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.

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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 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 paper 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 enables us to draw this distinction, thereby facilitating the identification of underwater mortgage repayment. As might be expected, though, the phenomenon is rare relative

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

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

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

[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.

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 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 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) is 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 as those analyzed in the literature on mortgage defaults. 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, 2023b). This association complicates the

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

task of estimating default costs for defaulters. However, a novel insight in our paper 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 paper. 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 reinforces 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 relevant to our work. Early contributions in this area include Kau, Keenan, and Kim (1993,9), Riddiough and Thompson (1993), Quigley and

[6]Using a structural model, Ganong and Noel (2023) deduce a "utility cost" from default equal to $100,000. 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 HAMP participants who obtained substantial principal reduction, which the authors attribute in part to high default costs.

Van Order (1995). More recent work by Bajari, Chu, and Park (2008) and 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 for example, Bajari et al. (2008), Goodman, Ashworth, Landy, and Yin (2010), Elul et al. (2010), 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 (2023b) 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

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

contribution, Low (2023a) presents a theoretical model with liquidity shocks and psychic moving costs to explain above-water defaults. Ganong and Noel (2023), Low (2023a), and Low's (2023) 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]

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

[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.

[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), Korgaonkar (2025)), and the role of subprime borrowers in driving the housing boom (Conklin, Frame, Gerardi, and Liu (2022)).

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 2001-07 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 (2023b), our sample also includes defaults by above-water borrowers, and we compare regressions results for the above-water subsample to those for underwater loans.

Our motivating example focused on the choice between repayment and default for a

[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).

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 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 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

[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.

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 paper 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 Sectin 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

[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 a 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.

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) 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 default cost is absent, and let P denote the value of the house and M the mortgage balance. Then, default 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 default cost be denoted C, net worth in the event of default becomes $A - C$ rather than A. Now default is preferred when

$$(2) \qquad E \ < \ -C, \quad \text{or} \quad E \ + \ C \ < \ 0,$$

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 paper.

This conclusion may 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

$$(3) \qquad E \ + \ C \ > \ 0 \quad \text{and} \quad L \ > \ -E.$$

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 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 transactions cost of selling the house as a cost of mortgage repayment. Ignoring the liquidity issue for the moment and letting transactions 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 is then optimal when

(4) $$E - T > -C \quad \text{or} \quad -E + T < C.$$

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 transactions cost of selling the house. In addition, (4) must be satisfied, so that repayment requires joint satisfaction of

(5) $$-E + T < C \quad \text{and} \quad -E + T < L.$$

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

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

Therefore, in a full model that includes both transactions 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 zero 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

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

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 proxy for default cost. But since borrowers with high credit scores are more likely to be liquid, the credit may also serve as a proxy for L. Therefore, the credit score can be viewing 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 the 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

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

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 transactions 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 transactions 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, default is the preferred termination choice even though $E > 0$. When defaulting, the borrower avoids the transaction cost of selling the house, although 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 (2023a,0) 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 accurately identify the source of repayment at termination, we merge ABSNet and data from RealtyTrac.[16] RealtyTrac uniquely identifies the property subject to

[14]Transaction costs alone are unlikely to fully explain above-water defaults. Ganong and Noel (2023) and Low (2023a,0) 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.

[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

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 Appendix 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

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; 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.

(refinancing or purchase), and number of units. After removing from our initial ABSNet sample loans with 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 Online Appendix 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 characteristics, though they appear modest in economic magnitude. (see Appendix 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 (Appendix 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 online appendix.[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]

[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 does not allow us to observe such servicing transfers. Observations where we cannot identify the method of termination will not be included in our analysis.

[19]In this paper 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,

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 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 five-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

merely eliminating negative equity is unlikely to be enough. The borrower must also bring the LTV ratio below 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 above). Our findings are unchanged when we include loans that terminated through refinance (not reported).

[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 five-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.

(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 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 paper 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.

[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.

As seen in the first two rows of Table 2, 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 (2023b), 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.

[Insert Table 1 approximately here]

[Insert Table 2 approximately here]

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.

[Insert Table 3 approximately here]

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

[25] Appendix 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

substantial differences 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 over-represented 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% vs. 26% and 17% vs. 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 from 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.

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 dataset 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.

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 was 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 vs. 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 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.

[Insert Table 4 approximately here]

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 the substantial amount of money that 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 value in the lowest quintile to −4.1% in the highest quintile, the 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 online appendix.

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.

[Insert Table 5 approximately here]

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 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 zero). 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 the 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 2 is property value, measured at mortgage termination. The prediction is that a high value, by raising transactions cost, is associated with a lower likelihood of repayment. This prediction 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 three 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 repay. 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 repay, 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

[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.

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 appendix.

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 appendix 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 appendix presents robustness checks for the basic specification in Table 5. To check the possible effect of measurement error in equity around the value of zero, 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 debt-to-income ratio (DTI) 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 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 $\widehat{C}$ denote this minimum value, which gives a lower bound on default cost and satisfies $-E + T = \widehat{C}$. In view of this equality, the lower bound $\widehat{C}$ depends on $-E$ and T, rising with both the absolute value of negative equity and transactions cost. Our approach is to use this insight, along with data on how negative equity and transactions cost vary across credit-score quintiles for mortgage repayers, to back out the variation of the lower bound on default cost across these quintiles.

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

[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.

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 cost 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 $\widehat{C} = -E + T$, 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 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.

As can be seen in the repayer panel 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]

[Insert Table 6 approximately here]

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, the defaulter panel of the table 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 ($\overline{C} > \widehat{C}$).[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

[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 zero, 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.

of Table 6 should probably be discounted even though it seems consistent with numbers in the upper panel.

Figure 1 graphs the median lower 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.

[Insert Figure 1 approximately here]

[Insert Figure 2 approximately here]

VII. Conclusion

This paper 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 paper 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 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 paper, 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.

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TABLE 1

Variable Descriptions

This table 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 ($0000s)	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 ($0000s)	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 judments	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 ($0000s)	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 rates 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 2007-11 and 2012-16 in thousand dollars ($000s)	ACS

TABLE 2

Descriptive Statistics

This table presents descriptive statistics for the full sample, and the negative equity sample, and the positive equity sample.

Variable	*Full Sample*		*Negative-Equity Loans*		*Positive-Equity Loans*	
	N. Obs.	*Mean*	*N. Obs.*	*Mean*	*N. 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 ($0000s)	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

Loan Termination by Borrower Equity Position

Our study sample includes loans showing in the ABSNet January 2008 loan update data set 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 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 five-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*	
	N. Obs.	*N. Obs.*	*%*	*N. 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*

TABLE 4

Loan Termination by Credit Score and Equity Quintiles

This table reports the number of loans (*N. 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:					
N. 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:					
N. 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:					
N. 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:					
N. 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

TABLE 5

Loan Repayment vs. Foreclosure as a Function of Credit Score and Equity

This table reports linear probability model (LPM) estimation using OLS of the likelihood of loan termination (repayment vs. foreclosure). *Repaid* is a binary variable identifying whether a loan was paid off with the sale of the property or the foreclosure of the property. Columns 1, 2, 3, and 4 report LPM likelihood of loan termination (repayment) 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 the appendix Table A4. In parentheses are White-robust standards errors clustered at the zip code level. *** p<0.001, ** p<0.01, * p<0.05.

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	Y	Y	Y	Y
Origination-Year FE	Y	Y	Y	Y
Termination-Year FE	Y	Y	Y	Y
Location (Zip Code) FE	Y	Y	Y	Y
Clustered SE (Zip Code)	Y	Y	Y	Y
Observations	*352,912*	*363,019*	*717,179*	*363,019*
Adjusted R-squared	*0.374*	*0.104*	*0.443*	*0.104*

TABLE 6

Default Costs by Credit Score Quintiles

This table 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*
Repayers:					
Median House Value	\$165,949	\$201,792	\$237,519	\$259,654	\$315,611
Median T (6% of value)	\$9,957	\$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*
Defaulters:					
Median Property Value	\$152,110	\$185,170	\$212,895	\$227,863	\$234,876
Median T (6% of value)	\$9,127	\$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*

FIGURE 1

Lower and Upper Bounds on Average Default Costs

This figure 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.

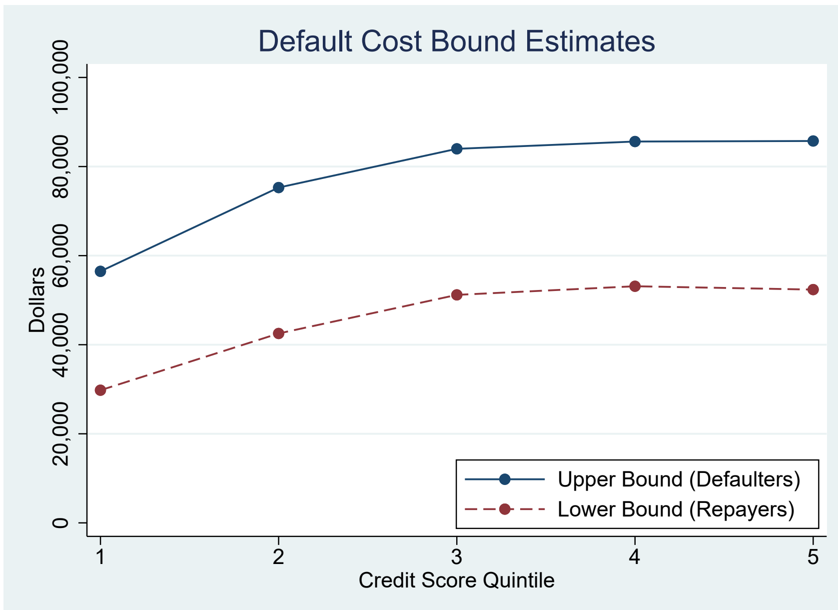
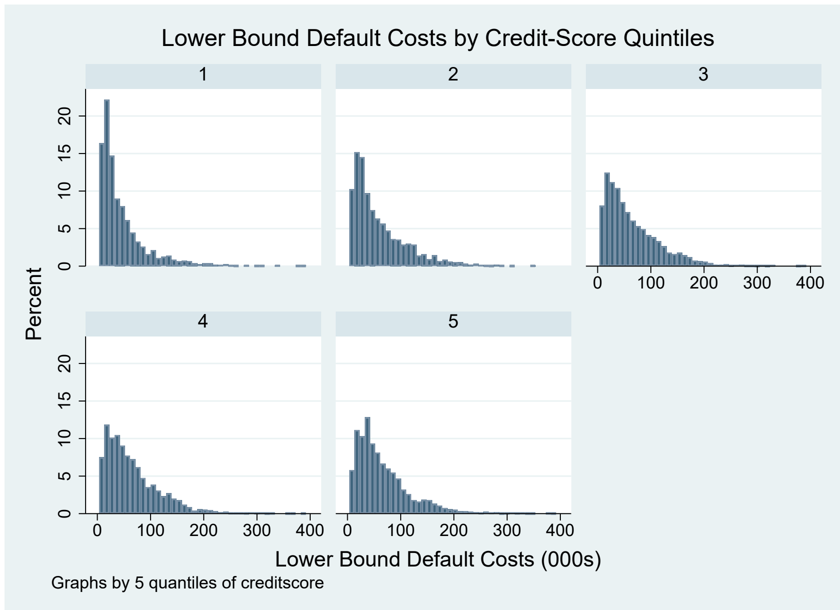


FIGURE 2

Histograms of Lower Bounds by Credit-Score Quintile

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



Internet Appendix

A. Data Matching Procedure

The primary data set used in this study consists of ABSNet securitized private-label (non-conforming) home mortgage origination and loan performance data compiled by Lewtan. The mortgage origination data consist of a comprehensive set of loan, borrower and property information at origination, such as loan purpose, amount, LTV, combined LTV, lien position, term, interest rate, interest rate type, documentation type, DTI, borrower credit score, number of units, and property location (Zip code). Unlike the static mortgage origination data, the performance data are monthly updates of the status of the loans after origination indicating whether a loan is active (current or delinquent), has been repaid voluntarily or involuntarily through foreclosure, or is currently in foreclosure. The loan performance data also provide monthly reports on the beginning balance, scheduled payment, and ending balance of the loans.

For the purposes of this study, our initial sample consists of non-conforming home mortgages still active at the end of 2007. We get loan characteristics at origination from the ABSNet loan origination file and loan status at the end of 2007 from the ABSNet loan performance files. We also use the performance data to track the status of the loans from January 2008 until termination or the end of our study period (March 2016) for loans still active.[31] In summary, the ABSNet loan origination and performance data allow us to identify our initial sample, get the loans' characteristics at origination and when they were terminated, and know how they were terminated, whether by voluntary repayment (loan refinancing or voluntary sale of

[31] Our last ABSNet loan performance update is March 2016.

property) or foreclosure. However, even though we will be able to identify the type of loan termination (voluntary or foreclosure) using ABSNet alone, the source of repayment (refinancing or sale of the property), which is a critical consideration in this study, is not recorded in ABSNet for voluntary loan terminations.[32] We use the RealtyTrac residential property data to classify the source of repayment of voluntarily terminated loans into loan refinancing or property sale.

The RealtyTrac residential property data comprise two complementary datasets: records of mortgage liens on residential properties from county recorder offices (the "recorder" data) and periodic property assessments for local tax purposes (the "assessor" data). The recorder data include property location (Zip Code), lien type (e.g., first or second lien), loan amount, transaction type (loan refinancing or home purchase), and deed type. For liens associated with a property sale, the transfer date and transfer value are also observed. The assessor files contain property assessment values, assessment dates, and the date and amount of the most recent transaction on the property, along with the property characteristics (type of property, total square footage, lot size, number of rooms, number of bathrooms, and property age). The assessor data also cross-reference the unique property identifiers included in the recorder data.

Starting with the ABSNet loan data, we restrict our sample to first-lien mortgages originated in the continental U.S. between 2001 and 2007 that were active at the end of 2007 and had no missing monthly performance updates thereafter. We keep loans with original amount between \$50,000 and \$5 million, appraisal value between \$50,000 and \$10 million, no missing property zip code, no missing borrower credit score, original LTV between 25% and 125%, secured by properties with fewer than 5 units or a missing number of units, and no missing

[32] Although the take-out loan may also be in ABSNet for loans repaid with a non-conforming mortgage, the two cannot be matched because there is no property identification number or detail description in ABSNet.

balance at termination. After applying these filters, we ended up, as reported in the paper, with approximately 5 million loans.

Next, we match our initial loan sample from ABSNet with the RealtyTrac lien data to determine whether the voluntarily terminated loans in ABSNet were repaid or refinanced. This match allows us to identify the properties associated with the ABSNet loans (lien) and then identify the next lien (subsequent to the lien for the ABSNet loan) on the same property. We match ABSNet loan to the recorder lien data using the property location and loan characteristics. More specifically, we match ABSNet to RealtyTrac using property location (zip code), original loan purpose (refinancing or purchase), number of units in the property, loan amount, and origination date. After restricting our original ABSNet sample to purchase and refinancing loans, 1- to 4-unit properties, and loans in the zip codes showing in the RealtyTrac data, our initial sample drops to 3.78 million loans before merging the two datasets.[33]

After matching the ABSNet loans with the RealtyTrac lien (recorder) data, which allows us to identify the property associated with each loan at origination, our sample dropped to 1.41 million loans, resulting in a match rate of 37.3%.[34] Our initial ABSNet-RealtyTrac matched sample includes 743,000 (52.7%) voluntarily paid-off loans (refinancing or sale of property),

[33]We dropped 525,000 loans with missing number of units, 312,000 with missing loan purpose, and 404,000 loans in zip codes not present in RealtyTrac.

[34]We use fuzzy matching based on property zip code, loan purpose (refinancing or purchase), number of units (1, 2, 3, or 4 units), loan amount (in thousands of Dollars), and loan origination date (in months). Our match rate is 100% when we only match on zip code only, 99. 7% when we use zip code and loan purpose, 98.4% when we add number of units, and 88. 5% when we also include loan amount. The final step involves matching the loan origination date in ABSNet with the lien registration date in RealtyTrac, which takes place after loan origination. We allow for up to a two-month delay in the registration of the lien relative to the loan's origination date and keep only unique matches.

641,000 (45.4%) loans involuntarily terminated through foreclosure, and 27,000 (1.9%) loans still active at the end of our study period. One potential concern is that our matched sample may not be representative of our original sample, which could bias our results. Table A1 reports variable means for the matched and unmatched loans for key variables. Except for the share of refinancing loans, which is slightly higher for the matched subsample, the two subgroups are similar, especially with respect to credit score, borrower equity, the share of negative equity loans, leverage (LTV and CLTV), and property values. Therefore, our matched ABSNet-RealtyTrac sample is representative of initial ABSNet sample.

Having identified voluntarily paid-off loans using the ABSNet performance data, we next explore how they were repaid (refinancing or sale of property) using RealtyTrac lien records and property assessments. First, we check whether a lien was registered on the property in RealtyTrac around the loan's termination date recorded in ABSNet and the purpose of the associated loan (refinancing or purchase). If no lien was found, we next examine the assessment data for any transaction on the property around the recorded termination date.

Using the RealtyTrac data, we were able to determine the source of repayment for 401,000 out of the 743,000 voluntarily terminated (repaid or refinanced) loans, which leaves 342,000 unmatched.[35] Table A2 shows that the matched and unmatched loans have similar average characteristics, suggesting that the matched sample is likely representative of the original sample. This first match of 54% of paid-off loans only identifies terminations by refinancing or

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[35]This match is based on the properties' unique identifiers. We keep matches where the lien registration month in RealtyTrac is within two months after the loan termination month reported in ABSNet.

property sales financed with a mortgage.[36] Approximately 107,000 (26.7%) of the 401,000 matched paid-off loans involved the sale of the property, with the remaining 294,000 loans terminated through refinancing. As expected, the overwhelming majority (93.7%) of the loans that were refinanced had a positive equity position at termination because refinancing generally requires significant equity (as discussed in footnote 20).

Next, we merge the previously unmatched 342,000 voluntary terminations with RealtyTrac assessor data to determine whether these loans were repaid or refinanced. In addition to periodic tax assessments, the assessor data reports the date and value of the most recent sales transaction on a property.[37] We use this data to compile transactions for properties associated with the unmatched paid-off loans, retaining the first transaction after the origination of the ABSNet loan. If this first sales transaction occurs within two months of the ABSNet loan termination, we classify it as a property sale, indicating repayment of the original loan. This second matching step allows us to identify 73,000 additional property sales, bringing the total number of classified voluntarily terminated loans to 474,000 or 63.8% of our original sample.[38] Because these additional transactions correspond to property sales, our expanded sample of 474,000 loans now consists of 180,000 (107,000 + 73,000) terminations by property sales and the 294,000 refinancings previously identified. Our final study sample of 821,000 loans consists of these 180,000 voluntary terminations by sale of property and 641,000 foreclosures. However, it would

[36]Cash sales will not be captured in this step because there will be no new lien in the recorder's data. We attempt to remedy this issue by merging with assessor's data, discussed momentarily.

[37]Note that the assessor data is available for a subset of the properties in the RealtyTrac recorder's data.

[38]This matching process is likely to capture cash sales that are recorded in the assessor data but do not appear in the recorder's lien data due to the absence of a corresponding mortgage.

be erroneous to use this ratio of repayers to defaulters as an estimate of the incidence of underwater mortgage repayments, particularly for negative-equity repayers, because we only identify about two-thirds of repayers, whereas all foreclosure sales are included. The primary objective of this study is to show that underwater repayments exist and matter. Our main analysis compares repayers (voluntary terminations by sale of property) and defaulters (involuntary termination through foreclosure). Although our main sample does not include loans that terminated through refinance, we conducted additional analysis that includes the 294,000 loans that terminated via refinancing (see footnote 20).

TABLE A1

ABSNet Loans-RealtyTrac Recorder Merged Sample

We merge the ABSNet loan sample to the RealtyTrac recorder (lien) data based on zip code, original loan purpose (refinancing or purchase), number of units in the property, loan amount, and origination date. Descriptive statistics for the matched and unmatched samples are presented on the left and right sides of the table, respectively.

Variable	*Matched*		*Unmatched*	
	N. Obs.	*Mean*	*N. Obs.*	*Mean*
Credit Score	1,410,398	6.863	3,596,637	6.799
Equity Amount	1,389,691	11.064	3,453,592	8.369
Equity Ratio	1,389,691	0.086	3,453,592	0.072
Negative Equity	1,410,398	0.318	3,596,637	0.320
Original CLTV	1,410,398	78.919	3,596,637	80.569
Original LTV	1,410,398	75.314	3,596,637	77.129
Property Value	1,389,691	41.284	3,453,592	35.610
Loan Amount	1,410,398	32.541	3,596,637	29.325
Refinancing Loan	1,410,398	0.555	3,596,637	0.491
Non-Owner Occupancy	1,410,398	0.132	3,596,637	0.149
Interest Rate	1,410,372	6.504	3,596,584	6.792
Loan Term	1,390,065	5.874	3,547,779	5.879
DTI	1,410,398	0.010	3,596,637	0.008
PMI	1,410,398	0.098	3,596,637	0.107
Neg. Amortization	1,410,398	0.093	3,596,637	0.074
ARM	1,410,398	0.595	3,596,637	0.603
Balloon	1,410,398	0.066	3,596,637	0.074
Interest Only	1,410,398	0.278	3,596,637	0.266
Single Family	1,410,398	0.966	3,596,637	0.803

TABLE A2

Unclassified Voluntarily Terminated Merged to RealtyTrac Assessor Data

For loans voluntarily terminated via repayment or refinancing, but without a subsequent lien observed in the RealtyTrac recorder data, we merge to the RealtyTrac assessor database to determine whether a property sale occurred near the mortgage termination date. Descriptive statistics for the matched and unmatched sample are presented on the left and right side of the table, respectively.

Variable	*Matched*		*Unmatched*	
	N. Obs.	*Mean*	*N. Obs.*	*Mean*
Credit Score	401,117	7.090	341,712	7.079
Equity Amount	394,802	21.758	335,668	23.216
Equity Ratio	394,802	0.286	335,668	0.353
Negative Equity	401,117	0.063	341,712	0.067
Original CLTV	401,117	74.453	341,712	71.802
Original LTV	401,117	71.696	341,712	69.439
Property Value	394,802	56.980	335,668	50.403
Loan Amount	401,117	39.019	341,712	32.242
Refinancing Loan	401,117	0.567	341,712	0.617
Non-Owner Occupancy	401,117	0.096	341,712	0.162
Occupancy Unknown	401,117	0.007	341,712	0.010
Interest Rate	401,115	6.168	341,710	6.143
Loan Term	398,363	5.853	339,670	5.815
DTI	401,117	0.007	341,712	0.006
PMI	401,117	0.145	341,712	0.107
Neg. Amortization	401,117	0.060	341,712	0.058
ARM	401,117	0.487	341,712	0.422
Balloon	401,117	0.030	341,712	0.027
Interest Only	401,117	0.249	341,712	0.218
Single Family	401,117	0.971	341,712	0.970

TABLE A3

ABSNet and National Survey of Mortgage Originations (NSMO) Data

This table compares the mean values of variables shared between the ABSNet and NSMO datasets. The NSMO survey, conducted by the Federal Housing Finance Agency (FHFA) in collaboration with the Consumer Financial Protection Bureau (CFPB), collects data on a nationally representative sample of newly originated closed-end, first-lien mortgages. The loans in the NSMO data were originated between 2013 and 2020. The two datasets use different credit scoring models (FICO and Vantage).

Variable	*ABSNet (Mean)*	*NMSO (Mean)*
FICO Score (00s)	6.694	
Vantage Credit Score (00s)		7.350
Original CLTV	83.368	77.062
Original LTV	78.872	76.792
Refinance Loan	0.516	0.473
Non-Owner Occupancy	0.143	0.096
Loan Term (ln)	5.907	5.727
DTI	29.581	35.842
PMI	0.115	0.287
ARM	0.716	0.063
Balloon	0.093	0.019
Interest Only	0.321	0.049
Single Family	0.963	0.840

TABLE A4

Likelihood of Loan Termination: Full Results

This table reports the full results of linear probability model (LPM) estimation of loan termination by repayment vs. foreclosure reported in Table 5 of the paper. The set of fixed effects includes loan origination and termination years, and location (zip code) fixed effects. In parentheses are White-robust standards errors clustered at the zip code level. *** p<0.001, ** p<0.01, * p<0.05.

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)
Non-Owner Occupancy	0.0104***	0.0068***	0.0045**	0.0066***
	(0.0026)	(0.0012)	(0.0016)	(0.0012)
Occupancy Unknown	0.0369***	0.0036	0.0172***	0.0036
	(0.0077)	(0.0043)	(0.0049)	(0.0043)
Interest Rate	-0.0448***	-0.0047***	-0.0217***	-0.0046***
	(0.0007)	(0.0002)	(0.0004)	(0.0002)
Loan Term	-0.0866***	-0.0141***	-0.1145***	-0.0141***
	(0.0061)	(0.0041)	(0.0048)	(0.0041)
DTI	-0.0220	-0.0190***	-0.0079	-0.0189***
	(0.0115)	(0.0031)	(0.0050)	(0.0031)
DTI Missing	-0.0033	0.0191***	0.0126***	0.0190***
	(0.0020)	(0.0008)	(0.0011)	(0.0008)
PMI	0.0103***	0.0120***	0.0064***	0.0120***
	(0.0029)	(0.0016)	(0.0017)	(0.0017)
PMI Missing	-0.0347***	-0.0097***	-0.0193***	-0.0097***
	(0.0018)	(0.0007)	(0.0010)	(0.0007)
Neg. Amortization	-0.2125***	0.0136***	-0.0938***	0.0137***
	(0.0046)	(0.0017)	(0.0028)	(0.0017)
ARM	-0.0925***	-0.0160***	-0.0658***	-0.0158***
	(0.0017)	(0.0010)	(0.0012)	(0.0010)
Balloon	-0.0477***	-0.0043**	0.0035	-0.0043**
	(0.0039)	(0.0014)	(0.0020)	(0.0014)
Interest Only	-0.0484***	-0.0031***	-0.0420***	-0.0031***
	(0.0021)	(0.0009)	(0.0012)	(0.0009)
Interest Only Missing	-0.0747***	-0.0057**	-0.0424***	-0.0057**
	(0.0052)	(0.0018)	(0.0027)	(0.0018)
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)
HPI End	0.0013***	0.0010***	0.0009***	0.0010***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)
HPI Origination	-0.0010***	-0.0005***	-0.0009***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
HPI Volatility	0.0047***	0.0016***	0.0031***	0.0016***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Fixed Effects	Y	Y	Y	Y
Observations	*352,912*	*363,019*	*717,179*	*363,019*
Adjusted R-squared	*0.374*	*0.104*	*0.443*	*0.104*

TABLE A5

Likelihood of Loan Repayment by Credit-Score Quintiles

This table reports linear probability model (LPM) estimation of loan termination (repayment vs foreclosure) using OLS for positive- and negative-equity loans at termination with the inclusion of credit-score quintiles (defined in Table 4) interacted with equity. *Repaid* is a binary variable identifying whether a loan was paid off with the sale of the property or foreclosed. The control variables included in these regressions are the same as in the appendix Table A4. In parentheses are White-robust standards errors clustered at the zip code level. *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Sample:	*Positive Equity*		*Negative Equity*	
Dependent Variable:	*Repaid*	*Repaid*	*Repaid*	*Repaid*
Credit-Score Quintile 2	0.0072***	0.0137***	-0.0014	-0.0007
	(0.0022)	(0.0038)	(0.0007)	(0.0013)
Credit-Score Quintile 3	0.0849***	0.1018***	0.0086***	0.0168***
	(0.0026)	(0.0041)	(0.0009)	(0.0016)
Credit-Score Quintile 4	0.1902***	0.2270***	0.0254***	0.0477***
	(0.0028)	(0.0043)	(0.0013)	(0.0022)
Credit-Score Quintile 5	0.3046***	0.3837***	0.0748***	0.1269***
	(0.0030)	(0.0049)	(0.0022)	(0.0039)
Equity Amount	0.0069***	0.0124***	0.0081***	0.0063***
	(0.0003)	(0.0007)	(0.0002)	(0.0003)
Credit-Score Quintile 2 × Equity Amount		-0.0018**		0.0003*
		(0.0006)		(0.0001)
Credit-Score Quintile 3 × Equity Amount		-0.0034***		0.0013***
		(0.0006)		(0.0001)
Credit-Score Quintile 4 × Equity Amount		-0.0049***		0.0030***
		(0.0006)		(0.0002)
Credit-Score Quintile 5 × Equity Amount		-0.0068***		0.0069***
		(0.0006)		(0.0004)
Property Value	-0.0035***	-0.0041***	-0.0040***	-0.0037***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Additional Control Variables	Y	Y	Y	Y
Origination-Year FE	Y	Y	Y	Y
Termination-Year FE	Y	Y	Y	Y
Location (Zip Code) FE	Y	Y	Y	Y
Clustered SE (Zip Code)	Y	Y	Y	Y
Observations	*352,912*	*352,912*	*363,019*	*363,019*
Adjusted R-squared	*0.383*	*0.389*	*0.108*	*0.112*

TABLE A6

Likelihood of Loan Repayment by Equity Quintiles

This table reports linear probability model (LPM) estimation of loan termination (repayment vs foreclosure) using OLS for positive- and negative-equity loans at termination with the inclusion of equity quintiles interacted with credit score. *Repaid* is a binary variable identifying whether a loan was paid off with the sale of the property or foreclosed. We generate separate quintile groups for positive and negative equity loans at termination. The control variables included in these regressions are the same as in the appendix Table A4. In parentheses are White-robust standards errors clustered at the zip code level. *** p<0.001, ** p<0.01, * p<0.05.

Sample:	*Positive Equity*		*Negative Equity*	
Dependent Variable:	*Repaid*	*Repaid*	*Repaid*	*Repaid*
Equity Quintile 2	0.1258***	-0.3979***	0.0118***	-0.0212**
	(0.0023)	(0.0172)	(0.0012)	(0.0078)
Equity Quintile 3	0.2495***	-0.4053***	0.0244***	-0.0729***
	(0.0029)	(0.0190)	(0.0017)	(0.0094)
Equity Quintile 4	0.3761***	-0.0922***	0.0464***	-0.2152***
	(0.0032)	(0.0216)	(0.0022)	(0.0118)
Equity Quintile 5	0.4610***	0.4617***	0.0819***	-0.4243***
	(0.0037)	(0.0266)	(0.0025)	(0.0146)
Credit Score	0.1381***	0.0864***	0.0290***	0.0028**
	(0.0014)	(0.0022)	(0.0008)	(0.0009)
Equity Quintile 2 × Credit Score		0.0787***		0.0054***
		(0.0026)		(0.0012)
Equity Quintile 3 × Credit Score		0.0977***		0.0155***
		(0.0028)		(0.0014)
Equity Quintile 4 × Credit Score		0.0698***		0.0405***
		(0.0031)		(0.0018)
Equity Quintile 5 × Credit Score		0.0032		0.0775***
		(0.0037)		(0.0023)
Property Value	0.0002**	0.0002***	0.0002	-0.0005**
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Additional Control Variables	Y	Y	Y	Y
Origination-Year FE	Y	Y	Y	Y
Termination-Year FE	Y	Y	Y	Y
Location (Zip Code) FE	Y	Y	Y	Y
Clustered SE (Zip Code)	Y	Y	Y	Y
Observations	*352,912*	*352,912*	*363,019*	*363,019*
Adjusted R-squared	0.418	0.422	0.106	0.113

TABLE A7

Equity Measurement Error, Default at Termination, and Borrower Income

This table presents robustness checks of our linear probability model (LPM) estimation of loan termination (repayment vs. foreclosure) using OLS for positive- and negative-equity loans at termination using the model as columns 1 and 2 of Table 5. *Repaid* is a binary variable identifying whether a loan was paid off with the sale of the property or foreclosed. Columns 1 and 5 control for potential error in equity value calculation by excluding loans with equity falling between -5% and 5%, exclusive. Columns 2 and 6 removed loans repaid loans that were delinquent at termination. Columns 3 and 7 control for both equity measurement errors and loan delinquency at termination. In addition to controlling for equity measurement errors and delinquency, columns 4 and 8 include borrower income estimated from DTI ratio at origination. The full set of control variables included in these regressions are the same as in the appendix Table A4. The fixed effects include origination-year, termination-year, and zip code fixed effects. In parentheses are White-robust standards errors clustered at the zip code level. *** p<0.001, ** p<0.01, * p<0.05.

Sample:	*Positve Equity*				*Negative Equity*			
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Dependent Variable:	*Repaid*	*Repaid*	*Repaid*	*Repaid*	*Repaid*	*Repaid*	*Repaid*	*Repaid*
Credit Score	0.1460***	0.1503***	0.1518***	0.1700***	0.0207***	0.0266***	0.0196***	0.0151***
	(0.0016)	(0.0015)	(0.0016)	(0.0032)	(0.0008)	(0.0008)	(0.0007)	(0.0009)
Equity Amount	0.0064***	0.0072***	0.0065***	0.0092***	0.0066***	0.0078***	0.0062***	0.0037***
	(0.0003)	(0.0003)	(0.0003)	(0.0010)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Property Value	-0.0033***	-0.0038***	-0.0034***	-0.0046***	-0.0031***	-0.0038***	-0.0030***	-0.0011***
	(0.0002)	(0.0002)	(0.0002)	(0.0008)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Unemployment Rate	-0.0136***	-0.0149***	-0.0148***	-0.0292***	-0.0000	-0.0002	-0.0000	0.0001
	(0.0017)	(0.0016)	(0.0017)	(0.0035)	(0.0009)	(0.0008)	(0.0008)	(0.0011)
Median Income	0.0013***	0.0011***	0.0012***	0.0013**	-0.0001	-0.0001	-0.0001	-0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0005)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Loan Amount	0.0015***	0.0021***	0.0016***	0.0021*	0.0043***	0.0051***	0.0041***	0.0019***
	(0.0002)	(0.0002)	(0.0002)	(0.0008)	(0.0003)	(0.0003)	(0.0002)	(0.0003)
Refinancing Loan	0.0032	0.0062***	0.0010	0.0029	-0.0024**	-0.0028***	-0.0025***	-0.0006
	(0.0018)	(0.0017)	(0.0018)	(0.0039)	(0.0008)	(0.0008)	(0.0007)	(0.0009)
Interest Rate	-0.0468***	-0.0428***	-0.0449***	-0.0299***	-0.0038***	-0.0043***	-0.0035***	-0.0014***
	(0.0008)	(0.0007)	(0.0008)	(0.0014)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
DTI	-0.0193	-0.0976***	-0.1053***	-0.1633*	-0.0223***	-0.0221***	-0.0240***	-0.0009
	(0.0128)	(0.0112)	(0.0127)	(0.0642)	(0.0028)	(0.0028)	(0.0025)	(0.0129)
ARM	-0.0941***	-0.0863***	-0.0883***	-0.0779***	-0.0137***	-0.0142***	-0.0120***	-0.0065***
	(0.0019)	(0.0017)	(0.0019)	(0.0041)	(0.0009)	(0.0009)	(0.0009)	(0.0012)
Borrower Income				0.0000				0.0000
				(0.0000)				(0.0000)
Additional Control Variables	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Equity Measurement Error	√		√	√	√		√	√
Default at Termination		√	√	√		√	√	√
Borrower Income				√				√
Observations	*310,044*	*340,276*	*297,850*	*67,506*	*323,624*	*362,102*	*323,012*	*99,380*
Adjusted R-squared	*0.370*	*0.381*	*0.379*	*0.349*	*0.082*	*0.099*	*0.078*	*0.081*