The Missing Loan-to-Value Cycle*

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August 19, 2026

Abstract

We show that the equilibrium loan-to-value (LTV) distribution in the US mortgage market has been remarkably stable over the last quarter century, both in aggregate and region-by-region, despite large, cross-sectionally heterogeneous house price cycles. While high-LTV mortgages changed from being explicitly government backed to privately securitized and back, their overall fraction remained unchanged. A repeat-sales methodology and an analysis of loan performance confirm that this stability in the distribution of LTVs holds even within subgroups of the population. These findings are inconsistent with models of credit cycles that use changes in collateral constraints to generate boom-bust dynamics in house prices.

JEL Classification: D30, E3, G21, G28, R30

Keywords: Household Finance, Mortgages, Loan-to-Value Ratios, Government Guarantees, Collateral Rates

*We thank seminar participants at Ball State University, the Bank of Portugal, Boston College, Boston University, the Chinese University of Hong Kong, Federal Reserve Bank of Boston, University of Maryland, MIT finance lunch, Nazarbayev University, NBER Corporate Finance Summer Institute and our discussant Claudia Robles-Garcia, Federal Reserve Bank of New York, NOVA School of Business and Economics, Federal Reserve Bank of Philadelphia, SFS Cavalcade and our discussant Gonzalo Maturana, UCLA finance lunch, and the Wabash River Finance Conference and our discussant Alexei Tchistyi, as well as Neil Bhutta, Christopher Foote, Ed Golding, Barney Hartman-Glaser, Christopher Palmer, Karen Pence, James Vickery, and Paul Willen for helpful comments. We thank Yuting Wang for outstanding research assistance. A previous version of this paper was circulated with the title "The Role of Government and Private Institutions in Credit Cycles in the U.S. Mortgage Market".

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1 Introduction

Housing markets in the United States and many countries around the world have been marked by recurring boom and bust cycles. A large literature aims to understand the drivers of these housing cycles and the role played by changes in lending standards. One influential set of theories of the credit cycle focuses on changes in loan-to-value (LTV) constraints as an indicator of loosening credit standards, since an increase in LTV levels allows more optimistic buyers to access larger loans against the same collateral and bid up house prices (Geanakoplos, 2010). Alternatively, other macroeconomic frameworks emphasize the amplifying role of house price expectations or collateral values in driving housing cycles, even in the absence of changes to LTV ratios (Bernanke et al., 1999; Kiyotaki and Moore, 1997). Understanding which of these frictions play a dominant role is important for modeling credit markets and has relevant policy implications for interventions during a crisis.

In this paper we find that the distribution of combined loan-to-value ratios (CLTVs) and the share of purchase mortgages with high CLTVs (95% or greater) in the US mortgage market have been remarkably stable over the last 25 years, even as prices have fluctuated significantly.[1] The reason for this stability in the CLTV distribution is that U.S. households had access to high LTV loans throughout the entire time period. What differed was the source of the high LTV loans: Prior to the boom of the 2000s the Federal Housing Administration (FHA) and the Veterans Administration (VA) provided these high-LTV loans, while during the boom these were provided by private lenders. After 2008, these loans moved back to being FHA- and VA-guaranteed.[2] Overall, the combined share of high-LTV loans, i.e. loans with an LTV above 95%, stayed around 40% per year across the sample period.

While we find cross sectional differences in LTV levels across regions, ZIP codes, and properties, the time series are very stable across regions and types of properties. Low down-

[1] LTV ratios are measured as CLTV to account for the fact that borrowers can take multiple loans against the same property.

[2] Of course, debt-to-income ratios changed dramatically over the credit cycle, as house prices rose more quickly than incomes, and thus even at the same LTV, households took on more credit.

payment mortgages have been used in the same places and to finance properties with similar characteristics over the last 25 years - only the source of those loans changed. Thus, we find no evidence of a change in the composition of borrowers or properties that are financed with high-CLTV mortgages over time, neither at the local level nor for the US overall.

We use mortgage-level data covering the near-universe of purchase transactions with at least one mortgage between 1999 and 2023 and focus on combined LTV (CLTV) ratios at the moment of purchase, including any second or third mortgages linked to the purchase transaction.[3] We then categorize ZIP codes based on the local house price sensitivities used in Guren et al. (2021) and inspired by earlier work by Palmer (2015) and again on the average income in the ZIP code as of 1998 to investigate how distributions change within regions.

CLTV ratios did not evolve differently in areas with more cyclical house prices, despite more pronounced house price movements (and a regional boom-bust-rebound cycle as described in Chodorow-Reich et al. (2024)). Instead, the data reveal a consistent fraction of very high-CLTV loans across time and regions, with a near-perfect substitution in the share of private and government-backed loans. Similarly, segmenting ZIP codes by pre-boom income levels using official Internal Revenue Service (IRS) data shows that while low-income areas consistently exhibit higher CLTV ratios than high-income areas, these level differences remain unchanged over time. We show that segmenting the data by lender composition, borrower sentiment, or house characteristics yields similar conclusions.

A new adaptation of the repeat-sales methodology allows us to analyze changes in loan-to-value ratios over time while controlling for compositional differences in transacting properties. By focusing on homes that sell multiple times, this approach isolates market-wide changes in CLTVs from shifts in the types of properties being sold. Our empirical model includes property fixed effects, allowing us to estimate annual changes in CLTVs. We confirm that CLTV ratios within the same properties fluctuate only within a narrow range

[3] We do not include refinances to alleviate the concern of potential bias in appraisals that would underestimate the true CLTV (Agarwal et al., 2015; Kruger and Maturana, 2020).

between 1999 and 2023, with a visible drop after the 2020 pandemic (a period of growing house prices). This finding suggests that the collateralizability of housing did not change significantly during these decades.[4]

While the focus of this paper is on the distribution of CLTVs, it is worth asking if the observable characteristics of private, high-CLTV versus government-guaranteed FHA/VA loans help explain why they become relatively more or less attractive over the cycle. A simple comparison of interest rates, payment-to-income ratios and credit scores does not point to an obvious reason why borrowers (or lenders) switch between FHA/VA and private-sector loans over time. It is possible that other features like the speed of approval, a preference for non-standard mortgage characteristics, or lower documentation (neither of which is available for FHA/VA loans) may explain these shifts over time.

In a final step, we therefore utilize ex-post loan performance data to assess whether high-CLTV loans guaranteed by FHA and VA differed in any meaningful way from their private-sector counterparts that were used heavily before the financial crisis. A determined skeptic might argue that, despite the observed stability in CLTV distributions and muted differences in observable characteristics, unobserved differences in borrower characteristics or property quality could still obscure important distinctions between the two loan types. While it is impossible to control for every potential confounder, examining loan performance provides a compelling test for such concerns. Our analysis reveals delinquency patterns that are remarkably consistent across government-backed and private-sector high-CLTV loans.

Our work is related to a series of empirical papers that have considered the time series of average LTVs in the U.S. Glaeser et al. (2012) show that average down payments did not change in the years between 1998 and 2008 and are therefore an unlikely culprit for the dramatic increase in house prices. Ferreira and Gyourko (2015) also use deeds data to show a time series of CLTV ratios for prime loans, subprime loans, FHA/VA, and small

[4]Although the repeat-sales index is limited to properties that transact multiple times, when combined with previous analysis, the evidence indicates that changes in CLTV ratios were small in economic magnitude and inconsistent with the narrative of housing leverage correlating strongly with house price movements.

lenders. More recent work has used improved data availability and more granular analysis and concluded that average CLTV ratios remained stable between 1999 and 2019 (Davis et al., 2023)), and that subprime lending expanded rapidly during the boom and subsequently contracted at the same time as government-backed lending – primarily through the Federal Housing Administration (FHA) and the Department of Veterans Affairs (VA) – expanded (Courchane et al., 2014; Davis et al., 2023; Passmore and Sherlund, 2021). We build on this literature and show, first, that the shift from FHA/VA lending to the private sector and back again for accessing *high-CLTV loans* explains the steady CLTV distribution over time. Furthermore, we take seriously the possibility that the allocation of high-CLTV loans might have changed over time such that, while aggregate CLTVs look stable, changes in observable loan characteristics might have resulted in shifts in conditional CLTVs. We use a number of strategies to demonstrate that the stability in aggregate CLTV distributions did not conceal subgroup variations in the use of low down-payment loans.

Taken together, the results in this paper suggest that using changes in maximum LTV ratios as a device to model a relaxation of credit constraints in the housing boom as used in several recent papers does not reflect the reality of the US mortgage market.[5] While changes in LTV ratios may be a convenient modeling device or a "stand-in" for other possible dimensions along which credit may be relaxed, such as higher payment-to-income (PTI) ratios (Greenwald (2018)), more complex mortgage instruments (Amromin et al. (2018), investor loans (Chinco and Mayer (2016)), loan misrepresentations in securitized mortgages (Piskorski et al. (2015), Griffin and Maturana (2016)) or weaker documentation requirements (Gerardi et al. (2008)), this choice might not be innocuous for housing market cycles. In fact, Greenwald (2018) shows that LTV and PTI constraints affect housing markets differently, and bind in different states of the world.

Our results also raise the natural question of why there is a missing LTV cycle. We show that, in the context of the US housing market, house price cycles are not well explained by

[5]For some papers with this modeling approach, see, for example, Corbae and Quintin (2015), Favilukis et al. (2017), Landvoigt et al. (2015), Justiniano et al. (2015), or Greenwald and Guren (2021)

changes in aggregate purchase CLTVs and that high-CLTV loans were available throughout this period from different sources. This points to the possibility that other margins of credit supply that we do not capture in our analysis may play a role (as discussed above), or that over-optimistic expectations are the more important source of house price movements over time (as argued, among many others, by Foote et al. (2012), Shiller (2014), Adelino et al. (2016), Glaeser and Nathanson (2017), and Chodorow-Reich et al. (2024)).

2 Institutional Detail

The government programs designed and operated by the Federal Housing Administration (FHA) and the Veteran's Administration (VA) share several characteristics. They both seek to encourage homeownership among their target populations: low- and middle-income households, first-time homeowners, and borrowers who are otherwise unable to meet the stricter requirements of conventional loans for the FHA and military families for the VA. The FHA requires FICO scores to be above 580 in order to qualify for minimum 3.5% down payment, debt-to-income ratios to be below some maximum (31% front-end, 45% back-end), and that the borrower buy mortgage insurance from the FHA. Both the FHA and the VA require that the home be the borrower's primary residence and that the borrower have proof of a source of steady income.

Bhutta and Ringo (2016) and Bhutta and Ringo (2017) show that the FHA-reliant segment of mortgage borrowers are highly sensitive to variation in the mortgage insurance premium, which, in turn, causes significant shifts in the market share of the FHA, particularly after the financial crisis. FHA-insured and VA-insured loans together account for almost all of the loans backed by "the full faith and credit guarantee of the US Government."[6]

Kim et al. (2018) provide an in-depth look at the origination of FHA and VA mortgages, including the institutional details of this market and the role of non-bank mortgage com-

[6] Government National Mortgage Association Mortgage-Backed Securities Program, accessed January 15, 2025.

panies. The paper focuses on the implications of the limited amount of capital of those companies on the stability of the financial sector and the potential need for a government bailout in an adverse event. Newberger (2011) and Courchane et al. (2014) analyze the evolution of the market share of FHA loans, as well as the characteristics of FHA borrowers and their regional distribution over time (Avery et al. (2006) shows similar market share data, as well as pricing, for the pre-crisis period).

The underlying argument for the existence of the FHA/VA programs is that they grant qualifying borrowers access to mortgage credit that they would not normally have access to in a world where mortgages are provided only by private markets. This paper shows that the share of high-CLTV loans made by the private market was highly pro-cyclical during the last two decades. Importantly, highly leveraged loans *were* made before the boom, as well as after the financial crisis, but only by government programs that had an explicit mission to encourage homeownership.

3 Data

3.1 Real Estate Data

Our primary dataset is a transaction-level panel built from publicly available records of property sales and mortgage originations. The raw data are sourced from county deeds offices and then curated and standardized by CoreLogic Solutions, LLC (hereafter "CoreLogic").[7] The dataset provides a record of ownership transfers, including transaction dates and sale prices. It also includes detailed information on all mortgage originations, including origination dates, loan amounts, lender names, and lien positions. Because these are drawn from official county records, the data are comprehensive and reliable. Importantly, we observe all loans used in home purchases, including second and third ("piggyback") mort-

[7] CoreLogic has since rebranded to Cotality, but to avoid confusion and to make clear the provenance of our data, we refer to it as CoreLogic throughout this manuscript.

gages. A companion dataset links each property to parcel-level characteristics from local tax assessor offices, including address, square footage, and year built.

To examine patterns in high-CLTV mortgage utilization across the United States over time, we construct a sample of transactions involving single-family homes, condominiums, and duplexes, for which we observe reliable data on both mortgage amounts and sale prices. We begin by excluding all-cash transactions, mortgage refinances, and transactions involving parcel splits or mergers. This yields a sample of approximately 140 million transactions involving a mortgage-backed change in ownership, including both traditional purchases and other forms of transfer. Year-by-year counts appear in the first column of Table A1.

Because our analysis relies on accurate measures of both mortgage amounts and property values, we further restrict the sample by excluding quitclaims, foreclosures, and non-arm's-length transfers. We identify non-arm's-length transactions using CoreLogic's proprietary classifications which flag "any transaction in which the two parties already share a relationship."[8] Finally, we exclude transactions with missing sale price information. These occur primarily in the twelve non-disclosure states that do not require prices to be reported on the deed (see Table A2). Columns (2) through (4) of Table A1 report the number of mortgage-backed transfers remaining after each restriction is applied.

Our final sample includes 70 million arms-length home transactions that were financed with mortgage debt. While this represents roughly half of the initial set of mortgage-backed property transfers, the exclusions significantly improve the integrity of the data by removing transactions that do not reflect market prices. As a result, the final sample is well-suited to studying changes in the collateralizability of housing and leverage choices over time. Importantly, these 70 million transactions contain the vast majority of arms-length home sales financed with mortgages. This sets our paper apart from those that focus on a limited segment of the mortgage market, such as loans securitized into private-label mortgage-backed securities or originated by a single institution. Because CoreLogic coverage begins

[8] Source: https://ript.corelogic.com/PCFRSWebElements/html/RiPTCodeValue.HTML, accessed June 24, 2025.

when a county digitizes its records, the dataset grows over time. As shown in Table A3, by the early 2000s it includes over 80% of the U.S. population, enabling a more representative view of who used, and who provided, high-CLTV mortgages.

To calculate combined loan-to-value (CLTV) ratios, we sum the amounts of each mortgage used to purchase the home, up to a total of three mortgages, and then divide this by the recorded sale price. Because we use data based on official county records, the measurement of CLTVs is immune to concerns about misreporting raised in the literature regarding mortgage-backed securities or other servicer-provided data (Griffin and Maturana, 2016; Piskorski et al., 2015). As we point out in the introduction, we also do not consider refinances to avoid contaminating the denominator of CLTVs with any bias coming from appraisals (Agarwal et al., 2015; Kruger and Maturana, 2020).

We define transactions as high-CLTV if the resulting ratio exceeds 94.5% (to account for rounding). We utilize CoreLogic's indicators for if the mortgage is insured by the FHA or guaranteed by the VA. Finally, we define each transaction as exactly one of the following four types: low-CLTV transaction with private mortgage, low-CLTV transaction with FHA or VA loan, high-CLTV transaction with private mortgages, and high-CLTV transaction with FHA or VA loan. The number of transactions in each category are reported in Table A4, and summary statistics for the final dataset appear in Table A5.

3.2 Loan Performance Data

One limitation of the deeds data is that we cannot observe the performance of the loan over time. To address the possibility of high-CLTV loans being used differently over time, we thus turn to data from the Credit Risk Insight Servicing McDash (CRISM) data set, developed by Equifax using a proprietary algorithm to match McDash's mortgage servicing records to individual-level Equifax credit data. This data set covers approximately two-thirds of first mortgages originated in the market from the second half of 2005 to the end of 2015.

McDash contains mortgage characteristics such as mortgage type (FHA, VA, or private), origination month, original loan amount, original property value, credit score at origination, front-end DTI, and also mortgage performance over time. Furthermore, Equifax keeps track of consumer's liabilities, and we can observe the number of both closed-end seconds (CESs) and home equity lines of credit (HELOCs) taken by the individual, as well as the date and the amount of the two largest loans of each type that are active at each month. This allows us to capture all second liens for over 90% of consumers which we use to estimate original CLTV. Specifically, we match McDash's first mortgages to Equifax's second mortgages taken by the same person at the same month. Finally, we also observe both the income and credit scores of the borrowers and can thus say a great deal about the types of borrowers using high-CLTV loans. The key limitation of McDash, and the reason we do the bulk of our analysis with the CoreLogic data, is that McDash does not share the exact parcel involved in the transaction and we are thus limited in our ability to control for the underlying quality of the collateral.

3.3 Other Data

Income. We characterize ZIP codes as high- or low-income using their adjusted gross income per capita as of 1998. These data come from the IRS and are publicly available.[9]

House Price Sensitivities. We compare properties located in areas with different levels of house price sensitivities using measures pioneered in Guren et al. (2021). Specifically, we assign each property to no more than one 2013 core based statistical area (CBSAs) and then classify CBSAs as having either low- or high-house price sensitivity using gamma as defined in Guren et al. (2021).[10]

Optimism. As another source of data on mortgage debt, house value, and borrower char-

[9] https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-zip-code-data-soi, accessed September 10, 2018.

[10] https://people.bu.edu/guren/gmns_gammas.zip, accessed February 23, 2019.

acteristics, in one robustness test in the Internet Appendix we use the 1995 through 2016 waves of the Federal Reserve Board Survey of Consumer Finances (SCF).[11] The SCF is a household survey that asks consumers for detailed information about their finances and savings behavior and is conducted every three years as a repeated cross-section. We follow the approach developed by Puri and Robinson (2007) to measure optimism based on self-assessed life expectancy.

4 Findings

4.1 Aggregate CLTVs, Government and Private High CLTV shares

Panel A of Figure 1 shows the distribution of CLTVs over time, as defined in Section 3.1, of all purchase mortgages made each year. We then calculate the mean CLTV along with the 5$^{\text{th}}$, 25$^{\text{th}}$, 75$^{\text{th}}$, and 95$^{\text{th}}$ percentile CLTV each year between 1999 and 2023. We plot these statistics to show the evolution of CLTVs over time in the first panel of Figure 1.

As documented in the literature, and confirmed in Table A4 and Figure A1, the period between 1999 and 2023 featured dramatic shifts in the frequency of home purchases and house price growth. However, despite the pronounced cycles in the housing market, the dollars of mortgage debt per dollar of housing collateral remained relatively unchanged. We see this both at the mean, which remained steady at just over 85%. But we also see it at the top ends of the CLTV distribution. In all of the last 25 years, more than a quarter of all purchase mortgages had CLTVs approaching 100%. Taken together, these empirical facts seem to refute the notion that changes in the frequency of purchases relying on high-CLTV mortgages can explain changes in house prices. If anything, the only co-movement between these two measures has occurred in recent years, where we see some evidence of increasing house prices coinciding with *lower* CLTVs, driven in particular by lower leverage at the very bottom of the distribution.

[11] https://www.federalreserve.gov/econres/scfindex.htm, accessed May 1, 2020.

Panel B of Figure 1 shows the well-known increase in private-sector loans with CTLVs ≥ 95% before 2008. To create this figure, we calculate the share of all purchase loans guaranteed by the FHA or the VA and the share of remaining loans with CLTVs ≥ 95% (the vast majority of FHA and VA loans are very high CLTV). The figure also shows that privately securitized high-CLTV loans were not the first product to allow for very low down payments, nor that these disappeared in the years since, but rather *replaced* the share of equally high (or higher) CLTV loans backed by the FHA and VA. In the decade and a half post-2008, high-CLTV loans continued to be originated, again with FHA and VA guarantees. The aggregate share of all loans (both government guaranteed and private-sector) with CLTVs ≥ 95% moved very little over the house price boom and subsequent bust.

This stylized fact – that the FHA played a downsized role during the boom, but stepped back up during the recession – has also been documented in extant work (see, for example, Courchane et al. (2014) and Passmore and Sherlund (2021)). Davis et al. (2023) further document the same aggregate changes in FHA/VA loans that we do here. We build on their work by more directly relating the steadiness in aggregate CLTVs to the changing FHA/VA share. Our analysis focuses specifically on comparing of the share of FHA/VA mortgages to the share of private sector mortgages with high CLTVs. Indeed, Figure 1 shows a near-perfect substitution between these two kinds of loans over time. Of course these aggregate patterns do not rule out the possibility that private-sector, high-CLTV loans during the 2002-2007 boom were used to finance different homes or by different borrowers in different parts of the country than FHA/VA loans in the years before and after. We now turn to this possibility.

4.2 Stable Allocations of High-CLTV Mortgages

In Section 4.1 we showed that neither the overall distribution of CLTVs nor the share of purchase loans with high CLTV ratios changed between 1999 and 2023. What did change was the share of all high-CLTV loans that were explicitly guaranteed by the government through the FHA and VA programs. This section of the paper asks a follow-up question: Does the steadiness of the CLTV distribution mask shifts in the regions, borrowers and types of properties financed with high-CLTV mortgages? In this section we show that CLTVs were stable within regions and properties, and largely disconnected from local house price cycles.

4.2.1 Metropolitan areas with Low and High Housing Supply Elasticity

We first look to the parts of the country with high local house price sensitivity and compare those to places where sensitivity to regional house price cycles is low Guren et al. (2021); Palmer (2015). This test is motivated by theoretical work that has argued looser borrowing constraints along the LTV dimension may be associated with higher house price growth. We confirm in Panels A and D of Figure 2 that house price cycles are typically more pronounced in metropolitan areas with low housing supply elasticity, or high gammas.[12] If a differentially changing availability of high-CLTV loans explained some of the housing cycle, then we should see increases in CLTVs exactly in those parts of the country where house prices increased the most.

To compare low- and high-gamma (high- and low-elasticity of housing supply, respectively) parts of the country, we create figures analogous to those presented in Figure 1 for each of these two subsamples. We present our results in Figure 2. Panels B and E reject the idea that CLTVs increased more in high gamma (low housing supply elasticity) areas where house prices increased more dramatically than in places with smaller house price moves. Looking in Panels C and F, we confirm that the substitution between private, high-CLTV loans and FHA/VA loans was nearly perfect in both types of regions.

[12]The gammas in each region are at the core-based statistical area (CBSA)-level and are obtained directly from Guren et al. (2021) and their estimation of equation (3) in that paper. Gammas are a proxy for the inverse of the region's housing supply elasticity.

4.2.2 Other Sample Splits

We show in the previous section that, despite very different house price cycles, differences between high-housing supply elasticity and low-housing supply elasticity regions do not change the main patterns of our paper. To address the possibility that access and use of high-CLTV mortgages may co-move with the housing cycle differently in high- and low-income areas, we use publicly available IRS data from 1998 to divide ZIP codes into five population-weighted, time-invariant quintiles of adjusted gross income. We re-create our two main figures for the lowest income quintile ZIP codes and then again for the highest income quintile ZIP codes in Appendix Figure A2. The figure shows that low-income ZIP codes are characterized by much higher CLTVs, much higher utilization of high-CLTV mortgages, and much lower house prices than high-income ones. But, within these ZIP codes, the CLTV distributions are very steady over time. Furthermore, while the FHA/VA share and and the private-sector, high-CLTV loan share changed dramatically over the time series, they did so in ways that perfectly offset each other in both groups.

In the appendix, we also reproduce our main findings of flat CLTVs and shifts in the importance of government guarantees for high-CLTV loans when splitting the sample based on the age of the lender (Figure A3), the optimism of the borrower as in Geanakoplos (2010), whereby buyers who value assets more bid up prices when they have access to more leverage (Figure A4), the size of the home (Figure A5), or the age of the home (Figure A6). We find that none of these dimensions contradicts the central result of the paper that observed mortgage CLTVs are largely immune to the housing cycle.

4.3 CLTV Index

Our next test uses a novel application of a repeat-sales index (see, for example, Case and Shiller (1989)). The intuition of the repeat-sales index for creating a house price index is that by using variation within property, compositional differences in the homes that transact are controlled for. By focusing on properties that sell multiple times, the repeat-sales index isolates changes in price attributable to market-wide factors rather than differences in the types or characteristics of homes being sold. This approach reduces bias introduced by the varying mix of properties transacting over time, providing a cleaner measure of price dynamics in the housing market. For our purposes, we adapt this methodology to measure changes loan-to-value ratios over time. Specifically, we estimate the following model:

$$\text{CLTV}_{it} = \sum_{t=1999}^{2019} \beta_t \text{Year}_t + \mu_i + \epsilon_{it} \tag{1}$$

where CLTV_{it} is the combined loan-to-value of the debt used to purchase home i in year t, Year_t is a dummy variable equal to 1 if the transaction takes place in Year_t, and μ_i is a property fixed effect. We estimate yearly effects, β_t. Standard errors are clustered at the county level. We plot the yearly effects, using 2001 as the base year, along with 95% confidence intervals in Figure 3.

The figure shows that, within the same properties, changes in LTVs over time vary within a band of just a few percentage points. The key advantage of this methodology is that the CLTV index can help rule out changes in time-invariant property characteristics. Of course, the index is only calculated using properties that transact multiple times. But, when combined with our aggregate results that compare small homes and large homes, our body of results is largely inconsistent with changes in CLTVs or the collateralizability of housing over the housing boom and bust.

4.4 Other Loan Characteristics

The previous sections establish that CLTV has been stable over the past decades for U.S. residential purchases, largely because of the fluctuations in the share of FHA/VA in high-CLTV loans over time. However, it is possible that government-guaranteed FHA/VA loans had different observable terms from high-CLTV mortgages supplied by the private-sector, such that a shift from FHA/VA to private credit may have meant that credit conditions loosened through terms other than the CLTV. In order to study the evolution of these characteristics, we use the Credit Risk Insight Servicing McDash (CRISM) data set described in Section 3.2, not Corelogic, as these variables are not available in county deeds records.

In Figure 4 we show the evolution of interest rates (Panel A), payment-to-income ratios (Panel B), and credit scores (Panel C) for FHA/VA loans, private-sector, high-CLTV loans, and private-sector loans with CLTVs below 95% (that we label "Low CLTV" in the figure). In each panel, we show the unconditional characteristics of each group of loans, as well as differences of the latter two groups relative to FHA/VA loans within county and year. The within-county-by-year differences are obtained with a regression of each characteristic on an indicator for each group of loans interacted with year indicator variables, controlling for county-by-year fixed effects. We repeat this analysis in the sample of mortgages with non-missing payment-to-income and credit score in Figure A7.

The figure shows that private, high-CLTV loans have interest rates that are about 40 basis points higher than FHA/VA loans in the early part of our sample, and that those differences become smaller after 2008. On this dimension, private, high-CLTV loans are not observably more "accessible" (cheaper) than FHA loans.[13] Interest rates on low-CLTV loans are broadly similar to those on FHA/VA loans throughout the whole sample period. Payment-to-income ratios are within 2 percentage points of the average FHA/VA PTI for both groups of private loans until 2008 when we look within county and year. The difference becomes significantly negative for both groups after 2008. Again, on this dimension, FHA/VA mortgages are associated with at least as high PTIs as privately supplied mortgages. Finally, credit scores are higher, on average, for both groups of private loans relative to FHA/VA. Within county and year, the difference is about 70 points for low-CLTV loans, and ranges from 0 to 50 points for high-LTV loans.

Taken together, the evidence in this section does not provide a clear reason why we observe large changes in the share of FHA/VA mortgages over time. There are many other

[13] The measure of interest rates we have access to does not include government-provided or private mortgage insurance premia.

features that could explain this preference, including non-standard mortgage types (Amromin et al. (2018)), speed of approval (Adelino et al. (2016)), documentation requirements (Gerardi et al. (2008)), among others. In the next section, we turn to *ex post* performance as a sufficient statistic that helps establish whether there are other (observable or unobservable) differences between borrowers and collateral using government- or privately-supplied high-CLTV loans that might indicate a relaxation of credit constraints.

4.5 Ex-Post Loan Performance

In this final section, we investigate the ex-post performance of high-CLTV loans guaranteed by the government versus those provided by the private-sector. This addresses the concern that unobserved characteristics of the borrowers or their collateral might mask differences in either the users of high-CLTV loans or the quality of homes those high-CLTV loans were being used to purchase. Of course, we cannot account for every possible dimension related to credit quality so, instead, we take advantage of hindsight and look to loan performance. If high-CLTV loans were somehow used differently over the housing cycle, we might expect to see differential loan performance after the fact. We would not be able to point to what the exact source of the differences in performance were, but this would be a compelling "smoking gun." Instead, we find no smoke at all. To reach this conclusion, we plot the share of loans of each type by origination-year cohort that are at some point 90+ days delinquent within three years of origination.

Figure 5 shows that, as expected, private-sector loans with CLTVs < 95% have significantly lower delinquency rates than loans with CLTVs ≥ 95%, regardless of source. Strikingly, though, is our finding that within cohorts, the rates of delinquency for FHA/VA loans is the same as for private loans with CLTVs ≥ 95%. This remains true when we control for county-by-year fixed effects (Panel B) and county-by-year fixed effects, FICO, interest rate, loan type, and PTI (Panel C). This means that, when we do a comparison of loans made in the same areas and to similar borrowers, the delinquency rates of the two types of loans are very similar. Appendix Figure A9 shows that the patterns are largely unchanged when we repeat the same figures only for the subset of loans with non-missing payment-to-income and credit scores.

5 Conclusion

We show that the stable CLTV distribution of purchase mortgages in the US over the last 25 years is closely connected to the fact that high-CLTV loans shift over time from being directly government guaranteed through the FHA and VA to being privately supplied, and then back. Earlier papers had pointed out that there was a sharp increase in privately securitized high CLTV loans. But it is not the distribution of observed high-CLTV loans but rather their source that changes over time.

The contribution of this paper is to document that local and regional house price cycles are largely disconnected from variation in CLTVs. We do not find changes over time in the type of borrower or properties for which high-CLTV loans were used. Put differently, not only did aggregate CLTVs not change over the time period (as shown in previous work), but neither did borrower-, lender-, or property quality-adjusted CLTVs.

Our results suggest that the fraction and composition of borrowers and types of housing collateral that were financed with very high-CLTV loans did not change over the house price cycle. These findings suggest that using changes in LTV ratios as a modeling device for credit cycles in the US mortgage market might be problematic, especially when trying to understand the mechanisms behind these boom and bust patterns over time.

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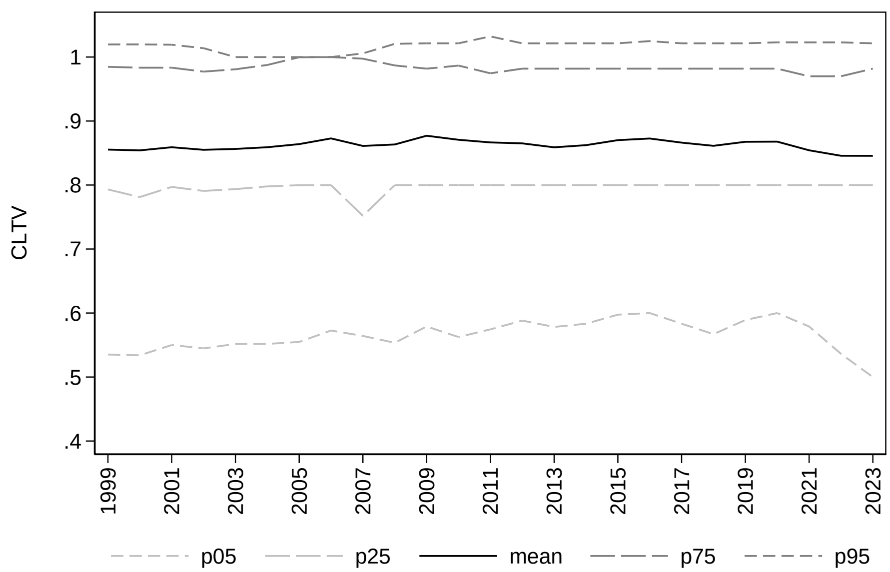
Figure 1: CLTVs and Sources of Mortgages Over Time

Panel A plots the distribution of combined loan-to-value (CLTV) ratios for the sample of transactions defined in Section 3.1. Appendix Tables A1 through A5 provide detailed counts and summary statistics for the sample used in this figure. Panel B reports the share of transactions that are both high-CLTV and either guaranteed by the Federal Housing Administration (FHA) or Veterans Affairs (VA), as well as the share that are high-CLTV and privately financed.

Panel A. Purchase Loan CLTV Ratios



Panel B. Sources of Purchase Loans

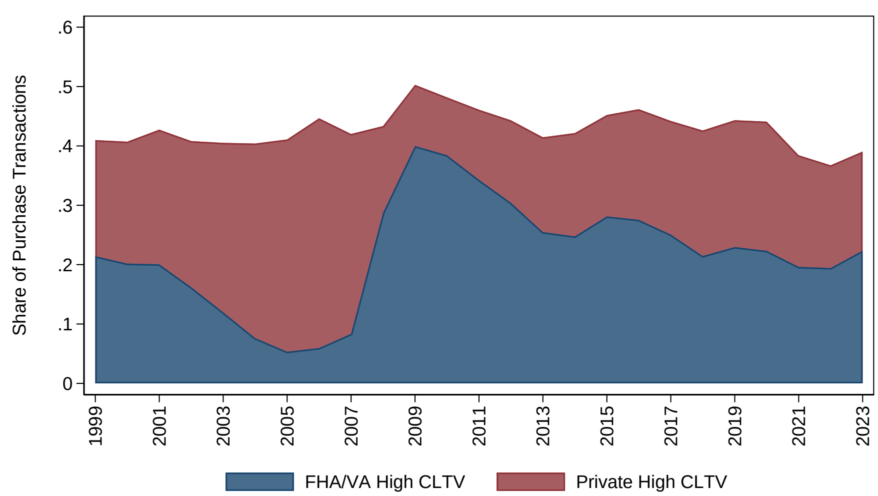


Figure 2: High and Low Housing Supply Elasticity

This figure splits the sample used to create Figure 1 at the median of Gamma, a proxy for housing supply elasticity estimated by Guren et al. (2021). Half of the sample is used in Panels A, B, and C and the other half is used in Panels D, E, and F.

Low Gamma (High Supply Elasticity) | **High Gamma (Low Supply Elasticity)**

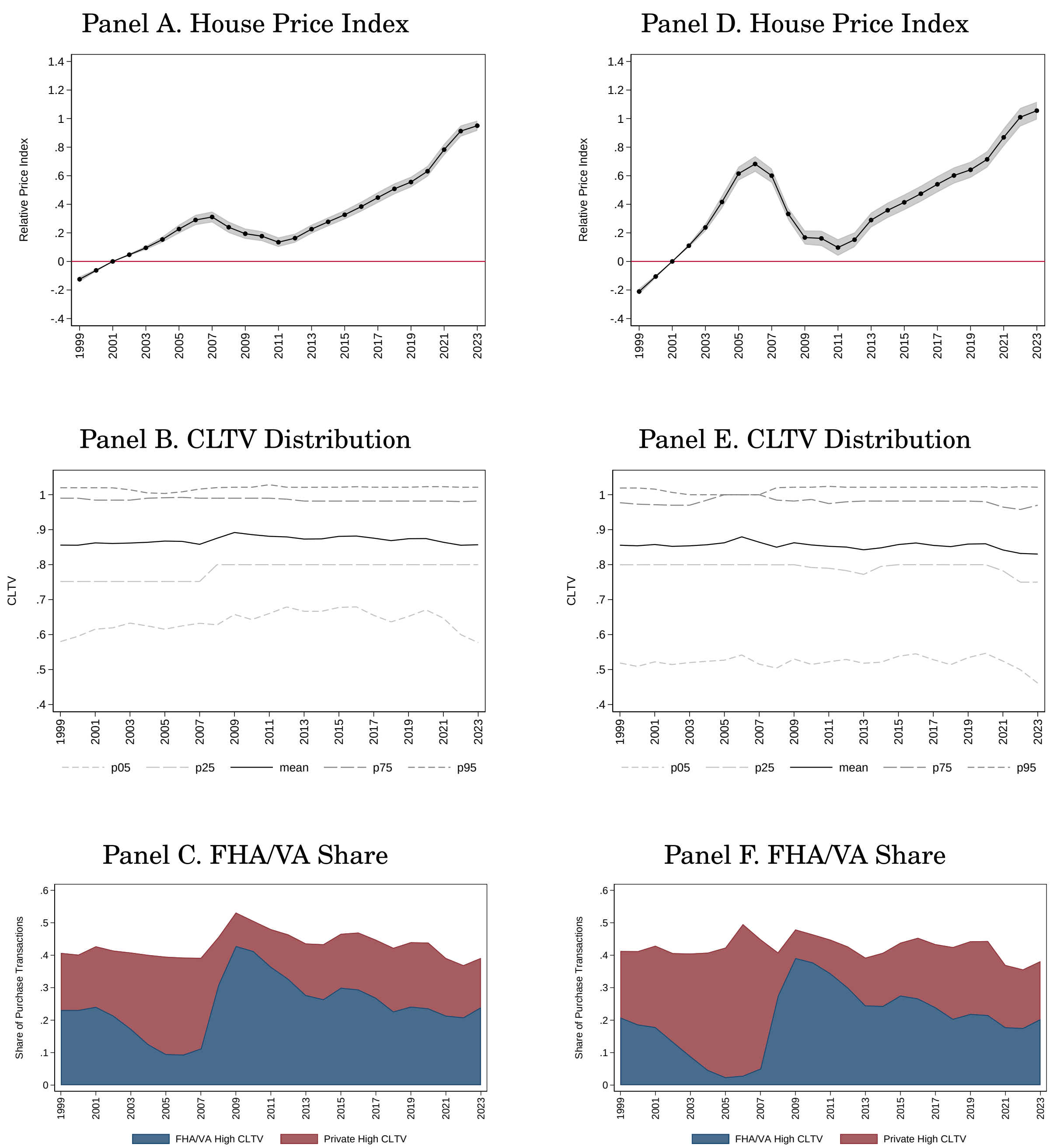


Figure 3: CLTV Repeat Sales Index (Relative to 2001 Baseline)

This figure uses the full sample from Figure 1 to plot a repeat sales index of combined loan-to-value (CLTV) ratios, normalized to a 2001 baseline. The index is constructed analogously to a standard house price index: CLTVs of purchase loans are regressed on year and property fixed effects. A more detailed description of the methodology is provided in Section 4.3. The figure displays the estimated year effects along with corresponding confidence intervals.

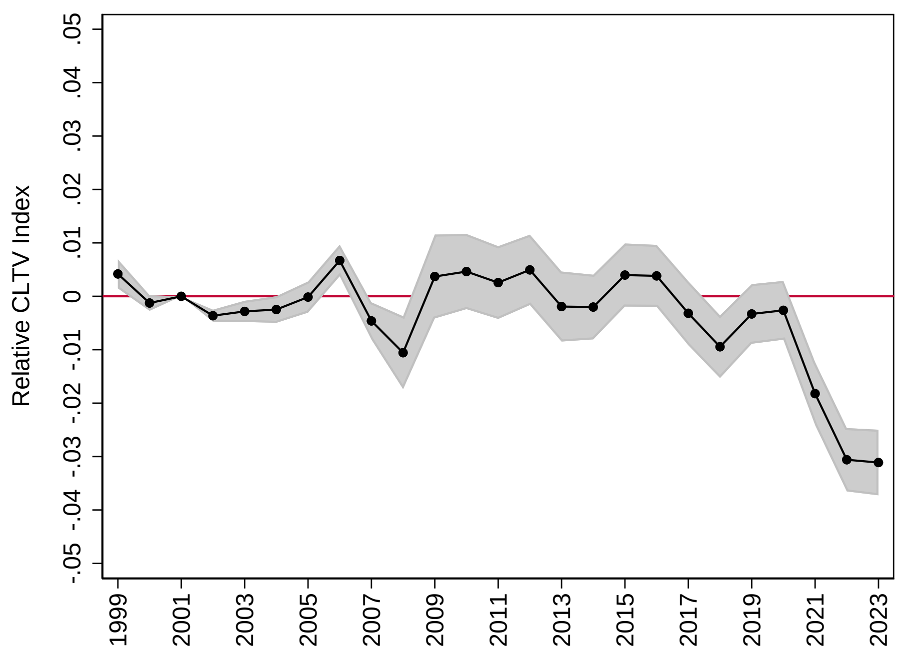
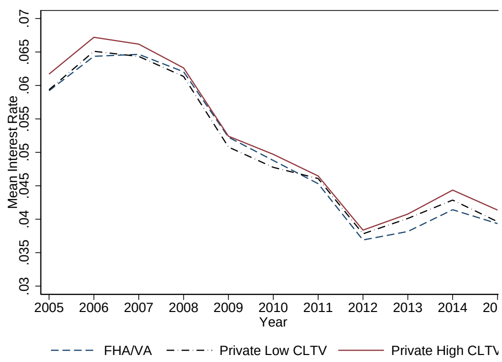


Figure 4: Interest Rates, Payment-to-Income Ratios, and Credit Scores by Type

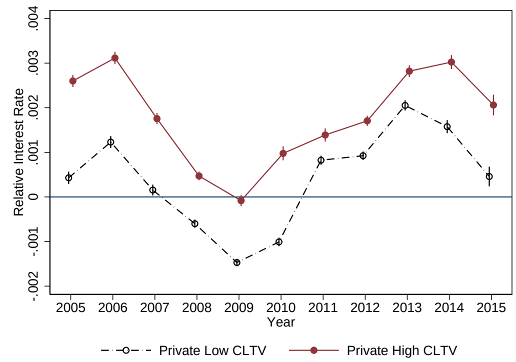
These figures use McDash data on first-lien mortgages to compare three loan groups: high-CLTV (combined loan-to-value > 94.5%) FHA/VA loans, high-CLTV private loans, and low-CLTV private loans. Panel A presents original interest rates; Panel B reports borrower payment-to-income (PTI) ratios; and Panel C shows borrower credit scores. In each panel, we first report unconditional means by loan type and year. We then estimate models with county-by-origination-year fixed effects and plot average differences relative to FHA/VA loans (the omitted group). Standard errors are clustered at the county level. Panel A excludes adjustable-rate mortgages; Panel B excludes loans with missing PTI; and Panel C excludes loans with missing credit scores. Figure 4 replicates the analysis in all three panels using only loans with non-missing PTI and credit score. Figure A8 reproduces Panel A including adjustable-rate mortgages.

Panel A. Original Interest Rate

(i) Unconditional

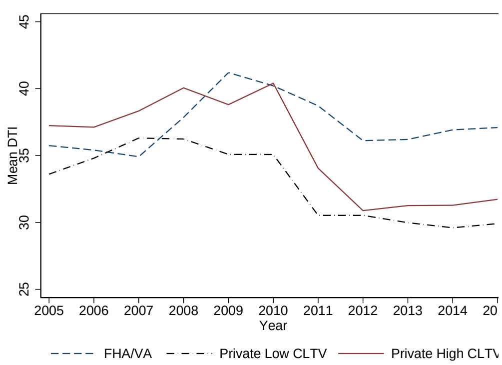


(ii) Within County-by-Year

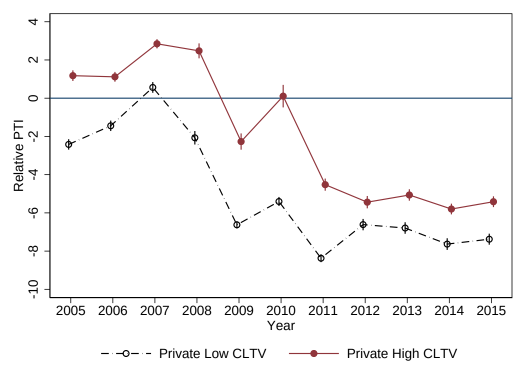


Panel B. Payment-to-Income Ratio

(i) Unconditional

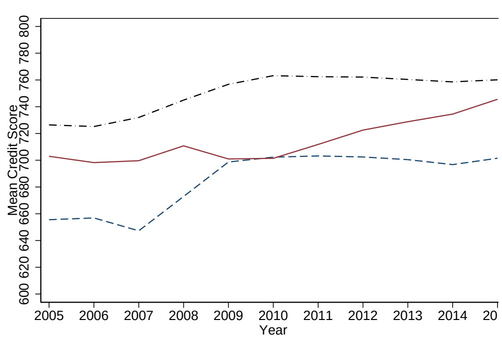


(ii) Within County-by-Year



Panel C. Credit Score

(i) Unconditional



(ii) Within County-by-Year

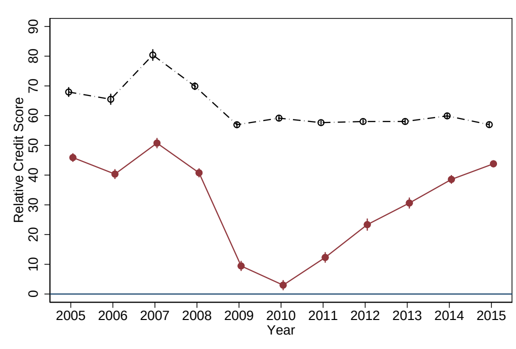
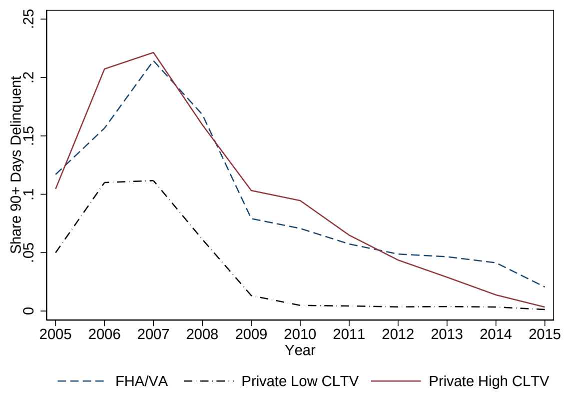


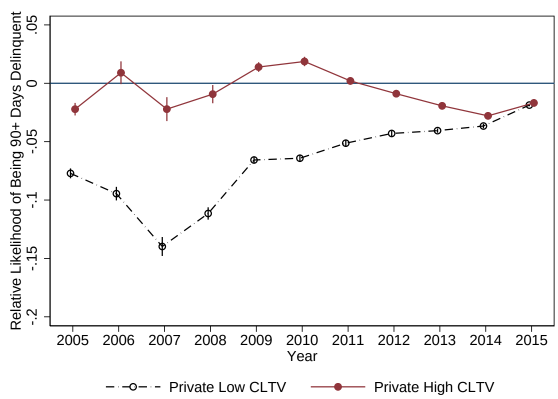
Figure 5: Share 90+ Days Delinquent Within 3 Years of Origination

These figures use McDash data to examine mortgage delinquency outcomes by loan type of first-lien mortgages. Panel A plots, by origination year, the share of loans in each category, high-CLTV FHA/VA, high-CLTV private, and low-CLTV private, that became 90 or more days delinquent within three years of origination. Panel B estimates models with county-by-year fixed effects and plots the relative delinquency rates of private-sector loans compared to FHA/VA loans. Panel C adds borrower and loan-level controls, including credit score and a dummy for missing credit score, payment-to-income ratio and a dummy for missing payment-to-income ratio interest rate, original interest rate, documentation status, an occupancy dummy, a jumbo-loan dummy, an interest-only dummy, and a fixed-rate mortgage dummy. Error bars represent 95% confidence intervals, with standard errors clustered at the county level.

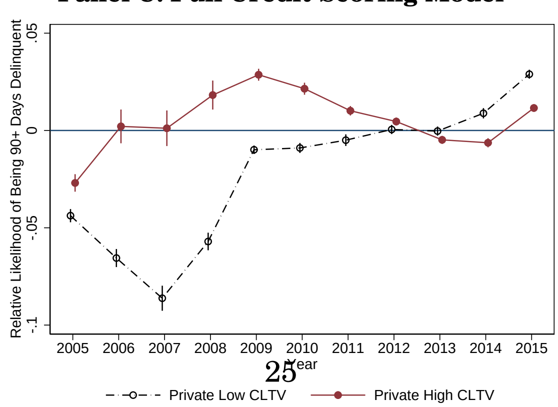
Panel A: Unconditional Delinquency Share



Panel B: Within County-by-Year



Panel C: Full Credit Scoring Model



Supplemental Appendix for: The Missing LTV Cycle

Manuel Adelino, W. Ben McCartney, and Antoinette Schoar

Online Appendix

Appendix A – Supplemental Figures and Tables

A Supplemental Figures and Tables

Table A1: The Effects of Sample Restrictions on Counts of Transactions

Year	Ownership Changes with Mortgage	Of Which Deeds	Of Which Arms Length	Of Which Observed Sale Price
1999	3,688,537	3,268,282	2,567,662	1,957,541
2000	4,535,006	4,020,881	3,063,386	2,445,016
2001	4,800,039	4,214,311	3,104,345	2,531,670
2002	5,240,669	4,567,269	3,298,184	2,704,623
2003	5,835,021	5,043,732	3,608,697	2,982,644
2004	6,303,049	5,499,977	4,065,145	3,439,970
2005	6,634,075	5,820,059	4,393,517	3,818,459
2006	5,935,283	5,163,569	3,949,465	3,445,346
2007	5,136,650	4,361,993	3,236,920	2,784,147
2008	4,650,450	3,779,077	2,555,895	2,165,467
2009	4,737,622	3,792,989	2,384,476	2,073,550
2010	4,591,404	3,580,890	2,144,528	1,871,712
2011	4,503,120	3,512,335	2,048,173	1,784,057
2012	5,009,048	3,901,537	2,311,050	2,022,250
2013	5,331,886	4,230,128	2,654,277	2,355,661
2014	5,396,540	4,327,708	2,829,957	2,547,332
2015	5,840,951	4,751,598	3,202,795	2,922,820
2016	6,078,990	4,993,913	3,432,071	3,151,426
2017	6,155,983	5,086,444	3,538,169	3,223,622
2018	6,267,669	5,204,117	3,603,401	3,251,153
2019	6,440,899	5,366,766	3,780,980	3,448,528
2020	6,785,052	5,752,464	4,039,746	3,684,096
2021	7,671,047	6,485,544	4,440,810	3,986,155
2022	6,819,127	5,696,146	3,831,483	3,422,741
2023	5,841,985	4,761,225	3,046,607	2,697,075
Total	140,230,102	117,182,954	81,131,739	70,717,061

This table documents the sequential application of sample selection criteria used to construct the final analysis sample. We begin with the universe of ownership transfers recorded in CoreLogic and retain only those transactions that reflect mortgage-financed changes in ownership of parcels that remain physically and legally unchanged. These restrictions exclude all-cash transactions, mortgage refinancings, and parcel splits or mergers, respectively. Next, we restrict the sample to deed transfers, excluding quitclaims and foreclosures. We then remove all transactions flagged by CoreLogic as non-arm's-length. Finally, we exclude observations with missing sales prices. The resulting sample comprises 69,714,610 transactions with non-missing sales prices and mortgage amounts, and thus well-defined combined loan-to-value (CLTV) ratios. Additional details on the sample construction are provided in Section 3.1.

Table A2: Counts of Transactions with Missing Sales Price by State

State	Arms Length Deeds	Missing Sales Price	With Sales Price	Share With Sales Price	Non-Disclosure State
Alabama	883,362	245,170	638,192	0.72	0
Alaska	232,230	48,342	183,888	0.79	1
Arizona	2,445,054	46,937	2,398,117	0.98	0
Arkansas	561,955	115,320	446,635	0.79	0
California	9,387,184	170,438	9,216,746	0.98	0
Colorado	2,068,011	25,779	2,042,232	0.99	0
Connecticut	900,400	10,449	889,951	0.99	0
Delaware	217,152	4,908	212,244	0.98	0
District of Columbia	154,837	328	154,509	1.00	0
Florida	6,772,561	40,964	6,731,597	0.99	0
Georgia	2,629,607	140,017	2,489,590	0.95	0
Hawaii	308,224	12,971	295,253	0.96	0
Idaho	718,860	233,534	485,326	0.68	1
Illinois	2,930,674	56,722	2,873,952	0.98	0
Indiana	1,994,173	769,922	1,224,251	0.61	0
Iowa	660,411	66,558	593,853	0.90	0
Kansas	777,351	230,492	546,859	0.70	1
Kentucky	681,844	123,081	558,763	0.82	0
Louisiana	635,213	129,418	505,795	0.80	1
Maine	209,961	71,116	138,845	0.66	0
Maryland	1,762,156	3,498	1,758,658	1.00	0
Massachusetts	1,009,535	48,887	960,648	0.95	0
Michigan	1,700,629	77,968	1,622,661	0.95	0
Minnesota	954,077	15,359	938,718	0.98	0
Mississippi	553,395	435,505	117,890	0.21	1
Missouri	2,210,083	941,818	1,268,265	0.57	1
Montana	452,838	223,693	229,145	0.51	1
Nebraska	434,779	52,954	381,825	0.88	0
Nevada	1,065,808	15,300	1,050,508	0.99	0
New Hampshire	273,568	4,851	268,717	0.98	0
New Jersey	2,085,450	15,050	2,070,400	0.99	0
New Mexico	617,439	235,607	381,832	0.62	1
New York	2,194,111	102,394	2,091,717	0.95	0
North Carolina	2,516,461	169,850	2,346,611	0.93	0
North Dakota	156,837	29,065	127,772	0.81	1
Ohio	2,586,332	83,811	2,502,521	0.97	0
Oklahoma	892,293	86,141	806,152	0.90	0
Oregon	1,140,526	14,155	1,126,371	0.99	0
Pennsylvania	2,583,115	265,592	2,317,523	0.9	0
Rhode Island	252,807	1,600	251,207	0.99	0
South Carolina	1,154,551	90,470	1,064,081	0.92	0
South Dakota	26,921	22,533	4,388	0.16	0
Tennessee	1,744,753	88,201	1,656,552	0.95	0
Texas	10,801,655	4,160,504	6,641,151	0.61	1
Utah	1,234,228	338,801	895,427	0.73	1
Virginia	2,289,110	109,149	2,179,961	0.95	0
Washington	2,038,738	68,063	1,970,675	0.97	0
West Virginia	130,565	46,200	84,365	0.65	0
Wisconsin	936,469	50,957	885,512	0.95	0
Wyoming	163,446	74,236	89,210	0.55	1
Total	81,131,739	10,414,678	70,717,061	0.87	12

This table reports, by state, the number of arm's-length deed transactions with non-missing sales prices that comprise the final analysis sample. Vermont is excluded due to the absence of CoreLogic coverage. "Non-Disclosure States" refer to states where the disclosure of sales prices on deeds is not legally required.

Table A3: CoreLogic Coverage of U.S. Counties by Year

Year	Percent of U.S. Counties	Percent of U.S. Population
1999	19.9	71.2
2000	24.1	75.5
2001	25.3	76.6
2002	27.2	78.1
2003	29.4	79.5
2004	35.6	82.2
2005	41.6	84.7
2006	45.3	86.4
2007	47.8	87.5
2008	48.9	87.6
2009	49.3	87.8
2010	55.9	89.9
2011	59.7	91.0
2012	61.5	91.7
2013	66.5	92.7
2014	70.5	93.6
2015	70.6	93.8
2016	71.2	94.1
2017	71.8	94.4
2018	73.1	95.2
2019	75.9	95.8
2020	76.8	96.1
2021	77.1	96.2
2022	77.5	96.3
2023	77.5	96.4

This table first reports the share of counties with at least one transaction in the final analysis sample. Because CoreLogic coverage is closely tied to the digitization of county deed records, counties typically enter the dataset in discrete jumps. The second panel presents the same measure weighted by annual county-level population estimates.

Table A4: Counts of Transaction Type by Year

	CLTV < 94.5%		CLTV ≥ 94.5%		
Year	Private	FHA/VA	Private	FHA/VA	Total
1999	1,127,125	28,236	382,628	419,552	1,957,541
2000	1,418,492	30,912	502,156	493,456	2,445,016
2001	1,417,258	32,171	574,243	507,998	2,531,670
2002	1,576,170	24,497	665,741	438,215	2,704,623
2003	1,756,727	17,534	851,097	357,286	2,982,644
2004	2,037,079	12,996	1,127,252	262,643	3,439,970
2005	2,239,017	10,411	1,365,322	203,709	3,818,459
2006	1,895,266	11,270	1,333,647	205,163	3,445,346
2007	1,602,581	11,950	937,036	232,580	2,784,147
2008	1,188,403	38,429	316,273	622,362	2,165,467
2009	968,504	62,131	213,630	829,285	2,073,550
2010	914,976	54,886	182,426	719,424	1,871,712
2011	912,571	48,881	210,650	611,955	1,784,057
2012	1,082,008	43,989	280,879	615,374	2,022,250
2013	1,329,526	49,523	376,170	600,442	2,355,661
2014	1,418,481	54,700	443,439	630,712	2,547,332
2015	1,531,175	70,153	499,260	822,232	2,922,820
2016	1,622,953	72,853	587,416	868,204	3,151,426
2017	1,719,294	79,298	616,764	808,266	3,223,622
2018	1,795,566	70,420	687,769	697,398	3,251,153
2019	1,842,188	77,513	736,883	791,944	3,448,528
2020	1,990,223	69,469	801,746	822,658	3,684,096
2021	2,366,697	87,604	749,341	782,513	3,986,155
2022	2,069,905	95,364	592,133	665,339	3,422,741
2023	1,558,491	85,216	450,148	603,220	2,697,075
Total	39,380,676	1,240,406	15,484,049	14,611,930	70,717,061

This table reports, by year, the number of transactions in each of the four mutually exclusive and collectively exhaustive categories comprising our final dataset of mortgage-financed ownership transfers. Detailed definitions of these transaction types are provided in Section 3.1.

Table A5: Summary Statistics

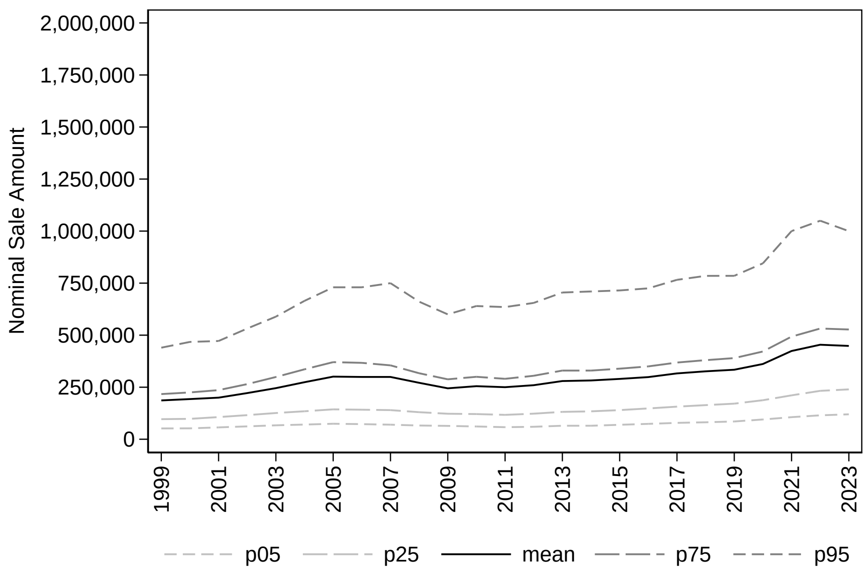
	Mean	Std Dev	10^{th} Pctile	25^{th} Pctile	75^{th} Pctile	90^{th} Pctile	Count
Loan Characteristics							
Combined Loan-to-Value Ratio	0.862	0.152	0.700	0.800	0.982	1.000	70,717,061
FHA or VA Guaranteed (=1)	0.224	0.417	0.000	0.000	0.000	1.000	70,717,061
ZIP Code Characteristics							
GNMS Gamma	1.044	0.580	0.388	0.553	1.399	1.639	66,067,050
AGI Per Capita, 1998	$47,855	$30,096	$27,821	$33,049	$53,708	$71,967	68,166,883
Lender Characteristics							
New Lender (=1)	0.024	0.154	0.000	0.000	0.000	0.000	68,571,704
Property Characteristics							
Square Footage	1894	1554	1015	1276	2270	3024	66,752,974
House Age	34	29	2	11	50	74	65,061,859

This table summarizes the final sample of mortgage-financed ownership transfers. Sample restrictions are described in Section 3.1, and loan characteristic definitions are provided in the main text. GNMS gamma, a measure of local house price sensitivity, is sourced from Guren et al. (2021). Adjusted Gross Income (AGI) per capita for 1998 is obtained from publicly available IRS data. A transaction is classified as involving a new lender if the lender on the first-lien mortgage is first observed in our data at some point in the preceding three years. Property characteristics are drawn from CoreLogic assessor files and reflect the most recent observation available for each parcel.

Figure A1: Sale Prices, Full Sample

Panel A plots the distribution of nominal house prices for the sample of transactions defined in Section 3.1 and described in Table A4 and Table A5. Panel B presents estimates from a standard house price index regression, in which house prices are regressed on year and property fixed effects. The figure plots the estimated year effects along with their corresponding confidence intervals.

Panel A. The Distribution of Nominal Sales Prices over Time



Panel B. Repeat-Sales Home Price Index

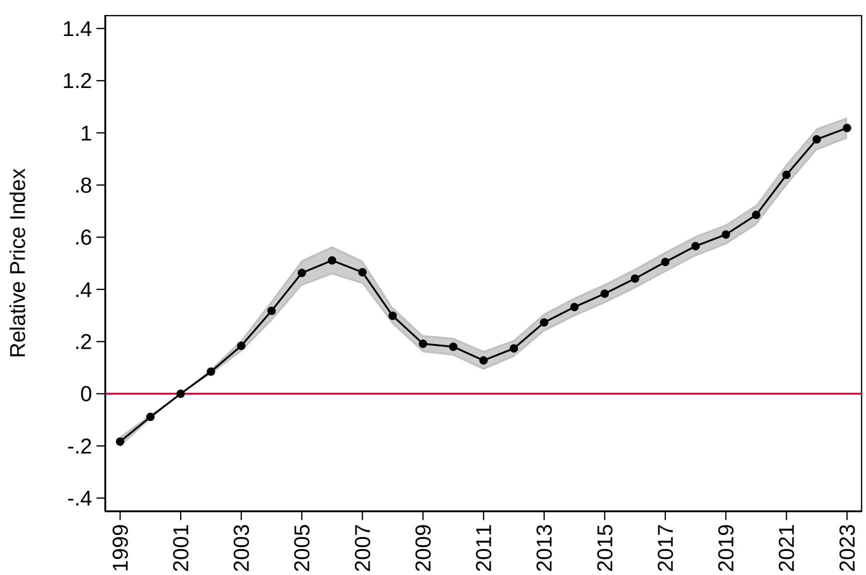
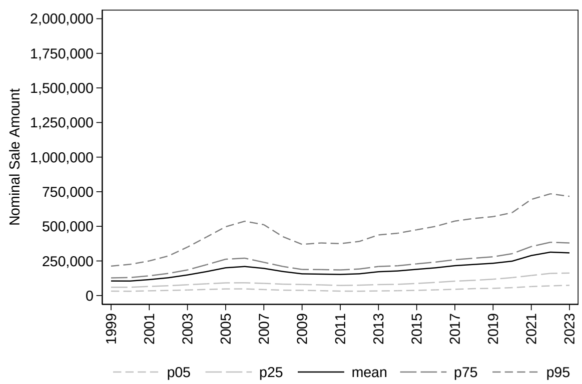


Figure A2: Low vs High Income Areas

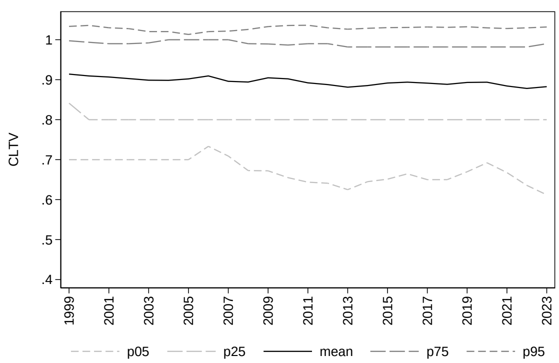
To create this figure, we split the sample used to create Figure 1 into five quintiles of 1998 adjusted gross income defined at the ZIP code level. The lowest income quintile is used in Panels A, B, and C and the highest income quintile of the sample is used in Panels D, E, and F.

Low Income

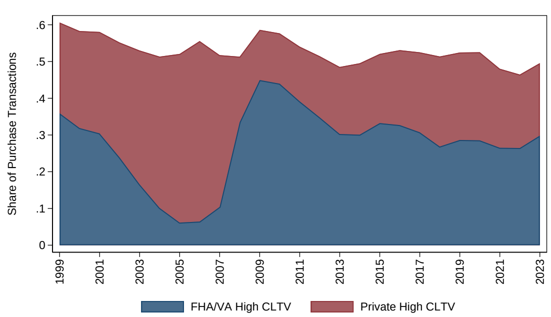
Panel A. House Price Distribution



Panel B. CLTV Distribution

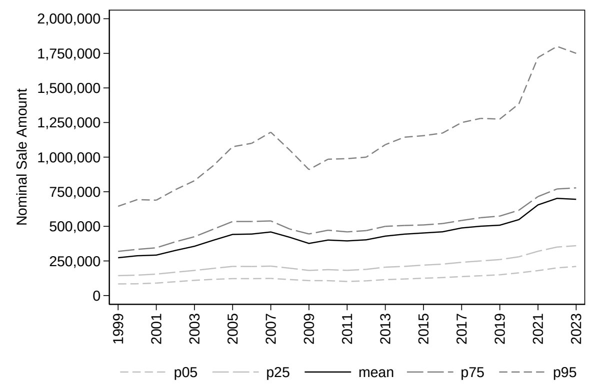


Panel C. FHA Share

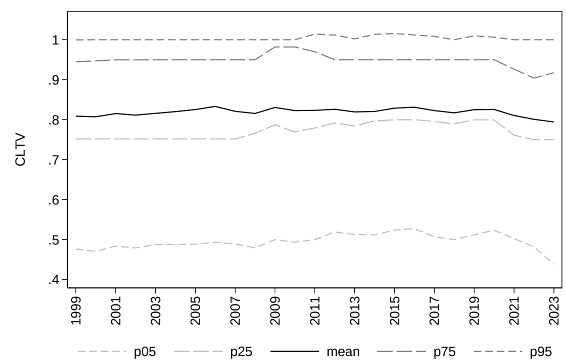


High Income

Panel D. House Price Distribution



Panel E. CLTV Distribution



Panel F. FHA Share

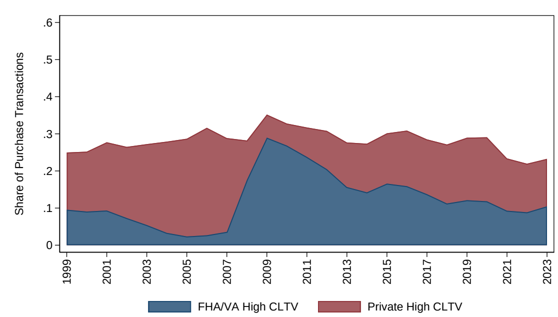
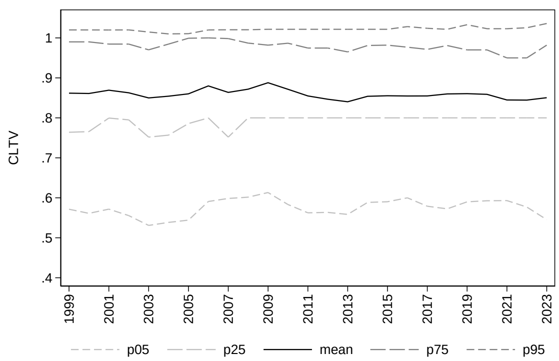


Figure A3: New vs Established Lenders

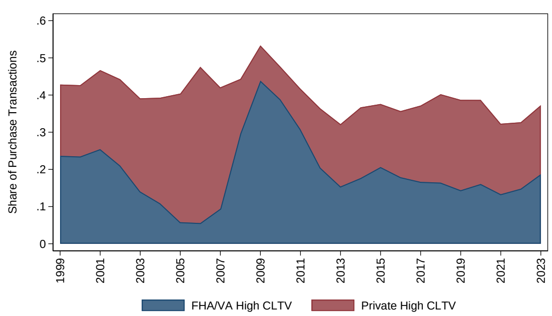
To create this figure, we split the sample used to create Figure 1 based on the age of the lender. Loans originated by lenders whose first loan is recorded in the most recent three years are used to create Panels A and B. Loans whose lenders made their first loan 3 or more years ago are used in Panels C and D.

New Lenders

Panel A. CLTV Distributions

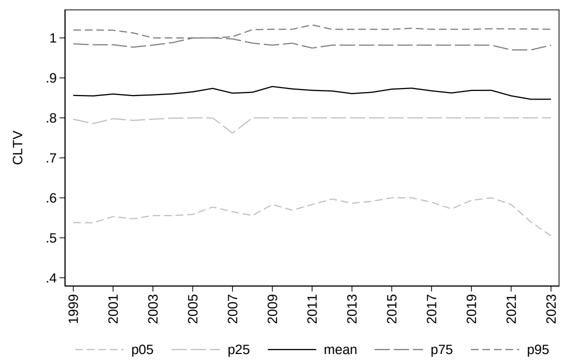


Panel B. FHA Share



Established Lenders

Panel C. CLTV Distributions



Panel D. FHA Share

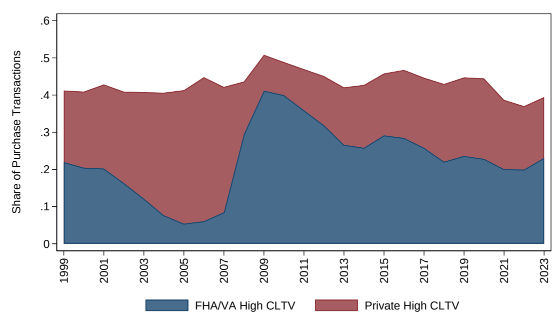
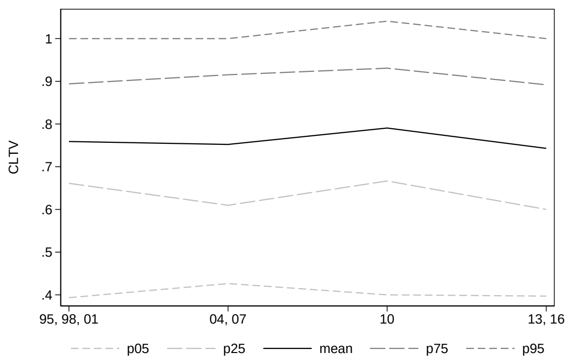


Figure A4: Pessimists vs Optimists

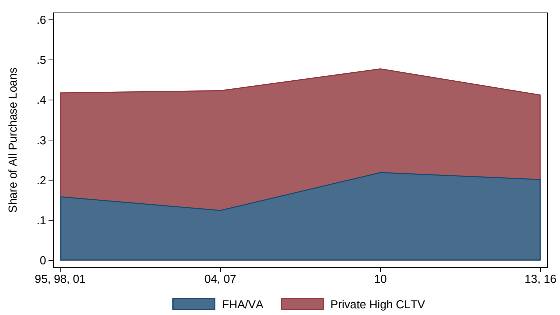
To create this figure, we split the SCF sample described in Section 3.3 into five quintiles of optimism as defined by Puri and Robinson (2007). The bottom quintile is used in Panels A and B and the top quintile of the sample is used in Panels C and D.

Pessimists

Panel A. CLTV Distributions

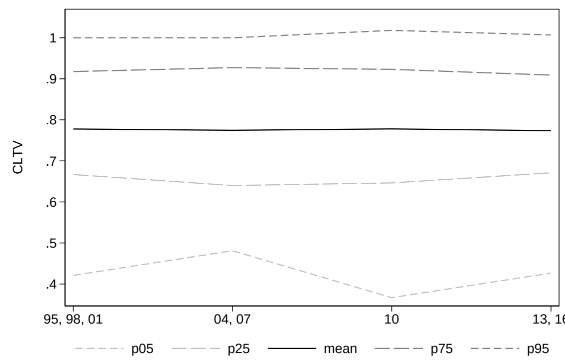


Panel B. FHA Share



Optimists

Panel C. CLTV Distributions



Panel D. FHA Share

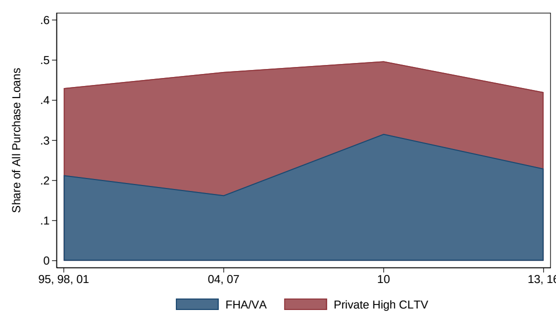
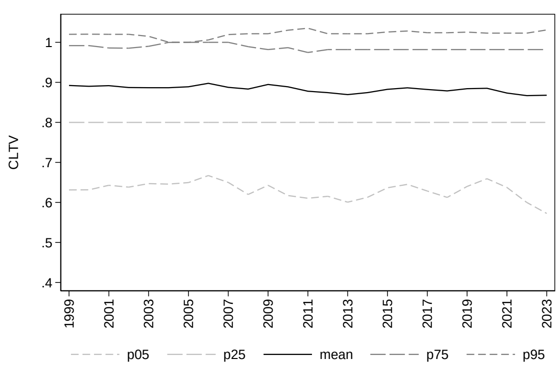


Figure A5: Small vs Large Homes

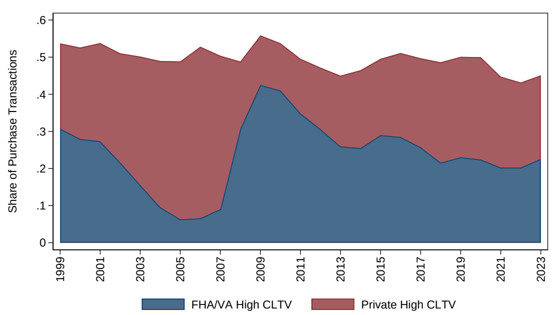
To create this figure, we split the sample used to create Figure 1 based on the size of the house. Homes with 1300 or fewer livable square feet are used to create Panels A and B. Homes with 2300 or more livable square feet are used in Panels C and D.

Small Homes

Panel A. CLTV Distributions

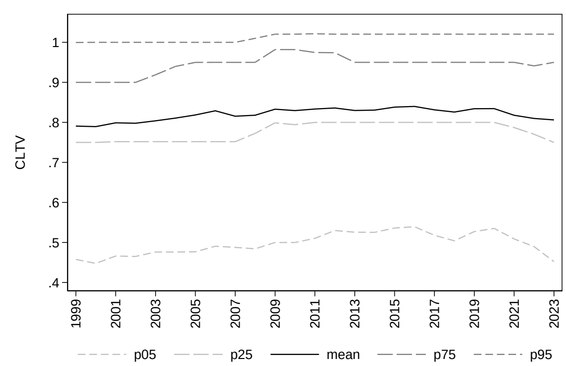


Panel B. FHA Share



Large Homes

Panel C. CLTV Distributions



Panel D. FHA Share

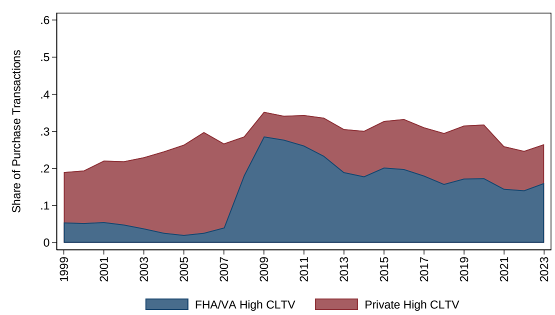
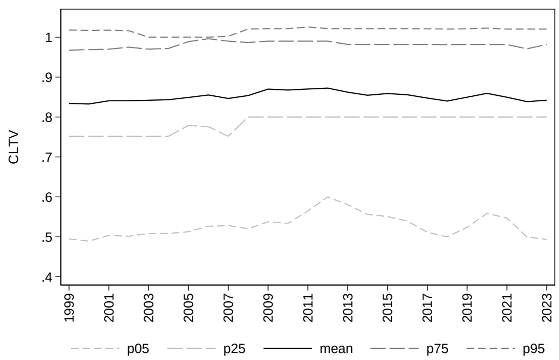


Figure A6: Young vs Old Homes

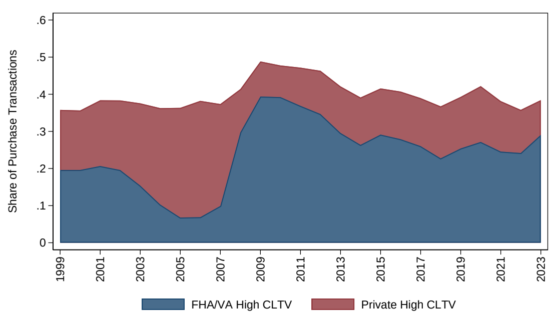
To create this figure, we split the sample used to create Figure 1 based on the age of the house. Homes constructed in the last two years are used to create Panels A and B. Homes built 20 or more years ago are used in Panels C and D.

Young Homes

Panel A. CLTV Distributions

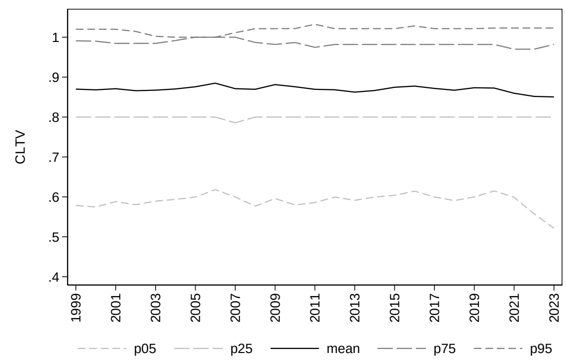


Panel B. FHA Share



Old Homes

Panel C. CLTV Distributions



Panel D. FHA Share

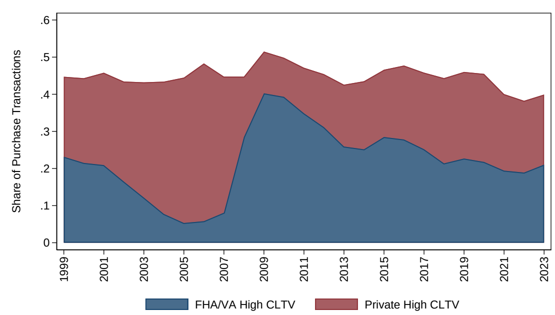
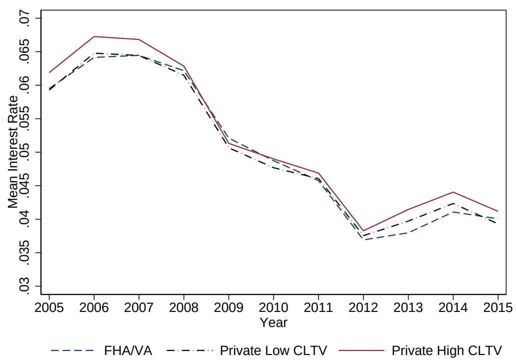


Figure A7: Excluding Loans with Non-missing Payment-to-Income and Non-missing Credit Score

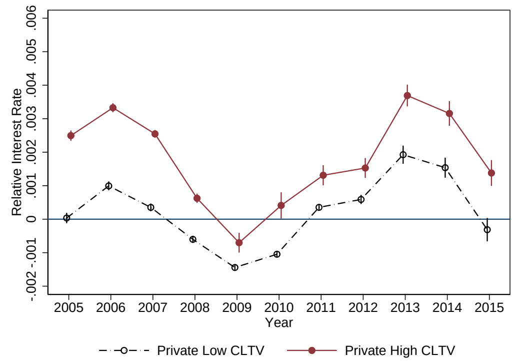
These figures are analogous to those presented in Figure 4, except these use just the sample of mortgages with non-missing payment-to-income and non-missing credit scores.

Panel A. Original Interest Rate

(i) Unconditional

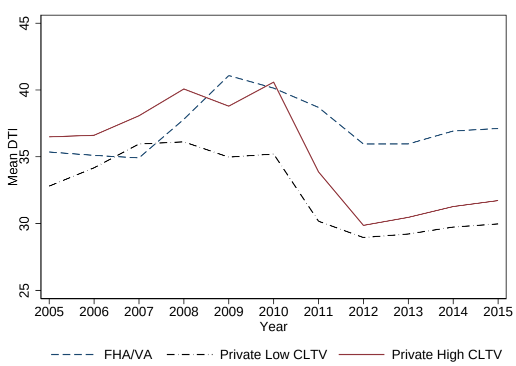


(ii) Within County-by-Year

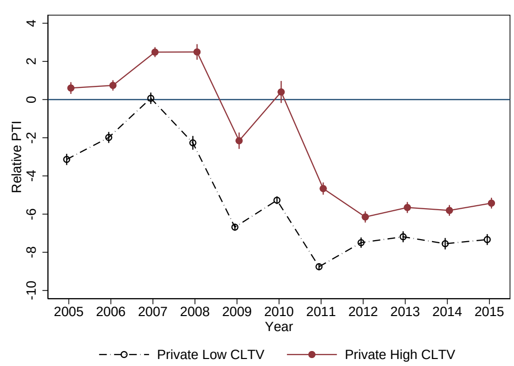


Panel B. Payment-to-Income Ratio

(i) Unconditional

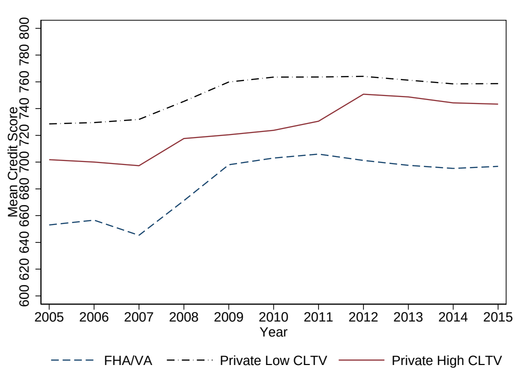


(ii) Within County-by-Year



Panel C. Credit Score

(i) Unconditional



(ii) Within County-by-Year

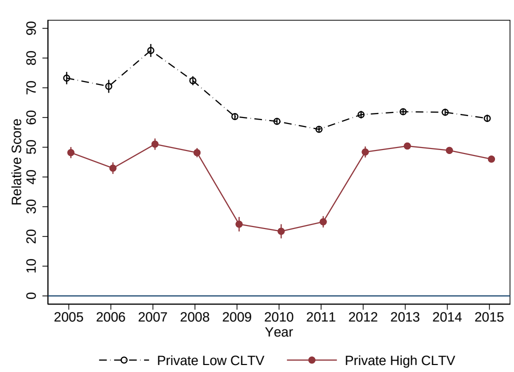


Figure A8: Including Adjustable-Rate Mortgages

These figures are analogous to those presented in the first panel of Figure 4, except these include adjustable-rate mortgages.

Panel A. Original Interest Rate

(i) Unconditional (ii) Within County-by-Year

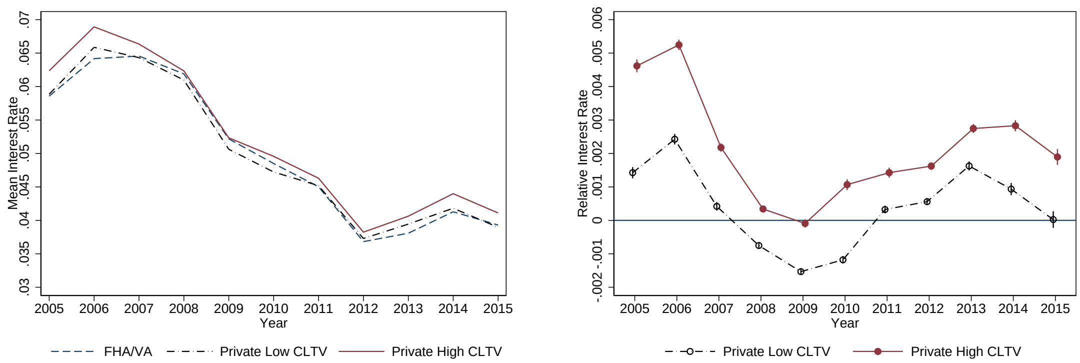
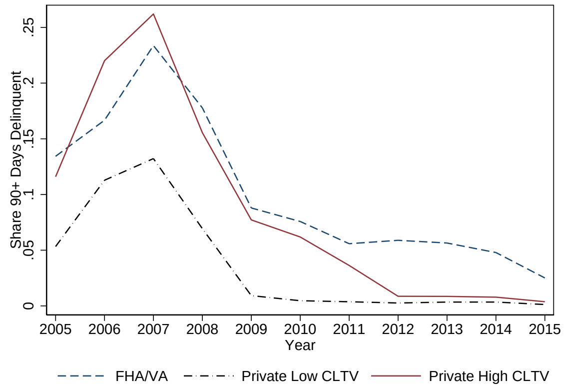


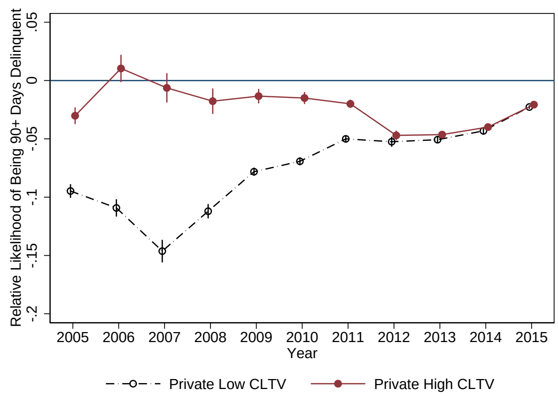
Figure A9: Excluding Loans with Non-missing Payment-to-Income and Non-missing Credit Score

These figures are analogous to those presented in Figure 5, except these use just the sample of mortgages with non-missing payment-to-income and non-missing credit scores.

Panel A: Unconditional Delinquency Share



Panel B: Within County-by-Year



Panel C: Full Credit Scoring Model