Do Government Guarantees Inhibit Risk Management? Evidence from Fannie Mae and Freddie Mac

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Abstract

Fannie Mae and Freddie Mac's implicit government guarantee is widely argued to cause irresponsible risk taking. Despite moral-hazard concerns, this paper presents evidence that Fannie Mae and Freddie Mac (the GSEs) more effectively managed home price risks during the 2000-2006 housing boom than private insurers. Mortgage origination data reveal that the GSEs were selecting loans with increasingly higher percentage of down payments, or lower loan to value ratios (LTVs), in boom areas than in other areas. 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 co-insured by private mortgage insurers. Private mortgage insurers also did not lower their exposure to home price risks along other dimensions, including the percentage of high LTV GSE loans they insured. To quantify how the GSEs' portfolios would have performed under alternative home price scenarios, I build an insurance valuation model based on competing-risk hazard regressions, calibrated Hull and White term-structure model, and forecasting prepayment and default speeds. I find that the GSEs' risk management would have been sufficient for the historically average 32% mean reversion but insufficient for the realized 95% mean reversion between 2006 and 2011. My results highlight that post-crisis reform of the mortgage insurance industry should carefully consider additional factors besides moral hazard, such as mortgage insurers' future home price assumptions.

Keywords: Risk Management; Government Guarantees; Fannie Mae and Freddie Mac; Term Structure Model; Monte Carlo Valuation; Competing Risks

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1 Introduction

From flood insurance to deposit insurance, from Medicare to mortgage default insurance, the risk management of publicly sponsored insurance draws frequent scrutiny both from academia and the popular press (Bin, Kruse, and Landry, 2008; King, 1994; McMillan, 2007; Michel-Kerjan, 2010; Oberlander, 1997; Pear, 1996). Economists have long reasoned that because taxpayers, not private investors, bear the downside risk of public insurance, the insurance managers have limited incentives to manage risk. Perhaps one of the most criticized public insurers is the "public/private partnership" of Fannie Mae and Freddie Mac (Acharya, Richardson, Van Nieuwerburgh, and White, 2011; Bernanke, 2015). The two government-sponsored enterprises (GSEs) had profit maximizing shareholders, but they also carried an implicit government guarantee, essentially eliminating any downside risk. Both academics and policy makers, including the Obama administration, have argued that this flawed structure caused the GSEs to "take on irresponsible risks" (Acharya, Richardson, Van Nieuwerburgh, and White, 2011; Hermalin and Jaffee, 1996; Jaffee, Quigley, and Noll, 2007; Quigley, 2006; Treasury, 2011). Based on this view, many post-crisis proposals suggest that the GSEs should be privatized, gradually replaced by private mortgage insurance companies, or only allowed to passively follow prices set by private insurers. (Acharya, Richardson, Van Nieuwerburgh, and White, 2011; Elenev, Landvoigt, and Van Nieuwerburgh, 2016; Jaffee and Quigley, 2012; Treasury, 2011).

A crucial assumption underlying these proposals is that by solving the incentive problem, private insurers will more effectively manage risk and set fairer prices than the GSEs did. Inconsistent with this assumption, I present evidence that the GSEs more effectively managed home price risk than private mortgage insurers did during the 2000s housing bubble. By increasing the percentage of down payments in boom areas, the GSEs reduced their exposure to a housing downturn. In contrast, little evidence suggests that private insurers were aware of the housing bubble or took precautionary measures for the looming home price crash. To study how the GSEs' risk management would have performed under alternative home price environments, I construct a mortgage insurance valuation model based on competing-risk hazard regressions, calibrated Hull and White term-structure model and forecasting prepayment and default speeds.

My analysis is based on the segmentation of GSE loans along 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 first loss position before the GSEs cover additional losses (Frame, Fuster, Tracy, and Vickery, 2015). I document 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 in these boom areas with greater risk of home price mean reversion (Cutler, Poterba, and Summers, 1991), the GSEs reduced their exposure to home price risk through lower default rates and lower losses given defaults. 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, in the LTVs above 80% segment, LTVs did not decline more in boom areas than elsewhere. Also, the share of mortgages with LTVs above 80% did not decline more in boom areas. Another example is that private mortgage insurers slightly increased their percentage of covered losses more in boom areas than in other areas. These results suggest that the GSEs more effectively managed their home price risk compared with private insurers.

The first set of empirical challenges of my paper is interpretation of the central result of declining LTVs in boom areas among GSE loans with LTVs at or below 80%. I conduct a series of tests to confirm that my results are most likely driven by the GSEs' risk management. Two plausible alternative explanations for this result are mortgagor demand-side story and reverse causality. For the demand-side story, perhaps declining LTVs in boom areas stem from borrowers' reluctance to take out high LTV loans rather than the GSEs' risk management. This is plausible because home buyers who traded up in 2005 might have carried the equity from their previous homes to their next mortgages. Trade-up buyers from boom areas had more equity in their previous homes than buyers from other areas, and thus voluntarily took low LTV loans. 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. In fact, it is far more likely that first-time home buyers would prefer higher LTVs instead of lower LTVs after rapid home price growth. I show that the relationship between home price appreciation and decline in LTVs among first-time home buyers and other buyers are both strongly significant and have similar magnitudes.

Another concern is reverse causality. Changes in LTV requirements, or collateral constraints, have causal impacts on home prices (Caballero and Krishnamurthy, 2001; Corbae and Quintin, 2015; Iacoviello, 2005; Kiyotaki, Moore, et al., 1997; Sommer, Sullivan, and Verbrugge, 2013). I show that the reverse causal story predicts the opposite sign of my coefficients. Lowering LTVs, or equivalently increasing percentages of down payments, would bring down home prices, not trigger a housing boom. My coefficients are likely biased towards zero by the reverse causal story. Another alternative story in this context is the mechanical effect of conforming loan limits. GSE-insured mortgages are required to be below a year-specific dollar amount. In high home price CBSAs with a large recent home price boom, their LTVs would have to be lowered to continue to satisfy the conforming loan limits. To address this, I conduct tests in two subsamples, one with only low-medium home price CBSAs, one restricting to loans under 95% of conforming loan limits. I find that the relationship between decline of LTVs and home price appreciation persists in these two subsamples. Other alternative stories that I address include dynamic selection into GSEs' Fixed Rate Mortgages (FRMs), competition from private label loans, second liens and effect of binding debt-to-income ratios (DTI) constraints.

LTVs are only one of the loan and borrower characteristics through which the GSEs manage default risk. To understand how risk management using LTVs fits in the overall risk structure of GSE loans, I study how other loan and borrower characteristics changed during the housing boom, including FICO scores, DTIs, original loan amount, interest rates and owner occupation. The two questions I aim to answer are: were LTVs the GSEs' main tool managing home price risk? Can risk taking along other dimensions undo the risk reduction along LTVs? Perhaps the most important among other loan and borrower characteristics is FICO scores. I show that average FICO scores of GSE loans declined more in boom areas than in other areas. In other words, the GSEs took an increasing amount of FICO risk in boom areas than elsewhere. A natural question is whether the risk taking along FICO scores is larger than risk management along LTVs. Using elasticities of default with respect to FICO scores and LTVs estimated from a proportional hazard model, I show that by a very conservative estimate, the risk reduction through LTVs is at least 3.6 times as large as risk taking through FICO scores.

Between 2008 and 2011, the GSEs lost $215 billion from their insurance business and received $187 billion capital injection from the federal government (Frame, Fuster, Tracy, and Vickery, 2015). This clearly indicates that their risk management was insufficient for the 2006-2011 housing bust. However this could be driven by the 95% home price mean reversion between 2006 and 2011, which was much larger than the historically average 32% mean reversion (Cutler, Poterba, and Summers, 1991; Glaeser, 2013; Glaeser and Nathanson, 2016). To quantify how the GSEs would have performed under alternative home price scenarios, I build a valuation model projecting the total discounted guarantee fees collected by the GSEs and costs paid by the GSEs to investors under four home price mean reversion scenarios. To do this, I first estimate how loan and borrower characteristics, the coupon gap, unemployment rate and home price appreciation affect borrowers' default and prepayment decision using competing-risk hazard regressions. These hazard parameters, together with four different assumed home price paths and projected future interest rates from a Hull and White term-structure model, are used to forecast prepayment and default speeds. The final step is to transform the future prepayment and default speeds to cash flows and discount them. Using this framework, I answer two questions: taking into account risk adjustment along all mortgage and borrower characteristics, did the GSEs' indeed lower their risk in boom areas than other areas? Would the GSEs' risk management have been sufficient for a typical housing downturn?

Figures 2 to 5 illustrate the results from the structural valuation model. From Figure 2, we see that risk management by the GSEs 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 3 shows that under a 10% home price mean reversion, boom areas would already have larger normalized cost than elsewhere. Figure 4 shows that under the historically average 32% mean reversion, all CBSAs would collect sufficient revenue to cover losses. This suggests that the GSEs' risk management would have been sufficient for an average downturn. Figure 5 shows that under the realized 95% mean reversion, the GSEs' cost would be much higher than revenue in many boom areas.

Besides the papers mentioned above, my findings contribute to the following literature: 1) understanding home price expectations, especially during the 2000s housing bubble; 2) GSEs' loan selection and risk management; 3) LTVs' role in housing policy; 4) The interaction between collateral constraints and home prices.

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 their housing portfolios. In this paper, I show that in contrast to the private label securitization chains, the GSEs were aware of the housing bubble, highlighting the different beliefs of public and private mortgage insurers. In particular, the lack of relationship between the change in private label LTVs and home price appreciation detailed in Section 4.5 is also consistent with the findings of Cheng, Raina, and Xiong (2014).

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). Between 2001 and 2005, home prices rose by 103% in Phoenix, 110% in Las Vegas and 154% in Los Angeles, much larger than the causal effects of credit expansion (Di Maggio and Kermani, 2015; Glaeser, 2013) [1]. Exuberant expectation of home prices is argued to be a major cause for the boom-bust

[1] To put those numbers in context, even with the very strong wage growth in the Bay Area between 2011 and 2015,

cycle (Glaeser, 2013). 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). In other words, the massive credit expansion was more from inflated optimism about home prices making lenders insensitive to borrower and loan characteristics, rather than a change in financial technology, for example the securitization of subprime mortgages fueling credit to low income borrowers. On one hand, we have the strong fact that housing markets mean revert (Cutler, Poterba, and Summers, 1991). On the other hand it seems that during each boom, people tend to think that "this time it's different". These two opposite effects make it difficult to infer whether people were really aware of the housing bubbles. On top of that, during the housing boom, there was a lively debate among prominent economists on whether home prices were reasonable (Davis, Lehnert, and Martin, 2008; Gallin, 2006, 2008; Himmelberg, Mayer, and Sinai, 2005; McCarthy and Peach, 2004).[2] The results from this paper show that the GSEs, the dominant insurers of the mortgage market, did take precautionary measures for the looming housing crash.

On the GSEs' loan selection, my paper is built on the premise of Kulkarni (2016) and Hurst, Keys, Seru, and Vavra (2016), namely, 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 strong evidence that the GSEs reacted to housing boom by lowering the share of high LTV loans in boom areas.

The LTV ratio is a macroprudential policy tool widely used to intervene in home prices in other 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). Academics also suggest that during a boom

home prices in San Jose rose by 60% , less than half of the home price appreciation Los Angeles experienced between 2000 and 2005.

[2]Among the optimists are Himmelberg, Mayer, and Sinai (2005) and McCarthy and Peach (2004). Among the pessimists are Gallin (2006, 2008) and Davis, Lehnert, and Martin (2008).

period, banks should use the long run home prices, instead of the current market prices, for mortgage underwriting (Glaeser, 2013). In the U.S., the government is reluctant to directly express views on asset prices. Unless asset prices have a large effect on inflation, the Federal Reserve Board tends not to adjust monetary policy for them. In this paper, I show that although the GSEs do not explicitly claim LTVs as a policy tool to express views on home prices, they do use LTVs in managing their home price risk.

I also contribute to the vast literature understanding how collateral constraints affect home prices and asset prices in general (Caballero and Krishnamurthy, 2001; Corbae and Quintin, 2015; Iacoviello, 2005; Kiyotaki, Moore, et al., 1997; Sommer, Sullivan, and Verbrugge, 2013). My contribution is that home prices can also affect collateral constraints, even if this channel is not explicitly stated by the GSEs.

The paper proceeds as follows. Section 2 gives a brief introduction of the institutional background. Section 3 describes data used in my analysis. Section 4 presents evidence that the GSEs reacted to the housing bubble by lowering LTVs in boom areas. Section 5 presents the insurance valuation framework. Section 6 concludes.

2 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 2.1 briefly discusses the history and business models of Fannie Mae and Freddie Mac. Section 2.2 discusses private mortgage insurance companies. Section 2.3 presents a numerical example of how private mortgage insurers take first loss positions for high LTV GSE loans.

2.1 Fannie Mae and Freddie Mac

Fannie Mae and Freddie Mac were established as government-sponsored enterprises by 1968 and 1970 legislation (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 involves providing 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).

2.2 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%.

Because the default rate 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, and one was placed into receivership. They also changed their behavior handling claims, for example, rejecting a unprecedented high fraction of claims and delaying settlements, so that they would suffer less loss at the expense of their clients.

2.3 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 $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 latter 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 along the LTV dimension, high LTV GSE loans are less risky than an 80% LTV GSE loan on the GSEs' balance sheet.

3 Data Description and Summary Statistics

The analysis in this paper is based on three different types of data: loan level mortgage origination and performance data, home price indexes and interest rate data. In the following, I go through how each of the data sets is constructed. Loan level mortgage origination data are used to study how loan characteristics, for example LTVs and FICO scores, evolved during the housing boom. House price indexes are used to differentiate between boom areas and other areas. Loan performance data, house price indexes and interest rates data are used to build a mortgage insurance valuation framework, studying how the GSEs' risk management would have performed under different house price mean reversion scenarios.

3.1 Loan Level Mortgage Origination and Performance Data

In this paper, I study both GSE loans and private label loans. For GSE loans, I use the public data collected from Fannie Mae and Freddie Mac's websites. Private label loans in my sample come from ABSNet. Both data have rich mortgage characteristics, including original LTV, original CLTV, FICO score, loan amount, loan purpose (purchase or refinance) and detailed monthly loan performance. The GSE data also have a variable indicating if a loan is taken by a first-time home buyer. As I will argue, this variable helps me address an important alternative story from the wealth effect of past home price appreciation. I keep all first lien purchase mortgages.

3.2 Home Price Index

CBSA level home price indexes are collected from FHFA. I choose CBSA level home price indexes over zip code level home price indexes because the finest geographic code in the public GSE data are at the CBSA level. FHFA home price indexes are typically used for mortgage modeling and stress testing.

3.3 Interest Rate Data

To value mortgage insurance, I collect interest rate data from Yield Book. Yield Book is a fixed income valuation service provided by Citi group widely used on Wall Street. They also provide historical data related to fixed income trading, including interest rate data. Interest rates affect the valuation of mortgage insurance through two ways. First, forecast interest rates are the discount rates for both the fixed leg and the floating leg of mortgage insurances. Second, a larger coupon gap, defined as the original ten year rate minus the current ten year rate, gives borrowers stronger incentives to refinance. This determines how long the insurance provider expects to collect premium and how long the insurance provider is exposed to house price risk.

3.4 Summary Statistics

Table 1 reports the summary statistics. There are 321 CBSAs in my sample and 1926 CBSA-year level observations between 2000 and 2006. In most of my specifications, separate regressions are run for GSE loans for first-time home buyers and other buyers, with LTVs below 80.5% or above 80.5%[3]. Thus Table 1 reports changes in loan and borrower characteristics separately for these four subsamples.

[3] I use 80.5% instead of 80% as the threshold because loans with LTVs just above 80% within round errors are treated by the GSEs as at 80%. They are exempt from the requirement for private mortgage insurance. By using 80.5% as the threshold, loans with LTVs just above 80% are classified as below or at 80%, consistent with the GSEs' definition.

We can see that 2000-2006 was a period with strong home price and wage growth. The rising debt-to-income ratios indicate that mortgage debt growth out paced wage growth. Interest rates significantly declined during this boom period. In both the above and below 80.5% segments, LTVs changed little on average. For first-time home buyers, the standard deviation of changes in log LTVs for the below 80.5% segment is three times the standard deviation of changes in log LTVs for the above 80.5% segment.

4 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. The central piece of evidence is the strong relationship between home price appreciation and the decline of average LTVs among mortgages insured by the GSEs only, *i.e.,* mortgages with LTVs at or below 80%. In contrast, little evidence suggests that private insurers lowered their home price exposure for mortgages with LTVs above 80%, where they would take first loss positions.

Section 4.1 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. Section 4.2 presents the main results.

Section 4.3 and Section 4.4 conduct robustness tests for private insurers and the GSEs respectively. In Section 4.3, 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. Section 4.4 focuses the results for the GSEs. I conduct a series of robustness tests to verify that the most likely explanation for my results is the GSEs' dynamic home price risk management. Alternative explanations that I address include reverse causality, upper bound on DTIs, risk adjustment along other dimensions, challenges in saving for 20% down payments, borrowers voluntarily switching to second liens, and private label ARMs or FRMs.

The main goal of this paper is to compare the GSEs' home risk management with private insurers'. Section 4.5 complements the main goal by presenting results for private label loans, showing that they are consistent with existing results in Cheng, Raina, and Xiong (2014), which finds that investment bankers working for the private label securitization chain were unaware of the housing bubble.

4.1 Empirical Model

The main specification is

$$\Delta \log LTV_{ct,LTV\leq 80.5\%} = \beta_{LTV}^{LTV\leq 80.5\%} \Delta \log HPI_{ct} + \beta_X \Delta X_{ct} + \alpha_c + \gamma_t + \epsilon_{ct}, \quad (4.1)$$

$$\Delta \log LTV_{ct,LTV>80.5\%} = \beta_{LTV}^{LTV>80.5\%} \Delta \log HPI_{ct} + \beta_X \Delta X_{ct} + \alpha_c + \gamma_t + \epsilon_{ct}, \quad (4.2)$$

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. Separate regressions are run for GSEs loans for first-time home buyers and GSEs loans for other buyers, explained in Section 4.1.2. $\Delta \log HPI_{ct}$ are changes in log home prices. ΔX_{ct} are CBSA-year level control variables, including changes in macroeconomic conditions measured by unemployment and average wage, changes in 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

$$\Delta \log FICO_{ct} = \beta_{FICO}^{LTV\leq 80.5\%} \Delta \log HPI_{ct} + \beta_X \Delta X_{ct} + \alpha_c + \gamma_t + \epsilon_{ct}. \quad (4.3)$$

Naturally, in the FICO score regressions, the set of control variables include changes in LTVs and exclude changes in FICO scores. Separate regressions are run for GSE loans by first-time home buyers (the full sample or the segment with LTVs below 80%) and private label ARMs. Regression (4.3) is studied for two reasons. First, they are to study how the GSEs and private insurers adjusted FICO scores to understand how LTV adjustment fits in the overall home risk management, detailed in Section 4.4.4. Second, the FICO score results are used to eliminate some alternative stories. For example, one concern is that rising house prices in boom areas drove up mortgage payments, forcing some low income borrowers to switch to ARMs with lower current interest rates than FRMs. This leaves the FRM borrower pool with good borrowers having enough savings for large down payments, explaining why LTVs declined in boom areas. If my results were driven by this story, we would expect a relative increase of FICO scores among GSE loans and a relative decline of FICO scores among ARMs from boom areas. However, Table 7 finds the exact opposite. Among GSE loans, FICO scores relatively declined in boom areas, while among ARMs, FICO scores relatively increased in boom areas.

Section 4.1.1 and Section 4.1.2 below argue that my preferred sample is GSE first-time buyers from low-to-middle home price areas to address two important alternative explanations. Section 4.1.1 discusses the mechanical effect of conforming loan limits and how it is addressed by excluding high home price CBSAs or restricting the sample to loans under 95% of the conforming loan limits. Section 4.1.2 describes how the wealth effect from past home price appreciation is addressed by restricting to first-time home buyers.

4.1.1 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 loan amount of GSE insured mortgages is required to be under the CLLs. Since LTVs are loan amount divided by house prices, in areas where house prices are high, LTVs of GSE loans have to be low to satisfy the CLL requirement. Thus past home price appreciation could mechanically bring down average LTVs among GSE loans.

To address this, I construct two samples where the CLLs are not binding. In the first sample, only CBSAs with low to middle home prices by 2006 are kept. Low to middle home price CBSAs are defined as CBSAs with more than 80% 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 80% selection criteria is very strict. All CBSAs in the remaining sample had home prices at least one hundred thousand dollars below the CLLs throughout the housing boom. Figure 1 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 us with 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 is presented in Table 12. We can see that my results persist in this subsample.

4.1.2 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, mainly accumulated from the rapid home price appreciation in the last two years, to their new home. Thus, trade-up buyers from boom areas in 2005 might naturally ask for a low LTV, 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. In fact, because of their limited savings, it is far more likely that first-time buyers on average would prefer lower LTVs than higher LTVs after large recent home price growth. 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.

4.2 Main Result

Table 2 and Table 3 report results from regressions (4.1) and (4.2), 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 1-3 are for the LTVs below 80% segment. Columns 4-6 are for the LTVs above 80% segment. Columns 1 and 4 control for year fixed effects only. Columns 2 and 5 add CBSA-year level controls, including changes in macroeconomic conditions, changes in loan and borrower characteristics. Columns 3 and 6 further add CBSA fixed effects. The most striking contrast in Panel A is the strongly negative coefficient in column 3 and the statistically insignificant coefficient in column 6. In the LTVs below 80% segment, LTVs significantly declined in boom areas than 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 our 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 4.1.1. As discussed in Section 4.1.1 and Section 4.1.2, my preferred sample is

GSE first-time home buyers from low to middle home price CBSAs, corresponding to Panel A of Table 3. Columns 1-3 show that the relationship between decline of LTVs and home price appreciation is always strong across different specifications in the LTVs below 80% segment. Columns 4-6 show that in the LTVs above 80% segment, boom areas did not have a disproportionately larger declines of LTVs. The estimate -0.053 in column 3 of panel A implies that a 10% home price appreciation leads to a 0.51% decline of LTVs.

Comparing Panel A and Panel B in Table 3, we see that in the low to middle home price sample, the coefficients for GSE first-time home buyers and GSE other buyers are similar to each other. The strong home price appreciation in boom areas should have led to large wealth differences between first-time home buyers and second time home buyers, and potentially different preferences for LTVs. With large equity in their previous homes, it is natural to expect second time home buyers to carry some equity to their next purchase loans. The similar coefficients for the two buyer groups are more consistent with the supply side story of the GSEs' risk management than the demand side story of boom area borrowers asking for lower LTVs.

4.3 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 than the other areas. To rule out this alternative story, I run the following regression

$$\Delta \log P_{ct,LTV>80.5\%} = \beta_{LTV>80.5\%} \Delta \log HPI_{ct} + \beta_X \Delta X_{ct} + \alpha_c + \gamma_t + \epsilon_{ct}, \qquad (4.4)$$

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 4 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 4 reports results from the following regression

$$\Delta \log CP_{ct} \quad = \quad \beta_{LTV>80.5\%} \Delta \log HPI_{ct} + \beta_X \Delta X_{ct} + \alpha_c + \gamma_t + \epsilon_{ct}, \tag{4.5}$$

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. The positive and significant coefficient in column (3) panel B means that they relatively increased percentages of covered losses in boom areas, the opposite of reducing home price risk exposure.

4.4 Robustness Tests for the GSEs

This section conducts a series of robustness tests to verify that the most likely explanation for the relative decline of LTVs in boom areas among the LTVs below 80% segment is the GSEs' home price risk management.

In Section 4.4.1, I show that the reverse causal story predicts the opposite sign of my findings. In other words, my estimates are biased towards zeros by the reverse causal story of stricter LTV requirements lowering house prices. In Section 4.4.2, I address three alternative stories related to borrowers' mortgage choice. All three of them are based on the idea that high LTV borrowers from boom areas were not credit rationed by the GSEs, but voluntarily switched to other mortgage products, including private label FRMs, ARMs, or second liens. I present evidence inconsistent with each of these three stories. For example, one could argue that borrowers might have switched to private label FRMs because they offered better interest rates. However, Table 5 shows that the GSEs offered better interest rates than private label FRMs in almost all market segments in each CBSA. Thus my results are more likely to be driven by the GSEs' voluntary risk management rather than being forced by competition from the private label segment.

Another alternative story is upper bounds on DTIs. If borrowers are already taking out the maximum loan amount allowed by DTI upper bounds, any more home price appreciation would lower LTVs. To address this, in Section 4.4.3, I drop loans with high DTIs under a number of DTI thresholds. My results persist in these low DTI subsamples.

Section 4.4.4 compare risk adjustment along FICO scores with risk management along LTVs and verify that LTVs is the main channel for the GSEs' home price risk management. The GSEs relatively lowered FICO scores in boom areas, or took more risk along FICO scores in boom areas than elsewhere. I show that the risk reduction along LTVs is much larger than risk taking along FICO scores.

Section 4.4.5 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. However, it was relatively easy to do with low home prices before the housing boom than the much higher home prices after the housing boom. This manifests as non-boom areas having an increasing concentration of LTVs at 80% than boom areas, explaining why boom area LTVs relatively declined in the LTVs under 80% segment. If my results are driven by this story, we would expect that after dropping loans with LTVs at 80%, the coefficients will become insignificant. However, I show that the results are stronger after dropping loans with LTVs between 79.5% and 80.5%.

4.4.1 Reverse Causality

One could argue that regressions (4.1) and (4.2) are subject to reserve causality. After all, the literature studying credit constraints and home prices largely focus on how credit conditions, including LTV requirements, would affect house prices (Corbae and Quintin (2015); Sommer, Sullivan, and Verbrugge (2013)). This reverse causal story predicts the opposite signs of my findings. The credit condition affecting house price channel predicts that declining LTVs, or equivalently requiring higher percentage of down payments, would lower home prices. In contrast, I find that LTVs for

GSE loans declined in boom CBSAs, the opposite of the causal effect of LTV requirement on house prices.

4.4.2 Borrowers' Mortgage Choice

The risk management story 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 switched to other products by choice. This section addresses three alternative stories along this line, that high LTV borrowers from boom areas voluntarily switched to private label FRMs, ARMs, or second liens.

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 FRMs and private label 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 to four ranges: below 79.5%, between 79.5% and 80.5%, between 80.5% and 90%, and above 90%. [4] 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 FRMs and private label 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

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

CBSA-segments, with 83 out 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 4-6 of Table 7, 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 1-3 of Table 7, 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

$$\Delta \log CLTV_{ct,LTV\leq 80.5\%} = \beta_{CLTV}^{LTV\leq 80.5\%}\Delta \log HPI_{ct} + \beta_X \Delta X_{ct} + \alpha_c + \gamma_t + \epsilon_{ct}, \quad (4.6)$$

$$\Delta \log CLTV_{ct,LTV>80.5\%} = \beta_{CLTV}^{LTV>80.5\%}\Delta \log HPI_{ct} + \beta_X \Delta X_{ct} + \alpha_c + \gamma_t + \epsilon_{ct}. \quad (4.7)$$

Table 6 reports the results. Comparing Table 6 with Table 3, we see that changing the left-hand-side variable to changes in CLTVs has almost no impact on the coefficients.

4.4.3 Upper Bound on Debt-to-Income Ratio

Another alternative story is that the debt-to-income ratios in boom areas might have got to the upper bounds allowed by the GSEs. Under a rising home price environment, these upper bounds on loan amounts 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 report the results. We can see that in the low DTI subsamples, my results continue to hold.

4.4.4 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 5 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 than 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.

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 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 5. From Table 14, we see that their default elasticities have similar magnitudes, while Table 9 shows that the GSEs' LTV response is 3.6 times as large as the GSE's FICO score response to rising home prices. Thus the GSEs' LTV home risk reduction dominates their FICO risk taking.

4.4.5 Difficulty of Obtaining 20% Down Payments

To address the story that rising home prices changed the difficulty of obtaining 20% down payments, I drop loans with binding LTVs-LTVs at 80%. Table 10 reports the results. We see that relationship between home price appreciation and decline of LTVs persists.

4.5 Results for Private Label FRMs

While the main goal of the paper is to study the GSEs and private insurers' home price risk management, in this section, I study if my results are consistent with previous results for the private label segment studied in Cheng, Raina, and Xiong (2014). Using securitization investment bankers' personal home transactions, Cheng, Raina, and Xiong (2014) find no evidence that investment bankers foresaw the housing crash. My results are consistent with their findings. Table 11 reports the result for private label FRMs. We see that after controlling for changes in macroeconomic conditions, loan and borrower characteristics, CBSA and year fixed effects, private label FRMs had relatively increasing LTVs in boom areas. This is consistent with the idea that the private label segment was unaware of the housing bubble.

5 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) Was the GSEs' risk management sufficient? For the second question, the GSEs' $215 losses from the insurance business between 2008 and 2011 suggest that their risk management was insufficient. However, one contributing factor to the large losses is the larger than historical average house price mean reversion between 2006 and 2011. For every $1 home price increase between 2001 and 2006 in a CBSA, it on average gave back 95¢between 2006 and 2011. This 95% mean reversion was much larger than the 32% historically average mean reversion. Thus the GSEs' failure alone does not imply that the GSEs' risk management was insufficient based on reasonable assumptions ex-ante. To quantify how the GSEs' portfolios would have performed under alternative scenarios, I consider four hypothetical housing markets: 0% mean reversion, or prices staying constant, 10% mean reversion, 32% mean reversion and 95% mean reversion.

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 5.1 describes the cash flows. Section 5.2 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 5.3 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 5.4 summarizes the data-generating process. Section 5.5 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.

5.1 Insurance Cash Flows

Mortgage default insurance provided by the GSEs have 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 are random events. Reasons for termination include default, being paid in full till 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.

5.2 Hazard Model

5.2.1 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 (5.8) and (5.9)

$$\begin{aligned}
\lambda_{ic}^{\text{Default}}(t) &\equiv \lim_{\xi\to 0}\frac{1}{\xi}\text{Pr}_{ic}^{\text{Default}}\left(t-\xi<\tau\leq t|\tau>t-\xi, X\right) \qquad (5.8)\\
&= \exp\left(X_{ict}'\beta^{\text{Default}}\right)\lambda_0^{\text{Default}}(t),\\
\lambda_{ic}^{\text{Prepay}}(t) &\equiv \lim_{\xi\to 0}\frac{1}{\xi}\text{Pr}_{ic}^{\text{Prepay}}\left(t-\xi<\tau\leq t|\tau>t-\xi, X\right) \qquad (5.9)\\
&= \exp\left(X_{ict}'\beta^{\text{Prepay}}\right)\lambda_0^{\text{Prepay}}(t),
\end{aligned}$$

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 (5.8) and (5.9), $\exp\left(X_{ict}'\beta^{\text{Default}}\right)$ 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 interests, 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, 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.

5.2.2 Estimation

The competing-risk hazard model specified in equations (5.8) and (5.9) 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 (5.8) and (5.9) 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

$$\Lambda(t) = \int_0^t \lambda(\tau) d\tau. \tag{5.10}$$

Using $\Lambda(t) = -\log(S(t))$ and identity (5.10), 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.

5.2.3 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.

5.3 Interest Rate Model

I calibrate the following Hull-White term-structure model

$$dr = (\theta(t) - \alpha r)dt + \sigma dw. \tag{5.4}$$

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

$$Z(t) = e^{at+bt^2+ct^3+dt^4+et^5} \tag{5.5}$$

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 (5.4).

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 5.5 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 (5.4). 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

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

5.4 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 5.5. 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 5.3. 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.

5.5 Results

Figure 2 through Figure 5 illustrate the results. Figure 2 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 4.4.4, 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 2, 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 3, 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. However, there are confounding factors that might have prevented the GSEs from implementing their believed house price mean reversion. One example is political pressure for uniform access to mortgage credit between CBSAs. Another example is that if the GSEs had asked for even higher percentages of down payments from boom areas, very few borrowers from boom areas could provide the down payments.

Two additional natural scenarios to test are the historically average 32%, and the realized 95% mean reversion. Somewhat surprisingly, under a 32% mean reversion assumed in Figure 4, all CBSAs would have costs lower than even 40% of their projected revenue. This implies that under a historically average mean reversion, the GSEs' expected revenue would be more than twice of the expected costs in every CBSA. 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 fives times of the projected revenue. This explains the unprecedented losses and government bailouts for the GSEs during the 2008 crash.

6 Conclusion

A common critique of the "public-private" partnership of Fannie Mae and Freddie Mac is that their implicit government guarantee reduces incentives for risk management and fosters irresponsible risk taking. Evidence from this paper suggests that Fannie Mae and Freddie Mac more effectively managed home price risk during the 2001-2006 housing boom than private mortgage insurance companies did.

These somewhat surprising results are nevertheless consistent with the history of 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 incentives, such as assumptions about future house prices, 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 reduce or remove 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.

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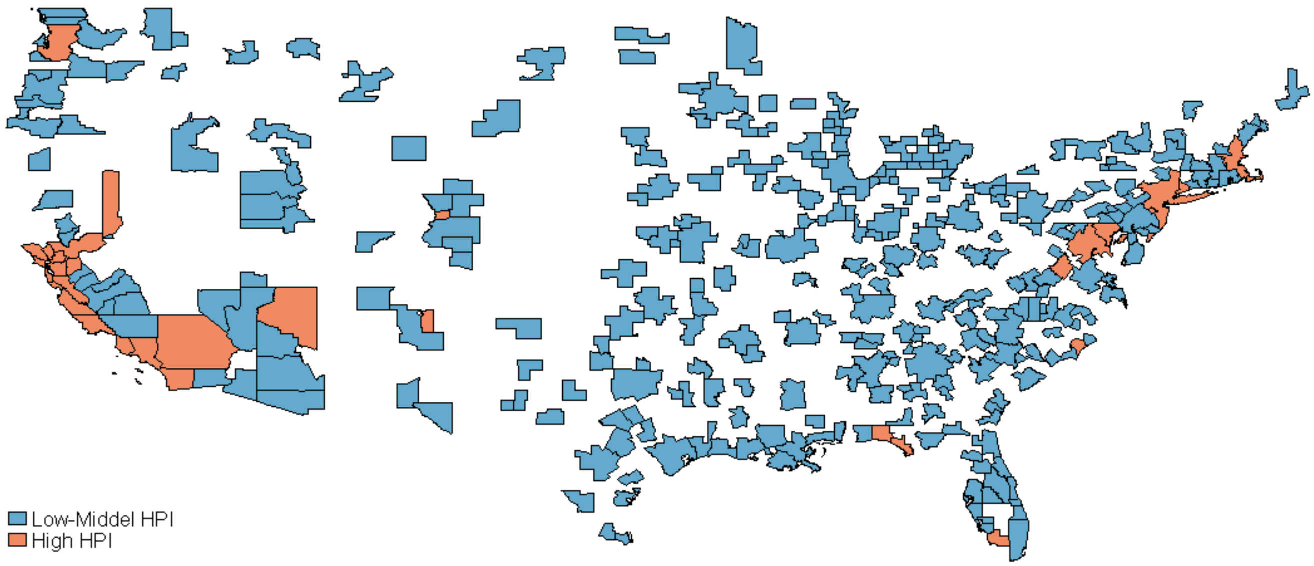
7 Figures and Tables

Figure 1: 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 4.1.1, 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 2: 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 5. 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 5.2. The Hull-White term-structure model and its calibration procedure is described in Section 5.3.

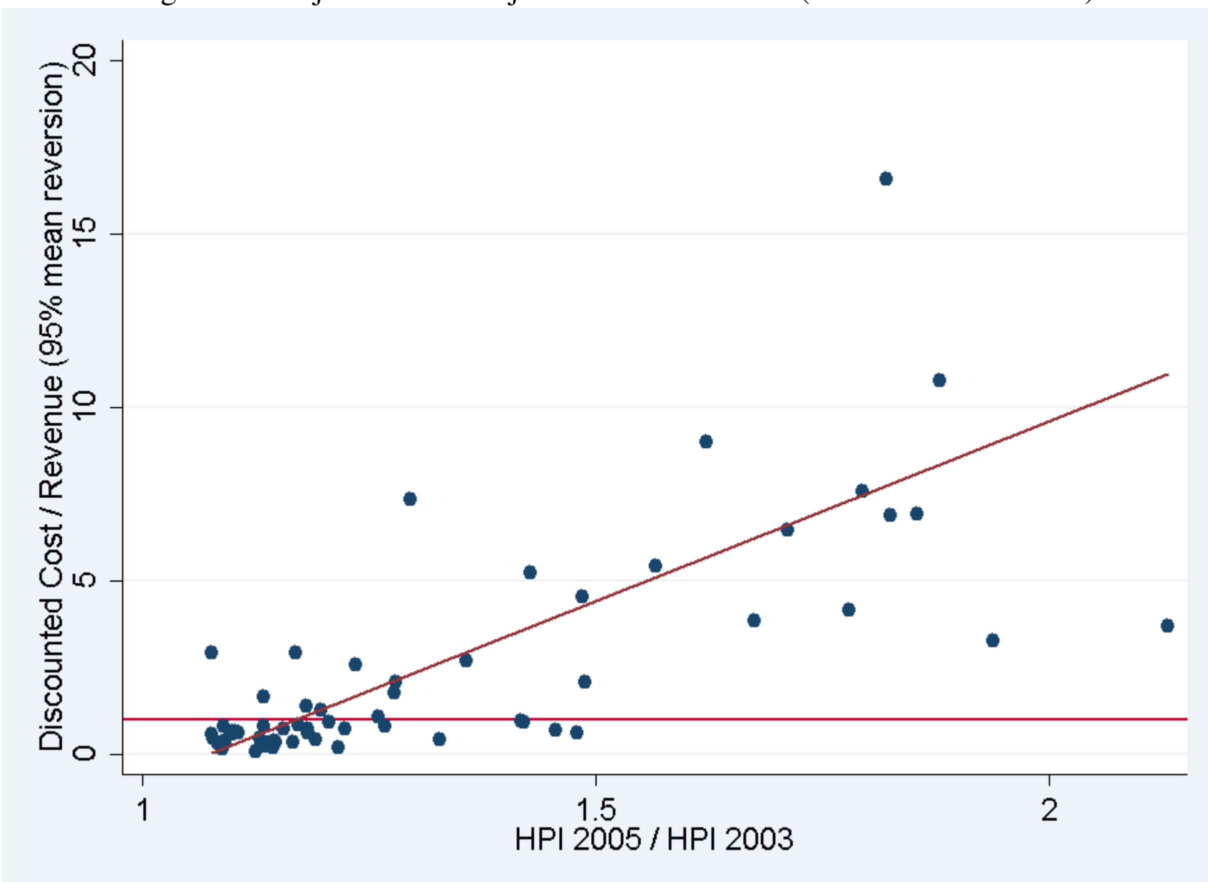
Figure 3: Projected Cost/Projected Guarantee Fees (10% Mean Reversion)

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 5. 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 5.2. The Hull-White term-structure model and its calibration procedure is described in Section 5.3.

Figure 4: Projected Cost/Projected Guarantee Fees (32% 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 5. The simulation setting assumes a 32% 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 5.2. The Hull-White term-structure model and its calibration procedure is described in Section 5.3.

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 5. 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 5.2. The Hull-White term-structure model and its calibration procedure is described in Section 5.3.

Table 1: Summary Statistics

	Mean	Std	Min	Max
$\Delta\log(HPI)$	0.080	0.058	-0.072	0.364
Δ(Unemployment)	0.138	0.830	-2.300	3.500
Δ(Wage)	749	1001	-13151	4509
$\Delta\log(LTV)$				
First-Time Buyers with LTVs $\leq$ 80.5%	0.001	0.015	-0.270	0.219
First-Time Buyers with LTVs $>$ 80.5%	0.001	0.004	-0.040	0.050
Other Buyers with LTVs $\leq$ 80.5%	-0.001	0.016	-0.134	0.081
Other Buyers with LTVs $>$ 80.5%	-0.000	0.003	-0.025	0.024
$\Delta(FICO)$				
First-Time Buyers with LTVs $\leq$ 80.5%	1.741	5.166	-51.333	73.167
First-Time Buyers with LTVs $>$ 80.5%	-0.019	5.864	-104.000	70.500
Other Buyers with LTVs $\leq$ 80.5%	1.942	2.967	-27.333	28.896
Other Buyers with LTVs $>$ 80.5%	0.459	4.138	-50.333	33.985
$\Delta(DTI)$				
First-Time Buyers with LTVs $\leq$ 80.5%	0.528	1.804	-16.450	17.136
First-Time Buyers with LTVs $>$ 80.5%	0.530	1.892	-16.348	22.500
Other Buyers with LTVs $\leq$ 80.5%	0.610	1.390	-9.320	11.700
Other Buyers with LTVs $>$ 80.5%	0.601	1.530	-23.333	35.500
Δ(Owner-Occupation)				
First-Time Buyers with LTVs $\leq$ 80.5%	0.000	0.005	-0.087	0.077
First-Time Buyers with LTVs $>$ 80.5%	-0.000	0.005	-0.077	0.077
Other Buyers with LTVs $\leq$ 80.5%	-0.010	0.021	-0.161	0.194
Other Buyers with LTVs $>$ 80.5%	-0.024	0.027	-0.500	0.208
Δ (Interest Rate)				
First-Time Buyers with LTVs $\leq$ 80.5%	-0.280	0.568	-1.342	0.881
First-Time Buyers with LTVs $>$ 80.5%	-0.458	0.536	-1.377	0.855
Other Buyers with LTVs $\leq$ 80.5%	-0.316	0.560	-1.194	0.762
Other Buyers with LTVs $>$ 80.5%	-0.464	0.519	-1.238	1.542
Observations (CBSA-years)	1926			

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. This table displays summary statistics for changes in loan and borrower characteristics in my sample of GSE loans at the CBSA-year level.

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)
$\Delta \log(HPI)$	-0.082***	-0.087***	-0.086***	-0.006***	-0.008***	-0.003
	(0.006)	(0.006)	(0.010)	(0.002)	(0.002)	(0.003)
Year FEs	y	y	y	y	y	y
Controls	n	y	y	n	y	y
CBSA FEs	n	n	y	n	n	y
Observations	1926	1926	1926	1926	1926	1926
R-squared	0.19	0.20	0.28	0.04	0.09	0.14

B: GSE Other Buyers

	LTVs $\leq 80.5\%$ Segement			LTVs $> 80.5\%$ Segement		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \log(HPI)$	-0.125***	-0.133***	-0.129***	-0.012***	-0.013***	-0.012***
	(0.005)	(0.005)	(0.007)	(0.001)	(0.001)	(0.002)
Year FEs	y	y	y	y	y	y
Controls	n	y	y	n	y	y
CBSA FEs	n	n	y	n	n	y
Observations	1926	1926	1926	1926	1926	1926
R-squared	0.48	0.52	0.61	0.19	0.23	0.29

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equations (4.1) and (4.2) 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 changes in macroeconomic conditions measured by unemployment rates and average wage, and changes in 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 3: Effect of Home Price Growth on Loan-to-Value Ratios (Excluding High HP Areas)

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)
$\Delta \log(HPI)$	-0.042***	-0.047***	-0.054***	-0.003	-0.006**	-0.001
	(0.007)	(0.007)	(0.011)	(0.002)	(0.002)	(0.004)
Year FEs	y	y	y	y	y	y
Controls	n	y	y	n	y	y
CBSA FEs	n	n	y	n	n	y
Observations	1794	1794	1794	1794	1794	1794
R-squared	0.09	0.10	0.15	0.04	0.09	0.14

B: GSE Other Buyers, Excluding High Home Price CBSAs

	LTVs $\leq 80.5\%$ Segement			LTVs $> 80.5\%$ Segement		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \log(HPI)$	-0.064***	-0.067***	-0.064***	-0.011***	-0.011***	-0.012***
	(0.004)	(0.004)	(0.006)	(0.001)	(0.001)	(0.002)
Year FEs	y	y	y	y	y	y
Controls	n	y	y	n	y	y
CBSA FEs	n	n	y	n	n	y
Observations	1794	1794	1794	1794	1794	1794
R-squared	0.48	0.50	0.54	0.18	0.22	0.28

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equations (4.1) and (4.2) 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 1, 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 changes in macroeconomic conditions measured by unemployment rates and average wage, and changes in 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 4: Effect of Home Price Growth on Private Insurers' Risk Management

A: $\Delta\log$*(Share of Loans with LTVs* $> 80.5\%$*)*

	(1)	(2)	(3)
$\Delta\log(HPI)$	0.055	-0.036	0.080
	(0.053)	(0.055)	(0.077)
Year FEs	y	y	y
Controls	n	y	y
CBSA FEs	n	n	y
Observations	1794	1794	1794
R-squared	0.31	0.36	0.46

B: $\Delta\log$*(Private Insurers' Coverage Percentage)*

	(1)	(2)	(3)
$\Delta\log(HPI)$	0.039**	-0.014	0.069***
	(0.020)	(0.016)	(0.025)
Year FEs	y	y	y
Controls	n	y	y
CBSA FEs	n	n	y
Observations	1794	1794	1794
R-squared	0.25	0.48	0.55

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. Panel A and B report estimates of Equations (4.4) and (4.5) 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-middel CBSAs, colored blue in Figure 1. CBSA-year level controls include changes in macroeconomic conditions measured by unemployment rates and average wage, and changes in loan and borrower characteristics including average FICO scores, debt-to-income ratios, interest rates and percentage of owner occupied mortgages.

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 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)
$\Delta \log(HPI)$	-0.049***	-0.059***	-0.054***	-0.003	-0.006**	-0.001
	(0.009)	(0.010)	(0.015)	(0.002)	(0.002)	(0.004)
Year FEs	y	y	y	y	y	y
Controls	n	y	y	n	y	y
CBSA FEs	n	n	y	n	n	y
Observations	1794	1794	1794	1794	1794	1794
R-squared	0.05	0.06	0.10	0.04	0.09	0.15

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)
$\Delta \log(HPI)$	-0.087***	-0.090***	-0.077***	-0.011***	-0.011***	-0.012***
	(0.005)	(0.005)	(0.007)	(0.001)	(0.001)	(0.002)
Year FEs	y	y	y	y	y	y
Controls	n	y	y	n	y	y
CBSA FEs	n	n	y	n	n	y
Observations	1794	1794	1794	1794	1794	1794
R-squared	0.39	0.40	0.44	0.19	0.22	0.28

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equations (4.6) and (4.7) 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 1, 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 changes in macroeconomic conditions measured by unemployment rates and average wage, and changes in 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 FICO

	Excluding High Home Price CBSAs					
	GSE First Time Buyers			Private Label ARMs		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \log(HPI)$	-0.009***	-0.010***	-0.020***	0.059***	0.009***	0.019***
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)
Year FEs	y	y	y	y	y	y
Controls	n	y	y	n	y	y
CBSA FEs	n	n	y	n	n	y
Observations	1794	1794	1794	1794	1794	1794
R-squared	0.21	0.26	0.31	0.70	0.86	0.87

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equation (4.3) in the text. The dependent variable is the annual change in log average FICO score. High home price CBSAs, colored orange in Figure 1, are excluded from the sample to address the potential effect of conforming loan limits. CBSA-year level controls include changes in macroeconomic conditions measured by unemployment rates and average wage, and changes in 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 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	DTI≤60%	DTI≤55%	DTI≤50%	DTI≤45%	DTI≤40%
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\log(HPI)$	-0.051***	-0.050***	-0.050***	-0.053***	-0.057***	-0.060***
	(0.016)	(0.016)	(0.017)	(0.017)	(0.018)	(0.020)
Obs	1794	1794	1794	1794	1794	1794
R squ	0.12	0.12	0.12	0.11	0.11	0.11

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equation (4.1) in the text for low debt-to-income ratio subsamples. The dependent variable is the annual change in log average LTV at the CBSA-year level. CBSA-year level controls include changes in macroeconomic conditions measured by unemployment rates and average wage, and changes in 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 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
$\Delta \log(HPI)$	-0.054***	-0.015***
	(0.011)	(0.006)
Year FEs	y	y
Controls	y	y
CBSA FEs	y	y
Observations	1794	1794
R-squared	0.15	0.19

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equations (4.1) and (4.3) 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 1, are excluded from the sample to address the potential effect of conforming loan limits. CBSA-year level controls include changes in macroeconomic conditions measured by unemployment rates and average wage, and changes in loan and borrower characteristics including average FICO scores, debt-to-income ratios, interest rates and percentage of owner occupied mortgages. 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)
$\Delta \log(HPI)$	-0.069***	-0.068***	-0.063**
	(0.018)	(0.019)	(0.028)
Year FEs	y	y	y
Controls	n	y	y
CBSA FEs	n	n	y
Observations	1794	1771	1771
R-squared	0.05	0.06	0.10

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equations (4.1) 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 1, are excluded from the sample to address the potential effect of conforming loan limits. CBSA-year level controls include changes in macroeconomic conditions measured by unemployment rates and average wage, and changes in 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 11: Results for Private Label FRMs

	Private Label FRMs Excluding High Home Price CBSAs		
	(1)	(2)	(3)
$\Delta \log(HPI)$	-0.026***	-0.020***	0.017*
	(0.005)	(0.006)	(0.009)
Year FEs	y	y	y
Controls	n	y	y
CBSA FEs	n	n	y
Observations	1792	1792	1792
R-squared	0.69	0.71	0.74

Source: ABSNet, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equations (4.1) in the text for private label FRMs. The dependent variable is the annual change in log average LTV. High home price CBSAs, colored orange in Figure 1, are excluded from the sample to address the potential effect of conforming loan limits. CBSA-year level controls include changes in macroeconomic conditions measured by unemployment rates and average wage, and changes in 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 12: 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)
$\Delta \log(HPI)$	-0.042***	-0.047***	-0.055***
	(0.007)	(0.007)	(0.011)
Year FEs	y	y	y
Controls	n	y	y
CBSA FEs	n	n	y
Observations	1794	1794	1794
R-squared	0.09	0.10	0.15

Source: Fannie Mae, Freddie Mac, FHFA, IRS, BLS, author's own calculations. This table reports estimates of Equations (4.1) 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 changes in macroeconomic conditions measured by unemployment rates and average wage, and changes in 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 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 summaries 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 (5.8) and (5.9) 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 5.2. Panel A and Panel B report the coefficients for static and dynamic covariates respectively.

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