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The Riskiness of Outstanding Mortgages in the United States, 1999 - 2019

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October 2021

Working Paper 21-03

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Please address correspondence to William Larson (william.larson@fhfa.gov). Special thanks to the NMDB team at FHFA for their time and effort assembling a wonderful database. Thanks also to Chuck Capone, Justin Contat, Tom Daula, Lynn Fisher, Steve Oliner, and seminar participants at FHFA for comments and encouragement.

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Abstract

This paper introduces summary measures of credit risk for the stock of all outstanding mortgages in the United States for each quarter between 1999 and 2019. Mortgage terminations play a fundamental role in offsetting risk introduced by the flow of new originations because of refinance activity and the often dual nature of home buyers as concurrent sellers. To illustrate these concepts in a policy setting, I show the Home Affordable Refinance Program increased origination risk metrics but reduced overall risk due to the associated terminations of even riskier loans. Generally, book-level risk tends to lag behind originations: while origination risk peaked in 2006, the risk of outstanding mortgages peaked in 2007, and while origination risk bottomed out in 2011 and has been rising since, book-level risk continued its downward trend in 2019. Other results highlight previously rarely-examined market segments, including credit unions, the Federal Home Loan Bank system, and loans guaranteed by the Farm Service Agency/Rural Housing Service.

Keywords: mortgage risk · systemic risk · housing cycles · stress test

JEL Classification: E32, G21, G28, H22, R31

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1 Introduction

Mortgage credit risk measurement has received substantial attention in the wake of the Great Recession. Efforts by researchers at the Urban Institute, the American Enterprise Institute (AEI), and the Federal Housing Finance Agency (FHFA), to name several, have resulted in an array of risk measures that seek to summarize and measure the credit risk of new originations in historically comparable ways.[1] While these measures are useful to help understand the riskiness of the *flow* of mortgage credit onto the balance sheets of banks, holders of mortgage backed securities, and other investors, there is no summary risk indicator that tracks the risk of the *stock* of existing mortgages over time. There is also no measure of potential *severity*, that is, the dollar value of existing mortgage debt that is vulnerable to default in times of crisis. In order to gain a clear picture of the overall level of mortgage risk in the economy, it is important to consider not just originations, but the full book of outstanding mortgage debt.

This paper attempts to fill these two gaps by extending the approaches pioneered in these previous efforts, in particular, Davis et al. (2021). There are two target metrics, the counterfactual "stressed default rate" (SDR) and the counterfactual "stressed debt at risk" (SDAR). The SDR is the predicted lifetime default rate of a loan as though it existed in quarter four of 2007, just before the beginning of the Great Recession. The SDR can be calculated for any loan at any time period in the sample using the loan's current characteristics. The SDAR is the SDR multiplied by the unpaid principal balance on the loan, thus giving a metric representing the expected balance of the mortgage debt that would have defaulted if loan existed in the counterfactual period. These loan-level SDR and SDARs are then aggregated to construct levels of average risk for the market as a whole, market segments, age cohorts, and other attributes.

There are many novel findings as the riskiness of outstanding mortgages is brought into focus, three of which are highlighted here. First, while origination risk peaked in 2006 and bottomed out in 2011, book-level risk did not peak until 2007, and has continued to fall through the end of the sample in 2019. The sum of the balance at risk peaked in 2007 at \$1.60 trillion, reached a trough of \$620 billion in 2017, and was \$630 billion at the end of

[1] See the Urban Institute's Housing Credit Availability Index (HCAI) (Li and Goodman, 2014), the American Enterprise Institute's National Mortgage Default Rate (NMDR) (Peter and Pinto, 2021), and a Federal Housing Finance Agency staff working paper (Davis et al., 2021).

2019. The difference in the time path of the book-level SDR and the SDAR is due to the changing average balance per loan, which has increased from $165,000 in 2008 to $184,000 in 2019 for loans with at least a 20% loan-to-value ratio at origination.

Second, average stress default rates for terminating mortgages are often between those of new originations and the outstanding book of business, suggesting substantial churn in the mortgage market. Using matched pairs of new Home Affordable Refinance Program (HARP) loans originated between 2009 and 2018, I show that in this particular policy setting, new origination risk rose due to the program, but book-level risk actually declined. This occurred because the seemingly risky originations were matched with terminations of even riskier loans. The approach used in this paper is potentially usable in future policy settings, including forbearance in the COVID-19 pandemic (see Gerardi et al., 2021).

Finally, segments that have gone unmeasured in prior studies show interesting trends for both origination and book-level risk. I include a mutually exclusive and exhaustive ten-segment breakdown, including Fannie Mae (FNM), Freddie Mac (FRE), the Federal Home Loan Banks (FHLB), Farm Service Agency/Rural Housing Service (FSA/RHS), credit unions (CU), non-credit union private conforming (NCUCON), non-credit union jumbo (NCUJUMBO), Veterans Administration (VA), Federal Housing Administration (FHA), and loans in private-label securities (PLS). Risk accumulation in one segment can mask decreases in another, making it crucial to disaggregate by segment when possible. For instance, by splitting the portfolio segment into credit union, jumbo, and conventional conforming segments, it is clear that there is important heterogeneity in the components. Credit unions have low and stable risk across all time periods, while non-credit union segments have high risk. Mortgages within the FSA/RHS and FHLB segments, which have previously received little attention, are included in the analysis.

To construct these metrics, I consider the full book of new and existing loans in each time period, not just new originations. The sub-sample of loans that are new originations gives SDRs that are similar to Li and Goodman (2014), Peter and Pinto (2021), and Davis et al. (2021). However, many originations are associated with terminations, such as in the course of a refinance mortgage or when a household moves, with a pre-payment of one mortgage simultaneous with an origination of another. In such cases, for the terminated and newly-originated loan, borrower and loan attributes are often very similar, with little overall effect on book-level risk. Additionally, the risk profile of the book of outstanding business may have different risk trends than new originations. Seasoned loans are conditioned on survival, amortize, and have changes in collateral value over time. These factors can increase or decrease risk over the life of the loan in both observable and unobservable ways.

These new metrics are made possible by using the National Mortgage Database® (NMDB). The NMDB is a joint effort between the FHFA and the Consumer Finance Protection Bureau to construct a comprehensive, nationally representative mortgage database. This database represents a one-in-twenty sample of all first-lien loans in the United States in existence since 1998. This database includes information on borrower and loan information at origination, and loan performance over time.

2 Counterfactual Risk Indicators

Standard mortgage databases contain origination and performance data on numerous borrower and loan characteristics, including (but not limited to) information on the loan-to-value ratio (LTV), the debt-to-income ratio (DTI), credit scores, and loan purpose. Many of these "primary risk factors" are associated with mortgage default risk. It has become common to use mortgage performance models, estimated using loans originated just before the beginning of the Great Recession, to calculate a counterfactual default rate for mortgages originated in *any* time period. These counterfactuals act as real-time stress tests, simulating how a loan would have performed, in expectation, if it existed during the modeled time period.

This counterfactual mapping has been widely adopted in order to facilitate the tracking of mortgage risk for new originations in summary form. By reducing each loan's dimensionality to a single value and then aggregating over various time periods or cross-sectional units (e.g. market segment, geography, loan type, or borrower attribute), the counterfactual stress indicator approach has made it much easier to measure and communicate trends in mortgage risk. This is particularly useful for comparisons across time because *expected* default rates vary with current economic conditions, whereas *counterfactual* default rates maintain a constant risk mapping throughout all time periods. Changes in calculated risk are therefore due exclusively to changes in the underlying attributes of the loan, borrower, and location, holding risk loadings of each attribute constant. The primary drawback to this approach is any selection into mortgage characteristics that changes over time will confound the measure (e.g. Brueckner, 1994). This can occur if latent default costs, credit supply, or risk preferences change over time. Despite this possible shortcoming, it is considered a necessary assumption in the stress-testing literature (Schuermann, 2014) and in the calculation of existing measures.

This section describes the methods used to construct the counterfactual stressed default rates (SDR) in this paper. The framework for the construction of the SDRs is straightforward and has been established in prior work (Davis et al., 2021). The basic approach proceeds in three steps: 1) identify a set of loans at the "cliff" right before the beginning of the Great Recession; 2) estimate a default model relating risk attributes to whether or not a loan defaults at any point in the future; and 3) use the estimated parameters to fit counterfactual default rates for loans in other time periods. What is new is the extension of the approach to seasoned loans. This facilitates calculation of risk metrics for portfolios of all mortgages in a particular portfolio, not just newly originated loans. There are additional complexities with modeling seasoned loans, including non-random selection and changing marginal effects of parameters with the age of the loan, and these will be discussed shortly. First, however, I outline the general approach.

With enough observations, and if models are properly specified, a logit model, a highly granular default grid, and machine learning models (including CART and random forest models), each give similar results (Davis et al., 2021). Because the NMDB is a one-in-twenty sample, it is necessary to economize on degrees of freedom and I proceed with a logit-based default model. Later, I validate this approach using new originations and comparing the metrics constructed here to alternative publicly available summary risk indicators. I also establish robustness with respect to the information set and functional form within the logit model framework. There is little difference due to functional form. Most differences are due to variables included in the model.

In the expression below, future default Y for loan i in some base period is estimated using a logit model as a function of a vector of covariates X, where the logit function is defined as $logit(\omega) = log(\frac{\omega}{1-\omega})$.

$$logit(Pr(Y_i = 1)) = X_i'\beta + e_i \tag{1}$$

The covariates in X include standard borrower and loan attributes, including credit score, DTI, interest rate spread, amortization term, loan age, and indicator variables for owner-occupied, ARM, single-borrower, first-time buyer, interest-only, balloon, and negative amortization; see Deng et al. (2000), Foote et al. (2008), and numerous other works on the subject. Other variables are described more fully in the next section, including market segment, loan type, various loan-to-value ratios, a burnout variable to account for prepayment tendencies among seasoned loans, and state-level foreclosure durations and laws.

In order to account for nonlinearities in modeling, facilitate missing variable handling, and provide for easy tabulation, most variables are assigned to a group or range bucket. Cutoffs are typically based on Davis et al. (2021), which are in turn based on widely-held notions of breakpoints in sorting caused by various mortgage lending rules. For instance, the DTI range of $[44, 51)$ includes the segment relevant to the Qualifying Mortgage (QM) patch,[2] and credit scores below 660 or 620 are often referred to as "sub-prime" (e.g. Mian and Sufi, 2009).

This model is non-causal and is meant to be estimated over book of loans in a particular age cohort. Age cohort-level specifications are critical when considering seasoned loans for three main reasons. First, some variables that are measured at origination change over time and thus become increasingly noisy signals of that which they once represented. Credit scores are one example of this type, which change over time for the same borrower. Second, selection into an age cohort is non-random, as those who are likely to prepay or default are more likely to have exited the cohort (Deng et al., 2000). Default association differences across cohorts due to non-random selection based on observables is of no issue because the model is meant to be predictive and not structural. Non-random selection that is based on unobservables is addressed using a "burnout" variable, as is standard; see Dunsky and Ho (2007), Agarwal et al. (2016), and others. Finally, some variables may become more relevant as the age of the loan increases, such as balloon loans or ARMs. Age cohort-specific models account for

[2] The Dodd-Frank Wall Street Reform and Consumer Protection Act, as implemented by the Consumer Financial Protection Bureau's 2014 "QM rule," defines a "qualifying mortgage" to have a DTI of 43 or less, with certain benefits ascribed to the lender meeting this and other requirements. There is currently a patch in effect which exempts loans sold to Fannie Mae and Freddie Mac from this requirement. This patch is currently set to expire in 2022.

each of these factors in an associative manner.[3]

The stressed default rate (SDR) for loan i in any time t is then calculated as

$$SDR_{it} = \frac{\exp X'_{it}\hat{\beta}}{1 + \exp X'_{it}\hat{\beta}} \ . \tag{2}$$

For loans not in the estimation sample period, this estimate acts as a counterfactual default rate. The counterfactual is the expectation of how a loan or portfolio of loans would have performed if it existed in 2007:Q4 over the remaining life of the loan. It is termed a "stressed" default rate because the sample period is chosen based on it being the last quarter before the mortgage market began experiencing the major economic stress of 2008 and the rest of the Great Recession.

3 Data

The focus of this section is to introduce the primary risk factors in the National Mortgage Database (NMDB). The NMDB provides a one-in-twenty random sample of nearly all first-lien U.S. mortgages from 1998 through 2021. The NMDB is based on credit repository data, meaning it tends to represent institutional closed-end loans.[4] This database includes information on borrower and loan information at origination, and loan performance over time. The major advantage of the NMDB is its comprehensive population from which it draws its sample, its exhaustive loan performance information, and its standardization of metrics. Its major drawback is that because it relies on credit repository data as the primary sample, and not administrative or servicer data which must be matched, explicit measurement of some

[3] This model also requires the assumption that right-censoring of mortgage performance information is inconsequential, that is, for the estimation sample, no defaults are likely beyond the horizon of the mortgage performance dataset. For the application in this paper, the estimation sample is in 2007 and the mortgage performance dataset runs through 2021. It is unlikely that loans origination in or before 2007 will default after 2021 in substantial numbers due to amortization, prepayment, and prior default.

[4] This misses seller-financed or boutique loans that do not report to credit repositories, and HELOC/HECM loans which are open-ended, and chattel loans. The NMDB is described fully in an online codebook; see `https://www.fhfa.gov/PolicyProgramsResearch/Programs/Pages/National-Mortgage-Database.aspx`.

variables, including DTI, LTV, and income documentation status, can be lacking at times.[5] Despite these shortcomings, as will be shown, the summary risk indicators calculated using the NMDB data give results that plausible and comparable to those calculated using servicer or administrative data as primary databases, including Davis et al. (2021).

Variables used in this paper are shown in Table 1.[6] This table includes the variable name, a short description, and means by loan age cohort. Age cohorts include the ranges of $0-1$ years, $>1-2$ years, $>2-3$ years, $>3-5$ years, $>5-7$ years, and $>7+$ years since origination. Values are shown for the estimation sample, all active loans in the 4th quarter of 2007.

Particularly noteworthy in this long list of variables are the different loan-to-value ratios and their components. The goal of a loan-to-value ratio is to represent the value of the collateral on the loan versus the loan amount. For seasoned loans, this ratio needs to consider changes to house prices and amortization/prepayments. Because the model considers future default, a modeled future house price shock is included as well. The house price shock is based on Smith et al. (2016) and Davis et al. (2021) and is described in the appendix. The preferred metric, the mark-to-market shock combined loan-to-value ratio (MTMS-CLTV) is calculated as follows for each loan i in time t, normalizing the origination period to time 0.

$$MTMSCLTV_{it} = (1+\delta_{i0})UPB_{it}/\left(V_{i0}(1+\Delta P_{it0})(1+\Delta P^{s}_{i,t+12})\right) \tag{3}$$

In the above expression, the term $UPB_{it} \times (1+\delta_{i0})$ is an estimate of the total debt secured by the property at time t. The variable UPB_{it} is the total unpaid principal balance on the loan at time t, and the variable δ gives the fraction of the debt at origination held by other liens which are not tracked after origination. The term $V_{i0}(1+\Delta P_{it0})(1+\Delta P^{s}_{i,t+12})$ gives the initial value of the home V_{i0} and multiplies it by two terms. The first is the appreciation from origination to time t, $(1+\Delta P_{it0})$, and the second is the the hypothetical 3-year (12

[5] For instance, for loans in existence in 2007:Q4, DTI is imputed for 38% of observations; LTV is imputed for 21%, structure type is imputed for 13%, and income documentation status is missing for 84%. Shares of loans with non-standard amortization and ARM status are also somwewhat lower in the NMDB than the data assembled by Davis et al. (2021).

[6] For additional stylized facts related to NMDB primary risk indicators and these various groupings, see `https://www.fhfa.gov/DataTools/Downloads/Pages/National-Mortgage-Database-Aggregate-Data.aspx` and the appendix to this paper.

quarter) appreciation in a severe shock environment, $(1 + \Delta P^s_{i,t+12})$.[7] For example, if the original LTV was 80 and a 2nd lien was an additional 15%, the original CLTV would be 95. If the home amortized 5% and the home appreciated 20% through time t, the mark-to-market CLTV would be $75 = (95 - 5)/1.2$. Then, if the stress house price shock was 30%, the mark-to-market shock CLTV would be $107.1 = 75/0.7$. This metric is updated for each loan in each quarter.

Loan types include purchase-money mortgages, cash-out refinances, and other refinances which are typically originated to adjust the rate and/or term on the mortgage. A refinance loan is considered a cash-out refinance if the principal on the new loan is at least 5% larger than the last unpaid principal balance on the prior loan.

Loans are divided into ten mutually exclusive and exhaustive market segments. These segments include Fannie Mae (FNM), Freddie Mac (FRE), the Federal Home Loan Banks (FHLB), Farm Service Agency/Rural Housing Service (FSA/RHS), credit unions (CU), non-credit union private conforming (NCUCON), non-credit union jumbo (NCUJUMBO), Veterans Administration (VA), Federal Housing Administration (FHA), and private-label security (PLS). Assignment to each market segment is based on a recursive "waterfall" based entirely on variables in the NMDB. This waterfall is constructed in accordance with the ultimate holder of the default risk, notwithstanding other risk-spreading efforts such as credit risk transfer securities or mortgage insurance.[8]

Two state foreclosure regime variables are included representing the average time-to-foreclosure and whether the state has judicial foreclosure resolution. These variables are based on an in-

[7] The house price shock depends on the state's house price level above its long-run trend and how far the states price level has ever fallen below the trend. Accordingly, during bubble periods, the model-generated shock variable is higher than after a bust.

[8] Assignment proceeds as follows, with each successive assignment overriding all prior assignment, where applicable. So, for instance, an FHA loan securitized by Fannie Mae would be assigned to FHA because (3) occurs after (1). The segmentation assignment waterfall proceeds as follows:

1. Assign the loan to the relevant GSE (FNM, FRE, FHLB) based on the "gse_flag" variable.
2. Assign the variable to PLS based on the "plmbs" variable.
3. Assign the loan to FHA, VA, or FSA/RHS based on the "loan_type" variable.
4. Assign the variable to the relevant Portfolio segment (CU if "cu_flag=1", NCUJUMBO if "cu_flag=0" and loan amount > conforming loan limit, NCUCON otherwise) if previously unassigned.

ternal FHFA report using data from NCLC (2019), Rao and Walsh (2009), and other sources from the National Consumer Law Center.

Finally, I include a "burnout" variable for the propensity of seasoned loans to have prepaid before entering the current portfolio, following Dunsky and Ho (2007), Agarwal et al. (2016), and others. This variable is defined as the number of quarters the rate on the note is at least 100 basis points (1%) lower than the prevailing fixed interest rate, conditional on the loan term. It is important to control for the selection of seasoned loans into a portfolio because prepayment propensity can be non-random and correlated with both default determinants and future default. For instance, a borrower with a positive call (prepayment) option for a number of years who does not execute the option may do so because they are wealthy (unobserved), have a low DTI, and a low default probability conditional on DTI. A sample over-represented by borrowers of this type would produce biased estimated parameters. The inclusion of a burnout variable is akin to including an inverse Mills ratio term, albeit in reduced form and under different functional form.[9] Prior default propensity assumed to be directly related to observed factors and with no additional controls necessary.

4 Results

Logit-based default models are estimated using the nationwide mortgage portfolio as it existed in the fourth quarter of 2007, at the dawn of the Great Recession. These models are used to produce counterfactual SDRs for every quarter from 1999 through 2019. This section proceeds with a description of the results in three parts.

First, model results show the partial effects of primary risk factors on defaults for the 2007:Q4 cohort. There are several interesting findings from the models, including deterioration of predictive power of the market segment and the origination DTI as a loan ages. Next, the SDR is shown for the market as a whole for new originations, the full book, and loans that exit the book (i.e. terminations) in each period. Book-level SDRs tend to lag behind origination-level SDRs: while origination risk peaked in 2006, book-level risk peaked in 2007,

[9] Rather than estimating $Y = X'B + aM(X,Z) + e$, where M is an inverse Mills ratio term or other predicted probability of prior survival, my approach is to estimate $Y = X'B + Z'A + e$ directly. In both cases, $Y = f(X,Z)$; the functional form is different. $\hat{B}^*$, estimated using the latter model will be different than $\hat{B}$ from the former because it will include selection effects, but observed selection differences that contribute to default are not harmful in a predictive setting such as this. The only thing that matters is controlling for variables that determine prior prepayment even if they do not directly determine future default. An additional alternative considered is to estimate cohort-specific hazard models.

and while origination risk bottomed out in 2011 and has been rising since, book-level risk continued its downward trend in 2019. Terminations tend to offset origination risk, though not completely. Finally, loan counts and SDRs are then broken down by loan cohort, loan purpose, and market segment. The waxing and waning of mortgage risk by levels of seasoning over time is noteworthy: the 2004 origination cohort was the largest in the sample, but the 2007 origination cohort was the riskiest. 2007 was the last year new originations were the riskiest mortgages until 2018. Throughout the sample, purchase-money mortgages were the riskiest, followed closely by cash-out refinances, with rate/term refinances the least risky. In terms of market segments, PLS was the riskiest group of loans from 2001 through 2018. In 2019, FSA/RHS was the riskiest, followed closely by FHA. Credit unions were the least risky throughout.

4.1 Model Estimates

The cohort-level default model parameter estimates are shown in Table 2. These partial correlates are of standard signs compared to the literature (e.g. Foote et al., 2008). Attributes associated with alternative loan products such as interest-only or negative amortization loans are positively associated with eventual default. Single-borrower households are highly associated with default. As the loan term increases, so to does default risk. The higher the interest rate spread at origination over the comparable market rate, the higher the risk. Mark-to-market shock combined LTVs exhibit consistently strong and highly predictive associations with default across age cohorts.

There are three main risk groups for new originations by market segment. VA and credit union loans are the least risky. Next, Fannie Mae, Freddie Mac, Federal Home Loan Bank, non-credit union jumbo, and FHA loans are all relatively similar risk, conditional on observables. Finally, loans in private-label securities, FSA/RHS, and non-credit union conforming loans are the riskiest. While these orderings exist for new originations, they do change somewhat over the life of the loan.

Purchase loans are slightly less risky than cash-out refinances, followed by rate/term refinances which are the riskiest, conditional on observables. Income documentation status is fraught by a large number of missing values, with affirmatively full documentation as the least risky, followed by affirmatively reduced income documentation, with a missing entry being the riskiest. Credit scores and DTIs behave as expected, with higher credit scores and lower DTIs associated with lower risk. However, while the effects of credit scores tend to strengthen with loan age, the predictive power of DTI attenuates.

4.2 Stressed Default Rate

The stressed default rate is shown in Figure 1 for the United States between 1999 and 2019, for three groups of loans, new originations, the full outstanding book of mortgages securitized or held in portfolio ("book"), and loans that terminated in the prior period. Each series is a four-quarter trailing moving average.

Origination risk is most volatile, with run-ups in the late 1990s, the pre-Great Recession period, and a slow increase since the Great Recession. Terminations have a similar profile as originations until about 2011, but the variation is more muted. This suggests newly-originated loans have similar risk-profiles as terminated loans over this period. Between 2011 and 2017, terminations were riskier than new originations, indicating prepayments and defaults of risky loans are being replaced in the book by low-risk originations.

The full outstanding book of mortgage debt outstanding is characterized by two main features, it tends to lag origination risk, and it tends to be a smooth, slowly-changing series compared to origination risk, which is much more volatile. The book underwent a steady run-up in risk through the end of 2007, then began a slow decline through the end of 2019, with only the single turning point. Book-level risk does not track originations-net-of-terminations perfectly for three main reasons. First, there is information in survival: as a loan cohort ages, marginal effects of variables change. Second, house price appreciation occurs, shifting the mark-to-market CLTV on the loan. Finally, each year represents a different time in the house price cycle for the county in which the collateral exists, meaning the estimated future house price shock in a stress environment is continually changing. These cohort-level effects are discussed shortly.

4.3 Geography

Because SDRs are estimated at the loan level, it is straightforward to summarize them across different dimensions, including spatial comparisons. There are intentionally no state-level fixed effects in the models used to generate the SDRs, instead relying on structural attributes such as house price changes, expected future shock house price declines, and a state's foreclosure regime. Accordingly, variation in SDRs is based on loan, borrower, county, and state-level attributes, and not some sort of inherent and immutable estimate of riskiness across states.

Figure 2 shows cuts of SDRs by state for two time periods, 2007:Q4 (the estimation period), and 2019:Q4, the final time period in the sample. We can see stark variation across space and over time in SDRs. Overall levels of risk tend to be higher in 2007 than 2019. The one exception is North Dakota, which has seen a substantial run-up in house prices dating back before the Great Recession. Nevada remains the riskiest state, with SDRs in 2019 that are higher than many states in 2007. Generally, the Midwest and the North East regions tend to exhibit the least risk.

4.4 Loan Purpose Types

Loan products have different counterfactual default rates due to the direct effect of product type in the default model and an indirect effect of correlations between other default determinants and product type. As can be seen from Figure 3, new purchase-money ("purchase") mortgages have higher stressed default rates than cash-out refinances, which are higher than rate/term refinances. This is precisely the opposite ordering of the partial effects in the default model for most age cohorts, with purchases as typically the safest, cash-out refinances as the middle, and rate/term refinances as the riskiest. This implies that overall, purchases have riskier primary risk factors than the other two segments. Overall, both composition of loan purpose types and SDRs for those types have been changing in important ways over time.

4.5 Loan Age Cohorts

Figure 4 shows loan counts and SDRs by loan age over time. Here, we can see how the composition of the book of outstanding mortgage debt has undergone dramatic changes in seasoning. Loans of 0 to 1 year of age were over twice as prevalent as any other cohort in 2004. However, by 2010, loans aged 7+ years were the highest, and the gap has remained high through the end of the sample. Overall, mortgage debt in the 2010s was made up of much older loans than the pre-Recession period.

In addition to these compositional differences, SDRs are also fluctuating significantly within age groups over time. We can see echoes of the risky 2006 cohort as it ages, with peaks in risk for each cohort advancing in a similar pattern. One of the more interesting patterns is the 7+ cohort. For a period between 2015 and 2018, these were the riskiest loans on the book. Despite their age, they contained features associated with elevated risk, such as non-standard amortization (e.g. interest-only or negative amortization) or a failure to refinance to lower interest rates even though rates had been low for quite some time. Only after 2016 did this cohort's risk profile decline, and it continues to be a source of falling book-level risk from this period through the end of the sample, offsetting some of the rise in the risk of newly-originated loans.

4.6 Market Segments

Market segment analysis is one of the key features of this research, with deeper levels of granularity compared to other publicly available sources. Figure 5 presents time series of the ten market segments' loan counts and SDRs. As with the other tabulations, there are substantial composition differences over time. As has been well-documented elsewhere, the rise of the market share of private-label securities occurred at the same time as relative declines in shares for the private-conforming, private-jumbo, and FHA segments. As PLS receded, FHA, VA, Fannie Mae, and Freddie Mac largely filled the gap.

The jumbo segment has seen perhaps the greatest variation in risk. It rose from moderate levels of risk in the late 1990s to the 2nd highest behind PLS in 2007, falling to the 2nd lowest at the end of 2019. Credit unions, a segment that has received little attention in the literature, have consistently low SDRs, never rising above 4%, all while gaining market share over the 20-year period. Perhaps surprisingly, PLS is the third riskiest segment of outstanding loans in 2019, indicating that 10 years after the start of the Great Recession, many of these loans still have not amortized and/or house prices have not recovered to the point where they are safe. The riskiest segment at the end of 2019 is the pool of Farm Service Agency/Rural Housing Service loans.

4.7 Discussion

This section described the main results in this paper, from the models used to generate the stressed default rates, to the SDRs themselves, and finally, various cuts long key dimensions. SDRs are defined at the loan-level, facilitating analysis on a variety of topics, and easily introduced as a variable in a data "cube."[10] There are important compositional changes in the book of mortgage debt that is outstanding in the United States, and conditional on composition, varying risk profiles over time.

The next three sections address several key items related to these main results. The first is an investigation into the role of terminations in offsetting origination risk. Next, a vari-

[10] A data cube is a multidimensional cross-tabulation that facilitates quick aggregation and data visualization. It is an intermediate data structure between a raw dataset and a custom aggregate.

able “stressed debt-at-risk” (SDAR) is introduced, a variable which is the total mortgage debt outstanding that is subject to future default under counterfactual stress. Finally, the robustness of the main results in the present section is examined in terms of the choice of variables in the default model, incorporation of delinquencies, and comparison with alternative summary risk indicators in the literature.

5 HARP and the role of terminations

One shortcoming of most mortgage databases, the NMDB included, is the difficulty in linking terminated loans with newly originated loans for the same borrower and address. FHFA’s internal MLIS database has a similar issue because loan numbers are unique to a particular Enterprise. One group of loans that does not suffer from this problem are loans issued under the Home Affordable Refinance Program (HARP). Because HARP terminations and originations are with the same Enterprise, they can be explicitly linked, allowing me to track risk characteristics between loans. HARP also serves as an interesting policy setting because HARP originations look extremely risky when viewed on their own, but as I will show, they significantly reduced default risk, measured using SDRs.

The Home Affordable Refinance Program (HARP) was a policy implemented by the FHFA in 2007 to enable borrowers who were underwater (or nearly underwater) in terms of MTM-LTV to refinance their loans. The loans were required to have been sold to Fannie Mae or Freddie Mac before 2009 and the borrowers needed to be current in their payments. Because the borrowers had extremely high levels of debt relative to the collateral, it would otherwise have been difficult to refinance their mortgages and take advantage of interest rates that were, at the time, near record lows. After some uptake in the early years of the program, HARP 2.0 went into effect in 2012 that relaxed MTM-LTV, credit score, and DTI restrictions. Overall, approximately 3.3 million borrowers refinanced their mortgages through the HARP program until its end in 2018.

Origination risk indicators show HARP loans are extremely risky (Davis et al., 2021). But when analyzing book-level risk using SDRs for seasoned loans, it is possible to compare the riskiness of the loans that terminated due to the HARP program and the newly originated HARP loans. Through this lens, we can begin to understand the extent to which HARP affected overall book-level mortgage risk. For this analysis, I turn to the FHFA’s internal Mortgage Loan Information System (MLIS) database to consider the universe of HARP loans.

Figure 6 shows SDRs for HARP originations and the loans that were terminated due to being refinanced as part of the HARP program ("HARP terminations"). In all periods, the refinanced loans are of lower risk than the terminated loans, with the gap expanding in 2015 through the end of the program. This is due to several characteristics of the loans changing. The panels of Figure 7 show some of the important characteristics of HARP originations versus their terminated counterparts. The main factors contributing to reductions in mortgage risk are the lower interest rates on the notes, which fell from just over 6% to typically between 4% and 5%, on average; the elimination of interest-only loans which have high differential levels of risk compared to other seasoned loans; and the elimination of reduced income documentation loans. Origination credit scores were also slightly higher for HARP refinances, likely because of the success of the borrowers in continuing to make payments over the period of the initial loan. Despite reductions in risk from these factors, DTIs actually rose between loans, contributing to a rise in risk. But on a net basis, as measured using SDRs, the HARP program significantly reduced book-level mortgage risk to Fannie Mae and Freddie Mac.

6 Stressed Debt at Risk

Indicators considered so far represent shares of loans at risk of default in times of stress. This section introduces a measure that represents total debt outstanding that is subject to stressed defaults. This intensive margin of credit risk represents a major contributor to gross credit losses in times of widespread default, the unpaid principal balance on the loan, before any collateral sales, mortgage insurance payments, or other losses or recoveries are taken into account.

The stressed debt at risk (SDAR) is defined as the current loan balance multiplied by the SDR.

$$SDAR_{it} = SDR_{it} \times UPB_{it} \tag{4}$$

The SDAR is shown for all mortgages over time in Figure 8 on both a per-loan and aggregate basis.

The first panel shows the SDAR for an average loan among the full book, new originations, and terminations. Prior to 2008, new originations were adding to book-level risk, as indicated by an average loan contributing more SDAR than the book. However, for most of this period, terminations also had higher risk than the book, meaning that originations were being somewhat offset by terminations in terms of the dollar value of risk exposure. Between 2008 and 2015, originations and terminations were both pulling down average loan-level book-level risk. Since 2015, originations have begun again contributing positively to the book SDAR.

The second panel shows the total SDAR for the entire U.S. mortgage market. Both the left and right axis scales are in billions of dollars, with the left representing originations and terminations, and the right representing the full book. The first result is that the gross dollar value of the SDAR is remarkably large. At its peak, $1.6 trillion was at risk in 2007. The SDR has leveled off at about $600 billion between 2017 through the end of 2019. Originations and terminations play an obvious role in adding or subtracting from the cumulative book-level total, with originations adding to the figure and terminations subtracting. Added to these factors, book-level risk rises or falls based on amortization/prepayments and changes to house prices.

As external validation of these seemingly large numbers, in 2007, there was about $11.2 trillion of mortgage debt outstanding on 1-4 unit residences, as reported by the Federal Reserve Board.[11] The SDAR for this period is about 14% of this amount, which almost exactly corresponds to the book-level SDR shown in Figure 1.

7 Robustness and External Validation

This section establishes the robustness of the measures in this paper to alternative models, variable choices, and other series resembling stressed default rates calculated in the literature. To establish the robustness of the SDRs, I first estimate a number of competing models. These models represent different parameter restrictions in the form of breaking out components of the MTMS-CLTV, eliminating variables that could be associated with period-specific sorting among unobservables, and a broader measure of default that includes all loans that are 180+ days delinquent. Estimated parameters are generally robust. The only major difference in SDRs over time occurs when future house price shocks are not included in the base-period model. In this case, the counterfactual is based on Great Recession-levels of house price declines, regardless of whether house prices are currently above or below long-run trends.

[11] See `https://fred.stlouisfed.org/series/ASHMA`.

When compared to externally produced measures that resemble SDRs for new originations, estimates are broadly similar, including those produced by the American Enterprise Institute and in a FHFA working paper. The one exception is the Urban Institute's credit availability index which shows lower increases in both the run-up to the Great Recession and in the recovery period in the 2010s. Overall, these checks to both internal and external validity serve to show that the baseline SDRs produced are both fairly consistent and in-line with what exists in the current state of the literature.

7.1 Robustness

Estimates from alternative models are shown in Table 3. In this table, loans across all loan cohorts are pooled, with the addition of cohort-group fixed effects. Model 8 is the cohort-pooled analogue to models 1-7, and this serves as the baseline.

The use of segment information in the baseline is subject to two potentially important criticisms. One criticism of involves a particular form endogenous sorting. Conceptually, the path a loan takes in the secondary market is non-random, and is instead a function of contemporaneous market factors which may vary over time and are unobserved. Econometrically, if some unobserved factor associated with default also causes a loan to be owned by a particular segment, then there is potentially endogeneity bias in the segment coefficients.[12] Another potential criticism is omitted variable bias. If there is an unobserved factor that is correlated with the market segment, and that factor is the true cause of default and not the segment itself, then explanatory power may be mis-attributed to the segment. This is not a problem if the correlation between segments and the unobserved variables is stable, but it is known that many segments' market shares have risen and fallen over time due to other factors; most notably PLS. In the run-up to the Great Recession, many of the worst loans were in private-label securities. In the current environment, this segment is almost completely absent, with a share of new originations just above 0% in 2019 versus its peak of near 30% in 2005. If PLS stood in as a proxy for another risk factor then the PLS segment would have information mis-attributed to it.

Model 9 is a segment-agnostic model that strips all information related to market segmentation from the specification. When the segment-agnostic model is used in place of the model

[12] For example, if borrowers can be divided into high versus low risk appetite categories, and one segment captures a disproportionate share of the high-risk appetite borrowers, then that segment may be associated with higher levels of default in a default model if risk appetites are unmeasured.

with segment information, overall fit declines slightly, as confirmed by the log-likelihood statistics and likelihood ratio tests. However, there is little effect on the aggregate statistics as seen in Figure 9, for a model where cohorts are estimate separately. There is perhaps some conditional correlation between segments and defaults, but there are only small predictive differences between the two models as the other variables capture the omitted explanatory power.

Another factor to consider in this analysis is the effect of local price dynamics in the run-up to the Great Recession and its aftermath. The baseline model uses the MTMS-CLTV, which implicitly treats paid principal balances, house price increases and future house price shocks the same when it comes to default propensity. These component factors may have different partial effects.

Models 10 and 11 consider the case where no future house price shock is modeled, and where the house price components are modeled individually alongside amortized CLTV, respectively. Model 10 shows omission of the modeled future house price shock substantially reduces the predictive power of the model. Model 11 shows the shock has about twice the magnitude of the house price change since origination. This model has a better fit than the baseline, making it a candidate to replace the baseline model. However, due to the parsimony of the MTMS-CLTV representation, it remains the preferred specification.

Model 12 removes the burnout variable from the baseline model. Overall fit declines slightly, but there is little effect on other parameters in the model. This suggests that prepayment propensity is mostly due to observables in the model.

Model 13 alters the definition of a "bad outcome" of the loan to be either default or if the loan ever becomes 180+ days delinquent, even if it were to cure at some point in the future. This model is useful to consider because this is the definition used by Davis et al. (2021), making estimates comparable. The major parameter differences are for the ARM variable, first-time homebuyer, and the balloon flag. Comparing model 8 to model 13, the first-time homebuyers and balloons are more likely to become delinquent but less likely to default.

Model 14 is a linear probability model. This model's parameters are useful to quickly establish partial effects of variables at their means. For instance, a MTMS-CLTV of 100 to 109 is 8.6pp more likely to default than a loan with less than a loan with a 39% LTV. While DTI has a significant effect, its magnitude is relatively small, conditional on other variables. Credit scores have very large partial effects.

Counterfactual default rates for these competing models are shown in Figure 9. All are nearly identical with the exception of the series with no house price shock. Risk accumulation between 2013 and 2019 is much more apparent in the local shock model because the MTM-CLTV is falling due to house price increases, but the MTMS-CLTV falls only slowly because some of the house price increases are offset by the modeled shock.

7.2 Comparison with other Great Recession counterfactuals

It is possible to compare alternative metrics similar to SDRs that exist in the literature. All series compared are new originations because the SDRs presented here is the only one that considers the full book of loans. One major difference is the definition of "default", which is D90+defaults for the Urban Institute ("UI-HCAI"), D180+defaults for the AEI ("AEI-NMDR") and the version in the prior FHFA working paper (DLOS, 2019), and defaults alone for the main results in the paper. Another difference is the Urban Institute's publicly available calculation which blends expected defaults with stress defaults and weights each by a probability.

Each of these four series are shown in Figure 10. There are several differences, but most conform to a similar trend. To start, each series begins at a different date. Davis et al. (2021) begins in 1994, UI-HCAI begins in 1998, the SDR series from the present paper begins in 1999, and AEI-NMDR begins in 2012. Starting in 1999, the SDR and UI enter at between 10% and 15%, versus the 20% to 25% of DLOS. Then, while the UI does not experience much increase, SDR and DLOS both increase rapidly between 2004 and 2006. The smaller peak in SDRs compared to DLOS is likely due to the poor information on income documentation status in the NMDB, which is an artifact of its basis on credit repository data. In 2006, UI and DLOS decline quickly whereas SDR takes another year to show signs of weakening. By 2012, all are near the minimum value for the respective series, with UI substantially below the other three. Beginning sometime between 2010 and 2012, each begins to increase slightly, resulting in values that are somewhat higher in 2019 than the minimum, but lower than at any point prior to 2008. Overall, these slight differences between origination risk indicators are reassuring, because it suggests that the logit-based approach used in this paper generates similar fluctuations as the much more granular and comprehensive data represented by the

Davis et al. (2021) measure.

8 Conclusion

This paper introduces two summary risk indicators for the U.S. mortgage market representing the riskiness of all outstanding loans. The first is the stressed default rate (SDR), which represents the expectation of how a loan or portfolio of loans would have performed if it existed in 2007:Q4, over the remaining life of the loan. The second is the stressed debt-at-risk (SDAR) which represents the current unpaid principle balance that is vulnerable to counterfactual default. These two metrics show the extent to which mortgage default risk has evolved since the beginning of the 21st century.

The riskiest year for the United States mortgage market was 2007, with SDARs at about $1.6 trillion on SDRs of about 14% of loans. In the wake of the Great Recession, the outstanding book of mortgage debt became much less risky, reaching a trough SDAR of $620 million in 2017, where it approximately stands at the end of 2019.

Origination risk is substantially offset by terminations, that is, when originations are riskier than the average loan in the book of business, terminations are also typically riskier. This points to substantial churn in the mortgage market, and highlights the need to focus on book rather than origination-level risk indicators to assess trends in mortgage risk.

There are rich dynamics within market segments, geography, and loan type, which advise disaggregate analysis whenever possible. Future research using the approaches in this paper should consider the interplay between house prices and mortgage risk, evolution of market shares and risk across market segments, and other efforts to more fully understand the drivers of both the aggregate and disaggregate series.

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Table 1: Variable Definitions and Summary Statistics

Variable	Description	As of 2007:Q4. Age cohort (years) in column						
		0-1	>1-2	>2-3	>3-4	>4-5	>5-7	>7
Owner-Occupied	Loan purpose is to finance an owner-occupied unit	90%	88%	88%	90%	93%	93%	95%
Loan Term	Loan amortization term in years	28.8	29.1	28.1	26.5	24.2	24.0	25.7
ARM	Adjustable-rate mortgage	16%	32%	31%	23%	8%	5%	9%
Single Borrower	One borrower on the loan	55%	57%	52%	47%	38%	41%	42%
First-time Homebuyer	The first time the primary borrower appears as having a mortgage	22%	23%	21%	21%	13%	22%	58%
Interest-Only	Interest-only for some part of the loan term	9%	12%	12%	5%	1%	0%	0%
Balloon	Loan requires a lump-sum payment at some time in its term	3%	5%	1%	1%	1%	1%	1%
Negative Amortization	Loan balance increases over the life of the loan	1%	2%	2%	1%	0%	0%	0%
LTV	Ratio of origination balance to origination value of property	77	76	75	74	69	72	78
CLTV	... sum of origination principal balances ...	79	80	78	76	70	73	78
A-CLTV	... sum of current principal balances ...	79	79	75	70	60	60	53
MTM-CLTV	... to current value of property	79	79	71	59	47	46	31
MTMS-CLTV	... to current value of property, subject to HPI Shock	114	116	103	82	65	62	42
HPI Change	House price change since origination	-1	-1	7	21	32	38	89
HPI Shock	Modeled hypothetical 3-year house price shock	29	30	29	28	28	26	26
Spread at Origination	Average difference in interest rate from PMMS value (positive)	80	108	96	71	36	40	72
Credit Score	Vantage Score	705	696	708	718	739	727	703
DTI	Ratio of debt service payments for all debt to income	39	38	37	35	32	32	33
Judicial Forec. State	0 = non-Judicial foreclosure state; 1 = judicial foreclosure state	40%	40%	40%	41%	41%	43%	45%
Time-to-forec.	Average time-to-foreclosure in months	18.6	18.7	18.7	18.6	18.7	18.7	19.1
Burnout	Quarters with PMMS interest rate + 1 < origination rate	0.32	1.45	1.21	1.19	0.66	6.35	22.01
No/Partial doc.	Loan has less than full income documentation	7%	15%	13%	7%	2%	1%	1%
Full doc.	Full income documentation	7%	14%	14%	11%	5%	4%	3%
Missing doc entry	Missing income doc. status in the NMDB	86%	72%	73%	82%	93%	95%	96%
Purchase	Loan intended for purchase of a home	50%	52%	48%	44%	25%	36%	72%
Rate/Term Refinance	Refinance of an existing loan	16%	16%	19%	27%	45%	35%	15%
Cash-out Refinance	Refinance of an existing loan where balance is > 5% than prior loan	34%	32%	33%	29%	30%	29%	12%
FHA	Federal Housing Administration	5.8%	4.1%	4.1%	6.0%	5.6%	8.4%	14.7%
VA	Veteran's Administration	1.6%	1.4%	1.5%	2.3%	2.9%	3.7%	10.7%
FHLB	Federal Home Loan Bank	0.4%	0.3%	0.5%	0.8%	2.0%	1.4%	0.0%
FNM	Fannie Mae	33.6%	24.9%	26.1%	31.6%	40.7%	35.7%	21.0%
FRE	Freddie Mac	21.5%	17.7%	19.9%	21.7%	25.9%	23.6%	14.7%
FSA/RHS	Farm Service Agency/Rural Housing Service	0.5%	0.4%	0.4%	0.4%	0.2%	0.3%	0.6%
PLS	Private-label security	11.9%	28.9%	27.5%	18.0%	7.3%	5.1%	4.0%
CU	Credit Union	2.3%	1.6%	1.5%	1.8%	1.7%	2.2%	2.2%
NCUCON	Non-credit union, private conforming	18.5%	17.5%	15.0%	14.8%	12.3%	18.4%	30.8%
NCUJUMBO	Non-credit union, jumbo	4.0%	3.2%	3.4%	2.5%	1.4%	1.2%	1.2%
Loan Count		431,489	457,529	436,879	339,706	515,008	293,258	298,725

Note: The sample includes all loans active in the 4th quarter of 2007 in the National Mortgage Database, subject to filters noted in the text. Borrower-level attributes are for the first listed borrower on the loan. For time series of relevant statistics, see the appendix.

Table 2: Default Model Results

Dependent Variable: Lifetime default, post-2007:Q4
Sample: All active loans as of 2007:Q4 by age cohort (listed in column)

Model Number	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Age Cohort (years)	0-1	>1-2	>2-3	>3-4	>4-5	>5-7	>7
Owner-Occupied	-0.259[a]	-0.248[a]	-0.217[a]	-0.277[a]	-0.226[a]	-0.256[a]	-0.141[a]
Loan Age	0.0793[a]	0.0201[a]	-0.0324[a]	-0.0379[a]	-0.0285[a]	0.0247[a]	-0.0123[a]
ARM	-0.00131	0.0760[a]	0.0395[a]	-0.0497[a]	-0.160[a]	-0.104[a]	-0.0778[b]
Single Borrower	0.462[a]	0.458[a]	0.462[a]	0.484[a]	0.557[a]	0.538[a]	0.489[a]
First-time Homebuyer	-0.0446[a]	-0.0512[a]	-0.0944[a]	0.00385	0.0604[a]	0.162[a]	0.248[a]
Interest-Only	0.372[a]	0.276[a]	0.192[a]	0.250[a]	0.290[a]	0.732[a]	1.145[a]
Balloon	-0.484[a]	-0.210[a]	-0.628[a]	-1.238[a]	-0.577[a]	-0.531[a]	-0.145[b]
Negative Amortization	0.0668[c]	0.0192	0.117[a]	0.146[a]	0.581[b]	-0.772	-0.819
Judicial Forec. State	0.0643[a]	0.0750[a]	0.124[a]	0.258[a]	0.407[a]	0.440[a]	0.351[a]
Time-to-forec.	-0.0163[a]	-0.0169[a]	-0.0176[a]	-0.0256[a]	-0.0379[a]	-0.0448[a]	-0.0333[a]
Burnout	0.0121	0.0169[a]	0.00604[a]	0.0108[a]	0.0120[a]	0.0147[a]	0.00892[a]
Loan Term (vs 15 year)							
20 year	0.245[a]	0.171[a]	0.204[a]	0.388[a]	0.259[a]	0.298[a]	0.268[a]
30 year	0.827[a]	0.734[a]	0.672[a]	0.618[a]	0.434[a]	0.395[a]	0.106[a]
40 year	0.939[a]	0.911[a]	0.978[a]	0.827[a]	0.659[a]	0.490[a]	-0.109
Segment (vs CU)							
FHA	0.693[a]	0.879[a]	1.121[a]	1.074[a]	1.201[a]	1.150[a]	1.755[a]
FHLB	0.695[a]	0.958[a]	1.268[a]	1.059[a]	1.108[a]	1.089[a]	2.240[a]
FNM	0.605[a]	0.612[a]	0.726[a]	0.698[a]	0.775[a]	0.882[a]	1.463[a]
FRE	0.537[a]	0.526[a]	0.684[a]	0.642[a]	0.764[a]	0.899[a]	1.445[a]
FSA/RHS	0.915[a]	0.813[a]	0.944[a]	0.956[a]	1.187[a]	1.190[a]	1.613[a]
NCUCON	0.982[a]	1.145[a]	1.226[a]	1.091[a]	1.210[a]	1.312[a]	1.887[a]
PLS	0.868[a]	1.088[a]	1.151[a]	0.963[a]	0.878[a]	1.075[a]	1.740[a]
VA	-0.0515	0.185[a]	0.507[a]	0.538[a]	0.550[a]	0.315[a]	0.961[a]
NCUJUMBO	0.707[a]	0.845[a]	0.963[a]	0.798[a]	0.533[a]	0.525[a]	1.066[a]
Spread at Origination (BPS, vs <25)							
25-49	0.229[a]	0.203[a]	0.187[a]	0.156[a]	0.188[a]	0.206[a]	0.202[a]
50-99	0.420[a]	0.338[a]	0.291[a]	0.319[a]	0.303[a]	0.285[a]	0.206[a]
100-399	0.554[a]	0.466[a]	0.539[a]	0.433[a]	0.360[a]	0.274[a]	0.124[a]
400+	0.490[a]	0.420[a]	0.572[a]	0.572[a]	0.531[a]	0.523[a]	0.271[a]
Loan Type (vs Cash-out Refinance)							
Purchase	-0.0622[a]	0.00852	-0.00126	-0.148[a]	-0.164[a]	-0.195[a]	-0.178[a]
Rate/Term Refinance	0.0979[a]	0.0895[a]	0.0262[b]	-0.113[a]	-0.222[a]	-0.180[a]	-0.0831[b]
Income Documentation Status							
Full doc.	-0.191[a]	-0.229[a]	-0.206[a]	-0.146[a]	-0.175[a]	-0.0064	0.209[a]
Missing entry	0.0837[a]	0.0520[a]	-0.0248	-0.107[a]	-0.219[a]	-0.0119	0.149[b]

Note: Table continues on next page.

Table 2: Default Model Results, Continued

Model Number	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Mark-to-market Shock Combined Loan-to-value Ratio (vs 1-39)							
40-49	-0.0648	0.128[c]	0.0765	0.0187	0.209[a]	0.168[a]	0.433[a]
50-59	0.0906	0.298[a]	0.146[b]	0.195[a]	0.457[a]	0.310[a]	0.559[a]
60-69	0.131[c]	0.376[a]	0.329[a]	0.351[a]	0.683[a]	0.575[a]	0.743[a]
70-79	0.301[a]	0.526[a]	0.482[a]	0.607[a]	1.046[a]	0.807[a]	1.001[a]
80-89	0.419[a]	0.685[a]	0.719[a]	0.845[a]	1.279[a]	1.045[a]	1.152[a]
90-99	0.600[a]	0.919[a]	0.925[a]	1.103[a]	1.527[a]	1.323[a]	1.369[a]
100-109	0.826[a]	1.128[a]	1.163[a]	1.358[a]	1.809[a]	1.531[a]	1.489[a]
110-119	1.042[a]	1.343[a]	1.382[a]	1.614[a]	2.058[a]	1.681[a]	1.615[a]
120-129	1.222[a]	1.544[a]	1.631[a]	1.815[a]	2.170[a]	1.869[a]	1.750[a]
130-139	1.417[a]	1.781[a]	1.921[a]	2.018[a]	2.454[a]	2.073[a]	1.503[a]
140-149	1.624[a]	1.997[a]	2.094[a]	2.299[a]	2.625[a]	2.253[a]	1.701[a]
150+	2.211[a]	2.590[a]	2.606[a]	2.484[a]	2.452[a]	1.547[a]	1.071[a]
Credit Score at Origination (vs <580)							
580-619	-0.178[a]	-0.145[a]	-0.144[a]	-0.159[a]	-0.207[a]	-0.178[a]	-0.306[a]
620-639	-0.199[a]	-0.211[a]	-0.235[a]	-0.294[a]	-0.388[a]	-0.285[a]	-0.411[a]
640-659	-0.357[a]	-0.304[a]	-0.336[a]	-0.396[a]	-0.465[a]	-0.438[a]	-0.587[a]
660-689	-0.509[a]	-0.398[a]	-0.489[a]	-0.532[a]	-0.663[a]	-0.630[a]	-0.724[a]
690-719	-0.705[a]	-0.575[a]	-0.685[a]	-0.822[a]	-0.968[a]	-0.923[a]	-1.037[a]
720-769	-1.073[a]	-0.942[a]	-1.050[a]	-1.312[a]	-1.514[a]	-1.392[a]	-1.507[a]
770+	-1.708[a]	-1.550[a]	-1.664[a]	-1.942[a]	-2.240[a]	-2.249[a]	-2.414[a]
Debt-to-Income Ratio (vs <24)							
24-28	0.0444[b]	0.0350[c]	0.0349[c]	0.00527	-0.0215	-0.00153	-0.0727[a]
29-33	0.107[a]	0.0594[a]	0.0527[a]	0.0477[b]	0.0661[a]	0.0211	-0.0647[b]
34-38	0.180[a]	0.108[a]	0.111[a]	0.0719[a]	0.0931[a]	0.00449	-0.0661[a]
39-43	0.226[a]	0.151[a]	0.154[a]	0.132[a]	0.127[a]	0.0786[a]	-0.0778[a]
44-50	0.261[a]	0.170[a]	0.198[a]	0.130[a]	0.166[a]	0.0876[a]	-0.0754[b]
51+	0.271[a]	0.167[a]	0.194[a]	0.149[a]	0.209[a]	0.0883[a]	-0.0656[c]
Constant	-3.675[a]	-3.829[a]	-3.421[a]	-2.865[a]	-2.951[a]	-3.817[a]	-3.476[a]
Obs	431,489	457,529	436,879	339,706	515,008	293,258	298,725
LL	-180,847	-211,301	-173,997	-96,305	-83,001	-59,031	-62,175
LL_0	-219,706	-267,485	-222,446	-120,062	-106,116	-75,173	-76,800

Note: The exponents a, b, and c denote significance at the 0.01, 0.05, and 0.1 levels, respectively. Parameters presented are estimates of log-odds coefficients. The sample includes all loans active in the 4th quarter of 2007 in the National Mortgage Database, subject to filters noted in the text. Borrower-level attributes are for the first listed borrower on the loan. All variables defined in Table 1. Variable groups are defined by first rounding down to the nearest integer. LL and LL_0 denote the log-likelihood for the regression and for model estimated using only the constant term, respectively.

Table 3: Default Model Robustness

Sample: All active loans as of 2007:Q4, age cohorts pooled

Model Number	[8]	[9]	[10]	[11]	[12]	[13]	[14]
Dependent Variable	Default	Default	Default	Default	Default	Default or D180	Default
Estimator	Logit	Logit	Logit	Logit	Logit	Logit	OLS
Owner-Occupied	-0.258[a]	-0.287[a]	-0.321[a]	-0.260[a]	-0.261[a]	-0.181[a]	-0.0195[a]
ARM	0.0282[a]	0.165[a]	0.144[a]	0.0265[a]	0.00449	-0.0185[a]	0.00901[a]
Single Borrower	0.488[a]	0.501[a]	0.487[a]	0.477[a]	0.488[a]	0.464[a]	0.0478[a]
First-time Homebuyer	-0.0142[b]	-0.0157[a]	-0.0539[a]	-0.00816	-0.0111[b]	0.0184[a]	-0.00175[a]
Interest-Only	0.309[a]		0.459[a]	0.295[a]	0.306[a]	0.294[a]	0.0443[a]
Balloon	-0.358[a]		-0.264[a]	-0.350[a]	-0.359[a]	0.246[a]	-0.0466[a]
Negative Amortization	0.126[a]		0.350[a]	0.133[a]	0.124[a]	0.170[a]	0.00745[a]
Judicial Forec. State	0.184[a]	0.164[a]	-0.00591	0.197[a]	0.186[a]	0.102[a]	0.0188[a]
Time-to-forec.	-0.0232[a]	-0.0221[a]	-0.00665[a]	-0.0242[a]	-0.0233[a]	-0.000970[b]	-0.00216[a]
Burnout	0.0109[a]	0.0146[a]	0.00853[a]	0.0174[a]		0.0105[a]	-0.000380[a]
Loan Term (vs 15 year)							
20 year	0.295[a]	0.318[a]	0.311[a]	0.288[a]	0.323[a]	0.244[a]	0.00401[a]
30 year	0.551[a]	0.514[a]	0.664[a]	0.562[a]	0.560[a]	0.584[a]	0.0194[a]
40 year	0.732[a]	0.649[a]	0.968[a]	0.751[a]	0.737[a]	1.115[a]	0.0741[a]
Segment (vs CU)							
FHA	1.010[a]		0.938[a]	1.007[a]	1.002[a]	1.051[a]	0.0597[a]
FHLB	1.035[a]		1.017[a]	1.038[a]	1.029[a]	0.954[a]	0.0552[a]
FNM	0.718[a]		0.708[a]	0.723[a]	0.713[a]	0.731[a]	0.0331[a]
FRE	0.672[a]		0.656[a]	0.676[a]	0.669[a]	0.677[a]	0.0320[a]
FSA/RHS	0.963[a]		0.853[a]	0.957[a]	0.957[a]	0.921[a]	0.0552[a]
NCUCON	1.184[a]		1.178[a]	1.206[a]	1.186[a]	1.222[a]	0.0661[a]
PLS	1.092[a]		1.108[a]	1.088[a]	1.103[a]	1.169[a]	0.0744[a]
VA	0.304[a]		0.244[a]	0.328[a]	0.294[a]	0.214[a]	-0.00642[a]
NCUJUMBO	0.880[a]		1.065[a]	0.948[a]	0.877[a]	1.148[a]	0.0305[a]
Spread at Origination (BPS, vs <25)							
25-49	0.210[a]	0.269[a]	0.224[a]	0.198[a]	0.216[a]	0.171[a]	0.0123[a]
50-99	0.342[a]	0.388[a]	0.340[a]	0.339[a]	0.362[a]	0.307[a]	0.0246[a]
100-399	0.458[a]	0.490[a]	0.438[a]	0.459[a]	0.509[a]	0.437[a]	0.0607[a]
400+	0.432[a]	0.511[a]	0.349[a]	0.452[a]	0.526[a]	0.480[a]	0.0708[a]
Loan Type (vs Cash-out Refinance)							
Purchase	-0.0471[a]	-0.0476[a]	-0.0970[a]	0.00104	-0.0448[a]	-0.133[a]	-0.0109[a]
Rate/Term Refinance	-0.0129[b]	-0.0163[a]	-0.0587[a]	0.00104	-0.0159[a]	-0.0750[a]	0.00175[a]
Income Documentation Status							
Full doc.	-0.202[a]		-0.290[a]	-0.197[a]	-0.200[a]	-0.265[a]	-0.0395[a]
Missing entry	-0.0101		-0.0547[a]	-0.0201[b]	-0.0136	-0.0492[a]	-0.0245[a]

Note: Table continues on next page.

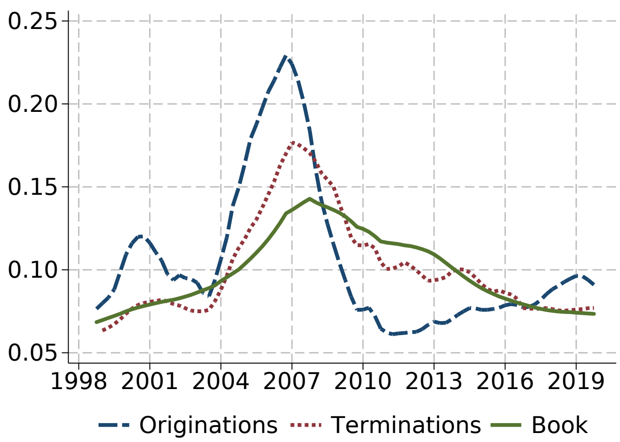
Table 3: Default Model Robustness, Continued

Model Number	[8]	[9]	[10]	[11]	[12]	[13]	[14]
Mark-to-market Shock Combined Loan-to-value Ratio (vs 1-39)							
HPI stress shock	Incl.	Incl.	No	0.0414[a]	Incl.	Incl.	Incl.
HPI change since orig.	Incl.	Incl.	Incl.	-0.0214[a]	Incl.	Incl.	Incl.
Amortization	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
40-49	0.336[a]	0.318[a]	0.462[a]	0.166[a]	0.309[a]	0.368[a]	0.00225[a]
50-59	0.506[a]	0.480[a]	0.734[a]	0.386[a]	0.473[a]	0.532[a]	0.00316[a]
60-69	0.700[a]	0.670[a]	0.981[a]	0.661[a]	0.665[a]	0.712[a]	0.00616[a]
70-79	0.956[a]	0.922[a]	1.218[a]	0.947[a]	0.921[a]	0.922[a]	0.0167[a]
80-89	1.174[a]	1.139[a]	1.513[a]	1.214[a]	1.140[a]	1.114[a]	0.0318[a]
90-99	1.407[a]	1.374[a]	1.754[a]	1.502[a]	1.373[a]	1.322[a]	0.0556[a]
100-109	1.627[a]	1.596[a]	2.247[a]	1.677[a]	1.593[a]	1.530[a]	0.0857[a]
110-119	1.839[a]	1.810[a]	2.297[a]	1.468[a]	1.805[a]	1.732[a]	0.120[a]
120-129	2.040[a]	2.021[a]	2.049[a]	1.448[a]	2.006[a]	1.945[a]	0.156[a]
130-139	2.280[a]	2.278[a]	2.119[a]	1.648[a]	2.246[a]	2.198[a]	0.205[a]
140-149	2.493[a]	2.494[a]	1.971[a]	1.513[a]	2.459[a]	2.430[a]	0.247[a]
150+	3.065[a]	3.091[a]	1.799[a]	1.303[a]	3.031[a]	3.060[a]	0.384[a]
Credit Score at Origination (vs <580)							
580-619	-0.199[a]	-0.210[a]	-0.181[a]	-0.183[a]	-0.204[a]	-0.373[a]	-0.0374[a]
620-639	-0.287[a]	-0.303[a]	-0.256[a]	-0.269[a]	-0.295[a]	-0.557[a]	-0.0570[a]
640-659	-0.407[a]	-0.427[a]	-0.370[a]	-0.389[a]	-0.416[a]	-0.718[a]	-0.0811[a]
660-689	-0.552[a]	-0.578[a]	-0.505[a]	-0.534[a]	-0.561[a]	-0.914[a]	-0.107[a]
690-719	-0.778[a]	-0.812[a]	-0.717[a]	-0.763[a]	-0.789[a]	-1.190[a]	-0.138[a]
720-769	-1.188[a]	-1.229[a]	-1.121[a]	-1.173[a]	-1.200[a]	-1.647[a]	-0.176[a]
770+	-1.853[a]	-1.907[a]	-1.801[a]	-1.839[a]	-1.866[a]	-2.361[a]	-0.194[a]
Debt-to-Income Ratio (vs <24)							
24-28	0.0133	0.0142	0.0308[a]	0.0154[c]	0.0145[c]	0.0227[a]	-0.00372[a]
29-33	0.0497[a]	0.0505[a]	0.0793[a]	0.0548[a]	0.0511[a]	0.0689[a]	-0.00318[a]
34-38	0.0911[a]	0.0902[a]	0.135[a]	0.0993[a]	0.0929[a]	0.111[a]	0.000119
39-43	0.134[a]	0.130[a]	0.187[a]	0.145[a]	0.136[a]	0.164[a]	0.00574[a]
44-50	0.160[a]	0.147[a]	0.221[a]	0.176[a]	0.164[a]	0.189[a]	0.0109[a]
51+	0.156[a]	0.118[a]	0.212[a]	0.181[a]	0.161[a]	0.202[a]	0.00758[a]
Loan Age FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-3.938[a]	-3.035[a]	-3.746[a]	-4.370[a]	-3.913[a]	-3.531[a]	0.158[a]
Obs	2,772,594	2,772,594	2,772,594	2,772,594	2,772,594	2,772,594	2,772,594
R^2							0.215
LL	-871,840	-879,780	-894,028	-870,965	-872,081	-986,989	
LL_0	-1,163,733	-1,163,733	-1,163,733	-1,163,733	-1,163,733	-1,379,342	

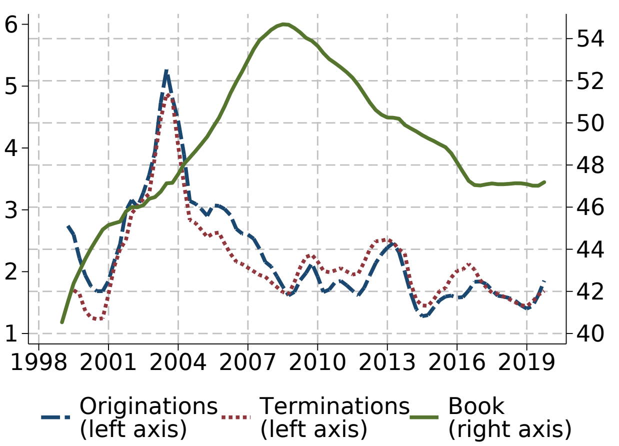
Note: The exponents a, b, and c denote significance at the 0.01, 0.05, and 0.1 levels, respectively. Parameters presented are estimates of log-odds coefficients. The sample includes all loans active in the 4th quarter of 2007 in the National Mortgage Database, subject to filters noted in the text. Borrower-level attributes are for the first listed borrower on the loan. All variables defined in Table 1. Variable groups are defined by first rounding down to the nearest integer. LTVs are calculated in various ways, with the baseline being the MTMS-CLTV. In model 10, the 3-year HPI shock is not included in the measure, giving a classic "MTM-CLTV". Model 11 gives an amortized version of the CLTV at origination, with HPI change since origination and the HPI shock variable included as separate variables. LL and LL_0 denote the log-likelihood for the regression and for model estimated using only the constant term, respectively.

Figure 1: Stressed Default Rates and Loan Counts

(a) Stressed Default Rates (SDR)



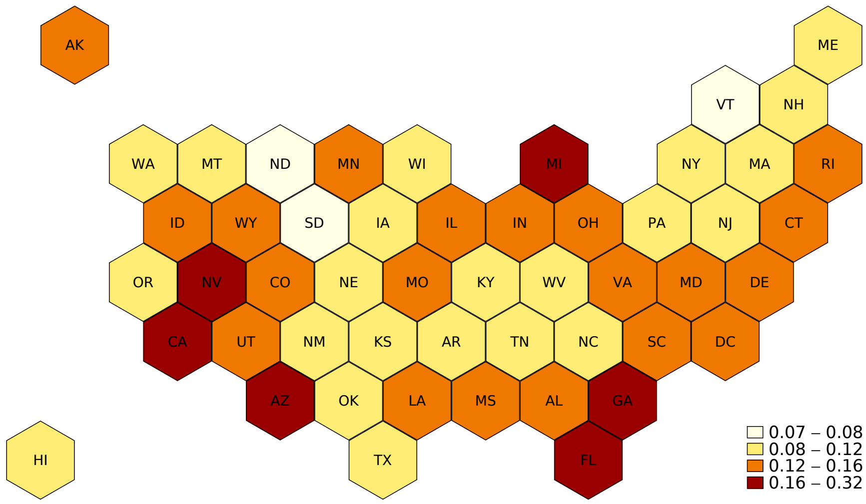
(b) Loan Counts (millions)



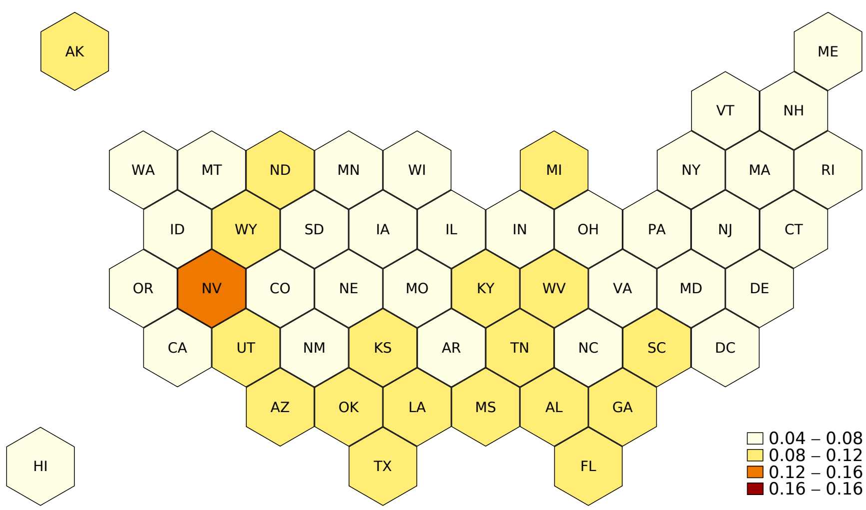
Note: This figure presents time series of "Stressed Default Rates" (SDRs) and scaled (x20) loan counts. SDRs are based on parameters from models of lifetime future default for loans active in the 4th quarter of 2007 in the National Mortgage Database, subject to filters noted in the text, along with loan attributes from the current period. The SDR is therefore a counterfactual indicator of risk for how a portfolio of loans would have performed had it existed in 2007:Q4. Three portfolios are shown: "originations", or all loans originated in the current quarter; "terminations" or all loans that terminated in the previous quarter; and "book", indicating the full book of outstanding mortgages in the current quarter. Lines shown are 4-quarter moving averages.

Figure 2: States and Book-level SDRs

(a) 2007:Q4



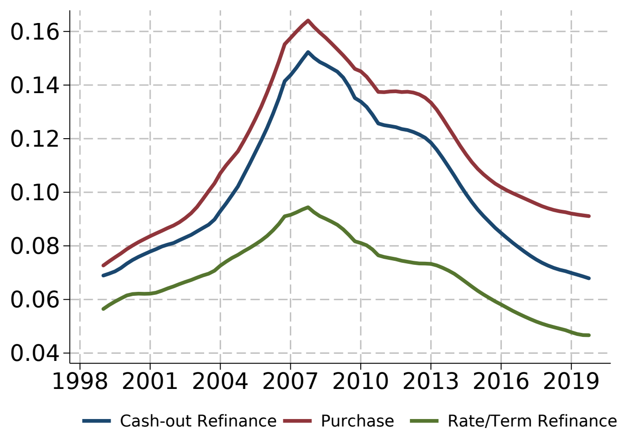
(b) 2019:Q4



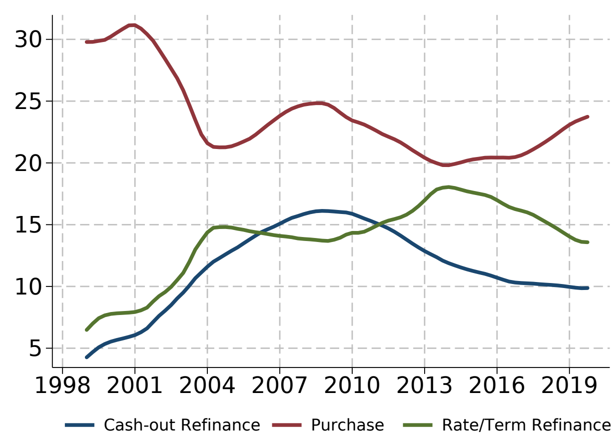
Note: This figure presents SDRs by state. SDRs are based on parameters from models of lifetime future default for loans active in the 4th quarter of 2007 in the National Mortgage Database, subject to filters noted in the text, along with loan attributes from the current period. The SDR is therefore a counterfactual indicator of risk for how a portfolio of loans would have performed had it existed in 2007:Q4.

Figure 3: Loan Type and Risk

(a) SDRs



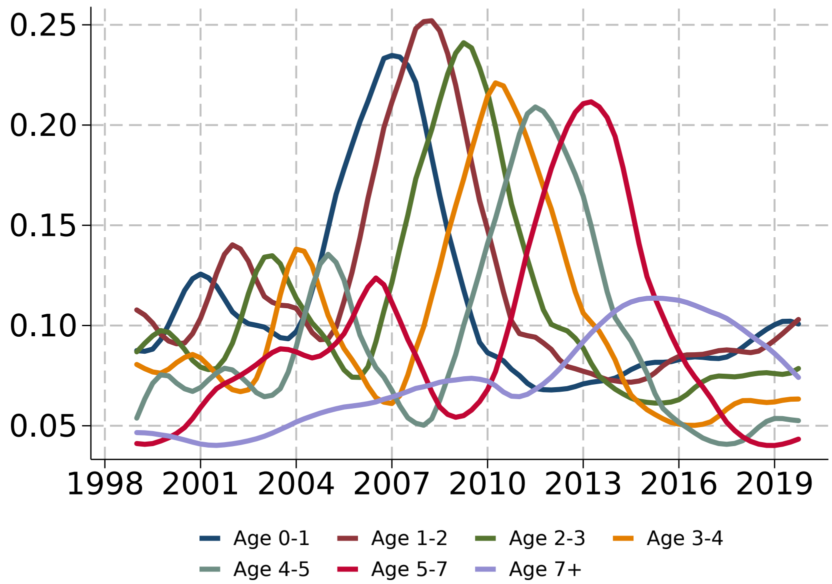
(b) Loan Counts (millions)



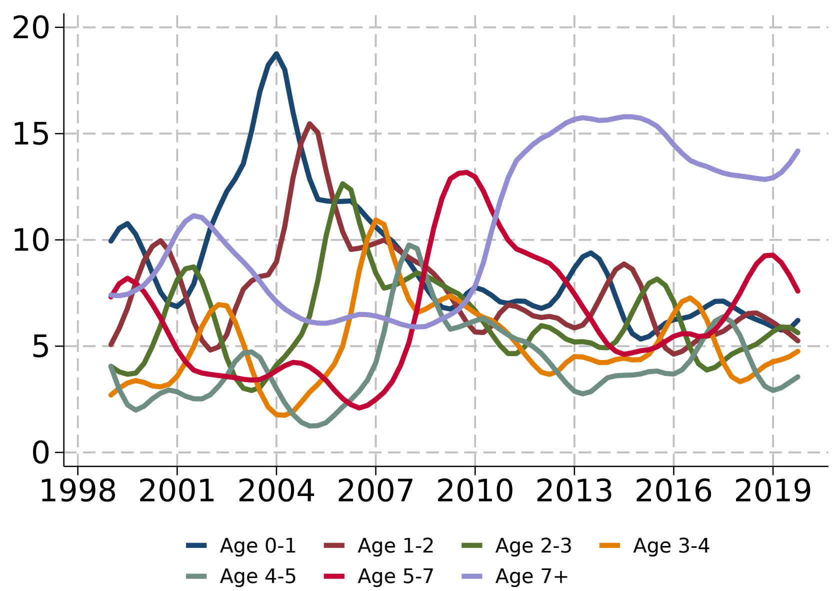
Note: This figure presents time series of SDRs and scaled (x20) loan counts for each loan type. Cash-out refinance is defined as an refinance mortgage where the origination balance is more than 5% greater than the balance on the associated terminated loan. Lines shown are 4-quarter moving averages.

Figure 4: Seasoning and Risk

(a) SDRs



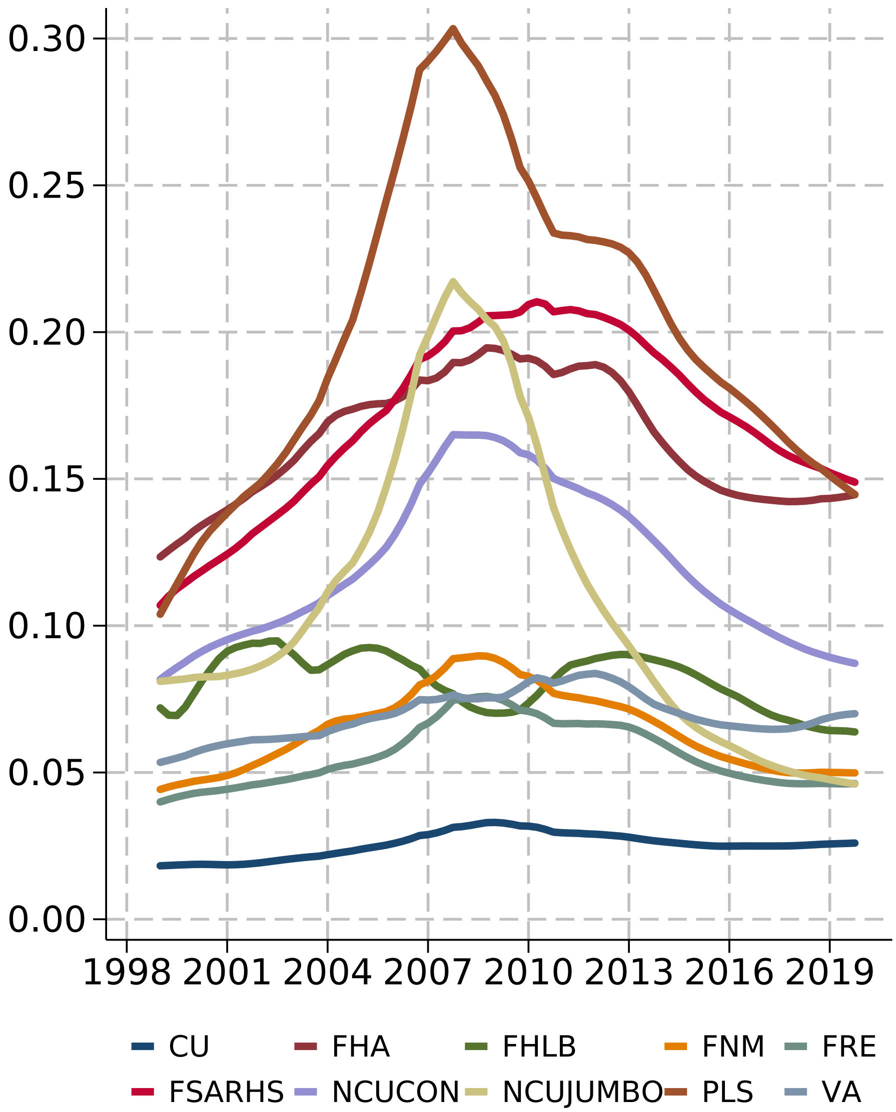
(b) Loan Counts (millions)



Note: This figure presents time series of SDRs and scaled (x20) loan counts for each loan type. Each age cohort is defined as the number of quarters since origination divided by 4, rounded down to the nearest integer. Lines shown are 4-quarter moving averages.

Figure 5: Market Segment and Risk

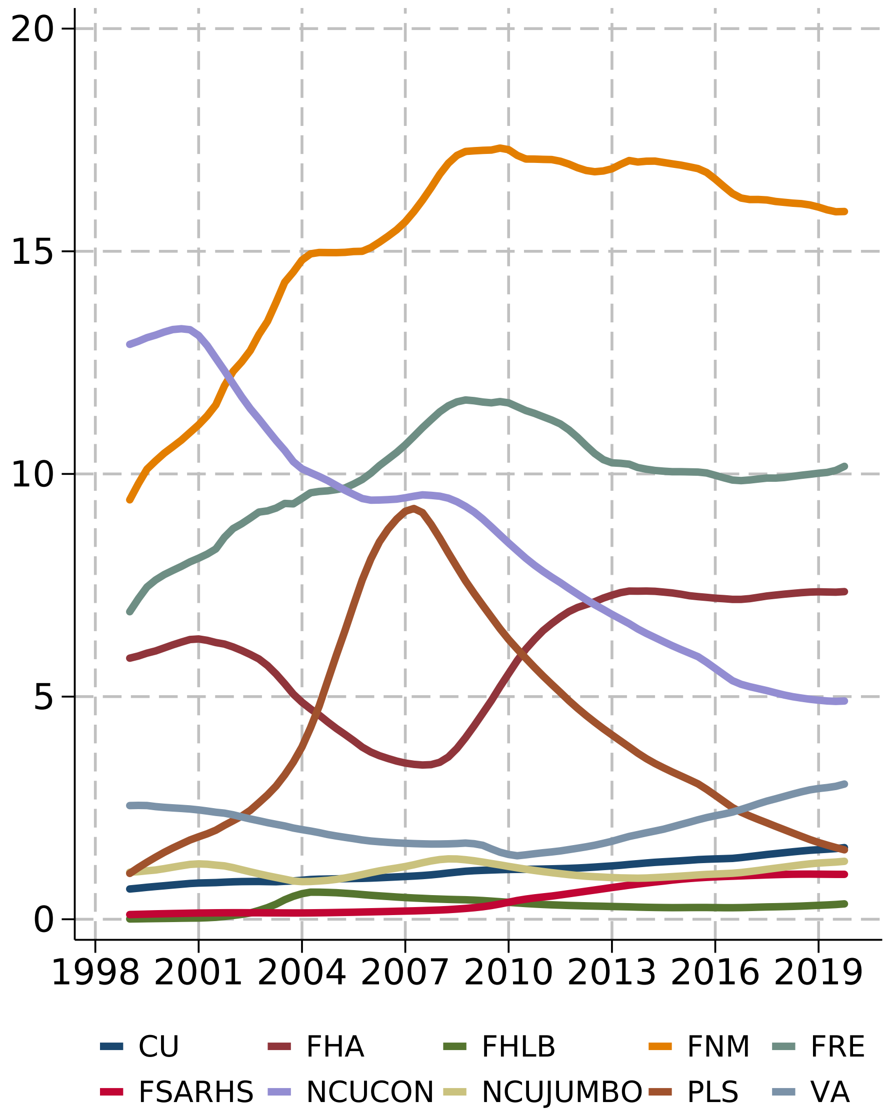
(a) SDRs



Note: Figure continues on next page.

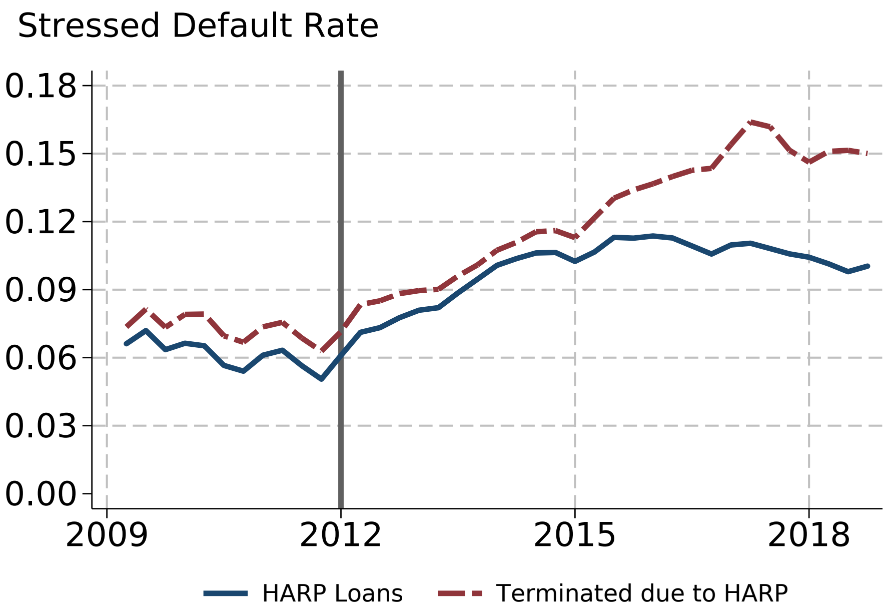
Figure 5: Market Segment and Risk, Continued

(b) Loan Counts (millions)



Note: This figure presents time series of SDRs and scaled (x20) loan counts for each loan type. Segments are defined as follows: Fannie Mae (FNM), Freddie Mac (FRE), the Federal Home Loan Banks (FHLB), Farm Service Agency/Rural Housing Service (FSARHS), credit unions (CU), non-credit union private conforming (NCUCON), non-credit union jumbo (NCUJUMBO), Veterans Administration (VA), Federal Housing Administration (FHA), and loans in private-label securities (PLS). Lines shown are 4-quarter moving averages.

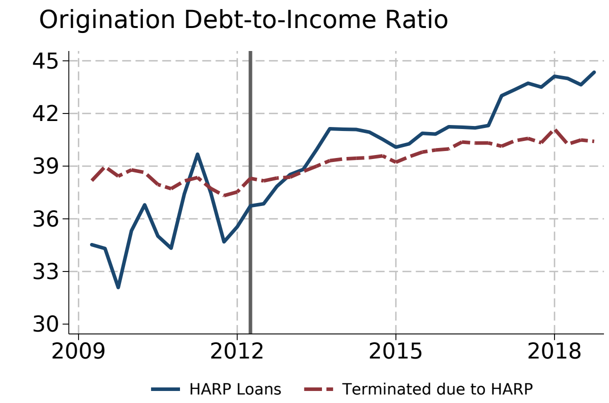
Figure 6: HARP Originations versus Associated Terminations



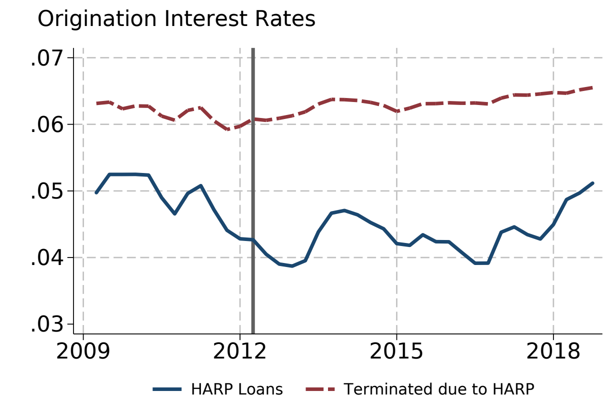
Note: This figure presents time series of SDRs all HARP originations in the FHFA's Mortgage Loan Information System (MLIS) dataset, and loans that were terminated and prepaid as part of a HARP refinance. HARP originations are assumed to be continuations of the prior loan when assessing loan cohort effects. The mark-to-market shock CLTV of the terminated loan is assumed to be equal to the origination shock CLTV on the HARP loan.

Figure 7: Characteristics of HARP Originations versus Associated Terminations

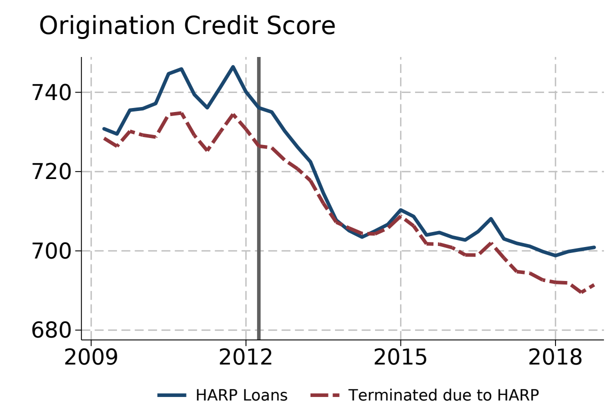
(a) Debt-to-Income Ratio



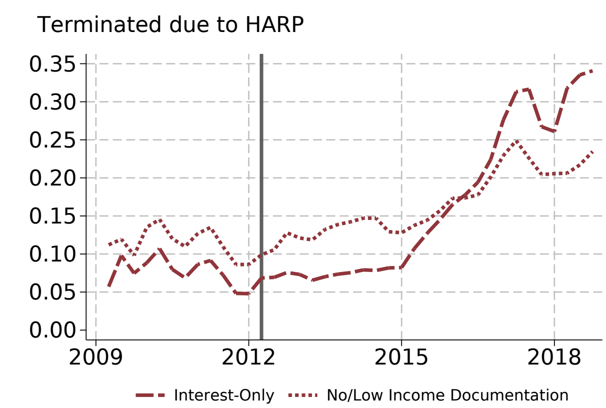
(b) Interest Rate



(c) Credit Score



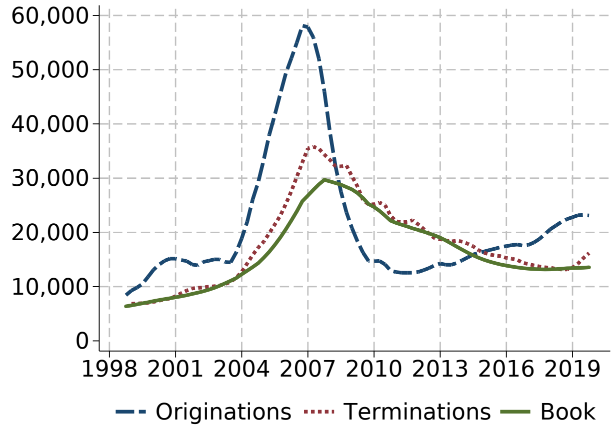
(d) Interest-Only and Income Doc. Status



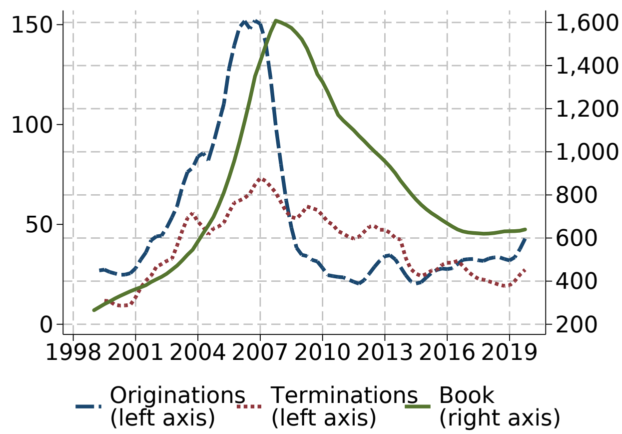
Note: This figure presents time series of primary risk factors for all HARP originations in the FHFA's Mortgage Loan Information System (MLIS) dataset, and loans that were terminated and prepaid as part of a HARP refinance. HARP originations are assumed to be continuations of the prior loan when assessing loan cohort effects. The mark-to-market shock CLTV of the terminated loan is assumed to be equal to the origination shock CLTV on the HARP loan.

Figure 8: Stressed Debt-at-Risk

(a) SDAR per loan



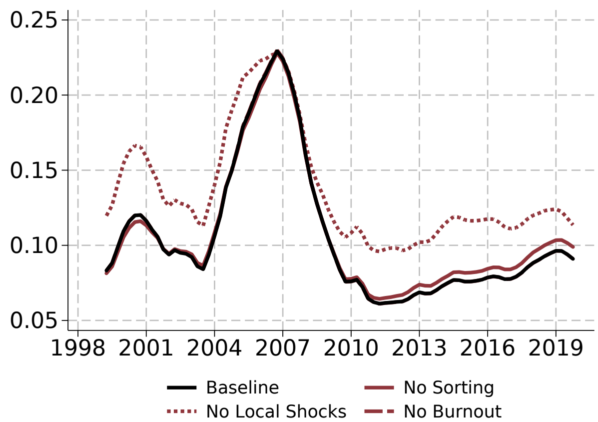
(b) Total SDAR ($ billions)



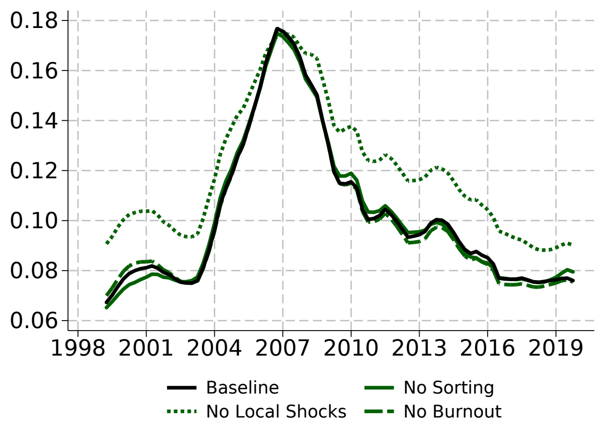
Note: This figure presents time series of SDARs on a per loan and total basis. The SDAR is calculated as the stressed default rate multiplied by the current unpaid principal balance on the loan. The total SDAR is calculated as the SDAR multiplied by the scaled (x20) number of loans in the particular category. Lines shown are 4-quarter moving averages.

Figure 9: Model Robustness

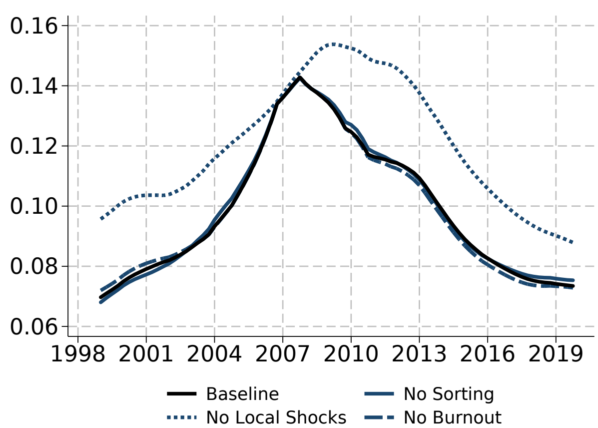
(a) Originations



(b) Terminations

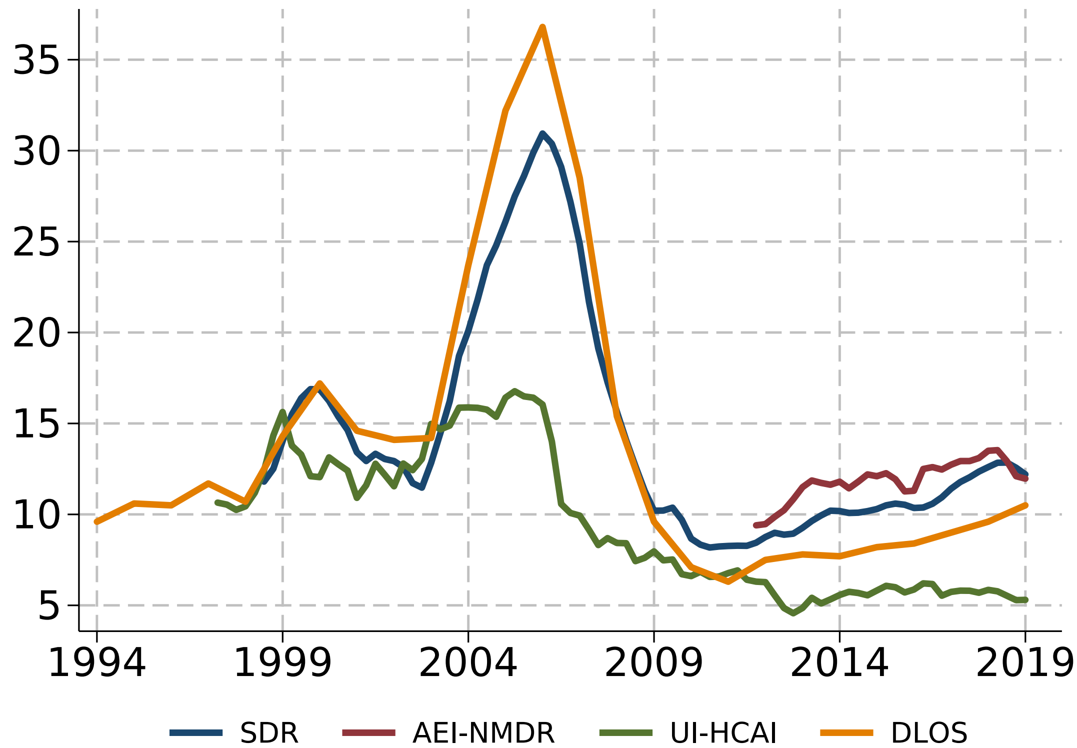


(c) Book



Note: This figure presents time series of SDRs under alternative modeling assumptions. For details of each modeling approach, see the main text.

Figure 10: Alternative Origination Mortgage Risk/Credit Availability Measures



Note: This figure presents alternative stress default/credit availability measures. All metrics are based on new originations and are based on loans that either defaulted or were 180+ days delinquent, with the exception of the UI-HCAI, which is based on all loans that went D90+. The SDR is from the present paper. The AEI-NMDR is the American Enterprise Institute's National Mortgage Default Rate (NMDR) (Peter and Pinto, 2021). UI-HCAI is the Urban Institute's Housing Credit Availability Index, (Li and Goodman, 2014). DLOS is the shock series from Davis et al. (2021).

Appendix

A.1 House Price Shock Construction

The house price shock variable is constructed following Smith et al. (2016), who describe a simple method for constructing a house price path associated with severe economic stress. The concept behind the method is that house prices tend to fall below a long-term trend during a period of severe stress. The trend serves as a reduced-form proxy for economic fundamentals, such as the house price-to-income ratio or the house price-to-rent ratio. Different locations face different degrees of variation around this trend, so both the house price level in relation to the trend and the history of price declines are taken into account when setting the shock value.

The following method is identical to the one used by Davis et al. (2021). I begin with a real house price series constructed using a nominal series divided by the consumer price index for all urban consumers (CPI). The construction of the shock proceeds in three steps, for each state:

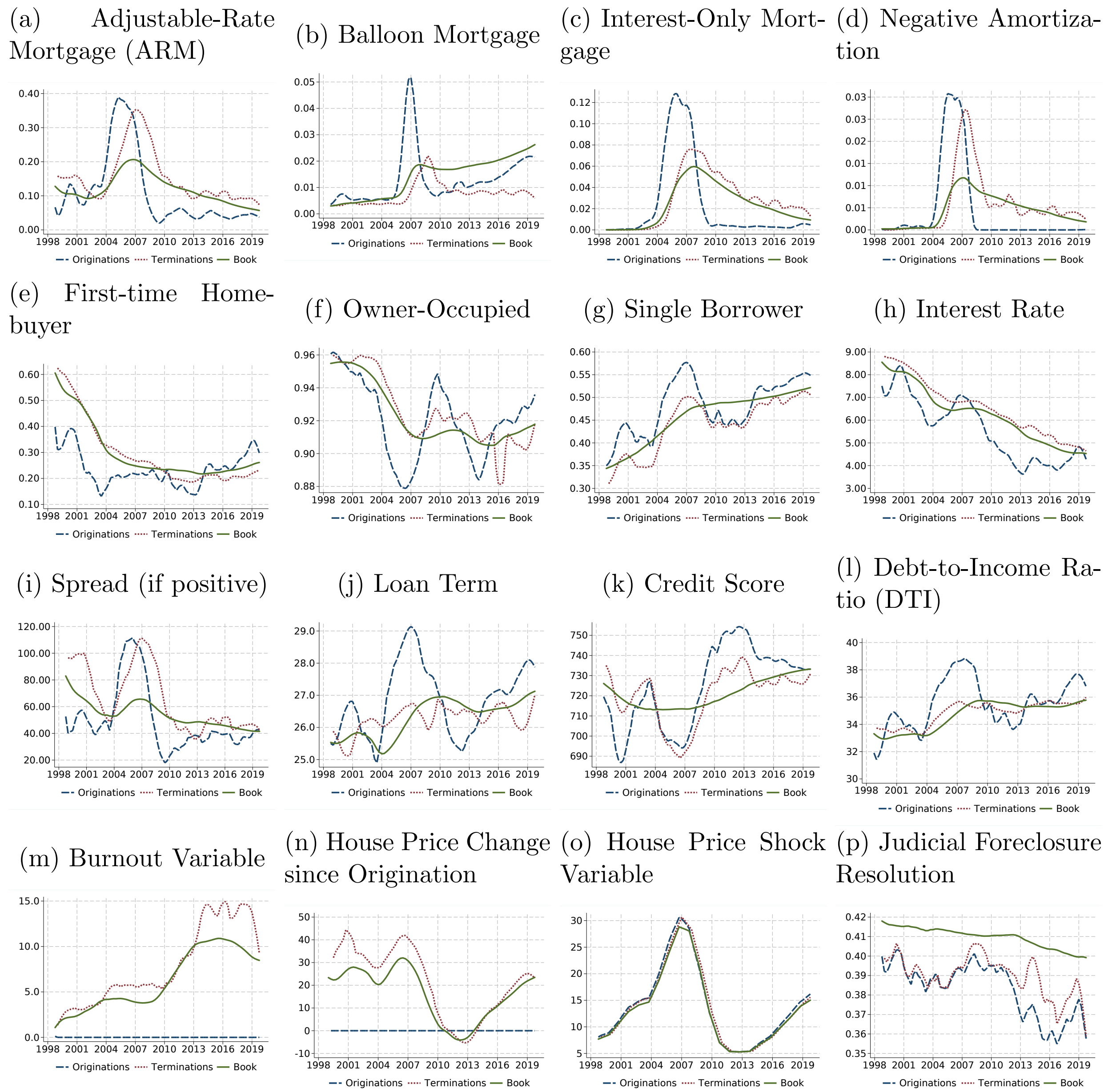
1. Fit a trend line to the series for real house prices for a given locality using annual data for 1975 through 2019. If the trend slope is negative, set it to 0. Convert the real trend back to nominal terms using the CPI, as all subsequent calculations are in nominal terms.

2. Considering the entire period 1975-2019, find the year in which the house price series was furthest below trend in percentage terms. Let T^* denote that year and let $L(T^*)$ denote the maximum percentage deviation below trend. $L(T^*)$ represents the amount by which the house price index is assumed to drop below trend under severe stress. I set $L(T^*)$ to be 5 percent if the unconstrained calculation yields a smaller drop below trend. The house price series used are the FHFA annual state indices described in Bogin et al. (2019).

3. Use $L(T^*)$ to calculate the stress loss in house value for each year, $\Delta V^S(T)$, as the percentage decline from the level of the house price index in year T to the below-trend level under severe stress three years in the future. I enforce a minimum stress loss of 5 percent in each year.

For each loan in the dataset in each time period, use $\Delta V^S(T)$ to calculate the MTMS-CLTV in equation 3.

Figure A.1: Time Series of Borrower and Loan Characteristics

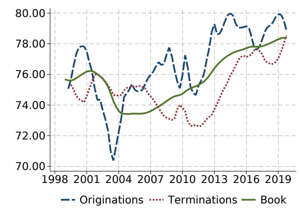


(a) Adjustable-Rate Mortgage (ARM)
(b) Balloon Mortgage
(c) Interest-Only Mortgage
(d) Negative Amortization
(e) First-time Homebuyer
(f) Owner-Occupied
(g) Single Borrower
(h) Interest Rate
(i) Spread (if positive)
(j) Loan Term
(k) Credit Score
(l) Debt-to-Income Ratio (DTI)
(m) Burnout Variable
(n) House Price Change since Origination
(o) House Price Shock Variable
(p) Judicial Foreclosure Resolution

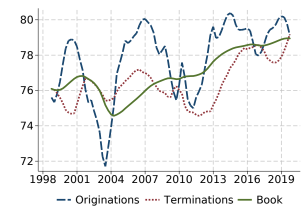
Note: Each figure presents time series of mean values or shares over all active loans in the NMDB in the particular time period, subject to filters noted in the text.

Figure A.2: Time Series of Various LTVs

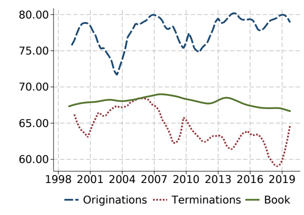
(a) LTV



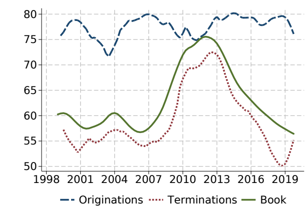
(b) CLTV



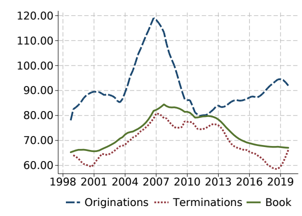
(c) A-CLTV



(d) MTM-CLTV



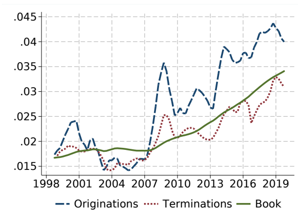
(e) MTMS-CLTV



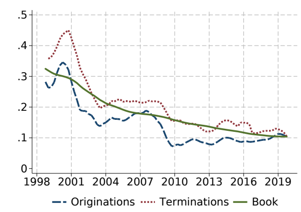
Note: Each figure presents time series of mean values over all active loans in the NMDB in the particular time period, subject to filters noted in the text.

Figure A.3: Time Series of Segment Shares

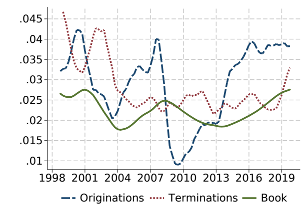
(a) Credit Union (CU)



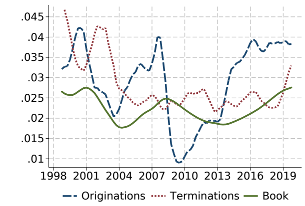
(b) Private Conforming, Non-CU (NCU-CON)



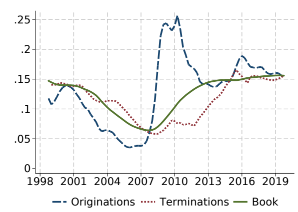
(c) Private Jumbo, Non-CU (NCU-JUMBO)



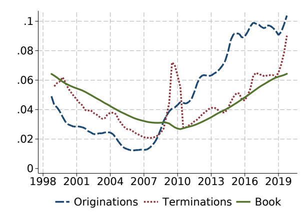
(d) Private Label Security (PLS)



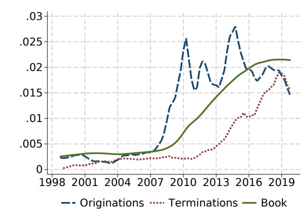
(e) Federal Housing Administration (FHA)



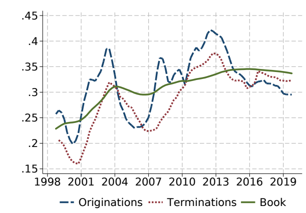
(f) Veteran's Administration (VA)



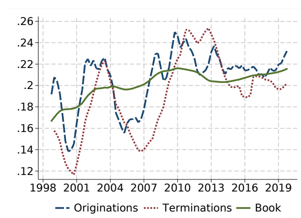
(g) Farm Service Agency/Rural Housing Service (FSA/RHS))



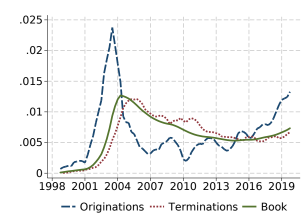
(h) Fannie Mae (FNM)



(i) Freddie Mac (FRE)



(j) Federal Home Loan Banks (FHLB)



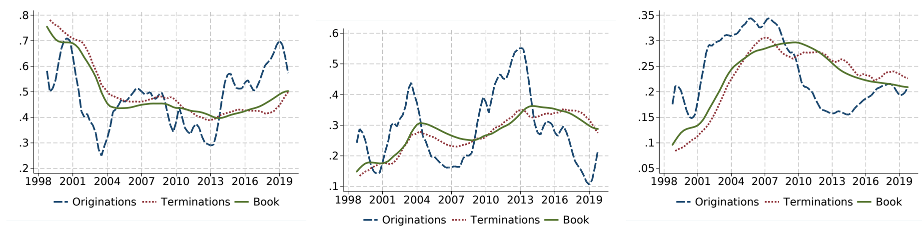
Note: Each figure presents time series of shares by market segment over all active loans in the NMDB in the particular time period, subject to filters noted in the text.

Figure A.4: Time Series of Product Type Shares

(a) Purchase

(b) Rate/Term Refinance

(c) Cash-Out Refinance



Note: Each figure presents time series of shares by product type in the NMDB in the particular time period, subject to filters noted in the text.