Does Skin-in-the-Game Discipline Risk Management? Evidence from Mortgage Insurance

Haoyang Liu*

September 25, 2017

Abstract

Many mortgage reform proposals suggest replacing Fannie Mae and Freddie Mac (the GSEs) with private entities. A common assumption underlying these proposals is that unlike the GSEs, private insurers will properly manage risk and set fair prices. Inconsistent with this assumption, this paper presents evidence that private insurers less effectively managed home price risks during the 2000-2006 housing boom than the GSEs did. Mortgage origination data reveal that the GSEs were selecting loans with increasingly higher percentages of down payments, or lower loan to value ratios (LTVs), in boom areas than in other areas. These lower LTVs in boom areas reduced the GSEs' exposure to overheated markets. Furthermore, the decline of LTVs in boom areas stems entirely from the segment insured by the GSEs only, and none of the decline stems from the segment where private mortgage insurers take the first loss position. Private insurers also did not lower their exposure to home price risks along other dimensions, including the percentage of high LTV GSE loans they insured and the percentage of insured mortgage balance. My results highlight that post-crisis reform of the mortgage insurance industry should carefully consider additional factors besides moral hazard induced by the government guarantees, such as mortgage insurers' future home price assumptions and the industry organization of the mortgage origination chain.

Keywords: Risk Management; Private Mortgage Insurance Companies; Fannie Mae and Freddie Mac; Home Price Risk; Macroprudential Policies

*Liu: Florida State University, hliu@business.fsu.edu. I particularly would like to thank Andreas Fuster for numerous comments that greatly improved the paper. I also want to thank David Scharfstein, Janice Eberly, Jennifer Carpenter, Edward Glaeser, Hoai-Luu Q. Nguyen, Ben R. Craig, Ellis W. Tallman, Richard Stanton, David Sraer, Jan-Peter Siedlarek, Johan Walden, Lauren Lambie-Hanson, Guodong Chen, James Conklin, Richard Martin, Brent Ambrose, Liang Peng, Jiro Yoshida, Paulo Issler, Tom Chappelear as well as the seminar participants at Florida State University, New York University, University of California Berkeley, Loyola Marymount University, the Federal Reserve Bank of Cleveland, and BlackRock for helpful comments. I especially wish to thank my advisers Nancy Wallace, Christopher Palmer, Amir Kermani, and late adviser Dwight Jaffee for their invaluable advice. For the latest version, please email me or visit liuhy.weebly.com. First version: October 2016

"Traditionally MIs (private mortgage insurance companies) added discipline to the system by pulling back from overheated regional markets or by changing their pricing in those markets. The MIs stopped carrying out those practices as lenders got larger, however, for fear of losing their business."

— Timothy Howard, *The Mortgage Wars*, page 93

1 Introduction

Finding a long-term solution for Fannie Mae and Freddie Mac (the GSEs) is one of the key remaining issues to resolve from the 2008 financial crisis. A common assumption in these policy discussions is that private mortgage insurance (PMI) companies will more effectively manage risk and set fairer prices than the GSEs did. Yet, with the important exception of concurrent work by Bhutta and Keys (2017)[1], there is limited empirical evidence either for or against this assumption. This paper presents evidence inconsistent with the assumption that private capital guarantees disciplined risk management. I show that between 2000 and 2006, the GSEs pulled back from bubble areas by lowering the loan-to-value ratios (LTVs) in these markets. In contrast, little evidence suggests that private insurers took precautionary measures for the looming housing downturn.

My analysis is based on the segmentation of GSE loans along loan-to-value ratios (LTVs). GSE loans with LTVs at or below 80% are insured by the GSEs only. For GSE loans with LTVs above 80%, private insurers take a first loss position before the GSEs cover additional losses (Bhutta and Keys, 2017; Frame, Fuster, Tracy, and Vickery, 2015). I show that in the LTVs at or below 80% segment, boom areas had a greater relative decline of LTVs than other areas. By lowering the LTVs

[1] Using different evidence from different time periods, both Bhutta and Keys (2017) and the current paper show that private capital did not discipline PMI firms' risk taking. Bhutta and Keys (2017) document that PMI insurance surged in 2007, when house prices were already declining. This paper focuses on the boom period of 2000-2006 and shows that the GSEs lowered their exposure to bubble markets using lower loan-to-value ratios, while the PMI firms did not pull back from these overheated areas. Section 2 reviews the findings of Bhutta and Keys (2017) and how the two papers are related in greater details.

in these boom areas, the GSEs reduced their exposure to a housing downturn. In contrast, in the LTVs above 80% segment, I find no evidence that private insurers lowered their home price risk along dimensions where they could have adjusted. For instance, private insurers did not pull back from the bubble markets by insuring a smaller percentage of loans from these markets. Also, LTVs did not significantly decline more in boom areas than elsewhere in the LTVs above 80% segment. Another example is that private mortgage insurers did not lower their percentage of covered losses in boom areas compared to other areas.

The lack of home risk management by PMI firms is particularly puzzling given their elevated exposure to home price risk. They take the first loss position for high LTV GSE loans, whose default rates are very sensitive to home price declines. One potential explanation for this puzzle is that the PMI companies did not foresee the 2007-2012 housing crash. However, this can not explain the 2007 surge in PMI issuance when home prices were already declining, documented by Bhutta and Keys (2017). One likely explanation for the PMI firms' behavior is their small bargaining power in front of the GSEs and large national banks (Bhutta and Keys, 2017; Howard, 2013). It could be that private insurers wanted to lower their home price risk exposure but could not due to competition to keep their clients. For example, Howard (2013) suggests that private insurers "stopped pulling back from overheated markets for fear of losing their business." Another piece of evidence is that PMI firms charge the same fee for loans from different areas, despite the different riskiness, because their clients prefer geographically uniform pricing. A second, and related, potential explanation is that compared with the GSEs, private insurers have far lower charter values. These smaller charter values give them less incentive to prevent bankruptcy, and encourage risk taking. This story echoes the banking literature finding that insured depository institutions with lower charter values are more risk taking (Allen and Rai, 1996; Gan, 2004; Keeley, 1990). More recently, Frame and White (2007) built on the "charter value" literature and successfully predicted that competition from the private label space would reduce the GSEs' charter values, leading to

their riskier loan selection towards the end of the housing boom (FCIC, 2011)[2].

The main empirical challenge in my paper is how to interpret the declining LTVs among GSE loans from boom areas. While this is consistent with the idea that the GSEs lowered their exposure to overheated markets, there are many other possible explanations. I set out the following major alternative hypotheses: mechanical effect of conforming loan limits, reverse causality, and borrowers' demand side stories. From the empirical tests described in the following, there is little evidence for any of these hypotheses.

The first alternative hypothesis that I test is driven by the conforming loan limits. GSE-insured mortgages are required to be under a year-specific size threshold, known as the "conforming loan limit" (CLL). In high home price CBSAs with a large recent home price boom, their LTVs would have to be lowered to still satisfy the CLL requirement. To address this, I exclude high home price CBSAs (colored orange in Figure 2) from my sample. I find that the relationship between decline of LTVs and home price appreciation persists in the remaining sample.

A second potential concern is reverse causality. Changes in LTV requirements have causal impacts on house prices (Caballero and Krishnamurthy, 2001; Corbae and Quintin, 2015; Iacoviello, 2005; Kiyotaki, Moore, et al., 1997; Sommer, Sullivan, and Verbrugge, 2013). Thus my results might represent the impact of credit constraints on house prices, instead of rising house prices driving the GSEs' risk management. However, the reverse causal story predicts the opposite sign of my coefficients. Lowering LTVs, or equivalently increasing percentages of down payments, would bring down house prices, not trigger a housing boom. The coefficient estimates presented in this paper are likely biased towards zero by reverse causality.

[2]See chapter 9 of the Financial Crisis Inquiry Report for evidence that the GSEs drastically increased their risk taking at the end of the housing boom, late 2005 to 2007. For example, in 2005 Freddie Mac's CEO Richard Syron fired David Andrukonis, Freddie's chief risk officer. Syron said one of reasons was that Andrukonis was concerned about relaxing underwriting standards to meet mission goals. For Fannie Mae, when the chairman of the board Stephen Ashley introduced the then new chief risk officer Enrico Dallavecchia in 2006, Ashley said that Dallavecchia "was not brought on-board to be a business dampener." The results presented in this paper are stronger if I exclude year 2006, the final year of the boom period, from my sample. However, to verify that the results are robust to including the end of the housing boom, year 2006 is added to the sample period. In Table A.4, I also verify that the results are robust to adding year 2007 into my sample, except in the bivariate regression.

Another important consideration in interpreting the result is demand side stories. The LTV above and below 80% segments are very different. Borrowers' mortgage demands in these two segments might have changed in important ways between 2000 and 2006, accounting for my results. To address this, I take several approaches. First, I conduct a placebo test using private label 30-year FRMs, where there is no significant segmentation at 80% LTV. I show that there is no statistically significant relationship between HPA and change in LTVs in either the LTV above or below 80% segments of private label 30-year FRMs. Second, to address the story that trade-up buyers from boom areas had larger housing wealth, and preferred lower LTVs on their next mortgages, I restrict the sample to first time home buyers. Within this subsample of loans, the results are still strongly significant. In addition, I also verify that the results are not driven by borrowers voluntarily switching to other mortgage products, including second liens, private label FRMs, or private label ARMs. These findings suggest that my results represent the GSEs' mortgage supply side factors, rather than variation in demand.

Besides discussing the three above hypotheses, other alternative stories addressed in the paper include the effect of binding debt-to-income ratios (DTI) constraints, changes in FICO scores, and difficulty in saving for the 20% down payments. I also verify that the results are robust to including refinance loans and mortgage products besides 30-year FRMs into the estimation sample.

To understand the magnitude of the GSEs' home price risk management, I build a fixed income valuation model projecting the total discounted guarantee fees collected by the GSEs and costs paid by the GSEs to investors under three home price mean reversion scenarios. Figures 3 to 5 illustrate the results from the structural valuation model. From Figure 3, we see that risk management by the GSEs indeed results in a net lower risk in boom areas compared to other areas if home prices stay constant. However, the magnitude of risk management is small. For example, Figure 4 shows that under a 10% home price mean reversion, boom areas would already have larger normalized cost than elsewhere. Figure 5 shows that under the realized 95% mean reversion, the GSEs' cost would be much higher than revenue in many boom areas, consistent with the findings in Frame, Gerardi,

and Willen (2015).

I stress that the evidence presented in this paper is not meant to suggest that the public-private partnership in the GSE model was flawless or reliable. In fact, Figures 3 to 5 show that the GSEs' risk management was insufficient for the home price crash. Also, while the GSEs' risk management was reasonably good up until 2005, there is numerous evidence that their risk discipline deteriorated in 2006 and 2007 (FCIC, 2011), after losing market share during the entire boom period. The surprising part of my results is that the PMI firms did even less reducing of their home price risk exposure than the GSEs did, despite private capital at stake. This suggests that besides introducing private capital, the GSE reform should also consider how to prevent the "race to the bottom" dynamics.

Comparing the GSEs' risk management with the PMI firms' has implications beyond the mortgage market. Many other credit and insurance markets are partially or fully sponsored by the government, including flood insurance, Medicare, and student loans. These government sponsored programs draw frequent scrutiny both from academia and the popular press because of moral hazard concerns (Bin, Kruse, and Landry, 2008; King, 1994; McMillan, 2007; Michel-Kerjan, 2010; Oberlander, 1997; Pear, 1996). My evidence highlights that whether private capital can discipline risk taking for these markets requires a case-by-case study.

The paper is structured as follows. Section 2 reviews related literatures. Section 3 gives a brief introduction of the institutional background. Section 4 describes data used in my analysis. Section 5 presents evidence that the GSEs reacted to the housing bubble by lowering LTVs in boom areas, while PMI firms did not. Section 6 presents the insurance valuation framework. Section 7 concludes.

2 Literature Review

My paper is most related to concurrent work by Bhutta and Keys (2017). Using different pieces of evidence, both Bhutta and Keys (2017) and the current paper show that the private capital did not discipline PMI firms' risk management. The central piece of evidence in Bhutta and Keys (2017) is the 2007 surge in PMI issuance, when home prices already started declining. The current paper focuses on the 2000-2006 boom period, and finds that the PMI firms did not prepare for the housing downturn while the GSEs did. Bhutta and Keys (2017) also document that PMI firms generally insured any loans approved by the GSEs during the housing boom. Taking this with evidence presented in the current paper reveals an interesting dynamic: the GSEs imposed stricter loan selection in bubble areas when they were the sole insurer, but did not pull back from the same overheated areas when they were essentially selecting loans on behalf of the PMI firms. This reinforces a crucial point made by Bhutta and Keys (2017): "rather than acting as a check, PMI companies compounded the moral hazard in the mortgage market during the housing boom."

Besides Bhutta and Keys (2017) and other papers mentioned above on GSE reforms, my findings relate to the following literature: 1) macroprudential policies; 2) understanding home price expectations, especially during the 2000s housing bubble; 3) GSEs' loan selection and risk management; 4) the interaction between credit conditions and home prices.

The LTV ratio is a macroprudential policy tool widely used to intervene in home prices in many countries, including Hong Kong, China, the Netherlands, Sweden, Singapore and New Zealand (Borio and Shim, 2007; Lim, Costa, Columba, Kongsamut, Otani, Saiyid, Wezel, and Wu, 2011; Shin et al., 2011; Wong, Fong, Li, and Choi, 2011). In the U.S., academics also suggest that during a boom period, banks should use the long run home prices, instead of the current market prices, for mortgage underwriting (Glaeser, 2013). The evidence presented in this paper shows that although the GSEs do not explicitly claim LTVs as a policy tool, they do use LTVs in managing their home price risk. My results also highlight a potential limitation of macroprudential policies

in the U.S. context. While it is possible for smaller countries, like Hong Kong, to raise minimum down payment percentages by 10% or 20% in reaction to a housing bubble (Wong, Fong, Li, and Choi, 2011), it might not be politically feasible for the U.S. to raise down payment percentages in just the bubble areas but not the others. The GSEs did select loans with lower LTVs in boom areas, but not nearly enough to offset the increased risk in these markets. One potential explanation is that the GSEs face political pressure to keep reasonable regional uniformity (Hurst, Keys, Seru, and Vavra, 2016). This prevented them from implementing drastically different lending standards in different parts of the country.

For the home price expectation literature, my findings complement Cheng, Raina, and Xiong (2014). Using investment bankers' personal home transactions, Cheng, Raina, and Xiong (2014) showed that private label securitization agents did not show an awareness of the housing bubble. In fact, some groups of private label securitization bankers were particularly aggressive in expanding the housing portfolios right before their housing crash. In this paper, I show that in contrast to the private label securitization chain, the GSEs were aware of the housing bubble, highlighting the different beliefs of the public and private segments of the mortgage market.

Understanding beliefs about home prices is crucial because the magnitudes of the last housing cycle far exceed what can be explained by credit expansion alone (Glaeser, 2013; Glaeser, Gottlieb, and Gyourko, 2012). Exuberant expectation of home prices is likely a major cause for the boom-bust cycle (Foote, Gerardi, and Willen, 2012; Kaplan, Mitman, and Violante, 2015). Recent studies also show that credit expansion itself was more likely to be driven by home price beliefs instead of changes in lending technologies (Adelino, Schoar, and Severino, 2016; Foote, Loewenstein, and Willen, 2016). A question in this literature is whether it was reasonable for people to realize the housing bubble prior to the crash. This has implications for whether it is feasible to define an "asset bubble" in real time before a bust and how the government should respond to it. Cortés (2015) shows that local lenders forecasted the housing bust and reduced their market shares. The current paper shows that the GSEs, the dominant insurers of the mortgage market, also foresaw the

housing crash to some extent and reacted based on the belief.

On the GSEs' loan selection, my paper builds on the premise of Kulkarni (2016) and Hurst, Keys, Seru, and Vavra (2016), namely, that the GSEs charge uniform prices across different areas, but adjust along the extensive margin. Kulkarni (2016) shows that the GSEs select more loans from lender-friendly states than neighboring borrower-friendly states. My contribution is presenting evidence that the GSEs reacted to the housing boom by lowering the share of high LTV loans in boom areas.

I also contribute to the vast literature studying how credit conditions interact with house prices (Caballero and Krishnamurthy, 2001; Corbae and Quintin, 2015; Iacoviello, 2005; Sommer, Sullivan, and Verbrugge, 2013). In the context of the early 2000s housing cycle, there is evidence that rising house prices relaxed lending standards through extrapolative home price expectation (Adelino, Schoar, and Severino, 2016; Brueckner, Calem, and Nakamura, 2012). My contribution is to show that home prices higher than the fundamentals can also tighten lending standards when cautious lenders prepare for a housing bust.

3 Institutional Background

This section gives a brief overview of the institutional settings studied in this paper. For more details, I refer the reader to Frame, Fuster, Tracy, and Vickery (2015); Jaffee and Quigley (2012); Weiss, Rosso, and Clymer (2012). Section 3.1 briefly discusses the history and business models of Fannie Mae and Freddie Mac. Section 3.2 discusses private mortgage insurance companies. Section 3.3 presents a numerical example of how private mortgage insurers take first loss positions for high LTV GSE loans.

3.1 Fannie Mae and Freddie Mac

Fannie Mae and Freddie Mac were established as government-sponsored enterprises by the 1968 and 1970 legislations (Jaffee and Quigley, 2012). They are private entities in that they have profit-maximizing shareholders with stocks traded on the New York Stock Exchange. They are also public entities in the sense that they were chartered by Congress, with some board members selected by the president. Their structure as government-sponsored enterprises is to remove their activity and debt from the federal budget, while still achieving some public policy goals.

Fannie Mae and Freddie Mac's activities take two broad forms. First, their credit guarantee business provides mortgage insurance. They purchase a pool of mortgages from originators, typically banks or mortgage companies, and then issue a security that receives cash flows from the mortgage payments, also called a mortgage backed security. They promise mortgage backed security investors timely payments of principal and interest, even if there are defaults and losses on the underlying loans. In return, the firms receive a monthly "guarantee fee" (Frame, Fuster, Tracy, and Vickery, 2015). The second form of Fannie Mae and Freddie Mac's business is to invest in assets including whole mortgages, their own agency mortgage-backed securities, nonagency mortgage-backed securities, and other types of fixed income securities, (Frame, Fuster, Tracy, and Vickery, 2015).

Notice that during the 2008-2011 crisis period, the credit guarantee business lost $215 billion. The investment business generated $85 billion profit during 2009-2011, despite the large initial loss of $83 billion in 2008 (Frame, Fuster, Tracy, and Vickery, 2015).

3.2 Private Mortgage Insurers

Private mortgage insurers are companies that provide mortgage insurance similar to the ones provided by the GSEs. They primarily provide credit enhancement for GSE loans with LTVs above 80%.

Given that the default rate of high LTV loans strongly co-moves with housing cycles, private mortgage insurers have had concentrated failures. In the 1930s, all 50 or so private mortgage insurance companies became insolvent (Weiss, Rosso, and Clymer, 2012). From the mid-1930s until the 1950s no private mortgage insurers existed and Federal Housing Administration (FHA) was the only provider of mortgage insurance. In the 1980s crash, about half of the private mortgage insurance companies stopped underwriting insurance. Only about a dozen companies survived. Due to the 2006-2011 housing crash, three out of the eight major mortgage insurers failed. They also changed their behavior in handling claims, for example, rejecting an unprecedented high fraction of claims and delaying settlements, so that they would suffer less loss at the expense of their clients. However, perhaps overshadowed by the highly publicized and controversial bailout of the GSEs, private mortgage insurers' failures have received relatively little attention from academics and the popular press.

3.3 Numerical Example of Insurance for High LTV GSE Loans

This section presents a numerical example of how private insurers take first loss positions for high LTV GSE loans, with the GSEs covering any additional losses.

Consider a mortgage with an initial balance of \$270,000 for a house valued at \$300,000 at origination. Since the initial LTV is 90%, higher than the 80% threshold, the mortgage requires private mortgage insurance to be eligible for the GSEs' purchase. The median percentage of loan balance covered by private insurers, also called *coverage ratio*, is 25% for high LTV GSE loans. Assume that two years later after origination, the borrower defaulted. At the time of default, the remaining balance was \$260,000 and the house value was \$150,000. The total loss for the lender is \$110,000, the difference between remaining balance and house value. Assuming a 25% coverage ratio, the private insurer would cover $25\% \times \$270,000 = \$67,500$. The GSEs would cover $\$110,000 - \$67,500 = \$42,500$.

Notice that in this example, since a private insurer covers 25% of the initial balance, the net LTV for the GSEs is $75\% \times 270,000/300,000 = 67.5\%$, much lower than the 80% threshold. This is typical for high LTV GSE loans. In other words, just in terms of LTVs, high LTV GSE loans are typically less risky than an 80% LTV conforming loan.

4 Data and Descriptive Statistics

4.1 Data

The primary loan-level datasets used in this paper are collected from Fannie Mae and Freddie Mac websites. These public datasets have rich mortgage characteristics, including original LTV, original CLTV, FICO score, loan amount, loan purpose (purchase or refinance) and detailed monthly loan performance. A unique feature of the GSE public data is that they have a first-time home buyer indicator. This variable helps me address an important alternative story from the wealth effect of past home price appreciation.

One limitation of the GSE public data is that they only cover 30-year FRMs, representing about 70% of the GSE loans during the housing boom (Frame, Fuster, Tracy, and Vickery, 2015). As a robustness test, I verify that the results are robust to including all mortgage products insured by the GSEs using a dataset provided by LPS Applied Analytics. Also, to conduct a placebo test using private label loans, I use a loan-level dataset provided by ABSNet.

Our CBSA level home price data come from FHFA. The FHFA home price index is typically used for mortgage modeling and stress testing. Interest rate data are from Yield Book, a fixed income valuation service provided by Citi group. Unemployment rates are collected from BLS. CBSA-year level income data are downloaded from the IRS website.

4.2 Summary Statistics

Table 1 reports the summary statistics for both GSE 30-year FRMs and private label 30-year FRMs. We can see that the average FICO scores and LTVs for GSE loans were relatively stable during the entire boom period. Average LTVs were around 92.8% for the above 80% LTV segment, and around 72.7% for the below 80% LTV segment. Average LTVs for private label 30-year FRMs varied slightly more during the boom period. FICO scores significantly changed for private label FRMs at the beginning and at the end of the housing boom. For loans with LTVs above 80%, the average FICO scores jumped from 661 in 2001 to 688 in 2003, and fell back to 665 in 2006. Considering this, in the placebo tests using private label FRMs, I also present results using the 2003-2005 period, when borrowers' characteristics were stable.

4.3 Descriptive Evidence

Figure 1 displays a binned scatter plot of change in LTVs versus home price appreciation between 2000 and 2006. We can see that there is a much stronger relationship in the LTVs below 80% segment than the LTVs above 80% segment. In fact, Section 5 shows that in the LTVs above 80% segment, after controlling for changes in macroeconomic conditions and other loan and borrower characteristics, the relationship between HPA and LTV growth becomes insignificant.

5 Home Price Risk Management through LTVs

This section presents evidence that during the 2000-2006 housing boom, the GSEs actively lowered their home price risk exposure through LTVs while private insurers did not.

Section 5.1 presents the empirical model and my estimation samples. To isolate two important alternative explanations, the mechanical effect of conforming loan limits and wealth effect from past home price appreciation, my preferred sample is purchase mortgages taken by first-time home

buyers from low to middle home price CBSAs. Results for both the full sample and the preferred sample are presented in Section 5.2.

Section 5.3 and Section 5.4 conduct robustness tests for the GSEs and private insurers respectively. Section 5.3 presents additional evidence for the risk management interpretation of the findings on the GSE segment. I consider alternative explanations including reverse causality, demand side stories, upper bound on DTIs, risk adjustment along other dimensions, challenges in saving for 20% down payments, mortgage products besides 30-year FRMs insured by the GSEs, and LTVs for refinance loans. In Section 5.4, I show that private insurers did not lower their home price exposure through two other channels along which they could have adjusted: share of high LTV loans and coverage percentage.

5.1 Empirical Model

The main specification is

$$\Delta \log LTV_{ct,LTV\leq 80.5\%} = \beta_{LTV}^{LTV\leq 80.5\%} \Delta \log HPI_{ct} + \beta_X \Delta X_{ct} + \alpha_c + \gamma_t + \epsilon_{ct}, \quad (5.1)$$

$$\Delta \log LTV_{ct,LTV>80.5\%} = \beta_{LTV}^{LTV>80.5\%} \Delta \log HPI_{ct} + \beta_X \Delta X_{ct} + \alpha_c + \gamma_t + \epsilon_{ct}, \quad (5.2)$$

where α_c and γ_t are geographic and year fixed effects respectively; $\Delta \log LTV_{ct,LTV\leq 80.5\%}$ and $\Delta \log LTV_{ct,LTV>80.5\%}$ are changes in logged average LTVs from year t to year $t+1$ in CBSA c for the LTVs below 80% and LTVs above 80% segments respectively. $\Delta \log HPI_{ct}$ are changes in log home prices. ΔX_{ct} are CBSA-year level control variables, including changes and levels of macroeconomic conditions measured by unemployment rate and average income, changes and levels of loan and borrower characteristics including average FICO scores, debt-to-income ratios, interest rates and percentage of owner occupied mortgages.

LTVs are among the many loan and borrower characteristics the GSEs and private insurers adjust. To complement the findings for LTVs, I also estimate the following regression for FICO

scores

$$\Delta \log FICO_{ct} \quad = \quad \beta_{FICO}^{LTV \leq 80.5\%} \Delta \log HPI_{ct} + \beta_X \Delta X_{ct} + \alpha_c + \gamma_t + \epsilon_{ct}. \tag{5.3}$$

Naturally, in the FICO score regressions, the set of control variables include changes in LTVs and exclude changes in FICO scores.

5.1.1 Mechanical Effect of Conforming Loan Limit

One important alternative explanation for declining LTVs in boom areas is the mechanical effect of the conforming loan limits (CLLs). The size of GSE loans is required to be under the CLLs. Since LTVs are loan amount divided by house prices, any increase in house prices above the CLLs would have to be compensated by a decrease in LTVs to still satisfy the CLL requirement.

To address this, I construct two samples where the CLLs are not binding. In the first sample, I restrict the sample to CBSAs with low to middle home prices by 2006, where house prices were well under the CLLs. Low to middle home price CBSAs are defined as CBSAs with more than 90% of private label loans in 2006 under the CLLs. I use the distribution of private label loans because their loan amount is not required to be under the CLLs. Notice that the 90% selection criteria is very strict. All CBSAs in the remaining sample had median home prices at least $100,000 below the CLLs throughout the housing boom. Figure 2 plots the excluded and selected CBSAs. Intuitively, many of the CBSAs on the two coasts have high home prices and are thus excluded. Some boom CBSAs with initial low home prices, including part of inland California and Florida, are kept in the remaining sample because their prices started low. This provides enough variation in HPA to study the relationship between HPA and changes in LTV. I report results from both the full sample and the low to middle home price CBSAs sample. In the second sample, I keep loans below 95% of the CLLs. The gap between their loan amount and the CLLs ensure that the CLLs are not binding for this universe of loans. Results under this robustness test are presented in

Table A.1. We can see that the results persist in this subsample as well.

5.1.2 Wealth Effect from Past Home Price Appreciation

One could also argue that the decline of LTV for GSE loans was driven by borrowers' demand for low LTV loans, not driven by the GSEs' supply of low LTV loans. This is especially plausible, since buyers who traded up in 2005 might have carried the equity in their previous home to their next mortgages. Since home equity is strongly correlated with past home price appreciation, trade-up buyers from boom areas in 2005 might have naturally asked for lower LTV than buyers from other areas, unrelated to GSEs' risk management. To address this, I run separate regressions for first-time home buyers and other buyers. First time home buyers are particularly unlikely to be affected by the wealth effect from past home price appreciation. I show that the relationship between home price appreciation and decline of LTVs persists in the first-time home buyer sample. This is more consistent with the supply side story from GSEs' risk management than the demand side story of boom area borrowers voluntarily taking low LTV loans. Section 5.3.2 presents more evidence to address demand side stories.

5.2 Main Result

Table 2 and Table 3 report results from regressions (5.1) and (5.2), estimating the effect of home price appreciation on LTVs. Table 2 reports results from all CBSAs while Table 3 excludes high home price CBSAs from the sample.

Panel A of Table 2 focuses on first-time home buyers. Columns 1- 4 are for the LTVs below 80% segment. Columns 5-8 are for the LTVs above 80% segment. Columns 1 and 5 report the results of bivariate regressions. Columns 2 and 6 control for year fixed effects only. Columns 3 and 7 add CBSA-year level controls, including changes and levels of macroeconomic conditions, and changes and levels of loan and borrower characteristics. Columns 4 and 8 further add CBSA

fixed effects. The most striking contrast in Panel A is the strongly negative coefficient in column 4 and the statistically insignificant coefficient in column 8. In the LTVs below 80% segment, LTVs significantly declined in boom areas compared to other areas, while there is no such pattern in the above 80% segment.

Panel B of Table 2 reports the results for other buyers. Comparing the coefficients for other buyers with the corresponding coefficients for first-time buyers in Panel A, we see that the LTVs always declined more among loans taken by other buyers than first-time buyers in boom areas. This is consistent with the hypothesis that second time home buyers voluntarily lowered their LTVs in response to home price booms from a wealth effect.

Table 3 excludes high home price areas to rule out the mechanical effect of conforming limits discussed in Section 5.1.1. As discussed in Section 5.1.1 and Section 5.1.2, my preferred sample is GSE first-time home buyers from low to middle home price CBSAs, corresponding to Panel A of Table 3. Columns 1- 4 show that there is a consistent relationship between decline of LTVs and home price appreciation in the LTVs below 80% segment. Columns 5-8 show that in the LTVs above 80% segment, boom areas did not have a disproportionately larger decline of LTVs. The estimate -0.045 in column 4 of panel A implies that a 10% home price appreciation leads to a 0.43% decline of LTVs.

5.3 Robustness Tests for the GSEs

I interpret the relative decline of LTVs in boom areas among the below 80% LTV segment as the GSEs' home price risk management. However, there could be many other different interpretations. This section considers a number of other alternative stories.

5.3.1 Reverse Causality

A first plausible concern for regressions (5.1) and (5.2) is that they are subject to reverse causality. After all, the literature studying how credit constraints interact with home prices largely focuses on how credit conditions, including LTV requirements, would affect house prices (Corbae and Quintin (2015); Sommer, Sullivan, and Verbrugge (2013)). However, this reverse causal story predicts the opposite signs of my findings. Absent of other changes, declining LTVs, or equivalently requiring higher percentage down payments, would lower home prices, not trigger a housing boom. In contrast, I find that LTVs for GSE loans declined in boom CBSAs, the opposite of the causal impact of LTV requirements on house prices.

5.3.2 Borrowers' Demand Side Stories

The risk management interpretation essentially means that high LTV borrowers from boom areas were credit rationed by the GSEs for home price risk management. One could argue that rather than being credit rationed, these borrowers voluntarily lowered their LTVs or switched to other products by choice. To address this, besides restricting to first-time home buyers, this section takes several other approaches. I first present a placebo test using private label 30-year FRMs, and then address three alternative stories along the line of borrowers switching to other products, including private label FRMs, ARMs, or second liens.

While GSE loans are divided by the 80% LTV cutoff in terms of who bears the default risks, the segmentation of private label loans at 80% LTV is much weaker. This provides us with a setting to conduct a placebo test using private label mortgages. Table 4 reports estimates from regressions (5.1) and (5.2) for GSE and private label 30-year FRM purchase loans. From Table 4, we can see that there is a strong contrast between the above and below 80% LTV segments among GSE loans, but there is no such pattern for private label loans. Table A.2 reproduces Table 4 using just the two years between 2003-2005, a period with the largest home price gains and when borrower

characteristics were stable for both private label and GSE 30-year FRMs. We can see that the results are consistent with Table 4.

One important limitation of Table 4 is that the loan sample includes all purchase mortgages, instead of restricting to first-time home buyers, because the ABSNet data does not provide a first-time home buyer indicator. This likely causes an upward bias between the estimates for the above and below 80% LTV segments among private label loans. We can see that despite this bias, the difference between these estimates is not statistically different from zero.

Next I consider whether my findings are driven by high LTV borrowers from boom areas switching to other mortgage products. The first example is that borrowers switched to private label FRMs because they offered better terms. To test this theory, I use interest rate data for both GSE 30-year FRMs and private label 30-year FRMs to test if private label FRMs offered better interest rates relative to GSE loans towards the end of the housing boom than in the beginning of the housing boom. I first divide mortgages into sixteen segments along two dimensions, LTV and FICO score. Along the LTV dimension, I divide LTV into four ranges: below 79.5%, between 79.5% and 80.5%, between 80.5% and 90%, and above 90% [3]. Along the FICO score dimension, I divide the spectrum into four ranges: below 660, between 660 and 720, between 720 and 760, and above 760. There are sixteen combinations of LTV ranges and FICO score ranges. For each CBSA and each combination of LTV and FICO score, I collapse the median interest rate for both GSE 30-year FRMs and private label 30-year FRMs. In each year, there are more than 4000 CBSA-segment combinations. Table 5 reports the percentage of CBSA-segment combinations in which private label FRMs had a lower median interest rate than GSE FRMs. We can see that in every year between 2000 and 2006, GSEs had an interest rate advantage in more than 94% of the CBSA-segment combinations. More importantly, the percentage of CBSA-segments in which private label loans had an edge was declining through the housing boom. Also, all of the CBSA-segments in which private loans had an interest rate edge in 2005 and 2006 were small CBSA-segments, with 83 out

[3] I define between 79.5% and 80.5% as a separate segment because many mortgages have LTVs very close to 80%.

of 133 having 3 or fewer private label FRMs. These results show that competition from private label loans is unlikely to drive my results.

The second alternative story is about borrowers switching to ARMs. It could be that because of the rising home prices, many borrowers in boom areas found FRM payments unaffordable and switched to ARMs for temporarily lower interest rates. With these low income borrowers leaving the FRM pool in boom areas, the remaining FRM pool improved and LTVs for GSE FRMs declined. There are two pieces of evidence inconsistent with this argument. First, an assumption in this argument is that relatively low income borrowers switched to ARMs in boom areas. However, as illustrated in columns 5-8 of Table 6, average FICO scores for ARMs relatively increased in boom areas across different specifications. In boom areas, good borrowers, rather than low income borrowers, were more likely to leave the FRM pool than the other areas. The second piece of evidence is that, illustrated in columns 1-4 of Table 6, average FICO scores for GSE first-time home buyers relatively declined in boom areas throughout the housing boom. It is unclear that the relative improvement of GSE loans' LTVs in boom areas is driven by improving borrower quality.

The third mortgage choice alternative explanation is that boom area borrowers could have switched to low LTV GSE loans but took out second liens instead. To address this, I use changes in combined-loan-to-value ratios (CLTVs) as the left-hand-side variable in the following regressions

$$\Delta \log CLTV_{ct,LTV\leq 80.5\%} = \beta_{CLTV}^{LTV\leq 80.5\%} \Delta \log HPI_{ct} + \beta_X \Delta X_{ct} + \alpha_c + \gamma_t + \epsilon_{ct}, \quad (5.4)$$

$$\Delta \log CLTV_{ct,LTV>80.5\%} = \beta_{CLTV}^{LTV>80.5\%} \Delta \log HPI_{ct} + \beta_X \Delta X_{ct} + \alpha_c + \gamma_t + \epsilon_{ct}. \quad (5.5)$$

Table 7 reports the results. Comparing Table 7 with Table 3, we see that changing the left-hand-side variable to changes in CLTVs has little impact on the coefficients.

5.3.3 Upper Bound on Debt-to-Income Ratio

Another alternative story is that the debt-to-income ratios (DTIs) in boom areas might have reached the upper bounds allowed by the GSEs. Because loan sizes were constrained by the DTI upper bound, any higher home prices would make larger down payments, or lower LTVs necessary. To rule out this story, I drop loans with high debt-to-income ratios by a number of different thresholds. By dropping these loans with possibly binding debt-to-income ratios, I test if the relationship between home price appreciation and decline of LTVs still holds. Table 8 reports the results. We can see that in the low DTI subsamples, the results continue to hold.

5.3.4 Comparing Magnitudes of Different Dimensions

LTVs are one of the dimensions through which the GSEs adjust risk. Other dimensions include FICO scores, debt-to-income ratios (DTIs), original loan amount, interest rates, and owner occupancy. One could argue that LTVs were not the main dimension of the GSEs' risk management. For example, the GSEs might adjust FICO scores between boom areas and non-boom areas much more than their LTV adjustment. For a complete analysis of the net risk management by the GSEs, I build a structural valuation framework in Section 6 based on calibration of term structure model, hazard regressions and forecasting future prepayment and default speeds. In this section, I conduct back of envelope analysis for the GSEs' risk taking or risk management along perhaps the most important dimension besides LTVs, FICO scores.

Table 9 compares how the GSEs adjusted LTVs and FICO scores side by side. Column 2 shows that average FICO scores of GSE loans declined more in boom areas than other areas. In other words, the GSEs took an increasing amount of risk in boom areas compared with other areas along the FICO score dimension. A natural question is whether the risk taking along FICO scores is larger than risk reduction along LTVs or the reverse.

I present evidence that risk reduction along LTVs dominates risk taking along FICO scores.

First of all, conceptually, lower LTVs reduce the GSEs' losses through two channels while lower FICO scores increase the GSEs' losses through only one channel. Lower LTVs reduce both default probabilities and loss-given-default. Lower FICO scores only increase default probabilities, and have ambiguous impact on loss-given-default. The loss-given-default channel, only present in tightening LTV requirement but not in relaxing FICO requirement, could be much larger than the default probability channel under moderate home price declines.

If we focus on the default probability channel, to compare the effects on default probabilities, I use the elasticities of default with respect to LTVs and FICO scores estimated from hazard regressions detailed in Section 6. From Table 14, we see that their default elasticities have similar magnitudes, while Table 9 shows that the GSEs' LTV response is 2.4 times as large as the GSEs' FICO score response to rising home prices. Thus the GSEs' LTV home risk reduction dominates their FICO risk taking. I stress that the ratio of 2.4 is a very conservative estimate given that the loss-given-default channel is shut down.

5.3.5 Difficulty of Obtaining 20% Down Payments

This section addresses a more subtle alternative story. It could be that borrowers always try to lower their LTVs to 80% to avoid a private mortgage insurance premium. It was relatively easy to do in a low home price environment before the boom. However, it got significantly harder after the boom with higher home prices in bubble areas. This manifests as non-boom areas having an increasing concentration of LTVs at 80%, unlike boom areas, explaining why boom area LTVs relatively declined in the LTVs under 80% segment. If my findings were driven by this story, we would expect that after dropping loans with LTVs at 80%, the coefficients would become insignificant. However, Table 10 shows that the results persist after dropping loans with LTVs between 79.5% and 80.5% except the specification controlling for CBSA fixed effects. The absolute magnitudes of the coefficients are always larger than the baseline coefficients in Panel A of Table 3, including all loans by first-time home buyers with below 80% LTVs.

5.3.6 Including Refinance Loans and Other Mortgage Products

The sample of GSE loans used so far is subject to two restrictions: they are all purchase loans, and they are all 30-year FRMs. While these sample restrictions, together with focusing on first-time home buyers, helps disentangle different interpretations of the results, they are only a subset of loans insured by the GSEs. This section expands the sample to all loans insured by the GSEs as a robustness test.

Table 11 reports the results. Panel A includes both purchase loans and refinance loans. Panel B uses the LPS data to further include mortgage products besides 30-year FRMs, including 15-year FRMs and various ARMs. We can see that the patterns in Table 11 are consistent with the baseline results in Table 3.

5.4 Robustness Tests for Private Insurers

One challenge in interpreting Table 3 is that the share of loans with LTVs above 80.5% might have changed over time. For instance, private insurers might have been concerned about the housing bubble and insured a decreasing number of LTVs above 80.5% loans in boom areas compared with the other areas. To rule out this alternative story, I run the following regression

$$\Delta \log P_{ct,LTV>80.5\%} = \beta_{LTV>80.5\%} \Delta \log HPI_{ct} + \beta_X \Delta X_{ct} + \alpha_c + \gamma_t + \epsilon_{ct}, \tag{5.6}$$

where $P_{ct,LTV>80.5\%}$ is the percentage of loans with LTV above 80.5% in CBSA c and year t. Panel A of Table 12 reports the results. We see that in my preferred sample, boom areas did not have a larger relative decline of share of high LTV GSE loans.

Another potential channel for private mortgage insurance companies' home price risk management is coverage percentage, the maximum percentage of loan amount they cover in case of defaults. They could have relatively lowered their covered losses in boom areas to reduce home

price risk. Panel B of Table 12 reports results from the following regression

$$\Delta \log CP_{ct} = \beta_{LTV>80.5\%} \Delta \log HPI_{ct} + \beta_X \Delta X_{ct} + \alpha_c + \gamma_t + \epsilon_{ct}, \tag{5.7}$$

where CP_{ct} is coverage percentage in CBSA c year t. We can see that private mortgage insurance companies did not lower insurance percentages more in boom areas than elsewhere.

6 Valuation of Insurance

In this section, I construct an insurance valuation framework quantifying the risk management of the GSEs. The goal of the framework is to answer two questions: 1) Combining risk adjustment using all loan and borrower characteristics, did the GSEs indeed lower their risk exposure more in boom areas than other areas?; 2) How large was the magnitude of the GSEs' risk management? For the second question, I consider three hypothetical housing markets: 0% mean reversion, or prices staying constant, 10% mean reversion, and the realized 95% mean reversion. Mean reversion is defined following Glaeser (2013). For example, a 95% mean reversion means that for every $1 home price increase between 2001 and 2006 in a CBSA, it on average gave back 95¢ between 2006 and 2011.

My valuation framework calculates the discounted cash flows for the mortgage insurance underwritten by the GSEs in 2005, the peak year of the housing boom. Section 6.1 describes the cash flows. Section 6.2 presents the competing-risk hazard regressions, from which the estimated hazard parameters are used to forecast default and prepayment speeds, and the cash flows. Section 6.3 introduces the term structure model, used both as the discount rates valuing the cash flows and to calculate the coupon gap, an important predictor for default and prepayment risks. Section 6.4 summarizes the data-generating process. Section 6.5 presents the results.

To make the computation manageable. I restrict my loan sample to purchase mortgages from

the 100 largest CBSAs in the U.S. They represent about 75% of all mortgages in the full sample.

6.1 Insurance Cash Flows

Mortgage default insurance provided by the GSEs has two legs of cash flows. The first leg is the premium collected by the GSEs from investors over the life of mortgages. The second leg is paid by the GSEs to investors to cover losses when borrowers default and the collateral value is lower than the remaining balance. To be consistent with the credit default swap terminologies, I refer to the insurance premium leg as the fixed leg, and the leg of loss covered by the GSEs as the floating leg.

Both legs of the cash flows are random. The fixed leg is collected by the GSEs until mortgage termination, which is a random event. Reasons for termination include default, being paid in full until maturity, and prepayment caused by, for example, moving or refinance. The floating leg, paid when borrowers default, is random as well. Table 13 summarizes how the cash flows evolve each month by different mortgage outcomes.

6.2 Hazard Model

6.2.1 Hazard Model Specification

Many factors affect borrowers' default and prepayment decisions. For example, we have the intuition that borrowers with lower initial FICO scores are more likely to default. Another example is that when interest rates decline, borrowers have larger incentives to refinance and are more likely to prepay. The goal of the competing-risk model presented in this section is to study the relative importance of how different factors affect default and prepayment risks. I estimate the following

proportional competing-risk hazard model specified in equations (6.8) and (6.9)

$$\begin{aligned}
\lambda_{ic}^{\text{Default}}(t) &\equiv \lim_{\xi \to 0} \frac{1}{\xi} \text{Pr}_{ic}^{\text{Default}} \left(t - \xi < \tau \leq t | \tau > t - \xi, X\right) && (6.8) \\
&= \exp\left(X_{ict}' \beta^{\text{Default}}\right) \lambda_0^{\text{Default}}(t), \\
\lambda_{ic}^{\text{Prepay}}(t) &\equiv \lim_{\xi \to 0} \frac{1}{\xi} \text{Pr}_{ic}^{\text{Prepay}} \left(t - \xi < \tau \leq t | \tau > t - \xi, X\right) && (6.9) \\
&= \exp\left(X_{ict}' \beta^{\text{Prepay}}\right) \lambda_0^{\text{Prepay}}(t),
\end{aligned}$$

where

$$\begin{aligned}
X_{ict}'\beta &= \theta_{\text{HPA}} \log(\text{HPA}_{ct}) + \theta_{\text{Unemp}} \text{Unemployment}_{ct} + \theta_C (\text{Coupon Gap}) \\
&\quad + W_{Bi}'\theta_B + W_{Li}'\theta_L + \alpha_c, \\
\text{Coupon Gap} &= r_{10,\text{origination}} - r_{10,t}, \\
\text{HPA}_{ct} &= \text{HP}_{ct}/\text{HP}_{c0}
\end{aligned}$$

$\lambda_{ic}^{\text{Default}}(t)$ and $\lambda_{ic}^{\text{Prepay}}(t)$ are the latent instantaneous default and prepayment probabilities for individual i from CBSA g with loan age t months respectively. $\lambda_0^{\text{Default}}(t)$ and $\lambda_0^{\text{Prepay}}(t)$ are the baseline default and prepayment hazard functions, estimated nonparametrically, following Han and Hausman (1990). In specifications (6.8) and (6.9), $\exp\left(X_{ict}'\beta^{\text{Default}}\right)$ and $\exp\left(X_{ict}'\beta^{\text{Prepay}}\right)$ proportionally scale up or down the hazards, depending on the signs of X_{ict} and coefficients β^{Default} and β^{Prepay}. β^{Default} and β^{Prepay} are the main parameters of interest, measuring how different factors affect default and prepayment risks. Covariates X_{ict} cover static and dynamic variables. Static variables include initial loan and borrower characteristics, denoted as W_{Li} and W_{Bi} respectively, including log FICO score, first-time home buyer indicator, owner occupancy, log original loan amount, log original LTV, and the difference between the original interest rate and the original ten year rate. Dynamic covariates include log cumulative home price changes since origination HPA_{it}, coupon gap, defined as the difference between the ten year rate at origination and the current ten

year rate, and unemployment rate. The estimation sample is mortgage performance data between 2000 and 2005. I truncate the performance data at the end of 2005 to make my estimation sample comparable to the data available for pricing mortgage insurance in 2005.

6.2.2 Estimation

The competing-risk hazard model specified in equations (6.8) and (6.9) is a continuous time model. However, loan performance is observed at the end of each month in discrete time. Assuming that the time varying covariates X_{ict} are constants in each discrete time interval $[t-1, t]$, the continuous time model in (6.8) and (6.9) can be transformed to a discrete time model. In greater details, let $S(t) = \text{Pr}(\tau > t)$ denote the survivor function and let $\Lambda(t) = -\log(S(t))$. $\Lambda(t)$ is also called the integrated hazard function because it satisfies the familiar identity

$$\Lambda(t) = \int_0^t \lambda(\tau) d\tau. \tag{6.10}$$

Using $\Lambda(t) = -\log(S(t))$ and identity (6.10), the probability of survival between $t-1$ and t conditional on that one survived the first $t-1$ periods is

$$\begin{aligned} \text{Pr}\left(\tau > t | \tau > t-1\right) &= \frac{S(t)}{S(t-1)} \\ &= \exp\left(\Lambda(t-1) - \Lambda(t)\right) \\ &= \exp\left(-\int_{t-1}^t \lambda(\tau) d\tau\right) \end{aligned}$$

In general $\lambda(\tau)$ depends on $X_{ic\tau}$, which is time varying between $t-1$ and t. Assuming that $X_{ic\tau}$ are constants when τ is between $t-1$ and t. We have

$$\begin{aligned} \text{Pr}\left(\tau > t | \tau > t-1\right) &= \exp\left(-\int_{t-1}^t \lambda(\tau) d\tau\right) \\ &= \exp\left(-\exp\left(X'_{ict}\beta\right)\lambda_0(t)\right), \end{aligned}$$

or equivalently

$$\begin{aligned}
\log\left(\log\left(\frac{S(t-1)}{S(t)}\right)\right) &= X'_{ict}\beta + \log(\lambda_0(t)) \\
\log\Big(-\log\Big(1-\Pr\big(\tau \in (t-1,t] | \tau > t-1\big)\Big)\Big) &= X'_{ict}\beta + \log(\lambda_0(t)),
\end{aligned}$$

which is the complementary log-log model I estimate in discrete time.

6.2.3 Results

Table 14 reports the hazard regression results. All coefficients have the expected signs. For example, a high LTV loan is much more likely to default than a low LTV loan. The coefficient on log(Original LTV) in column (1) implies that a 5% higher LTV increases default probability by 34.5%. A high FICO score borrower is much less likely to default and more likely to prepay than a low FICO score borrower. A positive and large coupon gap gives the borrower strong incentive to refinance, and leads to a larger prepayment risk. A 10% larger home price appreciation leads to a 36.7% lower default hazard and a 14.2% higher prepayment hazard.

6.3 Interest Rate Model

I calibrate the following Hull-White term-structure model

$$dr = (\theta(t) - \alpha r)dt + \sigma dw. \tag{6.4}$$

The calibration process is a three-step procedure:

1) From Yield Book, I collect interest rates, or equivalently discount factors, for ten maturities including 1-month, 3-month, 6-month, 1-year, 2-year, 3-year, 5-year, 7-year, 10-year, and 30-year. I first construct a continuous yield curve for all possible maturities by fitting the

discount function expressed as

$$Z(t) = e^{at+bt^2+ct^3+dt^4+et^5} \tag{6.5}$$

using observed discount factors for the ten available maturities. The estimated $\hat{Z}(t)$ is then used to calculate the forward rate function $\hat{f}(t, t')$.

2) Calibrate parameters α and σ in equation (6.4).

3) Calculate $\hat{\theta}(t)$ using the estimated forward rate $\hat{f}(0, t)$ from step 1), and estimated $\hat{\alpha}$ and $\hat{\sigma}$ from step 2).

Note that loans in my sample were originated in different months in 2005. To forecast how interest rates would evolve after loan originations, I calibrate the term-structure model for each origination month independently. For step 1), parameters a through e are estimated from first taking the log of both sides of 6.5 and then running a linear regression.

For step 2), I estimate α and σ using caplet prices and discount rates. Caplets are essentially European call options where the underlying is the interest rate with cash flow at time T_i proportional to $\max(r(T_{i-1}, T_i) - r_K, 0)$, where $r(T_{i-1}, T_i)$ is the floating rate at time T_{i-1} and maturity T_i, r_K is the strike interest rate. Intuitively, caplet prices, as prices for interest rate options, contribute to estimating the volatility parameter σ and the mean reversion parameter α in the term-structure model (6.4). α and σ are chosen to best fit all caplet prices by minimizing the following function

$$\min_{\alpha,\sigma} \sqrt{\sum_{i=1}^{I} \left(\frac{model_i(\alpha, \sigma) - market_i}{market_i} \right)^2}$$

where $model_i(\alpha, \sigma)$ and $market_i$ are, correspondingly, model and market caplet i cash prices. Model prices, $model_i(\alpha, \sigma)$-s, are based on the modified Black-Sholes formula.

For step 3), $\hat{\theta}(t)$ is calculated as

$$\hat{\theta}(t) = \frac{\partial \hat{f}(0,t)}{\partial t} + \hat{\alpha}\hat{f}(0,t) + \frac{\hat{\sigma}^2}{2\hat{\alpha}}\left(1 - e^{-2\hat{\alpha}t}\right),$$

where $\hat{f}(0,t)$ is the estimated interest rate between time 0 and time t

$$\hat{f}(0,t) = -\hat{a}t - \hat{b}t^2 - \hat{c}t^3 - \hat{d}t^4 - \hat{e}t^5.$$

6.4 Data-Generating Process

Data in my simulations are generated from the following sources. Loan and borrower characteristics are from the GSE public data. I keep purchase mortgages originated in 2005 from the largest 100 CBSAs in the U.S. There are 596,911 loans in my sample. I calculate the discounted cash flows for insurance underwritten on each loan and then collapse to the CBSA level and report the results in Section 6.5. Hazard parameters—measuring how covariates, loan and borrower characteristics affect default and prepayment speeds—are reported in Table 14. Interest rates are simulated using estimated parameters from Section 6.3. For each month, I simulate 200 antithetics interest rate paths. Future home prices follow assumed mean reversion. For example, for a 10% mean reversion, between 2005 and 2010, each CBSA would give back 10% of the increase in home prices between 2000 and 2005. Unemployment rates are simulated from AR(1) processes, with persistence parameters estimated for each CBSA using historical unemployment rates.

6.5 Results

Figure 3 through Figure 5 illustrate the results. Figure 3 focuses on the 0% mean reversion, or prices staying constant scenario. The assumption to test under this scenario is whether or not the GSEs took more precautionary measures in boom areas compared with other areas. As argued in

Section 5.3.4, risk management for mortgages is inherently a multidimensional problem because mortgages have many risk characteristics including FICO scores, debt-to-income ratios (DTIs), original loan amount, interest rates, and owner occupancy. To study whether the GSEs indeed lowered their risk exposure in boom areas more than other areas, a valuation model taking into account all characteristics, like the one presented in this section, is necessary. From Figure 3, we see that if home prices stay constant, boom areas indeed would have smaller losses than other areas. This is consistent with the hypothesis that the GSEs were aware of the housing bubble and lowered their home price risk exposure by originating safer loans in boom areas than elsewhere.

A natural question to ask is how large the GSEs' risk management was. To study this, I consider a 10% mean reversion scenario. Under a 10% mean reversion assumed in Figure 4, boom areas would have larger losses than other areas. This suggests that the implied GSEs' model mean reversion was small, between 0% and 10%, assuming that the GSEs adjust their insurance to be actuarially fair between CBSAs.

One additional scenario to test is the realized 95% mean reversion. Figure 5 shows the results under the realized 95% mean reversion scenario. In this case, guarantee fees collected in boom CBSAs are clearly insufficient to cover the costs, with 10 CBSAs having projected costs over five times of the projected revenue. This explains the unprecedented losses and government bailouts for the GSEs during the 2008 crash.

7 Conclusion

Many mortgage market reform proposals assume that private insurers will set fair prices and properly manage risk. Evidence from this paper suggests that private insurers less effectively managed home price risk during the 2000-2006 housing boom than Fannie and Freddie did.

These somewhat surprising results are nevertheless consistent with the history of the private mortgage insurance industry, including its repeated and concentrated failures. Most recently in

the 2008 crash, three out of the eight largest private mortgage insurers failed. However, perhaps overshadowed by the highly publicized and controversial bailout of the GSEs, private mortgage insurers' failures have received relatively little attention from academics and the popular press. Many post-crisis proposals also assume that replacing the GSEs by private insurers would be a Panacea. My results suggest that privatizing the GSEs alone is unlikely to ensure sufficient risk management in the mortgage insurance industry. Additional factors besides private capital, such as assumptions about future house prices and bargaining power of private insurers in front of large lenders, are important in shaping risk management practices. One way to establish reasonable house price assumptions is to stress test mortgage insurers, forcing the industry to consider their exposure to the housing downturn scenarios proposed by regulators.

The mortgage insurance industry plays a crucial role in financing Americans' mortgages. Their insurance reduces or removes mortgage default risks, thereby enhancing the liquidity of mortgage backed securities and lowering homebuyers' borrowing costs. The risks they face and the optimal regulatory structure for them deserve more study to prevent them from being a source of systemic risk in the financial system.

References

ADELINO, M., A. SCHOAR, AND F. SEVERINO (2016): "Loan originations and defaults in the mortgage crisis: The role of the middle class," *Review of Financial Studies*, p. hhw018.

ALLEN, L., AND A. RAI (1996): "Bank charter values and capital levels: An international comparison," *Journal of Economics and Business*, 48(3), 269–284.

BHUTTA, N., AND B. J. KEYS (2017): "Eyes Wide Shut? Mortgage Insurance During the Housing Boom," Working paper.

BIN, O., J. B. KRUSE, AND C. E. LANDRY (2008): "Flood Hazards, Insurance Rates, and Amenities: Evidence From the Coastal Housing Market," *Journal of Risk & Insurance*, 75(1), 63–82.

BORIO, C. E., AND I. SHIM (2007): "What can (macro-) prudential policy do to support monetary policy?," .

BRUECKNER, J. K., P. S. CALEM, AND L. I. NAKAMURA (2012): "Subprime mortgages and the housing bubble," *Journal of Urban Economics*, 71(2), 230–243.

CABALLERO, R. J., AND A. KRISHNAMURTHY (2001): "International and domestic collateral constraints in a model of emerging market crises," *Journal of monetary Economics*, 48(3), 513–548.

CHENG, I.-H., S. RAINA, AND W. XIONG (2014): "Wall Street and the Housing Bubble," *American Economic Review*, 104(9), 2797–2829.

CORBAE, D., AND E. QUINTIN (2015): "Leverage and the Foreclosure Crisis," *Journal of Political Economy*, 123(1), pp. 1–65.

CORTÉS, K. R. (2015): "Did local lenders forecast the bust? Evidence from the real estate market," .

FCIC (2011): *The Financial Crisis Inquiry Report, Authorized Edition: Final Report of the National Commission on the Causes of the Financial and Economic Crisis in the United States*. Public Affairs.

FOOTE, C. L., K. S. GERARDI, AND P. S. WILLEN (2012): "Why did so many people make so many ex post bad decisions? The causes of the foreclosure crisis," Discussion paper, National Bureau of Economic Research.

FOOTE, C. L., L. LOEWENSTEIN, AND P. S. WILLEN (2016): "Cross-sectional patterns of mortgage debt during the housing boom: Evidence and implications," Discussion paper, National Bureau of Economic Research.

FRAME, W. S., A. FUSTER, J. TRACY, AND J. VICKERY (2015): "The Rescue of Fannie Mae and Freddie Mac," *The Journal of Economic Perspectives*, 29(2), 25–52.

FRAME, W. S., K. GERARDI, AND P. WILLEN (2015): "The failure of supervisory stress testing: Fannie Mae, Freddie Mac, and OFHEO," .

FRAME, W. S., AND L. J. WHITE (2007): "Charter Value, Risk-Taking Incentives, and Emerging Competition for Fannie Mae and Freddie Mac," *Journal of Money, Credit and Banking*, 39(1), 83–103.

GAN, J. (2004): "Banking market structure and financial stability: Evidence from the Texas real estate crisis in the 1980s," *Journal of Financial Economics*, 73(3), 567–601.

GLAESER, E. L. (2013): "A Nation of Gamblers: Real Estate Speculation and American History," *American Economic Review*, 103(3), 1–42.

GLAESER, E. L., J. D. GOTTLIEB, AND J. GYOURKO (2012): "Can cheap credit explain the housing boom?," in *Housing and the financial crisis*, pp. 301–359. University of Chicago Press.

HAN, A., AND J. A. HAUSMAN (1990): "Flexible parametric estimation of duration and competing risk models," *Journal of applied Econometrics*, 5(1), 1–28.

HOWARD, T. (2013): *The mortgage wars: Inside Fannie Mae, big-money politics, and the collapse of the American dream*. McGraw Hill Professional.

HURST, E., B. J. KEYS, A. SERU, AND J. S. VAVRA (2016): "Regional redistribution through the US mortgage market," *American Economic Review*.

IACOVIELLO, M. (2005): "House prices, borrowing constraints, and monetary policy in the business cycle," *The American economic review*, 95(3), 739–764.

JAFFEE, D., AND J. M. QUIGLEY (2012): "The future of the government-sponsored enterprises: the role for government in the US mortgage market," in *Housing and the Financial Crisis*, pp. 361–417. University of Chicago Press.

KAPLAN, G., K. MITMAN, AND G. VIOLANTE (2015): "Consumption and house prices in the Great Recession: Model meets evidence," *Manuscript, New York University*.

KEELEY, M. C. (1990): "Deposit insurance, risk, and market power in banking," *The American Economic Review*, pp. 1183–1200.

KING, G. (1994): "Health care reform and the Medicare program," *Health Affairs*, 13(5), 39–43.

KIYOTAKI, N., J. MOORE, ET AL. (1997): "Credit chains," *Journal of Political Economy*, 105(21), 211–248.

KULKARNI, N. (2016): "Are Uniform Pricing Policies Unfair? Mortgage Rates, Credit Rationing, and Regional Inequality," Working paper.

LIM, C. H., A. COSTA, F. COLUMBA, P. KONGSAMUT, A. OTANI, M. SAIYID, T. WEZEL, AND X. WU (2011): "Macroprudential policy: what instruments and how to use them? Lessons from country experiences," *IMF working papers*, pp. 1–85.

MCMILLAN, C. M. (2007): "Federal Flood Insurance Policy: Making Matters Worse," *Hous. L. Rev.*, 44, 471.

MICHEL-KERJAN, E. O. (2010): "Catastrophe Economics: The National Flood Insurance Program," *Journal of Economic Perspectives*, 24(4), 165–86.

OBERLANDER, J. B. (1997): "Managed care and Medicare reform," *Journal of Health Politics, Policy and Law*, 22(2), 595–631.

PEAR, R. (1996): "Shortfall Posted by Medicare Fund Two Years Early," *The New York Times*, p. A1.

SHIN, H. S., ET AL. (2011): "Macroprudential policies beyond Basel III," *BIS papers*, 1, 5.

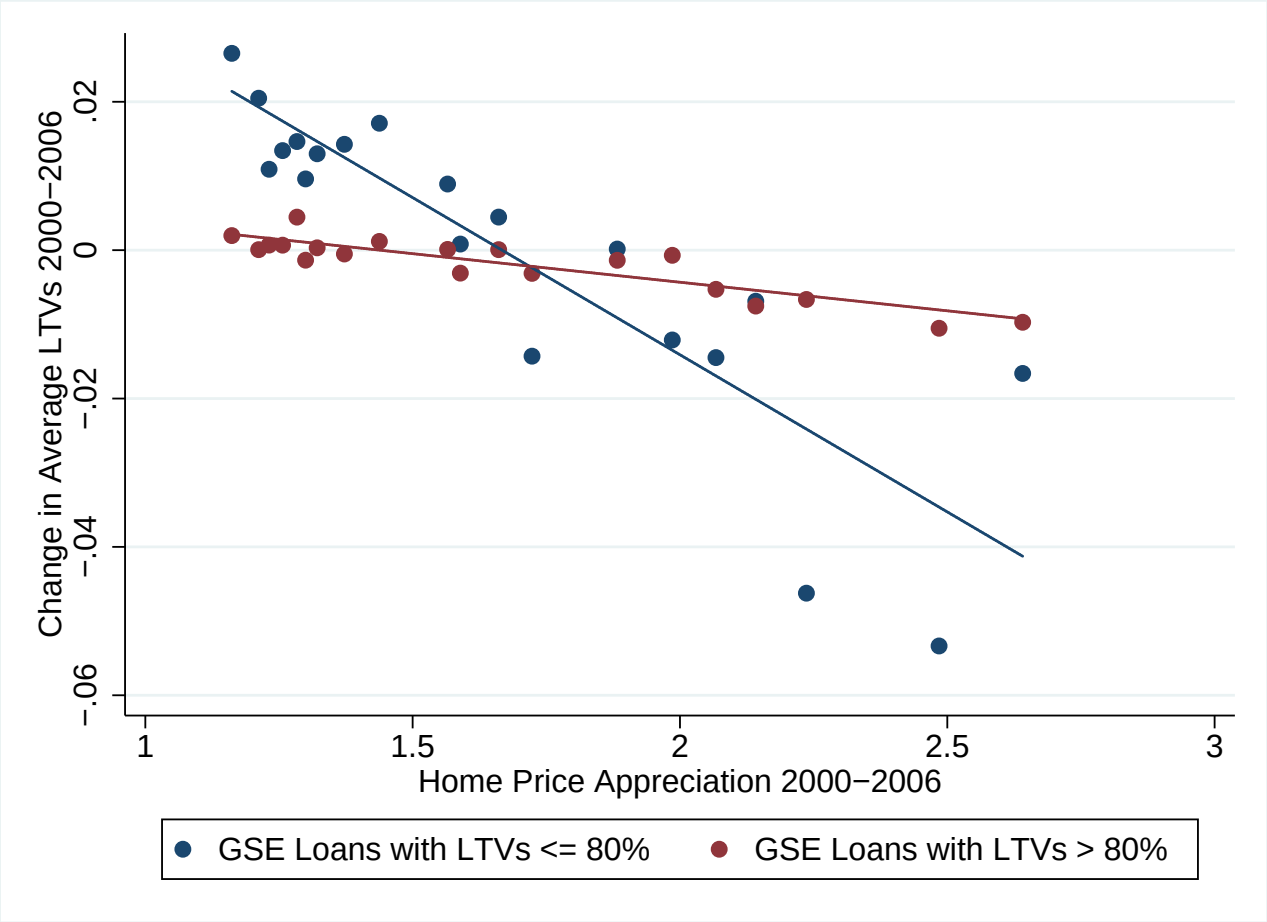
SOMMER, K., P. SULLIVAN, AND R. VERBRUGGE (2013): "The equilibrium effect of fundamentals on house prices and rents," *Journal of Monetary Economics*, 60(7), 854 – 870.

WEISS, D., M. ROSSO, AND W. CLYMER (2012): "What About Mortgage Insurers? A Case for Holding Mortgage Insurers Accountable for the Mortgage Crisis," *LexisNexis Emerging Issues Analysis*.

WONG, T.-C., T. FONG, K.-F. LI, AND H. CHOI (2011): "Loan-to-value ratio as a macroprudential tool-Hong Kong's experience and cross-country evidence," *Systemic Risk, Basel III, Financial Stability and Regulation*.

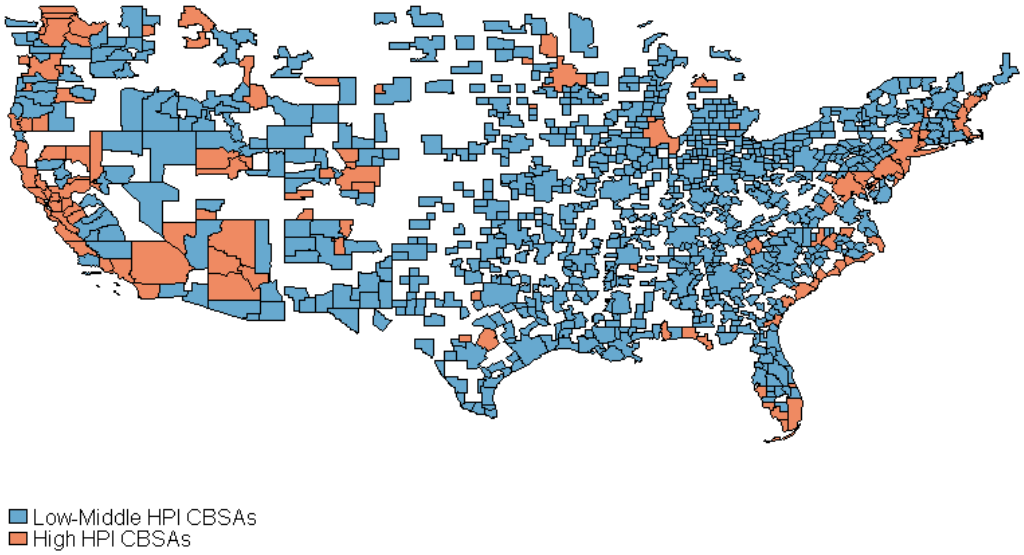
8 Figures and Tables

Figure 1: Change in LTVs vs Home Price Appreciation



This figure presents a binned scatter plot of the relationship between home price appreciation and change in LTVs in the GSE and the PMI segments. The points on the figure plot the average change in LTVs within each home price appreciation bin. The best-fit line is estimated using an OLS regression on the underlying CBSA-level data. The sample includes all 30-year fixed rate purchase mortgages from the Fannie Mae and Freddie Mac public data. Source: Fannie Mae, Freddie Mac, FHFA, and author's calculation.

Figure 2: CBSAs with High or Low-Middle Home Prices



Source: ABSNet, author's own calculations. This figures plots CBSAs classified as high and low-middle home-price CBSAs. Low-middle home-price CBSAs are defined as CBSAs with more than 80% of private label loans in 2006 under the conforming loan limits. As explained in Section 5.1.1, the low-middle home price CBSA subsample is used to address the potential effect of the conforming loan limits. To isolate this effect, I report estimation results from both the full sample and the subsample of low-middle home-price CBSAs.

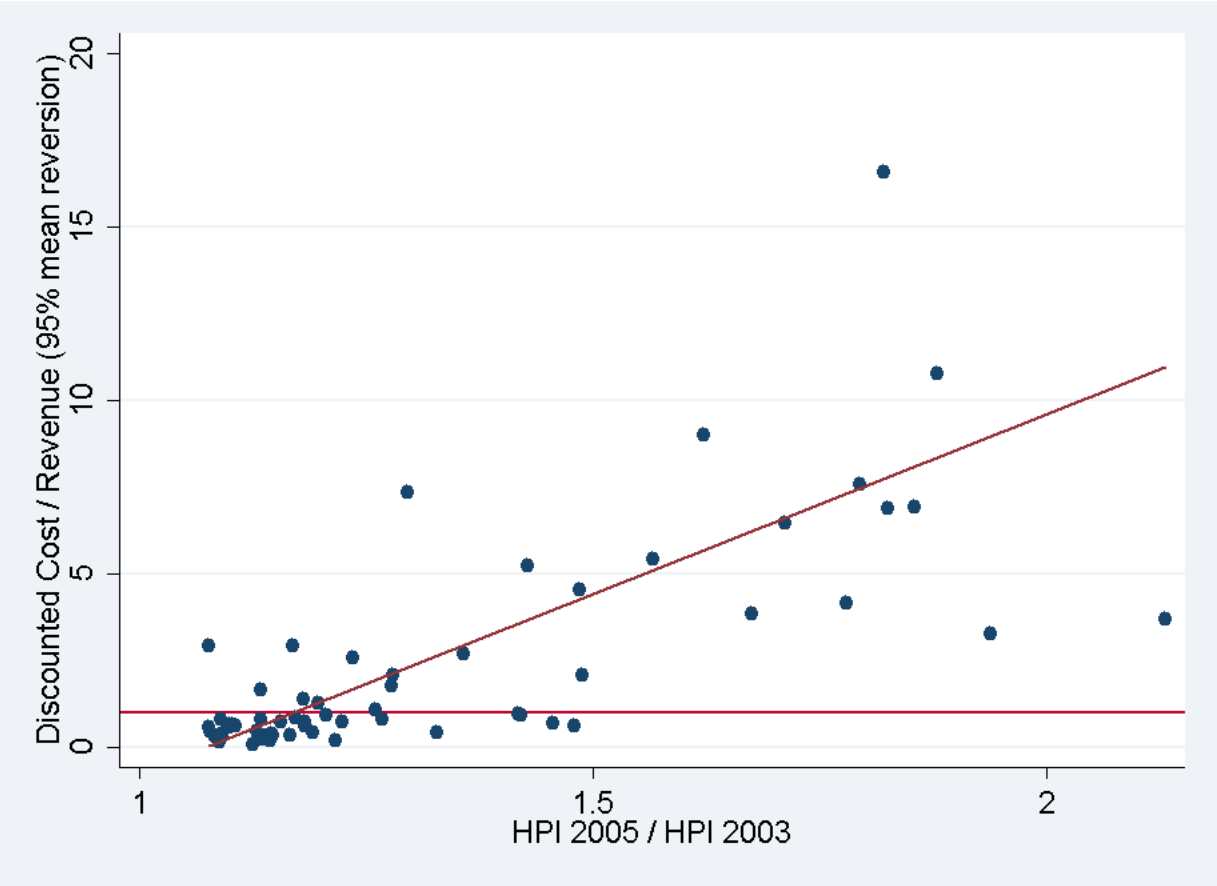
Figure 3: Projected Cost/Projected Guarantee Fees (0% Mean Reversion)

Source: Fannie Mae, Freddie Mac, FHFA, Yield Book and author's calculation. This figure plots the result from the default insurance valuation model, presented in Section 6. The simulation setting assumes a 0% home price mean reversion, or home prices staying constant. Each dot represents a CBSA among the largest 100 CBSAs in the U.S. The vertical axis is the total discounted cost for the GSEs from the insurance contracts normalized by the total discounted revenue. The magenta line is the fitted line. The valuation model builds on the competing-risk hazard estimates reported in Table 14 and a calibrated Hull-White term-structure model. Details of the competing-risk hazard regressions are described in Section 6.2. The Hull-White term-structure model and its calibration procedure is described in Section 6.3.

Figure 4: Projected Cost/Projected Guarantee Fees (10% Mean Reversion)

Source: Fannie Mae, Freddie Mac, FHFA, Yield Book and author's calculation. This figure plots the result from the default insurance valuation model, presented in Section 6. The simulation setting assumes a 10% home price mean reversion. Each dot represents a CBSA among the largest 100 CBSAs in the U.S. The vertical axis is the total discounted cost for the GSEs from the insurance contracts normalized by the total discounted revenue. The magenta line is the fitted line. The valuation model builds on the competing-risk hazard estimates reported in Table 14 and a calibrated Hull-White term-structure model. Details of the competing-risk hazard regressions are described in Section 6.2. The Hull-White term-structure model and its calibration procedure is described in Section 6.3.

Figure 5: Projected Cost/Projected Guarantee Fees (95% Mean Reversion)



Source: Fannie Mae, Freddie Mac, FHFA, Yield Book and author's calculation. This figure plots the result from the default insurance valuation model, presented in Section 6. The simulation setting assumes a 95% home price mean reversion. Each dot represents a CBSA among the largest 100 CBSAs in the U.S. The vertical axis is the total discounted cost for the GSEs from the insurance contracts normalized by the total discounted revenue. The magenta line is the fitted line. The valuation model builds on the competing-risk hazard estimates reported in Table 14 and a calibrated Hull-White term-structure model. Details of the competing-risk hazard regressions are described in Section 6.2. The Hull-White term-structure model and its calibration procedure is described in Section 6.3.

Table 1: Summary Statistics

	GSE 30-year FRMs				*Private Label 30-year FRMs*					
	LTVs $>$ 80%		LTVs $\leq$ 80%		LTVs $>$ 80%		LTVs $\leq$ 80%		*HPA*	
Year	LTVs	FICO	LTVs	FICO	LTVs	FICO	LTVs	FICO	Mean	Std
2000	92.9%	706	72.0%	730	93.7%	662	74.9%	701	N/A	N/A
2001	92.9%	707	72.7%	731	94.4%	661	75.5%	709	8.0%	3.0%
2002	92.9%	706	72.9%	732	95.1%	674	75.8%	712	7.2%	4.0%
2003	92.9%	708	73.3%	735	95.0%	688	75.1%	717	6.0%	3.8%
2004	92.8%	706	72.7%	735	94.0%	688	75.0%	714	12.3%	9.2%
2005	92.8%	711	72.5%	740	93.5%	685	75.5%	719	12.5%	9.1%
2006	92.8%	710	72.7%	741	94.8%	665	75.5%	714	7.0%	6.0%

Source: Fannie Mae, Freddie Mac, FHFA, author's own calculations. This table displays summary statistics for changes in loan and borrower characteristics in my sample at the CBSA-year level. The first eight columns report average LTVs and FICO scores of GSE 30-year FRMs and private label 30-year FRMs, broken down to the LTV under 80% category and the LTV above 80% category. The last two columns report means and standard deviations of home price appreciation relative to the prior year.

Table 2: Effect of Home-Price Growth on Loan-to-Value Ratios

A: GSE First-Time Home Buyers

	LTVs $\leq 80.5\%$ Segement				LTVs $> 80.5\%$ Segement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log(HPI)$	-0.093***	-0.084***	-0.088***	-0.101***	-0.007**	-0.006	-0.008	0.002
	(0.017)	(0.016)	(0.014)	(0.023)	(0.002)	(0.005)	(0.004)	(0.005)
Year FEs	n	y	y	y	n	y	y	y
Controls	n	n	y	y	n	n	y	y
CBSA FEs	n	n	n	y	n	n	n	y
Observations	1998	1998	1998	1998	1974	1974	1974	1974
R-squared	0.12	0.19	0.20	0.28	0.01	0.04	0.09	0.15

B: GSE Other Buyers

	LTVs $\leq 80.5\%$ Segement				LTVs $> 80.5\%$ Segement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log(HPI)$	-0.161***	-0.131***	-0.162***	-0.180***	-0.016***	-0.012**	-0.014**	-0.011
	(0.028)	(0.022)	(0.029)	(0.034)	(0.002)	(0.004)	(0.004)	(0.006)
Year FEs	n	y	y	y	n	y	y	y
Controls	n	n	y	y	n	n	y	y
CBSA FEs	n	n	n	y	n	n	n	y
Observations	1998	1998	1998	1998	1980	1980	1980	1980
R-squared	0.32	0.46	0.52	0.62	0.08	0.19	0.24	0.29

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equations (5.1) and (5.2) in the text. The dependent variable is the annual change in log average LTV at the CBSA-year level. Panel A and Panel B are for GSE first-time home buyers and other buyers respectively. CBSA-year level controls include the changes and levels in macroeconomic conditions measured by unemployment rates and average wage, the changes and levels in loan and borrower characteristics including average FICO scores, interest rates and percentage of owner occupied mortgages. Robust standard errors clustered by year are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Effect of Home Price Growth on Loan-to-Value Ratios (Excluding High HP Areas)

	A: GSE First-Time Home Buyers							
	LTVs $\leq 80.5\%$ Segement				LTVs $> 80.5\%$ Segement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log(HPI)$	-0.047**	-0.037***	-0.041***	-0.045**	-0.004	-0.006	-0.008*	0.003
	(0.015)	(0.007)	(0.007)	(0.014)	(0.005)	(0.005)	(0.003)	(0.006)
Year FEs	n	y	y	y	n	y	y	y
Controls	n	n	y	y	n	n	y	y
CBSA FEs	n	n	n	y	n	n	n	y
Observations	1584	1584	1584	1584	1584	1584	1584	1584
R-squared	0.02	0.07	0.08	0.12	0.00	0.06	0.10	0.16

	B: GSE Other Buyers							
	LTVs $\leq 80.5\%$ Segement				LTVs $> 80.5\%$ Segement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log(HPI)$	-0.085***	-0.059***	-0.065***	-0.068**	-0.013***	-0.011*	-0.013**	-0.012
	(0.012)	(0.005)	(0.010)	(0.021)	(0.001)	(0.004)	(0.003)	(0.006)
Year FEs	n	y	y	y	n	y	y	y
Controls	n	n	y	y	n	n	y	y
CBSA FEs	n	n	n	y	n	n	n	y
Observations	1584	1584	1584	1584	1584	1584	1584	1584
R-squared	0.13	0.41	0.43	0.48	0.03	0.16	0.22	0.27

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equations (5.1) and (5.2) in the text. The dependent variable is the annual change in log average LTV at the CBSA-year level. The difference of this table from Table 2 is that high home price CBSAs, colored orange in Figure 2, are excluded from the sample to address the potential effect of conforming loan limits. Panel A and Panel B are for GSE first-time home buyers and other buyers respectively. CBSA-year level controls include the changes and levels in macroeconomic conditions measured by unemployment rates and average wage, the changes and levels in loan and borrower characteristics including average FICO scores, interest rates and percentage of owner occupied mortgages. Robust standard errors clustered by year are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Effect of Home Price Growth on Loan-to-Value Ratios (Excluding High HP Areas)

A: GSE 30-year FRMs

	LTVs $\leq 80.5\%$ Segement				LTVs $> 80.5\%$ Segement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log(HPI)$	-0.079***	-0.058***	-0.061***	-0.070**	-0.010***	-0.010*	-0.013**	-0.011
	(0.011)	(0.004)	(0.008)	(0.020)	(0.002)	(0.004)	(0.004)	(0.007)
Year FEs	n	y	y	y	n	y	y	y
Controls	n	n	y	y	n	n	y	y
CBSA FEs	n	n	n	y	n	n	n	y
Observations	1584	1584	1584	1584	1584	1584	1584	1584
R-squared	0.14	0.39	0.40	0.45	0.02	0.11	0.17	0.24

B: Private Label 30-year FRMs

	LTVs $\leq 80.5\%$ Segement				LTVs $> 80.5\%$ Segement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log(HPI)$	-0.003	-0.012	-0.003	-0.002	-0.036**	-0.006	0.003	-0.009
	(0.008)	(0.007)	(0.006)	(0.018)	(0.012)	(0.011)	(0.015)	(0.009)
Year FEs	n	y	y	y	n	y	y	y
Controls	n	n	y	y	n	n	y	y
CBSA FEs	n	n	n	y	n	n	n	y
Observations	1398	1398	1398	1398	1542	1542	1542	1542
R-squared	0.00	0.12	0.13	0.22	0.03	0.36	0.47	0.51

Source: Fannie Mae, Freddie Mac, ABSNet, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equations (5.1) and (5.2) in the text. The dependent variable is the annual change in log average LTV at the CBSA-year level. Panel A and Panel B are for GSE and private label 30-year FRM purchase mortgages respectively. CBSA-year level controls include the changes and levels in macroeconomic conditions measured by unemployment rates and average wage, the changes and levels in loan and borrower characteristics including average FICO scores, interest rates and percentage of owner occupied mortgages. Robust standard errors clustered by year are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: Percentage of CBSA-mortgage segments where Private Labeled FRMs had Lower Interest Rates than GSE FRMs

	(1) Full Sample	(2) Low-to-Middle Home Price Sample
2000	5.2%	5.2%
2001	2.9%	2.9%
2002	5.2%	4.5%
2003	3.2%	3.6%
2004	2.1%	2.3%
2005	0.9%	1.0%
2006	2.1%	2.2%

Source: Fannie Mae, Freddie Mac, ABSNet, author's own calculations. This table reports the percentage of CBSA-mortgage segments where private label originators offered better interest rates than the GSEs during the housing boom. Mortgages from each CBSA-year are divided into sixteen segments along two dimensions, LTVs and FICO scores. Along the LTV dimension, the cutoffs are 79.5%, 80.5% and 90%. Along the FICO score dimension, the cutoffs are 660, 720 and 760. For each CBSA-year-LTV-FICO segment, I collapse the median interest rates for GSE FRMs and private label FRMs. This table reports the percentage of CBSA-mortgage segments where private label loans had lower median interest rates than GSE loans.

Table 6: Effect of Home Price Growth on FICO

	Excluding High Home Price CBSAs							
	GSE First Time Buyers				Private Label ARMs			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log(HPI)$	-0.001	-0.013**	-0.011***	-0.019*	0.053**	0.081***	0.028*	0.059***
	(0.012)	(0.003)	(0.002)	(0.008)	(0.020)	(0.013)	(0.012)	(0.010)
Year FEs	n	y	y	y	n	y	y	y
Controls	n	n	y	y	n	n	y	y
CBSA FEs	n	n	n	y	n	n	n	y
Observations	1572	1572	1572	1572	1572	1572	1572	1572
R-squared	0.00	0.20	0.25	0.30	0.04	0.67	0.84	0.85

Source: Fannie Mae, Freddie Mac, ABSNet FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equation (5.3) in the text. The dependent variable is the annual change in log average FICO score. High home price CBSAs, colored orange in Figure 2, are excluded from the sample to address the potential effect of conforming loan limits. CBSA-year level controls include changes and levels of macroeconomic conditions measured by unemployment rates and average wage, and changes and levels of loan and borrower characteristics including average FICO scores, debt-to-income ratios, interest rates and percentage of owner occupied mortgages.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Effect of Home Price Growth on Combined-Loan-to-Value Ratios

	A: GSE First Time Home Buyers, Excluding High Home Price CBSAs							
	LTVs $\leq 80.5\%$ Segement				LTVs $> 80.5\%$ Segement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log(HPI)$	-0.051*	-0.045**	-0.044*	-0.054*	-0.004	-0.006	-0.008*	0.002
	(0.021)	(0.011)	(0.017)	(0.022)	(0.004)	(0.004)	(0.004)	(0.006)
Year FEs	n	y	y	y	n	y	y	y
Controls	n	n	y	y	n	n	y	y
CBSA FEs	n	n	n	y	n	n	n	y
Observations	1584	1584	1584	1584	1584	1584	1584	1584
R-squared	0.01	0.04	0.05	0.11	0.00	0.05	0.10	0.16

	Panel B: GSE Other Buyers, Excluding High Home Price CBSAs							
	LTVs $\leq 80.5\%$ Segement				LTVs $> 80.5\%$ Segement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log(HPI)$	-0.097***	-0.081***	-0.085***	-0.093***	-0.013***	-0.011**	-0.012***	-0.011
	(0.015)	(0.006)	(0.015)	(0.019)	(0.002)	(0.004)	(0.003)	(0.006)
Year FEs	n	y	y	y	n	y	y	y
Controls	n	n	y	y	n	n	y	y
CBSA FEs	n	n	n	y	n	n	n	y
Observations	1584	1584	1584	1584	1584	1584	1584	1584
R-squared	0.13	0.32	0.34	0.42	0.03	0.17	0.22	0.27

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equations (5.4) and (5.5) in the text. The dependent variable is the annual change in log average CLTV, as opposed to LTV in Table 3, at the CBSA-year level. High home price CBSAs, colored orange in Figure 2, are excluded from the sample to address the potential effect of conforming loan limits. Panel A and Panel B are for GSE first-time home buyers and other buyers respectively. CBSA-year level controls include the changes and levels in macroeconomic conditions measured by unemployment rates and average wage, the changes and levels in loan and borrower characteristics including average FICO scores, interest rates and percentage of owner occupied mortgages. Robust standard errors clustered by year are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8: Effect of Home Price Growth on LTVs for Various Low Debt-to-Income Ratio Subsamples

	GSE First Time Home Buyers, Excluding High Home Price CBSAs					
	Full Sample (1)	DTI≤60% (2)	DTI≤55% (3)	DTI≤50% (4)	DTI≤45% (5)	DTI≤40% (6)
logChangeHPI	-0.043*	-0.046*	-0.053*	-0.049	-0.063**	-0.072**
	(0.021)	(0.021)	(0.026)	(0.029)	(0.024)	(0.020)
Year FEs	y	y	y	y	y	y
Controls	y	y	y	y	y	y
CBSA FEs	y	y	y	y	y	y
Obs	1572	1572	1572	1572	1572	1572
R squ	0.11	0.11	0.11	0.11	0.11	0.11

Source: Fannie Mae, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equation (5.1) in the text for low debt-to-income ratio subsamples. Because only Fannie Mae data provides debt-to-income ratio, only Fannie loans are used in the sample. The dependent variable is the annual change in log average LTV at the CBSA-year level. CBSA-year level controls include the changes and levels in macroeconomic conditions measured by unemployment rates and average wage, the changes and levels in loan and borrower characteristics including average FICO scores, interest rates and percentage of owner occupied mortgages. Robust standard errors clustered by year are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 9: The Relative Importance of Risk Taking in FICO and LTVs

GSE First Time Home Buyers with LTVs $\leq 80.5\%$ *Excluding High Home Price CBSAs*		
	(1) Changes in log LTVs	(2) Changes in log FICO
$\Delta \log(HPI)$	-0.045**	-0.019***
	(0.014)	(0.003)
Year FEs	y	y
Controls	y	y
CBSA FEs	y	y
Obs	1584	1584
R squ	0.12	0.20

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equations (5.1) and (5.3) in the text for GSE loans by first-time home buyers with LTVs below 80.5%. The dependent variable is the annual change in log average LTV in column 1, and annual change in log FICO score in column 2. High home price CBSAs, colored orange in Figure 2, are excluded from the sample to address the potential effect of conforming loan limits. CBSA-year level controls include the changes and levels in macroeconomic conditions measured by unemployment rates and average wage, the changes and levels in loan and borrower characteristics including average FICO scores, interest rates and percentage of owner occupied mortgages. Robust standard errors clustered by year are in parentheses. In the LTV regression reported in column 1, changes in LTVs are excluded from the controls. In the FICO score regression reported in column 2, changes in FICO scores are excluded from the controls.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 10: Robustness of LTV Results to Bunching at 80%

	GSE First Time Home Buyers with LTVs $\leq 79.5\%$ *Excluding High Home Price CBSAs*			
	(1)	(2)	(3)	(4)
$\Delta \log(HPI)$	-0.095***	-0.060***	-0.069**	-0.073
	(0.017)	(0.010)	(0.019)	(0.042)
Year FEs	n	y	y	y
Controls	n	n	y	y
CBSA FEs	n	n	n	y
Obs	1578	1578	1578	1578
R squ	0.01	0.03	0.05	0.09

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equations (5.1) in the text for GSE loans by first-time home buyers with LTVs below 79.5%. The dependent variable is the annual change in log average LTV. High home price CBSAs, colored orange in Figure 2, are excluded from the sample to address the potential effect of conforming loan limits. CBSA-year level controls include the changes and levels in macroeconomic conditions measured by unemployment rates and average wage, the changes and levels in loan and borrower characteristics including average FICO scores, interest rates and percentage of owner occupied mortgages. Robust standard errors clustered by year are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 11: Effect of Home Price Growth on Loan-to-Value Ratios (Excluding High HP Areas)

	A: GSE Purchase and Refinance Loans (Public Data)							
	LTVs $\leq 80.5\%$ Segement				LTVs $> 80.5\%$ Segement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log(HPI)$	-0.070	-0.127***	-0.125***	-0.093*	0.004	-0.013*	-0.017*	-0.006
	(0.043)	(0.023)	(0.029)	(0.042)	(0.012)	(0.005)	(0.007)	(0.009)
Year FEs	n	y	y	y	n	y	y	y
Controls	n	n	y	y	n	n	y	y
CBSA FEs	n	n	n	y	n	n	n	y
Observations	1584	1584	1584	1584	1584	1584	1584	1584
R-squared	0.06	0.68	0.70	0.75	0.00	0.72	0.73	0.76

	B: GSE Purchase and Refinance Loans (LPS Sample including ARMs and FRMs)							
	LTVs $\leq 80.5\%$ Segement				LTVs $> 80.5\%$ Segement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log(HPI)$	-0.055	-0.140***	-0.123***	-0.092**	-0.026**	-0.032***	-0.030*	-0.022
	(0.035)	(0.011)	(0.017)	(0.025)	(0.010)	(0.007)	(0.014)	(0.020)
Year FEs	n	y	y	y	n	y	y	y
Controls	n	n	y	y	n	n	y	y
CBSA FEs	n	n	n	y	n	n	n	y
Observations	1584	1584	1584	1584	1584	1584	1584	1584
R-squared	0.02	0.71	0.74	0.79	0.03	0.41	0.60	0.63

Source: Fannie Mae, Freddie Mac, LPS, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equations (5.1) and (5.2) in the text. The dependent variable is the annual change in log average LTV at the CBSA-year level. The difference of this table from Table 2 is that high home price CBSAs, colored orange in Figure 2, are excluded from the sample to address the potential effect of conforming loan limits. Panel A and Panel B are for GSE first-time home buyers and other buyers respectively. CBSA-year level controls include the changes and levels in macroeconomic conditions measured by unemployment rates and average wage, the changes and levels in loan and borrower characteristics including average FICO scores, interest rates and percentage of owner occupied mortgages. Robust standard errors clustered by year are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 12: Effect of Home Price Growth on Private Insurers' Risk Management

A: $\Delta \log$*(Share of Loans with LTVs* $> 80.5\%$*)*				
	(1)	(2)	(3)	(4)
$\Delta \log(HPI)$	-0.228	0.120	-0.088	0.106
	(0.142)	(0.079)	(0.091)	(0.157)
Year FEs	n	y	y	y
Controls	n	n	y	y
CBSA FEs	n	n	n	y
Observations	1584	1584	1584	1584
R-squared	0.01	0.27	0.33	0.40

B: $\Delta \log$*(Private Insurers' Coverage Percentage)*				
	(1)	(2)	(3)	(4)
$\Delta \log(HPI)$	-0.106	0.018	-0.025	0.083
	(0.073)	(0.049)	(0.036)	(0.075)
Year FEs	n	y	y	y
Controls	n	n	y	y
CBSA FEs	n	n	n	y
Observations	1578	1578	1578	1578
R-squared	0.01	0.21	0.21	0.29

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. Panel A and B report estimates of Equations (5.6) and (5.7) in the text respectively. In Panel A, the dependent variable is the annual change in log percentage of loans with LTVs above 80.5%. In Panel B, the dependent variable is the annual change in insurance percentage, percentage of initial loan balance covered by private insurers. The estimation sample is loans by GSE first-time home buyers from low-to-middle CBSAs, colored blue in Figure 2. CBSA-year level controls include the changes and levels in macroeconomic conditions measured by unemployment rates and average wage, the changes and levels in loan and borrower characteristics including average FICO scores, interest rates and percentage of owner occupied mortgages. Robust standard errors clustered by year are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 13: Cash Flows of Default Insurance

	Cash Flows	
Mortgage Monthly Outcome	Fixed Leg (Revenue)	Floating Leg (Cost)
Defaulted	0	Loan balance $-$ Value of the house
Prepaid or Matured	0	0
Paid Down	$\approx \frac{0.2\%}{12}$ of remaining balance	0

This table summarizes in each month how the cash flows evolve according to the loan outcomes.

Table 14: Default and Prepayment Hazard Estimates

	(1) Default Risk	(2) Prepayment Risk
	A: Static Covariates	
log(FICO)	-6.095***	1.233***
	(0.156)	(0.119)
First-Time Home Buyer	-0.071***	-0.053***
	(0.024)	(0.004)
Owner Occupied	-0.396***	0.274***
	(0.112)	(0.026)
Original r - Original 10 Year Rate	0.898***	0.771***
	(0.023)	(0.021)
log(Original Amount)	-0.045	0.773***
	(0.100)	(0.021)
log(Original LTV)	6.077***	-0.160***
	(0.272)	(0.026)
	B: Dynamic Covariates	
log(Cumulative HPA)	-4.790***	1.392***
	(0.629)	(0.226)
Coupon Gap	0.245***	0.912***
	(0.016)	(0.025)
Unemployment	0.099***	0.138***
	(0.035)	(0.017)
CBSA FEs	y	y
Observations	106,965,734	119,834,487

Source: Fannie Mae, Freddie Mac, FHFA, Yield Book, BLS, author's own calculations. This table shows estimates using maximum likelihood estimator of the hazard functions in (6.8) and (6.9) in the text, estimated using a continuous-time nonparametric baseline hazard function. Estimated coefficients are the effect of a given covariate on the log hazard rate of a mortgage. Details of the estimation procedure are described in Section 6.2. Panel A and Panel B report the coefficients for static and dynamic covariates respectively.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

A Appendix Tables

Table A.1: Robustness of LTV Results to Conforming Loan Limits

	GSE Loans by First Time Home Buyers with Loan Amount under 95% *of CLLs*			
	(1)	(2)	(3)	(4)
$\Delta \log(HPI)$	-0.093***	-0.084***	-0.090***	-0.105***
	(0.018)	(0.016)	(0.015)	(0.023)
Year FEs	n	y	y	y
Controls	n	n	y	y
CBSA FEs	n	n	n	y
Obs	1998	1998	1998	1998
R squ	0.12	0.18	0.19	0.27

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equations (5.1) in the text for GSE loans by first-time home buyers with with loan amount under 95% of conforming loan limits. The dependent variable is the annual change in log average LTV. CBSA-year level controls include the changes and levels in macroeconomic conditions measured by unemployment rates and average wage, the changes and levels in loan and borrower characteristics including average FICO scores, interest rates and percentage of owner occupied mortgages. Robust standard errors clustered by year are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.2: Effect of Home Price Growth on Loan-to-Value Ratios 2003-2005 (Excluding High HP Areas)

A: GSE 30-year FRMs

	LTVs $\leq 80.5\%$ Segement				LTVs $> 80.5\%$ Segement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log(HPI)$	-0.059***	-0.059***	-0.074***	0.022	-0.008***	-0.010***	-0.013***	-0.003
	(0.005)	(0.005)	(0.009)	(0.029)	(0.002)	(0.002)	(0.003)	(0.011)
Year FEs	n	y	y	y	n	y	y	y
Controls	n	n	y	y	n	n	y	y
CBSA FEs	n	n	n	y	n	n	n	y
Observations	530	530	530	530	530	530	530	530
R-squared	0.18	0.18	0.24	0.54	0.02	0.23	0.30	0.53

B: Private Label 30-year FRMs

	LTVs $\leq 80.5\%$ Segement				LTVs $> 80.5\%$ Segement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log(HPI)$	-0.017**	-0.014*	0.003	0.057	-0.010*	-0.013**	-0.002	-0.010
	(0.007)	(0.007)	(0.013)	(0.042)	(0.006)	(0.006)	(0.008)	(0.028)
Year FEs	n	y	y	y	n	y	y	y
Controls	n	n	y	y	n	n	y	y
CBSA FEs	n	n	n	y	n	n	n	y
Observations	530	530	530	530	530	530	530	530
R-squared	0.01	0.04	0.09	0.44	0.01	0.05	0.24	0.53

Source: Fannie Mae, Freddie Mac, ABSNet, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equations (5.1) and (5.2) in the text. The difference betwen this table and Table 4 is that the current table restricts the sample to years 2003-2005. The dependent variable is the annual change in log average LTV at the CBSA-year level. Panel A and Panel B are for GSE and private label 30-year FRM purchase mortgages respectively. CBSA-year level controls include the changes and levels in macroeconomic conditions measured by unemployment rates and average wage, the changes and levels in loan and borrower characteristics including average FICO scores, interest rates and percentage of owner occupied mortgages. Standard errors clustered by year are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.3: Effect of Home Price Growth on Loan-to-Value Ratios 2000-2007 (Excluding High HP Areas)

A: GSE First-Time Home Buyers

	LTVs $\leq 80.5\%$ Segement				LTVs $> 80.5\%$ Segement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log(HPI)$	-0.022	-0.043***	-0.045***	-0.058***	0.014	-0.009	-0.011**	-0.015
	(0.023)	(0.009)	(0.008)	(0.012)	(0.018)	(0.005)	(0.004)	(0.014)
Year FEs	n	y	y	y	n	y	y	y
Controls	n	n	y	y	n	n	y	y
CBSA FEs	n	n	n	y	n	n	n	y
Observations	1848	1848	1848	1848	1848	1848	1848	1848
R-squared	0.00	0.11	0.12	0.15	0.01	0.32	0.35	0.38

B: GSE Other Buyers

	LTVs $\leq 80.5\%$ Segement				LTVs $> 80.5\%$ Segement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log(HPI)$	-0.087***	-0.063***	-0.077***	-0.093***	-0.006	-0.012**	-0.014***	-0.015**
	(0.008)	(0.005)	(0.010)	(0.017)	(0.008)	(0.004)	(0.003)	(0.005)
Year FEs	n	y	y	y	n	y	y	y
Controls	n	n	y	y	n	n	y	y
CBSA FEs	n	n	n	y	n	n	n	y
Observations	1848	1848	1848	1848	1848	1848	1848	1848
R-squared	0.14	0.37	0.40	0.45	0.00	0.27	0.32	0.35

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equations (5.1) and (5.2) in the text. The dependent variable is the annual change in log average LTV at the CBSA-year level. The difference of this table from Table 2 is that high home price CBSAs, colored orange in Figure 2, are excluded from the sample to address the potential effect of conforming loan limits. Panel A and Panel B are for GSE first-time home buyers and other buyers respectively. CBSA-year level controls include the changes and levels in macroeconomic conditions measured by unemployment rates and average wage, the changes and levels in loan and borrower characteristics including average FICO scores, interest rates and percentage of owner occupied mortgages. Robust standard errors clustered by year are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.4: Effect of Home Price Growth on Loan-to-Value Ratios 2000-2007 (Excluding High HP Areas)

A: GSE First-Time Home Buyers

	LTVs $\leq 80.5\%$ Segement				LTVs $> 80.5\%$ Segement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log(HPI)$	-0.022	-0.043***	-0.045***	-0.058***	0.014	-0.009	-0.011**	-0.015
	(0.023)	(0.009)	(0.008)	(0.012)	(0.018)	(0.005)	(0.004)	(0.014)
Year FEs	n	y	y	y	n	y	y	y
Controls	n	n	y	y	n	n	y	y
CBSA FEs	n	n	n	y	n	n	n	y
Observations	1848	1848	1848	1848	1848	1848	1848	1848
R-squared	0.00	0.11	0.12	0.15	0.01	0.32	0.35	0.38

B: GSE Other Buyers

	LTVs $\leq 80.5\%$ Segement				LTVs $> 80.5\%$ Segement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log(HPI)$	-0.087***	-0.063***	-0.077***	-0.093***	-0.006	-0.012**	-0.014***	-0.015**
	(0.008)	(0.005)	(0.010)	(0.017)	(0.008)	(0.004)	(0.003)	(0.005)
Year FEs	n	y	y	y	n	y	y	y
Controls	n	n	y	y	n	n	y	y
CBSA FEs	n	n	n	y	n	n	n	y
Observations	1848	1848	1848	1848	1848	1848	1848	1848
R-squared	0.14	0.37	0.40	0.45	0.00	0.27	0.32	0.35

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equations (5.1) and (5.2) in the text. The dependent variable is the annual change in log average LTV at the CBSA-year level. The difference of this table from Table 2 is that high home price CBSAs, colored orange in Figure 2, are excluded from the sample to address the potential effect of conforming loan limits. Panel A and Panel B are for GSE first-time home buyers and other buyers respectively. CBSA-year level controls include the changes and levels in macroeconomic conditions measured by unemployment rates and average wage, the changes and levels in loan and borrower characteristics including average FICO scores, interest rates and percentage of owner occupied mortgages. Robust standard errors clustered by year are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$