation values and costs relate to ex-ante contract terms, we next examine their time-series properties. First, we show that liquidation costs decrease over the life of the loan. One potential explanation for this result is that borrower-specific human capital—such as expertise in project completion or property management—becomes less critical as projects mature, making assets easier to liquidate. Supporting this interpretation, we find that the decrease in expected liquidation cost is faster for construction loans, where borrower-specific human capital is likely most important.[7]

We next show that changes in liquidation values and costs are highly correlated within the same property types and across properties in the same counties. In contrast, property-type and location factors explain less of the variation in current property values. This suggests that there is more comovement in liquidation values than in current market values.

Having established this comovement in liquidation values, we next explore its potential sources. In Shleifer and Vishny (1992), industry-level distress leads to fire sale discounts because the natural buyers of distressed assets—other firms in the same industry—are themselves financially constrained during downturns. Hence, we test whether industry shocks contribute to the comovement we observe in the data. To do this, we match property types to their closest two-digit SIC industries and calculate quarterly industry-level stock return indices. We find that industry-level stock returns strongly predict changes in both liquidation values and liquidation costs. Importantly, these effects are estimated after controlling for changes in current property values, suggesting that industry conditions affect expected liquidation values beyond their impact on current valuations.

If industry-level shocks lead to changes in liquidation values, we would expect this effect to be stronger in industries with more correlated default rates. Intuitively, when defaults are idiosyncratic, fire sale effects should be mitigated because unconstrained buyers in the same industry can step in to buy distressed assets. In contrast, when defaults are correlated, there are fewer unconstrained buyers in the industry and hence,

[7] Intuitively, it is probably costlier to find a replacement construction company to complete an unfinished project as compared to finding a new owner of an already completed building.

liquidation values should decline more (e.g., Shleifer and Vishny (1992)). To test this hypothesis, we estimate default correlation within each property type by regressing each property's change in probability of default on the average change in probability of default among other properties of the same type. Consistent with this hypothesis, we find that the pass-through from industry shocks to liquidation values and costs is stronger among property types with more correlated default rates.

Overall, our findings provide empirical support for incomplete contracting theory and fire sale dynamics. Moreover, while both clearly matter, our evidence suggests that liquidation values, rather than current asset values, are the more important determinants of contract terms and renegotiation outcomes in these markets. As we discuss in more detail below, our results have implications for the microfoundations of macroeconomic models with financial frictions, in which either the liquidation value or the current value determines debt capacity.

2 Related Literature

To our knowledge, this is the first paper that directly observes both the market price of an asset and its expected liquidation value in default. We use this data to provide empirical support for theories of incomplete contracting and fire sale effects on equilibrium liquidation values. In doing so, we contribute to several different literatures.

First, several papers examine the relationship between loan contract terms and proxies for ex-ante expected liquidation values (e.g, Benmelech, Garmaise, and Moskowitz (2005), Benmelech and Bergman (2008), Benmelech (2009), Benmelech and Bergman (2009), Gavazza (2010), Kim and Kung (2017)).[8] For example, Benmelech, Garmaise, and Moskowitz (2005) use zoning regulations as a proxy for commercial real estate liquidation costs, showing that properties with more restrictive zoning—and thus lower redeployability—receive smaller loans with shorter maturities and higher interest rates.

[8]Another related literature analyzes the relationship between features of collateral and loan terms (e.g., Ramcharan (2020) Beyhaghi (2022), Auh and Landoni (2022), Benmelech, Kumar, and Rajan (2022), Barbiero, Schepens, and Sigaux (2024), Benmelech, Kumar, and Rajan (2024), Luck and Santos (2024) and Benmelech, Kumar, and Rajan (2025)). See Benmelech (2024) for an excellent survey on secured debt.

Benmelech and Bergman (2008) and Benmelech and Bergman (2009) employ similar approaches using aircraft route structures and railroad track gauges, respectively, as proxies for asset redeployability. We build on this literature by using a direct measure of the expected liquidation value, rather than a proxy. Second, their empirical strategies rely on cross-sectional variation in redeployability measures that are typically time-invariant. In contrast, our panel data allows us to study how, within-loan, expected liquidation values evolve and respond to different types of shocks. Third, by observing the expected liquidation value, we can quantify its relationship with ex-ante contracting terms and market conditions. Fourth, and related to the point above, because we observe current property values and expected liquidation values separately, we can test which matters more for contract terms. Consistent with incomplete contracting theory, we find that liquidation values have a stronger relationship with loan terms than current values.

Another literature attempts to measure liquidation values in bankruptcy (e.g., Warner (1977), Altman (1984), Weiss (1990), Andrade and Kaplan (1998), Maksimovic and Phillips (1998), Bris, Welch, and Zhu (2006), Davydenko, Strebulaev, and Zhao (2012), Bernstein, Colonnelli, and Iverson (2019), Kermani and Ma (2020) Kermani and Ma (2023)). The closest to us in this literature is Kermani and Ma (2023), who estimate liquidation recovery rates among corporations from Chapter 11 bankruptcy filings.[9] Our analysis differs in several respects. First, we directly observe the asset's current market value in addition to its expected liquidation value; whereas Kermani and Ma (2023) must infer the current value from book values adjusted for depreciation. Second, we observe banks' ex-ante liquidation value expectations at loan origination and throughout the loan life rather than ex-post in bankruptcy, which allows us to analyze the relationship between contract terms and ex-ante liquidation costs at *loan origination*. Kermani and Ma (2023) measure hypothetical liquidation values in Chapter 7, which are only observed when firms enter Chapter 11. This can create a selection problem whereby changes in market conditions alter which firms enter bankruptcy and the subsequently observed liquidation

[9] See also the companion paper Kermani and Ma (2020) using the same data.

values[10] Third, our measures of liquidation values and costs are asset-specific, which we relate to various characteristics of the property (e.g., type and location); whereas Kermani and Ma (2023) construct industry-level measures covering broad categories of assets. Finally, our quarterly panel structure enables us to examine how liquidation expectations evolve over time in response to industry and location-specific conditions.

A few studies use data from an anonymous global bank in which external appraisers report fair-market and orderly liquidation values to study the relationship between financial development, collateral, and recovery rates (e.g., Liberti and Mian (2010), Calomiris et al. (2017), Degryse et al. (2020)). Our data, measure of expected liquidation value and focus differ in several important respects. Moreover, our data and measure of expected liquidation value differ in several important respects. First, their liquidation values are defined under normal market conditions at origination, not conditional on default, and hence, do not incorporate fire sale discounts. Second, their data contain much less detail on loan characteristics, the underlying assets and ex post loan outcomes.[11] Third, they observe collateral valuations only at origination, while we observe them over the entire life of the loan. Fourth, the data come from a single bank from 2002 to 2004, whereas we use data from all the largest banks in the US over 10 years and exploit rich cross-sectional differences in local and industry characteristics. Finally, our paper tests predictions from the incomplete contracting literature, while also analyzing how expected liquidation values evolve over time and respond to aggregate shocks.

Finally, a large related empirical literature tests for fire sale effects by attempting to measure the costs of liquidating assets (e.g., Pulvino (1998), Ramey and Shapiro (2001), Coval and Stafford (2007), Eckbo and Thorburn (2008), Gavazza (2011), Campbell, Giglio, and Pathak (2011), Ellul, Jotikasthira, and Lundblad (2011), Andersen and Nielsen (2017), Chernenko and Sunderam (2020), Demirci, Gurun, and Yönder (2020),

[10] For an analysis of the selection issues that arise from conditioning outcomes on firms that enter bankruptcy, see Glover (2016).

[11] For example, they do not observe maturity, subsequent loan performance or whether the loan is renegotiated, and the assets are reported at broad levels rather than at the individual asset level.

Meier and Servaes (2019)).[12] This literature typically compares realized asset prices across different types of sellers or market conditions and argues that these differences reflect liquidation discounts arising from fire sales. However, these price differences could also reflect differences in asset quality and productivity across sellers or over time (e.g., Franks, Sussman, and Vig (2017) and Franks et al. (2021)).[13] Moreover, these studies cannot distinguish current market values outside of distress from expected liquidation values. In contrast, we directly observe both current property values and expected liquidation values for the same assets at the same time, allowing us to test for fire sales while controlling for quality. Consistent with Shleifer and Vishny (1992), we find that industry-level stock returns predict changes in expected liquidation values even after controlling for changes in current property values, with stronger effects when default rates are more correlated within an industry. Moreover, to our knowledge, we provide the first direct test of the general equilibrium properties of expected liquidation values (e.g., Shleifer and Vishny (1992)) given that our data allows us to observe them.[14]

Our paper also relates to a growing literature analyzing supervisory commercial real estate data (e.g., Black, Krainer, and Nichols (2020), Johnston Ross, Nichols, and Shibut (2021), Glancy, Kurtzman, and Loewenstein (2022), Glancy et al. (2023), Glancy and Kurtzman (2024), Hughes and Nichols (2025) and Glancy, Kurtzman, and Loewenstein (2025)). Our paper is the first to use the risk assessments in the Y-14Q data to infer the expected liquidation value of the underlying collateral.

3 Data

Our main data source is Schedule H.2 of the Federal Reserve's Y-14Q filings. The Federal Reserve began collecting these data to support the Dodd-Frank mandated stress tests and

[12]There is also a large theoretical literature on fire sales (e.g., Shleifer and Vishny (1992), Gromb and Vayanos (2002), Lorenzoni (2008), Brunnermeier and Pedersen (2009), Shleifer and Vishny (2010), Stein (2012), Caballero and Simsek (2013) and Weitzner (2020)). See Shleifer and Vishny (2011) for a review of this literature.

[13]Relatedly, Huang, Ringgenberg, and Zhang (2023) show that there is information in the choice of which assets a firm sells.

[14]While we do not directly analyze the "collateral channel", our paper relates to the literature analyzing (e.g., Gan (2007), Benmelech and Bergman (2011), Chaney, Sraer, and Thesmar (2012), Gupta, Sapriza, and Yankov (2022) and Catherine et al. (2022)).

the Comprehensive Capital and Analysis Review (CCAR). The sample includes commercial real-estate loans from bank holding companies (BHCs) with $50bn or more in total assets,[15] accounting for 86% of all assets in the banking sector (Beyhaghi et al. (2024)). Qualified institutions are required to report detailed quarterly loan and property-level data on commercial real estate loans of at least $1mm. Loans are included in the dataset if 1) the purpose is to acquire, develop, or construct real estate properties and 2) the cash flows from the underlying property are the main source of repayment.[16] These loans finance the construction or acquisition of various property types, which include retail, industrial, hotel and gaming, multi-family, homebuilders, condos, office, mixed, land and lot development, healthcare and warehouse/distribution properties.[17]

The data contains detailed information about the terms of the loans, such as the date of issuance, amount, interest rate, maturity, the type, current value and location of the collateral. According to the Basel Committee on Banking Supervision (Basel Committee on Banking Supervision (2023b)), the current value of the collateral must be valued at or below, "the current fair value under which the property could be sold under a private contract between a willing seller and an arm's-length buyer on the date of valuation."[18] Importantly, the value of the collateral is based on an "as is", "best-use" market value outside of distress. Banks are expected to monitor the value of the collateral frequently and at a minimum once per year (Basel Committee on Banking Supervision (2023b)).

Banks are also required to report their internal estimates of probability of default

[15] In 2019, this threshold was increased to $100bn. The most recent list of participating institutions can be found in Table 3 of the 2024 Federal Reserve Stress Test Results.

[16] Because of these restrictions, the data does not include owner-occupied corporate loans secured by real estate.

[17] Fannie Mae and Freddie Mac, i.e., the GSEs, do participate in some commercial real estate markets; however, many CRE loans do not qualify for GSE financing for several key reasons. First, Fannie and Freddie do not purchase loans secured by other major commercial property types such as office buildings, retail centers, hotels, or industrial properties. Second, even among multifamily properties, the GSEs impose certain qualification requirements that borrowers may not meet. Third, GSE loans typically limit commercial space in the property, making them unsuitable for mixed-use developments with substantial commercial components (e.g., see FNMA: Fannie Mae Mortgage Association in Commercial Real Estate). Fourth, borrowers may want to avoid prepayment penalties, which are typically associated with securitized GSE loans, or seek higher leverage or more flexible terms than GSE programs permit (e.g., see Fannie Mae vs Freddie Mac Multifamily Loans). Finally, the GSEs have purchase caps set by their regulator FHFA, with at least 50% of their activity required to support mission-driven affordable housing, which can limit availability for market-rate projects (e.g., see 2025 Multifamily Loan Purchase Caps for Fannie Mae and Freddie Mac).

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

(PD), loss given default (LGD) and exposure at default (EAD) for each loan in their Y-14Q filings. Specifically, PD is a long-run, average annual default rate, while LGD is a long-run, default-weighted, loss rate per dollar of exposure, where "all relevant factors should be taken into account."[19] Finally, EAD is long-run, default weighted, expected gross exposure of the loan upon default, which can be thought of as the expected size of the loan in default incorporating any unpaid accrued interest or changes in loan size, e.g., due to further drawings by the borrower or amortization. According to their instructions, internal estimates of PD, LGD and EAD "must incorporate all relevant, material and available data, information and methods. A bank may utilize internal data and data from external sources (including pooled data)." Moreover, banks must update these regularly and immediately after any material changes: "Borrowers and facilities must have their ratings refreshed at least on an annual basis... In addition, banks must initiate a new rating if material information on the borrower or facility comes to light." Consistent with the instructions, in Appendix Section B, we show that 1) PDs strongly predict realized default, 2) expected losses closely track banks' reported loan allowances, and 3) expected exposures at default strongly predict realized exposures.[20]

To analyze asset-specific liquidation costs, we restrict the sample to non-recourse loans collateralized by a single asset.[21] We also exclude loans in which the same property is used as collateral for multiple loans. As we explain below, these filters allow us to isolate the asset-specific recovery value as the lender has no other claim on borrowers' other assets. Further, we exclude the following loans from our analysis to ensure cross-market comparability and maintain a homogeneous sample: those originated by banks' non-domestic offices, secured by non-US properties, denominated in non-USD currencies and those that are participated or syndicated, or in non-first-lien positions, i.e., subordinated or mixed. Additionally, we exclude loans with origination amounts or property values

[19] These include "material discount effects and material direct and indirect costs associated with collecting on the exposure".

[20] These results are consistent with recent work in the corporate schedule of the data (Schedule H.1), in which bank risk assessments strongly predict future loan performance (Beyhaghi, Fracassi, and Weitzner (2025) and Weitzner and Howes (2025)) and public equity and bond returns (Beyhaghi, Howes, and Weitzner (2024)).

[21] One advantage of our data is that we can observe directly whether the loan is non-recourse, in contrast to other CRE datasets studying similar issues (e.g., Benmelech, Garmaise, and Moskowitz (2005)).

below \$1mm to be consistent with the data instructions, as well as those reported as defaulted on their first day of reporting to eliminate potential data anomalies. Our sample period is from 2014Q3 to 2024Q4.[22]

Panel A of Table 1 contains summary statistics for new loans, while Panel B contains summary statistics for existing loans. About two-thirds of new loans are income-producing, while the remainder are construction loans. The average size of the committed loan amount is \$15mm, while the median is around \$4mm. Hence, the loans in our sample are fairly small. The average loan-to-value ratio (LTV) is 60%.

3.1 Definition of Liquidation Value and Cost

In this section, we introduce our measure of expected liquidation value and cost.

The expected liquidation value is defined as follows:

$$\text{Expected Liquidation Value}_{i,t} = (1 - \text{LGD}_{i,t}) \times \text{EAD}_{i,t}.$$

This measure represents the amount the bank expects to recover from the collateral if the borrower defaults. Because, as mentioned earlier, we restrict our sample to non-recourse loans secured by a single asset, this variable measures the expected liquidation value of that asset.

In principle, the correlation between the realizations of LGD and EAD should affect the value of the expected liquidation value.[23] However, we believe this is a minimal concern for two reasons. First, banks and regulators do not consider this correlation important in practice.[24] Second, in Appendix Table C.2, we estimate the correlation between realized EAD and LGD in our sample and cannot reject the null that it is equal to zero.[25]

[22]The data is available starting in 2010; however, the recourse field did not distinguish between full and partial recourse before then (Glancy et al. (2023)). Hence, we begin our sample in 2014Q3.

[23]LGD and EAD are both reported as expectations.

[24]For example, Basel considers expected loss as the PD times LGD times EAD, without considering the correlation between the three inputs (e.g. , Basel Committee on Banking Supervision (2023b)).

[25]These results are consistent with other empirical studies finding no correlation between EAD and LGD (e.g., Asarnow and Edwards (1995), Carty (1996), and Thorburn (2000)).

Based on the expected liquidation value, we can calculate an expected liquidation cost in percentage terms:

$$\text{Expected Liquidation Cost}_{i,t} = 1 - \frac{\text{Expected Liquidation Value}_{i,t}}{\text{Current Property Value}_{i,t}}.$$

The expected liquidation cost is the fraction of the collateral's current value that is lost in default. Importantly, this definition is not the difference between the collateral's market value and its best use at the time of default. Rather, it encompasses the difference in value at the time of default, as well as the expected change in the asset's market value prior to default. Because of this, our measure of expected liquidation costs may appear fairly high relative to the estimates in the literature on bankruptcy costs (e.g., Bris, Welch, and Zhu (2006) and Kermani and Ma (2023)). Indeed, Table 2, which displays summary statistics on expected liquidation costs across different property types, shows that the average expected liquidation cost is about 66.7%.

Before proceeding, it is worth discussing the mechanics of default in these markets. When a borrower defaults, the lending bank typically forecloses on the property, rather than reorganizing the entity holding the property.[26] This is often more efficient given that CRE loans are often made to a single asset entity created for the purpose of holding the property (Glancy, Kurtzman, and Loewenstein (2025)).

After foreclosing, banks have high incentives to liquidate the collateral quickly for two reasons. First, regulators directly encourage them to (Handbook (2013)). Second, such "other real estate" have highly punitive risk-weights (Basel Committee on Banking Supervision (2023a)). Hence, the liquidation value reflects any potential fire-sale costs arising from the need to liquidate the real estate quickly.

[26] See Pence (2006) and Benmelech, Garmaise, and Moskowitz (2005) for discussions of how the foreclosure process works across different states.

4 Liquidation Values and Ex-ante Contract Terms

In this section, we analyze the relationship between expected liquidation values and ex-ante contract terms.[27] Because we are focused on ex-ante contract terms, we restrict the sample to new loans throughout this analysis. Our set of tests is similar to Benmelech, Garmaise, and Moskowitz (2005); however, we use banks' actual expectations of these liquidation values rather than a proxy.

We first examine the relationship between expected liquidation values and loan sizes. In several incomplete contracting models, higher liquidation values increase a borrower's debt capacity (e.g., Williamson (1988), Harris and Raviv (1990), Shleifer and Vishny (1992), and Hart and Moore (1994)). For example, in Hart and Moore (1994), when the liquidation value of the asset is higher, the lender is more comfortable extending credit to the borrower, given that its outside option is higher. Hence, these models would predict a positive relationship between liquidation values and total borrowing.[28]

To test this hypothesis, we first analyze the relationship between expected liquidation costs and leverage. Specifically, we estimate the following regression:

$$\text{LTV}_i = \beta \text{Liquidation Cost}_{i,t} + \delta_{b,t} + u_i, \tag{1}$$

where the dependent variable is the loan's loan-to-value ratio (LTV) at origination. We include bank×quarter ($\delta_{b,t}$) fixed effects to control for any differences in internal risk models across banks or within a bank over time. In some specifications, we also include additional controls and more granular fixed effects. We cluster our standard errors by county. The results are displayed in Table 3.

In column (1), the coefficient for the expected liquidation cost is -0.919 and statistically significant. This implies that a one percentage point increase in the expected liquidation cost reduces the LTV by about one percentage point. In column (2), we find very similar

[27] Henceforth, we refer to expected liquidation values (expected liquidation costs) and liquidation values (liquidation costs) interchangeably.

[28] In practice, borrowers typically choose leverage levels up to the maximum loan-to-value ratio or debt-service-coverage ratio possible; hence, the maximum debt capacity is typically binding (Benmelech, Garmaise, and Moskowitz (2005)).

results when we also include property type×quarter and county×quarter fixed effects. In column (3), we again find similar results when we include the operating income over property value (i.e., cap rate), which is an important determinant of LTVs (Titman, Tompaidis, and Tsyplakov (2005)), as an additional control.[29]

We next analyze separately the relationship between loan amounts and the two components of the liquidation cost (i.e., the current price and the liquidation value) by estimating the following regression:

$$Log(\text{Loan Amount})_i = \alpha + \beta_0 Log(\text{Current Value}_{i,t}) + \beta_1 Log(\text{Liquidation Value}_{i,t}) + \delta_{b,t} + u_i,$$

where the dependent variable is the committed loan amount and the main independent variables are the current value and expected liquidation value, all in logs. The main difference in this specification is that we can estimate the relative importance of the liquidation value and the property's current value in explaining loan amounts. The results are displayed in columns (4) - (6) in Table 3. Interestingly, both the current value and liquidation value have a positive relationship with the loan size; however, the liquidation value coefficient becomes larger than that of the current property value once we saturate the model with more granular fixed effects. These results suggest that the liquidation value has a larger impact on borrowing amounts than the current value of the collateral.[30]

These results have implications for macro-finance models, as different theories make different predictions about the importance of an asset's current value versus its liquidation value in determining debt capacity. For example, in Kiyotaki and Moore (1997) only the liquidation value matters, while in Holmstrom and Tirole (1997) the current value of the project drives debt capacity due to the moral hazard problem. Our results suggest that both components matter, but the liquidation value appears more important across the majority of specifications.

[29] Because many of our properties do not generate income, this variable is missing for several observations, resulting in a lower sample size.

[30] One concern is that higher debt levels change the default threshold, which can mechanically affect liquidation values. Although we cannot fully address this issue, to the extent that default thresholds are changing, this should be reflected in changes in probabilities of default. In Appendix Table C.3, we find our results are robust to including PD ventile fixed effects as well as controlling for PD and PD squared.

We next examine the relationship between expected liquidation costs and loan maturities. As discussed in Benmelech, Garmaise, and Moskowitz (2005), in the incomplete contracting literature, higher liquidation values predict longer debt maturities in (e.g., Shleifer and Vishny (1992), Hart and Moore (1994) and Benmelech, Garmaise, and Moskowitz (2005)). The basic idea is that when the liquidation value is higher, lenders have more security and are willing to wait longer to be repaid, given that their outside option is higher.

To test this prediction, we first reestimate (1) but replace the dependent variable with maturity (in log months). The results are displayed in columns (1) and (2) of Table 4. Across both specifications, there is a negative, statistically significant relationship between the liquidation cost and loan maturity. For example, in column (1), the estimated coefficient implies that a one standard deviation increase in the liquidation cost (14.8 percentage points) is associated with an 11.2% shorter maturity.

In columns (3) and (4), we separately analyze how the current property value and liquidation value affect loan maturity, while also controlling for the loan's size. We find a positive, statistically significant relationship between liquidation value and loan maturity, and a negative, statistically significant relationship between maturity and property value. This result is consistent with the idea that higher liquidation values make lenders more willing to lend long-term to borrowers.

Next, we examine whether banks charge higher interest rates for loans with higher expected liquidation costs. At first glance, it may seem obvious that loans with higher liquidation values should have lower interest rates; however, as we just showed, higher liquidation values are associated with larger loan amounts and longer maturities. Hence, the unconditional relationship may be ambiguous (e.g., Harris and Raviv (1990)).

We first examine the relationship between expected liquidation costs and interest rates in columns (1) - (3) of Table 5, estimating similar regressions to (1), but replacing the dependent variable with interest rate. We also include the probability of default as a control given that it is a strong predictor of interest rates (e.g., Beyhaghi, Fracassi, and

Weitzner (2025)).[31] Across all specifications, the coefficient on liquidation cost is positive and statistically significant.

In columns (4) - (6), we reestimate the regression, but remove expected liquidation cost and include the current property value and liquidation value separately. In columns (4) and (5), both the current property value and liquidation value are negative and statistically significant; however, the coefficient for liquidation value is larger in magnitude.[32] In column (6), when we control for the loan's cap rate, the property value is no longer statistically significant, whereas the liquidation value remains negative and statistically significant. These results suggest that liquidation values reduce interest rates, even more so than the current value of properties.

Finally, we examine the relationship between expected liquidation values and subsequent loan modifications. Intuitively, in incomplete contracting models, higher liquidation values give the lender greater bargaining power, making it more difficult for borrowers to renegotiate the loan. To determine whether a loan has been modified, we follow the approach of Glancy, Kurtzman, and Loewenstein (2022) in classifying loan modifications. Specifically, they consider a loan modified if any of the following conditions occur: 1) the loan switches from being amortizing to interest only, 2) if the committed balance rises, which is a sign that interest payments are being added to the loan balance as part of a forbearance plan), 3) if the committed balance falls at the same time of a positive cumulative charge-off, which indicates a write-off, 4) if the maturity date is extended outside of a pre-negotiated renewal, or 5) if the loan enters troubled debt restructuring. Based on this classification, we create a variable, Loan Modified, which is a dummy equal to one if the loan is modified at least once over its life.

To test the relationship between liquidation values and loan modifications, we first regress Loan Modified on the expected liquidation cost at origination, while also controlling for the loan amount, given that larger loans tend to be more likely to be modified as well as the loan's maturity, given that loans with longer maturities have more time to be

[31]This allows us to control for any other effects that endogenous loan characteristics, such as the size of the loan, have on the interest rate through the probability of default.

[32]In column (5) with the more granular set of fixed effects, we can reject the null that the coefficient estimates of current property value and liquidation value are the same at the 10% confidence level.

modified at some point in the life of the loan. The results are displayed in columns (1) - (3) of Table 6. In column (1), when we include only bank$\times$quarter fixed effects, we find a positive, statistically significant relationship between liquidation costs and the likelihood that the loan is modified. In particular, the estimated coefficient of 0.273 implies that a one standard deviation increase in the liquidation cost (14.8pp) increases the likelihood of the loan being modified by about 4pp, which compares to an unconditional likelihood of the loan being modified of 26pp. We find similar results in columns (2) and (3) when we include more granular fixed effects and also control for the loan's cap rate.

In columns (4) - (6), we again conduct a similar exercise as above, where we separately analyze the liquidation value and current property value. Across all specifications, there is a negative, statistically significant relationship between the liquidation value and the likelihood of loan modification. Taken together, these results are consistent with the idea that loans with higher liquidation values are less likely to be renegotiated, as predicted by incomplete contracting models.

5 Determinants of Liquidation Values

In the previous section, we examine the relationship between liquidation values and ex-ante contract terms. However, a unique feature of our data is that we can observe not only the liquidation value and the asset's value at origination, but also how they change over time. In this section, we analyze how liquidation values evolve over the life of the loan and respond to different types of aggregate shocks.

5.1 Liquidation Costs and Loan Age

We first examine how expected liquidation costs evolve over the life of the loan. To do this, we estimate the following regression:

$$\text{Liquidation Cost}_{i,t} = \beta Log(\text{Loan Age (Normalized)}_{i,t}) + \alpha_i + \delta_t + u_{i,t},$$

where the main independent variable is the loan's age, normalized to the range $[0, 1]$ based on the loan's original maturity.[33] We include loan fixed effects (α_i) to test how the expected liquidation cost changes as the remaining maturity on the loan reduces over time. We also include year-quarter (i.e., quarter) fixed effects to control for any aggregate components of expected liquidation costs. Once again, we cluster our standard errors by county.

The results are displayed in column (1) of Table 7. We find a negative and statistically significant relationship between the loan's age and the expected liquidation cost. This result is consistent with the idea that the borrower's expertise becomes less important over time, thereby reducing liquidation costs. In column (2), we also control for the probability of default to address potential survivorship biases and find similar results.[34]

If this mechanism explains these results, we would expect to see stronger effects for loans in which borrower expertise is more important. In column (3), we reestimate the regressions and interact the Loan Age (Normalized) with Construction, a dummy variable equal to one if the loan is a construction loan. Consistent with this hypothesis, we find stronger effects for construction loans. These results are also consistent with the main friction in Hart and Moore (1994), whereby the borrower can threaten to withhold his human capital from the project. Our results suggest that this threat decreases over the loan's life, where the decrease is more substantial for projects in which the borrower's human capital is more important.[35]

5.2 Liquidation Values and Market Conditions

In this section, we examine whether liquidation values and costs comove due to exposure to common shocks. In Table 8, we test the extent to which changes in market conditions affect expected liquidation values. In column (1), we regress changes in liquidation values

[33] For example, this variable will equal zero at origination and one at maturity. If the loan has a maturity at origination of six years, the variable will equal one-half after three years.

[34] Because defaulting loans drop from our sample, it could be that the older the loan is, the safer it is, which results in lower liquidation costs. By controlling for the probability of default, we mitigate such a bias.

[35] Further consistent with idea, in Table 2, construction loans have higher unconditional liquidation costs than other types of loans.

on quarter fixed effects. The R-squared is 0.008, suggesting that aggregate economy-wide factors explain little of the changes in expected liquidation costs. However, in column (2), when we regress changes in expected liquidation values on property type$\times$quarter fixed effects, the R-squared jumps to 0.167. Similarly, in column (3), county$\times$quarter fixed effects explain 0.172 of the variation in expected liquidation values. Finally, in column (3), when we include property type$\times$county$\times$quarter fixed effects, the R-squared is 0.362.

In Table 9, we find similar results when we conduct the same exercise but with changes in expected liquidation costs as the dependent variable. We also re-estimate the regressions in Table 8, but replace the dependent variable with changes in property values. Interestingly, the property type$\times$quarter fixed effects explain very little of the changes in the property's current value. Moreover, while county$\times$quarter fixed effects explain some of the variation in changes in current values, their explanatory power is much lower than for changes in liquidation values and costs.[36]

These results suggest that there is comovement in liquidation values across property types, even in different locations, which is not evident in current property values. We next explore potential sources of this comovement.

One potential source of comovement in property values may arise from fire-sale effects. In Shleifer and Vishny (1992), industry-level distress leads to fire sale discounts because the natural buyers of distressed assets—other firms in the same industry—are themselves financially constrained during downturns. Hence, industry-level shocks can have disproportionate effects on liquidation values through this fire-sale channel.

An empirical challenge in testing this mechanism is that industry distress may also lower the first-best use of assets outside of distress. For example, the reason that an industry goes into distress in the first place is that its business prospects deteriorate. Hence, it may not be the industry distress itself that causes lower liquidation values, but rather the fact that those assets are less valuable regardless of who owns them.

[36]One concern is that liquidation values and current property values may be updated at different frequencies, which can contribute to the explanatory power of these regressions. However, we find similar differences in explanatory power results if we condition on these measures being updated. Specifically, in Appendix Tables C.5 and C.6, we reestimate the specifications from Tables 8 and 9 but only include observations in which the LGD was updated and in Appendix Table C.7, we reestimate the specifications in Table C.7 but only include observations in which the current property value was updated.

Importantly, our data helps us mitigate this concern by allowing us to distinguish between the current market value and the asset's liquidation value, which we exploit in our next tests.

To test this fire sale mechanism, we first construct aggregate industry-level stock return measures by equal-weighting the returns of all firms in each industry based on two-digit SIC codes.[37] We then assign the property types in our data to the closest relevant industries based on the two-digit SIC codes. Appendix C.1 displays the mapping between property types and industries.

We then estimate the following regression:

$$\begin{aligned}\Delta\text{Liquidation Value}_{i,j,t} = {} & \beta_1 \text{Industry Return}_{j,t} + \beta_2 \Delta\text{Current Value}_{i,t} \\ & + \beta_3 \Delta\text{Housing Price Index}_{c,t} + \beta_4 \Delta\text{Probability of Default}_{i,t} + \delta_t + u_{i,j,t},\end{aligned} \tag{2}$$

where the dependent variable is the change in the liquidation value from the previous quarter and the main independent variable, Industry Return, is the return in industry j at time t. We also include as controls ΔCurrent Value, the change in the property's current value; ΔHouse Price Index, the change in the county-level house price index from Zillow; and ΔProbability of Default, the change in the loan's probability of default. [38] Here, we double-cluster our standard errors by time and county to account for any correlation in errors within time.

The idea of this regression is to see whether industry-level shocks affect liquidation values for properties most relevant to those industries. Importantly, this regression controls for the change in the current market value of properties, helping us disentangle fire-sale effects from changes in the value of these assets outside of distress.

The estimates are displayed in column (1) of Table 11. The coefficient for Stock Return is 0.196 and statistically significant. This result suggests that a 1% increase in industry-level stock returns increases a loan's liquidation value by 20 basis points (bps),

[37] We obtain stock return data from CRSP.

[38] We control for changes in local house prices, given that local factors seem to affect liquidation values.

even after accounting for changes in the property's current value.

As discussed above, if industry shocks reduce liquidation values due to a higher likelihood of fire sales, we should observe stronger effects in industries where firm distress is aggregate rather than idiosyncratic. To test this hypothesis, we estimate the correlation in changes in probabilities of default across property types by estimating the following regression for each property type j:

$$\Delta PD_{i,j,t} = \beta_j \Delta \bar{PD}_{j,t}^{(-i)} + u_{i,j,t}, \tag{3}$$

where $\Delta \bar{PD}_{j,t}^{(-i)}$ is the average change in the probability of default of all the other loans of the same property type j. The coefficient β_j can be interpreted as the sensitivity of an individual loan's probability of default to changes in the average probability of default of the other loans secured by the same property type. Appendix Table C.8 displays the results of the first-stage regression.

After estimating (3), we take the estimates of β, which we refer to as Default β's, for each property type and interact them with the industry-level returns variable in (2). The results for this regression are displayed in column (2) of Table 11. The interaction coefficient is positive and statistically significant, suggesting that industry-level stock returns have a stronger effect on changes in liquidation values in industries with higher default risk correlation.

In columns (3) and (4), we perform the same exercise but replace the dependent variable with the change in the liquidation cost and find similar results: higher industry-level stock returns lead to reductions in liquidation costs, where the effects are stronger in industries with higher default risk correlation. In columns (5) and (6), we replace the dependent variable with the change in the current value. Interestingly, we find no effect of industry-level stock returns on the current value, nor any variation in sensitivity based on the industry's default rate correlation.

These results provide direct evidence of fire-sale effects driven by industry-level distress, where, to our knowledge, this is the first paper to show this effect by directly analyzing expected liquidation values.

6 Conclusion

The expected liquidation value of an asset plays a crucial role in contract theory and macroeconomics, but it is difficult to analyze empirically because it is typically unobservable. In this paper, we create the first forward-looking measure of expected liquidation values in default using supervisory bank commercial real estate loan data. Consistent with the incomplete contracting literature, we find that loans secured by collateral with higher liquidation values relative to their current market values are larger, have longer maturities, and are less likely to be renegotiated.

We also exploit within-loan time-series variation in liquidation values to show that industry-level shocks affect liquidation values even after controlling for changes in the current property value. Consistent with fire-sale effects, the pass-through of these industry shocks is amplified among property types with more correlated default rates.

Our results also have implications for macrofinance models. In some models, the relevant state variable is the value of its assets in best use, i.e., current value (e.g., Holmstrom and Tirole (1997)). In contrast, in others, the liquidation value is the key state variable (e.g., Kiyotaki and Moore (1997)). Our empirical results, which importantly allow us to observe both of these objects, suggest that the latter is more important.[39]

Beyond the specific analysis of this paper, we believe our new measure of expected liquidation values opens many avenues for analyzing its properties and impact on the macroeconomy. For example, future work could use these data and our approach to measuring liquidation values to directly investigate the collateral channel (e.g., Kiyotaki and Moore (1997) and Chaney, Sraer, and Thesmar (2012)).

Finally, because our liquidation value measure is observable in real-time across entire loan portfolios, policymakers could use it to monitor fire-sale risk at the local, industry, or aggregate level. Future work could examine how this measure evolves over credit cycles or whether widening gaps between market and liquidation values predict subsequent market distress.

[39] Of course, our results are based on commercial real estate loans. Corporate loans may exhibit different properties (e.g., Lian and Ma (2021) and Benmelech, Kumar, and Rajan (2025)).

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Table 1: Summary Statistics

This table contains summary statistics. For variable definitions, see Appendix Section A.

Panel A: New Loans						
	N	Mean	Std Dev	P25	Median	P75
Interest Rate (%)	35,184	4.173	1.361	3.250	3.930	4.850
Loan Amount ($mm)	39,827	15.114	36.289	1.740	4.100	15.000
Property Value ($mm)	37,104	29.013	99.938	2.850	7.750	25.500
Cap Rate	24,389	0.051	0.024	0.041	0.051	0.060
Maturity (months)	39,760	158.108	135.097	60.000	121.000	360.000
Loan-to-Value Ratio	36,932	0.596	0.179	0.500	0.625	0.726
Probability of Default (%)	29,080	0.937	2.113	0.270	0.520	0.930
Loss Given Default (%)	28,463	31.730	12.961	24.000	31.000	41.000
Exposure at Default ($mm)	28,504	15.274	34.151	1.713	4.994	16.396
Construction Loan	39,827	0.337	0.473	0.000	0.000	1.000
Loan Modified	39,827	0.258	0.437	0.000	0.000	1.000
Panel B: New and Existing Loans						
	N	Mean	Std Dev	P25	Median	P75
Interest Rate (%)	449,829	4.151	1.476	3.240	3.840	4.750
Loan Amount ($mm)	465,160	12.198	25.085	1.759	3.513	10.951
Property Value ($mm)	458,473	25.781	63.101	3.650	8.300	24.000
Cap Rate	370,325	0.053	0.027	0.040	0.051	0.065
Remaining Maturity (months)	462,046	114.301	121.566	28.000	63.000	129.000
Loan-to-Value Ratio	454,500	0.524	0.192	0.407	0.550	0.659
Probability of Default (%)	327,376	2.169	8.986	0.230	0.480	1.040
Loss Given Default (%)	322,690	27.289	12.562	19.000	25.000	37.000
Exposure at Default ($mm)	318,780	13.740	26.465	1.803	3.986	13.750
Construction Loan	465,161	0.191	0.393	0.000	0.000	0.000
Loan Modified	465,161	0.442	0.497	0.000	0.000	1.000

Table 2: Summary Statistics: Expected Liquidation Costs by Property Type

This table displays summary statistics for expected liquidation costs by different property types.

Panel A: By Property Type

	N	Mean	Std Dev	P25	Median	P75
Retail	2,602	0.655	0.148	0.554	0.632	0.742
Industrial	1,765	0.686	0.157	0.576	0.677	0.811
Hotel/Hospitality/Gaming	780	0.649	0.131	0.573	0.649	0.717
Multi-Family	12,830	0.650	0.138	0.554	0.627	0.729
Homebuilders	1,531	0.775	0.144	0.683	0.780	0.897
Condo	166	0.832	0.180	0.692	0.947	0.975
Office	2,638	0.646	0.147	0.547	0.623	0.727
Mixed	282	0.729	0.157	0.600	0.727	0.883
Land Development	397	0.656	0.165	0.531	0.658	0.769
Other	2,577	0.689	0.147	0.593	0.673	0.781
Healthcare	9	0.613	0.172	0.562	0.600	0.630
Warehouse/Distribution	94	0.729	0.145	0.632	0.768	0.858
Total	25,671	0.666	0.148	0.562	0.645	0.763

Panel B: By Loan Purpose

	N	Mean	Std Dev	P25	Median	P75
Construction Build to Suit	182	0.761	0.159	0.700	0.807	0.870
Land Acquisition and Development	369	0.671	0.163	0.545	0.687	0.784
Construction Other	4,014	0.745	0.161	0.647	0.761	0.883
Acquisition	5,550	0.612	0.132	0.524	0.606	0.683
Refinance	12,423	0.676	0.139	0.576	0.650	0.765
Other	2,897	0.620	0.128	0.539	0.596	0.675
Mini-Perm	155	0.571	0.121	0.484	0.561	0.652

Table 3: Liquidation Values and Debt Capacity

In this table, we test the relationship between expected liquidation values and debt capacity. In all specifications, we restrict the sample to new loans. In columns (1) - (3), the dependent variable is the loan-to-value ratio, defined as the committed loan amount divided by the property value at origination. In columns (4) - (6), the dependent variable is the committed loan amount in logs. P-values from a t-test comparing the coefficient estimates of the property's current value and liquidation value are reported at the bottom of columns (4) - (6). Standard errors are shown below the parameter estimates in parentheses and are clustered by county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	LTV			Log(Loan Amount)		
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidation Cost	-0.919***	-0.952***	-1.102***			
	(0.038)	(0.032)	(0.027)			
Cap Rate			0.906***			2.971***
			(0.171)			(0.634)
Log(Property Value)				0.419***	0.398***	0.303***
				(0.048)	(0.052)	(0.064)
Log(Liquidation Value)				0.485***	0.511***	0.623***
				(0.041)	(0.048)	(0.065)
Bank-Quarter FE	Y	Y	Y	Y	Y	Y
Property Type-Quarter FE		Y	Y		Y	Y
County-Quarter FE		Y	Y		Y	Y
P-value				0.458	0.255	0.013
Observations	25,585	19,668	15,053	25,428	19,531	15,090
Adj. R-squared	0.603	0.711	0.789	0.933	0.947	0.961

Table 4: Liquidation Values and Debt Maturity

In this table, we test the relationship between liquidation values and debt maturity. In all specifications, we restrict the sample to new loans. The dependent variable is the log of the maturity at origination in months. P-values from a t-test comparing the coefficient estimates of the property's current value and liquidation value are reported at the bottom of columns (4) - (6). Standard errors are shown below the parameter estimates in parentheses and are clustered by county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(Maturity)			
	(1)	(2)	(3)	(4)
Liquidation Cost	-0.922***	-0.586***		
	(0.094)	(0.098)		
Log(Loan Amount)	-0.138***	-0.138***	-0.172***	-0.113***
	(0.007)	(0.009)	(0.024)	(0.021)
Log(Property Value)			-0.096***	-0.080***
			(0.020)	(0.022)
Log(Liquidation Value)			0.138***	0.061***
			(0.019)	(0.017)
Bank-Quarter FE	Y	Y	Y	Y
Property Type-Quarter FE		Y		Y
County-Quarter FE		Y		Y
P-value			0.000	0.000
Observations	25,537	19,624	25,381	19,488
Adj. R-squared	0.579	0.719	0.576	0.718

Table 5: Liquidation Values and Interest Rates

In this table, we test the relationship between liquidation values and interest rates. In all specifications, we restrict the sample to new loans. The dependent variable is the loan's interest rate at origination. Standard errors are shown below the parameter estimates in parentheses and are clustered by county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Interest Rate (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidation Cost	0.175*	0.189***	0.326***			
	(0.092)	(0.066)	(0.081)			
Probability of Default	2.896***	2.427***	2.259***	2.736***	2.338***	2.058***
	(0.384)	(0.417)	(0.491)	(0.362)	(0.396)	(0.482)
Cap Rate			3.452***			2.395***
			(0.602)			(0.542)
Log(Property Value)				-0.073***	-0.049***	0.007
				(0.014)	(0.016)	(0.015)
Log(Liquidation Value)				-0.106***	-0.102***	-0.162***
				(0.017)	(0.017)	(0.026)
Bank-Quarter FE	Y	Y	Y	Y	Y	Y
Property Type-Quarter FE		Y	Y		Y	Y
County-Quarter FE		Y	Y		Y	Y
P-value				0.256	0.066	0.000
Observations	23,637	18,004	14,199	23,583	17,940	14,231
Adj. R-squared	0.711	0.781	0.805	0.731	0.793	0.817

Table 6: Liquidation Values and Loan Modifications

In this table, we test the relationship between liquidation values and the propensity of loan modifications. In all specifications, we restrict the sample to new loans. The dependent variable is a dummy variable equal to one if the loan is modified at least once during its life. P-values from a t-test comparing the coefficient estimates of the property's current value and liquidation value are reported at the bottom of columns (4) - (6). Standard errors are shown below the parameter estimates in parentheses and are clustered by county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Loan Modified					
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidation Cost	0.273***	0.281***	0.324***			
	(0.037)	(0.065)	(0.096)			
Log(Maturity)	-0.055***	-0.065***	-0.092***	-0.074***	-0.078***	-0.097***
	(0.006)	(0.008)	(0.011)	(0.006)	(0.007)	(0.010)
Log(Loan Amount)	0.027***	0.024***	0.026***	0.068***	0.097***	0.159***
	(0.004)	(0.005)	(0.005)	(0.011)	(0.015)	(0.024)
Cap Rate			-0.486**			-1.055***
			(0.233)			(0.220)
Log(Property Value)				0.017***	0.006	-0.005
				(0.005)	(0.006)	(0.008)
Log(Liquidation Value)				-0.054***	-0.077***	-0.131***
				(0.012)	(0.018)	(0.027)
Bank-Quarter FE	Y	Y	Y	Y	Y	Y
Property Type-Quarter FE		Y	Y		Y	Y
County-Quarter FE		Y	Y		Y	Y
P-value				0.000	0.000	0.000
Observations	25,537	19,624	15,028	25,381	19,488	15,066
Adj. R-squared	0.223	0.266	0.247	0.235	0.269	0.252

Table 7: Liquidation Costs over the Life of the Loan

In this table, we examine how expected liquidation costs evolve over the life of the loan. The dependent variable, Loan Age (Normalized), is a variable between 0 and 1 that measures the length of time the loan has been outstanding, divided by the maturity of the loan at origination. Standard errors are shown below the parameter estimates in parentheses and are clustered by county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Liquidation Cost			
	(1)	(2)	(3)	(4)
Loan Age (Normalized)	-0.034***	-0.035***	-0.007	-0.008
	(0.003)	(0.003)	(0.006)	(0.005)
Probability of Default (%)		0.001***		0.001***
		(0.000)		(0.000)
Construction Loan			0.059***	0.058***
			(0.008)	(0.008)
Construction Loan × Loan Age (Normalized)			-0.112***	-0.112***
			(0.012)	(0.012)
Year-Quarter FE	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y
Observations	292,492	291,293	292,492	291,293
Adj. R-squared	0.866	0.867	0.869	0.869

Table 8: Aggregate Changes in Liquidation Values

This table examines the determinants of loan-level changes in liquidation values. The dependent variable is the change in liquidation value.

	Δ Liquidation Value			
	(1)	(2)	(3)	(4)
Quarter FE	Y			
Property Type×Quarter FE		Y		
County×Quarter FE			Y	
Property Type×County×Quarter FE				Y
Observations	263,323	263,311	244,960	220,965
R-squared	0.008	0.166	0.172	0.362

Table 9: Aggregate Changes in Liquidation Costs

This table examines the determinants of loan-level changes in liquidation costs. The dependent variable is the change in liquidation cost.

	Δ Liquidation Cost			
	(1)	(2)	(3)	(4)
Quarter FE	Y			
Property Type×Quarter FE		Y		
County×Quarter FE			Y	
Property Type×County×Quarter FE				Y
Observations	259,674	259,669	241,605	217,964
R-squared	0.016	0.199	0.177	0.377

Table 10: Aggregate Changes in Current Property Values

This table examines the determinants of loan-level changes in current property values. The dependent variable is the change in current property value.

	Δ Property Value			
	(1)	(2)	(3)	(4)
Quarter FE	Y			
Property Type×Quarter FE		Y		
County×Quarter FE			Y	
Property Type×County×Quarter FE				Y
Observations	258,697	258,693	240,710	216,738
R-squared	0.005	0.016	0.061	0.135

Table 11: Industry Shocks and Liquidation Values

This table tests the relationship between aggregate industry-level stock returns and changes in liquidation values, liquidation costs and current project values. In columns (1) - (2), the dependent variable is the percentage change in the expected liquidation value, in columns (3) - (4), the dependent variable is the change in the liquidation cost and in columns (5) - (6), the dependent variable is the change in current project value, in percent. Standard errors are shown below the parameter estimates in parentheses and are double-clustered by year-quarter and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Liquidation Value		Δ Liquidation Cost		Δ Property Value	
	(1)	(2)	(3)	(4)	(5)	(6)
Industry Return	0.196**	0.020	-0.088**	-0.016	-0.001	0.002
	(0.077)	(0.054)	(0.035)	(0.025)	(0.003)	(0.004)
Δ Property Value	0.136***	0.154***				
	(0.024)	(0.020)				
Δ Housing Price Index	0.214*	0.179*	-0.093*	-0.074*	0.052***	0.052***
	(0.109)	(0.094)	(0.051)	(0.043)	(0.016)	(0.016)
Δ Probability of Default	-0.028*	-0.031***	0.019***	0.020***	-0.021***	-0.021***
	(0.016)	(0.011)	(0.006)	(0.005)	(0.005)	(0.005)
Default β × Industry Return		0.194**		-0.073*		-0.001
		(0.092)		(0.043)		(0.004)
Default β		0.135***		-0.064***		-0.003**
		(0.024)		(0.010)		(0.001)
Year-Quarter FE	Y	Y	Y	Y	Y	Y
Observations	212,291	212,291	218,282	218,282	225,390	225,390
Adj. R-squared	0.026	0.086	0.033	0.101	0.007	0.007

Appendix A. Variable Definitions

Allowance for Loan Losses: The allowance for expected credit losses per ASC 326- 20, from Y-14.

Amount Outstanding at Default: Committed loan amount at the time of default, from Y-14Q.

Assets: Total assets, from Y-14.

Cap Rate: the current net operating income divided by the current property value, from Y-14Q.

Loan Amount: Committed loan amount, from Y-14Q.

Construction Loan: A dummy variable equal to one if the loan finances the construction of a property, from Y-14Q.

Current Value: The current value of the property securing the loan, from Y-14Q.

Default: A dummy variable equal to one if the loan defaults in the next year, from Y-14Q.

Exposure at Default (EAD): Exposure at default, from Y-14Q.

Liquidation Cost: 1- $\frac{\text{Liquidation Value}}{\text{Current Property Value}}$, from Y-14Q.

Liquidation Value: (1-LGD) $\times$ EAD, from Y-14Q.

Expected Loss: PD $\times$ LGD $\times$ EAD, from Y-14Q.

Housing Price Index: County-level house price index, from Zillow.

Interest rate: Interest rate, from Y-14Q.

Income Producing Property: Dummy variable equal to one if, from Y-14Q.

Loss Given Default (LGD): Loan-to-value ratio calculated as the total committed amount of the loan divided by the current value, from Y-14Q.

Loan Modified: A dummy variable equal to one if the loan is modified at any point over the life of the loan. We consider a loan to be modified according to the definition in Glancy, Kurtzman, and Loewenstein (2022). From Y-14Q.

Loan-to-value Ratio (LTV): Loan-to-value ratio calculated as the total committed amount of the loan divided by the current value, from Y-14Q.

Maturity at Origination: Maturity of loan at time of origination in months, from Y-14Q.

Maturity Extension: A dummy variable equal to one if the maturity of the loan is extended at any point over the life of the loan, from Y-14Q.

Loan Age (Normalized): Is a variable between 0 and 1 that measures the length of time the loan has been outstanding, divided by the maturity of the loan at origination, from Y-14Q.

Probability of Default (PD): The probability of default, from Y-14Q.

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

Realized Exposure at Default: EAD at the time of default, from Y-14Q.

Industry Return: Quarterly industry-level equal-weighted stock return, where Appendix Table C.1 displays the mapping between property types in Y-14Q to industry SIC codes. For mappings with more than one two-digit SIC code, we average returns across all stocks for each relevant SIC code, from CRSP.

Appendix B. Validity of Bank Risk Assessments

In this section, we provide evidence that banks' risk assessments accurately reflect banks' true beliefs regarding the risk of their loans.

We first test whether banks' probability of default (PD) estimates predict realized default. To do so, we restrict the sample to new loans and estimate the following regression:

$$\text{Default}_i = \beta PD_{i,t} + \delta_{b,t} + u_i,$$

where i, t and b index loan, date and bank, respectively and Default_i is an indicator equal to one if loan i defaults within one year of origination.[40] The main variable of interest is PD_i, which is the bank's probability of default estimate at loan origination. We include bank×quarter fixed effects ($\delta_{b,t}$) to absorb any differences in banks' risk assessment models and cost of capital and double-cluster our standard errors by year-quarter and county.

The results are displayed in Table B.1. In column (1), when we include PD without any controls, the coefficient is 1.177 and statistically significant. In column (2), the coefficient remains close to 1 and statistically significant when we include the committed loan balance, in logs and the LTV ratio. Finally, in column (3), we also include bank×quarter×property type fixed effects, and the coefficient remains positive and statistically significant. These results are consistent with Beyhaghi, Fracassi, and Weitzner (2025) and Weitzner and Howes (2025), who use Schedule H.1 of the Y-14Q data to show that PDs are strong predictors of realized default in the corporate loan market.

As discussed in Section 3.1, one of the two components of the liquidation value is the loan's exposure at default. We next examine whether banks accurately estimate exposure at default (EAD) by comparing their ex-ante estimates with realized exposures for loans that actually default. Specifically, we restrict the sample to loans that have defaulted and estimate:

$$\text{Realized EAD}_i = \beta \text{EAD Estimate}_i + \delta_{b,t} + u_i,$$

where the dependent is the EAD measured at the time of default. The results are displayed in column (1) of Table B.2. The estimated coefficient, which is statistically significant and the R-squared are both very close to one, suggesting that banks' EAD estimates strongly reflect their realized exposure at default. One concern is that EAD is an estimate generated by the bank, rather than an actual realized outcome. To address this concern, in column (2), we instead use the realized loan amount outstanding at the time of default as the dependent variable, rather than the banks' estimate of EAD at the time

[40] We use a one-year horizon given that PD is an annual default rate.

of default.[41] In this alternate specification, the coefficient is identical and the R-squared is slightly higher.

The second component of the liquidation value is the loss-given-default (LGD). We next validate the consistency of banks' LGD estimates by examining their relationship with loan loss allowances. Banks are required to report allowances based on expected losses, providing an independent measure of their loss expectations. However, these are only available after 2020, when CECL (Current Expected Credit Losses) was implemented.

We first restrict the sample to new loans and estimate the following regression:

$$\text{Log(Allowance for Loan Losses)}_{i,t} = \beta \text{Log(Expected Loss)}_{i,t} + \delta_{b,t} + u_{i,t},$$

where the dependent variable is the allowance for loan losses in logs, and the main independent variable is the expected loss, which is equal to PD $\times$ LGD $\times$ EAD, in logs. We also include bank$\times$quarter fixed effects and double-cluster the standard errors by year-quarter and county. Column (1) of Table B.3 presents the results. The estimated coefficient is 0.754 and statistically significant with an R-squared of 0.848. In column (2), we include existing loans in the sample, but also include loan fixed effects. This test examines how changes in expected losses relate to changes in loan loss allowances over the life of the loan. The estimated coefficient is 0.482 and statistically significant.

Given that both expected losses and allowances for loan losses are meant to capture loan-level losses, one might expect the coefficient to be one in these regressions. However, the expected loss reported in Y-14 is not exactly the same as that reported under CECL. CECL uses lifetime expected losses, while Y-14 is an annual.

Finally, we show that changes in local house prices are associated with changes in current property values. Specifically, we keep the full sample of new and existing loans and estimate the following regression:

$$\Delta\text{Property Value}_{i,t} = \beta \Delta\text{Housing Price Index}_{i,t} + \delta_t + u_{i,t},$$

where the dependent variable is the change in the current property value, and the independent variable is the change in the county-level house price index. The results are displayed in column (1) of Table B.4. Because banks do not update the valuation of the properties every quarter, in column (2), we reestimate the regression, but restrict the sample to loan quarters in which the property price was updated. The coefficient remains statistically significant and increases to 0.438. In columns (3) and (4), we replace the independent and dependent variables with log levels rather than changes, and include loan fixed effects, and obtain similar qualitative results. These results suggest that banks

[41] The downside of this approach is that it potentially excludes accrued interest; however, this appears not to be very important given how close the coefficient is to one.

are updating the current property values as local house prices change for the collateral securing the loans in our sample.

Table B.1: Probability of Default and Realized Default

This table tests whether probabilities of default predict subsequent realized default. The sample is restricted to new loans, and the dependent variable is a dummy variable equal to one if the loan defaults within the next year. Standard errors are shown below the parameter estimates in parentheses and are clustered by county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Default Within 1 Year		
	(1)	(2)	(3)
Probability of Default (%)	1.177***	0.897***	0.525***
	(0.139)	(0.146)	(0.129)
Log(Loan Amount)		-6.291***	-6.801***
		(0.538)	(0.680)
Loan-to-Value Ratio		20.005***	22.773***
		(4.805)	(2.912)
Bank-Quarter FE	Y	Y	
Bank-Quarter-Property Type FE			Y
Observations	28,964	26,830	25,565
Adj. R-squared	0.451	0.467	0.544

Table B.2: Expected Exposure at Default and Realized Exposure at Default

This table tests whether banks' expected exposure at default at origination predicts realized exposure in default. The sample is restricted to defaulting loans. Standard errors are shown below the parameter estimates in parentheses and are clustered by county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Realized Exposure at Default	Amount Outstanding at Default
	(1)	(2)
Exposure at Default	0.931***	0.931***
	(0.025)	(0.025)
Bank-Quarter FE	Y	Y
Observations	153	153
Adj. R-squared	0.969	0.971

Table B.3: Allowances for Losses and Expected Losses

In this table, we examine the relationship between bank allowance for loan losses and their reported expected losses in the Y-14Q data. The dependent variable is the expected loss ($PD \times LGD \times EAD$), in logs. The independent variable is. Column (1) restricts the sample to new loans, while column (2) includes new and existing loans. Standard errors are shown below the parameter estimates in parentheses and are clustered by county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(Allowance for Loan Losses)	
	(1)	(2)
Log(Expected Loss)	0.738***	0.476***
	(0.022)	(0.033)
Bank-Quarter FE	Y	Y
Loan FE		Y
Observations	2,065	125,782
Adj. R-squared	0.809	0.890

Table B.4: Local House Prices and Current Property Values

This table tests whether changes in local house prices are associated with changes in the current value of the property securing loans. In columns (1) and (3), we use the full sample of loans. In columns (2) and (4), we restrict the sample to quarters in which the current property value was updated. Standard errors are shown below the parameter estimates in parentheses and are clustered by county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Property Value		Log(Property Value)	
	(1)	(2)	(3)	(4)
Δ Housing Price Index	0.039***	0.438***		
	(0.007)	(0.058)		
Log(Housing Price Index)			0.154***	0.221***
			(0.015)	(0.030)
Sample	All loans	Property updated	All loans	Property updated
Quarter FE	Y	Y	Y	Y
Loan FE			Y	Y
Observations	372,962	23,478	438,579	44,728
Adj. R-squared	0.004	0.051	0.987	0.934

Appendix C. Additional Tables and Figures

Table C.1: Property Type to Industry Mapping

This table displays the mapping between property types in FR Y-14Q data and industries in CRSP based on their two-digit SIC codes. For mappings with more than one two-digit SIC code, we average returns across all stocks for each relevant SIC code.

Property Type	**SIC Code**	**Industry Description**
Retail	52 - 59	Retail
Industrial	20 - 39	Manufacturing
Hotel	70	Hotels & Lodging
Multi-family	65	Real Estate
Homebuilders	15	Construction
Condo/Co-op	65	Real Estate
Land and Lot Development	65	Real Estate
Other	99	Nonclassifiable Establishments
Healthcare	80	Health Services
Warehouse/Distribution	42	Transportation Services

Table C.2: Relationship Between Loss Given Default and Exposure at Default

This table tests the within-loan relationship between Loss Given Default and Exposure at Default. The dependent variable is Exposure at Default, in logs. The independent variable is Loss Given Default. Standard errors are shown below the parameter estimates in parentheses and are clustered by county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(Exposure at Default)
	(1)
Loss Given Default	-0.046
	(0.052)
Bank-Quarter FE	Y
Loan FE	Y
Observations	299,718
Adj. R-squared	0.967

Table C.3: Liquidation Values and Debt Capacity (Controlling for Probability of Default)

In this table, we test the relationship between expected liquidation values and debt capacity, while controlling for the probability of default. In all specifications, we restrict the sample to new loans and include PD ventile fixed effects. In columns (1) - (3), the dependent variable is the loan-to-value ratio, defined as the committed loan amount divided by the property value at origination. In columns (4) - (6), the dependent variable is the committed loan amount in logs. P-values from a t-test comparing the coefficient estimates of the property's current value and liquidation value are reported at the bottom of columns (4) - (6). Standard errors are shown below the parameter estimates in parentheses and are clustered by county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	LTV			Log(Loan Amount)		
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidation Cost	-0.864***	-0.884***	-1.005***			
	(0.029)	(0.025)	(0.034)			
Probability of Default (%)	-0.000	0.002	0.003	0.005	0.004	-0.003
	(0.002)	(0.003)	(0.002)	(0.005)	(0.007)	(0.005)
Probability of Default Squared (%)	-0.000	-0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cap Rate			0.946***			3.047***
			(0.163)			(0.601)
Log(Property Value)				0.437***	0.421***	0.334***
				(0.049)	(0.055)	(0.071)
Log(Liquidation Value)				0.469***	0.489***	0.594***
				(0.041)	(0.049)	(0.070)
Bank-Quarter FE	Y	Y	Y	Y	Y	Y
PD Ventile FE	Y	Y	Y	Y	Y	Y
Property Type-Quarter FE		Y	Y		Y	Y
County-Quarter FE		Y	Y		Y	Y
P-value				0.727	0.515	0.065
Observations	25,489	19,583	15,015	25,321	19,443	15,047
Adj. R-squared	0.639	0.741	0.813	0.938	0.950	0.963

Table C.4: Liquidation Values, Current Property Values and Maturity Extensions

In this table, we test whether loans with higher liquidation values at origination are less likely to have their maturities extended. We restrict the sample to new loans. The dependent variable is a dummy variable equal to one if the loan's maturity is ever extended. P-values from a t-test comparing the coefficient estimates of the property's current value and liquidation value are reported at the bottom of columns (4) - (6). Standard errors are shown below the parameter estimates in parentheses and are clustered by county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Maturity Extension					
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidation Cost	0.234***	0.331***	0.504***			
	(0.051)	(0.081)	(0.112)			
Log(Maturity)	-0.025***	-0.031***	-0.044***	-0.034***	-0.037***	-0.048***
	(0.003)	(0.004)	(0.007)	(0.003)	(0.003)	(0.006)
Log(Loan Amount)	0.006***	0.006***	0.013***	0.054***	0.095***	0.208***
	(0.002)	(0.002)	(0.003)	(0.012)	(0.018)	(0.030)
Cap Rate			0.631**			-0.157
			(0.280)			(0.149)
Log(Property Value)				0.016***	0.012	0.015*
				(0.006)	(0.008)	(0.009)
Log(Liquidation Value)				-0.063***	-0.101***	-0.214***
				(0.014)	(0.020)	(0.025)
Bank-Quarter FE	Y	Y	Y	Y	Y	Y
Property Type-Quarter FE		Y	Y		Y	Y
County-Quarter FE		Y	Y		Y	Y
P-value				0.000	0.000	0.000
Observations	25,537	19,624	15,028	25,381	19,488	15,066
Adj. R-squared	0.297	0.349	0.246	0.325	0.358	0.286

Table C.5: Aggregate Changes in Liquidation Values (Updated LGD)

This table examines the determinants of loan-level changes in liquidation values, restricting the sample to observations in which the LGD was updated from the previous quarter. The dependent variable is the change in liquidation value.

	Δ Liquidation Value			
	(1)	(2)	(3)	(4)
Quarter FE	Y			
Property Type×Quarter FE		Y		
County×Quarter FE			Y	
Property Type×County×Quarter FE				Y
Observations	42,959	42,938	36,597	30,738
R-squared	0.083	0.164	0.312	0.410

Table C.6: Aggregate Changes in Liquidation Costs (Updated LGD)

This table examines the determinants of loan-level changes in liquidation costs, restricting the sample to observations in which the LGD was updated from the previous quarter. The dependent variable is the change in liquidation cost.

	Δ Liquidation Cost			
	(1)	(2)	(3)	(4)
Quarter FE	Y			
Property Type×Quarter FE		Y		
County×Quarter FE			Y	
Property Type×County×Quarter FE				Y
Observations	42,524	42,501	36,148	30,367
R-squared	0.119	0.201	0.339	0.428

Table C.7: Aggregate Changes in Current Property Values (Updated Current Value)

This table examines the determinants of loan-level changes in current property values, restricting the sample to observations in which the current property value was updated from the previous quarter. The dependent variable is the change in current property value.

	Δ Property Value			
	(1)	(2)	(3)	(4)
Quarter FE	Y			
Property Type×Quarter FE		Y		
County×Quarter FE			Y	
Property Type×County×Quarter FE				Y
Observations	17,013	16,971	13,599	11,030
R-squared	0.058	0.112	0.255	0.299

Table C.8: Correlation in Default Rates Across Property Types

This table presents the results from estimating (3). Standard errors are shown below the parameter estimates in parentheses and are clustered by county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Property Type	Change in Peer PDs	Observations	R-squared
Retail	0.379***	32,114	0.016
	(0.117)		
Industrial	0.122	14,400	0.001
	(0.101)		
Hotel/Hospitality/Gaming	0.388***	7,363	0.112
	(0.044)		
Multi-Family	0.392***	140,092	0.007
	(0.069)		
Homebuilders	0.932***	11,351	0.726
	(0.083)		
Condo	0.018	3,418	0.001
	(0.012)		
Office	0.202***	35,230	0.020
	(0.022)		
Mixed	0.024	1,856	0.001
	(0.028)		
Land Development	-0.025	2,797	0.000
	(0.041)		
Other	0.115***	25,414	0.002
	(0.039)		
Healthcare	0.031***	588	0.014
	(0.010)		
Warehouse/Distribution	0.147**	2,786	0.001
	(0.073)		