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Default Costs and Repayment of Underwater Mortgages

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Abstract

We explore an overlooked phenomenon in mortgage markets: repayment of underwater mortgages. Using a sample of mortgages terminated between 2007 and 2016, we show that such repayment indeed occurs, and that it is affected by the same factors commonly used in studies of default: the magnitude of home equity and the borrower's credit score, which captures default cost as well as liquidity. A novel insight is that underwater repayers, unlike most defaulters, are not liquidity constrained, providing a much cleaner environment to study default costs. We estimate lower bounds on these costs. Our results indicate that default costs are substantial.

I. Introduction

Suppose that a homeowner's mortgage is underwater, with the loan balance exceeding the house value. The homeowner accepted a job in another city and therefore wants to terminate the mortgage. Termination could be achieved by defaulting or by selling the house and repaying the mortgage.[1] Along with transferring the sale proceeds to the lender, repayment in this situation would require an additional out-of-pocket payment to the lender equal to the homeowner's negative equity. Whether repayment is preferable to default depends on the magnitude of

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[1]Unless otherwise specified, the term "default" will be used throughout the article to refer to a delinquency that ultimately leads to foreclosure. Consequently, "default" and "foreclosure" will be used interchangeably.

negative equity (and thus the size of the required out-of-pocket payment) along with the magnitude of "default costs," which capture the various penalties associated with default.[2] While repayment of an underwater mortgage may be an unfamiliar notion, intuition suggests that paying off, say, $15,000 of negative equity could make sense for many borrowers. Doing so, for example, would allow our homeowner to secure immediate mortgage financing in the new location, rather than enduring the mortgage blacklisting that would result from default (one of its various costs). The homeowner might be reluctant, however, to pay off $75,000 of negative equity.

The first contribution of this article is to show that repayment of underwater mortgages *actually occurs*. In mortgage data sets commonly used in the literature, it is not possible to distinguish between loans that terminate through refinancing and those that are repaid. However, our unique data enable us to draw this distinction, thereby facilitating the identification of underwater mortgage repayment. As might be expected, though, the phenomenon is rare relative to default. The second contribution is to explore the determinants of underwater repayment. While home equity and default costs are recognized as determinants of default in the existing mortgage literature, we explore their role in the repayment of underwater mortgages. Both contributions are new to the literature. Our third contribution, which may be the most important, is the use of our simple theoretical framework, along with data on negative equity and house values for mortgage repayers, to estimate lower bounds on borrower default costs for repayers. Our results suggest that default costs are substantial.

To achieve these goals, we restrict our analysis to mortgages that have been terminated, either by default, repayment, or refinancing.[3] The literature on mortgage default, by contrast, uses data without this restriction, including mortgages with ongoing payments (current mortgages). In addition, we focus on termination that involves vacating the house, as happens with our homeowner, thus narrowing the sample to terminations that occur either by default or repayment, omitting loans that are refinanced.[4] Our empirical results thus show the factors that favor repayment over default for the set of borrowers who vacate the house upon termination of the loan.

Following the literature, default costs are partly captured by the borrower's credit score, reflecting the belief that people with good credit have more to lose from default than those whose credit is bad. This assumption is consistent with the work of Brevoort and Cooper (2013), who track credit scores in the years after default. They find that borrowers with higher scores before the event have larger score declines, often ending up in the subprime category regardless of their pre-default status. Furthermore, recovery to the initial status on average takes several years longer for those who initially had high scores. The borrower's credit score, however, may also be a proxy for liquidity, which can affect default and repayment

[2]Section II discusses various financial and nonfinancial costs associated with default.

[3]Because refinancing also involves the repayment of the existing mortgage, our use of "repayment" should be understood as the act of paying off the mortgage by selling the property.

[4]This omission partly reflects the relative scarcity of negative-equity loans, which constitute our main focus, among loans that are refinanced. Among such loans, only 4.4% have negative equity, while among loans that are repaid, 8.0% have negative equity, making them almost twice as common.

behavior. Greater liquidity will make paying off an underwater mortgage easier while also making default due to trigger events, such as a job loss, less likely.

Consistent with the view that default is less likely for borrowers with high default costs and high liquidity, our results show that a higher credit score makes a borrower more likely to repay an underwater loan.[5] In addition, repayment is more likely the larger (the less negative) the level of equity. These results thus show that the choice between repayment and default for borrowers with negative equity who are also vacating their house is a response to these same focal variables that have been shown to affect default in the existing literature. While this conclusion is perhaps natural, it provides a new insight into the behavior of mortgage borrowers. As discussed further below, our regressions also include a host of other variables that may affect borrower decisions.

While the concept of default cost is acknowledged in the mortgage default literature, it remains a subject of significant debate. Some models suggest minimal or even nonexistent default costs, whereas others imply substantial costs. Consequently, obtaining precise empirical evidence on the scale of default costs is of critical importance. However, recent studies indicate that most mortgage defaults are associated with liquidity constraints due to factors such as job loss or unforeseen expenses (Ganong and Noel (2023), Low (2023a)). This association complicates the task of estimating default costs for defaulters. However, a novel insight in our article is that underwater prepayers are not liquidity constrained, providing a much cleaner environment for the examination of default costs. By applying our theoretical framework, we can then estimate lower bounds on borrower default costs for repayers, showing that they are indeed substantial. In addition, by showing that lower bounds rise across credit-score quintiles, our analysis suggests that default cost is larger for the most credit-worthy borrowers than for borrowers in the lowest quintile, a finding that appears to validate our underlying view. This conclusion appears new to the literature and is a useful contribution of the article. But even if one doubts a connection between default costs and credit scores drawn solely from the behavior of lower bounds, the large sizes of these bounds reinforce previous work that shows even larger default costs, using approaches more complex than ours.[6] The existence of significant default costs helps to shed greater light on default behavior, where resistance to default among borrowers whose loans are substantially underwater has sometimes proved puzzling.

The literature on mortgage default, which is now vast, is well synthesized and surveyed by Foote, Gerardi, and Willen (2008) and Foote and Willen (2018). Within this literature, papers that focus on the role of default costs are particularly

[5]The credit score in our data is measured at the time of loan origination, not at termination. In the robustness section, we discuss why this approach is unlikely to be problematic.

[6]Using a structural model, Ganong and Noel (2023) deduce a "utility cost" from default equal to \$100,000. The default cost in Laufer (2018), again estimated via a structural model, equals 29% of permanent income, while Kaplan, Mitman, and Violante (2020) (also using a structural model) estimate the "disutility" from default equal to a 30% loss in annual consumption. Scharlemann and Shore (2016) note the modest reduction in default rates among Home Affordable Modification Program (HAMP) participants who obtained substantial principal reduction, which the authors attribute in part to high default costs.

relevant to our work. Early contributions in this area include Kau, Keenan, and Kim (1993), (1994), Riddiough and Thompson (1993), and Quigley and Van Order (1995). More recent work by Bajari, Chu, and Park (2008), Elul, Souleles, Chomsisengphet, Glennon, and Hunt (2010), Kau, Keenan, Lyubimov, and Slawson (2011), and Gyourko and Tracy (2014) includes borrower credit scores, as we do, in its default regressions. From a different perspective, Brueckner, Calem, and Nakamura (2012) show that, by reducing default concerns, strong state-level house-price appreciation allows more borrowers with poor credit scores (and thus low default costs) to secure mortgages in the state.[7]

Much of the advancement in the recent literature lies in clarifying the role of "trigger events" such as job loss, which affect the affordability of mortgage payments, in generating defaults. The traditional approach, which we follow, is to include the unemployment rate as a regression covariate (at the state level), expecting a negative repayment effect (see, e.g., Bajari et al. (2008), Goodman, Ashworth, Landy, and Yin (2010), Elul et al. (2010), and Gyourko and Tracy (2014)). Using newer approaches, Bhutta, Dokko, and Shan (2017) estimate default models with and without negative-equity covariates, viewing the gap in predictions as due to trigger events. Gerardi, Herkenhoff, Ohanian, and Willen (2018) use data that allow measurement of financial stress at the individual borrower level, thereby precisely capturing trigger events. Ganong and Noel (2023), who also have access to individual income (bank account) data, use defaults by above-water (positive-equity) borrowers in response to income losses to gauge the contribution of trigger events to default by underwater borrowers, finding it to be large relative to the effect of negative equity. Similarly, using survey data matched to mortgage data, Low (2023a) shows that nearly all mortgage defaults involve a liquidity shock (e.g., job loss, divorce, health shocks), and that above-water defaults induced by trigger events are not uncommon. In a related contribution, Low (2023) presents a theoretical model with liquidity shocks and psychic moving costs to explain above-water defaults. Ganong and Noel (2023) and Low's (2023), (2023a) investigations of positive-equity defaults are new to the literature, and the existence of such defaults by itself reveals the power of trigger events, showing that negative equity is not a default prerequisite, with a negative trigger often sufficient. By contrast, our motivating example for negative equity repayment can be thought of as a *positive trigger*. Moving to a new job in another city without the burden of mortgage blacklisting makes use of out-of-pocket funds to pay off the existing debt worthwhile.[8]

[7]Brueckner (2000) investigates distortions to the mortgage market when default costs are private information, unobservable to lenders.

[8]Using a wealth of data from the Chicago area, Diamond, Guren, and Tan (2020) provide comprehensive results on the effect of foreclosure on a host of post-foreclosure outcome variables, including dwelling size, neighborhood income, school quality, divorce, crimes committed, DUI convictions, and bankruptcies, all of which may be tied to unmeasured trigger events causing a default. For outcomes more connected to our view of default costs, they show a reduction in subsequent mortgage originations and greater unpaid collections (perhaps due to reduced credit access) but find little effect on credit scores, noting that such impacts may occur earlier, with the onset of loan delinquency.

As explained in more detail in Section III, our study sample comes from ABSNet,[9] a data provider that covers non-agency mortgages, capturing around 90% of the non-agency market during our sample period.[10] ABSNet records whether a loan terminates through foreclosure, but it does not distinguish between terminations that result from refinancing versus loans that are repaid when the owner vacates (sells) the property. To facilitate this distinction, we merge the mortgage data with deeds data from RealtyTrac to track ownership changes. For non-foreclosures, a mortgage termination that occurs with an ownership change indicates a property sale (repayment). After various exclusions, our final sample includes around 383,000 (469,000) loans that had negative (positive) equity at termination and were originated in the 2001–2007 period but terminated between 2007 and 2016 (as noted, termination is either by repayment or default). Our study thus includes mortgage terminations from the beginning of the great financial crisis in 2007, which led to the world's second-worst economic recession, through the subsequent economic and housing market recovery. This is an ideal period in which to explore our research question, for two reasons. First, as home prices cratered after the 2001–2007 housing market boom, many borrowers with mortgages originated during that period found themselves owing far more than their houses were worth. In addition, as the economic crisis deepened, many underwater borrowers also experienced unemployment. With this "double-trigger" event (negative equity along with unemployment) the conditions were ripe for widespread mortgage defaults. As in Ganong and Noel (2023) and Low (2023a), our sample also includes defaults by above-water borrowers, and we compare regression results for the above-water subsample to those for underwater loans.

Our motivating example focused on the choice between repayment and default for a negative-equity borrower who needs to terminate a mortgage in order to accept a job in another city. While our borrower is thus a mobile individual with good job opportunities, such unobservable borrower characteristics in reality are likely to differ between repayers and defaulters. Defaulters may have poorer labor-market opportunities and may be defaulting precisely because of a trigger event such as a job loss, which has occurred on top of an underwater mortgage. Repayers need not be as mobile as in our example (they may have simply bought another house in the same city), but a negative trigger event presumably plays no role in their mortgage termination. With unobservables likely to differ in these ways across defaulters and

[9]The ABSNet data were compiled by Lewtan Technologies, which sourced the data from trustees and servicers. The company was acquired by Moody's Analytics in 2014. ABSNet data has been used to study mortgage fraud (Griffin and Maturana (2016), Kruger and Maturana (2021)), the importance of mortgage originators having skin in the game (Demiroglu and James (2012)), mortgage servicer incentives (Diop and Zheng (2023)), the impact of state foreclosure laws on mortgage default (Demiroglu, Dudley, and James (2014)), mortgage modifications (Agarwal, Amromin, Ben-David, Chomsisengphet, Piskorski, and Seru (2017), Maturana (2017), Conklin, Diop, Le, and D'Lima (2019), and Korgaonkar (2025)), and the role of subprime borrowers in driving the housing boom (Conklin, Frame, Gerardi, and Liu (2022)).

[10]Non-agency mortgages are conventional mortgages not purchasable by the government-sponsored enterprises (GSEs): the Federal National Mortgage Association (Fannie Mae) and the Federal Home Loan Mortgage Corporation (Freddie Mac). They include loans to low-credit borrowers (subprime mortgages), loans exceeding the GSE lending limits (jumbo mortgages), and loans with deficient income/asset documentation (Alt-A mortgages).

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repayers, omitted variable bias becomes a possible threat. The absence in our data of any borrower characteristics aside from the credit score limits our ability to address this threat, but the inclusion of the state unemployment rate and median income is a rough attempt to control for trigger events, as in a number of previous papers. The upshot is that our motivating example depicts a much cleaner statistical context than we actually confront, requiring some caution in interpreting our results.[11]

Another crucial point to note is that, since our analysis is *conditional* on the termination of the mortgage, an option-based analysis like those common in the mortgage literature[12] plays no role. While this option approach, which considers the future evolution of interest rates and house prices, is needed to decide *whether* an ongoing mortgage should be terminated, the borrowers in our sample have *already made* a termination decision. Therefore, option elements such as future interest rate volatility are not relevant to our analysis. Instead, our goal is to analyze which termination method, repayment or default, is chosen *conditional on the mortgage being terminated.*[13]

The plan of the article is as follows: Section II presents a simple model of strategic default and repayment in the presence of default costs, while Section III discusses the data. Section IV presents descriptive statistics and highlights notable patterns in the data. Section V presents the regression results, while Section VI presents our attempt to gauge the magnitude of default costs. Section VII offers conclusions.

II. An Elementary Mortgage-Termination Model with Default Costs

This section presents a simple strategic model of default and repayment that frames our empirical question: if a mortgage is to be terminated, either by repayment or default, which is the best choice for the borrower? While the default option, which involves future opportunities, plays no role, the cost of default is crucial. As noted above, one element of default cost is mortgage blacklisting, which prevents the borrower from securing a new mortgage for a number of years following a default. Additional costs come from a reduction in the borrower's credit rating, which may raise the interest rate charged on other borrowing (such as car loans)

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[11] An alternative to repaying an underwater loan when vacating the house is renting out the property in anticipation that rising prices might eventually erase the negative equity. However, since all loans in our sample have been terminated, such borrowers are not included.

[12] See Deng, Quigley, and Van Order (2000) for a canonical study.

[13] It is worth noting that the existence of underwater mortgage repayment may help to explain mortgage servicer and lender decisions regarding short sales, where the lender allows the borrower to sell the property at a transaction price below the outstanding mortgage balance (short sales are not present in our sample). The shortfall is generally forgiven by the lender, who agrees to the short sale to avoid costs associated with foreclosure, and the damage to the borrower's credit is less than with a foreclosure. Because of these benefits to borrowers and lenders, many commentators questioned why short sales were not more common, and informational asymmetries related to underwater repayment may help to resolve this puzzle. Lenders want to avoid offering a short sale to borrowers who would fully repay an underwater mortgage, but this intention is unobserved by the lender, possibly reducing the level of short sales in equilibrium. This outcome is analogous to the "information theory" put forth by Adelino, Gerardi, and Willen (2013) in analyzing mortgage modifications.

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while making it harder to acquire new credit cards. Guilt from abrogating a financial contract may also be an element of default cost, as seen in Guiso, Sapienza, and Zingales (2013). While moving costs are a component of default cost when the choice is between default (which requires relocation) and mortgage continuation (which does not), moving costs play no role in the choice between repayment and default conditional on termination, since both choices require relocation.

Consider our homeowner from the introduction, who is moving to a different city and thus needs to terminate a mortgage. Suppose initially that the default cost is absent, and let P denote the value of the house and M the mortgage balance. Then, defaulting on the mortgage is preferable to repayment when

$$P < M, \tag{1}$$

with repayment preferred otherwise. Letting E denote home equity, which is given by $E = P - M$, the rule in (1) becomes $E < 0$, so that default is preferred when equity is negative, with the mortgage underwater, a familiar strategic-default rule that also maximizes the borrower's net worth. To see this point, let A denote other financial assets, $A + E$ represents our borrower's net worth after selling the house and repaying the mortgage, which generates positive proceeds when $E > 0$ but requires an out-of-pocket payment when $E < 0$. By contrast, net worth after default equals A since both the housing asset and the mortgage debt then disappear. Thus, when equity is negative, default is preferred since it yields a net worth of A instead of the smaller value of $A + E$ resulting from repayment.

Letting the default cost be denoted C, net worth in the event of default becomes $A - C$ rather than A. Now default is preferred when

$$E < -C, \text{ or } E + C < 0, \tag{2}$$

which requires that equity is negative enough to dominate the positive cost of default. The key implication of (2) is that a larger default cost makes (2) harder to satisfy, militating against default and in favor of repayment. With C mainly represented by the borrower's credit score in the regression, it follows that a larger credit score makes default less likely, and repayment more likely, when the mortgage is terminated. Larger (less-negative or more-positive) equity also makes (2) harder to satisfy, yielding the same conclusions.

It is crucial to note from (2) that repayment of the mortgage may be optimal when equity is negative. For this outcome to occur, equity must be less negative than the negative of default costs, or $E > -C$ with $E < 0$. In this case, the underwater loan is repaid – a borrower decision that is the focus of this article.

This conclusion may be overturned if the borrower faces a liquidity constraint, lacking the out-of-pocket funds needed to pay off an underwater mortgage. Letting L (liquidity) denote the amount of such funds, repayment of an underwater loan (with $E < 0$) requires

$$E + C > 0 \text{ and } L > -E. \tag{3}$$

The first inequality (the reverse of (2)) says that repayment is preferred, while the second inequality says that liquidity is large enough to pay off the negative equity.

The implication is that $E+C>0$ is no longer sufficient for repayment of a negative-equity loan; enough liquidity is also required. Note that, in the presence of trigger events such as a job loss, which reduce the ability to make mortgage payments, adequate borrower liquidity may reduce default. However, because our model is not rich enough to capture both strategic and trigger-based default, it does not contain this other channel.

This framework also omits the transaction cost of selling the house as a cost of mortgage repayment. Ignoring the liquidity issue for the moment and letting transaction cost be denoted T, net worth after repaying the mortgage equals $A+E-T$, with $E-T$ negative when $E<0$. With net worth under default again equal to $A-C$, repayment is then optimal when

$$E-T>-C \text{ or } -E+T<C. \tag{4}$$

When a liquidity constraint is reintroduced, repayment of a negative-equity loan requires satisfaction $L>-E+T$, indicating that liquidity is large enough to cover negative equity along with the transaction cost of selling the house. In addition, (4) must be satisfied, so that repayment requires the joint satisfaction of

$$-E+T<C \text{ and } -E+T<L. \tag{5}$$

The two conditions in (5) are both satisfied when $-E+T<min\{C,L\}$ or $-E+T-min\{C,L\}<0$. Multiplying through by -1, repayment is then optimal when

$$E-T+min\{C,L\}>0. \tag{6}$$

Therefore, in a full model that includes both transaction cost and a liquidity constraint, repayment is optimal when equity minus transaction cost plus the smaller of default cost and liquidity is positive.

To translate this framework into a regression context using a probit or linear probability model, the first step is to replace the 0 on the RHS of (6) with an error term ϵ (possibly capturing optimization error), so that the inequality becomes $E-T+min\{C,L\}>\epsilon$. Then letting F denote the cumulative distribution function of ϵ, the probability of repayment equals

$$\text{Prob}(repayment)=1-F(E-T+min\{C,L\}). \tag{7}$$

Given the presence of the min function, C only affects the repayment probability if $C<L$, while liquidity only affects the repayment probability if $L<C$.

Obstacles in estimating (7) are that C is unobservable and that L, while observable in principle, cannot be measured because data on the liquid assets of borrowers are lacking. As explained above, we address the first obstacle by using the borrower's credit score as a proxy for default cost. But since borrowers with high credit scores are more likely to be liquid, the credit score may also serve as a proxy for L. Therefore, the credit score can be viewed as capturing the effect on repayment of the entire $min\{C,L\}$ expression in (7), obviating the need to consider the (nonlinear) effects of its separate components. Thus, the credit score, denoted S, can capture the effects of both default cost and liquidity on mortgage repayment.

In addition to using S as a proxy, transaction cost T in (7) is proxied by the property value P, given that realtor commissions (the main cost component) amount to 6% of the house value. Other variables such as income and unemployment (measured at the state level), which may affect default cost and help to capture trigger events, are represented by a vector X that also includes additional controls. Making these substitutions and appending coefficients to all the variables, (7) becomes

$$\text{(8)} \qquad \text{Prob}(\textit{repayment}) = 1 - F(\alpha E + \beta P + \gamma S + X\theta).$$

We estimate (8) using a linear probability model, expecting positive effects for E and S and a negative effect for P.

It is important to note that the inclusion of transaction cost in this framework is crucial in gaining insight into positive-equity defaults, which we consider along with the most recent literature discussed above. In the model without T, such a choice cannot be optimal, because if equity is positive, then $E > -C$ holds and (2) cannot be satisfied, making repayment the preferred termination choice. But in the presence of transaction cost, if E is positive but small, then $E - T$ can be negative in (4), and if sufficiently negative, it can be less than $-C$. In this situation, the default is the preferred termination choice even though $E > 0$. When defaulting, the borrower avoids the transaction cost of selling the house, although the default cost must be borne. Thus, if E, T, C are properly aligned, the default choice can be preferred for an above-water mortgage. Ganong and Noel (2023) and Low (2023), (2023a) also acknowledge this argument as an explanation for positive-equity defaults, as these mortgages are effectively underwater once transaction costs are considered.[14]

III. Data

The mortgage data used in this study are from ABSNet, a non-agency mortgage data provider. ABSNet tracks loans from origination to termination, reporting whether a loan was voluntarily repaid by the borrower or foreclosed. Our initial sample includes first-lien mortgages that were outstanding at the end of 2007 with their final status recorded in the ABSNet loan history data file at the end of March 2016, the last reporting month available.[15] In addition to the loan origination data, we also collected from ABSNet the loans' balance and status at termination.

However, ABSNet misses a crucial piece of information about repaid loans that is required for this study. It does not specify whether the repayment of a loan was due to the sale or the refinancing of the property. ABSNet does note if a loan is a refinancing or purchase loan at origination, but the source of repayment when it is terminated is not given. Since, in the context of this study, it is important that we

[14]Transaction costs alone are unlikely to fully explain above-water defaults. Ganong and Noel (2023) and Low (2023), (2023a) show that default with substantial positive equity (e.g., larger than reasonable estimates of transaction costs) is not uncommon, likely due to a combination of borrower liquidity constraints and housing search frictions.

[15]This right-hand truncation of the sample should not be a major issue because 98.1% of the mortgages terminated before this date.

accurately identify the source of repayment at termination, we merge ABSNet and data from RealtyTrac.[16] RealtyTrac uniquely identifies the property subject to a lien and provides information on the lien, including the type of lien, the loan amount if applicable, and its purpose (purchase or refinancing). By matching ABSNet to RealtyTrac, we are able to track the next lien on the property and the purpose of the loan associated with that lien, which was used to repay the first loan. Our final sample consists of ABSNet-RealtyTrac matched loans derived in the following manner.

In this section, we provide an overview of our sample construction and merging procedures, while a more detailed description is available in Supplementary Material Section A. We started with an initial sample of about 5 million first-lien purchase and refinancing home mortgages originated in the continental U.S. between 2001 and 2007. These are loans appearing in the ABSNet December 2007 loan update file and the March 2016 ABSNet loan history file.[17] As discussed above, we matched these loans to the RealtyTrac lien (recorder) data in order to identify the nature of the termination (repaid, refinanced, or foreclosed). We performed this match using property location (zip code), lien type, loan amount (in thousands), origination date, loan purpose (refinancing or purchase), and number of units. After removing from our initial ABSNet sample loans with a missing number of units (525,000), those with missing loan purpose (312,000), and loans with zip codes not present in RealtyTrac (404,000), we end up with our "*matching sample*" of 3.78 million ABSNet loans. After matching these loans with RealtyTrac liens and keeping unique matches where the lien registration date in RealtyTrac is within 60 days of the loan origination date in ABSNet, we end up with 1.41 million loans. Section A of the Supplementary Material provides a detailed description of our data matching procedure.

The match rate of our ABSNet matching sample was 37.3%, which is better than the 30% success rate achieved by Diop et al. (2023) when matching RealtyTrac to McDash, a broader mortgage origination and servicing data set. One potential concern with the match rate is selection bias. To address this issue, we compare several key characteristics of our matched loans with the unmatched loans from the original sample of 5 million loans and find some differences in average loan

[16]RealtyTrac is a real estate information company that compiles mortgage liens sourced from public records and property assessment data sourced from municipal real estate assessment offices. RealtyTrac was owned by ATTOM Data Solutions, a company that provides publicly recorded data about mortgages, deeds, taxes, and foreclosures nationwide. In 2022, ATTOM sold the foreclosure business, along with the RealtyTrac brand name, to Nations Info Corp. The RealtyTrac data used in this study, which consist of property liens (i.e., recorder data) and property assessments (i.e., assessor data), are now part of the residential real estate data package marketed by ATTOM. RealtyTrac data are widely used in academic research, particularly in the mortgage literature (Mian, Sufi, and Trebbi (2015), Fogel, Kali, and Yeager (2011), Gerardi and Li (2010), Ferreira, Gyourko, and Tracy (2010), and Diop, Yavas, and Zhu (2023)).

[17]Our sample is restricted to loans with amounts between $50,000 and $5 million, appraised property value between $50,000 and $10 million, loan-to-value ratio between 25 and 125, and non-missing property zip code, and borrower credit score. We drop loans with missing loan balance information at the time of termination. We also drop loans on properties with more than 4 units but keep those with missing number of units initially.

characteristics, though they appear modest in economic magnitude (see Supplementary Material Table A1).

Our initial 1.41 million ABSNet-RealtyTrac matched loans include 743,000 (52.7%) voluntarily paid-off loans, 641,000 (45.4%) loans involuntarily terminated through foreclosure, and 27,000 (1.9%) loans still active at the end of our study period. Having identified voluntarily paid-off loans, we next determine the nature of their repayment (repaid from property sale or refinanced) by matching their termination dates to lien registrations in RealtyTrac using the properties' unique identifiers from the first match. This way, we were able to identify the source of repayment of 401,000 loans out of the 743,000 paid-off loans, of which 107,000 (26.7%) involved the sale of the property, with the remaining 294,000 loans terminated through refinancing. However, these identified paid-off loans do not include cash sales; they are only loan terminations partly financed with refinancing or a purchase mortgage. Despite this limitation, this match rate of 54% likely produces a representative sample because the average characteristics of matched and unmatched loans are similar (Supplementary Material Table A2). Finally, we use the RealtyTrac assessor data to identify 73,000 additional terminations involving property sales, which may capture cash sales. Again, we provide a detailed description of our matching procedure in the Supplementary Material.[18]

Because this study primarily focuses on terminations where the property is vacated, we use the subsample of 821,000 loans that were terminated by either repayment following the sale of the property or foreclosure, consisting of 641,000 foreclosures and 180,000 (107,000 + 73,000) repayments from property sales. Therefore, our final sample regroups loans that were terminated following these three mutually exclusive events: i) a positive equity property sale, ii) a foreclosure, or iii) a negative-equity property sale where the seller pays the lender for any shortfall between the mortgage balance and the sales proceeds. This third type of termination, which is largely ignored in the literature, is distinct from a short sale,[19] where the lender absolves the borrower for the shortfall.[20]

As is apparent in our discussion above, a critical piece of information required for our analysis is the borrower's equity position, or their perception of it, when the

[18]Of the loans that terminated voluntarily without a clearly identifiable method (repaid at sale or refinanced), some were likely paid off early through curtailments (McCollum, Lee, and Pace (2015)). Additionally, some of these loans may have been transferred to other servicers, but unfortunately, our data do not allow us to observe such servicing transfers. Observations where we cannot identify the method of termination are not included in our analysis.

[19]In this article, we focus on the *borrower's* decision regarding mortgage repayment upon vacating the property. Conversely, short sales necessitate lender approval, placing the decision-making authority in the hands of the lender rather than the borrower. Consequently, short sales, where the lender absolves the borrower for the shortfall, are excluded from our analysis as they fall within the lender's purview. It is worth noting that underwater repayers and defaulters in our sample may have pursued (but ultimately failed to engage in) short sales before opting for repayment or foreclosure.

[20]In theory, a borrower with an underwater mortgage can pay down the principal balance to refinance. However, merely eliminating negative equity is unlikely to be enough. The borrower must also bring the loan-to-value (LTV) ratio below the current underwriting guidelines. For example, if the guidelines allow for 80% LTV refinance loans, a borrower with 110% LTV needs to reduce the loan not by 10%, but by 30% of the property value to meet the criteria. Consequently, underwater mortgage refinances are rare (see footnote 4). Our findings are unchanged when we include loans that terminated through refinance (not reported).

loan was terminated, which, for simplicity, we take as the value of the property minus the outstanding loan balance at termination. Because there is no independent valuation (appraisal) of the property at termination, we must derive our own value estimate or use an outside automated valuation model (AVM) estimate.[21] We use the former approach to derive our main value estimate by marking to market the original appraised value reported in ABSNet using changes in the Census tract house price index (HPI) from the Federal Housing Finance Agency (FHFA) and the 5-digit zip code HPI from FHFA for properties with missing census tract HPIs.[22] After dropping short sales and observations with missing tract and zip code HPIs, we end up with 733,000 loans.[23] We measure equity as the difference between the mark-to-market value of the property and the combined balance of the first mortgage and the second mortgage, if any, at termination.

Identifying second mortgages is possible because ABSNet reports lien type, loan-to-value (LTV) ratio, combined loan-to-value (CLTV) ratio, and other typical loan origination information (e.g., origination date, loan type, loan amount, maturity date, interest rate, property type, occupancy type, and payment status at termination). To identify the remaining balance at termination on a second mortgage, we match the first and second liens using the loan origination date, property type, number of units, appraised value, and occupancy type. For the loans with matched second liens, we use the combined balance of the first and second liens at loan termination when computing borrower equity. For the remaining loans with CLTV greater than LTV, we use the amount of the first mortgage, LTV, and CLTV at origination to estimate the balance on the missing second mortgage at termination.[24]

IV. Descriptive Statistics and Notable Patterns

Table 2 presents the descriptive statistics for our final study sample, showing average variable values for the full sample as well as for the subsamples of positive- and negative-equity loans. The descriptions of the variables, not all of which are used in the regressions reported below, are in Table 1. Around 23% of the loans were repaid via property sale, while 77% were terminated in foreclosure. The average equity in the full sample, defined in this article as the ratio of equity (updated property value minus loan balance at termination) to the updated property value (*Equity Ratio*), is −9%. In the sample, 51% of loans experience negative equity based on our measure. As expected, borrowers' propensity to repay loans varies significantly with equity. As seen in the first 2 rows of Table 2,

[21]Alternatively, we could use the borrower's estimate of the value of the property. However, this information is unobservable in our data.

[22]The FHFA census tract and 5-digit zip code HPIs are annual series. We use a linear approximation to estimate the HPI at the loan's termination month.

[23]We drop short sales because the borrower does not have to repay any balance remaining on the loan after the sale of the property. Our initial study sample of 821,000 loans contains 46,000 short sales and 45,000 loans with missing local HPIs.

[24]We estimate the amount of the second mortgage at origination as $First\ Mortgage/LTV \times (CLTV - LTV)$. We use then the average amortization speed of the matched second liens in our sample to estimate the balance of the missing second mortgages at termination.

TABLE 1

Variable Descriptions

Table 1 presents variable names, descriptions, and data source.

Variable	Description	Source
Repaid	A binary variable set to 1 if the loan is terminated with the sale of the property	ABSNet/ RealtyTrac
Foreclosed	A binary variable set to 1 if the loan is terminated with the foreclosure of the property	ABSNet
Credit Score	The primary borrower's FICO score at loan origination divided by 100	ABSNet
Property Value	The estimated value (HPI adjusted appraised value) of the property at termination in ten thousand dollars ($0000 s)	ABSNet (estimated)
Negative Equity	A binary variable set to 1 if the estimated value of the property is less than the loan balance at termination	ABSNet (estimated)
Equity Amount	The HPI-adjusted appraised value minus the first and second mortgage loan balance at termination in ten thousand dollars ($0000 s)	ABSNet (estimated)
Equity Ratio	The ratio of HPI-adjusted appraised value minus loan balance at termination to the updated property value at termination	ABSNet (estimated)
Recourse	A binary variable equal to 1 if the loan is originated in a state allowing deficiency judgments	Ghent and Kudlyak (2011)
Original LTV	The loan-to-value (LTV) ratio of the loan at origination	ABSNet
Loan Amount	The loan amount at origination in ten thousand dollars ($0000 s)	ABSNet
Refinancing Loan	A binary variable set to 1 for refinancing loans	ABSNet
Non-Owner Occupancy	A binary variable equal to 1 if the property is not occupied by the owner	ABSNet
Occupancy Unknown	A binary variable equal to 1 if the occupancy of the property is unknown	ABSNet
Interest Rate	Original interest rate on the loan	ABSNet
Loan Term	The natural log value of the original loan term	ABSNet
DTI	Total debt-to-income ratio at origination	ABSNet
DTI Missing	A binary variable equal to 1 if DTI information is missing	ABSNet
Borrower Income	Estimated at origination using DTI and annual loan payment, in thousands ($000s)	ABSNet (estimated)
PMI	A binary variable equal to 1 if private mortgage insurance was required	ABSNet
PMI Missing	A binary variable equal to 1 if PMI information is missing	ABSNet
Neg. Amortization	A binary variable identifying mortgages with negative amortization	ABSNet
ARM	A binary variable identifying adjustable-rate mortgages	ABSNet
Balloon	A binary variable identifying mortgages with a balloon payment structure	ABSNet
Interest Only	A binary variable equal to 1 if the mortgage includes interest-only payments	ABSNet
Interest Only Missing	A binary variable identifying mortgages with missing interest-only information	ABSNet
Single Family	A binary variable identifying single-family properties	ABSNet
Inflation	Monthly consumer price index at loan termination	St. Louis Fed
Mortgage Rates	Monthly average 30-year fixed-rate mortgage rate at loan termination	St. Louis Fed
Unemployment Rate	Annual state unemployment rate	BLS
HPI End	Quarterly 3-digit zip code house price index at loan origination	FHFA
HPI Origination	Quarterly 3-digit zip code house price index at loan termination	FHFA
HPI Volatility	Standard deviation of quarterly 3-digit house price index over 20 quarters at loan termination	FHFA
Median Income	State median annual income of homeowners 2007–2011 and 2012–2016 in thousand dollars ($000s)	ACS

4% of our terminated negative-equity loans were repaid, with the rest being foreclosures. While repayment of underwater loans is therefore not very common, the volume of such loans is not inconsequential, justifying our focus on this phenomenon. As in Ganong and Noel (2023) and Low (2023a), we also observe a relatively high rate of positive-equity (above-water) foreclosures in Table 2. Only 44% of our positive-equity loans were repaid, a surprisingly low share. The high frequency of positive-equity foreclosure may suggest that other trigger events, such as unemployment, were significant drivers of foreclosure during the sample period. Alternatively, these positive-equity foreclosures could be the result of high transaction costs (T) or low default costs (C), as seen in our model.

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TABLE 2

Descriptive Statistics

Table 2 presents descriptive statistics for the full sample, the negative equity sample, and the positive equity sample.

Variable	Full Sample		Negative-Equity Loans		Positive-Equity Loans	
	No. of Obs.	Mean	No. of Obs.	Mean	No. of Obs.	Mean
Repaid	732,611	0.233	374,363	0.039	358,248	0.436
Foreclosed	732,611	0.767	374,363	0.961	358,248	0.564
Credit Score (00s)	732,611	6.694	374,363	6.646	358,248	6.744
Equity Amount ($0000s)	732,611	1.965	374,363	−7.284	358,248	11.629
Equity Ratio	732,611	−0.086	374,363	−0.389	358,248	0.230
Negative Equity	732,611	0.511	374,363	1.000	358,248	0.000
Recourse	732,611	0.554	374,363	0.445	358,248	0.668
Property Value ($0000s)	732,611	31.755	374,363	23.346	358,248	40.542
Original CLTV	732,611	83.368	374,363	87.265	358,248	79.296
Original LTV	732,611	78.872	374,363	82.074	358,248	75.525
Loan Amount ($0000 s)	732,611	30.327	374,363	30.135	358,248	30.528
Refinancing Loan	732,611	0.516	374,363	0.485	358,248	0.548
Non-Owner Occupancy	732,611	0.142	374,363	0.133	358,248	0.152
Occupancy Unknown	732,611	0.007	374,363	0.006	358,248	0.008
Interest Rate	732,600	6.719	374,358	6.729	358,242	6.710
Loan Term (ln)	717,921	5.907	364,214	5.933	353,707	5.881
DTI	732,611	0.012	374,363	0.015	358,248	0.009
DTI Missing	732,611	0.759	374,363	0.737	358,248	0.781
PMI	732,611	0.081	374,363	0.072	358,248	0.090
PMI Missing	732,611	0.295	374,363	0.303	358,248	0.287
Neg. Amortization	732,611	0.123	374,363	0.169	358,248	0.074
ARM	732,611	0.716	374,363	0.814	358,248	0.615
Balloon	732,611	0.093	374,363	0.130	358,248	0.055
Interest Only	732,611	0.315	374,363	0.369	358,248	0.258
Interest Only Missing	732,611	0.019	374,363	0.020	358,248	0.018
Single Family	732,611	0.963	374,363	0.964	358,248	0.961
Inflation	732,611	221.908	374,363	221.314	358,248	222.529
Mortgage Rates	732,611	4.790	374,363	4.738	358,248	4.844
Unemployment Rate	732,611	8.610	374,363	9.505	358,248	7.674
HPI End	732,611	196.189	374,363	186.439	358,248	206.378
HPI Origination	732,611	244.279	374,363	271.302	358,248	216.042
HPI Volatility	732,611	27.108	374,363	35.161	358,248	18.693
Median Income ($000s)	732,611	78.673	374,363	71.301	358,248	86.377

Table 3 shows a somewhat different loan breakdown. Of loans that were repaid, 9% had negative equity, with the remaining 91% being above water. Of foreclosed loans, almost two-thirds (64%) had negative equity, with the remainder being above water.

Returning to Table 2, the summary statistics show that our sample is overwhelmingly made up of single-family, owner-occupied properties: 96% single-family and roughly 85% owner-occupied. The average borrower has a credit score of 669 at origination, which indicates that our sample consists not only of subprime mortgages but also Alt-A and jumbo loans, which typically were associated with higher credit scores than subprime loans.[25] Table 2 shows no substantial differences

[25]Supplementary Material Table A3 presents a comparison of summary statistics between our ABSNet sample and more recent loan origination data from the National Survey of Mortgage Originations (NSMO). Conducted by the Federal Housing Finance Agency (FHFA) in collaboration with the Consumer Financial Protection Bureau (CFPB), the NSMO survey collects data on a nationally representative sample of newly originated closed-end, first-lien mortgages. The loans in the NSMO data set were originated between 2013 and 2020. Differences in summary statistics between the ABSNet and NSMO samples further highlight that the ABSNet sample primarily consists of subprime and Alt-A lending from the early-to-mid 2000s and is not necessarily representative of more recent mortgage lending trends.

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TABLE 3

Loan Termination by Borrower Equity Position

Our study sample in Table 3 includes loans showing in the ABSNet January 2008 loan update dataset that were terminated by the end as reported in the ABSNet March 2016 loan history database, the end of the study period, matched to loans in the RealtyTrac Recorder database, which allows us to link loans to properties to identify if loans were repaid with the sale of the property or refinanced. "*Repaid*" designates loans repaid from the sale of the property, whereas "*Foreclosed*" identifies loans whose properties were foreclosed due to borrower delinquency. We separately report loan statuses for the full sample and by borrower equity position (*"Positive Equity"* or *"Negative Equity"*) based on the estimated property values at loan termination—the adjusted appraisal values of the properties using tract house price indices (HPI), or 5-digit zip code HPIs for locations with missing tract numbers, from the Federal Housing Finance Agency (FHFA).

	Full Sample	Negative-Equity Loans		Positive-Equity Loans	
	No. of Obs.	No. of Obs.	%	No. of Obs.	%
Repaid	170,941	14,693	8.60	156,248	91.40
Foreclosed	561,670	359,670	64.04	202,000	35.96
Total	732,611	374,363	51.10	358,248	48.90

in property type, occupancy, and credit scores at origination between terminated positive- and negative-equity loans. As was typical during that period, the majority (72%) of our sample consists of adjustable rate mortgages (ARMs). Interestingly, ARM loans are overrepresented in the negative-equity loans (81% vs. 62% in the positive-equity group). This pattern could be due to borrowers taking advantage of lower interest rates on ARMs to secure larger loans. Table 2 also shows higher concentrations of interest-only and negative amortization loans among underwater mortgages: 37% versus 26% and 17% versus 7%, respectively. This pattern is not surprising because these loans amortize more slowly and are therefore more likely to end in negative-equity territory than loans without these features. The average original loan amount is slightly smaller for negative-equity loans ($301,000 vs. $305,000). However, as expected, borrowers who found themselves in negative-equity territory started with significantly higher leverage both in terms of LTV (82% vs. 76%) and CLTV (87% vs. 79%), which accounts for other reported loans. Loans originated to refinance existing debt are somewhat less common among underwater mortgages (49% vs. 55%). In summary, independent of the impact of changes in housing market conditions, loans that ended with negative equity started with a significantly higher balance, amortized more slowly, were more likely to be ARMs, and less likely to be refinancing loans.

Default and repayment behavior may depend on whether the state of origin is a recourse or a non-recourse state. However, any such effect is captured by the zip-code fixed effects used in all of our regressions (see below), which capture the effects of state-level as well as local unobservables. As will be seen, however, one of the regressions below uses a recourse variable as part of an interaction term, which is possible despite the presence of fixed effects. Loans in recourse states made up 55% of the overall sample, but accounted for a smaller share among negative-equity loans (45% vs. 67%).

As explained in the introduction, our main focus is on the effect of the credit score and equity on the type of loan termination (repayment or foreclosure). As a precursor to the regression results, Table 4 shows repayment versus foreclosure statistics by quintiles of credit score (Panel A) and quintiles of equity (Panel B). The lower part of Panel A, which pertains to negative-equity loans, shows that the split

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TABLE 4

Loan Termination by Credit Score and Equity Quintiles

Table 4 reports the number of loans (*No. of Loans*), average equity (*Average Equity*), and loan termination status (*Repaid* or *Foreclosed*) as a percentage of total loans by credit score quintiles in Panel A and equity quintiles in Panel B. The credit-score quintiles are based on credit scores at origination – credit score quintiles: FICO 300–623, 624–670, 671–711, 712–756, and 757–849 at origination. Panel B presents the same data by quintiles for positive- and negative-equity loans at termination. Our sample includes ABSNet-RealtyTrac matched loans as described in Table 3. *Average Equity* is the mean of borrower equity measured as the ratio of updated property value (HPI-adjusted appraised value) minus first and second mortgage balance at termination to the updated property value at termination.

Panel A. Credit Score Quintiles	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Positive Equity					
No. of Loans	90,519	74,970	72,235	65,386	55,138
Average Equity (%)	19.65	19.58	22.39	25.73	30.90
Loan Status:					
Repaid (%)	21.55	29.57	43.97	60.39	78.58
Foreclosed (%)	78.45	70.43	56.03	39.61	21.42
Negative Equity					
No. of Loans	92,900	106,072	88,786	59,004	27,601
Average Equity (%)	−37.91	−40.65	−39.71	−37.84	−35.69
Loan Status:					
Repaid (%)	2.06	2.57	3.88	5.87	11.38
Foreclosed (%)	97.94	97.43	96.12	94.13	88.62
Panel B. Equity Quintiles	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Positive Equity					
No. of Loans	112,802	87,218	71,543	52,755	33,930
Average Equity (%)	6.34	17.04	26.54	38.96	61.72
Loan Status:					
Repaid (%)	19.22	35.97	52.10	69.38	86.41
Foreclosed (%)	80.78	64.03	47.90	30.62	13.59
Negative Equity					
No. of Loans	81,766	79,293	76,272	72,002	65,030
Average Equity (%)	−93.02	−46.36	−26.84	−13.67	−4.05
Loan Status:					
Repaid (%)	1.27	1.91	2.99	5.32	9.28
Foreclosed (%)	98.73	98.09	97.01	94.68	90.72

between repayment and foreclosure shifts monotonically in favor of repayment moving up through the credit-score quintiles. In the lowest credit-score quintile, only 2.1% of loans are repaid, while in the highest quintile, 11.4% of loans are repaid. Note that negative equity is fairly stable across credit-score quintiles, ranging between −35.7% and −40.7% of the estimated property value. This pattern suggests that, holding negative equity constant, borrowers' propensity to repay negative-equity loans likely increases with the credit score. This pattern is a main prediction that we seek to formally establish.

The upper part of Panel A pertains to positive-equity loans. It shows that, as in the case of underwater loans, the share of loans repaid rises with the credit-score quintile. In each quintile, this share is higher than the corresponding share for underwater loans, rising from a low of 21.6% in the lowest quintile to 78.6% in the highest quintile. Positive equity also mostly rises across the credit-score quintiles, from a low of 19.6% of value in the lowest quintile to 30.9% in the highest quintile, indicating that a substantial amount of money is being left on the table by above-water defaulters. Of course, disentangling the separate credit score and equity effects requires the regression analysis that is reported below.

Panel B shows statistics by equity quintile, with the lower part again pertaining to negative-equity loans. As mean (negative) equity rises across quintiles, moving from −93.0% of the value in the lowest quintile to −4.1% in the highest quintile, the

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share of loans repaid rises as well, from 1.3% to 9.3%. The same pattern is seen for positive-equity loans in the upper part of Panel B. As mean equity in the quintiles rises from 6.3% to 61.7%, the share of these loans repaid rises from 19.2% to 86.4%. Again, the repayment percentages of positive-equity loans are larger in each case than for negative-equity loans. As noted, the importance of trigger events in mortgage default and, ultimately, foreclosure, is observed in the significant share of loans with large positive equity ending in foreclosure. For example, a staggering 47.9% of terminated loans with an average equity of 26.5% equity (third equity quintile of Panel B) ended in foreclosure.

V. Regression Results

While the descriptive statistics in Table 4 are suggestive, proper tests of our predictions require controlling for a host of other factors that may affect repayment. Accordingly, Table 5 reports the regression results using a variety of controls in addition to the focal variables measuring equity, credit score, and property value. The regressions are linear probability models with the dependent variable equal to 1 for loans that are repaid and 0 for foreclosures, with equity measured as a level rather than the percentage of property value used in Table 4. Results for positive-equity loans are shown in the first column, while the second column shows results for negative-equity loans. The third column shows results for the full sample, allowing the key coefficients to differ by subsample. All the regressions have fixed effects for origination and termination years and zip code, and coefficient standard errors are clustered by zip code. Full regression results, including coefficients on the additional control variables not shown in Table 5, are available in Table A4 in the Supplementary Material.

As was seen in Table 4, a higher credit score is associated with a greater likelihood of repayment for both positive- and negative-equity loans, as reflected in the significantly positive credit-score coefficients in the first two columns of Table 5. In addition, the positive coefficients on the equity measure show that higher equity is associated with more likely repayment for both positive- and negative-equity loans, as was seen in Table 4. As noted above, the credit score may be correlated with unobserved liquidity, with the credit score thus possibly proxying for *both* default cost and liquidity. As a result, while the positive credit-score coefficients in Table 5 suggest that high default costs (a high score) make loan repayment more likely, the coefficients may also capture the effect of higher liquidity on repayment. Indeed, one view is that the extent of liquidity is the crucial difference between repayers and defaulters among underwater borrowers, with low liquidity preventing repayment regardless of the magnitude of default costs. However, for higher-liquidity borrowers, for whom repayment is feasible, default costs may matter more.

Table 5 shows an additional pattern that the statistics in Table 4 could not reveal. In particular, while the equity coefficients are similar in magnitude in columns 1 and 2, the effect of the credit score on repayment is much *larger for positive-equity than for negative-equity loans.* Therefore, better credit appears to be more strongly correlated with repayment when a loan is above water than when it is underwater, a natural outcome given that a key force pushing the borrower toward default (negative equity) is then absent. These conclusions, however, are based only

TABLE 5

Loan Repayment Versus Foreclosure as a Function of Credit Score and Equity

Table 5 reports linear probability model (LPM) estimation of the likelihood of loan repayment. *Repaid* is a binary variable identifying whether a loan was paid off with the sale of the property. Columns 1, 2, 3, and 4 report LPM estimates for positive-equity loans, negative-equity loans, the full sample, and negative-equity loans, respectively. The additional variables included in these regressions are the same as in Supplementary Material Table A4. In parentheses are White-robust standard errors clustered at the zip code level. The labels *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Sample:	Positive Equity	Negative Equity	Full Sample	Negative Equity
Dependent Variable:	Repaid	Repaid	Repaid	Repaid
Credit Score	0.1453***	0.0279***	0.1168***	0.0266***
	(0.0015)	(0.0008)	(0.0012)	(0.0011)
Negative Equity × Credit Score			−0.0219***	
			(0.0004)	
Credit Score × Recourse				0.0030
				(0.0016)
Equity Amount	0.0072***	0.0082***	0.0078***	0.0079***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Negative Equity × Equity Amount			−0.0016***	
			(0.0003)	
Equity Amount × Recourse				0.0009***
				(0.0002)
Property Value	−0.0037***	−0.0039***	−0.0038***	−0.0039***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Unemployment Rate	−0.0138***	−0.0003	−0.0142***	−0.0001
	(0.0016)	(0.0009)	(0.0010)	(0.0009)
Median Income	0.0012***	−0.0001	−0.0004*	−0.0001
	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Loan Amount	0.0019***	0.0052***	0.0028***	0.0052***
	(0.0002)	(0.0003)	(0.0002)	(0.0003)
Refinancing Loan	0.0084***	−0.0028***	0.0138***	−0.0028***
	(0.0017)	(0.0008)	(0.0010)	(0.0008)
Interest Rate	−0.0448***	−0.0047***	−0.0217***	−0.0046***
	(0.0007)	(0.0002)	(0.0004)	(0.0002)
DTI	−0.0220	−0.0190***	−0.0079	−0.0189***
	(0.0115)	(0.0031)	(0.0050)	(0.0031)
ARM	−0.0925***	−0.0160***	−0.0658***	−0.0158***
	(0.0017)	(0.0010)	(0.0012)	(0.0010)
Single Family	0.0462***	0.0132***	0.0293***	0.0135***
	(0.0047)	(0.0019)	(0.0028)	(0.0019)
Inflation	−0.0014***	−0.0012***	−0.0019***	−0.0012***
	(0.0004)	(0.0002)	(0.0002)	(0.0002)
Mortgage Rates	0.0257***	0.0038***	0.0180***	0.0037***
	(0.0026)	(0.0011)	(0.0014)	(0.0011)
Additional Control Variables	Yes	Yes	Yes	Yes
Origination-Year FE	Yes	Yes	Yes	Yes
Termination-Year FE	Yes	Yes	Yes	Yes
Location (Zip Code) FE	Yes	Yes	Yes	Yes
Clustered SE (Zip Code)	Yes	Yes	Yes	Yes
No. of obs.	352,912	363,019	717,179	363,019
Adjusted R^2	0.374	0.104	0.443	0.104

on a comparison of coefficients from different regressions, and to carry out a proper statistical test, we use the full-sample regression in the third column of Table 5. In this regression, the credit-score and equity effects are allowed to differ by interacting a negative-equity dummy (*Negative Equity*) with each of these variables.

The uninteracted credit score and equity coefficients are positive, indicating positive effects for above-water loans (for which the dummy is 0). Moreover, for each of these variables, the interaction coefficient is significantly negative, indicating that the credit-score and equity effects are smaller for negative-equity loans than for positive-equity loans. This pattern confirms more rigorously the conclusion about the credit-score effect drawn from the separate regressions columns 1 and 2, but the regression now shows that the same effect is present for equity, whose effect is also smaller for negative-equity loans. This conclusion makes sense intuitively, since we would expect the impetus for repayment to be stronger for above-water loans than for underwater loans, so that the forces correlated with the borrower's decision to repay (a higher credit score and equity level) to have a greater effect for such loans.

An additional variable identified by the theory of Section II is the property value, measured at mortgage termination. The prediction is that a high value, by raising transaction cost, is associated with a lower likelihood of repayment. This prediction is upheld given the significantly negative property-value coefficients in columns 1–3.

Before turning to column 4 of the table, the effects of the control variables in the first 3 regressions in Table 5 deserve note. The variables designed to capture trigger events, the state-level unemployment rate and median income, perform somewhat as expected, with the unemployment coefficients negative in columns 1–3 and significant in the positive-equity and full-sample regressions, suggesting that high unemployment makes repayment less likely. The coefficient of median income, which may help capture liquidity effects, is positive and significant in the positive-equity regression but significant with an unexpected negative sign in the full-sample regressions, suggesting that this variable is not consistently capturing income-based trigger events.

Among the other controls, the results also show that large loans are more likely to be repaid, while repayment of refinancing loans is more (less) likely when equity is positive (negative). The refinancing effect for negative-equity loans could make sense because refinancing loans may reflect equity extraction by risky, financially constrained borrowers. Even though we control for equity in our regressions, the fact of equity extraction may imply that a borrower is unobservably riskier and less likely to repay the loan.

In addition, ARM loans and loans with a high initial interest rate are uniformly less likely to be repaid. The ARM effect possibly captures the default-inducing trigger event of an ARM interest-rate reset, an event that may be more punishing the higher is the initial interest rate. Single-family loans are more likely to be repaid, and higher mortgage rates at termination also make repayment more likely. This latter effect seems counterintuitive given that consumers are less likely to seek a mortgage on a new house, which requires repayment of their existing mortgage, when interest rates are high.[26] As seems natural, the effects on repayment of the debt-to-income ratio (DTI) and the consumer price index (inflation) are negative and often significant. The regressions contain a number of additional control variables whose coefficients are not reported, with the full set of results shown in Table A4 in the Supplementary Material.

[26]Indeed, the current interest rate might be viewed as affecting default cost, with a high rate reducing the loss from mortgage blacklisting (since a new mortgage is then less attractive). However, the result from Table 5 undercuts this view.

Column 4 of Table 5 introduces a new covariate, a dummy variable indicating whether the mortgage is originated in a recourse state, where defaulting borrowers can be sued for payment of the difference between the mortgage balance and house value (negative equity). Because our regressions already include zip code fixed effects, the recourse dummy, based on Ghent and Kudlyak (2011) state classifications, cannot be used in level form, but we instead use it in interaction terms involving the credit score and equity, focusing on underwater borrowers. The expectation is that recourse will amplify the positive associations of both variables with underwater repayment. In other words, borrowers with higher credit scores will be even more likely to repay an underwater mortgage in a recourse state since the consequences of defaulting are more severe. Similarly, we expect that loans with higher (less negative) equity are even more likely to be repaid in a recourse state. Both expectations are confirmed by the positive interaction coefficients in column 4, which strengthen the strategic view of repayment decisions embodied in our approach. Note that while the equity interaction coefficient is highly significant, the credit score interaction coefficient just misses significance at the 5% level (the p-value is 0.053).

Tables A5 and A6 in the Supplementary Material present the kinds of comparisons seen in Table 4 in a regression setting. Table A5 allows the effect of equity on repayment to depend on the credit-score quintile, while Table A6 allows the effect of the credit score to depend on the equity quintile. Table A7 in the Supplementary Material presents robustness checks for the basic specification in Table 5. To check the possible effect of measurement error in equity around the value of 0, the first robustness check drops observations where equity is between -5% and $+5\%$ of property value. The second check is to exclude loans in the repaid category that had been delinquent but were repaid at termination.[27] The third check is to add an observation-level income variable generated by using the DTI ratio for the loan at origination. The results in Table 5 are seen to be robust to these changes.

VI. Gauging the Magnitude of Default Cost

This section uses our data and theoretical framework to gauge the magnitude of default costs, complementing previous efforts in the literature (see footnote 6). Ignoring liquidity constraints for the moment, recall from (4) that repayment is optimal when $-E+T<C$. For an underwater mortgage, $-E+T$ is the positive out-of-pocket amount the borrower needs in order to pay off the loan, which is optimal when this amount is less than the default cost.

Viewed differently, when $-E+T<C$ holds as an equality, it indicates the *minimum value of default cost under which it makes sense to repay a mortgage.* Let $\hat{C}$ denote this minimum value, which gives a lower bound on the default cost and satisfies $-E+T=\hat{C}$. In view of this equality, the lower bound $\hat{C}$ depends on $-E$ and T, rising with both the absolute value of negative equity and transaction cost. Our approach is to use this insight, along with data on how negative equity and transaction cost vary across credit-score quintiles for mortgage repayers, to back out the variation of the lower bound on default cost across these quintiles.

[27]The intuition is that a borrower who has already fallen delinquent on their mortgage has little incentive to preserve their credit score by repaying an underwater loan.

TABLE 6

Default Costs by Credit Score Quintiles

Table 6 reports median property value, borrower equity, and default costs in dollars at termination for repaid and foreclosed negative-equity loans by credit score quintiles. The credit-score quintiles are based on credit scores at origination – credit score quintiles: FICO 300–623, 624–670, 671–711, 712–756, and 757–849 at origination. Our sample includes ABSNet-RealtyTrac matched loans as described in Table 3. Borrower equity is the updated property value (HPI-adjusted appraised value) minus the balance of the first and second mortgages at loan termination.

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Panel A. Repayers					
Median House Value	\$165,949	\$201,792	\$237,519	\$259,654	\$315,611
Median T (6% of value)	\$9957	\$12,108	\$14,251	\$15,579	\$18,937
Median Equity	-\$18,402	-\$26,766	-\$31,805	-\$31,261	-\$29,839
Median Lower Bound of C = Median (−Equity + T)	\$28,871	\$41,821	\$51,125	\$54,081	\$52,448
Panel B. Defaulters					
Median Property Value	\$152,110	\$185,170	\$212,895	\$227,863	\$234,876
Median *T* (6% of value)	\$9127	\$11,110	\$12,774	\$13,672	\$14,093
Median Equity	-\$45,439	-\$61,854	-\$68,478	-\$69,384	-\$68,886
Median Upper Bound of C = Median (−Equity + T)	\$56,473	\$75,284	\$83,981	\$85,618	\$85,739

The same logic could be applied to mortgage defaulters to find an upper bound on default costs. For default to be optimal, $-E+T>C$ must hold, implying that default costs must be *no larger* than $-E+T$ for default to make sense. Thus, letting $\overline{C}$ denote the upper bound on default cost for defaulters, $\overline{C}=-E+T$. While $-E+T$ therefore represents a *lower bound* on default costs in the case of repayers, it represents an *upper bound* on default costs in the case of defaulters. Using our data, we can also show how this upper bound varies across credit-score quintiles.

Does this logic require amendment in the presence of liquidity constraints? For mortgages that are repaid, it is crucial to recognize that no amendment is needed since the act of repayment means that the borrower *had sufficient liquidity to do so.* But for defaults, the condition $-E+T<C$, which is the first inequality in (5), may be satisfied (indicating the desirability of repayment), but the second inequality in (5) may be reversed, with $L<-E+T$. This latter inequality indicates insufficient liquidity, so that default occurs even though repayment is desirable. The upshot is that, while we can still compute a lower bound on default cost for repayers, equal to $\hat{C}=-E+T$, use of the same formula to produce an upper default-cost bound for defaulters may be illegitimate, given that their defaults may be driven by liquidity and not solely by equity and default costs. We will compute the upper bounds anyway, realizing that they are likely to be unreliable.

Table 6 presents the calculations for negative-equity borrowers, showing the medians of property value, transaction cost T (equal to 0.06 times property value), and equity E across the five credit-score quintiles while distinguishing between repayers and defaulters. Although the table shows the medians of these individual variables in separate rows, we appropriately compute the lower bound on C as the median of (−Equity + Transaction Cost), not as −median (Equity) + median(Transaction Cost), although the results are similar using the second approach.[28]

[28]In other words, for each loan in a given quintile and termination type (repayer or defaulter), we calculate (−Equity + Transaction Cost). We then take the median of those individual values within the quintile and termination type to calculate the median bounds on C.

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As can be seen in Panel A of Table 6, the median lower bounds on C are large, and the median bound rises across the credit-score quintiles (except for the slight drop in quintile 5), apparently validating the view that default cost rises with the credit-worthiness of a borrower. The median lower bound in quintile 5 is about \$23,000 higher than in quintile 1. This pattern is consistent with the results of Brevoort and Cooper (2013), who document the much greater cost of credit impairment and mortgage blacklisting for the most credit-worthy borrowers. Importantly, the pattern also validates our interpretation of the positive credit-score coefficients in the previous regressions as showing the positive effect of higher default costs on mortgage repayment.[29]

It could be argued that the increase of the lower bound across credit-score quintiles does not prove that default costs rise across the quintiles. Conceivably, defaults costs themselves could be constant or fall across the quintiles even when the lower bound is rising. The behavior of the lower bound is suggestive, nevertheless, and even if one doubts the conclusion we draw on the default-cost/credit-score correlation, Table 6 still shows that default costs themselves must be large (as seen elsewhere in the literature) due to the large sizes of all the lower bounds.

Similarly, Panel B of Table 6 shows that the median upper bound on C also rises across the credit-score quintiles, while also being appropriately larger than the lower bound in each quintile ($\overline{C} > \hat{C}$).[30] Despite this pattern, it should be recalled that the liquidity issues may invalidate the logic used to derive the upper bound, so that the information in the defaulter panel of Table 6 should probably be discounted even though it seems consistent with numbers in the upper panel.

Figure 1 graphs the median lower and upper bounds from Table 6, while Figure 2 shows histograms of lower bounds on C for individual borrowers within each credit-score quintile. Changes in the distributions across the quintiles confirm what is seen in the medians: a tendency for lower bounds to be lower in the lower quintiles.

VII. Conclusion

This article has explored an overlooked phenomenon in mortgage markets: repayment of underwater mortgages. Since repayment in this case requires the borrower to use out-of-pocket funds along with the proceeds from the house sale to settle the loan, it may appear unattractive and even irrational. But if the borrower's negative equity is less than the cost of default, which includes credit impairment and possible guilt, repayment of an underwater mortgage may be a wealth-maximizing strategy, provided that sufficient liquidity is available.

The article shows that repayment of underwater mortgages indeed occurs, and that it is affected by the same factors commonly used in previous studies of default: the magnitude of home equity and the borrower's credit score, which we view as capturing default cost along with borrower liquidity. An increase in either variable

[29] A version of Table 6 could also be constructed for positive-equity borrowers, but the lower bound is less useful for this group since $-E+T$ then tends to be close to 0, yielding a bound that is not very informative.

[30] While this size relationship is expected to hold if repayers and defaulters differ only in their levels of negative equity and property value, other unobservable differences between the groups could in principle disrupt it.

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FIGURE 1

Lower and Upper Bounds on Average Default Costs

Figure 1 presents the lower and upper bound estimates of default costs by credit score quintiles from Table 6. Lower bounds are estimated using the sample of negative equity repayers, while upper bound estimates are derived from negative equity defaulters.

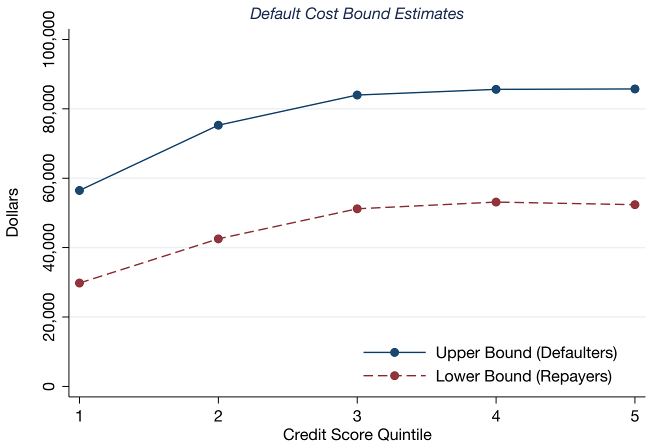
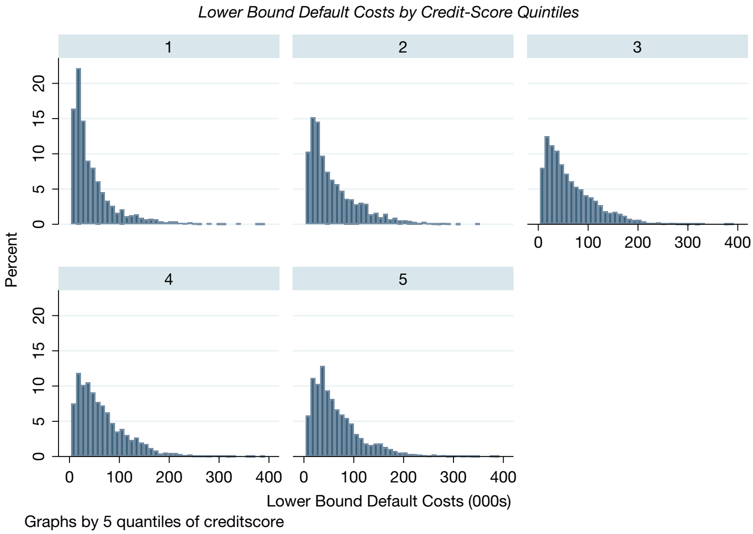


FIGURE 2

Lower Bounds by Credit-Score Quintile

Figure 2 presents histograms of lower-bound estimates of default costs by credit score quintiles. Lower bounds are estimated using the sample of negative equity repayers.



raises the likelihood that a loan is terminated by repayment rather than by default, doing so less strongly for underwater than above-water loans. Another contribution of the article, which does not rely on regression analysis, is the use of our theoretical model along with summary statistics by credit-score quintile to gauge the magnitude of default cost for mortgage repayers and how it varies across these quintiles. We show that the lower bound on default cost is much higher for the most credit-worthy repayers than for those in the lowest quintile, which may suggest that default cost rises with a borrower's credit worthiness, an empirical conclusion that would be new to the literature.

It could be argued, however, that our lower-bound pattern does not prove that default cost moves in step with the credit score, in which case our regression results showing the positive repayment impact of good credit could simply testify to the greater liquidity enjoyed by such borrowers. With greater liquidity, more funds are available to pay off an underwater mortgage or to cushion the impact of lost income, making default less likely. This alternate interpretation of our regressions matches the views of Ganong and Noel (2023) and Low (2023), who argue that defaults are typically not strategic (making default costs unimportant) but are more driven by liquidity issues. Even if one takes such a view, our results on the default-cost lower bounds nevertheless establish a different significant point: the large values of the bounds indicate that default costs are high, as argued in other papers in the literature.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109025101774.

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