

FHFA STAFF WORKING PAPER SERIES

Mortgage Risk Since 1990

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March 2019 (revised)
January, 2019 (original)

Working Paper 19-02

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Abstract

This paper provides a comprehensive account of the evolution of default risk for newly originated home purchase loans since 1990. We bring together several data sources to produce this history, including loan-level data for the entire Enterprise (Fannie Mae and Freddie Mac) book. We use these data to track a large number of loan characteristics and a summary measure of risk, the stressed default rate. Among the many results in the paper, we show that mortgage risk had already risen in the 1990s, planting the seeds of the financial crisis well before the actual event. Our results also cast doubt on explanations of the crisis that focus on low-credit-score borrowers. The aggregate series we present in this paper are available for download at <https://www.fhfa.gov/papers/wp1902.aspx>.¹

Keywords: mortgage risk · housing boom · default · foreclosure · house price · leverage

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

¹These indices are works in progress and all data, tables, figures, and other results in this working paper are subject to change.

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1. Introduction

In the decade since the global financial crisis, there has been an outpouring of research to understand the developments in the U.S. home mortgage market that precipitated the crisis.¹ Nonetheless, as valuable as this research has been, there is still no comprehensive account of the changes in mortgage risk that produced the worst foreclosure wave since the Great Depression.

This paper is an effort to fill that gap, covering essentially the entire market for home purchase loan originations in the United States from 1990 to 2017.² We bring together several data sources to construct this comprehensive historical picture, including the full set of home mortgages guaranteed by the government sponsored enterprises Fannie Mae and Freddie Mac (the Enterprises). To our knowledge, this is the first time the entire Enterprise book has been used in publicly-available research on mortgage risk.³ We supplement the Enterprise dataset with data covering more than 90 percent of the loans in private mortgage-backed securities and data from mortgage servicers for a large fraction of loans in the rest of the market (loans guaranteed by the Federal Housing Administration (FHA) and the Department of Veterans Affairs (VA) and unguaranteed loans held in the portfolio of banks and other lenders).⁴

We track many loan characteristics that, taken together, are highly predictive of loan performance. These characteristics include the borrower's credit score, the debt-payment to

¹ For readers seeking to explore this vast literature, the appendix table in Ferreira and Gyourko (2015) lists more than 30 papers on various aspects of the mortgage market. Foote and Willen (2018) discuss the post-crisis surge of research on the determinants of mortgage default. And Mian and Sufi (2018) cover research on the expansion of mortgage credit supply during the housing boom and its implications for house prices.

² Although our focus is on home purchase loans, we are in the process of analyzing the data for refinance loans and will provide a summary of results for those loans in a subsequent version of the paper.

³ The Enterprise data source is the FHFA Mortgage Loan Information System (MLIS). No personally identifiable information is contained in the tables, charts, or the database associated with this paper. Results presented pertaining to these data are aggregates (including model outputs) and rounded where appropriate.

⁴ For FHA and VA loans originated during 2013-2017, we also have Ginnie Mae data provided by the Center on Housing Markets and Finance at the American Enterprise Institute (AEI). Because the Ginnie Mae data maintained at AEI cover virtually all FHA and VA loans, we use these data for 2013-2017 originations in place of the servicer data.

income ratio (DTI), the combined loan-to-value ratio (CLTV) that accounts for any subordinate liens at origination, loan type (fixed or adjustable mortgage rate), loan term, loan purpose, whether the borrower's income is fully documented, and whether the mortgage has a feature that reduces the paydown of loan principal (such as a period of interest-only payments).

Given the multitude of loan characteristics, it is important to develop a publicly available summary measure of default risk. This measure should convey the risk of default in a simple, straightforward manner, and to be of most use to policymakers with prudential oversight responsibilities, it should focus on default under severely stressed conditions. To this end, we calculate what we call the "stressed default rate" for all loans in the dataset based on the observed default experience of similar loans originated nationwide in 2006 and 2007, just before the financial crisis. The stressed default rate for a given loan thus represents its expected default rate if it were hit shortly after origination with a replay of the financial crisis, including the observed national average decline in house prices and ensuing policy responses. Because the drop in house prices varied enormously across localities, the stressed default rate calculated in this way will only be valid for a national portfolio of loans. As an extension, we also calculate a stressed default measure for states and metropolitan areas. This extension embeds the estimated magnitude of a severe local house price shock in each year using the framework in Smith and Weiher (2012) and Smith et al. (2016).

The stressed default rates presented in this paper build on those currently published by the American Enterprise Institute's (AEI) Center on Housing Markets and Finance and the Urban Institute. AEI unveiled its National Mortgage Risk Index (NMRI) in 2013, while the Urban Institute introduced its Housing Credit Availability Index (HCAI) a year later in 2014. The NMRI uses highly accurate and complete data for government-guaranteed loans but only goes

back to late 2012 and does not cover private portfolio loans or loans in private mortgage-backed securities. The HCAI covers the entire market back to 1998 but misses developments over 1990-1997 that we cover, uses incomplete data for pre-2013 Enterprise loans, pays less attention to imputing missing loan information, and has a much less granular system for assigning stressed default rates.⁵ In short, we substantially improve the scope and quality of stressed default measures that already have a wide audience.

Our paper makes numerous contributions to the literature. The first, and most basic, is that we document the characteristics of the entire purchase loan market back to 1990 and provide a summary measure of risk over the same period. As a result, researchers and policymakers now have at their disposal more complete and more accurate historical information about the mortgage market.⁶ All the data presented in the paper and many other series are available for free download from the FHFA website at <https://www.fhfa.gov/papers/wp1902.aspx>.⁷

Among the insights provided by the longer historical analysis is that seeds of the financial crisis were planted in the 1990s. We show that across the entire market, the average CLTV on new home purchase loans increased substantially in the first half of the 1990s, and the average DTI trended sharply higher starting in 1992. By 2000, the stressed default rate for the purchase loan market was already above the levels seen in the 1990s, with the largest increase for loans

⁵ For more information on the NMRI and the HCAI, see <https://www.aei.org/housing/mortgage-risk-index/> and <https://www.urban.org/policy-centers/housing-finance-policy-center/projects/housing-credit-availability-index>. The HCAI is based on analysis in Li and Goodman (2014).

⁶ From the outset, we wish to make clear that while we focus on mortgage risk, there may be substantial benefits to increased access to credit. It is our hope that the metrics in this paper provide the basis for future benefit-cost analysis of policy decisions.

⁷ The available data include (a) annual series covering 1990-2017 for all of the risk factors at the national level that go into the stressed default rate, (b) the underlying default tables and adjustment factors used to construct stressed default rates, (c) loan counts in the cells of these default tables, and (d) the annual series over 1990-2017 for the baseline stressed default rate and the extension that incorporates potential shocks to house prices at the state and metro area level.

bundled into private-label securities (PLS). This finding calls into question the common view that mortgage lending conditions were normal in the early 2000s (CoreLogic, 2017; Goldman Sachs, 2014; Urban Institute, 2018).⁸

We also provide new evidence that credit standards across the market eased in the early and mid-2000s by documenting a compression of mortgage rate spreads between the riskiest and least risky loans. To cleanly identify changes in credit supply, we limit the analysis to loans for which lenders and investors fully bear the credit risk – private sector loans with no government guarantee and no private mortgage insurance. To our knowledge, this is the first exploration of spreads across risk tiers.⁹

Our results contribute as well to the ongoing debate about the role of “subprime” borrowers in the housing boom and bust.¹⁰ Mian and Sufi (2009, 2014, 2017a) have focused on an increase in credit availability for subprime borrowers, which they define as borrowers with a FICO score less than 660, while several recent papers have argued that the credit expansion was more widespread (Adelino, Schoar, and Severino, 2016, 2017; Albanesi, Di Giorgi, and Nosal, 2017; Conklin et al., 2018; Ferreira and Gyourko, 2015). Our results favor the latter view. We find that the low-credit-score share of home purchase loans fell slightly on net from the late

⁸ To be clear, we are not saying that every risk factor for every market segment experienced increases in mortgage risk before the early 2000s. However, combining the various risk factors, the average risk profile of newly-originated purchase-money mortgages began rising in the late 1990s.

⁹ For earlier discussions of mortgage spreads, see Demyanyk and van Hemert (2011), Justiniano, Primiceri, and Tambalotti (2017), and Mian and Sufi (2017a). Anenberg et al. (2018) complement this evidence by showing that the credit supply frontier – defined as the largest loan available for a given set of loan and borrower characteristics – shifted up during the early and mid-2000s.

¹⁰ Throughout the paper, we define low-credit-score borrowers as those with a credit score of less than 660 at origination. Such borrowers are often referred to as “subprime” in the academic literature. In other contexts, there is no agreed-upon definition of the term. Accordingly, we refrain from using the subprime label throughout the paper except in reference to others’ work.

1990s to the mid-2000s and that the stressed default rate for these loans rose in line with that of loans to higher-score borrowers, suggesting a similar expansion of credit supply for both groups.

Another question of interest is the role played by loans with risky product features in the buildup of risk during the boom. We define such loans to be ones with low or no documentation of borrower income, less than full amortization of loan principal, and a term greater than 30 years.¹¹ We find that these risky product features accounted for slightly more than half of the overall rise in the stressed default rate, with more standard forms of borrower leverage such as high payment burdens and small down payments accounting for the rest. Even though risky product features are largely absent from the mortgage market today, standard forms of leverage boosted risk a lot during the boom.

The final part of the paper brings house price risk explicitly into the analysis. We use a method based on Smith and Weiher (2012) and Smith et al. (2016) to construct severe potential house price shocks. The shocks vary over time and geography based on FHFA house price indices for states and metropolitan areas. We adjust each loan's reported CLTV at origination to reflect the lower house value if the shock were realized. With the large house price increases starting in the late 1990s, these "shock CLTVs" move further and further above the reported CLTVs. The average shock CLTV peaks in 2006 at nearly 140 percent, illustrating the enormous house price risk borne by lenders and mortgage insurers at that time.

2. Data

We rely on several sources of loan-level data over the period 1990-2017. For Enterprise loans, we use the internal, non-public data maintained by FHFA, the Mortgage Loan Information System (MLIS). The MLIS dataset covers all mortgage loans acquired by the Enterprises,

¹¹ This definition adopts some of the key product features that make a loan ineligible for Qualified Mortgage status under the Dodd-Frank Act and regulations adopted by the Consumer Financial Protection Bureau.

providing detailed information about loan characteristics and performance. As noted in the introduction, we believe our paper is the first to use the full book of Enterprise loans over such a long history.¹² The internal FHFA data have important advantages over the public-use loan-level data made available by the Enterprises, which are limited to fixed-rate mortgages with full documentation and full amortization of loan principal that were not part of designated affordable housing programs.¹³ By omitting adjustable-rate mortgages, loans with risky product features (such as low-doc loans), and many loans made under affordable housing programs, the publicly available datasets understate the risk in Enterprise-guaranteed loan portfolio, especially during the housing boom.¹⁴

For loans securitized in the private market without an Enterprise guarantee, we use the CoreLogic non-agency residential mortgage-backed securities dataset. The CoreLogic dataset is the most comprehensive source for loans included in private-label securities. It covers all segments of the PLS market, with the loans in the dataset accounting for more than 90 percent of the entire market. Many previous studies have used this dataset, including Adelino, Frame, and Gerardi (2017), Demyanyk and Van Hemert (2011), Houghwout, Peach, and Tracy (2008), Keys et al. (2010), and Mayer, Pence and Sherlund (2009). Our analysis builds on these studies by constructing much longer historical time series.

For loans held in portfolio by private lenders, we use the Loan-Level Market Analytics (LLMA) dataset from CoreLogic and the McDash dataset from Black Knight Financial Services.

¹² Other research has studied loan performance using internal Fannie Mae or Freddie Mac data over shorter periods. For example, Fout et al. (2018) use internal Fannie Mae loan data over 2002-2013, while Firestone, Van Order, and Zorn (2007) use internal Freddie Mac data over 1993-1997.

¹³ The publicly available data are Fannie Mae's Single-Family Loan Performance Dataset and Freddie Mac's Single-Family Loan-Level Dataset, which are posted at <http://www.fanniemae.com/portal/funding-the-market/data/loan-performance-data.html> and http://www.freddiemac.com/research/datasets/sf_loanlevel_dataset.html, respectively.

¹⁴ The publicly available datasets exclude 45 percent of all Enterprise home purchase loans originated during 2000-2007, with especially poor coverage of high LTV loans.

Both datasets compile information provided by large loan servicers, though the set of servicers differs across the two datasets. Studies that have used one of the servicer datasets include Bubb and Kaufman (2014), Courchane, Kiefer, and Zorn (2015), DeFusco, Johnson, and Mondragon (2017), Foote et al. (2010), and Keys, Seru, and Vig (2012), among others. In contrast to these studies, we merge the two datasets to provide broader coverage than with either one alone.

The identification of portfolio loans in the servicer datasets is challenging because one has to separate these loans from other conventional loans that were purchased by the Enterprises or securitized in the PLS market. Both datasets include investor codes to identify whether a loan was acquired by the Enterprises, but the information in this field is incomplete in both LLMA and McDash. We use the procedure described in Appendix A to remove loans that are reported to have been acquired by the Enterprises or are likely to be Enterprise loans. In addition, both datasets have limited information on whether a loan was securitized in the PLS market. We remove suspected PLS loans through loan-level matches to the PLS dataset. To be confident that we are only retaining portfolio loans, we purge from the dataset not only perfect one-to-one matches but other loans that are likely to be PLS loans. By drawing a wide net around potential Enterprise and PLS loans, some true portfolio loans inevitably will be removed as well.¹⁵

For FHA and VA loans, we use the two servicer datasets through 2012 and then switch over for 2013-2017 to the National Mortgage Risk Index (NMRI) dataset maintained by AEI's Center on Housing Markets and Finance. The NMRI dataset is a near-census of government

¹⁵ These identification challenges, along with McDash's limited market coverage in the 1990s, hold down the size of our portfolio dataset. We estimate that our coverage of portfolio loans peaks at roughly 60 percent in 2006 and is considerably lower in the 1990s. To correct for potential biases in the data, we weight the portfolio loans to be nationally representative.

guaranteed loans that provides detailed information about risk characteristics at origination. It is more comprehensive than the servicer datasets but is only available starting in late 2012.¹⁶

For all of these market segments, we use data on first-lien, 1-4 unit home purchase loans that pass a variety of data quality filters. These filters remove, for example, loans that lack information on such variables as origination year, loan term, and product type (ARM vs. fixed-rate).¹⁷ In all, the filters remove relatively small shares of the source data: about 1-2 percent of Enterprise and PLS loans, 5 percent of FHA/VA loans, and 15 percent of the private-sector loans that are candidates for inclusion in our portfolio loan dataset.¹⁸ After applying the filters and removing duplicate loans, the dataset includes roughly 85 million home purchase loans originated from 1990 through 2017.

Despite using the best available mortgage data, information on key risk factors is missing for many loans. This is especially true for the early years of our analysis, when the reporting of credit scores and DTIs is very spotty. While dropping observations with missing data may be conceptually simpler, we would lose information on the rest of the non-missing data fields that contain useful information on the likelihood of default. Furthermore, this information is not missing solely by chance, as the likelihood of a missing risk factor is correlated with observable borrower and loan characteristics. Hence, dropping observations with missing information

¹⁶ The NMRI dataset covers not only FHA and VA loans, but also loans guaranteed by the Rural Housing Service (RHS), which are not included in this analysis, and loans securitized by the Enterprises. The coverage of Enterprise loans is essentially the same as in FHFA's internal dataset, but the available history is much shorter. The source data for FHA, VA, and RHS loans are posted by Ginnie Mae at https://www.ginniemae.gov/data_and_reports/disclosure_data/pages/disclosure_history.aspx.

¹⁷ See Appendix A for full detail on these data quality filters and all other aspects of our data preparation.

¹⁸ These private-sector loans are only candidates for the portfolio dataset because we still have to remove PLS loans. In addition, because we merge data from the two servicer datasets to arrive at the candidate portfolio loans and the set of FHA/VA loans, there are many duplicates that must be removed. The percentages cited here represent the shares of loans in both groups that are removed by the data quality filters over and above the removal of duplicate loans.

would bias the sample and resulting statistics. We describe the imputation procedure in detail in Appendix A and provide a brief summary here.

To be able to use loans with incomplete information in our analysis, we impute missing values for five risk factors: credit score, DTI, occupancy status, loan documentation status, and amortization status. Table 1 shows the share of each of these risk factors that must be imputed in each market segment. As can be seen, we impute more than half of the DTIs for portfolio, PLS, and FHA/VA loans. In addition, roughly one-third of portfolio loans require imputations for credit score, documentation status, and amortization status. For the other cells in Table 1, imputations are less frequent.¹⁹ Figure 1 displays the share of imputations by year for the entire set of purchase loans. As shown, nearly all credit scores and DTIs are imputed for 1990-1992, but the imputation share for DTIs falls dramatically in 1993 and the share for credit scores drops in 1993, 1994, and 1996. Improved reporting for Enterprise loans largely accounts for these changes. For the other risk factors shown in the figure, the imputed share is relatively low in all years.

The imputations for all variables are done under the general framework of multiple imputation (Rubin, 1976).²⁰ Within this framework, we use a logit model to impute documentation status (full doc vs. low or no doc) and amortization status (fully amortizing vs.

¹⁹ Table 1 indicates that we do not impute occupancy status for FHA/VA loans or documentation status for Enterprise loans. This requires a bit of explanation. Some FHA/VA loans in the servicer dataset and the Ginnie Mae dataset maintained at AEI have missing data on occupancy status. We assume that these loans are actually for primary owner-occupied properties given that second-home loans and investor loans make up a very small share of the loans with reported occupancy status. A similar issue arises in the FHFA dataset, which shows many Enterprise home purchase loans as having an unknown documentation status. One Enterprise has missing documentation status for nearly all loans except those that are affirmatively no/low doc, and both Enterprises have some loans with missing documentations status even in the post-crisis period when it is required for all Enterprise loans to have full documentation. Accordingly, we assume all Enterprise loans with missing documentation status are full-doc.

²⁰ Multiple imputation preserves both the first and second moments of the underlying data, which is critical to our exercise; the relation between risk factors and default is often highly convex, making preservation of the second moment in the imputed data of paramount concern.

less than full amortization), and a multinomial logit model to impute occupancy status (primary owner-occupied, second home, or investor). Using these estimated models, we calculate the logit-based probability of the status outcomes for every loan with a missing value and assign the status with the highest probability. For the credit score and DTI imputations, we use predictive mean matching (PMM) as developed by Little (1988) because these variables are known to have non-normal distributions. To impute missing credit scores, the PMM procedure regresses reported scores on other loan characteristics, using the estimated coefficients to predict scores for all loans. Then, for each loan with an unreported credit score, the loans with the nearest predicted credit scores to its own predicted score form a set of potential “credit score donors.” The reported credit score from one of these donors is randomly selected to serve as the imputed credit score. The same process is repeated to fill in missing DTIs.

Both the logit models and PMM models are estimated separately for each market segment. To allow the estimated parameters to vary over time, we use the shortest estimation window that we judge to have sufficient data for reliable estimation; for Enterprise loans, we estimate separate regressions every quarter, while for other loans, we use a mix of quarterly, annual, and grouped-year windows. In addition, all the models use a rich set of loan characteristics as explanatory variables.²¹

Preliminary testing with the PLS dataset suggests that the uncertainty associated with the imputations has little effect on the summary statistics reported in the paper. In particular, as discussed in Appendix A, we construct 95 percent confidence bands for the three risk factors imputed for those loans – DTI, credit score, and documentation status – and for the implied

²¹ We exclude some risk factors, such as prepayment penalties and the incidence of fraud, that are frequently missing from our data or not measured at all. Insofar as these are correlated with other explanatory variables, the predictive power from these omitted variables will be subsumed in the coefficients for the observed factors.

stressed default rate. The confidence bands for the full set of PLS loans, including those with reported values for the variable shown, are uniformly tight except for the average DTI in 1990 and 1991.

Because the coverage of portfolio and FHA/VA loans in the servicer datasets is incomplete, we weight the included loans to be representative of the full national market. The first step is to construct national loan totals for both market segments using HMDA data, which we adjust to account for loans not subject to HMDA reporting.²² These adjustments provide estimated annual loan counts for the entire conventional mortgage market and the FHA/VA market. We then back out the total annual count of portfolio loans as the conventional market count minus the Enterprise loan count (from the FHFA dataset) and the PLS loan count (from the PLS dataset). With HMDA-based control totals for portfolio and FHA/VA loans in hand, we then divide the portfolio loans and the FHA/VA loans into a set of buckets for origination year, loan amount, and whether the state experienced an especially large house-price decline or not from 2006 to 2012.²³ The final step is to construct separate bucket-level weights for portfolio loans and FHA/VA loans equal to the adjusted HMDA count in each bucket divided by the count from our servicer-based dataset.

Figure 2 displays the annual shares of home purchase loans by market segment over 1990-2017 based primarily on the adjusted HMDA data and the Enterprise universe data from FHFA. The Enterprises generally accounted for about 40 to 50 percent of the total number of purchase loans over this period, with a spike above 50 percent in 2007. FHA/VA loans represented roughly another 20 percent of the market in the 1990s, then shrank during the boom

²² The details of these adjustments and other aspects of our weighting procedure can be found in Appendix A.

²³ Using the FHFA all-transactions house price index, the six states with the largest price declines were the “Sand States” (Arizona, California, Florida, and Nevada) plus Michigan and Rhode Island. We group these states together as those with especially large price declines. All other states and the District of Columbia are in the other group.

years in the 2000s, as they gave up market share to PLS loans, before rebounding in importance after the financial crisis. Altogether, government guaranteed loans have accounted for roughly 80 percent of the purchase loan market since 2009, a historically high share. The increased share has coincided with a significant reduction in loans held in portfolio and the near-disappearance of the PLS market.

3. Stressed default rates

As noted in the introduction, we calculate a stressed default rate for every loan in the dataset based on the observed default experience of similar loans originated nationwide in 2006 and 2007. We define a loan to have defaulted if it was ever 180 days delinquent or was terminated with the borrower forfeiting the property. Stressed default rates are calculated by measuring lifetime loan performance for fine disaggregations of the 2006-2007 cohort and then applying the cell-level default rates to all loans originated between 1990 and 2017. The cells are highly granular and span a number of loan-level risk factors. This approach can be thought of as equivalent to estimating a standard logit default model with nearly unlimited interaction terms among the modelled risk factors. It is less flexible than standard machine-learning algorithms such as CART models, which let the data determine the structure of the cells into which the loans are allocated. Nonetheless, as we show in Appendix B, the results from our approach are very similar to those from machine-learning models.

It is important to be clear about the interpretation of our default measure. The stressed default rate for a given loan represents its expected performance had it been hit shortly after origination with a replay of the financial crisis (including the observed policy response) *and* experienced the national average decline in house prices. The second part of the interpretation holds because the observed performance of 2006-2007 originations nationwide is used to estimate the stressed default rates. Given that the drop in house prices during and after the crisis

varied enormously across localities, the stressed default rate calculated in this way will only be valid for a national portfolio of loans. In section 5, we introduce an extension of the stressed default rate that incorporates location-specific house price shocks and thus is useful for states and metropolitan areas.

The stressed default rate is the analogue in the mortgage market to crash tests for motor vehicles or wind ratings for doors and windows in hurricane zones. In all of these cases, the goal is to assess performance under severe stress. This measure of mortgage risk should be of primary interest to policymakers because the stability of the mortgage market depends on its ability to withstand extreme events.

To capture the wide variation in default rates, we calculate eight separate default tables for loans originated in 2006-2007. Four tables apply to different types of fixed-rate mortgages, with a parallel set of tables for ARMs. As shown in Table 2, the four default tables cover each combination of documentation status (full doc or low/no doc) and amortization of principal (full amortization or less than full). The loans that we classify as not fully amortizing have an interest-only period, a period of negative amortization, or a balloon payment at the end of the loan. Each of the eight tables contains 320 cells to account for all combinations of eight credit score buckets, eight CLTV buckets, and five DTI buckets.²⁴ Given the eight tables and 320 cells per table, we allocate the 2006-07 home purchase originations across 2,560 cells in total.²⁵

²⁴ The credit score buckets are 579 or less, 580-619, 620-639, 640-659, 660-689, 690-719, 720-769, and 770+; the CLTV buckets (in percent) are 60 or less, 61-70, 71-75, 76-80, 81-85, 86-90, 91-95, and 96+; and the DTI buckets (in percent) are 33 or less, 34-38, 39-43, 44-50, and 51+.

²⁵ For the cells with 100 or more loans, we use the actual default rate for the loans in that cell. For cells with less than 100 loans, we use the average estimated default rate from a logit model built using all loans in the default tables; details of the logit model are available on request. Cells with no loans use the average estimated default rate from the logit model for a loan with the median value for each risk factor that defines the bucket. While a cutoff of only 100 loans leaves room for the actual default rate in the cell to be affected by idiosyncratic factors, our focus is on aggregate metrics, not cell-specific results. We are therefore able to rely on the central limit theorem to wash out these idiosyncratic errors. A final point that applies to the entire default table is that that cells with few observations have little effect on the aggregate stressed default rate due to the extremely low share of loans in those cells.

We produce separate default tables for Enterprise, PLS, FHA, and VA loans. However, we are unable to produce reliable tables for portfolio loans because we have incomplete information on loan performance. Accordingly, we use the default tables for Enterprise loans to assess the riskiness of portfolio loans. The maintained assumption is that portfolio loans originated in 2006-07 with the same risk characteristics would have the same default experience.²⁶

As an illustration of the default tables, Table 3 displays two slices from the default table for Enterprise 30-year fixed-rate mortgages with full documentation and full amortization. The top panel shows the slice of the table for credit scores of 720-769 and the bottom panel shows the slice for credit scores of 660-689. To help visualize the pattern of default rates in the table, the cells with default rates of 8 percent or less have green shading, those with default rates of 8.01 to 16 percent have orange shading, and those with higher default rates have red shading.²⁷

Both panels show that higher DTIs and CLTVs increase stressed default rates, though the CLTV effect is considerably stronger. Moving from the lowest CLTV bucket to the highest in either panel increases the stressed default rate by a factor between 6 to 12, while moving from the lowest DTI bucket to the highest raises stressed defaults by a factor of only 1.5 to 2.5. The effect of credit scores can be seen by comparing the same cells across the two panels. This comparison indicates that lower scores are associated with substantially higher default rates.

²⁶ Although this assumption seems reasonable, we know of no external data with which to test it. For FHA loans, we confirmed that the FHA default tables produce essentially the same stressed default rates as running the FHA loans through the Enterprise default tables, which indicates that the FHA and Enterprise tables are similar for the high CLTV loans that dominate the FHA book. In contrast, the default tables for VA loans generate lower stressed default rates for VA loans than does running these loans through either the FHA or Enterprise tables. This finding is consistent with results in Goodman, Seidman, and Zhu (2014).

²⁷ The default tables do not control for the influence of house prices, as they pool loans originated across the U.S. In Section 5, however, we amend the baseline default tables to incorporate loan-level effects of house price movements. Those tables display the same general effects of CLTVs, credit scores, and DTIs on stressed defaults as in Table 3.

Although Table 3 does not show the lowest and highest credit score buckets, the difference in default rates across those buckets is comparable to that for CLTVs. Thus, the default tables embed standard results from empirical studies of mortgage default – that credit scores and CLTVs at origination are highly predictive of loan performance, with DTIs contributing some additional information (see, for example, Mahoney and Zorn, 1997; Haughwout, Peach, and Tracy, 2008; Dunskey, Kelly, and Lam, 2013; and Fout et al., 2018).

A few studies have asserted that DTIs have less predictive power than credit scores and CLTVs, and add little (Avery et al., 1996; Foote et al., 2010) to default models. This conclusion is not supported by our results. The early research cited by Avery et al. (1996) was conducted in an era when underwriting practices generally kept DTIs within strict limits (Quercia and Stegman, 1992; Herzog and Earley, 1970). The limited variation may explain why these studies found that DTIs had so little explanatory power. More recently, Foote et al. (2010) studied the influence of DTIs on defaults for mortgages originated during 2005-2008, finding much smaller effects than those shown in Table 3. Their analysis, however, only tracked loan performance through the end of 2008, thus omitting about half of the total jump in the unemployment rate during the financial crisis. Thus, their results miss a good part of the income shock during the crisis, which mutes the estimated effect on households with heavy payment burdens. In contrast, our analysis – and that in DeFusco, Johnson, and Mondragon (2017) – tracks loan performance over a much longer period, which allows the full effect of payment burdens to emerge. A key takeaway from our research is that rising DTIs were a significant factor behind the wave of mortgage defaults during the housing bust.

All of the default tables pertain to 30-year purchase-money mortgages of owner-occupied properties. We then apply adjustment factors to these tables for loans with 15- or 20-year terms,

loans with 40-year terms, loans originated to investors, and loans used to purchase second homes. To calculate these adjustment factors, we estimate separate logit default models for Enterprise, PLS, and FHA/VA loans originated in 2006-2007. Each logit includes dummy variables for the four characteristics listed above. Then, for each of the four characteristics, we run loans with that characteristic (say, investor loans) through the model as reported and a second time with the characteristic set to the baseline value (primary owner-occupied in this case). The average default rate with the characteristic as reported divided by the average default rate with the characteristic “turned off” represents the adjustment factor. The adjustment factors for Enterprise and PLS loans substantially reduce the stressed default rates for 15- and 20-year loans, substantially increase the rates for 40-year loans and investor loans, and very slightly increase the rates for second-home loans. For FHA/VA loans, the only important difference is that 15- and 20-year loans are not estimated to have a lower stressed default rate than 30-year loans.²⁸

4. Main results

This section reports the main results from our analysis of the data on home purchase loans described in Section 2.

Stressed default rate

Figure 3 shows the results for the stressed default rate – our summary measure of risk – from 1990 to 2017. The top left panel plots the series for the mortgage market as a whole, while

²⁸ We apply the adjustment factors from the Enterprise logit results to portfolio loans, consistent with our use of the Enterprise-based stressed default tables for these loans. The actual adjustment factors used in the analysis include a refinement beyond this basic description. After calculating the logit-based estimate of each loan’s default rate, we divide the loans with the characteristic in question into two groups – those with estimated default rates above the median and those below the median. We then calculate the adjustment factor for each group separately. This refinement allows the adjustment factors to have a different effect on defaults for relatively low risk and relatively high risk loans.

the other panels disaggregate the full market into major segments. All panels use the same scale so that differences in levels across segments are readily apparent. Also, to facilitate comparisons of the rate at which risk changed across the market segments, we use a ratio scale in each panel.

The top left panel shows that mortgage risk for the market as a whole dropped and then swung back up between 1990 and 1995, followed by a gradual upward trend through 2003 and a steep rise over 2004-2006. From 2007 through 2013, mortgage risk fell sharply as credit standards tightened in the wake of the housing bust. In recent years, the risk measure has edged higher, but as of 2017 it remained near the bottom of the range observed since 1990.

The swing in the stressed default rate over the first half of the 1990s appears to reflect a combination of factors. The Federal Reserve's Survey of Senior Loan Officers shows a tightening of mortgage lending standards during the second half of 1990 and throughout 1991, likely in response to the 1990-91 recession, followed by a considerable easing of standards in 1993 and 1994. Part of this tightening owed to lenders clamping down on loans with less than full documentation, which had been found to perform poorly (Sichelman, 1990). But the path for mortgage rates also influenced the stressed default rate. The 30-year fixed mortgage rate fell from roughly 10 percent in 1990 to 7.3 percent in 1993 in response to a substantial easing of monetary policy, and then rose more than 1 percentage point in 1994 as the Federal Reserve surprised the financial markets by reversing course. These changes in mortgage rates, all else equal, pushed down the average DTI through 1993 and then boosted it in 1994, which showed through to the stressed default rate. In addition, as mortgage rates fell, many borrowers switched to 15- and 20-year loans, which are notably less risky than 30-year loans; this pattern then reversed as rates rose.

The low level of the stressed default rate in recent years also deserves comment. An important factor is the relatively high credit scores for most borrowers. If the average credit score in 2017 (about 730) were instead at the average level over the 1990s (about 695), we estimate that the stressed default rate in 2017 would have been similar to its average over 2000-2003 – that is, during the early stage of the housing boom. We take a closer look at DTIs, credit scores, and other risk factors after completing the discussion of stressed default rates.

The remaining panels in Figure 3 display the stressed default series for loans guaranteed by the Enterprises and FHA/VA and for two splits of unguaranteed private-sector loans. The Enterprise stressed default series has the same broad contour as the total market series, though it increased more noticeably from 1998 to 2003 than did the market-wide aggregate. Risk for FHA/VA loans increased gradually in the second half of the 1990s, similar to the total market, but then changed little through 2007, which contrasts with the explosion of risk in the rest of the market. In terms of the levels for the stressed default rate, Enterprise loans consistently have had lower risk than the market as a whole, while FHA/VA loans have been more risky except in the peak years of the housing boom, when risk surged for PLS and portfolio loans.

For portfolio and PLS loans, the lower left panel shows that risk in the PLS market skyrocketed from 1998 through 2006, while the sharp rise for portfolio loans began later, in 2004. With the collapse of the PLS market in 2007, risk dropped sharply for the modest volume of new originations, and in recent years, both PLS and portfolio loans have had risk levels well below those for any pre-crisis year back to 1990.

When we perform a different decomposition of private-sector loans, interesting results emerge. This alternative decomposition separates private-sector loans that fit inside the Enterprises' conforming loan limits from jumbo loans that are larger than the limit amount and

hence are ineligible for purchase by the Enterprises. Each group includes a mix of portfolio and PLS loans. Because jumbo loans have the largest loan amounts in the mortgage market, they tend to be taken out by affluent borrowers. Importantly, from 1990 through 2002, the stressed default rate for jumbo loans declined on net (with significant year-to-year volatility), in contrast to the upward trend for private conforming loans. This implies that risk in the full conforming loan market –which includes Enterprise, FHA/VA, and private non- Enterprise conforming loans and accounts for the vast majority of all purchase loans – was already on the rise in the 1990s. Only the relatively small jumbo market ran counter to this trend.

This result is relevant for evaluating the common view that the early 2000s represent a normal period in the mortgage market, a benchmark by which to assess whether lending standards in other periods are loose or tight (CoreLogic, 2017; Goldman Sachs, 2014; Urban Institute, 2018). The shading in Figure 3 covers the period 2000-2003 to facilitate the comparison to earlier years. For the market as a whole, the stressed default rates in 2000-2003 were above those in the 1990s, powered by increases in the PLS share of the mortgage market and by rising risk profiles for both PLS and Enterprise loans. Determining what constitutes “normal” lending conditions is inherently subjective. Some observers will view the late 1990s as normal, others will focus on the early 1990s, and others still will prefer an earlier period. The new evidence presented here calls into question the common view that the early 2000s represented a period of normal lending conditions.

Risk factors

Figures 4-8 present the time series for key risk factors using the same four-panel format as in Figure 3.

CLTVs

The upper left panel of Figure 4 shows that the average CLTV for purchase loans rose in two phases: a large net increase in the first half of the 1990s and a second leg up from 2004 to 2007. The average CLTV changed little on balance from the mid-1990s through 2004 and again over the decade after the financial crisis. Its level in 2017, about 86 percent, remains close to peak for the series, indicating that high borrower leverage in the form of small down payments continues to be the norm. The longest similar measure in the literature, compiled by Ferreira and Gyourko (2015), starts in 1997 and thus does not document the large run-up in the average CLTV in the first half of the 1990s, highlighting the value of our longer history.

A possible concern is that the CLTVs in our dataset may not fully capture the second liens taken out in connection with home purchases (so-called “piggyback” loans). We examined this question by comparing the prevalence of such loans in our dataset to the HMDA-based estimates in Bhutta and Keys (2018) and LaCour-Little, Calhoun, and Yu (2011), who show that the use of piggybacks jumped between 2003 and 2006 and then plummeted over the next three years. Although our dataset does not explicitly identify piggyback loans, we deem a piggyback to exist whenever the CLTV at origination exceeds the LTV by at least 5 percentage points.²⁹ For 2003 and later years, the occurrence of piggybacks in our data closely tracks the HMDA-based estimates. Thus, the average CLTV shown in the upper left panel of the figure appears to be accurate from 2003 forward. Before 2003, however, the reporting of piggybacks in our dataset is incomplete. Our rough estimate is that the true CLTV for 2002 and earlier years could

²⁹ This assumption is based on the observation that piggybacks tend to occur at 5 percentage point intervals; histograms have major spikes at 10, 15, and 20 percentage points, with a small bump at 5 percentage points. Accordingly, we set the minimum threshold at a 5 percentage point difference between the LTV and CLTV to infer the existence of a piggyback loan.

be understated by $\frac{1}{2}$ to $\frac{3}{4}$ percentage point. Correcting for this understatement would not materially change the contour shown in the upper left panel.³⁰

Notably, the sharp rise in CLTVs for Enterprise loans that started in 1991 was not evident in the private mortgage market until a few years later. The average CLTV for portfolio loans dropped from 1990 to 1992 and did not exceed the 1990 level until 1994. For PLS loans, the average CLTV was little changed from 1990 to 1992 and then rose gradually over the next three years.

DTIs

As shown in the upper left panel of Figure 5, the average market-wide DTI moved down over 1990-92 – likely due in large part to the decline in mortgage rates discussed above – and then trended sharply higher for the next 15 years.³¹ The average DTI retraced about half of this increase during and shortly after the financial crisis, before increasing again from 2012 to 2017. As of 2017, the average market-wide DTI stood at a relatively high level by historic standards.

Since the financial crisis, the average DTI for FHA/VA loans has risen, reaching an historically high level in 2017. The average DTI on Enterprise loans has also increased in recent years. In contrast, the average DTI for portfolio and PLS loans remains near the bottom of the range seen since 1990. This divergence reflects the impact of the Qualified Mortgage (QM) rule

³⁰ In addition to piggyback loans, second liens can be taken out after the purchase date by borrowing against accumulated home equity. We do not track these subsequent second liens. Using data for one of the Enterprises, Leventis (2014) estimated that approximately 5 percent of the first liens originated in 2006-2007 had a subsequent second lien. Thus, the performance of the 2006-2007 loans used to calculate our default tables would reflect the CLTV at origination and, to a modest extent, unobserved subsequent claims against home equity.

³¹ Although Foote, Loewenstein, and Willen (2018) do not directly measure DTIs, they present evidence consistent with this increase in the average DTI. Specifically, using loan-level data, they regress the purchase loan amount at origination on borrower income and a set of control variables. They find that the relationship between the loan amount and income became weaker over the 1990s and into the 2000s, indicating that income constraints on loan size had loosened.

issued by the Consumer Financial Protection Bureau in 2013.³² The Dodd-Frank Act and the QM rule grant private lenders a safe harbor against borrower lawsuits for loans that have DTIs of 43 percent or less (and other risk-reducing features). As DeFusco, Johnson, and Mondragon (2017) show, lenders have responded by sharply limiting the origination of high DTI loans that they hold in portfolio. However, Dodd-Frank permanently exempted the FHA and VA (along with other smaller guarantee programs) from the 43 percent limit, and the QM rule granted the Enterprises an exemption until 2021. Accordingly, the risk associated with high DTI loans has migrated to government guarantee programs.

Credit scores

Figure 6 presents the average credit score for the total purchase loan market and the same market segments as in previous figures. As shown in the top left panel, there was no obvious trend in the average credit score for the market as a whole during the 1990s. From 2000 until the market peak in 2007, the average score edged up on net; it then posted a large and sustained rise through 2012 and has edged down in recent years. Although there are some differences among the market segments, the broad outline of the story is the same across the various panels in Figure 6.

There are two important takeaways from this figure. First, the substantial increase in risk for home purchase loans before the financial crisis was not due to a shift toward lower-score borrowers. We provide more detail below on the low-credit-score part of the purchase loan market, but it is already clear that higher CLTVs and higher DTIs contributed to the buildup of risk while credit scores played no parallel role. Second, credit scores remain unusually high despite the downdrift in recent years for government guaranteed loans. The higher average scores

³² For a summary of the QM rule, see https://files.consumerfinance.gov/f/201411_cfpb_atr-qm_small-entity-compliance-guide.pdf.

likely represent a combination of tighter credit supply and weaker demand from high-risk borrowers. Regardless of the relative importance of supply versus demand factors, high credit scores have caused stressed default rates to remain low despite the high level of borrower leverage in today's market.

Other risk factors

Our analysis tracks a number of other significant factors that affect loan performance. Figure 7 shows the share of home purchase loans that had less than full documentation of the borrower's income or assets. Borrowers who are self-employed or who have highly variable income often rely on such loans, though they also have been used to fraudulently overstate income. In 1990, a bit more than 15 percent of all home purchase loans had less than full documentation, a share that fell to a range of 8 to 15 percent for the rest of the 1990s as lenders cut back these offerings after experiencing worse-than-expected loan performance (Sichelman, 1990). During the first half of the 2000s, low/no doc loans grew in popularity, accounting for about one-third of all home purchase loans in 2005-2006. Many borrowers used low/no doc loans to overstate their true income and preserve buying power in the face of rising house prices (see, for example, Mian and Sufi, 2017b). Since the housing bust, low/no doc loans have nearly disappeared from the market, as the ability-to-repay rules in Dodd-Frank require the documentation of borrower income for virtually all closed-end home mortgage loans.³³

The story is much the same for loans with less than full amortization, which includes interest-only, negative amortization ("neg am"), and balloon loans. As shown in Figure 8, from 1990 through 2002, about 5 percent of all home purchase loans, on average, had less than full amortization. This share jumped over the next three years and exceeded 30 percent in 2005 for

³³ See section 3.13 of https://files.consumerfinance.gov/f/201411_cfpb_atr-qm_small-entity-compliance-guide.pdf for the very limited exceptions to this requirement.

the purchase loan market as whole. The peak share varied widely by market segment, ranging from a bit more than 10 percent for the Enterprises to nearly 70 percent for jumbo loans.

Amromin et al. (2018) and Garmaise (2018) show that the borrowers taking out loans with less than full amortization were primarily higher income households with prime credit scores buying homes in states with rapidly rising house prices. Like low/no doc loans, these loans were used to maintain buying power in an environment in which household income was rising much more slowly than house prices. This strategy worked as long as house prices continued rising but was associated with high default rates once prices came down. After the housing bust, these loans became extremely uncommon, largely because loans must fully amortize to qualify for QM status.

Figure 9 shows the prevalence of three additional risk factors for home purchase loans, without the segment detail in previous figures. All three factors contributed to the build-up of mortgage risk during the boom. The ARM share of purchase loans (upper panel) jumped from 2002 to 2005, peaking at almost 50 percent in 2005 before plummeting. The investor share (middle panel) also peaked in 2005, and the share of loans with terms of 15 or 20 years (bottom panel) trended lower from 1998 to 2005, which slowed the accumulation of borrower equity.³⁴ The shift from fixed-rate mortgages to ARMs, from owner-occupied loans to investor loans, and from 15- or 20-year loans to 30-year loans each propelled the stressed default rate to higher levels.

Role of risky product features during the boom

³⁴ The swing in the first half of the 1990s is also of interest. The 15- and 20-year share rose from 1990 to 1992 as the sharp drop in mortgage rates encouraged borrowers to take out loans that paid off quickly – a factor behind the decline in mortgage risk in those years. However, the rise in the 15- and 20-year share had fully unwound by 1994 with the jump in mortgage rates in that year.

How much of the build-up of risk during the housing boom can be traced to standard forms of borrower leverage (such as rising DTIs) versus the growing use of risky products (such as interest-only loans)? We address this question by comparing the stressed default rate shown above, which incorporates the full set of risk factors, to an alternative stressed default rate that omits a specified set of risky product features.

The risk factors we classify as risky product features are guided by the QM rule. To meet the QM definition, a loan must fully amortize, must have a term of 30 years or less, and must have full documentation of income. Thus, we define risky product features as those characteristics that make a loan ineligible for QM status – less than full amortization, less than full documentation, and a term greater than 30 years. To calculate our alternative stressed default rate that excludes risky product features, we run low/no doc loans and loans with less than full amortization through the default tables as loans without those features and we remove the adjustment factor for loans with a 40-year term.

Figure 10 displays the results of this exercise. The solid line shows the standard stressed default rate that embeds all risk factors, while the dashed line shows the alternative series that excludes risky product features. Over the period 1998-2006, the alternative series increased by 7.5 percentage points, which represents 45 percent of the 16.5 percentage point rise for the standard series. This decomposition indicates that both “plain vanilla” leverage and risky product features played an important role in the run-up of mortgage risk during the boom.³⁵

Mortgage rate spreads

³⁵ Li and Goodman (2014) perform a similar decomposition and find a larger role for risky product features. This difference likely relates to their estimate of a very small rise in stressed defaults for Enterprise loans, with portfolio and PLS loans accounting for nearly the entire increase in the market-wide stressed default rate. Since risky product features were more common in portfolio and PLS loans than in Enterprise loans, these features end up dominating plain vanilla leverage in the Li-Goodman decomposition. However, our results imply that they substantially understated the rise in risk for Enterprise loans, which calls their decomposition into question.

Our results document a sharp rise in the riskiness of home purchase loans during the early and mid-2000s. This finding, on its own, does not identify whether the increase in risk owed to an expansion of credit supply, greater credit demand, or both. However, the literature provides ample evidence that an easing of credit supply was at least part of the story.³⁶

One of the key pieces of evidence supporting an expansion of credit supply is that mortgage rate spreads came down during the boom period (Demyanyk and van Hemert, 2011; Justiniano, Primiceri, and Tambalotti, 2017; Mian and Sufi, 2017a). This decline implies that the supply of credit increased by more than enough to accommodate any outward shift in mortgage demand. Our data add to this body of evidence. In particular, we show that rate spreads for the mortgages with the highest stressed default rates compressed sharply during the boom years, which indicates that lenders and mortgage investors became significantly more willing to extend credit to high-risk borrowers. To our knowledge, this is the first exploration of spreads across risk tiers.

Figure 11 presents the results. We limit our attention to loans for which lenders and investors fully bear the credit risk – PLS and portfolio loans without any private mortgage insurance – to get a clean read on changes in supply. The figure shows the average annual spreads for loans with stressed default rates in progressively higher risk buckets measured relative to the mortgage rate for loans in the lowest stressed default rate bucket (0-10 percent).

For PLS loans (left panel), the level of spreads corresponds one-for-one with the ordering of the risk buckets, confirming that the market is pricing for risk. Spreads for the highest two

³⁶ See Mian and Sufi (2017a) for a discussion of the evidence. Anenberg et al. (2018) provide a nice summary measure of the expansion of mortgage credit supply during the boom by estimating a supply frontier, which represents the maximum loan size that could be obtained for a given set of observable borrower and loan characteristics; they show that the frontier moved substantially higher from 2001 to 2005-2006. Despite this evidence, Albanesi et al. (2017) question whether there was any increase in credit supply based on their finding that mortgage debt growth was strongly correlated with income growth over this period. This correlation, however, would be consistent with a broad-based increase in credit supply throughout the income distribution.

risk buckets fell dramatically between 2001 and 2005, before turning up in 2006-2007, when investors began to have concerns about the performance of PLS loans. Spreads for the third highest risk bucket also fell noticeably. For portfolio loans, spreads also compressed relative to the lowest risk bucket, with most of the narrowing having occurred by 2002. Interestingly, the average level of spreads for the two highest risk buckets is lower than in the PLS market, and the two spreads essentially lie on top of one another; this contrast to the PLS market is worthy of further analysis. Overall, these results provide additional evidence of an expansion of credit supply for riskier borrowers.

Borrowers with low credit scores

An ongoing debate in the literature concerns the role of “subprime” borrowers in the housing boom and bust.³⁷ Mian and Sufi (2009, 2014, 2017a) have emphasized the importance of mortgage lending to marginal borrowers, who traditionally would have been denied credit. However, a number of recent papers have questioned the focus on this sector, arguing that (a) the growth of mortgage debt was spread across the credit score distribution, (b) loan defaults during the crisis were more skewed toward middle- and higher-income borrowers than in previous periods, and (c) house prices increased the most in areas with relatively weak lending to borrowers with low credit scores (Adelino, Schoar, and Severino, 2016 and 2017; Albanesi, Di Giorgi, and Nosal, 2017; Conklin et al., 2018; Ferreira and Gyourko, 2015).

We make two contributions to this debate. First, using our data for the entire mortgage market, we track the low-credit-score share of home purchase loans. And, second, we examine whether low-credit-score loans became markedly riskier than other loans during the boom. Our

³⁷ As stated previously, we define low-credit-score borrowers as those with a credit score of less than 660 at origination. Such borrowers are often referred to as “subprime” in the academic literature. In other contexts, there is no agreed-upon definition of the term. Accordingly, we refrain from using the subprime label throughout the paper except in reference to others’ work.

definition of low-credit-score loans as those with scores below 660 follows Adelino, Schoar, and Severino (2016, 2017), Conklin et al. (2018), and Mian and Sufi (2009).

Figure 12 displays the annual low-credit-score share of purchase loans over 1990-2017. For the total market, the share fell on net from 2000 to 2007. The pattern varied a bit across the market segments, but no segment shows an uptrend from 2000 to 2007. These results are inconsistent with an emphasis on low-score borrowers having driven the growth of home purchase lending during the boom.

Figure 13 compares the stressed default rate and selected risk characteristics for loans below the 660 credit score threshold versus loans with higher scores. As shown, the stressed default rate for low-score loans moved essentially in tandem with that for higher-score loans over the entire period from 1990 to 2007. There was no systematic increase in the riskiness of low-score loans relative to other loans. The risk characteristics shown in the figure explain why. The average CLTV rose about the same amount for both sets of loans, and while the average DTI increased a bit more for low-score loans, the low/no doc share rose less.

All in all, these results point to a broad-based rise in mortgage risk during the 1990s and the boom years in the 2000s. Risky loans became more plentiful and on more favorable terms to both low- and high-credit-score borrowers.³⁸

5. Incorporating House Price Shocks

Measuring Shock CLTVs

³⁸ An alternative definition of subprime loans in the literature uses 620 as the credit score threshold. Our results are very similar to those based on the 660 threshold score. The only difference of note is an even more pronounced rise in the low/no doc share for loans above the score threshold, which translates into a somewhat larger relative increase in the stressed default rate for these loans. Thus, the results using the 620 threshold are, if anything, even less favorable to the view of the housing boom that emphasizes low-score borrowers.

An implicit assumption in the national stressed default rate is that each loan is subjected to the average house price decline in the U.S. during and after the Great Recession. The purpose of this assumption was to intentionally constrain the resulting risk indicator to reflect only borrower and mortgage characteristics. But for some applications, it may be desirable to add additional loan-level information. For instance, local risk indicators require the use of location-specific house price risk given the wide variation in house price movements across the country. In this section, we implement local stress measures in a direct and straightforward manner by incorporating hypothetical local house price shocks in the construction of risk indicators.³⁹

We define a “shock combined loan-to-value” ratio at origination (SCLTV) as the ratio of the unpaid principal balance at origination (UPB) divided by the “shock house value,” which is set equal to the house value at origination (V) multiplied by one plus a projected 3-year house price shock.

$$SCLTV = \frac{UPB}{V \times (1 + \Delta V^s)}$$

The SCLTV represents the expected combined loan-to-value ratio of a loan three years after the onset of severely stressed conditions. Because the assumed shock involves a drop in house prices, ΔV^s is negative, causing the SCLTV to be higher than the stated CLTV at origination.

Our price shock variable is constructed following Smith and Weiher (2012) and Smith et al. (2016), who describe a simple method for constructing a house price path associated with severe economic stress. The concept behind this 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 that are more traditionally modeled, such as the house price-to-income

³⁹ Other location-specific stresses could potentially be implemented, including negative income shocks (via DTIs) and possible credit score deterioration.

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 negative price movements are taken into account when setting the shock value.

We begin with a real house price series constructed using a nominal series divided by the all-items consumer price index for all urban consumers (CPI). The construction of the SCLTV then proceeds in 5 steps:

1. Fit a trend line for the series for real house prices using data for 1975 through 2017. If the trend slope is negative, set it to 0.⁴⁰
2. Calculate the “maximum differential” as the largest percent difference between the trend and the below-trend values of the series, or 5 percent, whichever is larger.
3. Calculate the “lower bound” in each year as the trend minus the maximum differential defined in the previous step. If the lower bound calculated in this way is less than 5 percent below the house price index for a given year, set the lower bound for that year to be 5 percent below the price index.⁴¹
4. Calculate the “stress loss” as the difference between the current value of the house price index and the lower bound price level three years in the future.⁴² The use of the lower bound price level three years ahead allows the price shock to play out over a realistic time horizon.
5. Convert the real stress loss to a nominal stress loss, ΔV^s using the CPI.

A visual depiction of this procedure is shown in Figure 14 for the Washington, DC CBSA. The real house price trend is estimated over the entire series as 1.4 percent per year. The maximum differential is achieved in 1999 at 15 percent below the trend, giving a lower bound of 15 percent below the trend in all periods except 1996 through 2000, 2012, and 2013, where the

⁴⁰ The house price series used are the FHFA annual State and CBSA indices from Bogin, Doerner, and Larson (2018).

⁴¹ For any house price index that requires the imposition of this 5 percent gap, it is needed, by definition, in the year of the maximum differential, but it can be required in other years too.

⁴² Because the real house price trend is log-linear, in practice, we calculate the lower bound as the current trend value plus three times the trend slope minus the maximum differential. This value is then set to the house price index minus 5 percent if the value is smaller in magnitude. All variables are in real terms for this calculation.

lower bound is set to the minimum of 5 percent below the price index. The maximum stress loss is 41 percent in 2006, which is calculated using the index value for 2006 and the lower bound value for 2009.

This procedure is repeated for each metropolitan statistical area (MSA) and each state. For each loan in the database, the SCLTV is then calculated using the MSA index if available. If the MSA index is unavailable – for instance in small cities where city-specific indices are not available or in rural areas that are not part of an MSA – the maximum stress loss is constructed using the state index.

After calculating loan-level SCLTVs, we implement the procedure outlined in Section 3 to construct stressed default rates for each loan in the database based on SCLTVs substituted for CLTVs at origination. The key difference is the grid cutoffs for SCLTVs, which are now (in percent) 60 or less, 61-80, 81-100, 101-115, 116-130, 131-145, 146-160, and 160+. We then revise the default tables to use the SCLTV buckets and construct national, state, and MSA stressed default rate by averaging the loan-level stressed default rates by year.

Results

The average SCLTV for the nation as a whole is shown in the top panel of Figure 15. By construction, the SCLTV is higher than the unadjusted CLTV for every loan because the value of the home is at least 5 percent lower than the value used to construct the CLTV. The extent to which the average SCLTV exceeds the CLTV depends on the average location-specific house price shock averaged over the country as a whole. The top panel of the figure shows that the average SCLTV varies much more over time than the unadjusted average CLTV. In 2006, the national average SCLTV reached 139 percent, indicating the enormous collateral risk due to above-trend house prices.

The bottom panel shows that the stressed default rate calculated using the SCLTV exhibits a greater degree of pro-cyclical behavior than when calculated using the unadjusted CLTV. This occurs because the changes in house price risk over the cycle greatly amplify the observed variation in CLTVs at origination, as shown in the upper panel. The stressed default rates converge in the 2006-2007 period by construction, as both sets of default tables reflect the observed performance of loans originated in those years.

There are two periods, in particular, that highlight the usefulness of the stress default measure calculated using SCLTVs. The first is the 1996-2002 period, where this measure shows a significant increase in risk, while the standard stressed default measure shows a much milder rise in risk. The second is the 2013-2017 period, where similarly, the measure based on the SCLTVs shows a more pronounced rise in risk. In both cases, while risk based solely on borrower and loan characteristics is rising slowly, house price risk is steepening the overall risk trajectory. This brings into focus one of the key insights of this extension of the standard measure. It shows that default risk can rise substantially even when there are only modest overall changes in borrower and mortgage characteristics.

The second main purpose of SCLTV-based default risk estimates for individual loans is that they can be aggregated at fine levels of geography to construct measures of local risk. We calculate stressed default rates for all 50 states, the District of Columbia, and 367 MSAs. These indicators show wide variation in stressed default risk both across areas and over time, reflecting regions-specific lending and house price patterns.

Figure 16 shows local stressed default rates by quintile for states and MSAs, averaged over 2006-2007. Areas with the highest stressed default rates include the well-known “Sand States” (Arizona, Nevada, Florida, and California) as well as Maryland, Michigan, Oregon,

Rhode Island, and Idaho. These states had the highest stressed default risk at the onset of the Great Recession, accounting for the combination of loan characteristics and the potential for severe house price declines. Areas with the lowest risk included the vertical band of states ranging from Texas through North Dakota, Iowa, several Appalachian states, and Vermont.

The MSA panel paints a more nuanced picture of mortgage risk. In some states, including California and Nevada, the MSA patterns match that for the state as a whole, but in other states, there is wide variation. For instance, the state-level indicator for Ohio puts it in the middle quantile of default risk. However, the MSA map shows that the state-level indicator averages relatively low risk in Cincinnati and Columbus with higher risk elsewhere in the state.

Figures 17 and 18 show variation in stressed defaults for both states and MSAs over time, respectively. The states in Figure 17 were chosen to represent a diverse sampling of geographies and populations; the MSAs in Figure 18 are located within those states. The purpose of these figures is to highlight three things. First, there are periods (such as the mid-1990s and 2010s) during which the risk profiles are similar across states or MSAs, yet in other periods (especially the late 1990s through the mid-2000s), the risk profiles are remarkably different. Second, there are cases where MSAs have higher risk than the state in which they are located (Detroit relative to Michigan), and there are cases where the opposite is true (San Francisco relative to California in the mid-2000s). Finally, the rank-order among MSAs and states in the riskiness of originated purchase-money mortgages varies over time. For example, in the figure, while Detroit had the highest stressed default rate in the run-up to the Great Recession, it has had the second or third lowest since.

6. Conclusion

Understanding the evolution of risk in the mortgage market before the financial crisis and after requires a long historical account built from comprehensive and accurate data. Until now, that historical record did not exist, and this paper takes a major step toward filling the gap. We bring together several sources of data, including the entire Enterprise book, to cover essentially the entire market for home purchase loans from 1990 to 2017. We track important loan characteristics and compute a summary measure of risk under stressed conditions.

We use the data to reach a number of conclusions. First, we show that loan risk had already risen during the 1990s, calling into question the common view that the early 2000s represented a period of normal lending conditions. This conclusion is reinforced when we account for the widening gap between house prices and their longer-term trend levels, which effectively made the CLTVs at origination higher than their stated level.

Second, we provide new evidence that credit standards eased in the early and mid-2000s by documenting a compression of mortgage rate spreads between the riskiest and least risky loans in the PLS market and in lenders' portfolios. Third, the rise in risk was very similar for borrowers with low credit scores and those with higher scores. This fact, combined with a downward drift in the low-credit-score share of purchase loans during the housing boom, undercuts explanations of the crisis that focus on low-score borrowers. Fourth, while risky product features accounted for a bit more than half of the rise in risk during the boom years, plain-vanilla factors such as higher DTIs and CLTVs accounted for a large portion as well. Finally, in today's market, overall risk is near all-time lows, despite high average DTIs and CLTVs, as risky product features have largely disappeared and average credit scores remain elevated. This highlights that the post-crisis regulatory environment succeeded, at least through 2017, in limiting mortgage risk.

Table 1: Share of Home Purchase Loans with Imputed Risk Factors, 1990-2017
(percent)

Risk Factor	Enterprise	Portfolio	PLS	FHA/VA
Credit score	16	30	7	24
DTI	12	62	52	58
Documentation status	0	36	2	0
Payment-reducing features	0	30	0	0
Occupancy status	0	13	0	0

Note: For portfolio and FHA/VA loans, the shares pertain to the loan-level source data before weighting to ensure that the data are nationally representative. The loan-level Enterprise and PLS source data are not weighted. Payment-reducing features refers to whether a loan fully amortizes or has less than full amortization through the use of an interest-only period, a period of negative amortization, or a balloon payment.

Source: Authors' calculations using data from FHFA (for Enterprise loans), Black Knight, Inc. (for portfolio and FHA/VA loans), CoreLogic® (for portfolio, PLS, and FHA/VA loans), and Ginnie Mae data processed by AEI's Center on Housing Markets and Finance (for FHA/VA loans).

Table 2: Default Tables

Fixed-rate Mortgages	ARMs
Full doc / Full amortization	Full doc / Full amortization
Full doc / Less than full amortization	Full doc / Less than full amortization
Low or no doc / Full amortization	Low or no doc / Full amortization
Low or no doc / Less than full amortization	Low or no doc / Less than full amortization

Note: “Less than full amortization” indicates that the loan has a feature that reduces principal payments for some period of time. These features include interest-only payments, negative amortization, or a balloon payment at the end of the stated term.

Table 3: Stressed Default Rates for Enterprise 30-year Fixed-Rate Loans with Full Documentation and Full Amortization (in percent)

Credit Scores of 720-769

DTI (%)	CLTV (%)							
	1-60	61-70	71-75	76-80	81-85	86-90	91-95	≥ 96
1-33	1.04	2.42	3.46	4.11	3.89	6.26	7.42	10.68
34-38	1.75	3.47	4.30	6.09	5.64	8.33	9.73	13.18
39-43	1.88	4.31	5.03	7.11	6.89	10.05	11.58	15.48
44-50	1.98	4.36	6.10	8.07	8.43	11.23	13.31	17.89
≥ 51	1.95	4.39	6.46	8.30	9.09	12.43	15.84	24.12

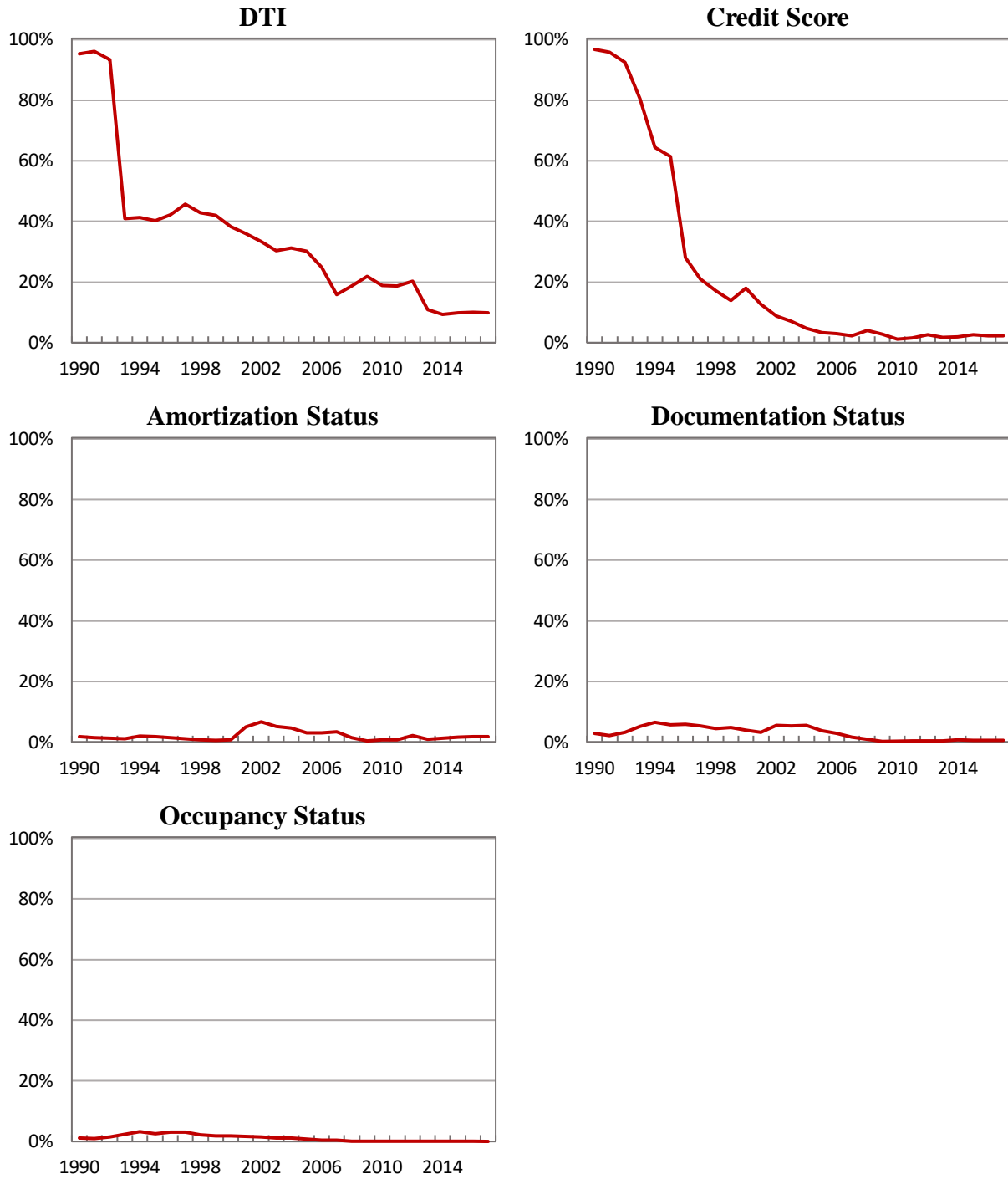
Credit Scores of 660-689

DTI (%)	CLTV (%)							
	1-60	61-70	71-75	76-80	81-85	86-90	91-95	≥ 96
1-33	3.23	5.90	8.74	8.56	8.15	12.90	14.54	22.55
34-38	3.87	7.03	8.84	12.21	13.17	15.69	17.61	26.45
39-43	4.29	10.09	11.37	13.17	14.45	18.92	20.58	29.76
44-50	5.35	9.77	12.69	15.03	16.45	21.05	23.34	32.30
≥ 51	4.67	11.24	14.23	16.04	21.12	23.26	28.72	39.62

Note: Shading: green for stressed default rates of 8% or less, orange for 8.01% to 16%, and red for more than 16%. See the text for details about the calculation of the stressed default rates.

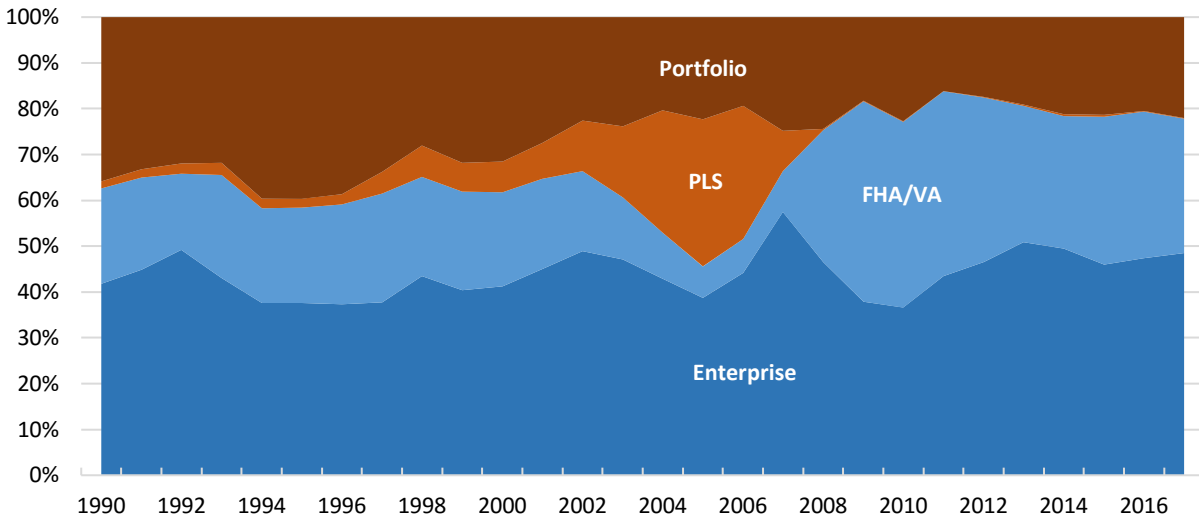
Source: Authors' calculations using FHFA data for Enterprise loans.

Figure 1: Imputation Share for Home Purchase Loans, Total Market, 1990-2017



Note: Results pertain to 1-4 unit purchase-money mortgages and are based on unweighted loan counts.
Source: Authors' calculations using data from FHFA, Black Knight, Inc., CoreLogic®, FHFA, and Ginnie Mae data processed by AEI's Center on Housing Markets and Finance.

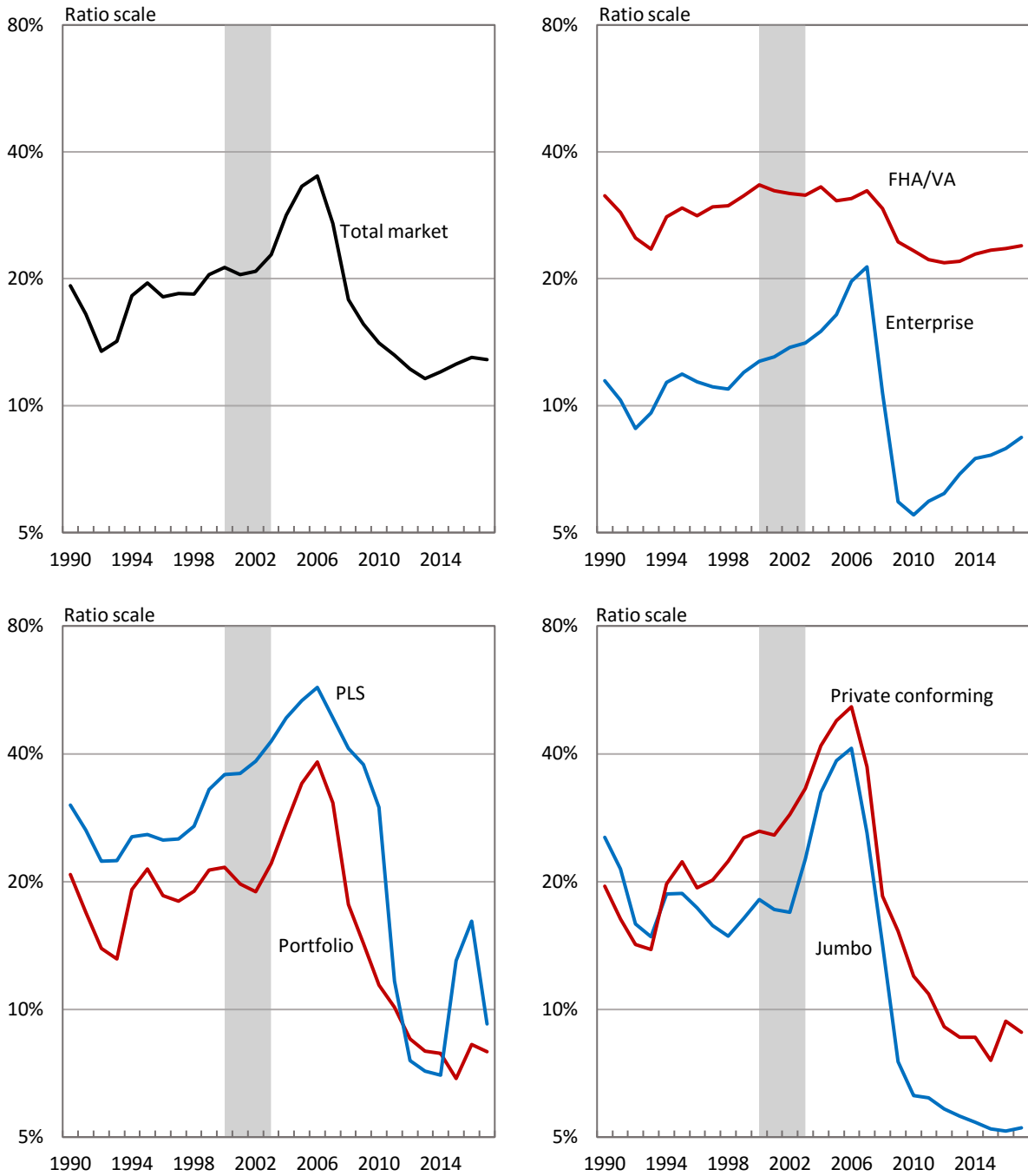
Figure 2: Market Shares of Home Purchase Loans



Note: Shares pertain to 1-4 unit purchase-money mortgages and are based on loan counts. The share for portfolio loans is calculated as a residual given shares for Enterprise loans, PLS loans, and FHA/VA loans. The counts for the total market and FHA/VA loans are based on HMDA data and are grossed-up by an estimate of the undercount in HMDA. The Enterprise count comes from FHFA data and is assumed to cover the universe of such loans. The PLS count from CoreLogic® is believed to cover nearly the entire market and thus is also not grossed up. Because HMDA only began to collect information on lien status in 2004, the shares for 1990-2003 include first liens and subordinate liens. Starting in 2004, the shares are based on first liens only.

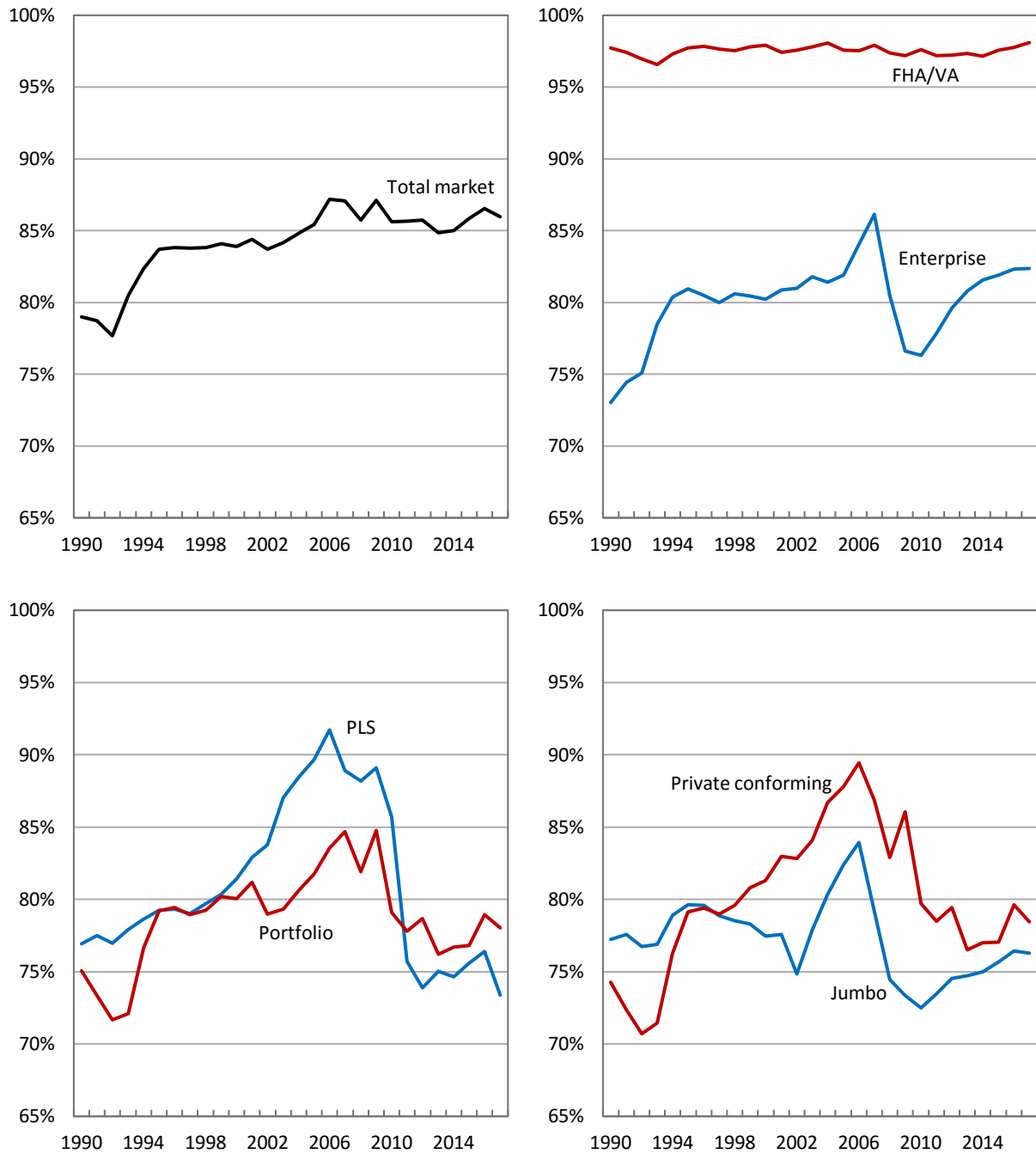
Source: Authors' calculations using data from FHFA, Black Knight, Inc., CoreLogic®, and Ginnie Mae data processed by AEI's Center on Housing Markets and Finance, and HMDA.

Figure 3: Stressed Default Rate for Home Purchase Loans, 1990-2017



Note: Results pertain to 1-4 unit purchase-money mortgages. Private conforming loans include portfolio and PLS loans with initial loan amounts below the applicable Enterprise conforming loan limit. Shading is for 2000-2003. *Source:* Authors' calculations using data from FHFA (for Enterprise loans), Black Knight, Inc. (for portfolio and FHA/VA loans), CoreLogic® (for portfolio, PLS, and FHA/VA loans), and Ginnie Mae data processed by AEI's Center on Housing Markets and Finance (for FHA/VA loans).

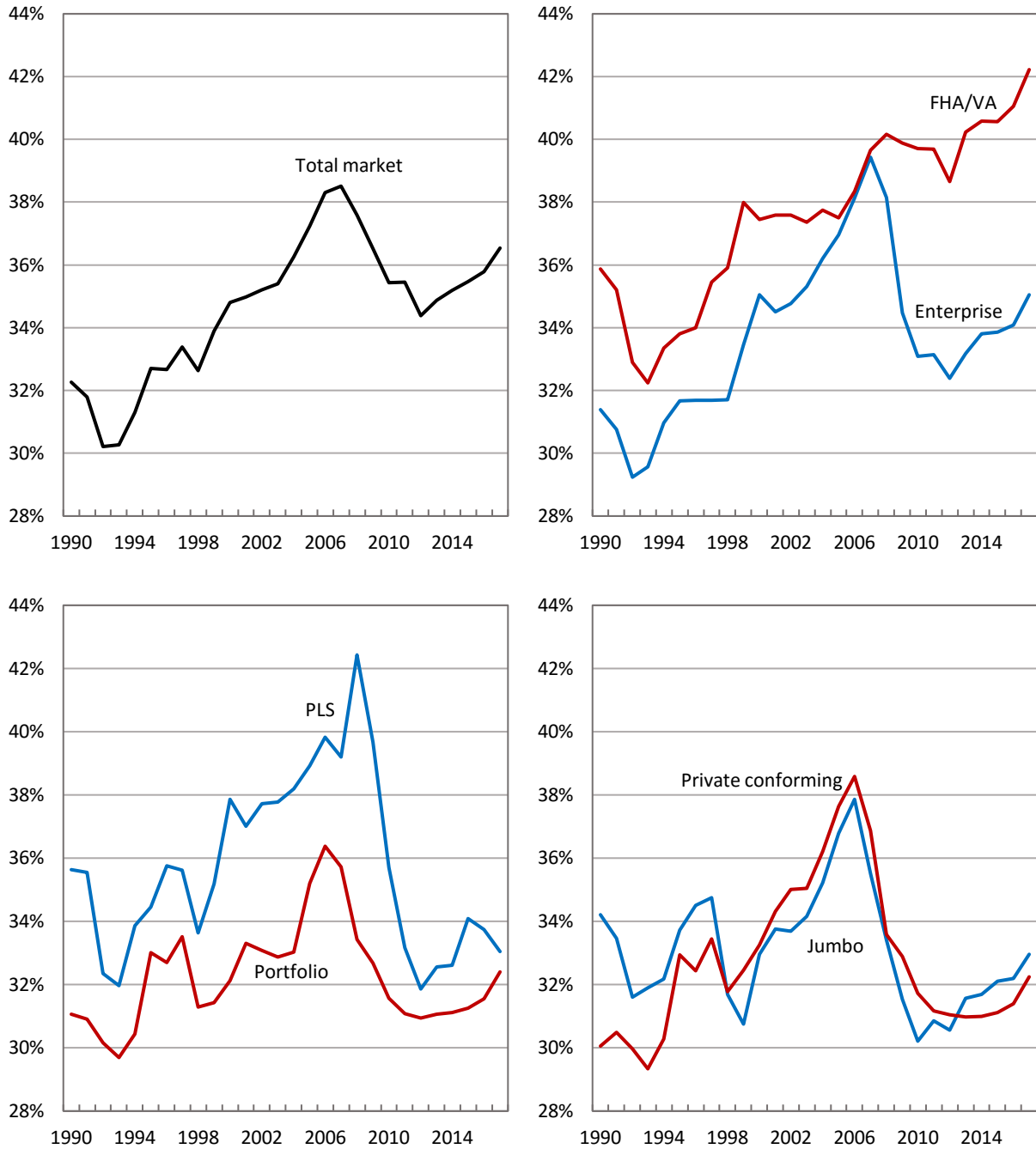
Figure 4: Average CLTV for Home Purchase Loans, 1990-2017



Note: Results pertain to 1-4 unit purchase-money mortgages. Private conforming loans include portfolio and PLS loans with initial loan amounts below the applicable Enterprise conforming loan limit.

Source: Authors' calculations using data from FHFA (for Enterprise loans), Black Knight, Inc. (for portfolio and FHA/VA loans), CoreLogic® (for portfolio, PLS, and FHA/VA loans), and Ginnie Mae data processed by AEI's Center on Housing Markets and Finance (for FHA/VA loans).

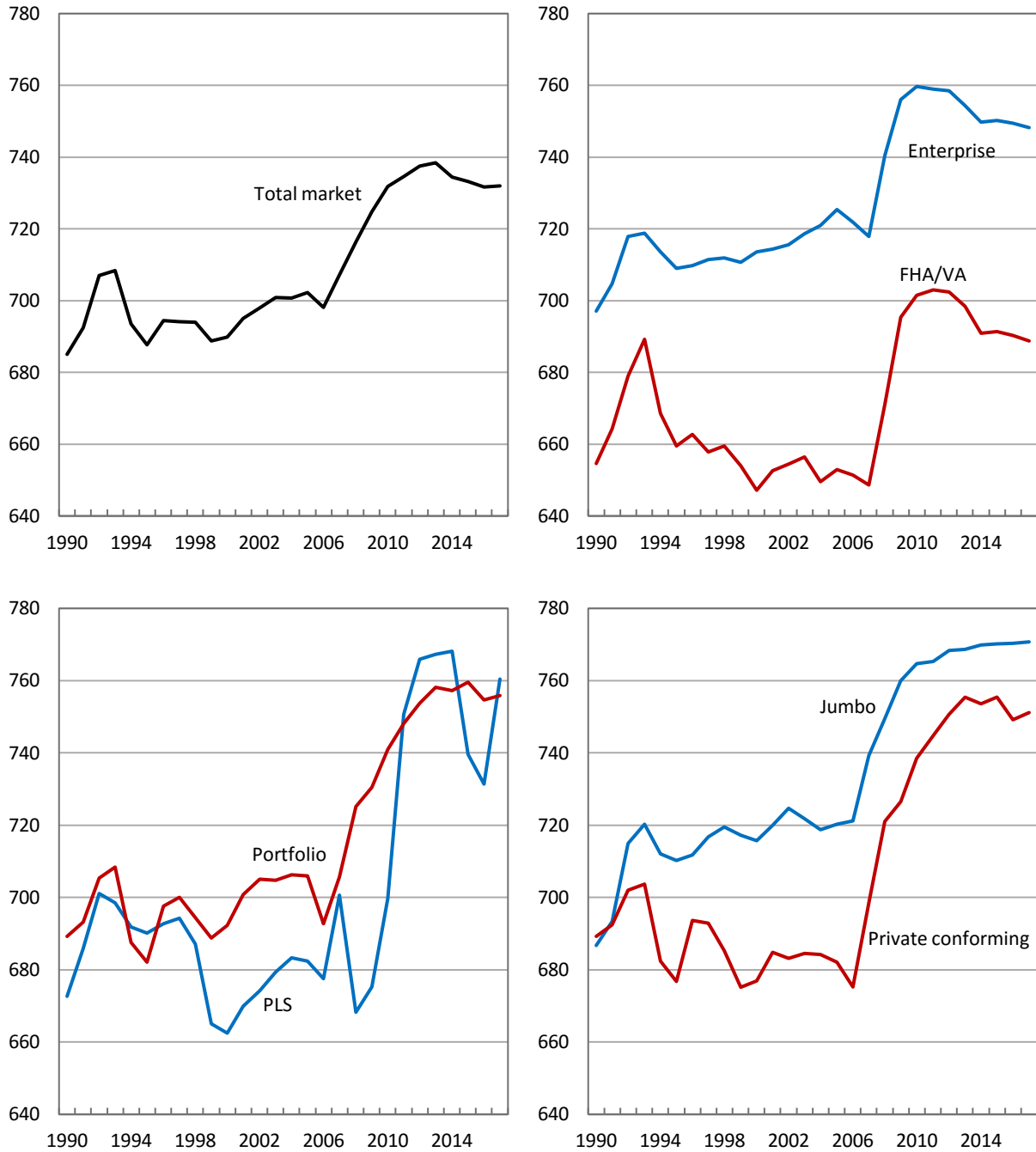
Figure 5: Average DTI for Home Purchase Loans, 1990-2017



Note: Results pertain to 1-4 unit purchase-money mortgages. Private conforming loans include portfolio and PLS loans with initial loan amounts below the applicable Enterprise conforming loan limit. Missing DTIs are imputed using regression techniques.

Source: Authors' calculations using data from FHFA (for Enterprise loans), Black Knight, Inc. (for portfolio and FHA/VA loans), CoreLogic® (for portfolio, PLS, and FHA/VA loans), and Ginnie Mae data processed by AEI's Center on Housing Markets and Finance (for FHA/VA loans).

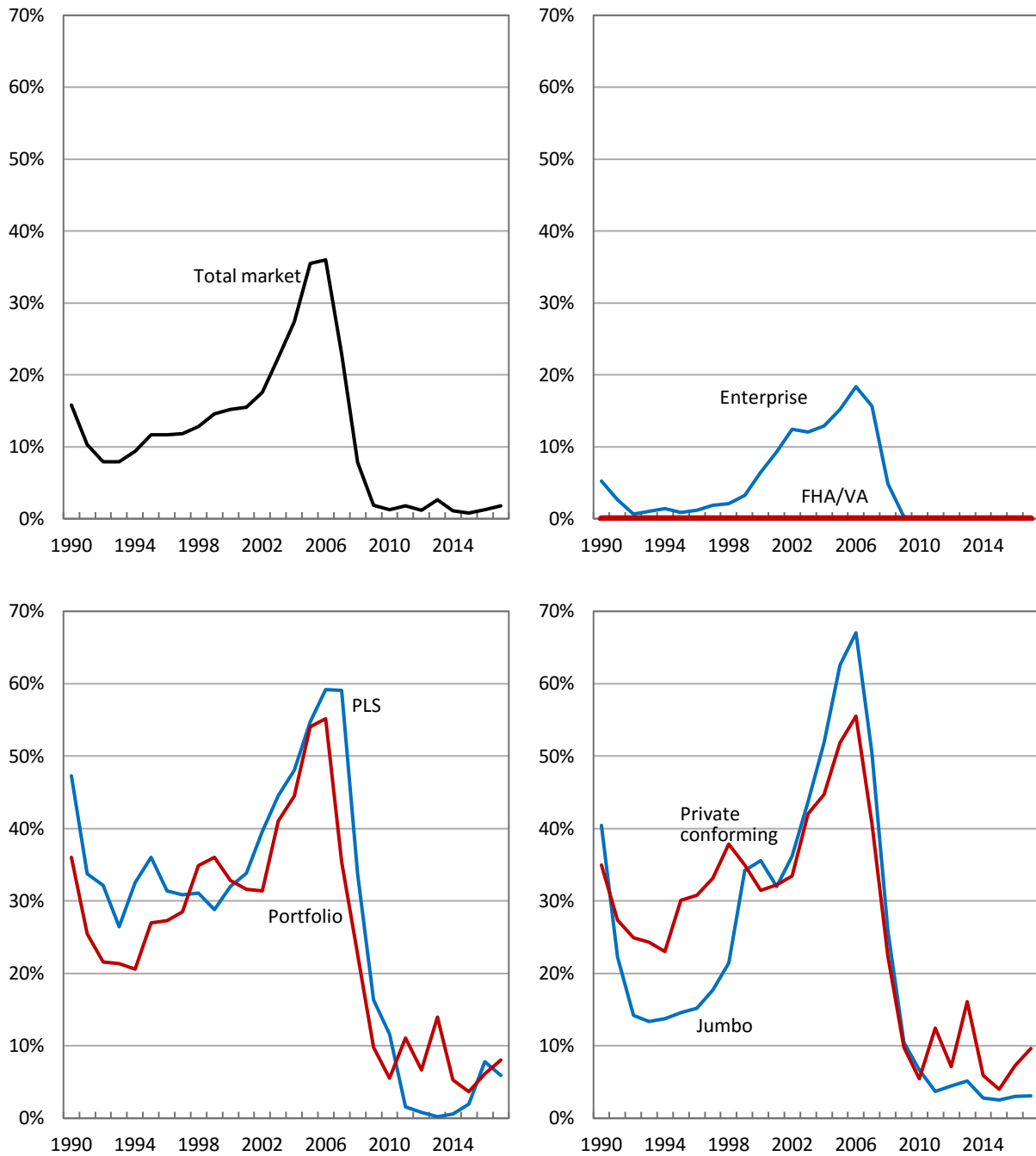
Figure 6: Average Credit Score for Home Purchase Loans, 1990-2017



Note: Results pertain to 1-4 unit purchase-money mortgages. Private conforming loans include portfolio and PLS loans with initial loan amounts below the applicable Enterprise conforming loan limit. Missing credit scores are imputed using regression techniques.

Source: Authors' calculations using data from FHFA (for Enterprise loans), Black Knight, Inc. (for portfolio and FHA/VA loans), CoreLogic® (for portfolio, PLS, and FHA/VA loans), and Ginnie Mae data processed by AEI's Center on Housing Markets and Finance (for FHA/VA loans).

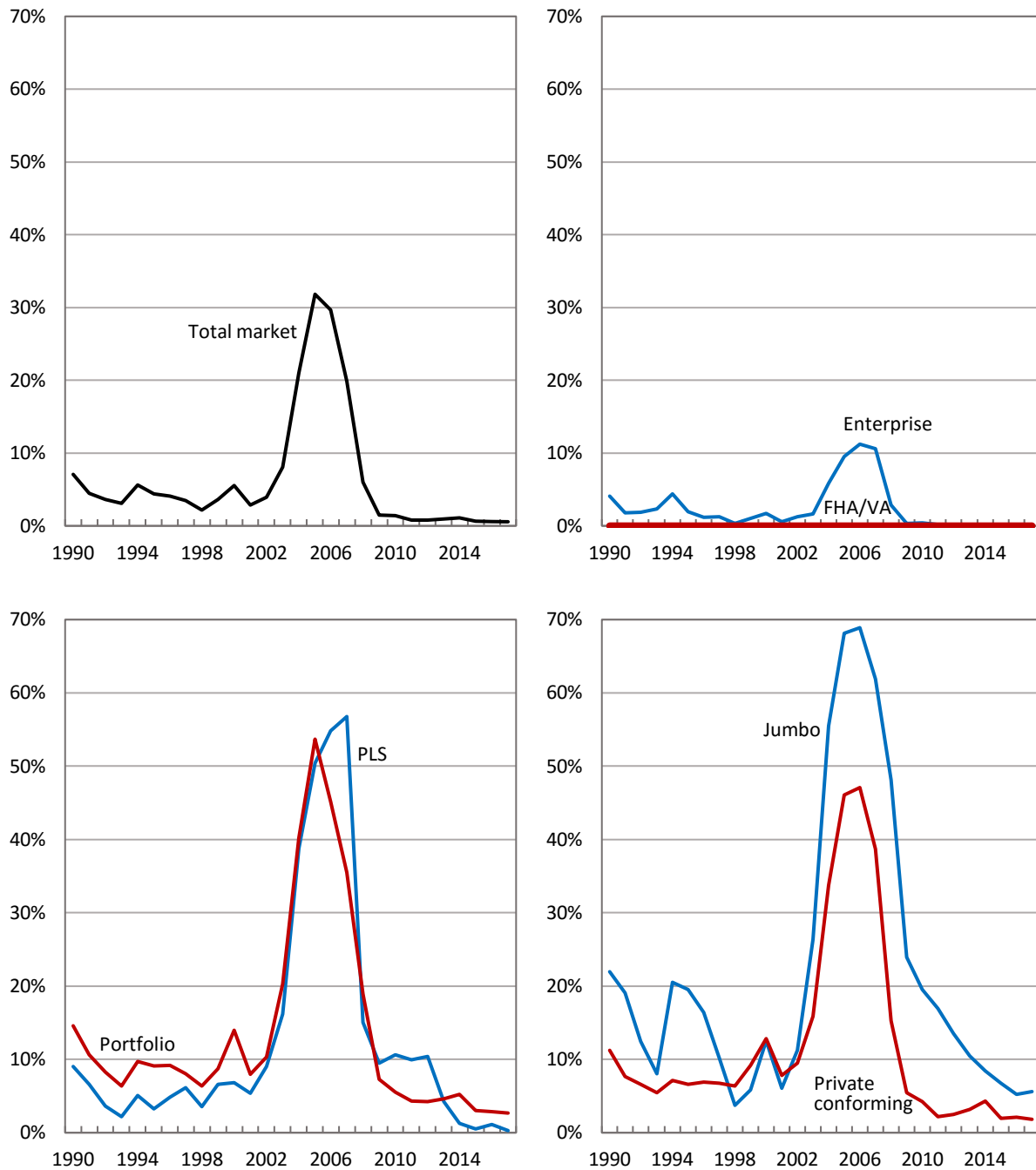
Figure 7: Share of Home Purchase Loans with Low or No Documentation, 1990-2017



Note: Results pertain to 1-4 unit purchase-money mortgages. Private conforming loans include portfolio and PLS loans with initial loan amounts below the applicable Enterprise conforming loan limit. Missing documentation status for portfolio and PLS loans is imputed using regression techniques.

Source: Authors' calculations using data from FHFA (for Enterprise loans), Black Knight, Inc. (for portfolio and FHA/VA loans), CoreLogic® (for portfolio, PLS, and FHA/VA loans), and Ginnie Mae data processed by AEI's Center on Housing Markets and Finance (for FHA/VA loans).

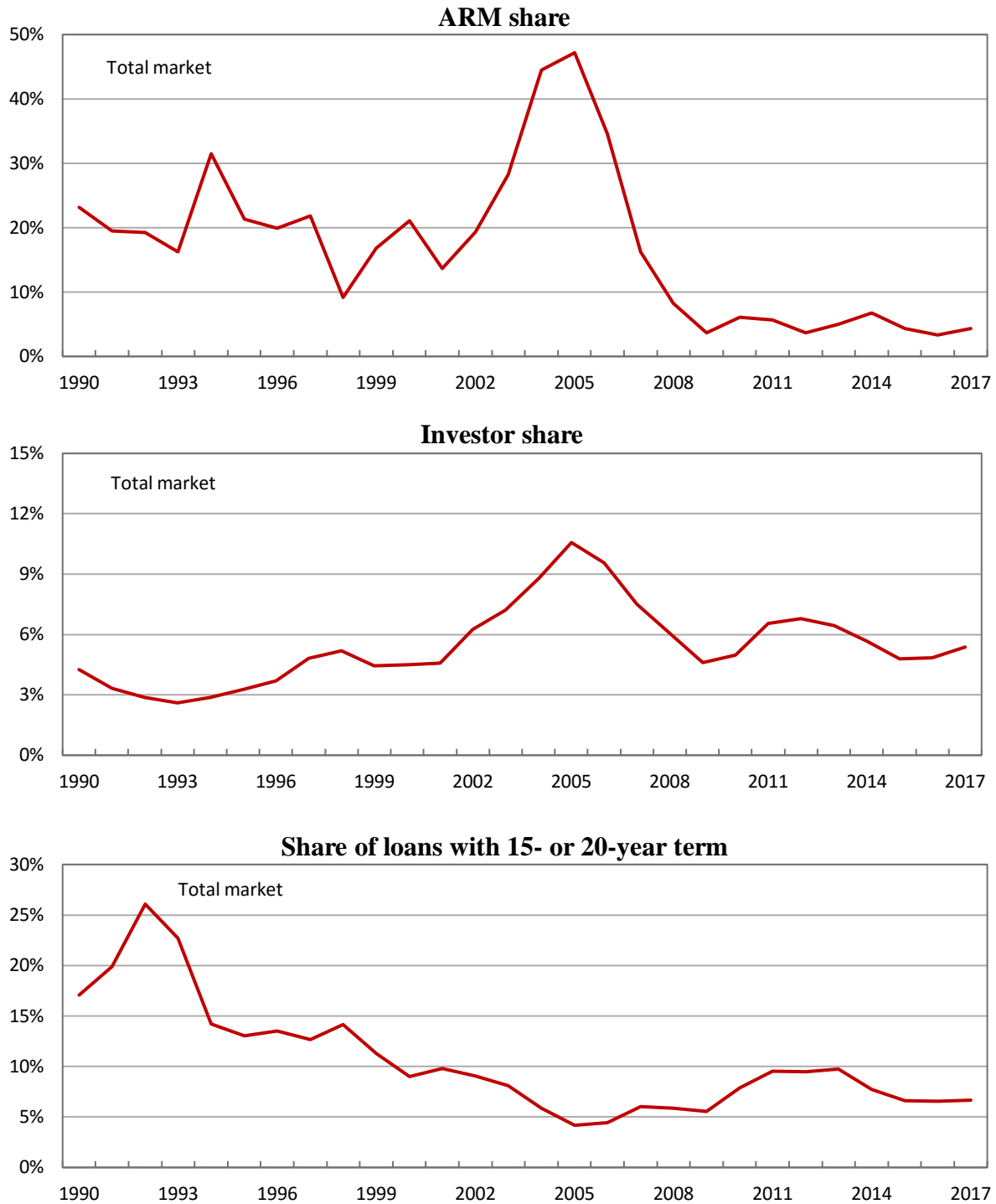
Figure 8: Share of Home Purchase Loans with Less Than Full Amortization, 1990-2017



Note: Results pertain to 1-4 unit purchase-money mortgages. Private conforming loans include portfolio and PLS loans with initial loan amounts below the applicable Enterprise conforming loan limit. A loan is classified as having less than full amortization if it has an interest-only period, negative amortization, and/or a balloon payment. Missing information on whether the loan has such features is imputed using regression techniques; this imputation is necessary only for portfolio loans.

Source: Authors' calculations using data from FHFA (for Enterprise loans), Black Knight, Inc. (for portfolio and FHA/VA loans), CoreLogic® (for portfolio, PLS, and FHA/VA loans), and Ginnie Mae data processed by AEI's Center on Housing Markets and Finance (for FHA/VA loans).

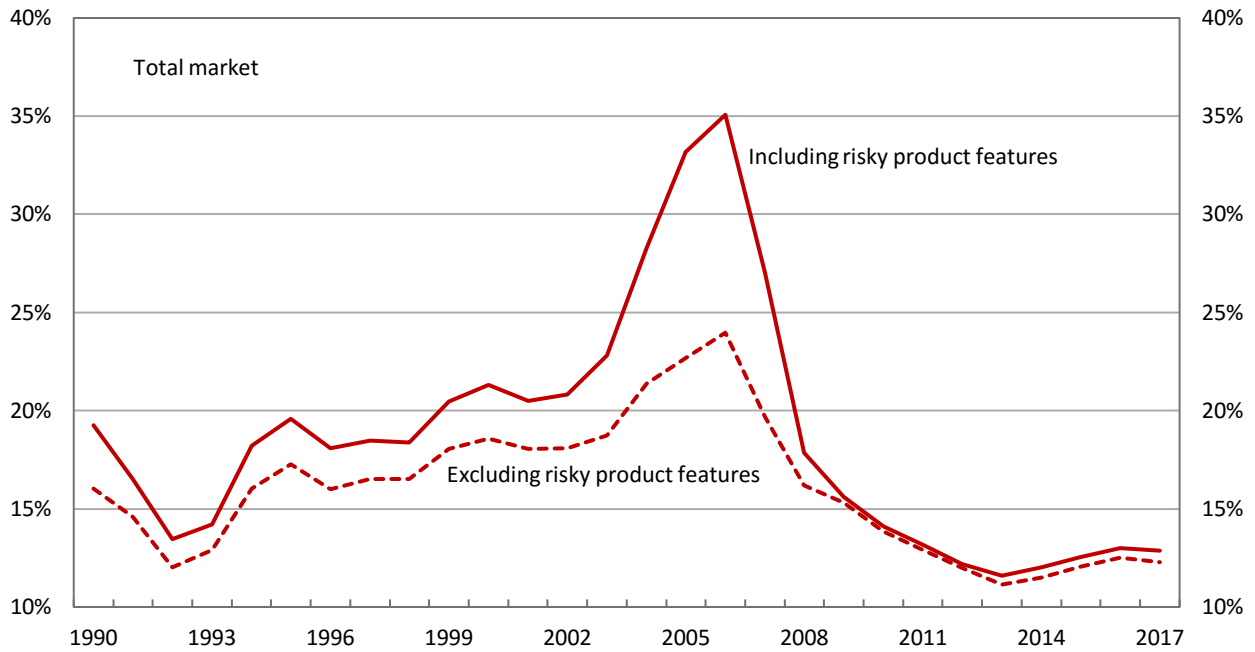
Figure 9: Other Characteristics of Home Purchase Loans, 1990-2017



Note: Results pertain to 1-4 unit purchase-money mortgages.

Source: Authors' calculations using data from FHFA (for Enterprise loans), Black Knight, Inc. (for portfolio and FHA/VA loans), CoreLogic® (for portfolio, PLS, and FHA/VA loans), and Ginnie Mae data processed by AEI's Center on Housing Markets and Finance (for FHA/VA loans).

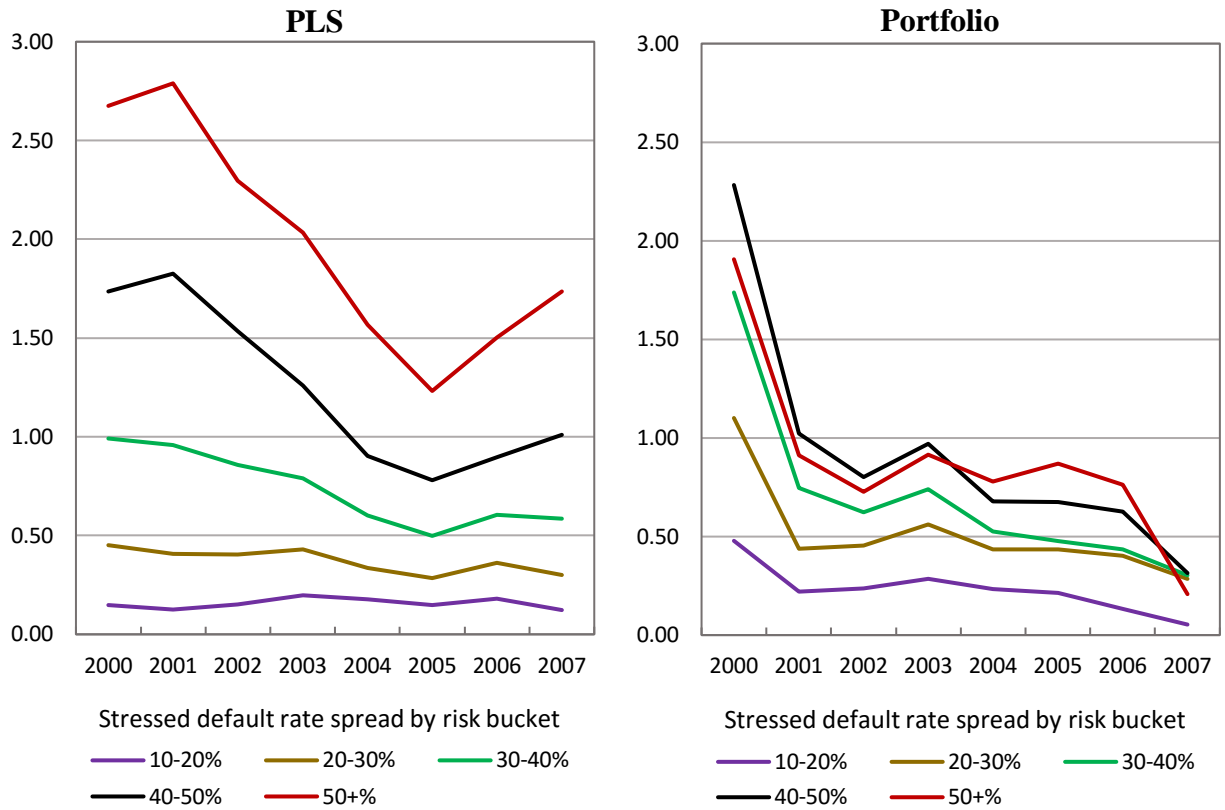
Figure 10: Influence of Risky Product Features on the Stressed Default Rate for Home Purchase Loans, Total Market, 1990-2017



Note: Results pertain to 1-4 unit purchase-money mortgages. Risky product features include low/no documentation, less than full amortization, and a loan term greater than 30 years. The stressed default rate without risky product features uses the same loans as the rate with risky product features but runs those loans with those features through the default tables as full doc, full amortization, 30-year loans.

Source: Authors' calculations using data from FHFA (for Enterprise loans), Black Knight, Inc. (for portfolio and FHA/VA loans), CoreLogic® (for portfolio, PLS, and FHA/VA loans), and Ginnie Mae data processed by AEI's Center on Housing Markets and Finance (for FHA/VA loans).

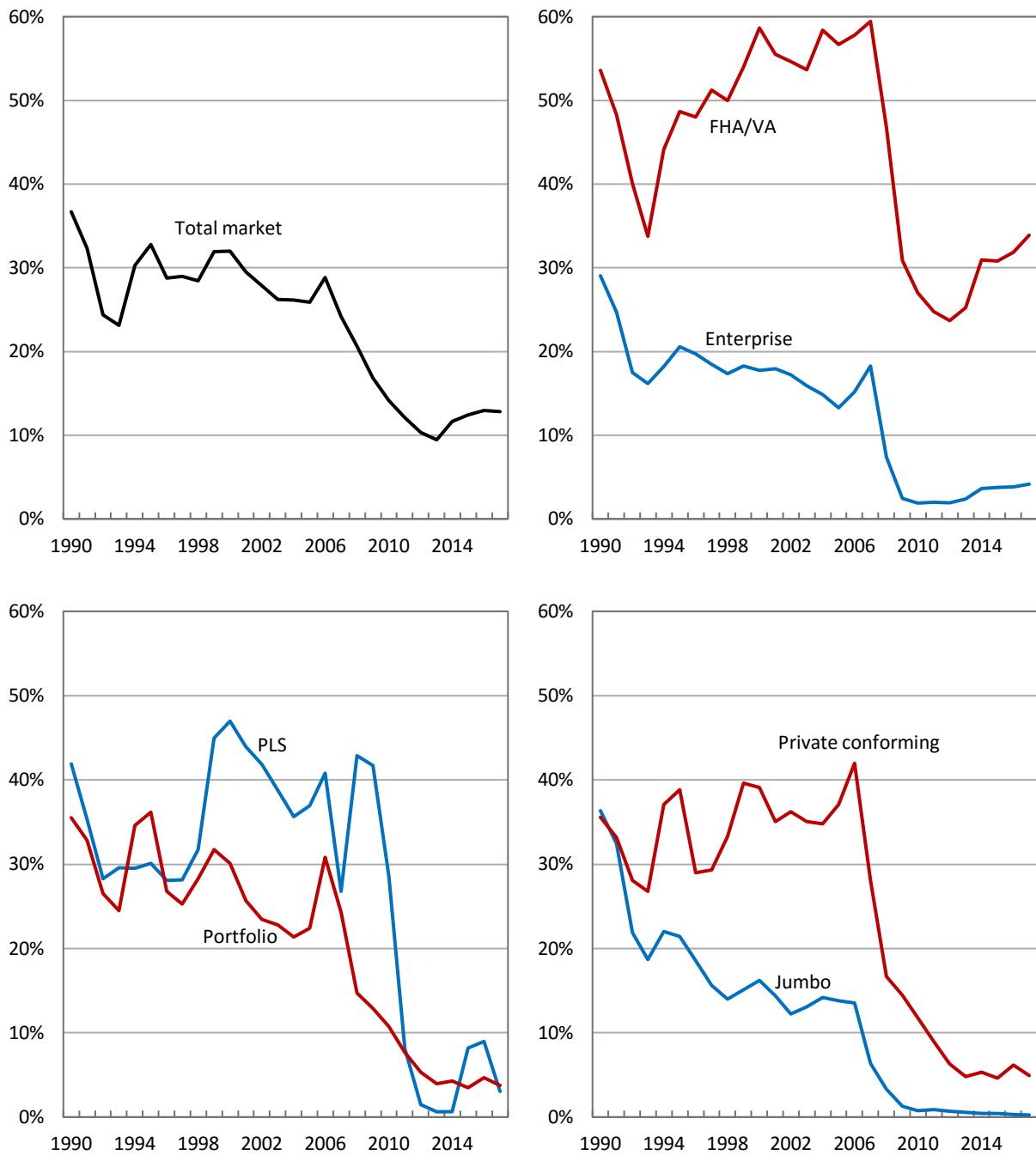
Figure 11: Average Mortgage Rate Spread within a Market Segment, by Stressed Default Rate, 2000-07
(in percentage points)



Note: The spreads in each panel pertain to 30-year, fixed-rate 1-4 unit purchase-money mortgages and are calculated relative to the average mortgage rate for the lowest-risk group in that market segment (the group with stressed default rates of 0-10 percent). We exclude loans with private mortgage insurance to obtain spreads for lenders and investors that fully bear the credit risk.

Source: Authors' calculations using data from Black Knight, Inc. (for portfolio loans) and CoreLogic® (for portfolio and PLS loans).

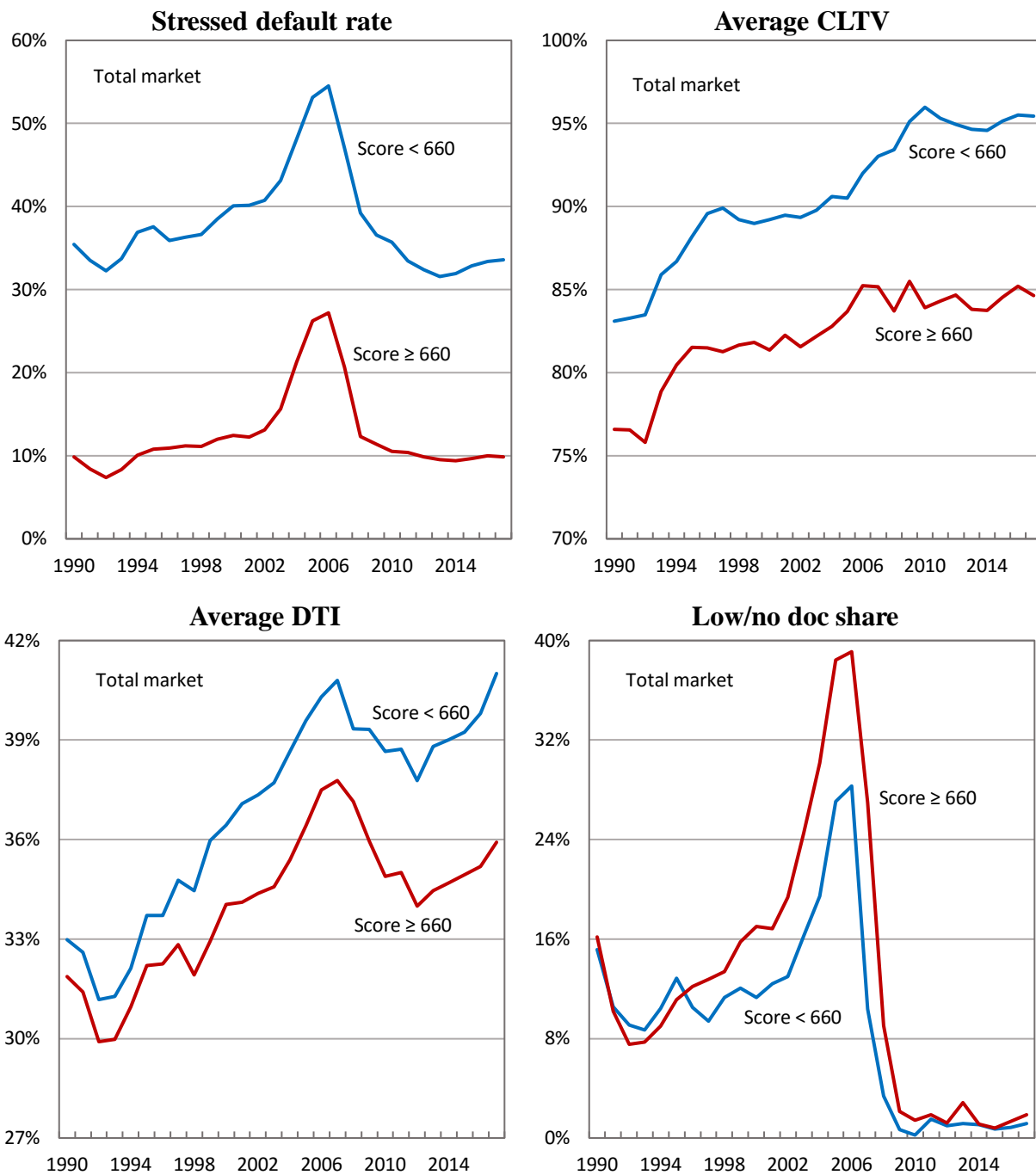
Figure 12: Low-Credit-Score Share of Home Purchase Loans, 1990-2017



Note: Results pertain to 1-4 unit purchase-money mortgages. Private conforming loans include portfolio and PLS loans with initial loan amounts below the applicable Enterprise conforming loan limit. Low-credit-score loans are defined as those with credit scores below 660. Missing credit scores are imputed using regression techniques.

Source: Authors' calculations using data from FHFA (for Enterprise loans), Black Knight, Inc. (for portfolio and FHA/VA loans), CoreLogic® (for portfolio, PLS, and FHA/VA loans), and Ginnie Mae data processed by AEI's Center on Housing Markets and Finance (for FHA/VA loans).

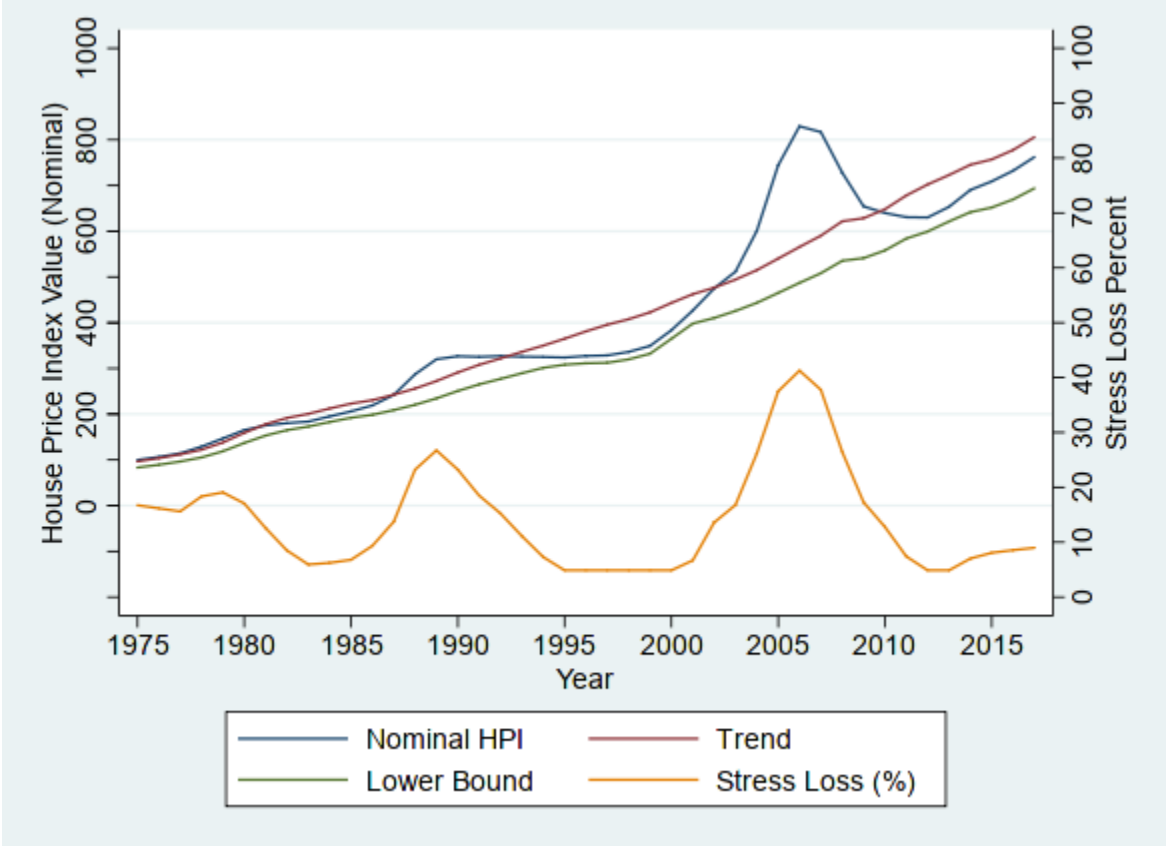
Figure 13: Stressed Default Rate and Key Risk Factors for Low-Credit-Score vs. Higher-Score Home Purchase Loans, Total Market, 1990-2017



Note: Results pertain to 1-4 unit purchase-money mortgages. Low-credit-score loans are defined as those with credit scores below 660; higher-score loans have scores greater than or equal to 660. Missing credit scores are imputed using regression techniques.

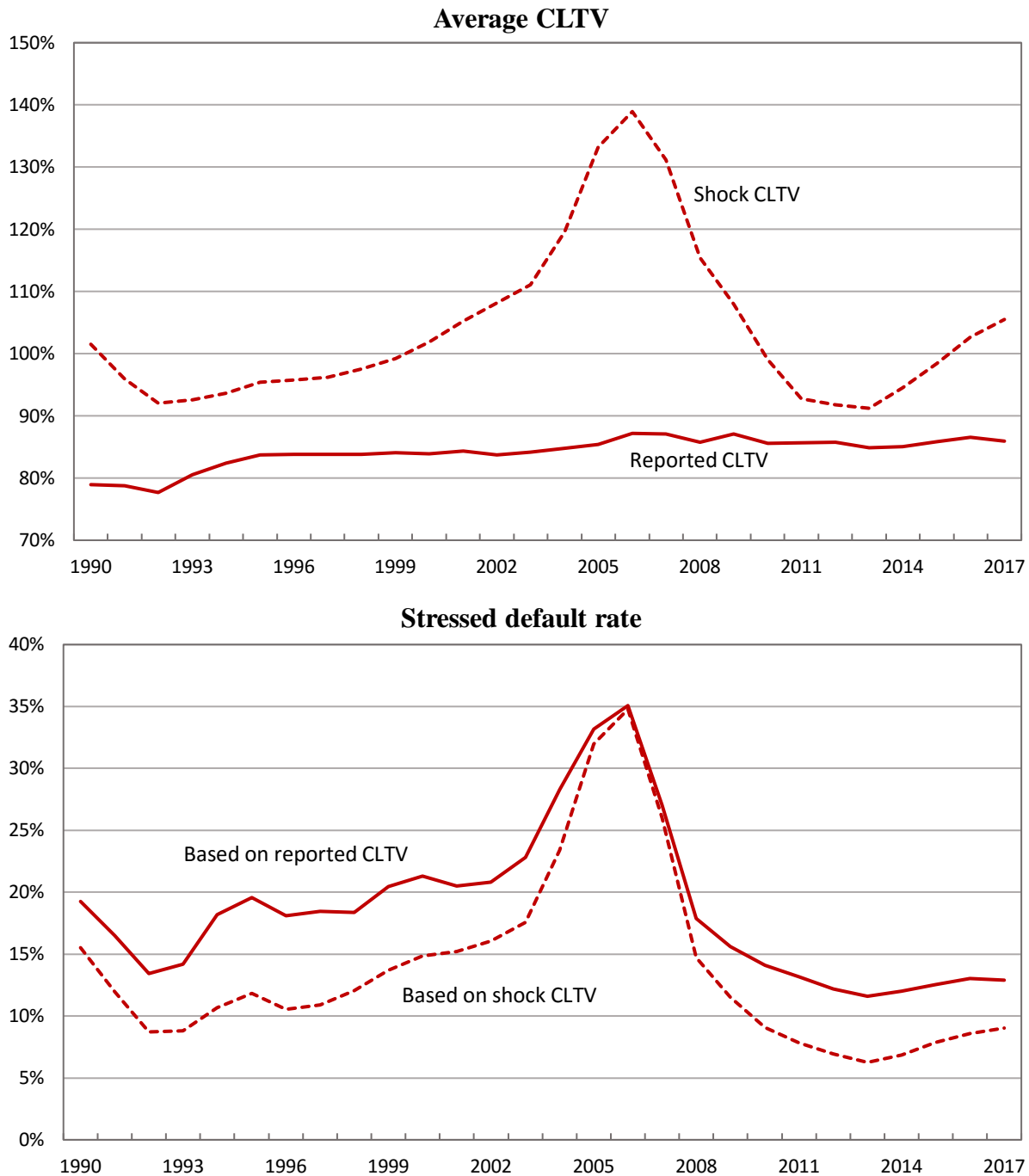
Source: Authors' calculations using data from FHFA (for Enterprise loans), Black Knight, Inc. (for portfolio and FHA/VA loans), CoreLogic® (for portfolio, PLS, and FHA/VA loans), and Ginnie Mae data processed by AEI's Center on Housing Markets and Finance (for FHA/VA loans).

Figure 14: Construction of House Price Shock Series for Washington, DC CBSA



Source: Authors’ calculations using the FHFA house price index for CBSA 47900 in Bogin, Doerner, and Larson (2018).

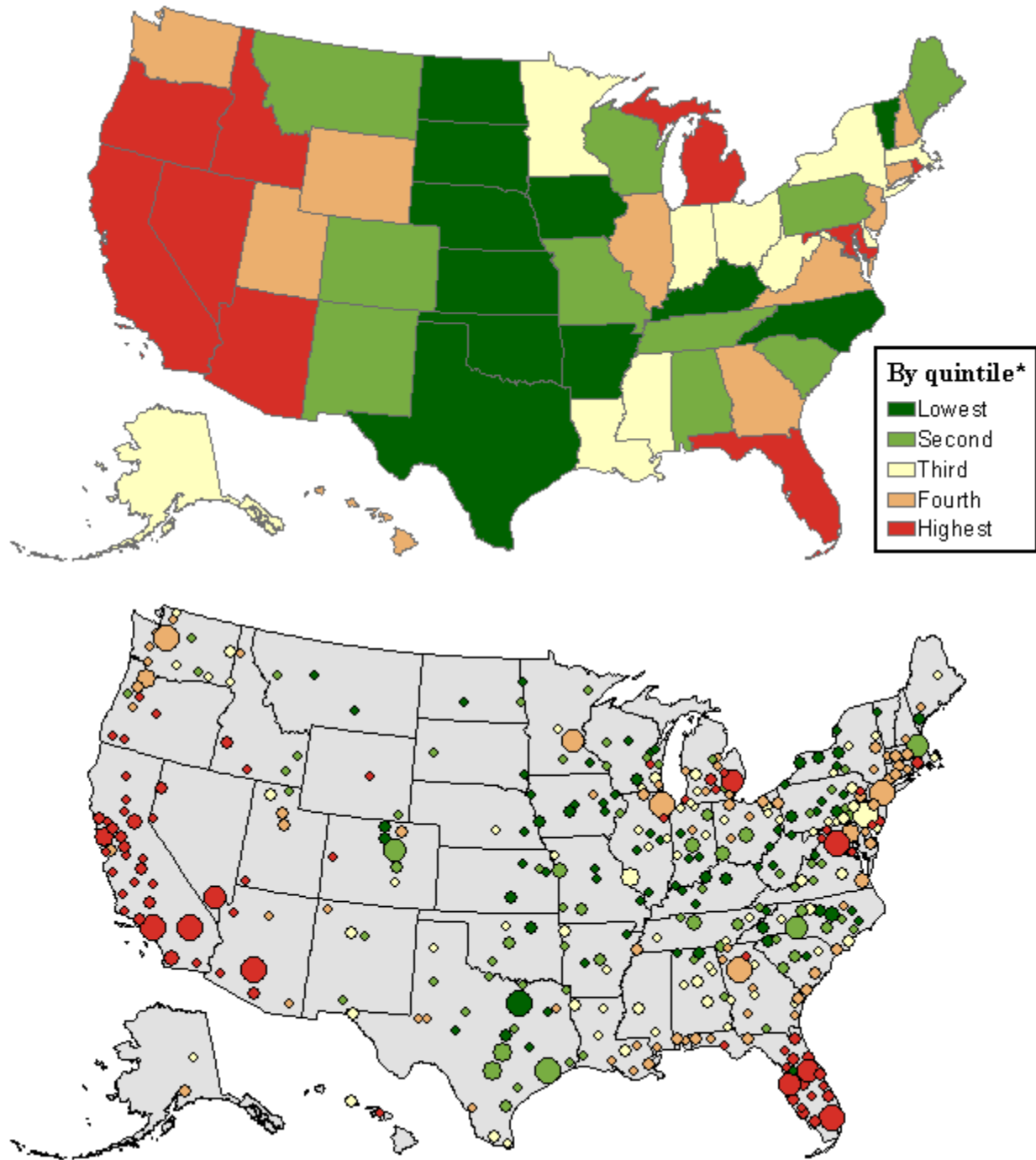
Figure 15: Two Versions of the Average CLTV and Stressed Default Rate for Home Purchase Loans, Total Market, 1990-2017



Note: Results pertain to 1-4 unit purchase-money mortgages. The shock CLTV adjusts the reported CLTV to reflect an estimate of the decline in home value that would occur in a severely stressed scenario.

Source: Authors' calculations using data from FHFA (for Enterprise loans), Black Knight, Inc. (for portfolio and FHA/VA loans), CoreLogic® (for portfolio, PLS, and FHA/VA loans), and Ginnie Mae data processed by AEI's Center on Housing Markets and Finance (for FHA/VA loans).

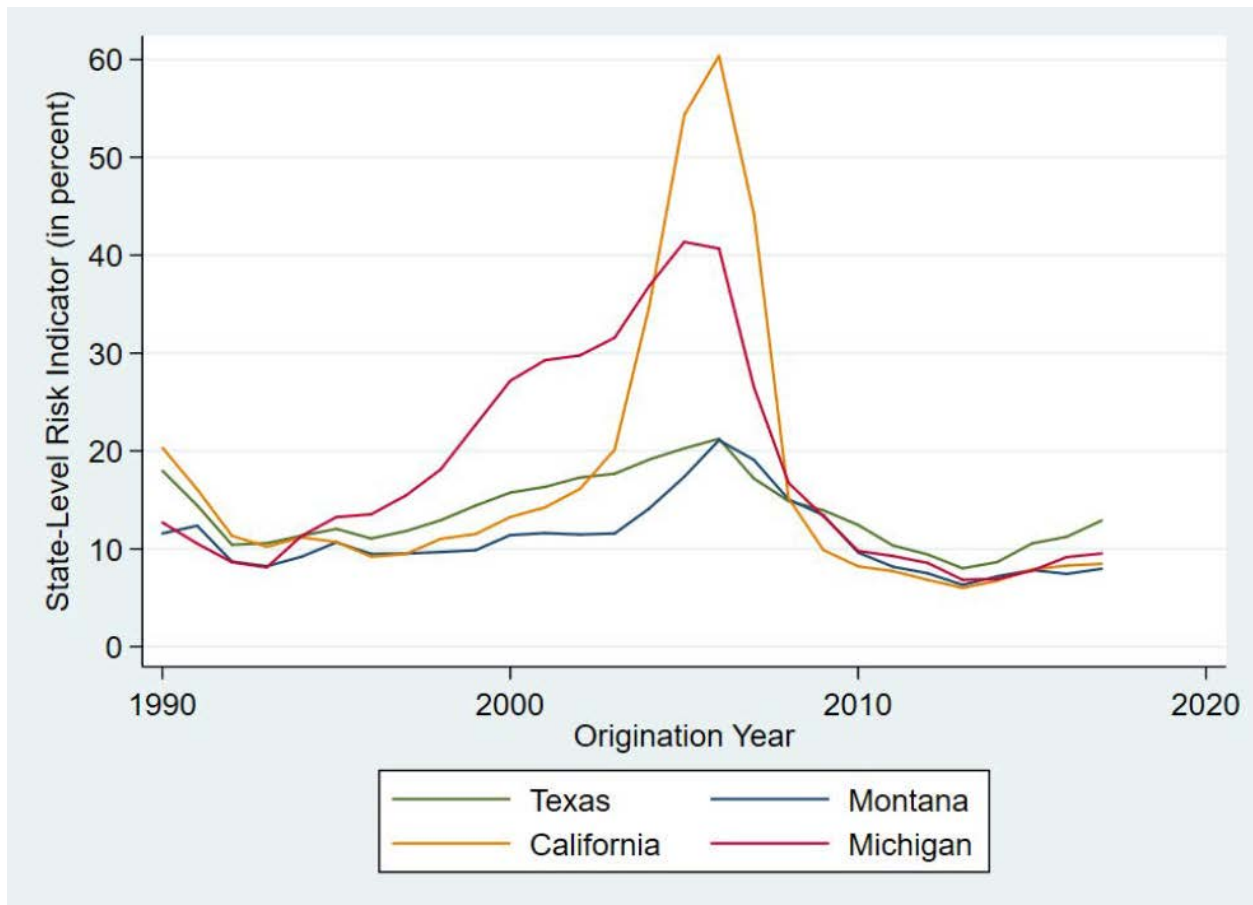
Figure 16: Stressed Default Rate using Shock CLTV, by State and MSA, 2006-2007



Note: Results pertain to 1-4 unit purchase-money mortgages. Range of state stressed default rates by quintile (rounded to the nearest 1%) is 14% to 19%, 19% to 21%, 21% to 25%, 25% to 31%, and 31% to 61%. Range of MSA stressed default rates by quintile (rounded to the nearest 1%) is 8% to 18%, 18% to 21%, 21% to 24%, 24% to 34%, and 34% to 69%. Circle sizes represent estimated mortgage lending volume in 2006 and 2007.

Source: Authors' calculations using data from FHFA (for Enterprise loans), Black Knight, Inc. (for portfolio and FHA/VA loans), CoreLogic® (for portfolio, PLS, and FHA/VA loans), and Ginnie Mae data processed by AEI's Center on Housing Markets and Finance (for FHA/VA loans).

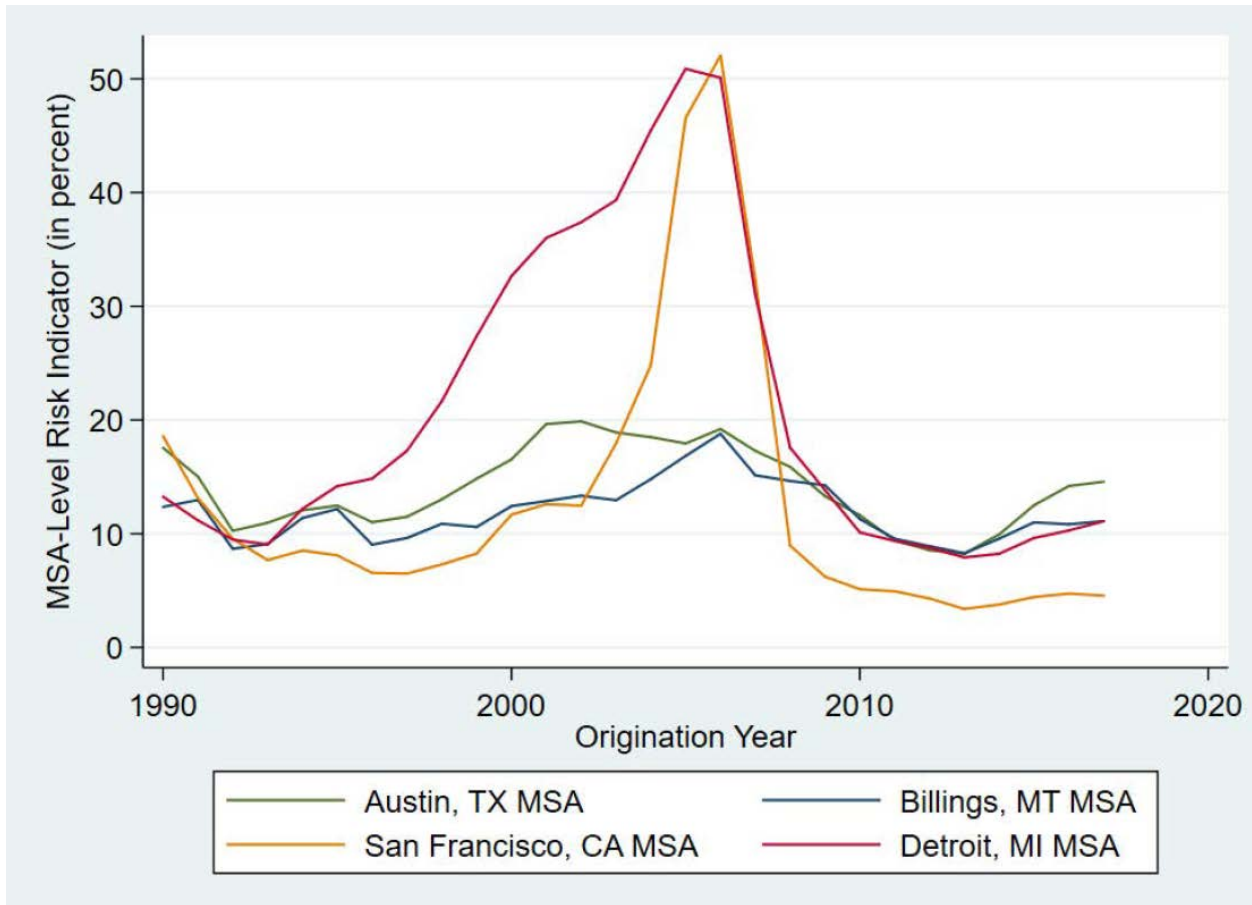
Figure 17: State-Level Stressed Default Rate



Note: Results pertain to 1-4 unit purchase-money mortgages.

Source: Authors' calculations using data from FHFA (for Enterprise loans), Black Knight, Inc. (for portfolio and FHA/VA loans), CoreLogic® (for portfolio, PLS, and FHA/VA loans), and Ginnie Mae data processed by AEI's Center on Housing Markets and Finance (for FHA/VA loans).

Figure 18: MSA-Level Stressed Default Rate



Note: Results pertain to 1-4 unit purchase-money mortgages.

Source: Authors' calculations using data from FHFA (for Enterprise loans), Black Knight, Inc. (for portfolio and FHA/VA loans), CoreLogic® (for portfolio, PLS, and FHA/VA loans), and Ginnie Mae data processed by AEI's Center on Housing Markets and Finance (for FHA/VA loans).

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Appendix A: Data Preparation

Scope of the dataset

As noted in the main text, our analysis uses data on first-lien purchase-money mortgages originated in 1990-2017 to purchase 1-4 unit residential properties in the 50 states and the District of Columbia. The purchases include second homes and investment properties in addition to primary owner-occupied homes. The dataset covers all major segments of the mortgage market, including loans guaranteed by the Enterprises, FHA, and VA as well as loans without a government guarantee that are bundled into private-label securities (PLS) or held in the portfolios of banks and other lenders.

Identifying portfolio loans

The portfolio loans used in our analysis are drawn from two servicer datasets, the Loan-Level Market Analytics (LLMA) dataset from CoreLogic and the McDash dataset from Black Knight, Inc. Both datasets identify conventional home purchase loans, but neither one fully identifies the subset of such loans that lenders hold in portfolio (rather than selling to the Enterprises or PLS securitizers). As the first step in identifying these portfolio loans, we include all conventional home purchase loans that are ever reported as private and that are never reported as having been acquired by the Enterprises; we also include loans that are never reported to be private but have loan amounts at origination that are above the applicable Enterprise conforming loan limit. We obtain this information on private/ Enterprise status by checking the entire monthly sequence of investor codes for every conventional loan in LLMA and McDash. This initial set of potential portfolio loans still needs to be purged of PLS loans, duplicate copies of true portfolio loans, and loans judged likely to be Enterprise loans after further scrutiny. Before

undertaking that task, we apply a set of data cleaning filters to the potential portfolio loans and to Enterprise, PLS, and FHA/VA loans.

Filtering out loans from the source datasets

Table A.1 summarizes the exclusion of loans from the source datasets. We first remove loans for which the loan amount, LTV, state in which the property is located, and ZIP code are not reported, as these are essential loan characteristics for our analysis. We then remove duplicates of loans that appear more than once in the source data.⁴³ Duplicates are common for both the potential portfolio loans and FHA/VA loans because both types of loans are drawn from the combination of LLMA and McDash. Many potential portfolio loans and FHA/VA loans appear in both datasets, and some appear more than once within each dataset. We also remove loans from the potential portfolio dataset that we flag as likely to be Enterprise or PLS loans. After these exclusions, we further clean the dataset by removing loans for which product type (fixed rate versus adjustable rate) or property type is either not reported or reported with incomplete or inconsistent information. In the Enterprise and PLS datasets, we remove the very small share of loans with missing occupancy status; in contrast, in the FHA/VA dataset, we assume loans with missing occupancy status are owner-occupied given that this is the norm for FHA/VA loans, and in the potential portfolio dataset, we impute occupancy status for the loans that are missing this information. We also remove loans with LTVs below 25 percent, which we suspect are second liens incorrectly reported as first liens, and loans with CLTVs above 135 percent, which likely are erroneous. As shown in the row labelled “Total percent excluded,” these exclusions taken together remove only about 1-2 percent of Enterprise and PLS loans. A much larger fraction of potential portfolio and FHA/VA loans are excluded, but most of these are

⁴³ Loans with missing information on loan amount, LTV, and property location are excluded before we check for duplicates because those loan characteristics are needed for the matching algorithm that identifies duplicates.

duplicate loans or potential portfolio loans we believe to be Enterprise or PLS loans. After netting out these exclusions, the data filters remove about 15 percent of potential portfolio loans and about 5 percent of FHA/VA loans. Overall, the table shows that we use the vast majority of unique loans in the source data.

Detail on removing duplicate loans from the servicer datasets

In our FHA and VA datasets, we attempt to match every FHA loan with every other FHA loan, and do the same for VA loans. If the loans in a given pair do not match on specified characteristics (described below), we declare them not to be duplicates. Because some data are erroneously reported, we allow some differences across the match fields based on extensive testing to validate whether these differences represent truly unique loans or duplicates. When a pair of loans satisfies the match criteria, we deem that pair to be duplicates and exclude one of the loans from the dataset.

Our matching proceeds in three steps:

1. Declare a non-match for a given pair of loans when any of the following is true: the county⁴⁴ is different, the loan type is different, the origination date differs by more than one month, or the rounded original loan amount differs by more than \$1,000. These non-matching pairs are deemed not to be duplicates.
2. For all remaining loans, declare a non-match when more than one of the following are true: the month of origination differs, the rounded original loan amount differs, the ZIP code

⁴⁴ The servicer data report the property's ZIP code but not its county. To identify the county, we match ZIP codes to counties using data from the Missouri Census Data Center and the U.S. Department of Housing and Urban Development. A complication is that some ZIP codes span more than one county. When this happens, we cannot be sure of the county for the loan's subject property. In such cases, we include the loan in the match algorithm for every possible county. Thus, a loan from a ZIP code that has ever spanned two counties would appear in the match algorithm twice: once from County A, once from County B.

differs, the credit score differs, or the interest rate differ by more than 5 basis points.⁴⁵ As in step 1, non-matching pairs are deemed not to be duplicates.

3. For all remaining pairs of loans, score their similarity across a given set of fields. The fields used to score the loans are LTV, CLTV, DTI, credit score, product type, occupancy type, loan term, loan performance, origination month, original loan amount, ZIP code, and interest rate. We declare pairs that match perfectly to be duplicates, and use a scoring algorithm to declare that additional pairs are duplicates if they match on a large majority of the fields.

The procedure for removing duplicates from the dataset of potential portfolio loans is very similar to that for FHA and VA loans. We repeat steps 1 and 2 described above but modify step 3 to include the presence of private mortgage insurance as an additional matching field.

When we remove duplicate loans, we use all available information on loan characteristics across the two loans. For example, if one loan in the pair has a reported DTI but the other does not, we keep the reported DTI. In other cases, duplicate loans can have different values for one or more loan characteristics. The differences generally are small – otherwise the two loans would not have had a high match score in step 3 above. In these cases, we have a set of decision rules for which value to keep. When the value for a particular characteristic has been rounded in one loan but not the other, we keep the more specific value. In addition, we keep the highest CLTV as some servicers may not record all liens against the property. Otherwise, the decision rules involve essentially arbitrary selection.

⁴⁵ When the credit score or interest rate is not reported for either loan in a pair, that field is not used in this step.

Detail on removing PLS loans from the potential portfolio dataset

Although the previous steps have removed duplicate loans from the potential portfolio dataset, the dataset still contains PLS loans. Thus, the next step is to remove PLS loans as fully as possible by matching to the separate CoreLogic PLS dataset.

We consider two types of matches: one-to-one matches and one-to-many matches. To establish one-to-one matches between loans in the two datasets, we use steps 1-3 above and remove loans that match to the PLS dataset. Because our goal is to remove essentially all PLS loans – even if that means losing true portfolio loans – we perform additional one-to-many matches between individual loans in the PLS dataset and multiple loans in the potential portfolio dataset. For this one-to-many matching, we perform step 1 described above, which looks for matches based on origination month, original loan amount, county, and loan type. We know there will not be one-to-one matches at this stage because those loans were removed in the one-to-one matching just completed. For one-to-many matches that involve up to four loans in the potential portfolio dataset, we remove all the matched loans. For matches that involve more than four loans, we do additional diagnostics to identify the four most likely matches and remove those four loans. After removing suspected PLS loans with the one-to-one and one-to-many matches, the loans that remain constitute our portfolio loan dataset.

Detail on removing Enterprise loans from the potential portfolio dataset

We follow a similar procedure to remove loans from the potential portfolio dataset that likely were acquired by the Enterprises. Earlier, we removed loans that were affirmatively shown by the investor information in LLMA and McDash to have been acquired by the Enterprises. We now look for matches between loans that remain in the potential portfolio dataset and the affirmatively Enterprise loans that were removed before. In effect, we are

searching for duplicates of these loans that may have had incomplete investor information in one of the servicer datasets. To establish matches, we use the same process as with PLS loans to remove potential portfolio loans that are one-to-one matches to Enterprise loans.⁴⁶ As additional safeguards against the inadvertent retention of Enterprise loans, we remove conforming loans with very spotty investor information as well as conforming loans with more complete investor information that nonetheless records the loan as private in less than half of the months of its total lifespan. We also remove loans that transfer from one servicer to another with no information provided by the second servicer.

Weighting of loan data

Because our FHA, VA, and portfolio datasets do not constitute the universe of such home purchase loans, we weight the data to be nationally representative based on adjusted loan counts for originated purchase loans from the Home Mortgage Disclosure Act (HMDA) Loan Application Register. For FHA and VA loans, we partition both our dataset and the HMDA data by year, loan type (FHA or VA), loan amount buckets, and states grouped by the magnitude of the house-price decline over 2006-2012 (Arizona, California, Florida, Michigan, Nevada, and Rhode Island versus all others). To correct for the undercount of loans in HMDA,⁴⁷ we increase the HMDA counts assuming that HMDA coverage of FHA and VA loans starts at 90 percent in 1990 and increases monotonically to 100 percent in 2010 where it remains for later years. This assumed pattern is based on the coverage results for FHA loans in Scheessele (1998) and Szymanoski et al. (2011) and the results for FHA and VA loans together in Williams (2015). For

⁴⁶ Because McDash only reports 3-digit ZIP codes for Enterprise loans, we require loans matching only on a 3-digit ZIP basis to have a higher score than loans matched on a 5-digit ZIP basis.

⁴⁷ For information about the regulatory changes affecting the undercount of mortgages reported in HMDA, see <https://www.ffiec.gov/hmda/history2.htm>

each cell in the partition described above, we use the ratio of the adjusted HMDA loan count to the count in our dataset as the sampling weight.⁴⁸

For purchase loans held in lenders' portfolios, we use the same partition as for FHA and VA loans. To estimate the true size of the portfolio market, we begin by summing the number of total conventional purchase loans and Enterprise purchase loans reported in HMDA.⁴⁹ Loans sold to the Enterprises after the year of origination are not counted as Enterprise loans in HMDA. To correct for this undercount, we increase the HMDA count of Enterprise purchase loans by the share of such loans acquired after the year of origination according to FHFA data. We then estimate the true HMDA undercount of Enterprise purchase loans as the ratio of the count in the FHFA dataset to the HMDA count that includes the post-origination year acquisitions. We calculate this ratio by year and assume that the proportional undercount in HMDA for all conventional purchase loans is the same as for Enterprise loans. Figure A.1 shows the estimated annual share of total conventional purchase loans reported in HMDA; we divide the reported annual HMDA counts by the annual shares in Figure A.1 to estimate the total count of conventional purchase loans. Finally, we calculate the universe count of portfolio loans for each cell in the partition as the adjusted HMDA count of conventional loans minus the Enterprise count from the FHFA data and the PLS loan count from the CoreLogic data. Our sampling weight for each cell in the partition equals the ratio of the estimated universe count for portfolio loans to the count in our dataset.

For Enterprise and PLS loans, the underlying source data represent a universe count (Enterprise loans) or close to a universe count (PLS loans). Accordingly, we do not apply the

⁴⁸ For a small number of cells, the count in our dataset exceeds the adjusted HMDA count. In those instances, we use our loan count rather than the HMDA-based count, in effect setting the weight to one.

⁴⁹ The Enterprise count includes both loans that are sold directly to the Enterprises and loans that are first sold to another HMDA reporter and then sold to the Enterprises.

weighting process just described to these loans. However, for the purpose of calculating annual shares of the purchase loan market, we do add back the 1-2 percent of Enterprise and PLS loans that were removed by our data cleaning.

Imputation of missing values for risk factors

As described in Section 2 of the paper, we use the multiple imputation approach (Rubin, 1976) to impute missing data. But before proceeding, a relevant question is why impute at all: dropping observations with missing information is conceptually much simpler. The key issue is whether information is missing completely at random (MCAR), missing at random (MAR), or missing not-at-random (MNAR).⁵⁰ If missing information is not correlated with any observed or unobserved variables, it is classified as MCAR, and observations with missing information can be safely dropped and statistics will be unbiased. However, if missing information is correlated with observables, then information is classified as MAR and dropping observations will result in biased statistics.⁵¹

If the data were MCAR then we should observe uniform missing values across segments (PLS, FHA, Enterprise) and risk characteristics (DTI, credit scores, etc.). Yet, there is substantial evidence that missing information in mortgage data is MAR. For instance, Enterprise loans without credit scores tend to have lower reported incomes. Because missing information is MAR, we proceed with an imputation strategy rather than dropping observations to avoid a known bias in the reported statistics.⁵²

⁵⁰ When missing information is correlated with unobservables, it is MNAR, but this is, by definition, impossible to verify.

⁵¹ Under MAR, it is also important to point out that the fraction of missing values only affects the uncertainty of the imputation. Conversely, the more MAR data that is dropped the higher the potential bias.

⁵² Multiple imputation is based on having access to infinite imputations, but according to Rubin (1987), an average of just two imputations has 90% asymptotic efficiency with a 50% rate of missing values. For higher missing rates, the consequence is reduced efficiency but not of bias. To assess the accuracy of the imputations for the first and second moments, we have performed a cross-validation exercise for PLS imputations and found them to be closely

Within the multiple imputation framework, we employ one method for quantitative variables (credit score and DTI) and another for categorical variables (documentation status, amortization status, and occupancy status). Specifically, because credit scores and DTIs are not normally distributed, we use predictive mean matching (PMM) as developed in Little (1988) and Rubin (1986). The PMM procedure uses regression-based predictions of credit scores and DTIs to find the nearest “donors” of either variable for loans with missing values. We randomly select one of the eight closest donors to provide the missing value. We use a logit model to impute documentation status and amortization status and a multinomial logistic model to predict occupancy status. To allow the estimated parameters to vary over time, every PMM and logit model is run over the shortest time windows that we judged to have sufficient data for reliable estimation. For Enterprise loans, we estimate separate regressions every quarter. For other loans, we use a mix of quarterly, annual, and grouped-year windows depending on loan counts. See Table A.2 for details.

All of our models include a matrix of explanatory variables \mathbf{Z} , which require no imputation, and a second matrix of explanatory variables \mathbf{T} , which may require imputation. \mathbf{Z} includes the number of units, interest rate, state, product type, property type, loan amount, loan term, CLTV, and month of origination, while \mathbf{T} includes DTI, credit score, documentation status, amortization status, and occupancy status. CLTVs are included in the model as dummy variables representing ranges of values to allow for non-linear effects. For instance, CLTVs ranging from 1 to 60 percent are grouped as a dummy variable, as are CLTVs ranging from 61 to 70 percent, 71 to 75 percent, etc. Interest rates, DTIs, and credit scores are also broken up into a set of

aligned with observed moments. This satisfies our concerns of potential bias in the mean or variance of the imputations.

dummy variables.⁵³ The categorical variables in \mathbf{T} also include a dummy variable for when the value is missing. For every model, \mathbf{T} excludes the variable being imputed.

With one exception, we impute missing values for each risk factor independently from the imputation for other risk factors. We attempted to use chained equations that iteratively impute missing values for one risk factor using the imputation results for other risk factors but found that the computing time – which was already substantial – increased roughly eleven-fold, and thus we elected to use independent imputation models.

The one exception is that DTI and documentation status are imputed recursively because documentation status is directly related to the reported DTI (via the borrower's income used in the denominator of the DTI). We first estimate the logit model for documentation status where the matrix \mathbf{T} described above excludes the DTI as an explanatory variable. Then, using the imputed documentation status from the logit model as an explanatory variable, DTI is imputed from the PMM model described above.

To test the robustness of our imputed values, we repeated the imputation procedure 40 times with both the PLS and portfolio datasets. We used these results to construct 95 percent confidence bands for the risk factors imputed for those loans and for the implied stressed default rate. The confidence bands pertain to the full respective sets of loans, including those with reported values for the variable shown. Figures A.2 and A.3 display the results for PLS and portfolio loans, respectively. For PLS loans, the confidence bands are fairly tight except for the average DTI in 1990 and 1991, where the bands span a range of about 2 percentage points.

⁵³ As the values for these variables are sometimes missing, each variable has a dummy for missing values in addition to the set of dummies for the reported values. The dummies for non-missing values are defined so every dummy is estimated with at least 500 loans. This requirement results in a differing number of dummy variables across the estimation windows. For example, there can be as few as two dummies for non-missing DTIs when the reporting of DTIs is scant and as many as ten dummies when DTIs are well reported.

Despite the wide band in that case, we find nonetheless that the decline in the average DTI from 1990-91 to 1992 is statistically significant. Confidence intervals for portfolio loans are slightly narrower than for PLS loans during the 1990s for the average DTI and average credit score, the two heavily imputed risk factors.⁵⁴ Overall, Figures A.2 and A.3 indicate that the uncertainty associated with loan-level imputations has little effect on the summary statistics we report in the paper.

Finally, we should note that we selectively modified the DTI imputations for FHA and VA purchase loans. For both types of loans, a large share of the reported DTIs from 1990 through 1995 have the same value, which seems implausible. Thus, we estimate the DTI imputation regression using data for 1996 and use the 1996 originations as potential donors to impute DTIs for loans originated in 1990-1995. Additionally, we benchmark our DTI results for FHA loans to An et al. (2007) and Newberger (2011), forcing our imputed values to match the parameters of the distributions reported there. These external benchmarks exist for 1992, 1996, and 2000-2009. For the intervening years (1993-1995 and 1997-1999), we linearly interpolate the median DTI between the benchmark year medians. We found no similar benchmark information for VA loans for the 1990s. However, Ginnie Mae data for 2013-2017 and VA data for 1999-2003⁵⁵ show that the median DTI for VA purchase loans has been on average 2 percentage points below the median for FHA purchase loans, and we adjust the median DTI for VA loans to maintain this gap in other years as well.

⁵⁴ This may seem surprising given that a larger share of portfolio loans require imputations over 1990-2017 as a whole. However, in the early 1990s, when the confidence bands are the widest, the reporting of DTIs and credit scores was worse for PLS loans than for portfolio loans. In addition, in the early and mid-1990s, the number of portfolio loans far exceeded the number of PLS loans, with the greater sample size working to narrow the confidence intervals for the estimated sample means.

⁵⁵ See table 5-25 in https://www.benefits.va.gov/homeloans/documents/docs/final_report.pdf

Table A.1: Exclusions of Home Purchase Loans

	Type of Loan			
	Enterprise	Potential Portfolio	PLS	FHA/VA
Initial count (millions)	50.23	17.82	8.57	34.93
<i>Percent excluded for reason shown</i>				
Loan amount not reported	<0.01	0.01	<0.01	0.01
LTV not reported	<0.01	5.08	0.26	7.76
State not reported	0.00	0.52	0.18	0.34
ZIP code not reported or not valid	0.00	0.39	1.11	0.35
Duplicate loans	0.00	28.40	0.00	40.35
Removal of PLS Loans	NA	17.85	NA	NA
Removal of Enterprise Loans	NA	5.28	NA	NA
Term not reported	0.02	0.16	0.21	0.09
Product type not reported or reported inconsistently	<0.01	0.68	0.04	0.44
Property type not reported or not specified	0.00	7.49	0.33	5.32
Occupancy status not reported	0.00	NA	0.11	NA
LTV < 25 percent	0.73	9.47	0.14	0.06
CLTV > 135 percent	<0.01	0.26	0.28	0.07
Total percent excluded	0.76	60.06	2.34	44.94
Final count (millions)	49.85	7.12	8.37	19.23

Note: The counts represent first liens originated in 1990-2017 used to purchase 1-4 unit properties. The percent of loans excluded is rounded to the nearest 0.01. The total percent excluded will be less than the sum of the percent excluded in the preceding rows because some loans are excluded for more than one reason. NA in the row for occupancy status indicates that we did not exclude these loans when occupancy status was missing. As noted in the text, we assumed all FHA/VA loans with missing data were primary owner-occupied, and we imputed missing occupancy status for potential portfolio loans.

Source: Authors' calculations using data from Black Knight, Inc., CoreLogic®, FHFA, and Ginnie Mae data processed by AEI's Center on Housing Markets and Finance.

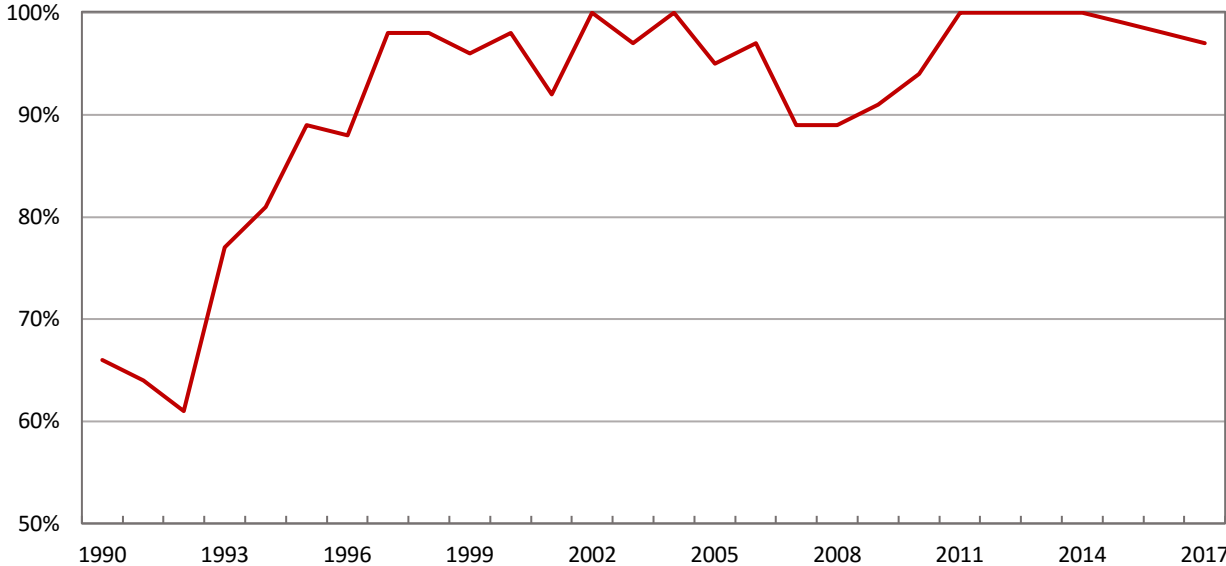
Table A.2: Estimation Periods for Imputation Regressions

Risk factors	Estimation periods
Enterprise	
Credit score	Individual quarters: 1990:Q1-2017:Q4
DTI	Individual quarters: 1990:Q1-2017:Q4
PLS	
Credit score	Individual quarters: 1997:Q1-2007:Q4* Individual years: 1996, 2013, 2014 Grouped years: 1990-93, 1994-95, 2008-12, 2015-17
DTI	Individual quarters: 1999:Q1-2007:Q4* Individual years: 1998 Grouped years: 1990-93, 1994-95, 1996-97, 2008-12, 2013-14, 2015-17
Portfolio	
Credit score	Individual years: 1990-2017
DTI	Individual years: 1990-2017
Documentation status	Individual years: 1990-2017
Amortization status	Individual years: 1990-2017
Occupancy status	Individual years: 1999-2012 Grouped years: 1990-94, 1995-96, 1997-98, 2013-14, 2015-17
FHA/VA	
Credit score	Individual years: 1990-2017
DTI**	Individual years: 1997-2017 Grouped years: 1990-96

*2007 is imputed by quarter in Q1 and Q2, while Q3 and Q4 are imputed together.

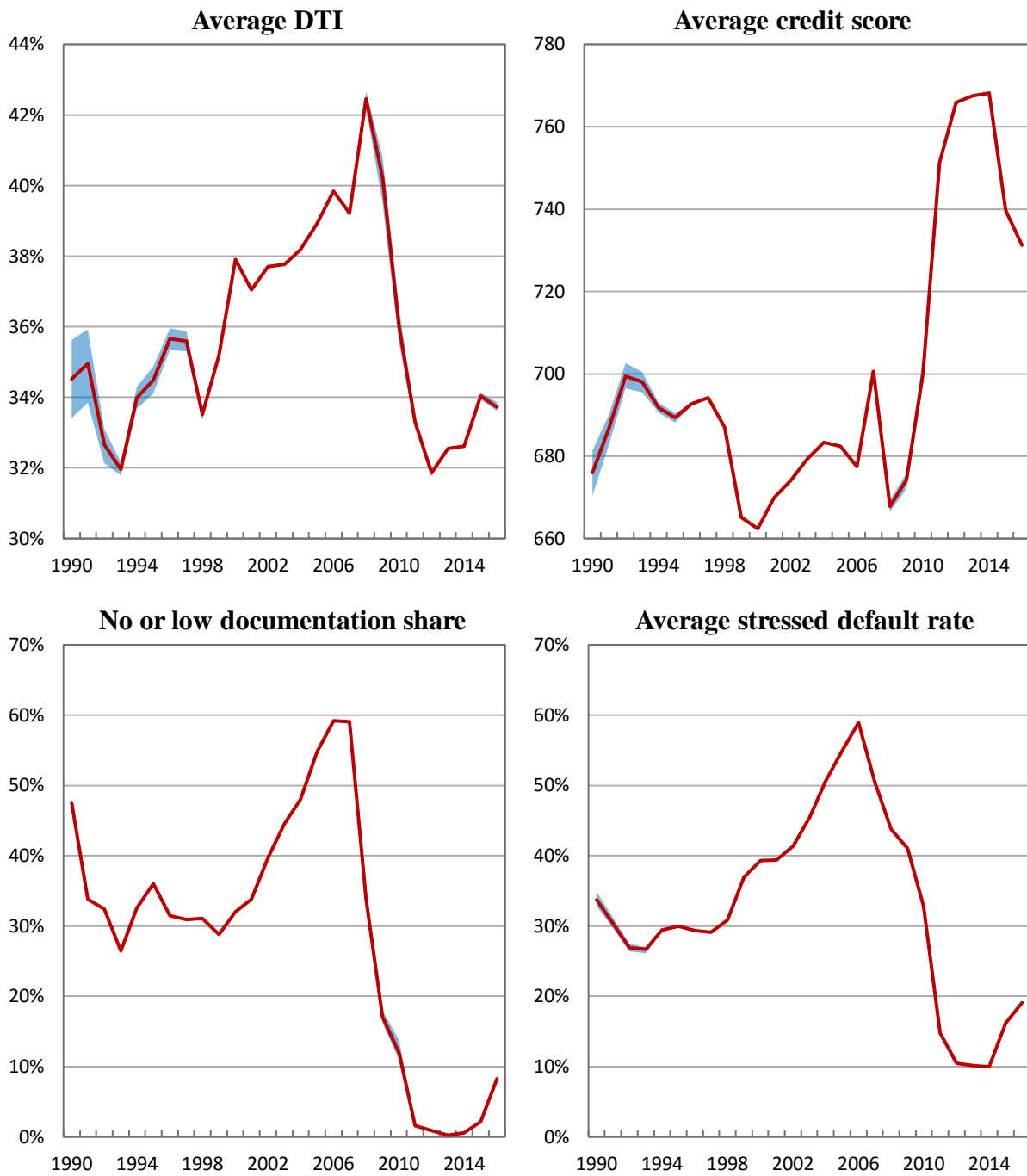
**See text for post-imputation adjustments to FHA/VA DTIs.

Figure A.1: Estimated Share of Total Conventional Purchase Loans Reported in HMDA
(percent, rounded)



Source: Authors' calculations using data from HMDA and FHFA.

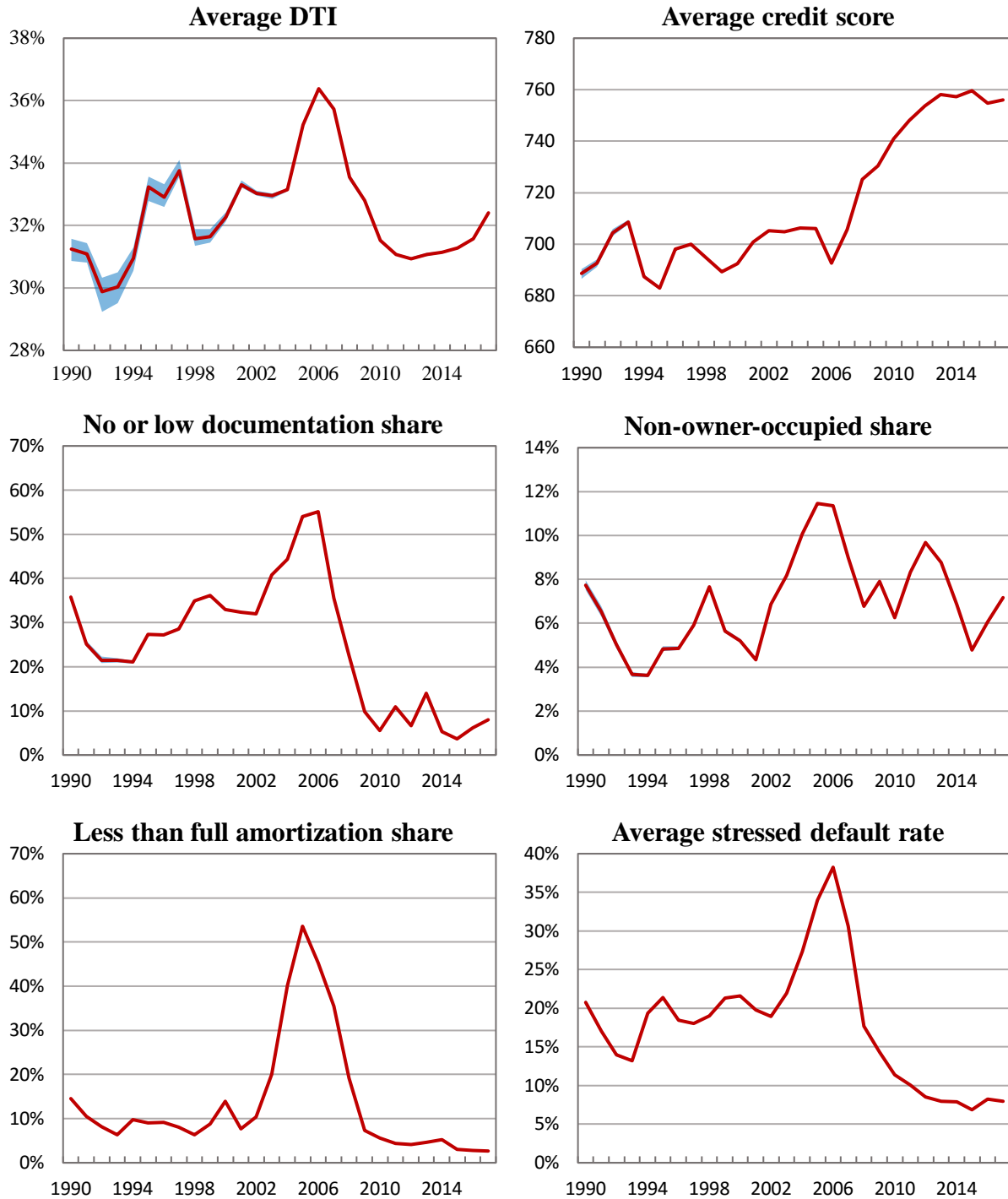
Figure A.2: Estimated Characteristics of PLS Purchase Loans, 1990-2016



Note: Results pertain to 1-4 unit purchase-money mortgages. Area in blue represents the 95% confidence interval that accounts for the imputation of missing values for risk factors.

Source: Authors' calculations using data CoreLogic®.

Figure A.3: Estimated Characteristics of Portfolio Purchase Loans, 1990-2017



Note: Results pertain to 1-4 unit purchase-money mortgages. Area in blue represents the 95% confidence interval that accounts for the imputation of missing values for risk factors.

Source: Authors' calculations using data from Black Knight, Inc. and CoreLogic®.

Appendix B: Robustness Tests

To test the robustness of our baseline default-table methodology, we construct three additional indicators of mortgage risk for PLS and Enterprise loans using a logit model and two machine learning models. For all three models, we use the same set of risk factors as in the default tables and implement the models using home purchase loans originated in 2006 and 2007.

We specify the logit model as

$$d_i = \Phi(\boldsymbol{\beta}\boldsymbol{\delta}_{im} + \varepsilon_{im})$$

where Φ is the logit function; d_i is a binary variable capturing whether loan i defaulted⁵⁶; $\boldsymbol{\delta}_{im}$ is a matrix of explanatory variables that includes the borrower's credit score, CLTV, and DTI as numerical values, and loan term, occupancy status, amortization status, income documentation status, and loan type (fixed-rate versus adjustable rate) as categorical dummy variables; $\boldsymbol{\beta}$ is a vector containing the coefficient estimates; and ε_{im} is the error.

The second model uses the same specification of $\boldsymbol{\delta}_{im}$ to build a regression tree based on the idea first proposed in Breiman, Friedman, Olshen, and Stone (1984).⁵⁷ The model, which performs functionally like a decision tree, compares splits of the data on all eight risk characteristics to find which one produces the most productive split and then repeats this step until only 500 loans are left in each bucket.⁵⁸ Then, the model builds 20 additional trees using 95 percent of the data, with the remaining 5 percent kept for cross-validation. The results from the 20 cross-validations determine the amount of tree complexity associated with the maximum

⁵⁶ The definition of default for these models is the same as in the baseline default-table approach: we deem a loan to have defaulted if it was ever 180 days' delinquent or was terminated with the borrower forfeiting the property.

⁵⁷ The package `rpart` was used to create these trees. For more on recursive partitioning, see: <https://cran.r-project.org/web/packages/rpart/vignettes/longintro.pdf>.

⁵⁸ For an overview of productive splits, see chapter 3 of the link in the previous footnote.

predictive power. We then apply this complexity parameter to the initial decision tree, which “prunes” branches from the tree that are caused by spurious correlation. In the end, the final regression tree built using PLS loans has 438 decision nodes and 469 terminal nodes. The 469 terminal nodes are the counterpart in the regression tree to the 2,560 cells in the default tables.

Figure B.1 depicts the first several splits in the PLS regression tree. The ordering of the splits provides information about the relative importance of the various risk factors for explaining defaults in the PLS market. The initial split is based on the loan’s credit score, indicating that it is the single most informative risk factor. In all, credit scores account for 41 percent of the tree’s fit, followed by CLTVs at 28 percent, amortization status at 10 percent, income documentation status at 8 percent, with the remaining risk factors making up the rest. While regression trees can be used to impute missing variables, we choose not to do this as simulations showed that loans run through the model from the 1990s have different correlations among risk factors than loans used to build the model from 2006 and 2007. Instead, we use the imputation methodology as described in Appendix A.

We also build a high-performance random forest to capture further relationships between variables in our dataset.⁵⁹ Random forests, proposed in Breiman (2001), are an extension of regression trees. We construct our forests as follows: first, we randomly select three of our eight risk factors; second, we construct a training sample by picking observations with replacement such that approximately two-thirds of the total sample is drawn to construct a given tree; and finally, we build a regression tree using those observations and variables. We repeat these steps 500 times to construct a proverbial “forest” of decision trees. By using only a subset of our risk factors and observations in every tree, each one captures a unique relationship among the

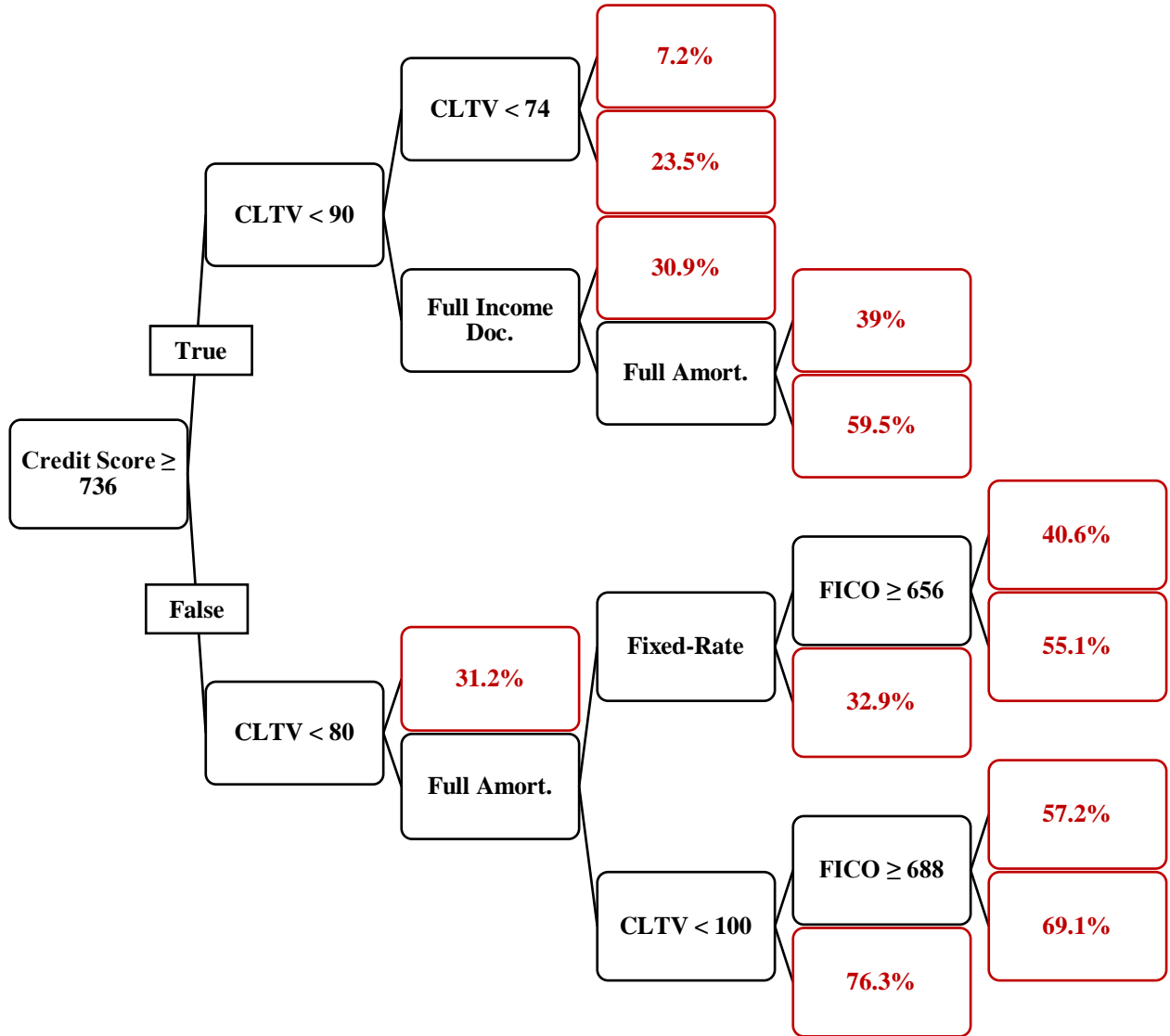
⁵⁹ The package Rborist was used to implement this model. For more on random forests, see: <https://cran.r-project.org/web/packages/Rborist/index.html>.

selected risk factors. Additionally, selecting only a portion of loans to build each decision tree allowed us to validate our model using the out-of-sample observations. The random forest model built using PLS loans confirms many of the findings from the regression tree, notably that credit scores and CLTVs are the most highly predictive risk factors for default.

For each of the three alternative models (logit, regression tree, and random forest), we generated stressed default rates that can be compared to those from our baseline methodology. To create these alternatives default series, we calculate the predicted default rate for every loan originated from 1990 to 2017 using the results for each model. We then compute the average predicted default rate for each origination year, just as in our baseline methodology.

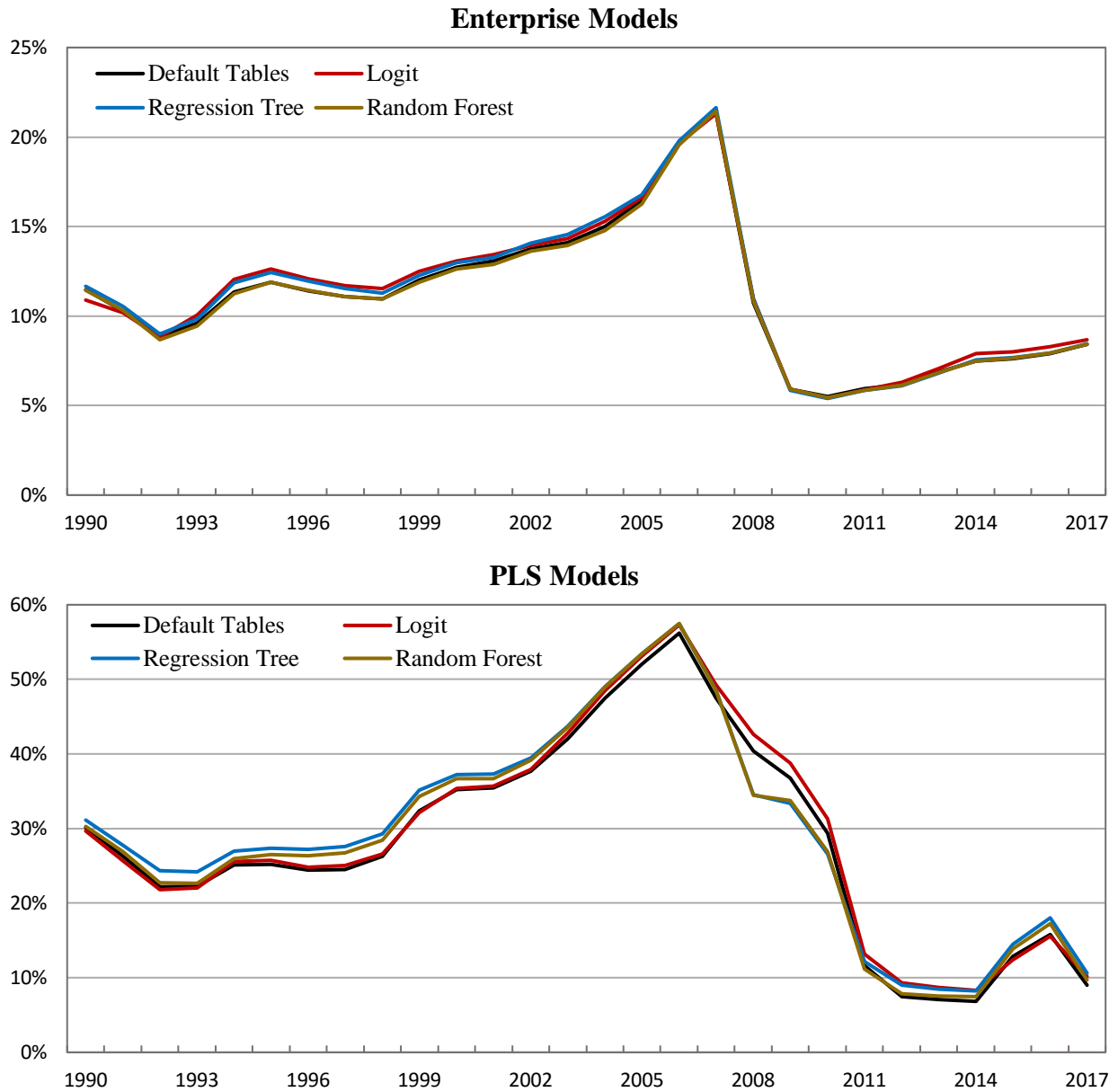
Figure B.2 presents the results from this comparison. The figure shows a high correlation between our baseline results and the three alternatives. For Enterprise loans, the four stressed default series are almost indistinguishable from one another. Although there are wider differences among the PLS series – most notably in 2008 and 2009 when the regression tree and random forest models find a faster decline in mortgage risk – they all trace the same contour over 1990-2017. The bottom line from this exercise is that our baseline results are robust to the use of alternative default models.

Figure B.1: Visualization of the First (Most Important) Splits in the PLS Regression Tree



Note: For each split, the upward arm indicates that the condition shown in the decision node is true, while the downward arm indicates that the condition is false. Black represents decision nodes, while red represents terminal nodes. The value in every terminal node represents the default rate for loans in that node. Results pertain to 1-4 unit purchase-money mortgages in PLS originated in 2006 and 2007.
Source: Authors' calculations using data from CoreLogic®.

Figure B.2: Stressed Default Rates from Different Models, Enterprise and PLS Purchase Loans, 1990-2017



Note: Results pertain to 1-4 unit purchase-money mortgages.
Source: Authors' calculations using data from FHFA and CoreLogic®.