Expected Liquidation Values*

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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 the default risk of similar peer properties and liquidation values, even after controlling for current property values. Our results provide support for incomplete contracting theory and fire sale dynamics. Finally, our new measure of expected liquidation discounts can be used by policymakers to monitor fire sale risk in real time.

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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 peer distress within the same property type, and find evidence consistent with fire sale effects depressing 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 in default 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 discount, conditional on default, as a percentage of the current property value as follows:[3]

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

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 within-loan time-series 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 discounts, we also show that PDs are strong predictors of future realized default.

We next examine the relationship between ex-ante liquidation discounts 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 discounts rather than a proxy.

Consistent with these predictions, we find that liquidation values are significant predictors of loan amounts, maturities, and interest rates. Importantly, when we include both the liquidation value and current property value in the same specification, the liquidation value has a stronger relationship with these contract terms, suggesting 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 superior 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 27% 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 with incomplete contracting theory.

After analyzing how liquidation values relate to ex-ante contract terms, we next examine their time-series properties. First, we show that liquidation discounts 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 discount is faster for construction loans, where borrower-specific human capital is likely most important.[6]

We next show that changes in liquidation values and discounts 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. In our setting, the natural buyers of commercial real estate are typically other investors who specialize in the same property type. When these natural buyers face financial distress, they themselves are less likely to purchase assets in liquidation, further depressing liquidation values. We test this mechanism by examining the relationship between liquidation values and the default risk of similar properties. We find that increases in peer probabilities of default, calculated among loans secured by the same property type, are negatively related to liquidation values. Importantly, these effects hold even after controlling for changes in current property values, suggesting that peer distress affects expected liquidation values beyond its impact on fundamentals.

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

[6] 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.

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, our paper is the first to directly observe both the asset's market price 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 bodies of literature.

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)).[7] For example, Benmelech, Garmaise, and Moskowitz (2005) use zoning regulations as a proxy for commercial real estate liquidation discounts, showing that properties with more restrictive zoning—and thus lower redeployability—receive smaller loans with shorter maturities and higher interest rates. 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. Moreover, rather than relying on cross-sectional variation in redeployability measures that are typically time-invariant, our panel data allows us to study how, within-loan, expected liquidation values evolve and respond to different types of shocks. Finally, because we observe both current property values and expected liquidation values separately, we can quantify their relationships with ex-ante

[7]Degryse et al. (2025) estimate the elasticity of loan amounts to collateral value using bank-reported collateral values from the euro area credit registry; however, they observe only the current market value of collateral and cannot separate the roles of current values and liquidation values. 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.

contracting terms and market conditions, and test which matters more. 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) and 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.[8] Our analysis differs in several respects. First, we directly observe the asset's current market value and its expected liquidation value, whereas Kermani and Ma (2023) proxy for the current market 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 discounts 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 values.[9] Third, our measures of liquidation values and discounts 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

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

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

et al. (2017), Degryse et al. (2020)). Our data, measure of expected liquidation value, and focus differ in several important respects. First, their liquidation values are defined under normal market conditions at origination, not conditional on default, and therefore, do not incorporate fire sale discounts. Second, their data contain much less detail on loan characteristics, the underlying assets and ex post loan outcomes.[10] Third, they observe collateral valuations only at origination, while we observe them over the entire life of the loan. Fourth, their 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), Bernstein, Colonnelli, and Iverson (2019), Chernenko and Sunderam (2020), Demirci, Gurun, and Yönder (2020), Meier and Servaes (2019)).[11] 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)).[12] 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

[10]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.

[11]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.

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

Shleifer and Vishny (1992), we find that peer default rates among same-type properties predict changes in expected liquidation values even after controlling for changes in current property values. 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.[13]

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 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 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,[14] 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.[15] 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

[13]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)).

[14]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.

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

lot development, healthcare and warehouse/distribution properties.[16]

The data contains detailed information about the terms of the loans, such as the date of issuance, amount, interest rate, maturity, type, current value based on an appraisal, and the 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."[17] Importantly, the value of the collateral is based on the "best-use" market value outside of distress. Banks are expected to monitor the value of collateral frequently, 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 (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."[18] 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 the 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

[16] 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 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).

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

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

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 these instructions, in Appendix 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.[19]

To analyze asset-specific liquidation discounts, we restrict the sample to non-recourse loans collateralized by a single asset.[20] 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 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.[21]

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.[22] 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%.

[19]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 Howes and Weitzner (2025)) and public equity and bond returns (Beyhaghi, Howes, and Weitzner (2024)).

[20]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)).

[21]The data is available starting in 2010; however, the detailed recourse field is available only after 2014Q3 (Glancy et al. (2023)). Hence, we begin our sample in 2014Q3.

[22]Appendix Table C.1 provides separate summary statistics for income-producing and construction loans.

3.1 Definition of Liquidation Value and Discount

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

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 LGD and EAD realizations should affect the expected liquidation value, since both are reported as expectations. However, we believe this is a minimal concern for two reasons. First, banks and regulators do not consider this correlation important in practice.[23] Second, in Appendix Table C.2, we estimate the within-loan time series relationship between EAD and LGD in our sample and cannot reject the null that it is equal to zero.[24]

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

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

The expected liquidation discount 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 discounts may appear fairly high relative to the estimates in the literature on bankruptcy costs (e.g.,

[23] 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)).

[24] 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)).

Bris, Welch, and Zhu (2006) and Kermani and Ma (2023)). Indeed, Table 2, which displays summary statistics on expected liquidation discounts across different property types, shows that the average expected liquidation discount is about 66.5%.

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 that holds it.[25] 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.

Finally, one concern is that banks may have incentives to misreport these risk measures (e.g., Behn, Haselmann, and Vig (2022) and Plosser and Santos (2018)). For this reason, in most specifications, we include bank-by-time fixed effects, which control for potential aggregate underreporting of risk assessments by banks to reduce their capital requirements. Moreover, the risk-weighted capital requirements have been far from binding during our sample period, thereby reducing banks' incentives to manipulate their risk assessments (Greenwood et al. (2017), Walz (2024) and Dubois and Rintamäki (2025)).

4 Liquidation Values and Ex-ante Contract Terms

In this section, we analyze the relationship between expected liquidation values and ex-ante contract terms.[26] Because we are focused on ex-ante contract terms, we restrict the sample to new loans throughout this analysis. We follow a very similar approach to Benmelech, Garmaise, and Moskowitz (2005), who analyze the relationship between

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

[26]Henceforth, we refer to expected liquidation values (expected liquidation discounts) and liquidation values (liquidation discounts) interchangeably.

redeployability measures and loan contract terms, while controlling for the asset's current value; however, we use banks' actual expectations of the liquidation value 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 asset's liquidation value is higher, the lender is more comfortable extending credit to the borrower, since the lender's outside option is higher. Hence, these models would predict a positive relationship between liquidation values and total borrowing.[27]

To test this hypothesis, we estimate the following regression:

$$\begin{aligned} \text{Log(Loan Amount)}_i = \alpha + \beta_0 \text{Log(Current Value}_{i,t}) \\ + \beta_1 \text{Log(Liquidation Value}_{i,t}) + \delta_{b,t} + u_i, \end{aligned} \tag{2}$$

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. 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. We cluster our standard errors by county. The results are displayed in Table 3.

In columns (1) and (2), we first include the liquidation value and the current property value separately. The univariate coefficients are nearly identical (0.813 and 0.815, respectively), suggesting that both are strongly associated with loan size. However, when we include both variables jointly in column (3), the liquidation value coefficient (0.507) is larger than the current property value coefficient (0.383). In column (4), when we saturate the model with property type-quarter and county-quarter fixed effects, this gap widens further (0.538 vs. 0.360), and we can reject the null that the two coefficients are equal at the 10% significance level. Finally, in column (5), we again find similar results

[27]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)).

when we include the operating income-to-property value (i.e., cap rate), an important determinant of loan amounts (Titman, Tompaidis, and Tsyplakov (2005)), as an additional control.[28] These results suggest that the liquidation value has a stronger relationship with loan amounts than the current value of the collateral.[29]

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, whereas in Holmstrom and Tirole (1997) the current value of the project drives debt capacity due to the moral hazard problem. These results suggest that both components matter, but the liquidation value appears more important.

We next examine the relationship between expected liquidation values 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 regress the log of maturity at origination on the expected liquidation discount, controlling for the log of the loan amount. 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 discount and loan maturity. For example, in column (1), the estimated coefficient implies that a one standard deviation increase in the liquidation discount (14.8 percentage points) is associated with a 13.6% shorter maturity.

In columns (3) and (4), we separately analyze how the current property value and

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

[29]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 change, this should be reflected in changes in the 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.

liquidation value affect loan maturity, while controlling for loan 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 discounts. 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 discounts and interest rates in columns (1) - (3) of Table 5, estimating similar regressions to (2), 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)).[30] Across all specifications, the coefficient on liquidation discount is positive and statistically significant.

In columns (4) - (6), we reestimate the regression, but remove the expected liquidation discount 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.[31] 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

[30]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.

[31]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% significance level.

renegotiate the loan (e.g., Benmelech and Bergman (2008)).[32] To determine whether a loan has been modified, we follow the approach of Glancy, Kurtzman, and Loewenstein (2025) 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 discount 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 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-quarter fixed effects, we find a positive, statistically significant relationship between liquidation discounts and the likelihood that the loan is modified. In particular, the estimated coefficient of 0.322 implies that a one-standard-deviation increase in the liquidation discount (14.8 pp) increases the likelihood of the loan being modified by about 4.8 pp, which compares with an unconditional likelihood of 27 pp.

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. In contrast, the current property value has no statistically significant relationship with modifications in any specification. 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.

[32]Consistent with this idea, Dinc and Yönder (2022) find that most commercial real estate defaults are strategic, suggesting that borrowers actively use the threat of default as a bargaining tool.

In Table 7, we complement the cross-sectional analysis above by examining whether within-loan changes in liquidation values predict subsequent loan modifications. Using a panel specification with loan and bank-quarter fixed effects, we regress a dummy for whether the loan is modified in quarter t on the lagged liquidation value and other loan characteristics.[33] In column (1), the coefficient for lagged log liquidation value is negative and statistically significant (-0.061), while lagged log property value is close to zero and statistically insignificant. We find similar results in column (2), where we use the lagged liquidation discount rather than the liquidation value as the main predictor. These results reinforces the idea that higher liquidation values are associated with a lower likelihood of renegotiation.

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 Discounts and Loan Age

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

$$\text{Liquidation Discount}_{i,t} = \beta \text{Normalized Loan Age}_{i,t} + \alpha_i + \delta_t + u_{i,t},$$

where the main independent variable is the loan's age, normalized to the range $[0, 1]$ based on the loan's original maturity.[34] We include loan fixed effects (α_i) to test how

[33]We lag liquidation values and loan characteristics by one quarter, since the face value of debt and other loan characteristics may change in the quarter of renegotiation.

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

the expected liquidation discount changes as the remaining maturity on the loan reduces over time. We also include year-quarter (δ_t) fixed effects to control for any aggregate components of expected liquidation discounts. Once again, we cluster our standard errors by county.

The results are displayed in column (1) of Table 8. We find a negative and statistically significant relationship between the loan's age and the expected liquidation discount. This result is consistent with the idea that the borrower's expertise becomes less important over time, thereby reducing liquidation discounts. In column (2), we also control for the probability of default to address potential survivorship biases and find similar results.[35]

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 Normalized Loan Age 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.[36] 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.[37] In Appendix Table C.5, we confirm these results using actual loan age in years rather than normalized age, restricting the sample to the first five years after origination.

We also examine how liquidation values and property values evolve separately for construction and non-construction loans in Appendix Table C.6. For income-producing properties, liquidation values remain stable while property values decline gradually, consistent with physical depreciation narrowing the liquidation discount. For construction loans, liquidation values increase sharply as projects near completion, consistent with the

[35]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 discounts. By controlling for the probability of default, we mitigate such a bias.

[36]These results are also consistent with anecdotal evidence that uncompleted construction projects are extremely difficult to liquidate (e.g., Heitz, Martin, and Ufier (2022)).

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

resolution of borrower-specific human capital frictions.

5.2 Liquidation Values and Market Conditions

In this section, we examine whether liquidation values and discounts comove due to exposure to common shocks. In Table 9, we test the extent to which changes in market conditions affect expected liquidation values. In column (1), we regress changes in liquidation values on quarter fixed effects. The R-squared is 0.008, suggesting that aggregate economy-wide factors explain little of the changes in expected liquidation discounts. However, in column (2), when we regress changes in expected liquidation values on property type-quarter fixed effects, the R-squared jumps to 0.163. Similarly, in column (3), county-quarter fixed effects explain 0.167 of the variation in expected liquidation values. Finally, in column (4), when we include property type-county-quarter fixed effects, the R-squared is 0.356.

In Table 10, we find similar results when we conduct the same exercise but with changes in expected liquidation discounts as the dependent variable. We also re-estimate the regressions in Table 9, but replace the dependent variable with changes in property values. Interestingly, the property type-quarter fixed effects explain very little of the changes in the property's current value. Moreover, while county-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 discounts.[38] These results imply comovement in liquidation values across property types, even in different locations.

One potential source of comovement in liquidation 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.

[38]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.7 and C.8, we reestimate the specifications from Tables 9 and 10 but only include observations in which the LGD was updated and in Appendix Table C.9, we reestimate the specifications in Table C.9 but only include observations in which the current property value was updated.

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, an industry goes into distress in the first place because its business deteriorates. 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 (e.g., Franks et al. (2021)). 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 for fire sale effects, we exploit the fact that the natural buyers of commercial real estate assets are typically other investors and developers who specialize in the same property type. For example, the most likely buyers of a distressed office building are other office investors, and the most likely buyers of a distressed hotel are other hospitality firms. When these natural buyers themselves face financial distress, they are less able to bid for assets in liquidation, depressing expected recovery values. We proxy for the financial health of this natural buyer pool using the average probability of default among all other loans secured by the same property type. Intuitively, when the average default risk of other properties of the same type is high, the investors who would typically purchase these assets in liquidation are more likely to be financially constrained, reducing the expected liquidation value.

Specifically, we estimate the following regression:

$$\text{Log(Liquidation Value)}_{i,t} = \beta_1 \text{Peer PD}_{j,t}^{(-i)} + \beta_2 \text{PD}_{i,t} + \alpha_i + \delta_{b,t} + u_{i,t},$$

where Peer $\text{PD}_{j,t}^{(-i)}$ is the leave-one-out average probability of default among all other loans secured by the same property type j at date t. We include the loan's own probability of default to ensure that the peer effect is not simply capturing the loan's own credit risk. We also include loan fixed effects (α_i) and bank-quarter fixed effects ($\delta_{b,t}$), so the coefficient β_1 is identified from within-loan variation in peer default risk, after absorbing any bank-level time trends in banks' risk assessments.

The results are displayed in Table 12. In column (1), the coefficient on peer PD is

-0.006 and statistically significant, indicating that higher default rates among same-type properties reduce the expected liquidation value of an individual loan's collateral. This effect operates after controlling for the loan's own probability of default, which rules out the possibility that the result simply reflects common shocks to asset quality within a property type. In column (2), we additionally control for the current property value and find nearly identical results. This is important because it addresses the identification concern raised above: if higher peer default rates simply reflected deteriorating fundamentals for this type of property, we would expect this to be captured by changes in the property's current market value. The fact that the peer PD coefficient remains unchanged after controlling for the current value suggests that peer distress affects liquidation values through the availability of buyers rather than through the asset's first-best value. In columns (3) and (4), we replace the dependent variable with the liquidation discount and find consistent results: higher peer default rates are associated with higher expected liquidation discounts.[39]

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.

[39] In Appendix Table C.11, we complement this analysis by matching property types to their closest two-digit SIC industries and testing whether industry-level stock returns predict changes in liquidation values. Consistent with the peer default results, we find that industry-level stock returns positively predict changes in liquidation values even after controlling for contemporaneous changes in current property values.

We also exploit within-loan time-series variation in liquidation values to show that peer default rates among same-type properties reduce individual liquidation values, even after controlling for the loan's own default risk and current property value. This result is consistent with fire sale effects: when the natural buyers of an asset are themselves in distress, liquidation values decline.

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.[40]

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.

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

References

Altman, Edward I, 1984, A further empirical investigation of the bankruptcy cost question, *the Journal of Finance* 39, 1067–1089.

Andersen, Steffen and Kasper Meisner Nielsen, 2017, Fire sales and house prices: Evidence from estate sales due to sudden death, *Management Science* 63, 201–212.

Andrade, Gregor and Steven N Kaplan, 1998, How costly is financial (not economic) distress? evidence from highly leveraged transactions that became distressed, *The journal of finance* 53, 1443–1493.

Asarnow, Elliot and David Edwards, 1995, Measuring loss on defaulted bank loans: A 24-year study, *The Journal of Commercial Lending* 77, 11–23.

Auh, Jun Kyung and Mattia Landoni, 2022, Loan terms and collateral: Evidence from the bilateral repo market, *The Journal of Finance* 77, 2997–3036.

Barbiero, Francesca, Glenn Schepens, and Jean-david Sigaux, 2024, Liquidation value and loan pricing, *The Journal of Finance* 79, 95–128.

Basel Committee on Banking Supervision, 2023a, Cre: Calculation of rwa for credit risk — standardised approach: Individual exposures (cre20), Working paper, Bank for International Settlements.

Basel Committee on Banking Supervision, 2023b, Irb approach: minimum requirements to use irb approach (cre36), Working paper, Bank for International Settlements.

Behn, Markus, Rainer Haselmann, and Vikrant Vig, 2022, The limits of model-based regulation, *The Journal of Finance* 77, 1635–1684.

Benmelech, Efraim, 2009, Asset salability and debt maturity: Evidence from nineteenth-century american railroads, *The Review of Financial Studies* 22, 1545–1584.

Benmelech, Efraim, 2024, The benefits and costs of secured debt, *Annual Review of Financial Economics* 16, 325–342.

Benmelech, Efraim and Nittai K Bergman, 2008, Liquidation values and the credibility of financial contract renegotiation: Evidence from us airlines, *The Quarterly Journal of Economics* 123, 1635–1677.

Benmelech, Efraim and Nittai K Bergman, 2009, Collateral pricing, *Journal of financial Economics* 91, 339–360.

Benmelech, Efraim and Nittai K Bergman, 2011, Bankruptcy and the collateral channel, *The Journal of Finance* 66, 337–378.

Benmelech, Efraim, Mark J Garmaise, and Tobias J Moskowitz, 2005, Do liquidation values affect financial contracts? evidence from commercial loan contracts and zoning regulation, *The Quarterly Journal of Economics* 120, 1121–1154.

Benmelech, Efraim, Nitish Kumar, and Raghuram Rajan, 2022, The secured credit premium and the issuance of secured debt, *Journal of Financial Economics* 146, 143–171.

Benmelech, Efraim, Nitish Kumar, and Raghuram Rajan, 2024, The decline of secured debt, *The Journal of Finance* 79, 35–93.

Benmelech, Efraim, Nitish Kumar, and Raghuram G Rajan, 2025, Debt and assets, *Available at SSRN 5245950* .

Bernstein, Shai, Emanuele Colonnelli, and Benjamin Iverson, 2019, Asset allocation in bankruptcy, *The Journal of Finance* 74, 5–53.

Beyhaghi, Mehdi, 2022, Third-party credit guarantees and the cost of debt: Evidence from corporate loans, *Review of Finance* 26, 287–317.

Beyhaghi, Mehdi, Cesare Fracassi, and Gregory Weitzner, 2025, Adverse selection in corporate loan markets, *Journal of Finance* forthcoming.

Beyhaghi, Mehdi, Murray Z Frank, Ping McLemore, and Ali Sanati, 2024, Monetary policy and corporate investment: The equity financing channel, *Available at SSRN 4793393* .

Beyhaghi, Mehdi, Cooper Howes, and Gregory Weitzner, 2024, The information advantage of banks: evidence from their private credit assessments, *Available at SSRN* .

Black, Lamont K, John R Krainer, and Joseph B Nichols, 2020, Safe collateral, arm's-length credit: Evidence from the commercial real estate market, *The Review of Financial Studies* 33, 5173–5211.

Bris, Arturo, Ivo Welch, and Ning Zhu, 2006, The costs of bankruptcy: Chapter 7 liquidation versus chapter 11 reorganization, *The journal of finance* 61, 1253–1303.

Brunnermeier, Markus K and Lasse Heje Pedersen, 2009, Market liquidity and funding liquidity, *The review of financial studies* 22, 2201–2238.

Caballero, Ricardo J and Alp Simsek, 2013, Fire sales in a model of complexity, *The Journal of Finance* 68, 2549–2587.

Calomiris, Charles W, Mauricio Larrain, José Liberti, and Jason Sturgess, 2017, How collateral laws shape lending and sectoral activity, *Journal of Financial Economics* 123, 163–188.

Campbell, John Y, Stefano Giglio, and Parag Pathak, 2011, Forced sales and house prices, *American Economic Review* 101, 2108–2131.

Carty, Lea V., 1996, Defaulted bank loan recoveries., a moody's special report .

Catherine, Sylvain, Thomas Chaney, Zongbo Huang, David Sraer, and David Thesmar, 2022, Quantifying reduced-form evidence on collateral constraints, *The Journal of Finance* 77, 2143–2181.

Chaney, Thomas, David Sraer, and David Thesmar, 2012, The collateral channel: How real estate shocks affect corporate investment, *American Economic Review* 102, 2381–2409.

Chernenko, Sergey and Adi Sunderam, 2020, Do fire sales create externalities?, *Journal of Financial Economics* 135, 602–628.

Coval, Joshua and Erik Stafford, 2007, Asset fire sales (and purchases) in equity markets, *Journal of Financial Economics* 86, 479–512.

Davydenko, Sergei A, Ilya A Strebulaev, and Xiaofei Zhao, 2012, A market-based study of the cost of default, *The Review of Financial Studies* 25, 2959–2999.

Degryse, Hans, Olivier De Jonghe, Luc Laeven, and Tong Zhao, 2025, Collateral and credit, ECB Working Paper Series 3095, European Central Bank.

Degryse, Hans, Vasso Ioannidou, José María Liberti, and Jason Sturgess, 2020, How do laws and institutions affect recovery rates for collateral?, *The Review of Corporate Finance Studies* 9, 1–43.

Demirci, Irem, Umit G Gurun, and Erkan Yönder, 2020, Shuffling through the bargain bin: Real-estate holdings of public firms, *Review of Finance* 24, 647–675.

Dinc, S and Erkan Yönder, 2022, Strategic default and renegotiation: Evidence from commercial real estate loans, Working paper, Working Paper, Rutgers University.

Dubois, Basile and Paul Rintamäki, 2025, Banking under large excess reserves, *Working Paper* .

Eckbo, B Espen and S Karin Thorburn, 2008, Automatic bankruptcy auctions and fire-sales, *Journal of Financial Economics* 89, 404–422.

Ellul, Andrew, Chotibhak Jotikasthira, and Christian T Lundblad, 2011, Regulatory pressure and fire sales in the corporate bond market, *Journal of Financial Economics* 101, 596–620.

Franks, Julian, Oren Sussman, and Vikrant Vig, 2017, The privatization of bankruptcy: Evidence from financial distress in the shipping industry, *Unpublished, London Business School* .

Franks, Julian R, Gunjan Seth, Oren Sussman, and Vikrant Vig, 2021, Decomposing fire sale discounts, *European Corporate Governance Institute–Finance Working Paper* .

Gan, Jie, 2007, Collateral, debt capacity, and corporate investment: Evidence from a natural experiment, *Journal of Financial Economics* 85, 709–734.

Gavazza, Alessandro, 2010, Asset liquidity and financial contracts: Evidence from aircraft leases, *Journal of financial Economics* 95, 62–84.

Gavazza, Alessandro, 2011, The role of trading frictions in real asset markets, *American Economic Review* 101, 1106–1143.

Glancy, David, Robert Kurtzman, and Lara Loewenstein, 2025, The value of renegotiation frictions: Evidence from commercial real estate, *Journal of Financial Intermediation* 62, 101144.

Glancy, David, Robert Kurtzman, Lara Loewenstein, and Joseph Nichols, 2023, Recourse as shadow equity: Evidence from commercial real estate loans, *Real Estate Economics* 51, 1108–1136.

Glancy, David and Robert J Kurtzman, 2024, Determinants of recent cre distress: Implications for the banking sector .

Glover, Brent, 2016, The expected cost of default, *Journal of Financial Economics* 119, 284–299.

Greenwood, Robin, Jeremy C Stein, Samuel G Hanson, and Adi Sunderam, 2017, Strengthening and streamlining bank capital regulation, *Brookings Papers on Economic Activity* 2017, 479–565.

Gromb, Denis and Dimitri Vayanos, 2002, Equilibrium and welfare in markets with financially constrained arbitrageurs, *Journal of financial Economics* 66, 361–407.

Gupta, Arun, Horacio Sapriza, and Vladimir Yankov, 2022, The collateral channel and bank credit, Working paper, Federal Reserve Bank of Richmond.

Handbook, Comptroller's, 2013, Other real estate owned .

Harris, Milton and Artur Raviv, 1990, Capital structure and the informational role of debt, *The journal of finance* 45, 321–349.

Hart, Oliver and John Moore, 1994, A theory of debt based on the inalienability of human capital, *The Quarterly Journal of Economics* 109, 841–879.

Heitz, Amanda, Christopher Martin, and Alexander Ufier, 2022, Bank monitoring with on-site inspections, *FDIC Center for Financial [Research Paper No. 2022-09]. http://dx. doi. org/10.2139/ssrn* 4197344.

Holmstrom, Bengt and Jean Tirole, 1997, Financial intermediation, loanable funds, and the real sector, *the Quarterly Journal of economics* 112, 663–691.

Howes, Cooper and Gregory Weitzner, 2025, Bank information production over the business cycle, *Review of Economic Studies* forthcoming.

Huang, Sheng, Matthew C Ringgenberg, and Zhe Zhang, 2023, The information in asset fire sales, *Management Science* 69, 5066–5086.

Hughes, Samuel and Joseph Nichols, 2025, No news is bad news: Monitoring, risk, and stale financial performance in commercial real estate, *FEDS Working Paper* .

Johnston Ross, Emily, Joseph Nichols, and Lynn Shibut, 2021, Determinants of losses on construction loans: Bad loans, bad banks, or bad markets?, *FDIC Center for Financial Research Paper* .

Kermani, Amir and Yueran Ma, 2020, Two tales of debt, Working paper, National Bureau of Economic Research.

Kermani, Amir and Yueran Ma, 2023, Asset specificity of nonfinancial firms, *The Quarterly Journal of Economics* 138, 205–264.

Kim, Hyunseob and Howard Kung, 2017, The asset redeployability channel: How uncertainty affects corporate investment, *The Review of Financial Studies* 30, 245–280.

Kiyotaki, Nobuhiro and John Moore, 1997, Credit cycles, *Journal of political economy* 105, 211–248.

Lian, Chen and Yueran Ma, 2021, Anatomy of corporate borrowing constraints, *The Quarterly Journal of Economics* 136, 229–291.

Liberti, José M and Atif R Mian, 2010, Collateral spread and financial development, *The journal of finance* 65, 147–177.

Lorenzoni, Guido, 2008, Inefficient credit booms, *The Review of Economic Studies* 75, 809–833.

Luck, Stephan and Joao AC Santos, 2024, The valuation of collateral in bank lending, *Journal of Financial and Quantitative Analysis* 59, 2038–2067.

Maksimovic, Vojislav and Gordon Phillips, 1998, Asset efficiency and reallocation decisions of bankrupt firms, *The Journal of Finance* 53, 1495–1532.

Meier, Jean-Marie and Henri Servaes, 2019, The bright side of fire sales, *The Review of Financial Studies* 32, 4228–4270.

Pence, Karen M, 2006, Foreclosing on opportunity: State laws and mortgage credit, *Review of Economics and Statistics* 88, 177–182.

Plosser, Matthew C and Joao AC Santos, 2018, Banks' incentives and inconsistent risk models, *The Review of Financial Studies* 31, 2080–2112.

Pulvino, Todd C, 1998, Do asset fire sales exist? an empirical investigation of commercial aircraft transactions, *The Journal of Finance* 53, 939–978.

Ramcharan, Rodney, 2020, Banks' balance sheets and liquidation values: Evidence from real estate collateral, *The Review of Financial Studies* 33, 504–535.

Ramey, Valerie A and Matthew D Shapiro, 2001, Displaced capital: A study of aerospace plant closings, *Journal of political Economy* 109, 958–992.

Rampini, Adriano A and S Viswanathan, 2025, Collateral and secured debt, Working paper, National Bureau of Economic Research.

Shleifer, Andrei and Robert Vishny, 2011, Fire sales in finance and macroeconomics, *Journal of economic perspectives* 25, 29–48.

Shleifer, Andrei and Robert W Vishny, 1992, Liquidation values and debt capacity: A market equilibrium approach, *The journal of finance* 47, 1343–1366.

Shleifer, Andrei and Robert W Vishny, 2010, Asset fire sales and credit easing, *American Economic Review* 100, 46–50.

Stein, Jeremy C, 2012, Monetary policy as financial stability regulation, *The Quarterly Journal of Economics* 127, 57–95.

Thorburn, Karin S, 2000, Bankruptcy auctions: costs, debt recovery, and firm survival, *Journal of financial economics* 58, 337–368.

Titman, Sheridan, Stathis Tompaidis, and Sergey Tsyplakov, 2005, Determinants of credit spreads in commercial mortgages, *Real Estate Economics* 33, 711–738.

Walz, Stefan, 2024, Monetary policy complementarity: Bank regulation and interest rates, *Columbia Business School Research Paper* .

Warner, Jerold B, 1977, Bankruptcy costs: Some evidence, *The journal of Finance* 32, 337–347.

Weiss, Lawrence A, 1990, Bankruptcy resolution: Direct costs and violation of priority of claims, *Journal of Financial Economics* 27, 285–314.

Weitzner, Gregory, 2020, Margin lending and information production, *Working Paper* .

Williamson, Oliver E, 1988, Corporate finance and corporate governance, *The journal of finance* 43, 567–591.

Table 1: Summary Statistics

This table contains summary statistics. Panel A includes new loans, while Panel B includes both new and existing loans. For variable definitions, see Appendix Section A.

Panel A: New Loans						
	N	Mean	Std Dev	P25	Median	P75
Interest Rate (%)	35,501	4.177	1.363	3.250	3.930	4.850
Loan Amount ($mm)	40,215	15.033	36.150	1.728	4.043	15.000
Property Value ($mm)	37,527	28.896	99.434	2.860	7.700	25.400
Cap Rate	24,516	0.051	0.024	0.041	0.051	0.060
Maturity (months)	40,147	158.289	135.280	60.000	121.000	360.000
Loan-to-Value Ratio	37,274	0.598	0.181	0.500	0.625	0.727
Probability of Default (%)	29,383	0.944	2.109	0.270	0.530	0.930
Loss Given Default (%)	28,714	31.735	12.975	24.000	31.000	41.000
Exposure at Default ($mm)	28,626	15.238	34.101	1.708	4.979	16.331
Construction Loan	40,215	0.341	0.474	0.000	0.000	1.000
Loan Modified	40,215	0.272	0.445	0.000	0.000	1.000
Realized Default (%)	40,215	0.895	9.419	0.000	0.000	0.000
Panel B: New and Existing Loans						
	N	Mean	Std Dev	P25	Median	P75
Interest Rate (%)	451,853	4.152	1.478	3.240	3.840	4.750
Loan Amount ($mm)	467,437	12.187	25.062	1.757	3.515	10.916
Property Value ($mm)	461,296	25.833	62.994	3.700	8.350	24.000
Cap Rate	373,420	0.053	0.027	0.040	0.051	0.065
Remaining Maturity (months)	464,274	114.156	121.534	28.000	63.000	129.000
Loan-to-Value Ratio	456,707	0.525	0.193	0.408	0.550	0.660
Probability of Default (%)	328,569	2.171	8.989	0.230	0.480	1.050
Loss Given Default (%)	323,795	27.320	12.584	19.000	25.000	37.000
Exposure at Default ($mm)	319,720	13.737	26.461	1.801	3.988	13.733
Construction Loan	467,438	0.193	0.395	0.000	0.000	0.000
Loan Modified	467,438	0.472	0.499	0.000	0.000	1.000
Realized Default (%)	467,438	3.370	18.045	0.000	0.000	0.000

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

This table displays summary statistics of expected liquidation discounts, as calculated in (1), by different property types.

Liquidation Discounts by Property Type								
	N	Mean	Std Dev	P10	P25	Median	P75	P90
Retail	2,612	0.654	0.149	0.486	0.553	0.632	0.740	0.896
Industrial	1,778	0.683	0.160	0.482	0.575	0.675	0.811	0.908
Hotel/Hospitality/Gaming	780	0.649	0.131	0.488	0.573	0.649	0.717	0.807
Multi-Family	12,839	0.649	0.138	0.495	0.554	0.627	0.729	0.868
Homebuilders	1,536	0.774	0.145	0.568	0.683	0.778	0.897	0.960
Condo	167	0.830	0.182	0.548	0.690	0.943	0.975	0.975
Office	2,650	0.645	0.149	0.479	0.546	0.622	0.726	0.892
Mixed	282	0.729	0.157	0.529	0.600	0.727	0.883	0.935
Land Development	400	0.655	0.166	0.435	0.530	0.657	0.769	0.904
Other	2,595	0.688	0.148	0.509	0.592	0.673	0.781	0.916
Healthcare	9	0.612	0.174	0.282	0.562	0.600	0.630	0.896
Warehouse/Distribution	94	0.729	0.145	0.547	0.632	0.768	0.858	0.895
Total	25,742	0.665	0.148	0.494	0.562	0.645	0.762	0.898

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. 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 (3) - (5). 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(Loan Amount)				
	(1)	(2)	(3)	(4)	(5)
Log(Liquidation Value)	0.813***		0.507***	0.538***	0.627***
	(0.009)		(0.039)	(0.045)	(0.062)
Log(Property Value)		0.815***	0.383***	0.360***	0.297***
		(0.021)	(0.046)	(0.048)	(0.062)
Cap Rate					2.912***
					(0.616)
Bank-Quarter FE	Y	Y	Y	Y	Y
Property Type-Quarter FE				Y	Y
County-Quarter FE				Y	Y
P-value			0.145	0.054	0.008
Observations	27,847	37,409	25,770	20,376	15,887
Adj. R-squared	0.890	0.867	0.928	0.943	0.960

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 (3) - (4). 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 Discount	-0.919***	-0.604***		
	(0.093)	(0.100)		
Log(Loan Amount)	-0.138***	-0.139***	-0.164***	-0.129***
	(0.007)	(0.008)	(0.021)	(0.022)
Log(Property Value)			-0.103***	-0.080***
			(0.017)	(0.021)
Log(Liquidation Value)			0.131***	0.072***
			(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	25,614	20,266	25,722	20,332
Adj. R-squared	0.579	0.726	0.573	0.723

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 Discount	0.157*	0.174***	0.300***			
	(0.091)	(0.063)	(0.075)			
Probability of Default	2.923***	2.434***	2.236***	2.733***	2.306***	2.045***
	(0.384)	(0.401)	(0.488)	(0.359)	(0.384)	(0.482)
Cap Rate			3.447***			2.400***
			(0.601)			(0.542)
Log(Property Value)				-0.070***	-0.049***	0.003
				(0.014)	(0.015)	(0.014)
Log(Liquidation Value)				-0.109***	-0.099***	-0.155***
				(0.016)	(0.016)	(0.024)
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				0.159	0.059	0.000
Observations	23,679	18,570	14,730	23,767	18,630	14,762
Adj. R-squared	0.709	0.795	0.818	0.730	0.805	0.829

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 Discount	0.322***	0.322***	0.331***			
	(0.037)	(0.059)	(0.085)			
Log(Maturity)	-0.071***	-0.081***	-0.094***	-0.076***	-0.085***	-0.096***
	(0.006)	(0.007)	(0.010)	(0.006)	(0.007)	(0.010)
Log(Loan Amount)	0.041***	0.035***	0.033***	0.105***	0.115***	0.170***
	(0.004)	(0.005)	(0.005)	(0.010)	(0.013)	(0.022)
Cap Rate			-0.475*			-1.204***
			(0.274)			(0.268)
Log(Property Value)				0.008	0.003	-0.010
				(0.005)	(0.007)	(0.009)
Log(Liquidation Value)				-0.074***	-0.086***	-0.131***
				(0.011)	(0.016)	(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	25,614	20,266	15,613	25,722	20,332	15,651
Adj. R-squared	0.247	0.302	0.281	0.244	0.302	0.285

Table 7: Liquidation Values and Loan Modifications: Time Series Evidence

This table examines whether lagged liquidation values predict future loan modifications. The dependent variable is an indicator that equals 1 if the loan is modified in quarter t. Standard errors are clustered by county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Loan Modification$_t$	
	(1)	(2)
Log(Liquidation Value$_{t-1}$)	-0.061***	
	(0.021)	
Log(Property Value$_{t-1}$)	0.011	
	(0.008)	
Log(Probability of Default$_{t-1}$)	0.001	0.001
	(0.000)	(0.000)
Log(Normalized Loan Age$_{t-1}$)	0.187***	0.196***
	(0.015)	(0.014)
Log(Remaining Maturity$_{t-1}$)	-0.001***	-0.001***
	(0.000)	(0.000)
Log(Liquidation Discount$_{t-1}$)		0.264***
		(0.071)
Loan FE	Y	Y
Bank-Quarter FE	Y	Y
Observations	261,731	260,311
Adj. R-squared	0.488	0.485

Table 8: Liquidation Discounts over the Life of the Loan

In this table, we examine how expected liquidation discounts evolve over the life of the loan. The dependent variable, Normalized Loan Age, 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 Discount			
	(1)	(2)	(3)	(4)
Normalized Loan Age	-0.033***	-0.034***	-0.006	-0.007
	(0.003)	(0.003)	(0.006)	(0.005)
Probability of Default (%)		0.001***		0.001***
		(0.000)		(0.000)
Construction Loan			0.058***	0.057***
			(0.008)	(0.008)
Construction Loan × Normalized Loan Age			-0.111***	-0.112***
			(0.012)	(0.012)
Year-Quarter FE	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y
Observations	293,345	292,142	293,345	292,142
Adj. R-squared	0.865	0.866	0.867	0.868

Table 9: 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	270,549	270,520	260,686	235,122
R-squared	0.008	0.163	0.167	0.356

Table 10: Aggregate Changes in Liquidation Discounts

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

	Δ Liquidation Discount			
	(1)	(2)	(3)	(4)
Quarter FE	Y			
Property Type×Quarter FE		Y		
County×Quarter FE			Y	
Property Type×County×Quarter FE				Y
Observations	266,767	266,757	257,042	232,022
R-squared	0.016	0.193	0.171	0.367

Table 11: 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 Current 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	269,416	269,406	259,567	233,941
R-squared	0.005	0.016	0.062	0.135

Table 12: Peer Default Rates and Liquidation Values

This table examines whether peer default rates (average PD of other loans with the same property type) predict changes in individual loan liquidation values. The dependent variable is Log(Liquidation Value) in columns (1)-(2) and Liquidation Discount in columns (3)-(4). All specifications include loan and bank-quarter fixed effects. Standard errors are double-clustered by year-quarter and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(Liquidation Value)		Liquidation Discount	
	(1)	(2)	(3)	(4)
Probability of Default (%)	-0.002***	-0.002***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Peer PD	-0.006***	-0.006***	0.002***	0.002***
	(0.002)	(0.002)	(0.000)	(0.000)
Log(Property Value)		0.108***		0.017***
		(0.020)		(0.004)
Bank-Quarter FE	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y
Observations	299,124	296,081	294,332	294,309
Adj. R-squared	0.964	0.965	0.863	0.864

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.

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 Discount: 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.

Loss Given Default (LGD): The estimated average loss given default per dollar of expected loan exposure, 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 (2025). From Y-14Q.

Loan Modification: A dummy variable equal to one if the loan is modified in the quarter. We consider a loan to be modified according to the definition in Glancy, Kurtzman, and Loewenstein (2025). 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.

Normalized Loan Age: 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.10 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' 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.[41] 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 control for 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 Howes and Weitzner (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 is statistically significant, and the R-squared is 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

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

as the dependent variable, rather than the banks' estimate of EAD at default.[42] 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-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 0.740 and statistically significant with an R-squared of 0.807. 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 0.476 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 property valuations every quarter, in column (2) we reestimate the regression, restricting the sample to loan quarters in which the property price was updated. The coefficient remains statistically significant and increases to 0.362. 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 are updating the

[42]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.

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

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 (%)	1.174***	0.885***	0.517***
	(0.137)	(0.146)	(0.129)
Log(Loan Amount)		-6.227***	-6.741***
		(0.542)	(0.665)
Loan-to-Value Ratio		19.599***	22.268***
		(4.607)	(2.880)
Bank-Quarter FE	Y	Y	
Bank-Quarter-Property Type FE			Y
Observations	29,273	27,091	25,804
Adj. R-squared	0.451	0.466	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)	(0.026)
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 Allowances for Loan Losses, in logs. The independent variable is the expected loss ($PD \times LGD \times EAD$), in logs. 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)	0.740***	0.476***
	(0.022)	(0.033)
Bank-Quarter FE	Y	Y
Loan FE		Y
Observations	2,092	126,234
Adj. R-squared	0.807	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	0.033***	0.362***		
	(0.005)	(0.060)		
Log(Housing Price Index)			0.173***	0.302***
			(0.020)	(0.033)
Sample	All loans	Property updated	All loans	Property updated
Quarter FE	Y	Y	Y	Y
Loan FE			Y	Y
Observations	387,077	26,079	444,658	43,718
Adj. R-squared	0.004	0.049	0.982	0.922

Appendix C. Additional Tables and Figures

Table C.1: Summary Statistics by Loan Type

This table compares the characteristics of income-producing loans (Panel A) versus construction loans (Panel B) at origination. Income-producing loans are secured by properties that generate rental or operating income, while construction loans finance property development.

Panel A: Income-Producing Loans						
	N	Mean	Std Dev	P25	Median	P75
Interest Rate (%)	23,656	4.166	1.349	3.310	4.000	4.840
Loan Amount ($mm)	26,505	19.390	41.331	2.981	7.500	21.375
Property Value ($mm)	24,795	37.728	113.562	6.000	14.000	36.500
Cap Rate	24,049	0.051	0.023	0.041	0.051	0.060
Maturity (months)	26,458	152.696	116.966	61.000	121.000	181.000
Loan-to-Value Ratio	24,705	0.557	0.177	0.466	0.589	0.674
Probability of Default (%)	22,399	0.890	2.248	0.300	0.480	0.750
Loss Given Default (%)	22,393	31.997	11.862	24.000	30.000	41.000
Exposure at Default ($mm)	22,405	17.809	36.563	2.425	6.820	20.250
Loan Modified	26,505	0.244	0.429	0.000	0.000	0.000
Panel B: Construction Loans						
	N	Mean	Std Dev	P25	Median	P75
Interest Rate (%)	11,845	4.201	1.390	3.250	3.750	4.900
Loan Amount ($mm)	13,710	6.609	20.570	1.260	1.702	3.000
Property Value ($mm)	12,732	11.698	59.828	1.742	2.435	4.237
Cap Rate	467	0.040	0.046	0.000	0.038	0.061
Maturity (months)	13,689	169.099	164.481	19.000	60.000	361.000
Loan-to-Value Ratio	12,569	0.681	0.159	0.596	0.714	0.797
Probability of Default (%)	6,984	1.117	1.570	0.270	0.690	1.620
Loss Given Default (%)	6,321	30.809	16.285	14.000	33.000	41.000
Exposure at Default ($mm)	6,221	5.980	20.666	0.672	1.500	3.998
Loan Modified	13,710	0.326	0.469	0.000	0.000	1.000

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	-0.041
	(0.052)
Bank-Quarter FE	Y
Loan FE	Y
Observations	300,693
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.

	Log(Loan Amount)				
	(1)	(2)	(3)	(4)	(5)
Log(Liquidation Value)	0.814***		0.509***	0.538***	0.626***
	(0.009)		(0.039)	(0.045)	(0.062)
Probability of Default (%)	0.008***	0.023***	0.026***	0.027***	0.024***
	(0.003)	(0.007)	(0.004)	(0.004)	(0.004)
Probability of Default Squared (%)	-0.000*	-0.001**	-0.001***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(Property Value)		0.817***	0.383***	0.362***	0.299***
		(0.024)	(0.046)	(0.048)	(0.062)
Cap Rate					2.946***
					(0.607)
Bank-Quarter FE	Y	Y	Y	Y	Y
Property Type-Quarter FE				Y	Y
County-Quarter FE				Y	Y
P-value			0.141	0.056	0.009
Observations	27,734	27,167	25,659	20,283	15,835
Adj. R-squared	0.890	0.855	0.929	0.943	0.960

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 extended at any point over the life of the loan. 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 Discount	0.225***	0.313***	0.480***			
	(0.050)	(0.076)	(0.102)			
Log(Maturity)	-0.025***	-0.031***	-0.043***	-0.028***	-0.035***	-0.046***
	(0.003)	(0.004)	(0.007)	(0.003)	(0.003)	(0.007)
Log(Loan Amount)	0.005***	0.005***	0.012***	0.069***	0.093***	0.206***
	(0.002)	(0.002)	(0.003)	(0.014)	(0.017)	(0.030)
Cap Rate			0.595**			-0.197
			(0.269)			(0.146)
Log(Property Value)				0.007	0.008	0.013
				(0.006)	(0.007)	(0.009)
Log(Liquidation Value)				-0.071***	-0.098***	-0.210***
				(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	25,614	20,266	15,613	25,722	20,332	15,651
Adj. R-squared	0.296	0.351	0.248	0.301	0.358	0.288

Table C.5: Liquidation Discounts Over the Life of the Loan: First Five Years

This table estimates a version of Table 8 by using loan age in years, rather than normalized age and restricting the sample to the first five years after origination. The dependent variable is the expected liquidation discount. Standard errors are clustered by county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Expected Liquidation Discount			
	(1)	(2)	(3)	(4)
Loan Age	-0.013^{***}	-0.013^{***}	-0.012^{***}	-0.012^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Probability of Default (%)		0.000^{***}		0.000^{***}
		(0.000)		(0.000)
Construction Loan			0.046^{***}	0.047^{***}
			(0.008)	(0.008)
Construction Loan × Loan Age			-0.099^{***}	-0.101^{***}
			(0.007)	(0.007)
Loan FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Observations	227,696	226,675	227,696	226,675
Adj. R-squared	0.82	0.82	0.83	0.83

Table C.6: Loan Value Evolution: Construction vs. Non-Construction

This table examines how liquidation values and property values evolve differently for construction loans versus income-producing properties using normalized loan age. Columns (1)-(2) examine log liquidation values, while columns (3)-(4) examine log property values. Standard errors are clustered by county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(Liquidation Value)		Log(Property Value)	
	(1)	(2)	(3)	(4)
Normalized Loan Age	-0.057	0.701***	-0.136***	0.110*
	(0.051)	(0.077)	(0.029)	(0.065)
Log(Current Maturity)	0.013**	0.110***	-0.008**	0.031*
	(0.005)	(0.014)	(0.004)	(0.016)
Probability of Default (%)	-0.002***	0.000	-0.004***	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)
Sample	Income Producing	Construction	Income Producing	Construction
Loan FE	Y	Y	Y	Y
Bank-Quarter FE	Y	Y	Y	Y
Observations	255,227	41,150	261,187	45,622
Adj. R-squared	0.977	0.917	0.985	0.965

Table C.7: 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	44,104	44,081	39,121	32,871
R-squared	0.081	0.161	0.310	0.405

Table C.8: Aggregate Changes in Liquidation Discounts (Updated LGD)

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

	Δ Liquidation Discount			
	(1)	(2)	(3)	(4)
Quarter FE	Y			
Property Type×Quarter FE		Y		
County×Quarter FE			Y	
Property Type×County×Quarter FE				Y
Observations	43,660	43,639	38,704	32,532
R-squared	0.114	0.194	0.334	0.419

Table C.9: 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 Current 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	17,181	17,138	13,952	11,237
R-squared	0.060	0.111	0.259	0.303

Table C.10: 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.11: Industry Shocks and Liquidation Value

This table tests the relationship between aggregate industry-level stock returns and changes in liquidation values, liquidation discounts and current project values. We assign each property type to an industry using the mapping in Table C.10. In column (1), the dependent variable is the percentage change in the expected liquidation value, in column (2), the dependent variable is the change in the liquidation discount and in column (3), 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 Discount	Δ Property Value
	(1)	(2)	(3)
Industry Return	0.191**	-0.088**	-0.000
	(0.075)	(0.035)	(0.003)
Δ Property Value	0.129***		
	(0.026)		
Δ Housing Price Index	0.202*	-0.094*	0.044***
	(0.113)	(0.051)	(0.015)
Δ Probability of Default	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Year-Quarter FE	Y	Y	Y
Observations	220,157	223,911	233,754
Adj. R-squared	0.023	0.032	0.006