The Role of Government and Private Institutions in Credit Cycles in the U.S. Mortgage Market*

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Abstract

The fraction of mortgages with very high combined loan-to-value (CLTVs) ratios has been remarkably stable in the U.S. since 1995. But the *source* of high-CLTV loans changed from directly government-guaranteed mortgages through FHA and VA to private securitization during the boom of the 2000s and back to FHA/VA after 2008. This substitution holds within ZIP codes and properties and did not affect the composition of high-CLTV borrower types. Furthermore, both groups exhibited similar delinquency rates and the change followed local house price appreciation. These findings suggest that high-CLTV mortgages are a constant feature of the U.S. housing market.

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

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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 that lead to expansions and contractions in the amount of mortgage debt that households take on.[1] Understanding the exact nature of the credit expansion is key to explaining the role of finance in boom and bust cycles. Credit standards for mortgages can change along two dimensions. If contract enforcement is costly or limited, lenders impose loan-to-value (LTV) limits to ensure repayment and discourage strategic default (Rampini and Viswanathan (2010)). In addition, lenders impose debt-to-income (DTI) constraints to ensure that borrowers have the financial resources to make loan payments.

An influential literature in macroeconomics on the credit channel highlights the role of house prices in creating a multiplier feedback loop for asset values and the broader economy (see Bernanke et al. (1999) and Kiyotaki and Moore (1997)). Even without any change in LTV standards, higher asset prices allow borrowers to access more credit relative to their income. In contrast, a more recent theory literature on the leverage cycle proposes that LTV constraints themselves can become relaxed in a boom, which allows more optimistic buyers to bid more aggressively and drive up prices (see, for example, Geanakoplos (2010)).[2]

In this paper we show that the leverage cycle in the U.S. mortgage market is significantly affected by implicit and explicit government guarantees for very high LTV credit. While loan sizes at origination vary significantly with the housing cycle (driven by changes in house values), the distribution of combined LTV (CLTV) ratios has been remarkably stable over the last two decades, including the fraction of very high CLTV loans.

Prior research has shown that DTI ratios rose significantly during the housing boom of the early 2000s across the whole income distribution (Adelino et al. (2016, 2017), Foote

[1] Recent work has shown that credit expansions often precede financial crises (Greenwood et al., 2020; Krishnamurthy and Muir, 2017; Mian et al., 2017).

[2] See Greenwald (2018) for an analysis of how LTV and DTI constraints differentially affect house price cycles and monetary policy transmission.

et al. (2016), Foote and Willen (2018), and Albanesi et al. (2019)). This increase in DTI did not go hand in hand with a relaxation in LTVs (Glaeser et al. (2012), Ferreira and Gyourko (2015) and Adelino et al. (2018)). In this paper we show that this remarkable stability in the distribution of CLTV ratios is explained by a significant shift in the *sources* of high CLTV loans. Even before the housing boom, U.S. households could obtain very high CLTV loans (above 95% CLTV) via directly government-backed mortgages from the Federal Housing Administration (FHA) and the Department of Veterans Affairs (VA).[3] During the boom of the 2000s, high CLTV loans shifted from FHA/VA to private lenders. And post-2008 these high CLTV loans go back to being originated with FHA and VA guarantees. While the share of privately securitized high-CLTV loans for home purchases increased substantially during the housing boom (in line with the findings in Pinto (2010) and Keys et al. (2012)), we show that these mortgages *replaced* one-for-one the share of equally high (or higher) CLTV loans backed by the FHA and VA. As a result, aggregate CTLV ratios at origination remained stable over the boom and bust period.[4]

We next document that the shift in the source of high-CLTV loans during the boom did not change the *composition* of borrowers that were able to access high-CLTV loans. Even with stable CLTVs during these two decades, one might worry that stability in the aggregate could mask significant variation in the types of borrowers or properties that obtained high-CLTV loans. We find that the borrower-quality adjusted CLTVs did not change over time. In fact, high-CLTV loans are used by similar borrowers and for very similar housing collateral over time. It is just the source of the high-CLTV funding that shifts, switching between FHA/VA and privately guaranteed.

We first show that there was very limited reallocation of high-CLTV loans across ZIP

[3](Foote et al. (2012) discuss the use of these government-backed very low down payment loans in the post World War II era)

[4]This paper focuses on CLTVs at the time of home purchase to analyze the role of access to finance in house price formation. Doing so also alleviates the concern of potential bias in appraisals that would affect measurement of CLTV for refinances. Earlier papers have shown that households borrowed heavily against the increase in house prices, increasing *current* LTVs (Mian and Sufi (2011), Justiniano et al. (2015)), and consumed out of the increased borrowing (Campbell and Cocco (2007), Mian et al. (2013)).

codes over time. The ZIP codes with a high share of FHA and VA loans in the early 2000s were the same ones in which the high-CLTV private loan share expanded rapidly post-2002 and crowded out FHA/VA loans. These same ZIP codes saw FHA share surge post-2008. This is also true when we look across areas with high and low house price appreciation and recourse or non-recourse states. In all cases, we confirm that there was no reallocation of high-CLTV loans from some parts of the country to others.

Second, the type of collateral backing purchase transactions did not change over the cycle. The distribution of age and size of houses purchased with FHA/VA versus private, high-CLTV loans was very similar over time. In addition, we use a novel application of the repeat-sales methodology (Case and Shiller, 1989) to show similar stability in the use of high-CLTV loans even within properties over time. The same properties are financed with high-CLTV loans from the different sources throughout the whole sample period.

Third, we look at the purchase decisions of individual households to better understand if borrowers using high-CLTV, government loans pre-boom were different from those using privately provided, high-CLTV loans during the boom. We track the borrowing decisions of specific households in North Carolina that move within their county. Consistent with the ZIP code and property-level evidence, households who used FHA or VA loans between 1996 and 2003 are much more likely to use private-sector loans with CLTVs ≥ 95% during the 2004-2007 period, and then to switch back to FHA-VA loans after the boom.[5]

To rule out the possibility that the places or borrowers who used private-sector, high-CLTV loans were unobservably different from those using FHA and VA loans on dimensions not captured above, we also look at ex post loan performance. If private lenders were taking on hidden risks, we would expect to see differences in delinquency. In contrast, we show that loan delinquency rates for the two groups of high-CLTV loans were indistinguishable

[5] A key feature of models of leverage cycles, Geanakoplos (1997, 2010), is that high-CLTV loans allow more optimistic buyers to bid up asset prices. We find that more optimistic home buyers do not change their choice of high-CLTV loan sources over the boom. We measure a person's optimism using her forecast life expectancy relative to observed characteristics as in Puri and Robinson (2007). The fraction of optimists with high-CLTV loans from private and government-guaranteed sources did not change significantly over time.

from each other controlling for the usual loan characteristics. We also show that the DTI of FHA and private, high-CLTV borrowers is very similar even at the peak of the boom.

In the final part of the paper, we investigate whether the switch in the provision of loans from FHA/VA to private sources might itself be a driver of the house price cycle. We show that the shift to privately supplied high-CLTV loans *followed* the growth in house prices but did not lead it. Therefore, the areas where prices rose the most saw higher prices *before* the increase in private high-CLTV share (consistent with the results in Ferreira and Gyourko (2011)). We also use the house price instrument developed by Palmer (2015) and Guren et al. (2018) to isolate house price changes that are not driven by credit expansion. Using this methodology, we find that, as before, house prices increased first and were followed by a switch from FHA/VA to private high-CLTV loans.

Similarly, we show that this switch from FHA to privately-held high-CLTV mortgages happened even *within* existing lenders. The majority of high-CLTV private loans made during the housing boom were made by lenders that previously were providing FHA/VA loans in the same areas. Loans made by new lenders had similar CLTVs to those made by extant lenders and both new and continuing lenders switched away from FHA and VA mortgages to private-sector, high-CLTV loans at similar rates and at the same time.

In sum, 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. However, what changed dramatically was who was holding this risk in the economy. This has important implications for the functioning of the financial sector and the economy overall, as we saw after the burst of the housing bubble. Why did borrowers switch from FHA to privately originated high-CLTV loans? The literature generally suggests that borrowers switched away from the FHA because of its laborious processing requirements (GAO, 2007; Kogler et al., 2006), since, especially in hot real estate markets, borrowers value the quicker closing time and easier documentation of the private sector loans (see LaCour-Little (2007) and Wei and Zhao (2020) for evidence on closing times for privately securitized loans). But a better understanding of what drove borrowers to switch from the FHA to the private sector remains an important area for future work.

Our results raise important questions about how to model credit cycles in the U.S. mortgage market. Highly levered loans were available throughout the last two decades, suggesting that the housing boom and subsequent financial crisis cannot be explained by changes in aggregate purchase CLTVs. Instead, credit expanded in proportion to rising house prices and DTI ratios increased across the population. Our results suggest that the dynamic of the U.S. housing market is in line with models that rely on changes in collateral values (credit cycle models) or broad changes in house price expectations. An influential early literature on credit cycles going back to Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) emphasizes the role of collateral values in creating a multiplier-accelerator feedback channel in models with limited enforcement.[6] Since firms and households are constrained in how much they can borrow by the value of their assets, an increase in asset values makes it easier to borrow, which improves the productive use of the asset, and, as a result, increases asset values even further. In these models, credit facilitates house price increases but does not cause them.

A recent literature on the leverage cycle, see Geanakoplos (1997, 2010), suggests that pro-cyclical fluctuations in LTV ratios can be a causal driver of boom-bust cycles in credit markets. The idea is that when volatility is low for an extended time period, lenders might allow higher LTV ratios because they feel more secure stretching the available collateral. If there is a class of buyers who value the asset more highly than others, the relaxation in LTV constraints allows these borrowers to bid prices up. Several recent papers have used changes in the LTV constraint as a modeling device for the credit expansions of the early 2000s (Corbae and Quintin, 2015; Favilukis et al., 2017; Landvoigt et al., 2015), although Hornstein (2009) argues that a general equilibrium model of demand for housing with collateral constraints has a hard time matching the observed house price dynamics.

[6] See Guerrieri and Uhlig (2016) for a review of the literature exploring how credit cycles interact with cycles in house prices.

Our results show that the leverage cycle was muted in the U.S. given the specific nature of U.S. mortgage markets, in particular by the fact that high-CLTV loans with explicit government backing were available even before the boom. Some models may use looser CLTV limits as a "stand-in" for a broader relaxation of credit constraints, possibly through higher DTI ratios or weaker documentation requirements. But existing work suggests that different constraints bind in different states of the world and have different effects when they do (Greenwald, 2018). Our results highlight the importance of considering the type of intermediary providing the riskiest kinds of loans, and their potential implications for financial stability.

Our work is also related to papers that have looked at the time series of average LTVs in the U.S. population and found stable averages over time. Glaeser et al. (2012) show that 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 lenders. Another set of studies has looked specifically at private-label mortgage-backed securities using data from CoreLogic. Demyanyk and Van Hemert (2009), Keys et al. (2012), and Gerardi et al. (2008) document the increase in CLTVs for privately securitized mortgages in the early 2000s. Pinto (2010) shows that the share of mortgages purchased by Fannie Mae and Freddie Mac using CLTVs above 97% increased from 5% in 1996 to 40% in 2007.[7] We build on this prior work by analyzing the substitution effects between FHA/VA guarantees and private sector securitization in supplying high-CLTV loans and its impact on house prices across the distribution of households and properties.

[7]The 2009 FHA Actuarial Study is available here: https://www.hud.gov/sites/documents/DOC_16571.pdf. The actuarial study includes refinance loans and imputes the values for those properties when calculating its LTV ratios. This imputation may lead to measurement error in CLTVs (Aragon et al., 2010).

2 Institutional Detail and Data Description

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-income, middle-income, and first-time homeowner households for FHA and military families for 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 has some proof of employment. 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."[8] Kim et al. (2018) provide an in-depth look at the current origination of FHA and VA mortgages, including the institutional details of this market and the role of non-bank mortgage companies. 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).

Securities backed by FHA loans are guaranteed by the U.S. government through the Government National Mortgage Association (Ginnie Mae), while the VA provides partial guarantees, and servicers provide the rest. Ginnie Mae provides additional residual protection in case servicers default. Fannie Mae and Freddie Mac (other government-sponsored

[8]See https://www.hud.gov/hudprograms/Ginnie_Mae_I, accessed August 1, 2019.

entities) purchase loans from the issuing lenders and then securitize mortgages they purchase. Ginnie Mae, in contrast, gives lenders approval to issue securities with a guarantee, and then guarantees bondholders timely payment of principal and interest. The lenders themselves then package their government-guaranteed loans into mortgage-backed securities. Any losses are first covered by the equity that a borrower may have in the home, and then by the insurance premiums the FHA requires borrowers of its guaranteed loans to purchase. Further losses are covered by servicers themselves and, if servicers are not able to make these payments, ultimately payment is guaranteed by the U.S. government.

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.

2.1 Data sources

We require a data set that satisfies three requirements. First, it must include every loan (including second and third mortgages) that the borrower used to finance the purchase of their home. Figure A1 shows the incidence of second and third liens over time in the data and their changing importance over the time series. Second, the data must include a value of the home at the time the mortgage was originated. Third, the data set must include the universe of mortgages, and not just those packaged in private-label securities or originated by one bank. The deeds data, kept in county recorder's offices and then collected and published by data company CoreLogic, meet all three of these criteria.[9]

[9] Our final sample includes all mortgages used to finance purchases of single-family residences, condos, apartments, and duplexes, triplexes, and quadplexes. We omit transactions where CoreLogic flags the buyer as a corporation or business. CoreLogic does not allow us to identify investors or flippers, but previous work shows

In this project, we focus on purchase transactions. An important limitation of the deeds data—and indeed almost every data set on mortgages-—is that measures of value are only reliable at the time of purchase. By using the actual sale value of the home, we assuage concerns about bias in appraisal values (which would affect measured CLTVs for refinance loans (Agarwal et al., 2015), (Kruger and Maturana, 2020)). One potential solution is to use data from a lender as in Bernstein (2018), but then we no longer observe the universe of loans.

In the deeds data, we cannot observe the income or credit scores of the borrowers. To answer questions that require credit scores and income, we use 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. We then estimate original CLTV by matching McDash's first mortgages to Equifax's second mortgages taken by the same person at the same month.

As a final source of data on mortgage debt, house value, and borrower income, the paper uses the 1998 through 2016 waves of the Federal Reserve Board Survey of Consumer Finances (SCF). 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 use these data to construct a DTI measure that includes all payments

that investors' CLTVs are similar to CLTVs used by the population of borrowers conditional on a mortgage being used (DeFusco et al., 2020; Haughwout et al., 2011).

for all mortgage-related debt, as well as questions about personal beliefs that allow us to extract a measure of individual optimism.

3 High-CLTV Mortgages over the Cycle

Using the deeds data for all U.S. counties covered by CoreLogic, we calculate the CLTV of every purchase loan and whether that loan was an FHA- or VA-guaranteed loan. The CLTV is defined as follows: We sum the mortgage amounts for each house purchase, up to three mortgages, and then divide that sum by the sale price.

3.1 Stability of the aggregate CLTV and the role of government-guaranteed loans

We show the evolution of CLTVs for all years in the sample in Figure 1. During this same period, house prices experienced a large run-up (up to 2005) and subsequent collapse and recovery. Even while house values and the frequency of new purchases changed dramatically over the time series (see Figure A3), the dollars of mortgage debt per dollar of housing collateral was very steady in the data. We obtain a very similar picture when we value-weight each loan (Figure A4). We exclude cash purchases from our main analysis, but we show those separately in Figure A2. In this figure, we see that transactions that did not use any leverage steadily increase during our sample period, from a level of about 5% early in the sample to over 20% of all purchases. This implies a steadily dropping aggregate average CLTV during the period if we include these transactions. Since we are interested in the role of government guaranteed debt in the mortgage market, we largely ignore these transactions.

Panel A of Figure 2 shows the cumulative distribution function of CLTVs at purchase for all purchase mortgages originated in 1999 (dashed line) and 2006 (solid line). The distributions in 1999 and 2006 are remarkably similar. In 1999, 68% of all mortgages had CLTVs strictly less than 95%, and this share hardly moves in 2006 when 66% of loans had CLTVs under 95%. The steadiness of the CLTVs documented in the figure masks large changes in the source of high-CLTV loans. Panel B of Figure 2 illustrates the large increase in aggregate CLTVs of private-sector loans, particularly those with CLTVs above 95%. This increase is shown as a share of all loans in the top panel of Figure 3. The share of private-sector loans with CLTVs ≥ 95% increases from less than 10% of all origination to nearly 30% of all purchase loans at the height of the housing boom in 2006.

How can the share of such high CLTV mortgages have increased so dramatically with no contemporaneous increase in the distribution of CLTVs? The answer becomes clear in Panel B of Figure 3, which plots the share of all purchase loans guaranteed by the FHA and the VA that also had CLTVs ≥ 95%. What this figure shows is that the share of all loans (both government guaranteed and private-sector) with CLTVs ≥ 95% hardly budged during the housing boom.

Figure A5 provides another look at the role of government guaranteed loans in the mortgage market. To create this figure we classified loans into one of five types. FHA- and VA-guaranteed loans with CLTV either below or above 95%, and then all other loans. The key takeaways from this figure are twofold. First, as seen in Panel B of Figure 3, the share of loans guaranteed by FHA or VA dropped from 25% before the boom to about 5% during the boom and then up to nearly 50% of all purchase loans in 2010. The second takeaway is that almost all of the loans guaranteed by these two programs are very high CLTV loans. In no year are fewer than 90% of FHA- and VA- insured loans mortgages with CLTVs of at least 95%.

4 Stable Composition of High-CLTV Loans

Section 3.1 shows that the share of purchase loans with high CLTV ratios did not change over the time series, nor did the overall distribution of CLTVs. Despite wildly changing house prices and dramatic shifts in purchase and mortgage origination activity, the debt capacity of housing did not change. What did change was the share of high-CLTV loans explicitly guaranteed by the government through the FHA and VA programs. This section of the paper asks an important follow-up question: Were the high-CLTV loans guaranteed by the government before the boom and displaced by the private-sector in the boom going to the same types of borrowers? Or does the steadiness of the CLTV distribution mask shifts in where and to whom the high-CLTV loans were going?

4.1 Steady high-CLTV utilization within geographies

The first panel of Figure 4 plots ZIP codes with at least five purchase transactions with mortgages in both 1999 and 2006. The figure shows a positive relationship between the share of loans that were in 1999 guaranteed by either the FHA or the VA and the increase between 2006 and 1999 of the share of private-sector high-CLTV loans. The correlation between these two variables is .464 and demonstrates that, within 5-digit ZIP codes, knowing the importance of government-guaranteed loans in the mortgage market is strongly predictive of the share of the 2006 cohort of purchase loans that will be private-sector high-CLTV loans. This result helps to rule out the possibility that the steadiness of the CLTV distribution is masking shifts in the geographic distribution of high-CLTV loans. For example, it could have been that high-CLTV, government-guaranteed loans were going to some parts of the country in 1999 (ZIP codes not in the sand states of AZ, CA, FL, and NV), and then, during the boom, the private-sector's high-CLTV loans were all made to borrowers buying homes in the sand states. But this is not consistent with the results in Panel A of Figure 4.

Panel B of the figure moves along the time series and plots an analogous scatter plot comparing the increase in share of purchase loans insured by the FHA or the VA during the recovery to the share of loans that were in 2006 high-CLTV, private-sector mortgages. As before, we document a strong correlation consistent with the idea that ZIP codes are switching their source of high-CLTV loans from the government, to the private sector, and then back to the government.

We next use publicly available IRS data from 1998 to divide ZIP codes into ten population-weighted deciles of adjusted gross income. To create Figure 5, we compute the share of purchase loans in each income decile that are FHA/VA and private, high-CLTV. We compute these shares at three different points in time: pre-boom (1999), boom (2006), and post-boom (2013). There are three key takeaways from this figure. First, there is a downward trend in the use of high-CLTV mortgages as income increase. Second, this downward trend stays roughly the same over the whole time series. That is, within each income decile over time, the share of purchase loans that are high-CLTV remains similar. Third, in contrast to the smoothness of the first two takeaways, within each income decile over time, the share of high-CLTV loans that are government guaranteed goes from almost all of them, to almost none of them, and then back to almost all of them.

Rather than dividing ZIP codes by income, we next split the country's ZIP codes into ten deciles based on house price growth between June 2002 and June 2006. In Figure A6, we use the same methodology used to create Figure 1 for the bottom two HP-growth deciles and again for the top two deciles. If CLTVs were steady overall, but higher in high-HP growth areas and lower in low-HP growth areas, this figure would reveal this pattern. We find this is not the case. In both cases, the distributions are very steady.

Finally, we split the United States into recourse states and non-recourse states. Figure A7 again shows a steady-CLTV picture within both recourse and non-recourse states. This suggests that the dynamics of collateral rates were not very affected by creditors' ability to pursue legal action against defaulting borrowers.

4.2 Property characteristics by loan type

Despite the results above, it is possible that the quality of the collateral backing FHA and private loans could be very different, so that different loans were used to purchase different types of properties. In this section, we look at two characteristics – home age and home size – of all properties traded over the time series. For two samples, the sample of homes purchased using FHA-guaranteed loans and the sample of homes purchased using private, high-CLTV loans, we calculate the distribution of age and square footage. We plot these distributions in Figure 6 demeaned at the ZIP-by-year level. We find that the characteristics of homes financed using high-CLTV loans were similar over the time series, inconsistent with a world where the provision of CLTV-credit changed dramatically during the boom. One exception is that homes financed with FHA-guaranteed loans became relatively larger during the recovery, possibly due to an increase in the maximum loan limit. This makes sense since the private, high-CLTV market all but disappeared, and the FHA became the only source of high-LTV loans for all homes, not just small ones.

4.3 Within-property analysis

In order to rule out the possibility that unobservable geography-related characteristics might be changing despite the stable CLTVs, we consider a sample of properties that traded both pre-boom and during the boom or both during the boom and the recovery period.

Figure A8 shows a repeat-sales index of LTVs constructed using the same methodology employed for measuring house prices over time (see, for example, Case and Shiller (1989)). The figure shows that, within the same properties, changes in LTVs over time vary within a band of 4 percentage points and are, if anything, inversely related to house price movements.

Next, we employ a different repeat-sales methodology to answer the question of whether switching between private and public sources of high-CLTV loans occurred within properties. Our specification asks what the relationship is between the likelihood a property is purchased with a high-CLTV private-sector loan during the boom if it was financed with a government-guaranteed loan (FHA or VA) when purchased pre-boom. We run regressions of the following form for each property i:

$$\textit{High-CLTV}_{i,2004-2007} = \textit{Govt Guarantee}_{i,1996-2003} + \eta_t + \eta_{t+1} + \eta_{County} + \varepsilon_i, \tag{1}$$

where η_{County} represents county fixed effects to absorb differences across the country in average use of government-guaranteed mortgages, and η_t and η_{t+1} represent year fixed effects for the first and second transactions to absorb overall changes in the rate that borrowers used different types of loans over time.

We present some simple summary statistics in Table 1. We show that, among loans taken out in the period 2004-2007 for this sample, 24% ((379,697 + 193,464) / (2,362,806)) were private, high-CLTV loans. Of properties financed with FHA/VA loans during the pre-boom, 33.1% of them are financed with high-CLTV private loans during the boom, compared to just 21.4% of properties that were not financed with government-guaranteed loans pre-boom.

The first column of Table 2 estimates the model in Equation 1 on the more than two million properties across the United States that were purchased by one household at some point between 1996 and 2003 (pre-boom) and by a different household between 2004 and 2007 (boom). We restrict the sample to properties where both trades were at arm's length and the buyer financed the purchase with a mortgage. We find a statistically significant and economically meaningful relationship. A property is 11.4 percentage points more likely to be purchased with a high-CLTV private mortgage if the property was purchased pre-boom with a government-guaranteed loan (comparable to the unconditional results in Table 1).

We run an analogous regression for the crisis and recovery period, focusing on those properties traded first during the boom and then again during the recovery (2008-2015):

$$\textit{Govt Guarantee}_{i,2008-2015} = \textit{High-CLTV}_{i,2004-2007} + \eta_t + \eta_{t+1} + \eta_{County} + \varepsilon_i. \tag{2}$$

The results are presented in the second column of Table 2 and are qualitatively very similar to the pre-boom to boom test. In short, even at the property level, we document a striking switching between government-guaranteed, high-CLTV mortgages and high-CLTV mortgages provided by the private-sector. While it can be argued that the ZIP code correlations might not be evidence of switching if the types of houses trading are dramatically different pre- and post-boom compared to during the boom, that same argument struggles to explain the results just presented, where the homes are not different, but, in fact, precisely the same.

4.4 High-CLTV loan choice by borrower types

We next turn to the characteristics of borrowers, including within-household analysis, DTI choice and loan delinquency. We start with a subsample of the deeds data within which we can track households as they move. To build this data set, we merge the North Carolina deeds data with the North Carolina voter registration records. The voter rolls data include the address of registered voters, and, if voters moves within county, their address is updated in their voter registration record. The results, presented in Table 3 and Table 4, are analogous to those in Table 1 and Table 2, except instead of focusing on properties that transact twice, we use borrowing households that borrowed twice to purchase two different properties.

As with the property switching results, the unconditional results for borrower switching presented in Table 3 tell the same story. Borrowing households that use government-guarantees for access to high-CLTV loans pre-boom switch to private, high-CLTV loans during the boom. And those households that first purchase during the boom and use high-CLTV, private mortgages switch to government-guaranteed mortgages post-boom. In North Carolina, 15.5% of households that did not use FHA or VA loans for their pre-boom mortgage used a high-CLTV, private mortgage during the boom compared to 27% of households who did. Similarly, the rate of using FHA or VA loans during the post-boom was 24.6% for those borrowers who used high-CLTV, private mortgages for the boom purchase, compared to a smaller 18% for borrowers who did not.

The sample used is small but still produces estimated effect sizes that are both statistically and economically significant. Looking at the first specification in Table 4, we see that borrowers are 11.3 percentage points more likely to use a private-sector loan with a high

CLTV if their pre-boom loan was FHA- or VA-guaranteed; 17.1% ((1,026 + 282) / (7664)) of in-sample purchase mortgages originated in NC during the boom were private, high-CLTV mortgages. So an 11.3 percentage point increase amounts to a 66% increase from the mean. The model estimating switching in the second half of the time series finds a 6.74 percentage point increase or 34.8%[10] increase from the mean.

In Figure 7, we consider how the DTI ratio of FHA loans compares to private high-CLTV loans of similar and higher credit scores at the peak of the housing boom (2005-2007). DTI is computed as the share of a household's income that goes toward mortgage and mortgage-related expenses (like insurance) and comes from the Credit Risk Insight Servicing McDash (CRISM) dataset. Panel A shows that FHA loans have a DTI of around 37%, measured as payments relative to the mortgage (including FHA insurance premia) as a share of monthly income. Panel B considers borrowers with a credit score below 660 and shows that those borrowers carry higher DTIs of around 39% to 40%. This is consistent with more aggressive lending standards by subprime lenders, particularly those who specialized in these types of loans. Middle- and high-credit score borrowers have either equal or lower DTI as FHA loans.

We obtain similar results when we consider the Survey of Consumer Finances data. We focus on recent movers (those who moved in the previous 2 years) and all mortgage-related payments. The results are in Table 5. We find that, on average, FHA loans are associated with lower DTI (measured as mortgage-related payments divided by income), but that this difference becomes smaller and insignificant in the boom. The interest rate between FHA and private, high-CLTV loans is also small and insignificant during the boom. Finally, FHA borrowers are more likely to state that the reason for choosing their loan was that this was the only loan they were able to qualify for, although, again, this difference decreases during the boom.

[10]Calculation: .0674/[(1,686 + 613) / (11,863)]

4.5 Loan and leverage choice by optimists and pessimists

In this section, we consider whether there was a change in how optimists and pessimists sorted into high-CLTV loans over the credit cycle. This analysis addresses one of the important mechanisms in Geanakoplos (2010), whereby buyers who value assets more bid up prices when they have access to more leverage. We follow the approach developed by Puri and Robinson (2007) to measure optimism based on self-assessed life expectancy from the Survey of Consumer Finances. After controlling for observable characteristics like age, education, and income, the size and sign of the residual allows us to sort people cross-sectionally into optimistic versus pessimistic types (see also Heimer et al. (2019)). It is important to note that this measure of optimism cannot capture longitudinal variation, i.e., we cannot ask whether the population overall becomes more or less optimistic over time. But the measure does pick up information about an individual's outlook in life, and it correlates with whether people think the economy will do well in the next year, which is something people do not have any control over (Figure A9).

We use this data for two purposes. First, we are interested in whether optimists were significantly more likely to take on high LTV loans during the boom.[11] Second, we look at changes in LTV, DTI inclusive of all mortgage payments (including mortgage insurance), current interest rate, and reason for choosing a loan.

We start by showing that the percentage of optimists taking on high LTV loans in the pre-period versus the boom did not change significantly (Figure A10). The highest two quintiles of optimism together make 45% of the high LTV loan prior to the boom and stay at 47% during the height of the boom. A similar picture emerges when looking at low LTV loans; again we do not see a strong dislocation of high-CLTV credit toward more optimistic borrowers.

In Figure 8, we break out the presence of optimists versus pessimists among FHA and

[11] Our focus is on the time series of LTV choice by pessimists and optimists. Bailey et al. (2019) consider LTV choice in the cross-section by these two groups using social network data from Facebook.

private high-CLTV loans. Interestingly, we find that optimists maintained stable proportions among these two types of loans. In Figure A11 of the Online Appendix, we show that the choice of high-LTV loans is more frequent for optimists across all income quintiles when we do a two-way split by optimism and income quintiles both in the pre-period and in the boom.

4.6 Performance of government-guaranteed and private, high-CLTV loans

In this section, we investigate the ex-post performance of high-CLTV loans guaranteed by the government versus those provided by the private-sector. If the two types of mortgages were not being used interchangeably by the same types of borrowers in the same types of places, we would expect to see differential delinquency rates. This is not what we find.

Figure 9 plots the share of loans of each type by origination-year cohort that are at some point 90+ days delinquent within three years of origination. As expected, private-sector loans with CLTVs $< 95\%$ have significantly lower delinquency rates than loans with CLTVs $\geq 95\%$, regardless of source. Strikingly, though, is the finding that within cohorts, the rates of delinquency for FHA/VA loans is the same as for private loans with CLTVs $\geq 95\%$. 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 DTI (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.

5 House Price Increases and High-CLTV Loan Source

One question that our results raise is whether the changes in the source of high-CLTV loans are merely correlated with the house price cycle or if there is a causal link between the two. While we cannot provide a definitive answer to this question, one natural approach is to ask which comes first – the change in house prices or the switch from FHA/VA to private sources for high-CLTV loans. We show the results of this analysis in Figure 10 and Table 6. In both cases, we find that the increase in house prices during the housing boom precedes the large increase in private high-leverage lending rather than the reverse.

Figure 10 sorts ZIP codes into deciles based on the house price growth between 2002 and 2006 and plots both house price growth and the change in private high-CLTV share at the ZIP code level. The three panels split the time period of 1999-2006 into three subperiods (the first four years and then 2003-2004 and 2005-2006). The figure shows clearly that changes in house prices were higher for the top deciles both in the beginning of the period and in the middle, whereas the changes in private high-CLTV share only sort on house prices strongly at the end of the period. While it is, of course, possible that prices rose in anticipation of looser credit, this simple analysis suggests that it is more likely that higher prices were, instead, the reason behind the reduction in FHA/VA share and the increase in the private high-CLTV segment (possibly because these allowed borrowers to participate in "hotter" markets). These results are consistent with Ferreira and Gyourko (2011) who show that increases in subprime lending happen *after* prices start rising more significantly in most neighborhoods in the U.S.

In Table 6, we use the same instrument developed in Palmer (2015) and Guren et al. (2018) to generate a cross-section of commuting zones (CZ) in the U.S. by their propensity to exhibit large house price movements. Panel A shows that the instrument is highly predictive of house prices. In Panels B and C, we look at how the instrument sorts CZs based on changes in the FHA/VA share and changes in private high-CLTV loans. As in the previous analysis, we see that the increase in private high-leverage loans is only related to the places with larger price movements at the peak of the boom and not before. This suggests that it is unlikely that the switch to high CLTV-private loans was causally responsible for the higher prices. Instead it appears that they were the results of increasing house prices.

6 Lender Analysis

In this section, we explore whether new and existing lenders originated loan types at different rates. A lender is classified as new if it made its first loan at some point in the previous three years. Since our CoreLogic data begin in 1996, the first year we identify new lenders is in 1999 (lenders who made their first mortgage in 1997, 1998, or 1999).[12] New lenders are re-defined each year. Therefore, once a lender has been making loans for four years it is no longer considered new. In Figure 11, we present the share of all purchase mortgages made by new lenders. The solid line illustrates that at the height of the boom, in 2005 and 2006, more than 95% of loans were being originated by lenders that had existed for at least four years. The same figure also shows that the number of unique lenders rose dramatically during the boom (Bhutta and Canner, 2013). However, these new lenders played a diminishing role in the mortgage market between 2000 and 2005.

Next, we examine, in Figure 12, the rate at which established lenders and new lenders made VA, FHA, and private high-CLTV loans. The figure shows that both types of lenders made these kinds of loans at very similar rates over the whole time series. We also confirm that the CLTV distributions of new and existing lenders is very similar (Figure A12). If it were the case, for example, that new lenders were especially likely to make high-CLTV loans we would expect to see that the distributions in Panel A were higher than those in Panel B, but this is not what we find.

Finally, we revisit the repeat-sales index of LTVs. In Figure A8, we looked at properties that traded multiple times. We obtain a very similar picture when we include bank-by-county fixed effects rather than property fixed effects, suggesting that even within lenders the patterns are the same (Figure A13).

[12] We use the lender names listed for the first mortgage in each purchase transaction in the deeds registry.

7 Conclusion

This paper shows that the stability of CLTV ratios for purchase mortgages in the U.S. over the past 20 years relies on households' access to loans with very high CLTVs via directly government-guaranteed mortgages. The increase in private-sector high-CLTV loans during the housing boom almost one for one replaced the share of FHA and VA loans. After the 2008 crisis, when privately securitized credit dried up again, we see FHA/VA loans go back up and become a significant share of the market.

The shift from directly government-backed, high-CLTV loans to privately securitized loans *follows* house price increases, it does not lead them. These findings suggest that predictions of models of the housing market that include government-guaranteed mortgages should assume relatively stable collateral ratios. In contrast, the leverage channel—Geanakoplos (2010)—is a good description of privately-supplied loans, but is muted in the aggregate since borrowers can access very high CLTV loans through directly government-guaranteed mortgage programs.

The exact nature by which loans are guaranteed may be important for understanding how house price movements affect financial markets and the economy. Double trigger models of default explicitly consider separately the roles of debt overhang and ability to pay as triggers of mortgage defaults (see Foote and Willen (2018) for a review of this literature and Mayer et al. (2009) for a more real-time analysis). In addition, the fact that high-CLTV loans went from being explicitly guaranteed by the government during some periods (through FHA/VA insurance) and then became privately securitized may have implications for the types of risks that the mortgage markets originate and the overall financial stability. Private securitization might create misaligned incentives to underwrite risky mortgages, especially if participants expect implicit government guarantees through too-big-to-fail or other government backstops.

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Figure 1: A Steady Distribution of Purchase Loan CLTV Ratios over Time

This figure plots the combined loan-to-value ratios (CLTVs) of the universe of purchase transactions financed with at least some debt covered in the CoreLogic deeds data between 1996 and 2015. Each purchase transaction includes data on up to three mortgages: one primary mortgage and up to two piggyback mortgages.

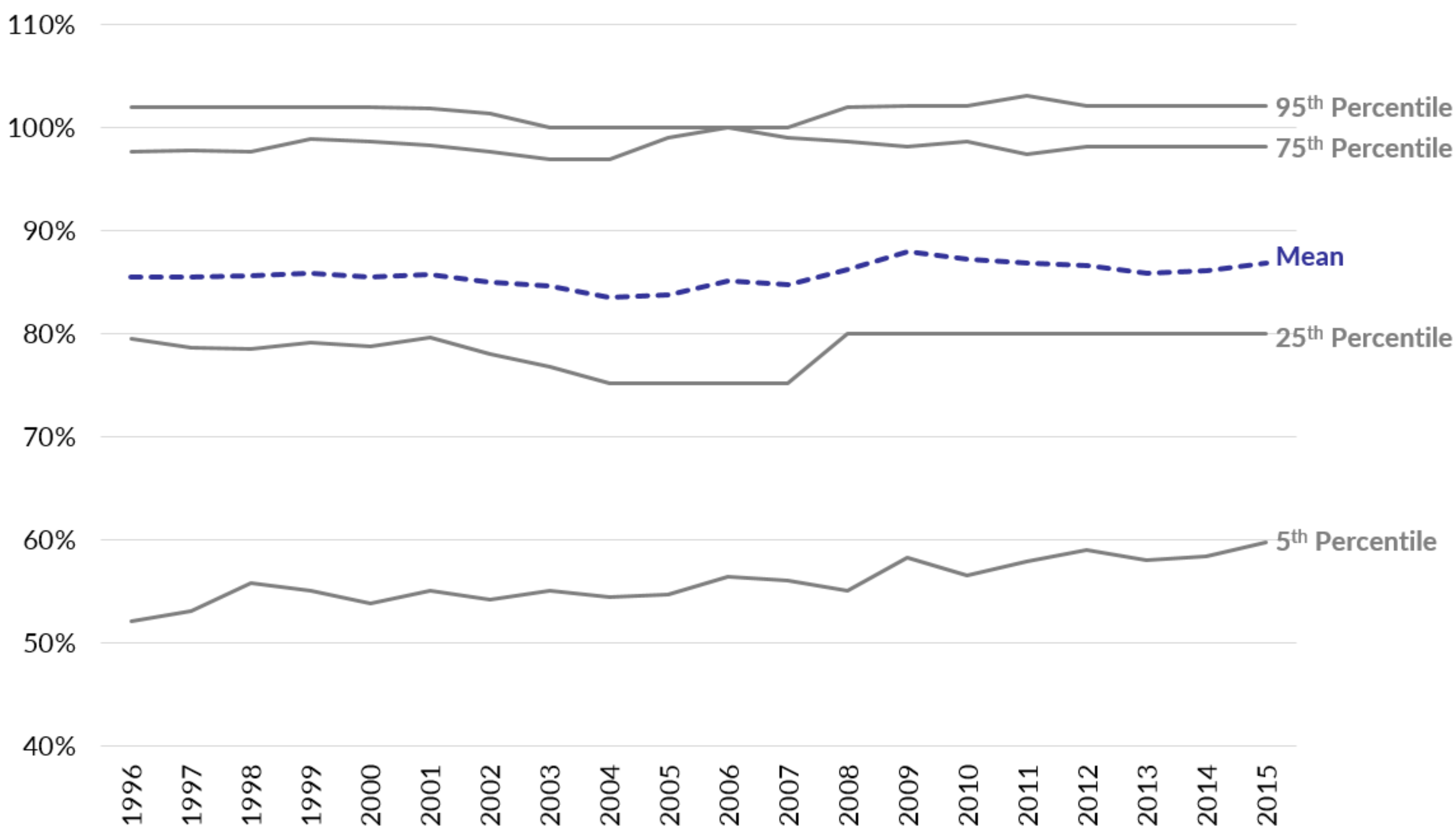


Figure 2: Cumulative Distribution Functions of CLTVs

This figure shows cumulative distribution of combined loan-to-value ratios in CoreLogic for all loans (Top Panel) and for those that are not classified as either FHA or VA (Bottom Panel). This includes Fannie Mae and Freddie Mac, any privately securitized loans, or loans held on the portfolios of private financial institutions.

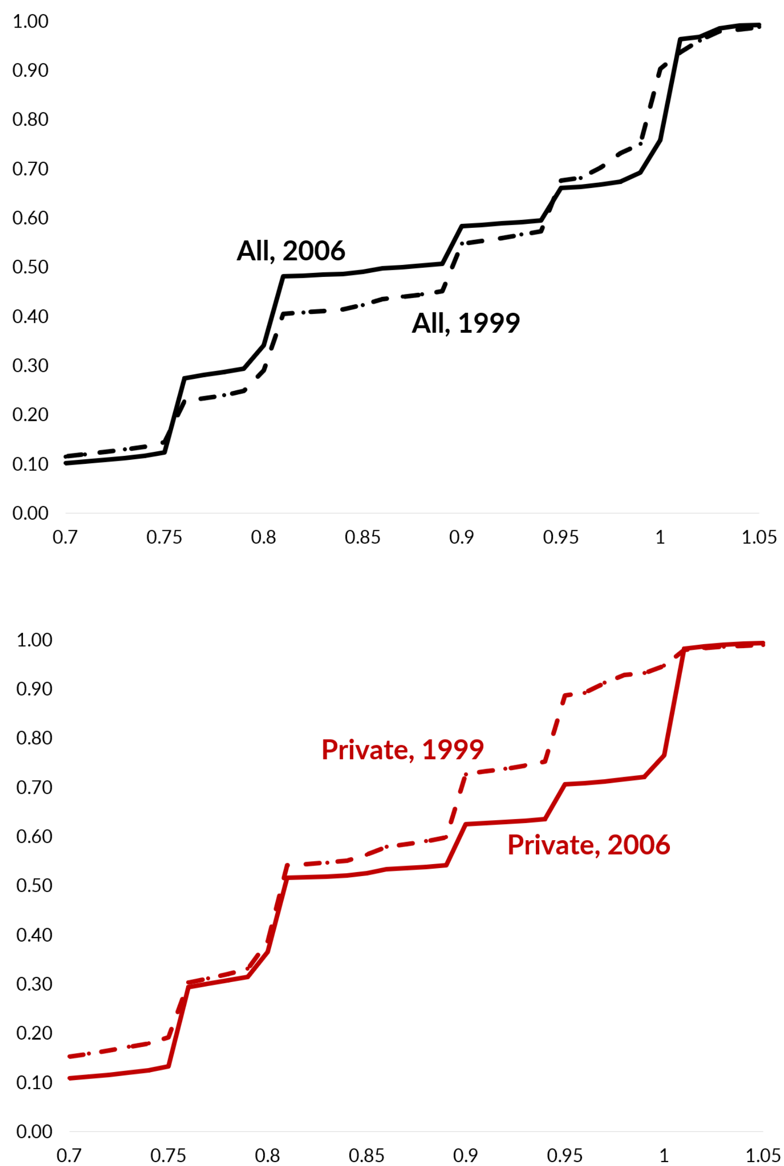
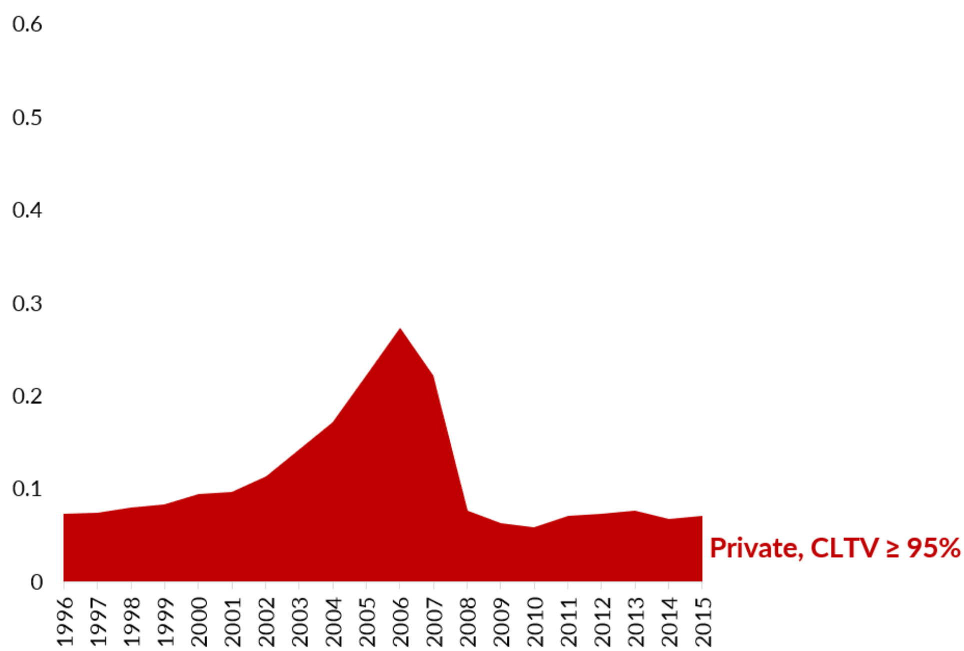


Figure 3: Share of All Purchase Loans by Year

In this figure, purchase loans are grouped into one of four types: FHA with CLTV ≥ 95%, VA with CLTV ≥ 95%, non-FHA/VA loans with CLTV ≥ 95%, and all other loans (whose CLTVs < 95% by construction). The top figure plots the share of all purchase loans that were not explicitly government guaranteed and had CLTV ratios ≥ 95%. The second plot adds the share of high-CLTV loans explicitly guaranteed by the government.



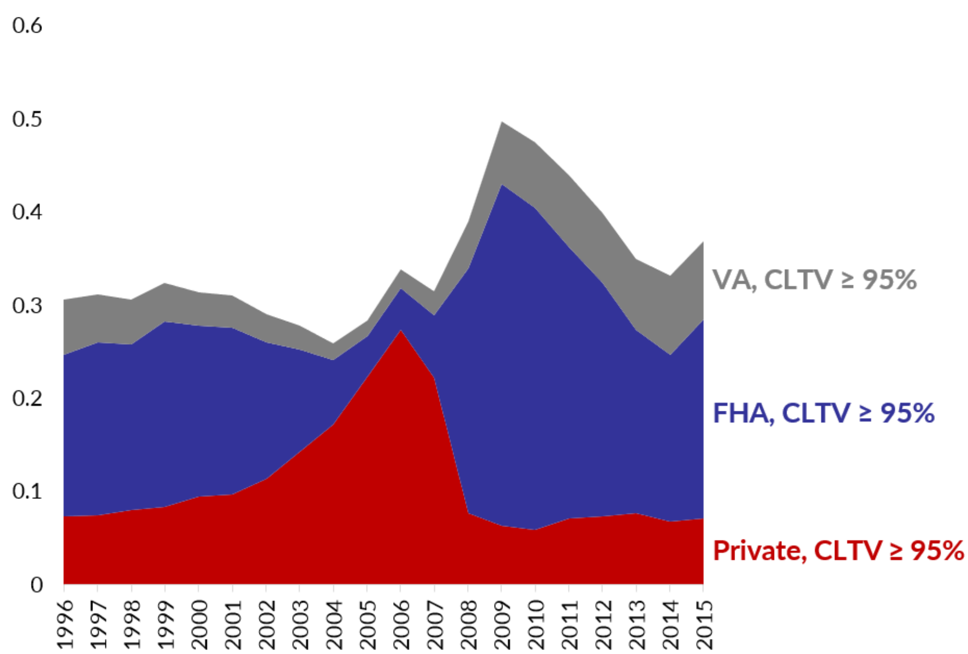
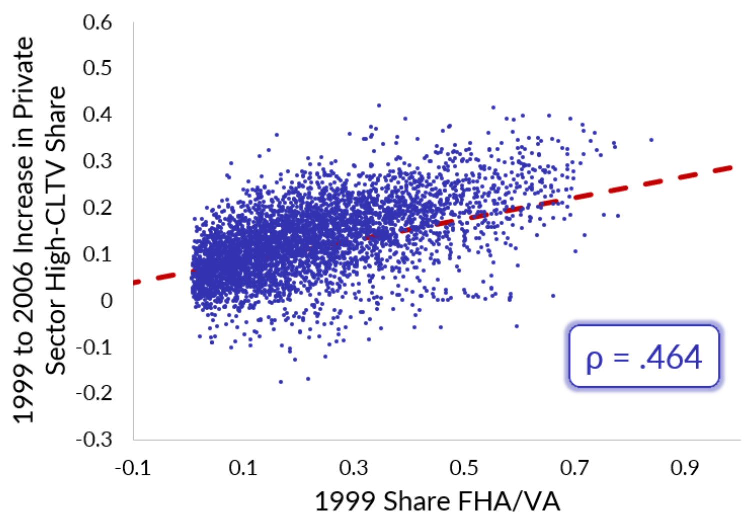


Figure 4: Change in ZIP Code Level Share of Loan Types

The first panel of this figure plots ZIP codes based on the share of 1999 purchase loans in that ZIP code that were FHA- or VA-guaranteed (on the x-axis) and the difference between the share of 2006 purchase loans in that ZIP code that were not FHA or VA and had CLTVs ≥ 95% and the share of such loans in 1999 (on the y-axis). The second panel of this figure plots ZIP codes based on the share of 2006 purchase loans in that ZIP code that were not FHA or VA and had CLTVs ≥ 95% (on the x-axis) and the difference in the share of 2013 purchase loans guaranteed by either the FHA or VA and the share of such loans in 2006 (on the y-axis).



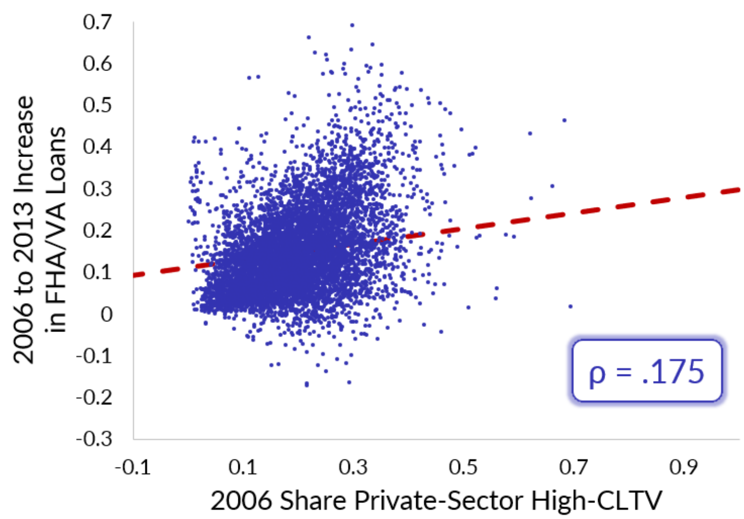


Figure 5: Share Government-Guaranteed and Private Sector Across Incomes Deciles over Time

To produce this graph, we created ten deciles of 1998-ZIP code income. Deciles are population weighted such that each decile contains ten percent of the population of the United States. For each year, we calculate the share of purchase loans that are guaranteed by the government and the share that are private-sector with CLTVs ≥ 95%. The ZIP code-level income data are from the IRS, https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-zip-code-data-soi.

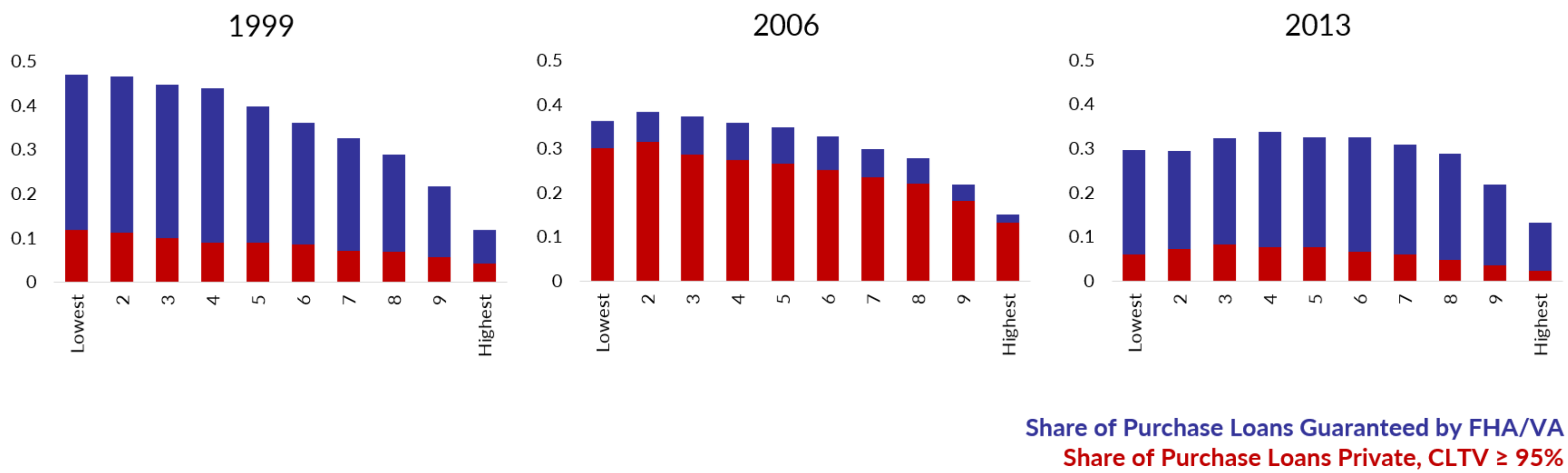
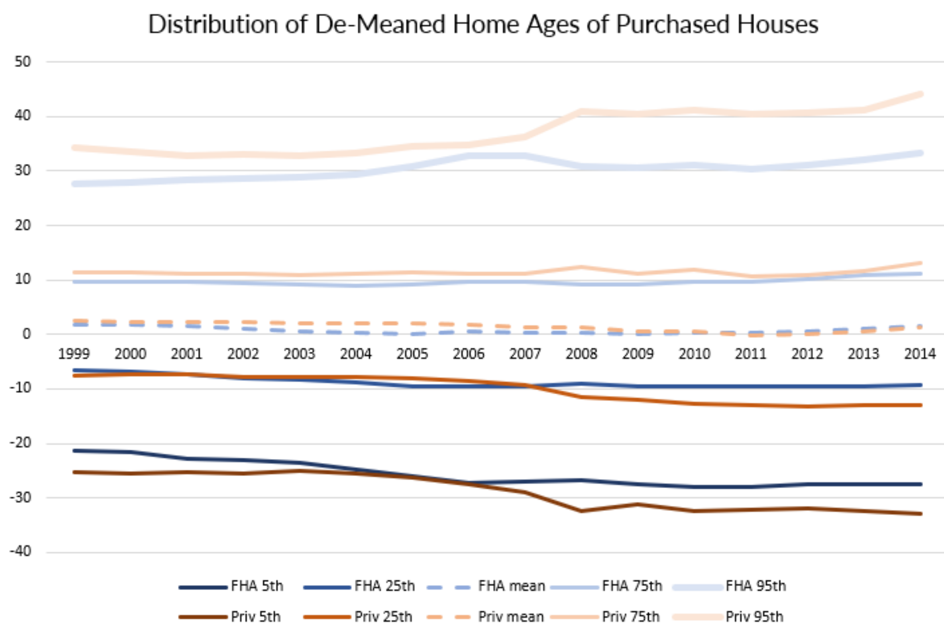


Figure 6: Age and Square Footage of Homes Purchased Each Year

The first figure plots the distribution of home age of homes purchased year by year, the second figure plots square footage. Both variables are de-meaned by the average home age and square footage of homes sold in the same ZIP code-by-year. Included are purchases financed with FHA loans (blue) and homes purchased with private-sector loans with CLTVs ≥ 95% (red).



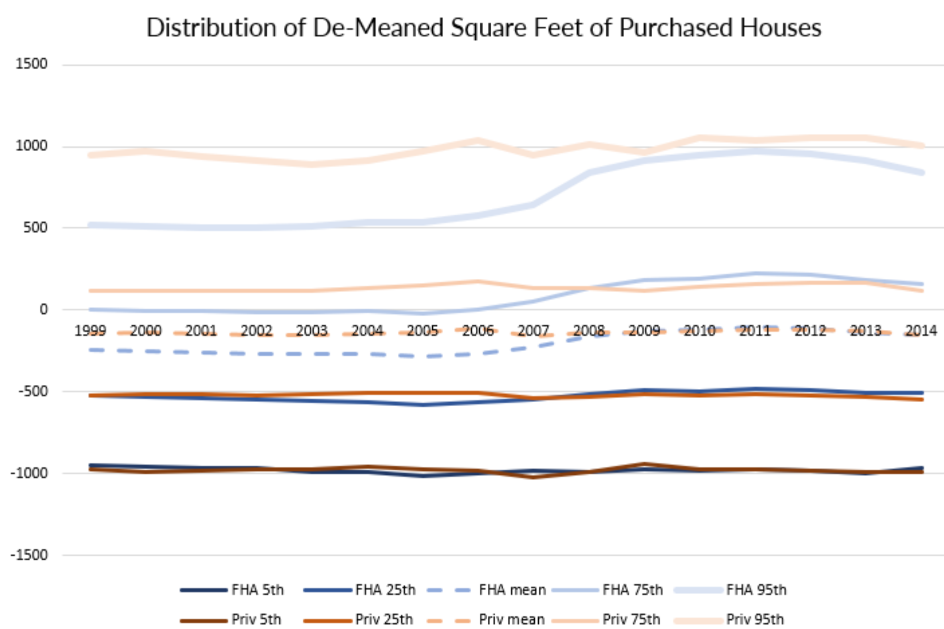
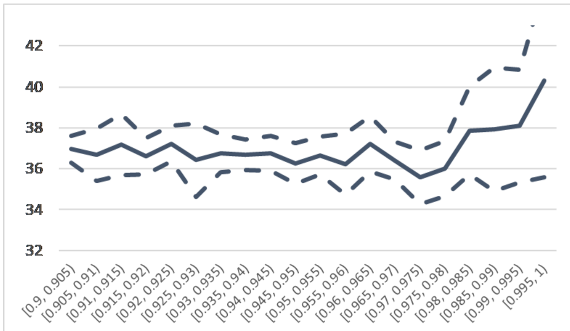


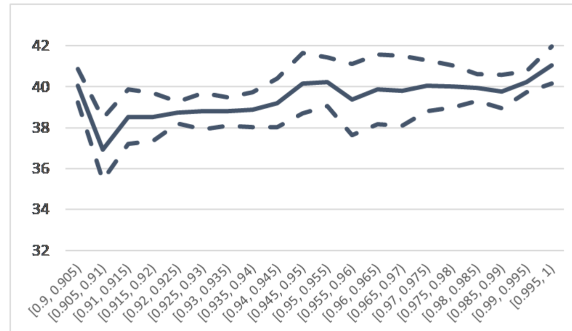
Figure 7: Debt-to-Income by Loan-to-Value, 2005-2007 Originations

This figure shows point estimates and standard errors for debt-to-income levels regressed on loan-to-value bin indicators. The sample includes only full documentation loans and loans with a combined loan-to-value ratio above 90%. Data come from First American LoanPerformance, McDash Analytics.

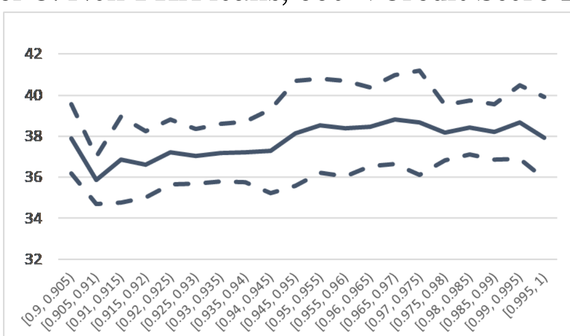
Panel A: FHA loans



Panel B: Non-FHA loans, Credit Score ≤ 660



Panel C: Non-FHA loans, 660 < Credit Score ≤ 720



Panel D: Non-FHA loans, Credit Score > 720

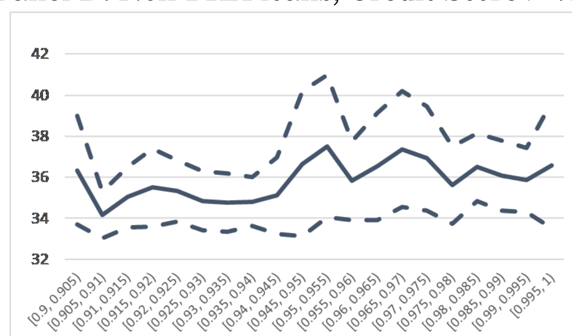


Figure 8: Are Optimists Switching Within High-LTV Loan Types?

Data are from the Survey of Consumer Finances (SCF). Optimism is measured as in Puri and Robinson (2007). The pre-period uses SCF waves 1995, 1998, and 2001. The boom period uses SCF waves 2004 and 2007, Bust: 2010 wave, and Post: 2013 and 2016 waves. High-LTV borrowers are those who report outstanding mortgage balances valued at more than 80% of the value of their home.

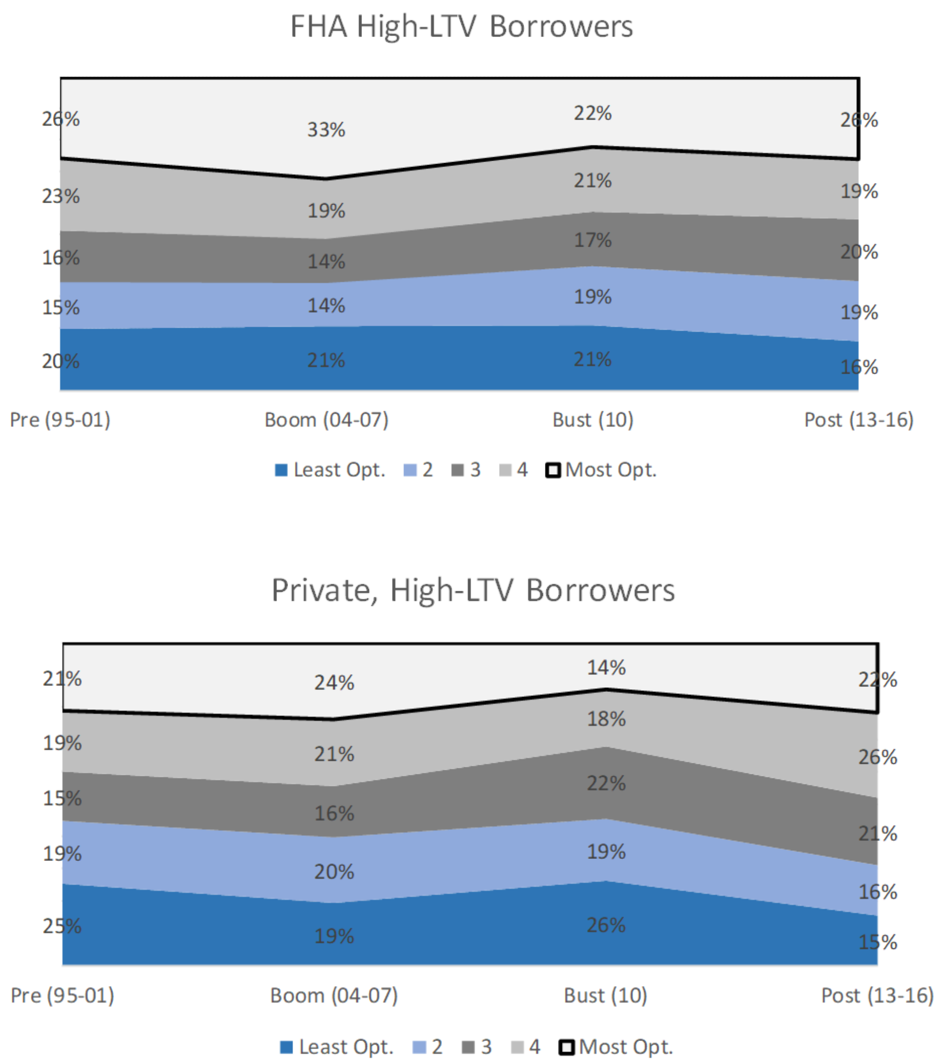
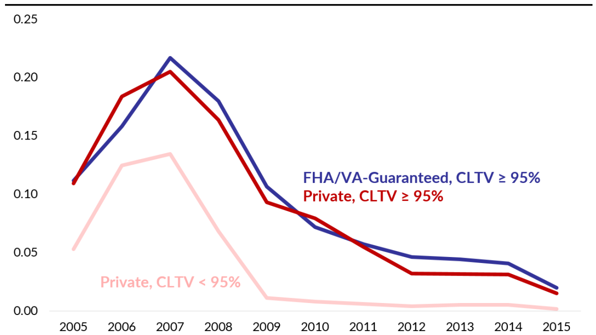


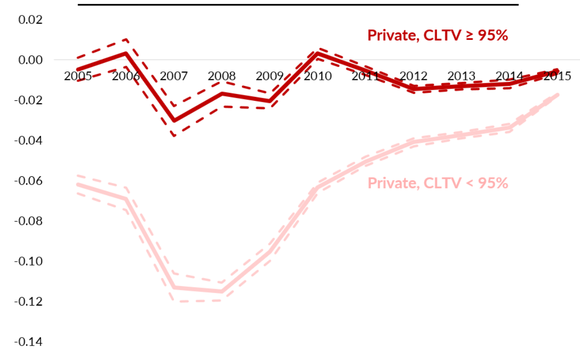
Figure 9: Share 90+ Days Delinquent Within 3 Years of Origination

These figures use McDash data starting in the second half of 2005 to plot the delinquency rates of private mortgages relative to those guaranteed by the government. The first figure calculates, year by year, the share of loans originated within each category that were 90+ days delinquent at some point in the three years after origination. The second figure includes county-by-year fixed effects and plots private-sector mortgage delinquency rates relative to government-guaranteed loans' delinquency rates. The third panel further adds controls for credit score, interest rate, loan type, and DTI. Dashed lines indicate 95% confidence intervals.

Panel A: Unconditional Delinquency Share



Panel B: Within County-by-Year



Panel C: Full Credit Scoring Model

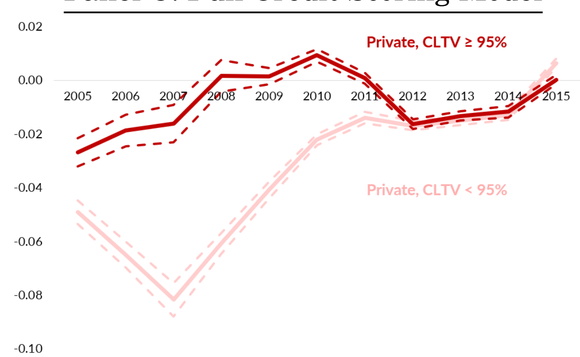
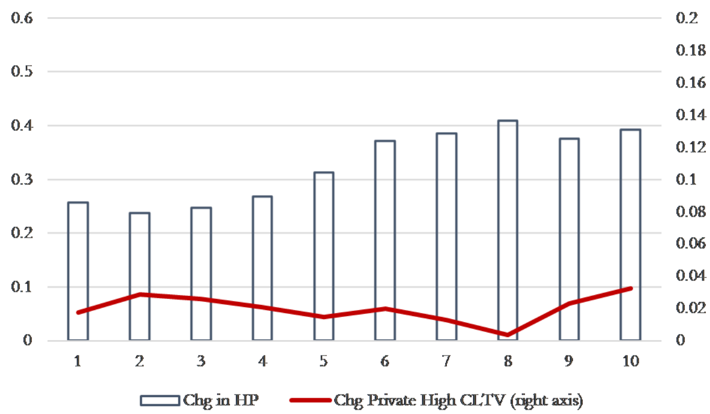


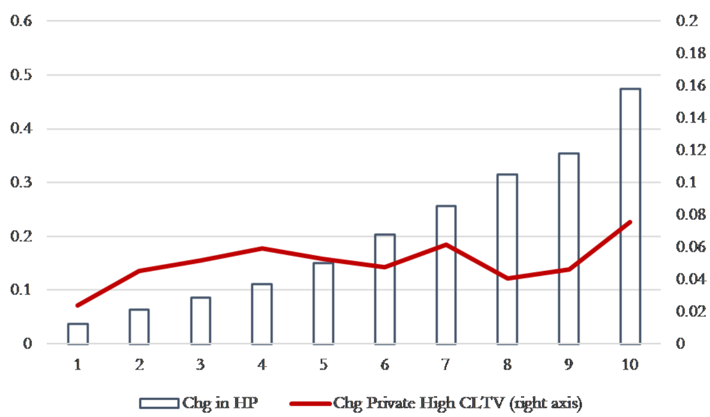
Figure 10: Changes in Private, High-CLTV Share by House Price Change

Figure shows averages of house price changes and the change of high-CLTV purchase loans at the ZIP code level. ZIP codes are grouped into deciles by the change in house prices between 2002 and 2006.

Panel A: 1999-2002 (4 years)



Panel B: 2003-2004 (2 years)



Panel C: 2005-2006 (2 years)

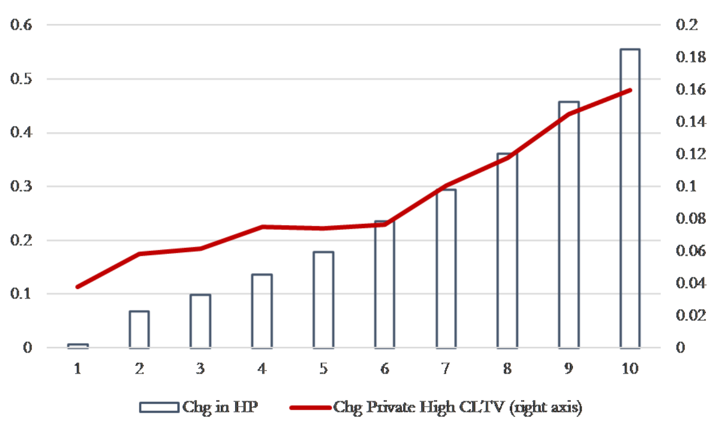


Figure 11: Percent of Purchase Loans Made by New Lenders

This figure presents the share of all purchase loans made by new lenders each year. New lenders are defined each year as those lenders who made their first loan at some point in the previous three years. Since data coverage begins in 1996, we are not able to define new lenders until 1999 (those who made their first loan in 1997, 1998, or 1999). This figure also presents a count of the number of unique lenders each year. Only lenders who make at least 100 loans between 1996 and 2015 are included in this analysis.

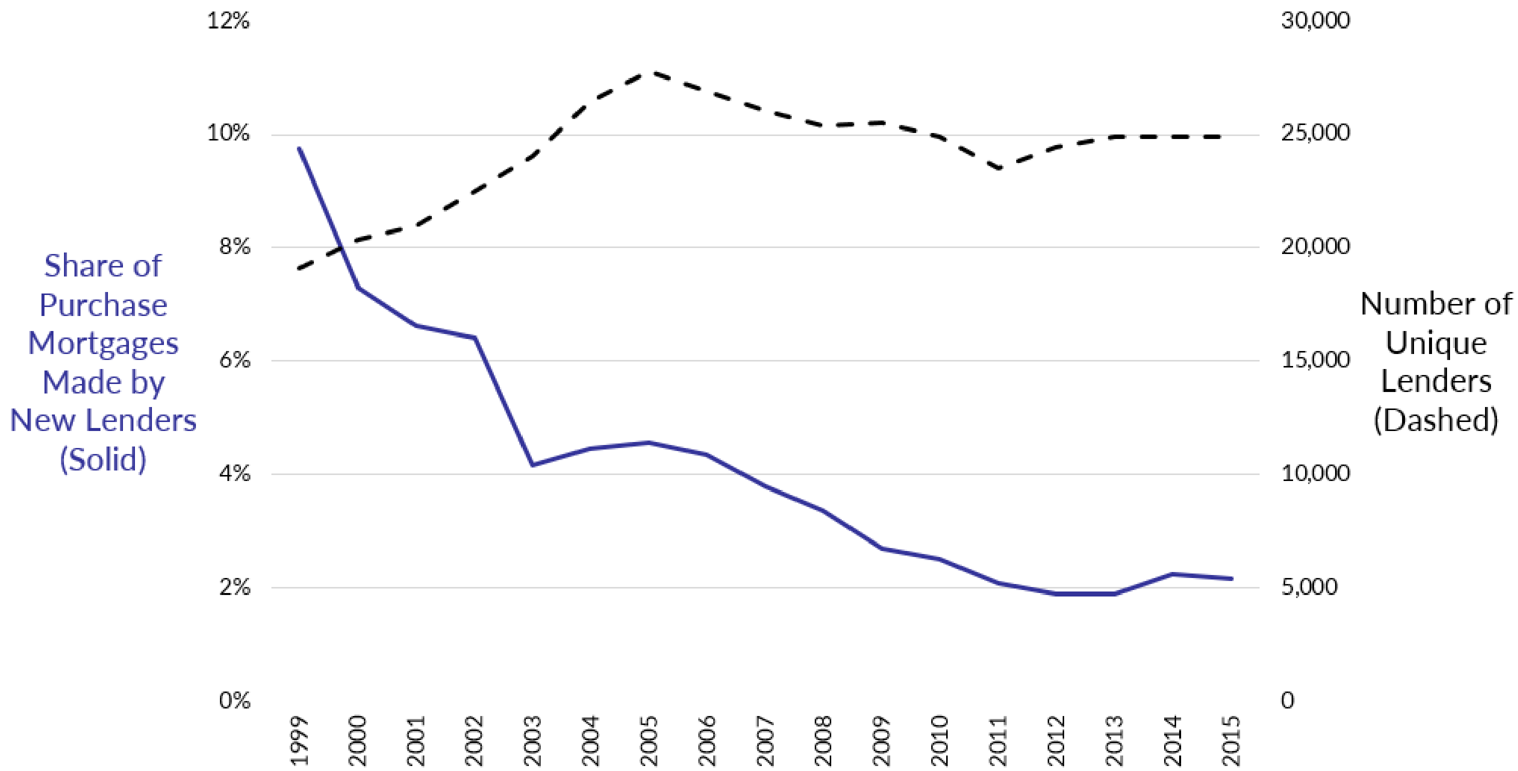


Figure 12: Loan Types of New and Existing Lenders

Purchase loans are grouped into one of four types: FHA with CLTV ≥ 95%, VA with CLTV ≥ 95%, non-FHA/VA loans with CLTV ≥ 95%, and all other loans (whose CLTVs < 95% by construction). These figures plot the share of all purchase loans of each type made by new lenders (Panel A) and all other lenders (Panel B). New lenders are defined each year as those lenders who made their first loan at some point in the previous three years. Each loan has one lender defined as the lender of the primary mortgage.

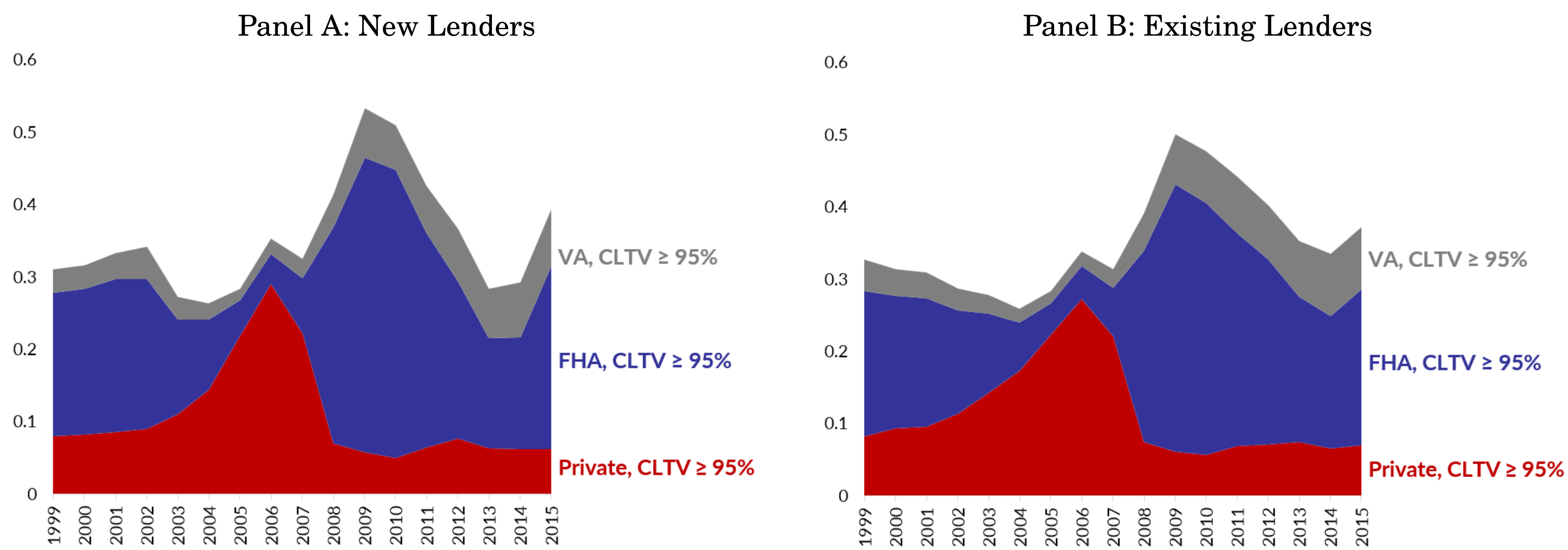


Table 1: Summary Statistics of Properties Transacting Twice

This table uses CoreLogic data and presents counts and shares by type of mortgage originated in the 1996-2003, 2004-2007, and 2008-2015 periods for those properties that saw exactly one transaction during the boom and exactly one transaction pre-boom (Panel A) or post-boom (Panel B).

Sample:		*Properties with 1 purchase in 96-03 and 1 purchase in 04-07*		
		04-07 Loan		
		NOT Private, CLTV ≥ 95%	IS Private, CLTV ≥ 95%	
96-03 Loan	NOT FHA/VA	1,398,185 78.6%	379,697 21.4%	1,777,882 100%
	IS FHA/VA	391,460 66.9%	193,464 33.1%	584,924 100%

Sample:		*Properties with 1 purchase in 04-07 and 1 purchase in 08-15*		
		08-15 Loan		
		Not FHA/VA	IS FHA/VA	
04-07 Loan	NOT Private, CLTV ≥ 95%	286,135 63.5%	164,593 36.5%	450,728 100%
	IS Private, CLTV ≥ 95%	95,383 51.9%	88,417 48.1%	183,800 100%

Table 2: Switching Between Loan Types (Properties Transacting Twice)

This table uses CoreLogic data. The first sample includes all those properties we observe trade at arms-length exactly one time in the period 1996-2003 and exactly one time in the period 2004-2007. The second sample is analogous for the periods 2004-2007 and 2008-2015. Standard errors clustered at the county level are reported in parentheses. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively.

Sample:	*Properties with 1 purchase in 96-03 and 1 purchase in 04-07*	*Properties with 1 purchase in 04-07 and 1 purchase in 08-15*
Dependent Variable:	04-07 Loan Is Private with CLTV ≥ 95%	08-15 Loan Is FHA/VA
96-03 Loan FHA or VA	0.114***	
	(0.007)	
04-07 Loan Private with CLTV ≥ 95%		0.0941***
		(0.006)
Fixed Effects		
County	Y	Y
Year of First Loan	Y	Y
Year of Second Loan	Y	Y
N	2,362,748	634,495
R-squared	0.098	0.088

Table 3: Summary Statistics for Households in North Carolina with Two Transactions

This table uses CoreLogic data and voter registration data from North Carolina. The table presents counts and shares of certain types of mortgages originated in the 1996-2003, 2004-2007, and 2008-2015 periods for those households that made exactly one purchase transaction during the boom and exactly one purchase transaction pre-boom (Panel A) or post-boom (Panel B).

Sample:		*NC Households with 1 purchase in 96-03 and 1 purchase in 04-07*		
		04-07 Loan		
		NOT Private, CLTV ≥ 95%	IS Private, CLTV ≥ 95%	
96-03 Loan	NOT FHA/VA	5,593	1,026	6,619
		84.5%	15.5%	100%
	IS FHA/VA	763	282	1,045
		73.0%	27.0%	100%

Sample:		*NC Households with 1 purchase in 04-07 and 1 purchase in 08-15*		
		08-15 Loan		
		Not FHA/VA	IS FHA/VA	
04-07 Loan	NOT Private, CLTV ≥ 95%	7,690	1,686	9,376
		82.0%	18.0%	100%
	IS Private, CLTV ≥ 95%	1,874	613	2,487
		75.4%	24.6%	100%

Table 4: Switching Loan Types (Households in North Carolina with Two Transactions)

This table uses CoreLogic and voter registration data from North Carolina. The first sample includes all those households we observe take out exactly one loan in the period 1996-2003 at one property and exactly one loan in the period 2004-2007 at another property in North Carolina. The second sample is analogous for the periods 2004-2007 and 2008-2015. Standard errors clustered at the county level are reported in parentheses. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively.

Sample:	*NC Households with 1 purchase in 96-03 and 1 purchase in 04-07*	*NC Households with 1 purchase in 04-07 and 1 purchase in 08-15*
Dependent Variable:	04-07 Loan is Private with CLTV ≥ 95%	08-15 Loan is FHA/VA
96-03 Loan FHA or VA	0.113***	
	(0.014)	
04-07 Loan Private with CLTV ≥ 95%		0.0674***
		(0.011)
Fixed Effects		
County	Y	Y
Year of First Loan	Y	Y
Year of Second Loan	Y	Y
N	7,660	11,858
R-squared	0.031	0.054

Table 5: Characteristics of FHA and Private, High-CLTV Loans in the Survey of Consumer Finances

Data are from the Survey of Consumer Finances (SCF). The pre-period uses SCF waves 1995, 1998, and 2001. The boom period uses SCF waves 2004 and 2007, Crisis: 2010 wave, and Recovery: 2013 and 2016 waves. Sample is restricted to borrowers who purchased a home in the previous two years with non-missing LTV and have reported mortgage balances of more than 80% of the value of their home. Age, race, education level, and gender fixed effects are included in all regressions. DTI represents all mortgage-related payments by the household scaled by annual income, and "Only Qualify" is an indicator variable for whether the household reports choosing the loan or the lender because it was "easier to qualify" or was the only option it qualified for. Standard errors are clustered at the age and year level. Coefficients significant at the 10%, 5%, and 1% levels are marked with a *, **, and ***, respectively.

	LTV	DTI	Interest rate	Only Qualify
FHA	0.027***	-0.010***	-40.6***	0.105**
	(0.001)	(0.002)	(12.4)	(0.046)
Boom period	0.016***	0.046*	-170.0***	-0.014
	(0.002)	(0.025)	(18.7)	(0.036)
Crisis period	0.030***	0.029***	-270.0***	-0.064**
	(0.004)	(0.006)	(7.2)	(0.032)
Recovery period	0.018*	0.008	-400.0***	-0.011
	(0.010)	(0.016)	(13.5)	(0.039)
FHA#Boom	-0.019**	0.007	30.1***	-0.083*
	(0.008)	(0.012)	(8.3)	(0.050)
FHA#Crisis	-0.009***	0.027***	42.8***	-0.023
	(0.003)	(0.007)	(7.2)	(0.053)
FHA#Recovery	-0.032***	0.019***	39.9***	-0.074
	(0.010)	(0.003)	(12.6)	(0.053)
DTI			44.9	0.137
			(30.8)	(0.118)
LTV			64.6*	0.204**
			(33.8)	(0.083)
Fixed effects	Age, Race, Education, Gender			
N	5,130	5,081	5,070	5,081
r2	0.10	0.19	0.64	0.10

Table 6: Changes in HP and Private, High-CLTV Loans on HP Instrument

Table shows regressions by sub-periods (in 2-year intervals) of changes in three outcome variables (shown in panel titles) at the commuting zone level on the gamma instrument in Guren et al. (2018) and Palmer (2015). Heteroscedasticity-robust standard errors and t-statistics shown.

Panel A: Change in HP

Period:	00-02	02-04	04-06	06-08	08-10
Gamma	0.054	0.185	0.111	-0.124	-0.141
	0.016	0.030	0.013	0.019	0.012
	3.45	6.10	8.84	-6.37	-11.52
N	150	175	229	285	305
R-squared	0.11	0.43	0.21	0.32	0.44

Panel B: Change in FHA/VA

Period:	00-02	02-04	04-06	06-08	08-10
Gamma	-0.147	-0.152	-0.169	12.508	-0.173
	0.024	0.032	0.042	3.387	0.022
	-6.10	-4.78	-4.00	3.69	-7.77
N	149	168	223	281	301
R-squared	0.23	0.00	0.03	0.03	0.14

Panel C: Change in Private, High-CLTV loans

Period:	00-02	02-04	04-06	06-08	08-10
Gamma	0.026	0.101	0.433	-2.302	0.029
	0.049	0.065	0.076	0.714	0.045
	0.53	1.54	5.72	-3.23	0.65
N	149	173	220	270	302
R-squared	0.00	0.00	0.16	0.03	0.00

A Internet Appendix – Supplemental Tables

Figure A1: Use of Junior Liens over Time

This figure plots the share of all home purchases financed, as per the deeds records, with more than one mortgage among home purchases financed with at least one mortgage. These second and third mortgages are often called "piggyback" mortgages.

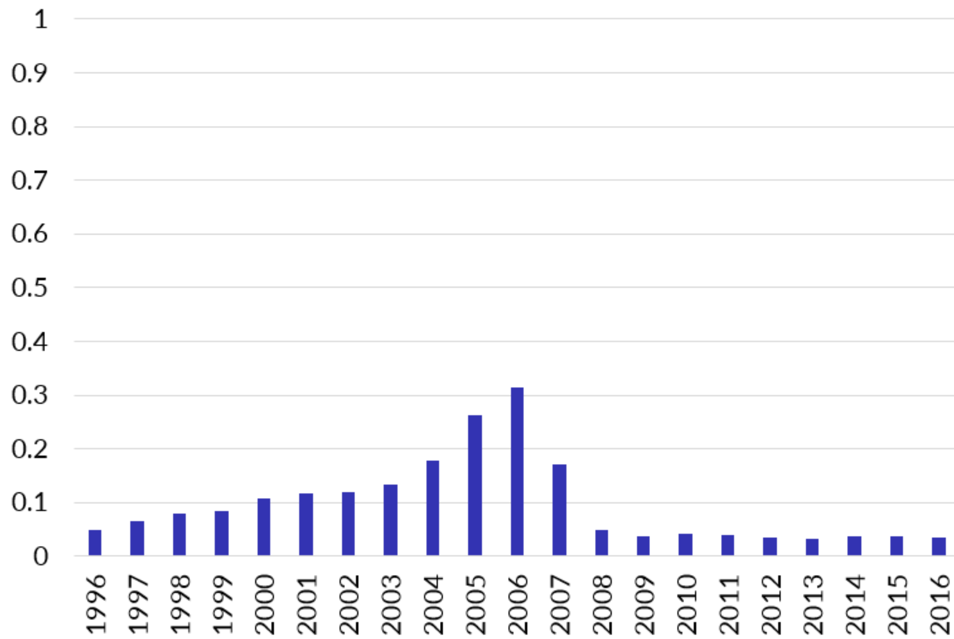


Figure A2: Cash Purchases over Time

This figure plots the share of all home purchases financed, as per the deeds records, with 100% cash.

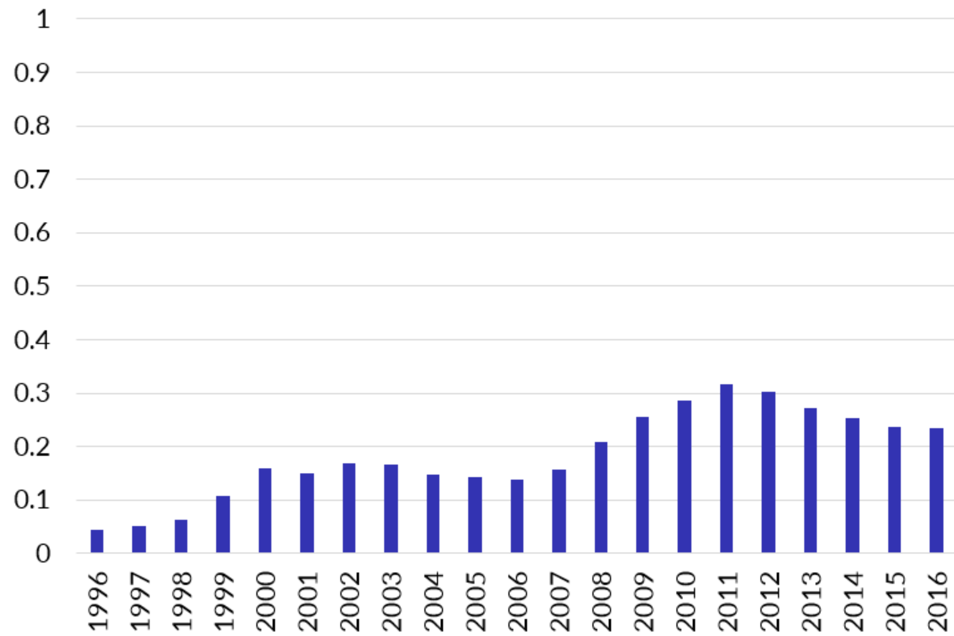


Figure A3: Frequency of New Purchase Mortgage Originations over Time

This figure plots the frequency of all home purchases financed with mortgages between 1996 and 2015.

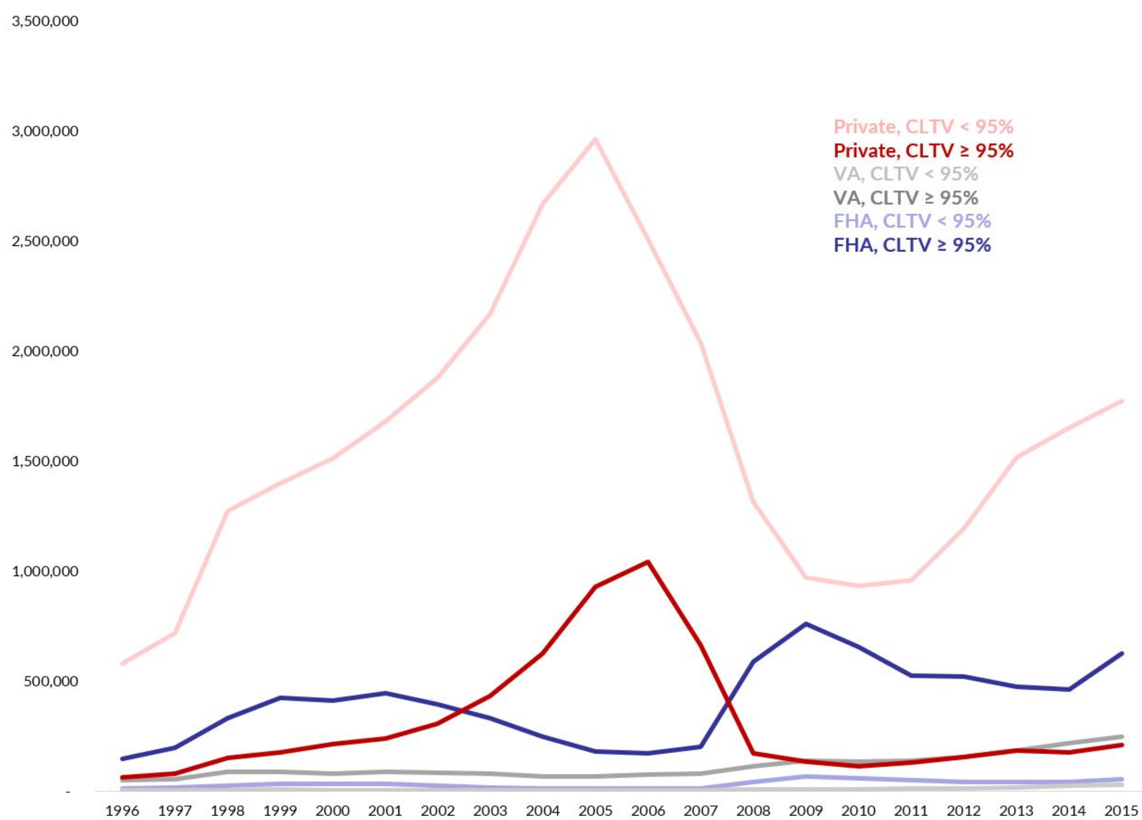


Figure A4: Value-Weighted Distributions of Purchase Loan CLTV Ratios over Time

This figure plots the combined loan-to-value ratios (CLTVs) of the universe of purchase transactions financed with at least some debt covered in the CoreLogic deeds data between 1996 and 2015. Loans are weighted by loan amount. Each purchase transaction includes data on up to three mortgages: one primary mortgage and up to two piggyback mortgages.

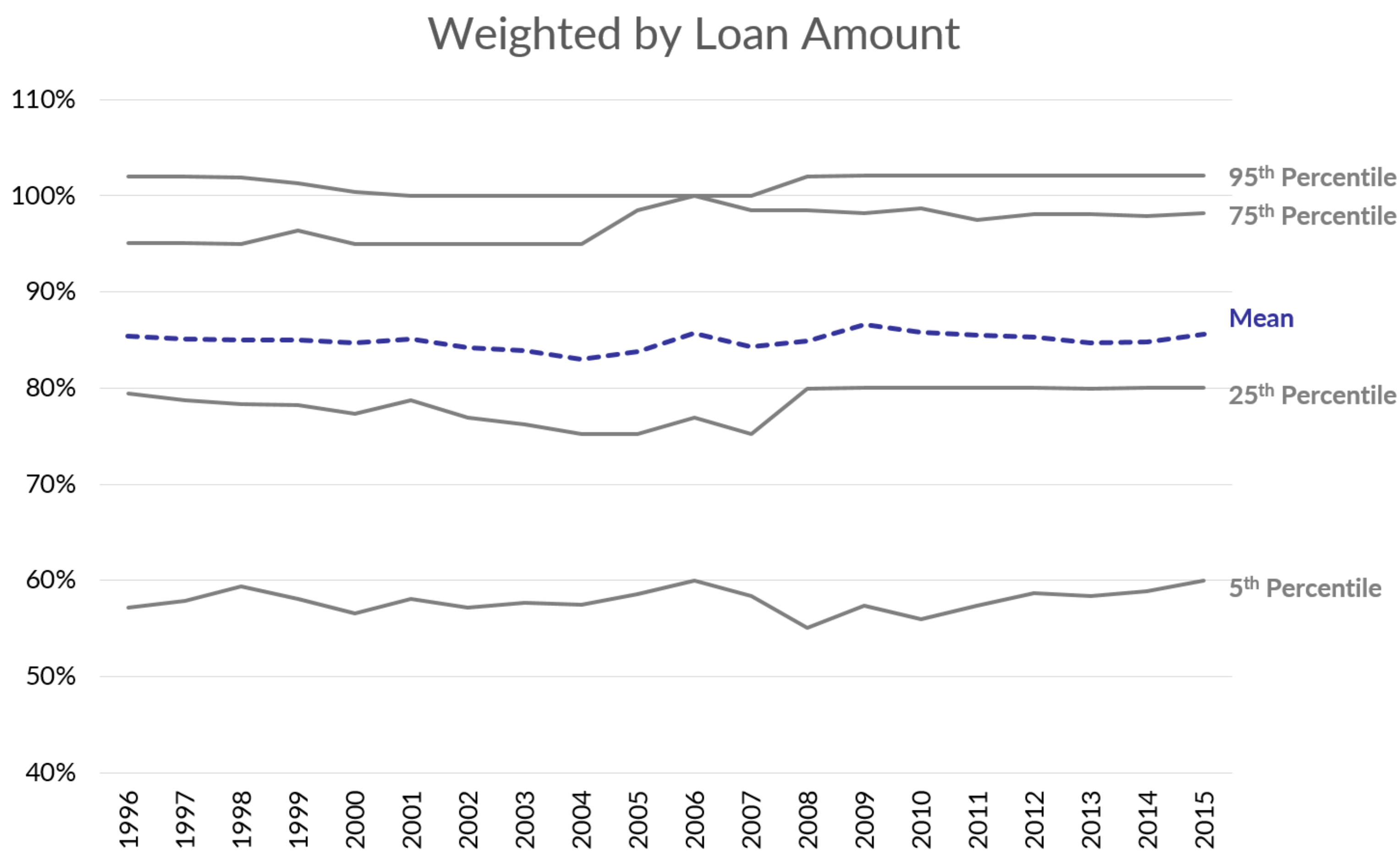


Figure A5: A Changing Share of Government-Guaranteed Mortgages

To produce this figure, purchase loans are grouped into one of five types: the four explicitly plotted below and everything else. The figure plots the share of each type totaling up to 100% of all purchase loans. Data are from CoreLogic.

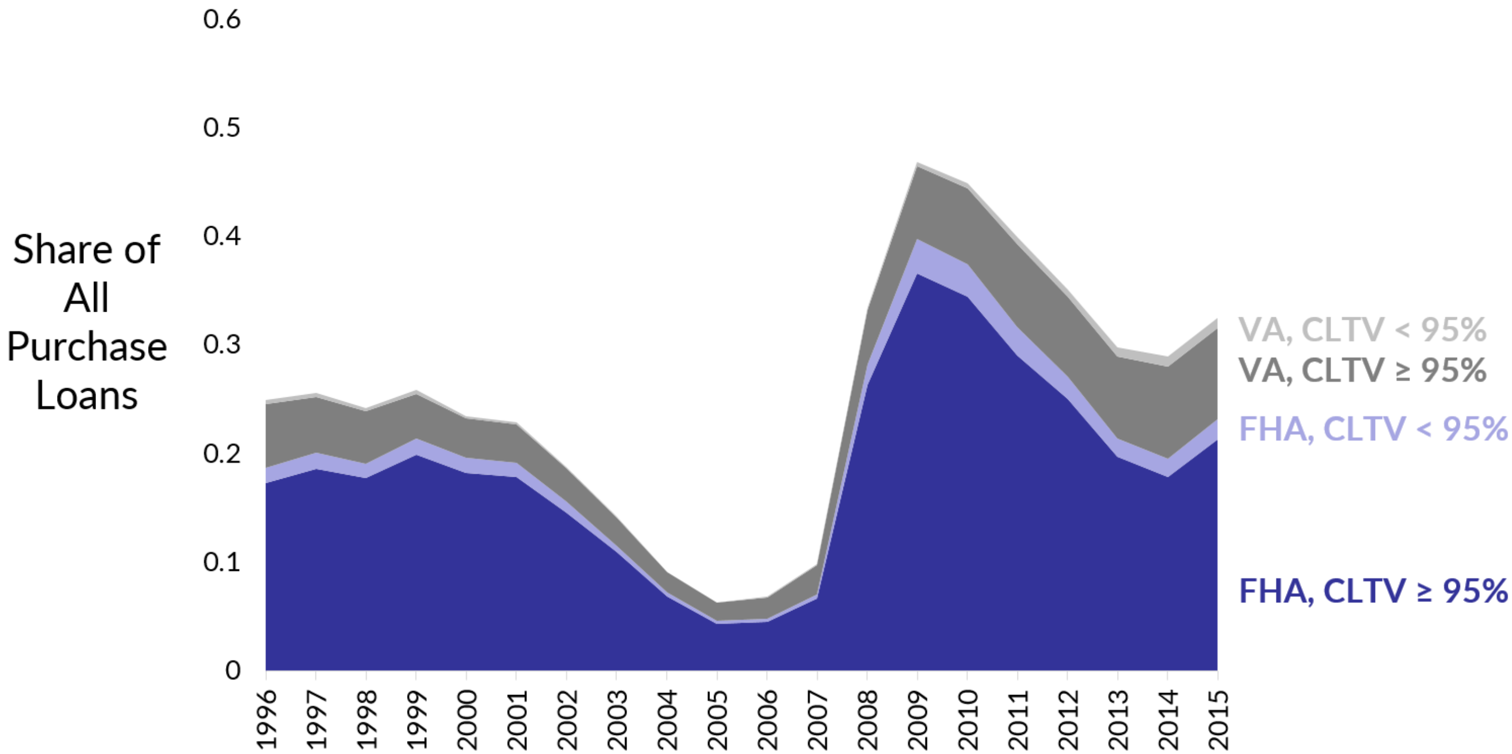
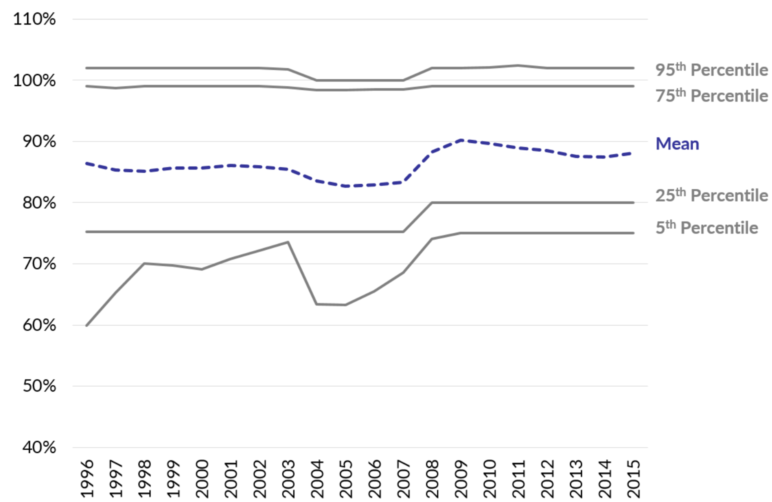


Figure A6: Comparing Low- and High-HP Growth Regions

These figures plot the combined loan-to-value ratios (CLTVs) of the universe of purchase transactions financed with at least some debt covered in the CoreLogic deeds data between 1996 and 2015. Each purchase transaction includes data on up to three mortgages: one primary mortgage and up to two piggyback mortgages. States are classified as low-HP growth regions, corresponding to the bottom two deciles of house price growth between June of 2002 and June of 2006 (left panel), or high-HP growth regions, corresponding to the top two deciles (right panel).

Panel A: Bottom 2 HP Growth Deciles



Panel B: Top 2 HP Growth Deciles

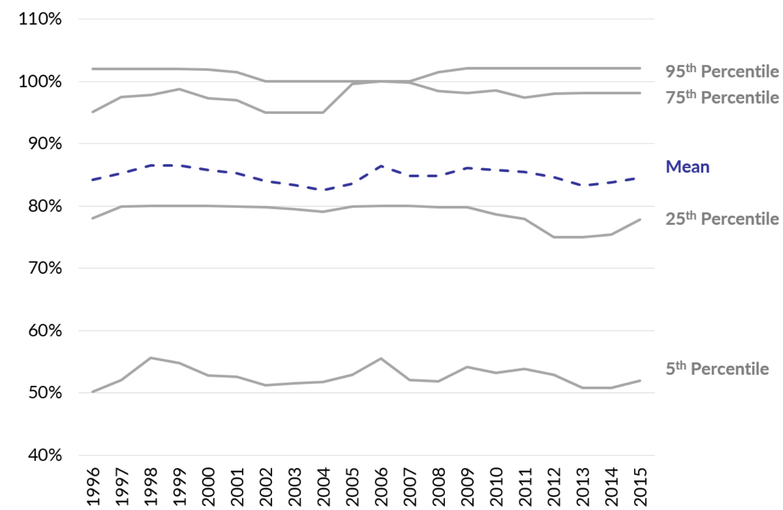


Figure A7: Comparing Recourse and Non-Recourse States

These figures plot the combined loan-to-value ratios (CLTVs) of the universe of purchase transactions financed with at least some debt covered in the CoreLogic deeds data between 1996 and 2015. Each purchase transaction includes data on up to three mortgages: one primary mortgage and up to two piggyback mortgages. States are classified as either recourse (left panel) or non-recourse (right panel) as in Ghent and Kudlyak (2011).

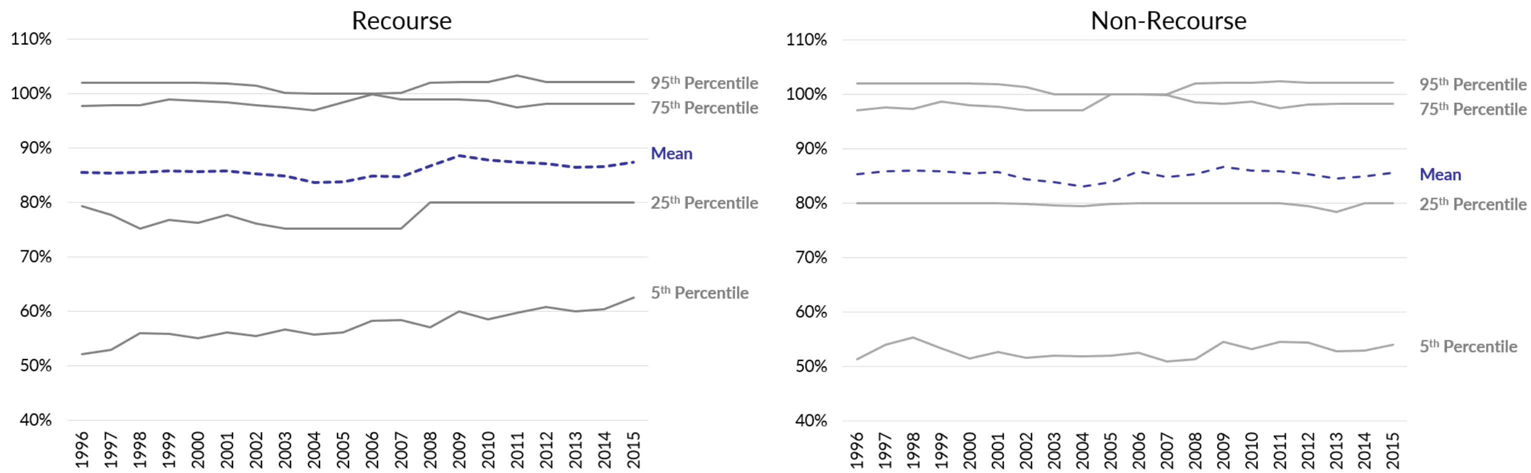


Figure A8: CLTV Repeat Sales Index (Relative to 2001 Baseline)

This figure plots a CLTV repeat sales index relative to a 2001 baseline. The construction is analogous to the standard house price index. CLTVs of purchase loans are regressed on year fixed effects and, importantly, property fixed effects. In this way, CLTV differences are calculated using only within-property variation over time. The estimates and confidence intervals of each year's effect are graphed below.

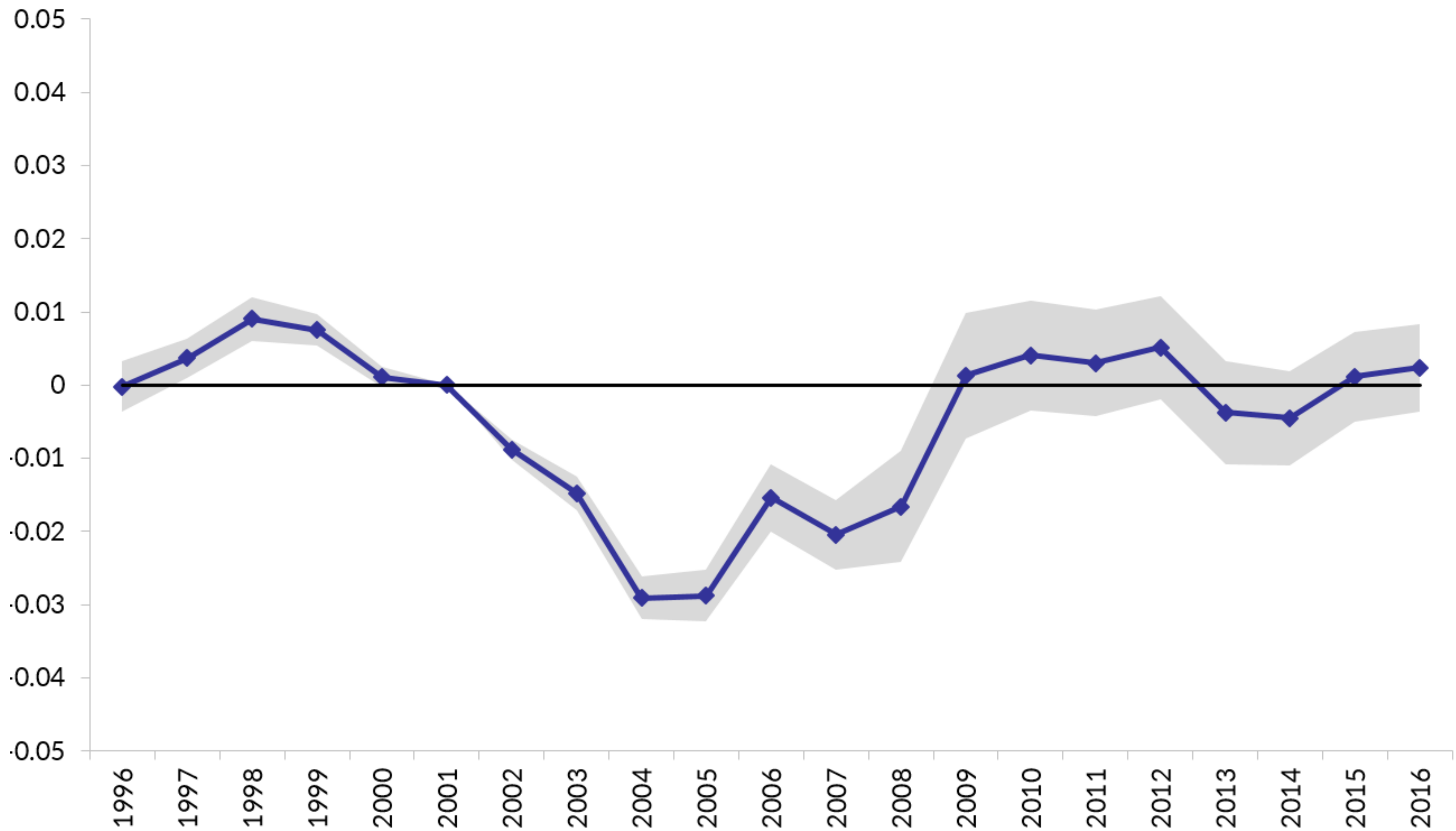


Figure A9: Optimism and Outlook on the Economy

This figure shows the percentage of individuals who believe the economy will improve over the subsequent 12 months. Optimism is measured using a residual of life expectancy after controlling for year fixed effects, as well as observable individual characteristics like age, income, education, gender, smoker status, and perceived health status. Deciles are formed using survey weights. Data are from the Survey of Consumer Finances (SCF) waves between 1998 and 2016.

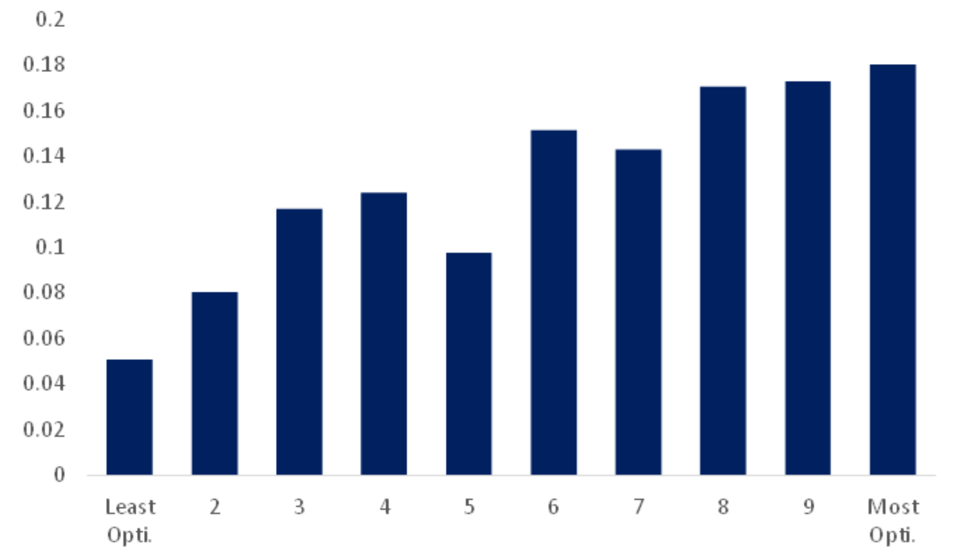
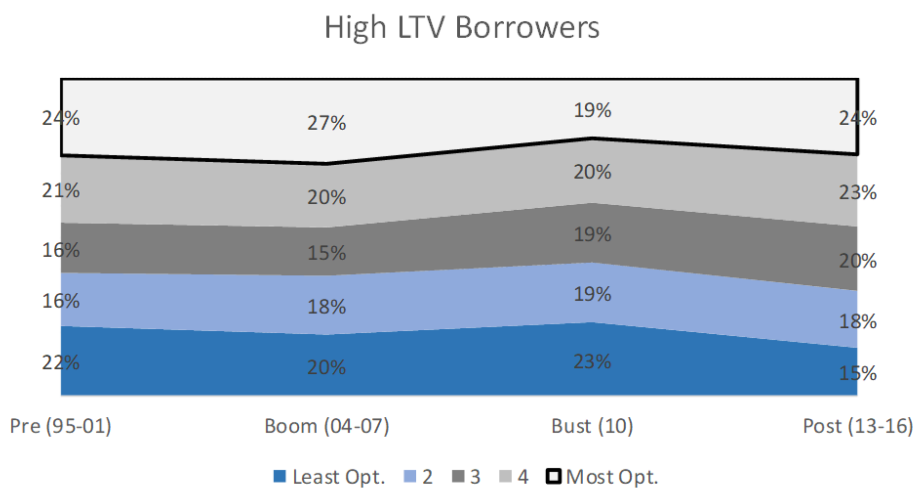


Figure A10: Do Optimists Choose Higher LTV Loans

Data are from the Survey of Consumer Finances (SCF). Optimism is measured as in Puri and Robinson (2007). The pre-period uses SCF waves 1995, 1998, and 2001. The boom period uses SCF waves 2004 and 2007; Bust 2010 wave, and Post 2013 and 2016 waves. High-LTV borrowers are those who report outstanding mortgage balances valued at more than 80% of the value of their home, low-LTV otherwise.



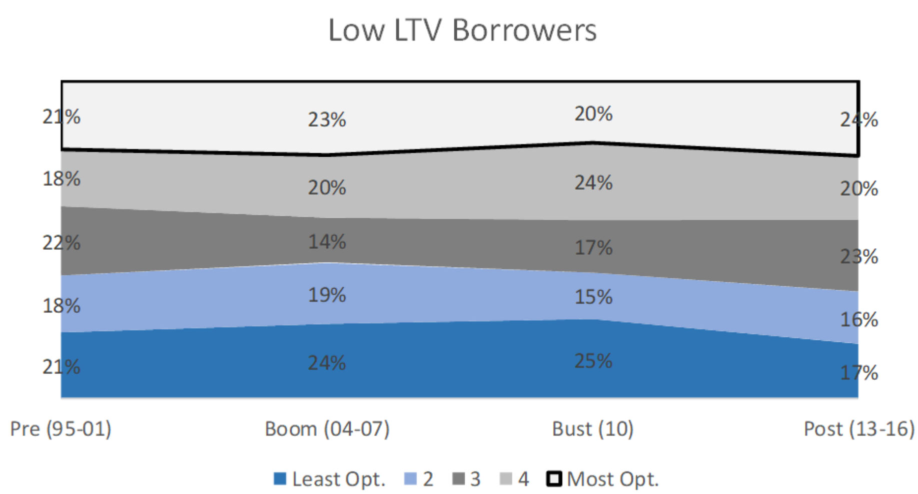
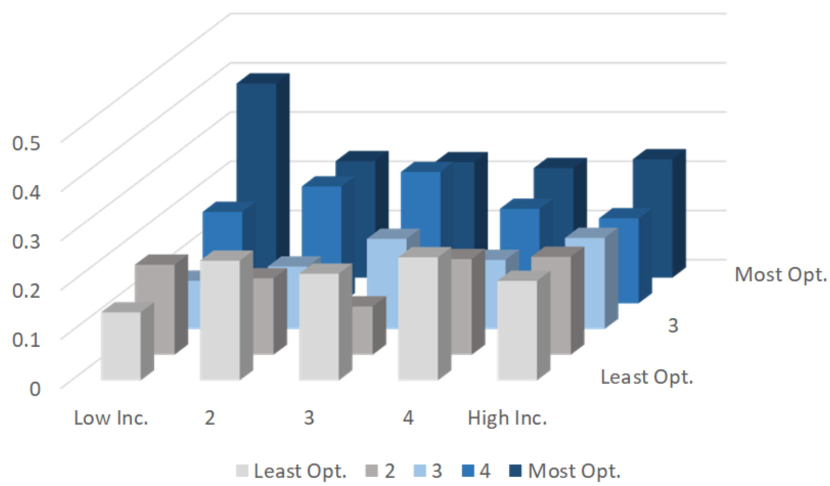


Figure A11: Income-by-Optimism choice of High-LTV Loans

This table shows the share of households purchasing a home in the last two years with a high-LTV loan (FHA or private) in each period. High-LTV borrowers are those who report outstanding mortgage balances valued at more than 80% of the value of their home. Shares sum to one by income quintile. Optimism is measured using a residual of life expectancy after controlling for year fixed effects, as well as observable individual characteristics like age, income, education, gender, smoker status, and perceived health status. The pre-period uses SCF waves 1995, 1998, and 2001 (top figure). The boom period uses SCF waves 2004 and 2007 (bottom figure). Quintiles of income and optimism are formed using survey weights.



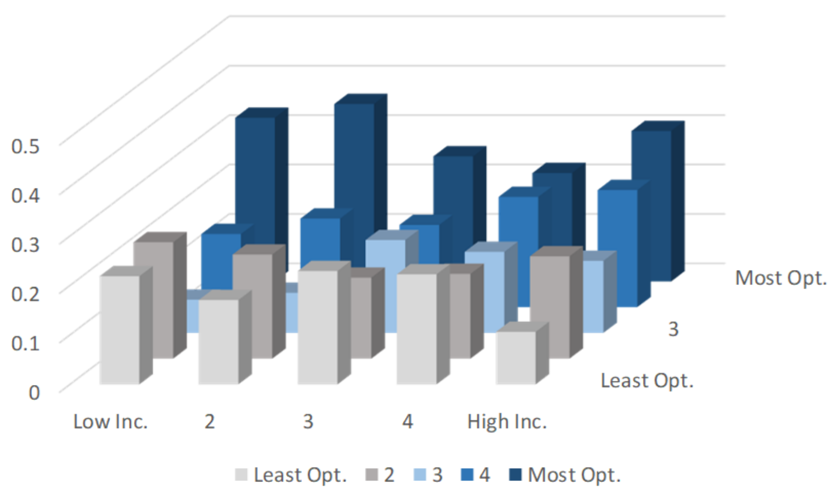


Figure A12: CLTV Distributions of New and Existing Lenders

These figures plot the combined loan-to-value ratios (CLTVs) of purchase transactions from new lenders (Panel A) and all other lenders (Panel B). New lenders are defined each year as those lenders who made their first loan at some point in the previous three years. Each purchase transaction includes data on up to three mortgages: one primary mortgage and up to two piggyback mortgages. Each loan has one lender defined as the lender of the primary mortgage.

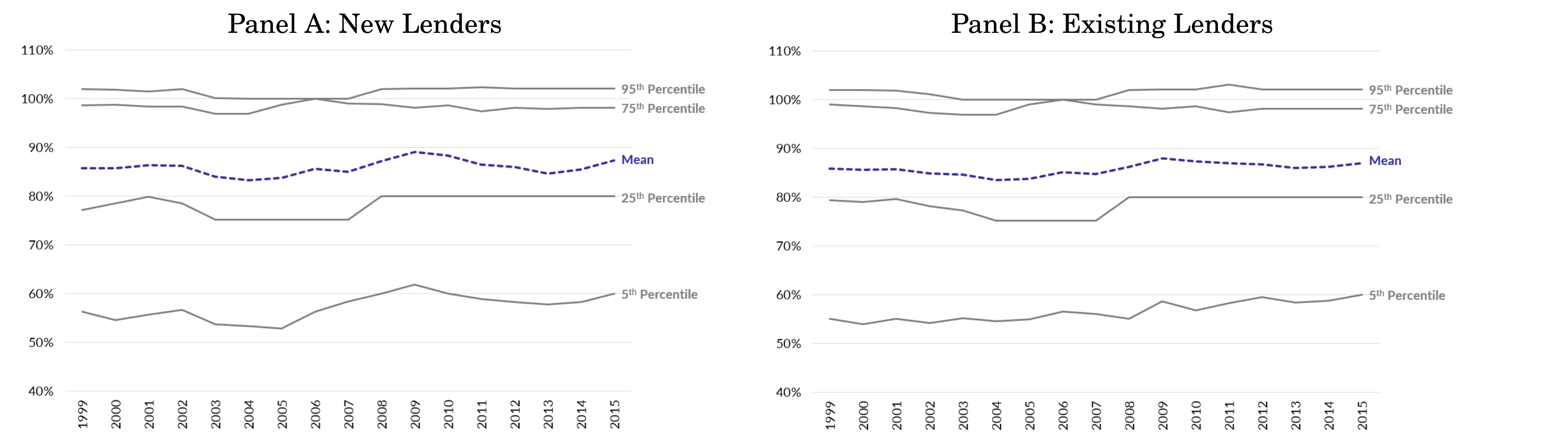


Figure A13: CLTV Lender-by-County Index (Relative to 2001 Baseline)

This figure plots a CLTV index relative to a 2001 baseline. Instead of property fixed effects as used in Figure A8, this figure includes lender-by-county fixed effects. In this way, CLTV differences are calculated using only variation with lender-by-county loans over time. The estimates and confidence intervals of each year's effect are graphed below.