Lender Steering in Residential Mortgage Markets

Sumit Agarwal

Georgetown University, ushakri@yahoo.com

Brent W. Ambrose

Institute for Real Estate Studies and the Department of Risk Management, The Pennsylvania State University, bwa10@psu.edu

Vincent W. Yao

J. Mack Robinson College of Business, Georgia State University, wyao2@gsu.edu

December 6, 2016

Abstract

In this paper we examine the incentives for lenders to steer borrowers into piggyback loan structures to circumvent regulations requiring primary mortgage insurance (PMI) for loans with loan to value ratios (LTV) above 80%. Our empirical analysis focuses on propensity score matched portfolios of piggyback and single-lien loans having the same combined LTV based on a full set of observed risk characteristics. Our results confirm that mortgages originated with the piggyback structure have much lower *ex post* default rates and faster prepayment speeds than corresponding PMI loans. We also find a significant causal effect of interstate banking deregulation on the growth of piggybacks in these years, confirming that the *ex post* performance gap is primarily driven by lender steering on the supply side and not by borrower self-selection. We then perform a number of tests to explore different origination and execution channels of mortgage steering.

Key words: Steering, Securitization, Banking Deregulation, Insurance

JEL Classification: G2

Electronic copy available at: https://ssrn.com/abstract=2670211

1. Introduction

In the aftermath of the Great Recession of 2007-2008, a growing body of research focuses on identifying the causes of the crisis and prescribing policy recommendations to avoid a repeat event. One area receiving considerable attention is the causal role of misaligned incentives and fraud in the U.S. mortgage market during the period prior to the crisis.[1] Of particular concern is the possibility that lenders may have engaged in origination practices to steer borrowers with certain characteristics into products that generated short-term profits at the expense of long-term performance. For example, Agarwal and Evanoff (2013) provide evidence that lenders associated with predatory lending engaged in mortgage steering practices. In fact, they report that lender steering had an economically meaningful impact of increasing the average steered borrower's interest rate by 40 to 60 basis points. In this paper, we extend this line of literature to examine whether lender steering took advantage of differential pricing in the mortgage market that resulted from regulations requiring borrowers to purchase private mortgage insurance when the loan-to-value ratio exceeded 80 percent.

The seeds for potential lender steering lie in the institutional mortgage origination framework established in the 1930s. Prior to the Great Depression, lenders would rarely originate first mortgages with loan-to-value (LTV) ratios greater than 50 percent. In response to the massive dislocations in the housing market during the Great Depression, Congress passed the National Housing Act of 1934, which created the Federal Housing Administration (FHA) and introduced the modern, fully amortizing mortgage.[2] One of the outcomes of this initiative was a new mortgage loan program that created uniform underwriting criteria allowing loan-to-value ratios up to 80 percent. Although the U.S. mortgage market has matured and transformed over the decades since the Great Depression, the 80 percent LTV limit remains one of the central risk metrics used in determining proper loan underwriting practice. As a result, borrowers seeking mortgages with LTV ratios in excess of 80 percent are required to offset the additional risk through the purchase of primary mortgage insurance (PMI).[3] Thus, the enshrined 80 percent LTV

---

[1] See for example, Jiang et al (2014), Mian and Sufi (2015), and Ambrose, Conklin and Yoshida (2016).

[2] See Hyman (2011) for an extensive history of the creation of the FHA and the subsequent development of the U.S. mortgage market.

[3] The government sponsored enterprises (Fannie Mae and Freddie Mac) are mandated by their federal charters that all mortgages with LTVs greater than 80 percent have mortgage insurance as a condition of their eligibility for purchase by the GSEs.

Electronic copy available at: https://ssrn.com/abstract=2670211

regulation created an inflection point where costs increase substantially for borrowers seeking loans with LTVs above 80 percent.

During the previous decade, the substantial growth in housing prices coupled with an increase in asset securitization created additional incentives for lenders to engage in mortgage origination activities that would offer potential homeowners greater financing choices. For example, lenders could originate a first mortgage with a LTV up to 80 percent coupled with a second mortgage that effectively increased the borrower's total loan amount up to the desired LTV without having to pay PMI premium — a so called "piggyback" mortgage. The growth in asset securitization further encouraged the origination of piggyback mortgages by providing a platform for banks to securitize the junior lien mortgages in addition to the first. Figure 1 shows the growth in first and second lien mortgage volume along with the seasonally adjusted FHFA national purchase-only house price index from the first quarter of 2000 through the start of the financial crisis in fourth quarter of 2007. Figure 1 illustrates that as house price growth accelerated in 2004 and 2005, growth in second lien mortgage securitization also accelerated. One of the outcomes of this growth in second lien securitization is that it may have reduced the consequences of relaxing the 80 percent LTV underwriting standard; thereby creating an incentive for lenders to engage in origination practices to circumvent the use of PMI since they would no longer retain the risk position associated with these non-insured high-LTV mortgages.

In this paper we examine whether banks steered lower risk borrowers to the piggyback loans to circumvent the role of PMI companies. Our study focuses on a set of piggyback loans matched to single-lien loans based on many observable characteristics using the propensity score matching method. By our design the two groups have similar *ex ante* risks and they are also closely comparable with the same combined LTV (CLTV). For example, the 85% LTV portfolio contains a set of borrowers with a 85% LTV 1st lien mortgage and a set of borrowers with a combination of an 80% LTV first lien mortgage and a 5% second lien home equity credit. From the borrower's viewpoint, both mortgage combinations offer the same leverage (85%) and require the same downpayment (15%). Borrowers accept the offer if the cost associated with the extra charged interest rate on the second lien is lower than the PMI premium. From the lender's perspective, their profit incentive is to offer the piggyback mortgage option only to lower risk borrowers since the risks on the second mortgage must be less than the foregone PMI premium. We empirically show that borrowers with second liens are less likely to default and more likely to prepay than borrowers with a similar single-lien debt position with PMI. The lower default risk and faster prepayment incentivize lenders to essentially circumvent the role of PMI and also retain the refinance business when borrowers prepay the existing business. Our analysis of lender's profits and losses using historical PMI premium support that lenders can significantly increase their profit by steering lower risk borrowers into the piggyback loans.

One viable alternative explanation is that savvy borrowers could self-select into the piggyback products to take advantage of lower borrowing costs instead of being steered by lenders. We circumvent this issue via two robustness checks. First, we perform a matched sample analysis where remaining loans are matched by borrower characteristics used in underwriting and pricing decisions. Second, we use the advent of interstate banking deregulation from 1995 to 2005 resulting from the Interstate Banking and Branching Efficiency Act (IBBEA) to test the causal effect on the origination activities of piggyback lenders. Recent research documents that banking deregulation increased competition thereby lowering borrowing costs, increasing credit supply, and increasing asset prices (Di Maggio, Kermani and Korgaonkar 2015; Favara and Imbs 2015; Rice and Strahan 2010). For example, Favara and Imbs (2015) study the effect of interstate banking deregulation on the credit supply in mortgage market and house prices. They find that depository commercial banks experienced significantly higher deposit growth and charged lower rates. In areas primarily operated by these institutions, credit terms improved, and borrowing and housing demand increased. To the extent that this exogenous shock resulted in greater bank competition and caused lenders to seek alternative loan products, then we should observe an increase in lender steering borrowers into piggyback loans. We adopt an identification strategy similar to that employed by Favara and Imbs (2015), but study the effect on banks' steering of a particular mortgage product. Our results confirm a significant positive effect of banking deregulation on the share of piggyback business at the zip code level. Lender steering instead of borrower's self-selection primarily drives the difference in ex post performance of piggyback vs PMI loans. Thus, our results provide new evidence on the effect of credit supply on real estate markets through banking deregulation and increased competition.

We also perform a number of tests to explore different origination and execution channels of mortgage steering. Our results are stronger when loans are originated through brokers, purchased by commercial banks, originated in competitive markets, and originated during the peak of the securitization boom. First, we note that mortgage brokers sell loans to banks and have strong incentives to originate loans customized to bank demands. If lenders were incentivized to steer borrowers, then brokers would be in a perfect position to collude since they do not hold any risk associated with steering after origination. Second, we note that different institutions purchase, service, hold and securitize loans. As non-depository institutions, mortgage banks do not have access to other loan or savings products that could provide additional information about borrowers. In contrast, commercial banks take retail deposits and hold diversified asset portfolios, including credit cards and student loans, which provide them with potential information unobservable to mortgage banks. Thus comparing mortgage banks with commercial lenders shows that piggyback loans funded by depository institutions are less risky than similar loans originated by mortgage banks, providing support for the hypothesis that commercial banks were able to use their private information about customers to steer borrowers into piggyback loans. Finally, with expansion in securitization, banks were able to sell securitized pools of second loans without having to hold any position on their balance sheet. As a result, securitization increased banks' incentive to buy or originate more junior mortgages. Thus, we see greater evidence of steering as securitization of second loans increased.

We also provide a battery of robustness checks to further control for endogeneity concerns about borrower selection and mortgage default. Our concern is that the borrower's choice of a PMI loan versus a piggyback structure could be endogenous to unobserved risk characteristics. Thus, as a robustness check, we compare the default rate on unsecured credit card debts and confirm that there is no significant difference in the unsecured debt default rate between PMI and piggyback borrowers. Furthermore, we see no significant shift in the default hazard rates across time.

Finally, we conduct a decomposition analysis of the differences in Piggyback versus PMI loan performance. The results show that differences in loan types are entirely attributable to differences in unobserved heterogeneity across borrowers (the coefficient effect). Specifically, the coefficient effect is stronger for PMI loans than for piggyback loans.

This paper directly contributes to the growing literature that finds evidence linking the creation of the real estate bubble in the early 2000s to misaligned incentives of intermediaries due to securitization. Fox example, Keys et al (2010, 2012) find that existing securitization practices did adversely affect the screening incentives of subprime lenders. In addition, Piskorski, Seru and Witkin (2015), Piskorski et al (2010) and Agarwal et al (2011) support the view that frictions introduced by securitization created a significant challenge to effective renegotiation of residential loans.

Our paper is organized as follows. Section 2 describes the data and presents unconditional univariate analysis suggesting that lenders steered borrowers based on observable information. Section 3 tests for the causal effect of interstate banking deregulation on the increase of piggyback originations. Section 4 follows with a formal analysis based on standard proportional hazard models of loan default and prepayment. Section 5 presents an analysis of lender's profit and loss per different risk scenarios to explain lender incentives to steer better borrowers into the piggyback structure. To confirm the baseline results, we present a battery of robustness checks in section 6 that verify our primary results. Last section concludes.

2. Data and Unconditional Analysis

Our data comes from a national institution that creates a secondary market for residential mortgages. Based on the research design (discussed below), we selected all mortgages originated to finance home purchases between 2001 and 2008 in the 20 largest MSAs (by loan volume) and that had loan-to-value (LTVs) ratios within +/- 1 percentage point of the standard LTV ratio knots (i.e., 85%, 90%, 95%, and 100%). The resulting dataset contains 592,636 mortgages. These mortgages are conventional, conforming loans (not government insured) made to prime borrowers. Conforming mortgages meet the government sponsored enterprise (GSE) conforming loan limit, which has been \$417,000 since 2006 for single-family one-unit properties in most of the U.S with higher limits in high-cost areas. The loans were originated to borrowers with relatively high credit scores (620 or higher) compared to subprime borrowers with blemished credit.

From the mortgage data, we know the information used in underwriting the loans at origination. This information includes an external measure of the borrower's credit quality (the FICO score), the mortgage loan-to-value (LTV) ratio, the loan characteristics (origination balance, note rate, and term), the backend ratio, whether the loan was originated through a broker, and the location of the mortgaged property (zip code, city (MSA) and state). In addition to the borrower's summary credit score, we also have the borrower's full credit report that includes credit card balances and indicators for whether any debt is in delinquency. The credit report as well as mortgage performance are updated every month following origination till the loan liquidates or the end of the sample period (December 2014). Panel A in Table 1 provides the summary statistics for these mortgages. The statistics confirm that the sample represents a set of relatively high quality, prime mortgages. For example, the average borrower credit (FICO) score was 693 and the average monthly income was $6,059. The borrowers had an average credit card delinquency rate at the time of mortgage origination of 3.3% and a backend ratio of 40.7%. The average loan amount was $179,692 with a mean interest rate of 6.5%. Consistent with the increase and subsequent decrease in house prices from origination through 2014, we see that 21% of the mortgages defaulted and 71.6% prepaid by the end of 2014.

We make use of the information on the combined loan-to-value ratio at origination and whether the borrower is paying a PMI premium to identify first-lien mortgages that were likely originated as part of a piggyback loan structure versus those that were not. First, we identify loans to borrowers who financed home purchases with a single mortgage having a LTV ratio above 80%. Since the LTV ratio is above 80%, these borrowers had to purchase Primary Mortgage Insurance (PMI) as required by federal charters for the GSEs. We refer to these mortgages as PMI loans. Next, we note that first-lien loans that were originated as part of a piggyback loan structure have a LTV ratio equal to 80% and do not have a PMI premium, but have a combined LTV (CLTV) ratio greater than 80%. Although we refer to these loans as 'piggyback' mortgages, our empirical analysis is based on only the first-lien mortgage part of the piggyback combination. By originating the primary loan at an 80% LTV ratio, the borrower avoided the PMI requirement.

To create a clean experiment, we restrict the sample to all plain vanilla loans. In other words, these are fully documented, fixed-rate 30-year, fully amortizing mortgages. All mortgages were originated for single-family properties used for owner occupied primary residence. Figure 2 shows the frequency distribution of PMI versus piggyback originations through time and reveals that the piggyback structure gained popularity as the housing bubble expanded. For the 90% and 95% CLTV categories, Figure 2 shows that the piggyback structure dominated the origination activity between 2005 and the 2nd quarter of 2007, the peak period of the housing boom. However, for the 85% and 100% CLTV category, PMI loans dominated the market throughout the period. Interestingly, Figure 2 clearly shows a temporal pattern of banks moving down the LTV spectrum to offer the piggyback structure at lower second-lien percentages as the housing bubble inflates such that by the peak of the housing bubble (2006/2007), piggyback loans accounted for approximately 40% of the 85% CLTV category.

To ensure the comparability of the piggyback loans to PMI loans, we then created a matched sample using propensity score matching based on CLTV, credit (FICO) score, loan balance, back-end ratio, broker origination dummy, borrower age, property zip code, and origination year and quarter. Table 2 reports the estimated coefficients from the propensity score logistic model. Regression (1) is used to implement the propensity score matching while regression (2) is an alternative specification that shows variations of piggyback loans by lender size, over time and across markets. The results show that piggyback loans are more likely to have higher credit scores, larger loan balances, and lower back-end ratios. They are also more likely to be originated by mortgage brokers, and borrowers of piggyback loans are slightly younger. The largest banks are less likely to originate piggyback loans compared to small and mid-size banks while banks in the second largest category are more likely to originate piggyback loans than small and mid-size banks. The year fixed-effects indicate that piggyback loan origination activity increased steadily since 2001. It also appears that regions that experienced more rapid home price appreciation during these years have lower likelihood of originating piggyback loans while those with more moderate growth have the most positive fixed effects.

With matching based on a full range of borrower and mortgage attributes along with many fixed effects, the *ex ante* risk of the PMI and piggybacks are essentially very similar. Thus, our final sample contains 192,023 mortgages where 56,550 observations (29%) are identified as piggyback loans and 135,473 (71%) observations are PMI mortgages. Panel B in Table 1 provides the summary statistics for the matched sample. As expected, the matching procedure resulted in a PMI mortgage set that is observationally similar to the piggyback mortgages across the various underwriting dimensions (e.g. loan amount, LTV, and back-end ratio.)

We next sub-divided the piggyback and PMI mortgages into four categories based on CLTV ratios of 85%, 90%, 95%, and 100%. A mortgage with a x_i% combined LTV ratio is classified in the x% combined LTV group if x_i in [x-1, x+1]. For example, mortgages with CLTVs between 89% and 91% are classified in the 90% CLTV group. Thus, each CLTV category contains two sets of first-lien mortgages: PMI loans with a CLTV ratio equal to x%, and piggyback mortgages with a first-lien loan having an LTV ratio equal to 80% and a CLTV ratio of x% implying a second-lien mortgage of (x% - 80%). For example, the 100% CLTV category contains first-lien PMI mortgages with LTV ratios equal to 100% and first-lien piggyback loans with LTV ratios of 80% and second-lien loans with LTVs of 20%. Panel C in Table 1 reports the descriptive statistics for each CLTV group.

To measure default, we track loan performance through 2014 to determine the number of months after origination that a loan becomes 90-days past-due, enters foreclosure, is classified as real estate owned, or undergoes involuntary liquidation. Approximately 17% of PMI loans and 12% of piggyback loans in our sample enter default at some point and the average time-to-default is 55 and 57 months, respectively. Panel C of Table 1 reveals that although borrower characteristics are similar by mortgage structure, their ex post performance is different. PMI borrowers have higher default rates and lower prepayment rate than piggyback borrowers across all CLTV categories except 85%.

3. **Baseline Results**

Two interesting facts emerge from Table 1 concerning borrower *ex ante* and *ex post* risk. First, we see that after matching borrowers based on characteristics known at origination (Panels B and C), observable borrower risk at origination is very similar between mortgages originated with PMI and piggyback structures across all LTV categories, indicating that their *ex ante* risk is very comparable. PMI loans have slightly higher FICO scores, but the difference in FICO scores diminishes as CLTV increase. Second, *ex post* we see that borrowers with PMI have consistently higher unconditional default rates across all CLTV categories except for the 85% category. This suggests that lenders may have been steering lower risk borrowers based on unobservable information into the piggyback structure.

Second, we also observe differences in *ex post* prepayment rates across the CLTV categories. Consistent with previous research, we see a decline in prepayment rate as CLTV increases as borrowers need positive equity to qualify for refinancing and higher LTV loans have lower probabilities of positive equity. However, we do observe a consistent pattern of PMI loans having lower unconditional *ex post* prepayment rates than piggyback borrowers. Since the primary motivation for borrowers to prepay is to refinance during periods of declining interest rates, steering borrowers with lower prepayment proclivity would be a profitable strategy for originating lenders as secondary market prices are typically higher for mortgage pools with slower prepayment speeds.

To formally examine the differences in conditional default and prepayment rates between Piggyback and PMI mortgages, we estimate a standard proportional hazard model of loan default and prepayment based on loan performance from origination up to December 2014. Columns (1) and (2) in Table 3 report the estimated coefficients using the matched sample. In each regression, the PMI mortgage is the control group and the coefficients for the LTV variables interacted with the piggyback dummy variable. We set the 100% LTV loan category as the reference group. Column (2) includes time-varying control variables that reflect differences in geographic risk factors (unemployment and house prices) and economic environment (interest rates).[4]

Focusing first on default risk, as expected, the estimated coefficients reveal an increase in the hazard of default as loan-to-value increases. The negative and statistically significant coefficients for each of the LTV categories indicate that the 85%, 90% and 95% LTV groups have significantly lower default hazards than the mortgages in the 100% LTV group. Furthermore, we note that default hazard increases in CLTV, e.g., the default hazard more than doubles from -1.55 to -0.72 when CLTV moves up from 85 to 90. This is equivalent to an increase of odds ratio by 129% (= exp(-0.72 – (-1.55)) – 1). Likewise, the odds of default increase by 31% (= exp(-0.45 – (-0.72)) – 1) when CLTV moves up from 90 to 95 and by 39% (= exp(-0.45 – 0) – 1) when CLTV moves up from 95 to 100.

The interaction of the piggyback loan indicator variable with the loan-to-value ratio category variables allows us to test the default hazard of originating a piggyback loan combination relative to a similar (*ex ante*) PMI loan at a similar CLTV level. The negative and statistically significant coefficients for the 90%, 95%, and 100% LTV categories indicate that the first lien mortgage in the corresponding piggyback loan combination has a lower probability of default than the associated PMI loan with the same combined LTV. In contrast, the coefficient for the interaction of the 85% LTV and piggyback indicator is positive and marginally significant suggesting that there is little difference in the default hazards between the 85% LTV piggyback and PMI loans. At CLTV around 90, piggyback loans are 25% (= exp(-0.29) – 1) less risky than similar PMI loans. That performance gap widens to 28% (= exp(-0.33) – 1) at 95 CLTV and further to 32% (= exp(-0.38) – 1) at 100 CLTV. Thus, overall the results confirm the

[4] As a robustness check, we also included location (MSA) and origination time (year-quarter) fixed effects but without the time-varying variables. Since the signs and statistical significance levels are consistent across the model, we confine our discussion of the results to the model with time-varying variables since estimation of the Cox models with time and location fixed effects is computationally inefficient.

interpretation of the *ex post* default risk identified in the univariate statistics (Table 1) while controlling for other factors. Recall, the summary statistics indicated that on average, the default rate for piggyback loans was lower than PMI loans.

Turning to prepayment risk, column (3) in Table 3 examines the differences in prepayment rates between piggyback combinations and PMI loans. As expected, we see that lower LTV mortgages have higher rates of prepayment than loans with larger LTVs since they are more likely to be eligible for refinance due to credit score and equity available. Coefficients on the interaction of the piggyback indicator with the LTV categories reveal that loans originated as part of a piggyback combination have consistently higher prepayment rates than the associated PMI loans. The coefficients on the interaction terms implies that the prepayment hazard rates for piggyback loans across the 85%, 90%, 95%, and 100% CLTV categories are 15%, 20%, 21% and 7% faster, respectively, than the corresponding PMI loans in those CLTV categories. The finding is consistent with the result by CLTV that borrowers with better credit quality and more equity are more likely to refinance given piggyback loans are less risky. Furthermore, borrowers who can refinance are less likely to default when they are impacted by an adverse shock – simply because they can lower their monthly payments or extract home equity from refinance. Thus, the results from the default and prepayment models (columns 2 and 3) both suggest that borrowers with piggyback loans have lower credit risk but faster prepayment speed than the similar PMI.

4. **Impact of Credit Supply**

There are two competing explanations for lower *ex post* risk in piggybacks loans. First, lenders steer the better quality borrowers into the structure simply because they essentially circumvent the role of PMI companies at origination. In order for lenders to profit, the credit risk in these loans must be no greater than the premium PMI companies would have charged. Otherwise lenders are better off buying protection from PMI companies. Second, savvy borrowers self-select into the piggyback structure because it saves them PMI premium as soon as the savings are more than usually higher interest rate on the second mortgage. This is less likely for a number of reasons. First, the findings of better *ex post* performance of piggyback loans are based on carefully matched sample. Loans with PMI and with piggyback structure are very similar otherwise. Second, piggyback structure is a very complicated mortgage contract which requires synchronization of two mortgages to be originated by different banks and settled at the same time. Without professional counseling and advice, it is very hard for borrowers to understand the details.

Regardless, we adopt an exogenous shock, the IBBEA of 1994, from credit supply side to test the increase of piggyback originations is due to credit supply or lender competition, not from credit demand or borrower selection. Although the IBBEA authorized free interstate banking in 1994, US states retained the right to oppose out-of-state branching by imposing restrictions on (i) de novo interstate branching, (ii) the minimum age of the target institution in case of mergers, (iii) the acquisition of individual branches without the acquisition of the entire bank, and (iv) statewide deposit caps controlled by a single bank or bank holding company. Rice and Strahan (2010) construct a time-varying index at state level that capture the differences in regulatory constraints between 1994 and 2005 and takes values between zero and four. The index is reversed so that high values refer to deregulated states. Recently a number of papers have documented that the banking deregulation increases the competition among banks, lowering borrowing cost, increasing credit supply, and increasing asset prices (Rice and Strahan 2010; Favara and Imbs 2015). If the credit supply increases as a result of the exogenous supply shock coming from greater competition due to the banking deregulation brought about by the IBBEA, then banks may choose to steer borrowers to piggybacks in order to compete for customers and maximize their profit.

In Table 4, we regress the share of piggybacks at zip level on the lagged deregulation index controlling for other state-level factors. In order to interpret the effect of full deregulation, one needs to multiply the coefficient by 4 since the deregulation index 4 represents the full deregulation. There is a positive and statistically significant effect of interstate banking deregulation on the increase of piggyback products. The result suggests that the share of piggybacks at the zip level located in deregulated states is 23% higher than in fully regulated states. Therefore popularity of piggyback structure is primarily driven by banking competition and the associated differences in *ex post* performance of piggyback vs PMI loans are also primarily driven by lender steering instead of borrower's self-selection.

Table 4 also includes a regression of home price growth from 2004 to 2007 on share of piggyback loans at zip level during the same period to see if growth of piggyback loans is related to any economic consequence. Because of the lower risk in piggybacks, we believe that markets featured with more piggybacks are less likely to experience unsustainable home price appreciation. The results suggest that high share of piggyback loans is associated with lower home price appreciation.

5. Impact of Steering on Expected Lender Profitability

To further illustrate lender incentives to steer better borrowers into the piggyback structure, we simulate in Table 5 a lender's profit and loss based on a standard menu of PMI premiums in 2005.[5] Panel A shows that a borrower who originates a PMI loan with an LTV between 80% and 85% paid an annual premium of 0.32% of loan balance to insure the ultimate loss exposure of lenders down to the 80% LTV. The premium increases with LTV due to higher risk exposure. PMI companies also offer borrowers the option to pay a lifetime premium based on approximately 5 years of expected life. For loans at or below 85% LTV, the lifetime premium was 1.6%. Since borrowers avoid paying the PMI premium by originating a piggyback loan, the bank's expected revenue from offering this structure is defined by the foregone PMI premium.

In Panel B, we create a hypothesized distribution of loans by probability of default (PD) that shows an increasing frequency of mortgages with higher PD as CLTV levels increase – consistent with the distribution of loans from our mortgage sample. For example, 20% of loans at 95.01-100% CLTV have PD of 20% while only 6% of loans in this CLTV category have a PD of 0.1%. In contrast, at the 80.01-85% CLTV category, loans are distributed in the opposite pattern with more loans in the lower PD region than in the higher PD area.

In Panel C, we show that the expected PD at each CLTV level is simply the average PD weighted by the distribution of loans in Panel B. For example, the expected PD of loans in the CLTV 95.01-100% category is 9.4%. The expected PD gradually decreases as CLTV ratios fall, down to 3.6% for the CLTV category of 80.01-85%. For simplicity, we assume loss severity – a measure of how much the lender can recover after seizing the property – to be 40%. The expected net loss is defined as the product of PD and loss severity. Thus, the expected net loss increases from 1.5% of UPB to 3.8% as CLTV increases. We use these expected net losses to calculate losses for loans distributed in each cell in Panel B.

In Panel D, we calculate the lender's expected net profit for individual loans in each cell of Panel B as well as overall expected net profit at each CLTV level. The expected net profit at a

[5] The mortgage premiums are taken from:
http://www.mtgprofessor.com/A%20-%20PMI/sample_mortgage_insurance_premiums.htm

CLTV level (e.g., 95.01-100%) is the average net profit weighted by distribution of loans in Panel B. There are two important observations. First, although profits are negative for some loans, the overall profit at all four CLTV levels is slightly positive – suggesting PMI business is sustainable based on these assumptions. Second, there is great variation in the profit across individual loans. In general, we see that lenders expect to collect more profit from loans with lower PD – a clear objective of lender steering. Furthermore, the potential gains from steering borrowers are greater with loans in the higher CLTV category while potential losses from taking risky borrowers are greater with loans in the lower CLTV categories. As illustrated, loans in bold are potential targets for lender steering due to their low PD and positive profits.

6. **Robustness Tests**

6.1. Endogeneity Due to Unobserved Characteristics

One concern is that we may not have controlled for all potential risk characteristics. That is, borrower choice of the PMI or piggyback loan structure could be endogenous to some unobserved risk characteristics. Thus, as a robustness check we compare the default rate on credit card debt based on the matched sample. If the mortgage default results are impacted by endogeneity, then we would expect to find a similar relation in the analysis of credit card defaults. That is, PMI borrowers should have higher credit card default rates than piggyback borrowers since the underserved factor would affect secured and unsecured debts in similar ways. However, as seen in Table 3 column (4) the marginal effects of the credit card default model from the logit regression show no significant difference between piggyback and PMI borrowers across the CLTV categories. This supports our contention that the difference in ex post performance is driven by decisions to steer them into different products, not borrower risk characteristics.

6.2. Hold-up Risk

Evidence also exists indicating that junior lien lenders/investors hold up the loan modification. For example, Agarwal et al (2014) show that servicers are less likely to modify mortgages owned by investors when they themselves own the second lien claim secured by the same property. To explore the hold-up risk, we estimate a similar model of whether the loan is modified when they become 60-day delinquent and the result is reported in Table 3 column (5). While the results show no significant difference in loan modification outcome between piggyback and PMI borrowers in the two lower CLTV categories, there is a significant and negative effect on loan modification for piggyback loans in the two higher CLTV categories. This supports the hypothesis that junior lien holders hold up the loan negotiation, compared to the PMI loans which do not have the similar constraint.

6.3. Changes in Underwriting Standards over Time

Previous research shows that mortgage originators may have altered underwriting standards or increased securitization efforts as house prices increased up to the start of the financial crisis. In particular, growth in securitization of the second-lien mortgage portion of the piggyback structure was especially evident during this period. Thus, to test whether lenders systematically increased efforts to steer higher risk borrowers into PMI backed loans during the run up to the housing and financial crisis, we segment the default analysis by loan origination year cohort. Furthermore, for each origination year cohort using the propensity-matched sample, we isolate the effect of the growth in securitization of second-lien mortgages on originator risk-taking.

Panel A of Table 6 reports the results for the default and prepayment model estimations by origination year cohort. As before, we note that the control variables have the predicted effects. For example, borrowers in areas with higher house price appreciation are less likely to default and borrowers with greater interest rate savings, relative market rates are also less likely to default. Furthermore, the coefficients for the baseline CLTV variables show the consistent pattern that loans with larger downpayments have lower default risk regardless of origination year cohort. However, we do see a relative flattening of the difference in default hazard across CLTV categories for loans originated in 2006 and 2007 (just prior to the peak in the housing market). For example, the default hazard rate for loans in the 85% CLTV category in 2004 was 89% lower than 2004 loans in the 100% CLTV group. In contrast, in 2006 (the peak of the housing market) the 85% CLTV loans had default hazard rates that were only 65% lower than the loans in the 100% CLTV category.

Turning to the interaction terms that identify piggyback combinations by LTV group and focusing first on loans originated in years 2001 through 2003, we find no clear pattern to indicate a systematic difference in the default risk between PMI and piggyback combinations. In contrast, the negative and statistically significant coefficients for the 90%, 95%, and 100% categories in years 2004 through 2007 indicate that piggyback loans are consistently less likely to default than their PMI counterparts. Furthermore, we see no significant shift in the relative difference in the default hazard rates across time. For the loans in the 85% LTV category, we find no statistical difference between PMI and piggyback loans (across all years). Thus, the results in Table 6 suggest that lenders steered higher risk borrowers into PMI mortgages in the higher CLTV categories at the peak of securitization.

Turning to the prepayment hazard rate estimates by origination year cohorts, we see that lower LTV mortgages have higher rates of prepayment and the piggyback interaction term suggests that piggyback loans have higher prepayment rates than similar PMI loans for origination years 2005 through 2007. Again, this confirms the results from Table 2 that lenders were adversely selecting against PMI insurers by originating higher credit risk but lower prepayment risk borrowers in PMI backed loans while focusing on lower credit risk and higher prepayment loans in the piggyback structure.

6.4. Impact of Origination Channel

Next, in Panel B of Table 6 we focus on the role of mortgage origination channel in steering. We recognize that lenders have different incentives and mechanisms at origination and in post-origination processes. For example, brokers originate and immediately sell loans to banks without funding or holding any liability for origination quality. Mortgage brokers sell loans to banks and have strong incentive to originate loans customized to banks' demand compared to retail bank business. If lenders are incentivized to steer borrowers, brokers would be in a perfect position to collude since they don't hold any risk after origination and are more likely to meet lenders' demands.

In general, we find that the default hazard rate for piggyback loans originated by brokers is lower than loans by their counterparts, but the differences are relatively small. For example, in Table 2 we saw that the default hazard for piggyback loans in the 100% CLTV category was 32% lower than the corresponding PMI loans. However, the coefficients in Panel B show that piggyback loans originated by brokers have default hazard rates that are 36% lower than corresponding PMI loans, and for piggybacks loans by retail banks, it's only 27% lower. As a result, the results suggest that the observed differences in *ex post* mortgage performance are attributable to origination channel and there is also more steering among these loans originated by brokers.

We also examine the role of mortgage banks versus commercial banks in steering. After origination, there are different types of institutions that purchase, service, hold and securitize loans. Mortgage banks are non-depository institutions and thus do not have access to other loan or savings products that could provide additional information about borrowers. In contrast, depository institutions, such as commercial banks, can use retail deposits to fund their loan originations, have multiple retail lending products (e.g. credit cards, personal loans, student loans, auto loans, etc.) and therefore may have an information advantage allowing them to sort borrowers along additional risk dimensions. Thus, to confirm the comparability of banks, we restrict the non-mortgage banks to similar size of mortgage banks; that is, we exclude large national banks and small banks from the analysis. In this restricted subset, the results show that risk gradients along CLTV are very similar between mortgage banks and commercial banks except for 95% CLTV. The 95% CLTV result is driven by the fact most of these loans funded by mortgage banks were originated before 2004. For other CLTVs that have similar risk gradients, piggyback loans funded by commercial banks are much less risky than PMI loans. For example, the default hazard for piggyback loans funded by depository institutions in the 100% CLTV category was 41% lower than the corresponding PMI loans. In contrast, for those funded by mortgage banks, it is only 34% lower.

6.5. Impact of Market Competition

Obviously lenders or banks may exercise steering power to obtain the best execution to maximize their profits. If there is limited competition in the market and lenders are able to profit by charging a premium on everyone, they may not need to steer borrowers. To test the role of competition in limiting lender steering, we constructed a Herfindahl-Hirschman Index (HHI) at county and year level based on HMDA data, matched with our sample. A higher HHI is associated with a lower level of competition. We estimate our hazard regressions by levels of market competition. The results in Panel C of Table 6 suggest that lenders are only motivated to steer the lower-risk borrowers to PMI loans in the high-competition market. In the low- and medium-competition markets, we see no statistically significant difference in the piggyback or PMI default hazard rates. Consistent with our prior finding that the surge in piggyback loans is primarily due to banking deregulation and increased competition, lenders appear to be steering lower risk borrowers into the piggyback structure only in the most competitive markets.

7. Decomposition Analysis

Our objective is to study the difference in the default and prepayment risks between PMI loans and piggyback loans. In the previous sections, we found that the default risk of piggybacks is significantly lower while their prepayment is faster than PMI loans at similar CLTV and after controlling for other factors; in this section we decompose the mean difference in default and prepayment risks based on linear regression models. We use the Blinder–Oaxaca decomposition (Blinder, 1973; Oaxaca,1973) for the panel of loan-quarter data used for hazard regressions. The Blinder–Oaxaca decomposition allocates the observed difference in either default or prepayment into three components: (1) that explained by differences in characteristics; (2) that explained by differences in the coefficients of those characteristics; and (3) the part related to the interaction between the two. We define the expected default and prepayment difference, D, as:

$$
\begin{aligned}
D &= E\left(R_{pmi}\right) - E\left(R_{piggyback}\right) \\
&= \left\{E\left(X_{pmi}\right) - E\left(X_{piggyback}\right)\right\} \times \beta_{piggyback} + E\left(X_{pmi}\right) \times \left\{\beta_{pmi} - \beta_{piggyback}\right\} + \\
&\quad \left\{E\left(X_{pmi}\right) - E\left(X_{piggyback}\right)\right\} \times \left\{\beta_{pmi} - \beta_{piggyback}\right\} \qquad (1)
\end{aligned}
$$

In Equation (1), the first term on the right hand side is the portion of the difference in expected performance that is attributable to the difference in characteristics between PMI and piggyback loans. The second term is the portion attributable to differences in the estimated responses (coefficients) and the third term is the interaction effect. Note that the first term (known as the endowment effect) will be zero if the characteristic vectors are the same for the two market segments; the second term will be nonzero whenever the coefficients differ; and the third term will be zero if either the characteristics or coefficients are the same. The Blinder–Oaxaca decomposition entails estimating default or prepayment separately for each group and using the estimated parameters to decompose the overall difference in them.

We use all variables in Table 2 and group them into two categories: the CLTV category includes all CLTV dummies while the economic environment category includes unemployment change, interest savings and home price appreciation. We also add another variable – the portion of mortgage pricing not explained by observable characteristics used in our propensity score matching. The observables include LTV dummies, FICO dummies, loan amount, debt-to-income ratio, mortgage broker loans dummy, borrower age, and zip code fixed effects as well as year and quarter fixed effects. These variables represent a full set of hard information used by loan officers, investors, and government regulators to assess the credit risk of loans and determine the pricing. Combined they explain over 60% of variation in pricing. However, lenders may also use information in their pricing that is not verifiable to a third party, known as "soft information" (Stein 2002). Hard information became increasingly important to market participants as securitization expanded. Regulators use this information to determine capital requirements, rating agencies rely on it to provide ratings, investors use it to screen investment and manage portfolios, and lenders depend on it to make underwriting and pricing decisions. Rajan, Seru and Vig (2015) show that lenders' reliance on hard information to price mortgages steadily increased until the collapse of the subprime market in 2007. However, the loan interest rate becomes a worse predictor of ex post default as securitization increases. Since we find evidence that supports lender steering better borrowers to piggyback loans and away from the PMI structure to maximize their profits, we include a measure of soft information in our equation to test the different screening efforts. This measure, the unexplained portion of interest rate on loans in our sample, explains the other 40% of variation in pricing.

Table 7 reports the results from the Blinder–Oaxaca decomposition. We find that the differences in default and prepayment between PMI and piggyback loans are entirely attributable to differences in coefficients effect (Panel A). In fact, endowment and interaction effects help offset less than half of the differences in coefficients. The observed differences would be even greater if observable characteristics included on right hand side were more favorable for PMI loans. Specifically inside the endowment effect (Panel B), more PMI loans are in the lower CLTV groups while piggyback loans tend to be concentrated in higher CLTV categories. As a result, we find no significant differences between piggyback and PMI loans in terms of soft information and economic environment. Inside the coefficient effect (Panel C), we find that the coefficient on CLTV and economic variables are more responsive for PMI loans than piggyback loans. The coefficient on soft information is greater for piggyback loans, suggesting that the predictive power of soft information used in screening piggyback loans is much greater than that for PMI loans even though lenders do not rely on soft information differently in piggyback loans versus PMI loans (Panel D).

8. Conclusions

In this paper we investigate whether lenders during the period leading up to the Great Recession effectively steered borrowers into piggyback loan products to circumvent the role of PMI. The extra risk lenders were willing to take is bound by the premium that otherwise would be charged by the PMI company. This creates an incentive for lenders to steer the low risk borrowers into the piggyback structure. Our analysis of lender's profits and losses using the historical PMI premium show that lender can significantly boost their profits by steering lower risk borrowers into the piggyback loans.

To control for observed risk characteristics that might differ between piggyback and PMI loans, our analysis uses a propensity score matched sample based on many observable characteristics as well as at very similar CLTV levels. Although the two subsamples have very similar *ex ante* risks, the ex post default risk of piggyback loans is significantly lower by 25% to 32% for CLTVs above 85%. Their ex post prepayment speed is faster by 7% to 20% across CLTV levels. To test whether this is due to lender steering or borrower self-selection, we regress the share of piggyback loans at zip code level on interstate banking deregulation index. The result confirms that the popularity of piggyback products is mainly driven by banking deregulation and increased competition, which is consistent with the hypothesis that the difference in *ex post* performance of piggyback vs PMI loans is primarily driven by lender steering.

We also find stronger evidence on steering when loans are originated through brokers, purchased by commercial banks, originated in more competitive markets, and originated during the peak of the securitization boom. The evidence suggests that mortgage brokers collude with banks to meet their steering demands. Commercial banks used their private information about customers to identify more creditworthy borrowers for steering. Securitization provides lenders with more incentives to steer borrowers into the piggyback products since they can securitize the second liens and sell to investors to increase their profits. All of these steering efforts only take place in the most competitive market.

Finally, we also provide a battery of robustness checks to further control for endogeneity to unobserved risk characteristics. The results on the *ex post* performance of unsecured credit card debts confirm that no unobserved factors contribute to the *ex post* performance gap between PMI and piggyback borrowers. However, compared to PMI loans, junior lien holders of the piggyback loans can hold up the loan modification.

References

Agarwal, Sumit and Amromin, Gene and Ben-David, Itzhak and Chomsisengphet, Souphala and Zhang, Yan, 2014,Second Liens and the Holdup Problem in Mortgage Renegotiation, SSRN Working Paper.

Agarwal, Sumit, Brent W. Ambrose, Souphala Chomsisengphet, and Chunlin Liu, 2006, An Empirical Analysis of Home Equity Loan and Line Performance, Journal of Financial Intermediation 15, 444 – 469.

Agarwal, Sumit, Brent W. Ambrose, and Vincent W. Yao, 2014, The Effects and Limits of Regulation: Appraisal Bias in the Mortgage Market, Working paper, Available at SSRN: http://ssrn.com/abstract=2487393 or http://dx.doi.org/10.2139/ssrn.2487393.

Agarwal, Sumit, Gene Amromin, Itzhak Ben-David, Souphala Chomsisengphet, and Douglas D Evanoff, 2011, The role of securitization in mortgage renegotiation, Journal of Financial Economics 102, 559–578.

Agarwal, Sumit, Itzhak Ben-David, and Vincent Yao, 2015, Collateral valuation and borrower financial constraints: Evidence from the residential real estate market, Management Science 61, 2220–2240.

Agarwal, Sumit, and Douglas D. Evanoff, 2013, Loan product steering in mortgage market, Working paper, Available at SSRN: http://ssrn.com/abstract=2204400 or http://dx.doi.org/10.2139/ssrn.2204400.

Ambrose, Brent W., James Conklin, and Jiro Yoshida, 2016, Credit rationing, income exaggeration, and adverse selection in the mortgage market, Journal of Finance, 71:6, 2637-2685.

Ambrose, Brent W., Richard J. Buttimer, Jr., and Charles A. Capone, Jr., 1997, Pricing mortgage default and foreclosure delay, Journal of Money, Credit and Banking, 29:3, 314-325.

Ben-David, Itzhak, 2011, Financial Constraints and Inflated Home Prices During the Real Estate Boom, American Economic Journal: Applied Economics 3, 55–87.

Blinder, A., 1973. Wage discrimination: reduced form and structural variables. Journal of Human Resources 8, 436–455.

Brueggeman, William B., and Jeffrey D. Fisher, 2005, Real Estate Finance and Investment, 12th edition (McGraw-Hill Irwin, New York, NY).

Di Maggio, Marco, Amir Kermani, and Sanket Korgaonkar, "Deregulation, Competition and the Race to the Bottom." Working Paper, SSRN (2015).

Favara, Giovanni, and Jean Imbs, "Credit Supply and the Price of Housing," *American Economic Review*, 105 (2015), 958–992.

Garmaise, Mark J., 2015, Borrower Misreporting and Loan Performance, Journal of Finance Forthcoming.

Griffin, John M., and Gonzalo Maturana, 2015, Who Facilitated Misreporting in Securitized Loans?, Journal of Finance Forthcoming.

Hyman, Louis, 2011, Debtor nation: the history of American in red ink (Princeton University Press, Princeton, NJ).

Jiang, Wei, Ashlyn Aiko Nelson, and Edward Vytlacil, 2014, Liar's loan? effects of origination channel and information falsification on mortgage delinquency, Review of Economics and Statistics 96, 1–18.

Keys, Benjamin J., Tanmoy Mukherjee, Amit Seru, and Vikrant Vig, 2010, Did Securitization Lead to Lax Screening? Evidence from Subprime Loans, The Quarterly Journal of Economics 125, 307–362.

Keys, Benjamin J., Amit Seru, and Vikrant Vig, 2012, Lender Screening and the Role of Securitization: Evidence from Prime and Subprime Mortgage Markets, Review of Financial Studies 25, 2071–2108.

Mian, Atif, and Amir Sufi, 2015, Fraudulent Income Overstatement on Mortgage Applications During the Credit Expansion of 2002 to 2005, NBER Working Paper #20947.

Oaxaca, R., 1973. Male-female wage differentials in urban labor markets. International Economic Review 14, 693–709.

Piskorski, Tomasz, Amit Seru, and Vikrant Vig, 2010, Securitization and distressed loan renegotiation: Evidence from the subprime mortgage crisis, Journal of Financial Economics 97, 369 – 397.

Piskorski, Tomasz, Amit Seru, and James Witkin, 2015, Asset Quality Misrepresentation by

Financial Intermediaries: Evidence from the RMBS Market, Journal of Finance Forthcoming.

Rajan, Uday, Amit Seru and Vikrant Vig. (2015). "The Failure of Models that Predict Failure: Distance, Incentives, and Defaults." *Journal of Financial Economics* 115(2), 237-260.

Rice, Tara, and Philip Strahan, Does Credit Competition Affect Small-Firm Finance? *Journal of Finance,* 65 (2010), 861–889.

Stein, J. C. (2002). "Information Production and Capital Allocation: Decentralized versus Hierarchical Firms." *Journal of Finance* 57(5), 1891-1921.

Table 1 Summary Statistics

		FICO	Note Rate	Log (UPB)	Broker	Backend	Income	Borrower Age	Loan Age	Default Rate	Time to Default	Prepay-ment	Credit Card Dlq.	Number of obs
		A. Full Sample - All CLTV Groups												
PMI	mean	692.8	6.55	12.10	0.56	0.41	6,059	36.76	49.05	0.21	51.18	0.72	0.03	592,636
	(std dev)	(60.7)	(0.68)	(0.42)	(0.50)	(0.12)	(3213)	(10.20)	(36.4)	(0.41)	(28.92)	(0.45)	(0.18)	
Piggyback	mean	729.0	6.21	2.51	0.46	0.39	7,425	36.73	55.80	0.14	56.26	0.78	0.04	192,023
	(std dev)	(46.7)	(0.52)	(0.03)	(0.50)	(0.12)	(3634)	(9.70)	(34.3)	(0.34)	(24.71)	(0.41)	(0.19)	
		B. Propensity Matched Sample - All CLTV Groups												
PMI	mean	733.6	6.23	2.52	0.42	0.39	7,181	36.92	56.89	0.17	54.63	0.74	0.01	56,550
	(std dev)	(47.5)	(0.54)	(0.03)	(0.49)	(0.12)	(3626)	(9.87)	(35.0)	(0.38)	(24.56)	(0.44)	(0.11)	
Piggyback	mean	726.6	6.19	2.51	0.47	0.39	7,526	36.65	55.34	0.12	57.23	0.80	0.02	135,473
	(std dev)	46.2	0.51	0.03	0.50	0.11	3,632	9.62	33.97	0.33	24.74	0.40	0.12	
		C. Propensity Matched Sample by CLTV Groups												
		CLTV = 85%												
PMI	mean	765.0	5.94	2.52	0.27	0.33	8,466	38.02	64.44	0.06	63.11	0.86	0.01	1,762
	(std dev)	(33.5)	(0.48)	(0.02)	(0.44)	(0.12)	(5272)	(9.17)	(32.3)	(0.23)	(23.72)	(0.35)	(0.09)	
Piggyback	mean	732.9	6.06	2.52	0.39	0.38	7,718	37.40	55.63	0.07	60.58	0.87	0.01	3,861
	(std dev)	(48.6)	(0.49)	(0.03)	(0.49)	(0.11)	(3713)	(9.10)	(33.9)	(0.25)	(24.74)	(0.34)	(0.12)	
		CLTV = 90%												
PMI	mean	739.3	6.14	2.51	0.42	0.37	7,411	38.48	58.33	0.13	57.36	0.78	0.01	17,100
	(std dev)	(46.4)	(0.52)	(0.03)	(0.49)	(0.12)	(3896)	(10.26)	(36.2)	(0.33)	(24.74)	(0.42)	(0.11)	
Piggyback	mean	731.5	6.08	2.52	0.43	0.37	8,034	37.73	55.03	0.09	59.53	0.84	0.02	39,024
	(std dev)	(46.8)	(0.48)	(0.03)	(0.49)	(0.11)	(3884)	(9.59)	(34.4)	(0.28)	(25.28)	(0.36)	(0.12)	
		CLTV = 95%												
PMI	mean	732.3	6.17	2.51	0.40	0.38	7,213	36.93	56.94	0.16	57.21	0.75	0.01	22,728
	(std dev)	(47.3)	(0.54)	(0.03)	(0.49)	(0.12)	(3509)	(9.70)	(36.3)	(0.36)	(25.69)	(0.43)	(0.11)	
Piggyback	mean	726.8	6.13	2.52	0.44	0.38	7,714	36.39	54.56	0.10	58.93	0.83	0.01	54,944
	(std dev)	(45.0)	(0.50)	(0.03)	(0.50)	(0.11)	(3542)	(9.35)	(34.9)	(0.30)	(25.47)	(0.38)	(0.12)	
		CLTV = 100%												
PMI	mean	725.5	6.48	2.52	0.47	0.42	6,718	35.01	54.28	0.27	50.70	0.65	0.01	14,960
	(std dev)	(48.2)	(0.50)	(0.03)	(0.50)	(0.11)	(3146)	(9.42)	(31.6)	(0.44)	(22.88)	(0.48)	(0.10)	
Piggyback	mean	720.7	6.42	2.50	0.57	0.41	6,707	35.84	56.78	0.19	54.78	0.71	0.02	37,644
	(std dev)	(46.2)	(0.47)	(0.03)	(0.50)	(0.11)	(3334)	(9.99)	(32.0)	(0.40)	(23.69)	(0.45)	(0.13)	

Table 2 Regressions for Propensity Score Matching

	(1)	(2)		
CLTV = 85	-0.718***	-0.566***		
	(-30.50)	(-22.74)		
CLTV = 90	0.502***	0.703***	MSA Fixed Effects	
	(44.02)	(58.15)	Los Angeles	-1.334***
CLTV = 95	0.414***	0.599***	Las Vegas	-1.137***
	(42.12)	(56.40)	New York	-1.088***
CLTV = 100	0.000	0.000	Chicago	-0.743***
	(.)	(.)	Cleveland	-0.705***
FICO	0.013***	0.013***	Tampa	-0.626***
	(173.52)	(172.15)	Minnenapolis	-0.608***
Loan balance	1.582***	2.244***	Boston	-0.491***
	(141.99)	(165.11)	San Diego	-0.477***
Backend	-2.727***	-2.811***	Phoenix	-0.345***
	(-78.41)	(-78.54)	Seattle	-0.235***
Broker dummy	-0.412***	-0.380***	Detroit	-0.224***
	(-51.62)	(-43.31)	Denver	-0.054*
Borrower age	-0.008***	-0.011***	San Francisco	-0.005
	(-20.29)	(-26.37)	Atlanta	0
Credit card dlq	-0.193***	-0.194***	Washington, DC	0.059**
	(-6.81)	(-6.86)	Charlotte	0.201***
Largest Banks		-0.437***	Portland	0.417***
		(-34.55)	Dallas	0.695***
Second Largest Banks		0.058***		
		(4.14)	Year Fixed Effects	
			2001	-1.550***
			2002	-0.711***
			2003	-0.118***
			2004	0.761***
			2005	1.142***
			2006	1.167***
Fixed Effects	Zip-code x YYQQ			
Observations	531317	534315		
Pseudo R2	0.308	0.319		

Table 3 Baseline Hazard Regressions

	(1)	(2)	(3)	(4)	(5)
	Default	Default	Prepay	Credit Card Dlq.	Loan Modified
CLTV = 85	-1.816***	-1.553***	0.212***	-0.024***	0.069
	(-18.12)	(-15.48)	(7.65)	(-4.03)	(1.08)
CLTV = 90	-0.899***	-0.719***	0.120***	-0.016***	0.022
	(-33.77)	(-26.90)	(8.95)	(-6.18)	(1.34)
CLTV = 95	-0.659***	-0.449***	0.090***	-0.012***	0.036*
	(-28.60)	(-19.39)	(7.04)	(-4.73)	(2.47)
CLTV = 100	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Piggyback x CLTV=85	0.371**	0.279*	0.136***	0.007	-0.051
	(3.18)	(2.39)	(4.37)	(1.11)	(-0.74)
Piggyback x CLTV=90	-0.301***	-0.285***	0.183***	-0.002	-0.021
	(-10.92)	(-10.31)	(17.77)	(-0.94)	(-1.39)
Piggyback x CLTV=95	-0.365***	-0.332***	0.190***	-0.003	-0.058***
	(-17.00)	(-15.41)	(21.15)	(-1.69)	(-4.81)
Piggyback x CLTV=100	-0.395***	-0.384***	0.071***	0.004	-0.041***
	(-20.17)	(-19.58)	(6.00)	(1.68)	(-3.57)
Unemployment change		0.060***	-0.048***		
		(15.12)	(-25.14)		
Interest savings		-0.413***	-0.797***		
		(-42.50)	(-193.67)		
HP Appreciation		-0.029***	0.016***		
		(-60.85)	(96.93)		
Observations	3610916	3609292	3609292	187171	26319
Pseudo R2	0.007	0.037	0.012	0.002	0.002
Log Likelihood	-295766	-286347	-1685055		
Chi Square	4270.2	21946.5	42257.7		

Table 4 Effects of Supply Shocks

	(1)	(2)
	% Piggyback	HP Appreciation in 2004-2007
Deregulation Index	0.057*	
	(2.21)	
% Piggyback		-4.242**
		(-3.37)
MSA FE	Yes	Yes
Observations	389	369
Adjusted R-squared	0.045	0.449

Table 5 Simulated Lender's Profitability from Steering

CLTV	A. Expected Revenue	
	Annual Premium	Lifetime Premium
95.01-100%	0.96%	4.8%
90.01-95%	0.78%	3.9%
85.01-90%	0.52%	2.6%
80.01-85%	0.32%	1.6%

CLTV	B. Distribution of Loans (Row Percent) by PD								Total
	0.1%	1%	2%	3%	6%	10%	15%	20%	
95.01-100%	6%	8%	10%	12%	12%	15%	17%	20%	100%
90.01-95%	9%	11%	12%	14%	12%	13%	14%	15%	100%
85.01-90%	15%	14%	13%	12%	14%	12%	11%	9%	100%
80.01-85%	23%	19%	16%	15%	11%	10%	4%	2%	100%

C. Expected Net Loss = Expected Probability of Default (PD) x Loss Severity (LS)

Expected Net Loss of Individual Loans Given PD							
0.1%	1%	2%	3%	6%	10%	15%	20%
0.0%	0.4%	0.8%	1.2%	2.4%	4.0%	6.0%	8.0%

CLTV	Expected PD = Weighted Average PD	Expected Net Losses = Weighted Average Net Losses
95.01-100%	9.4%	3.8%
90.01-95%	7.9%	3.2%
85.01-90%	6.3%	2.5%
80.01-85%	3.6%	1.5%

CLTV	D. Expected Net Profit = Expected Revenue - Expected Net Losses: Profit of Individual Loans by PD								Expected Net Profit
	0.1%	1%	2%	3%	6%	10%	15%	20%	
95.01-100%	**4.8%**	**4.4%**	**4.0%**	**3.6%**	**2.4%**	**0.8%**	-1.2%	-3.2%	**1.0%**
90.01-95%	**3.9%**	**3.5%**	**3.1%**	**2.7%**	**1.5%**	-0.1%	-2.1%	-4.1%	**0.7%**
85.01-90%	**2.6%**	**2.2%**	**1.8%**	**1.4%**	**0.2%**	-1.4%	-3.4%	-5.4%	**0.1%**
80.01-85%	**1.6%**	**1.2%**	**0.8%**	**0.4%**	-0.8%	-2.4%	-4.4%	-6.4%	**0.1%**

Table 6 Robustness Tests

A. Hazard Regressions by Origination Year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			Default					Prepayment		
	2003	2004	2005	2006	2007	2003	2004	2005	2006	2007
Piggyback x CLTV=85	1.409	0.886*	0.309	-0.097	0.278	0.179*	0.034	0.076	0.026	0.148
	(1.90)	(2.22)	(1.41)	(-0.52)	(1.04)	(2.04)	(0.47)	(1.19)	(0.35)	(1.94)
Piggyback x CLTV=90	0.112	-0.357***	-0.257***	-0.317***	-0.335***	0.066**	0.139***	0.267***	0.207***	0.217***
	(1.01)	(-4.27)	(-4.57)	(-6.01)	(-6.53)	(2.84)	(5.35)	(9.75)	(7.54)	(9.01)
Piggyback x CLTV=95	-0.083	-0.524***	-0.444***	-0.341***	-0.149***	0.094***	0.143***	0.259***	0.228***	0.214***
	(-0.96)	(-8.73)	(-10.02)	(-7.96)	(-3.73)	(4.81)	(6.54)	(10.55)	(8.91)	(9.66)
Piggyback x CLTV=100	-0.003	-0.339***	-0.454***	-0.480***	-0.179***	0.045	0.075*	0.068**	0.105***	-0.084**
	(-0.02)	(-4.51)	(-10.83)	(-14.96)	(-5.15)	(1.12)	(2.53)	(2.70)	(4.57)	(-3.21)
Observations	596027	658499	807769	711036	564706	596027	658499	807769	711036	564706
Pseudo R2	0.008	0.013	0.018	0.017	0.015	0.003	0.004	0.005	0.006	0.008

B. Hazard Regressions by Origination Channels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Default					Prepayment	
	Retail Bank	Mortgage Broker	Commercial Bank	Mortgage Bank	Retail Bank	Mortgage Broker	Commercial Bank	Mortgage Bank
Piggyback x CLTV=85	0.327*	0.058	0.325	0.192	0.145***	0.074	0.158**	0.155
	(2.30)	(0.29)	(1.26)	(0.43)	(3.84)	(1.32)	(2.72)	(1.24)
Piggyback x CLTV=90	-0.252***	-0.321***	-0.393***	-0.275*	0.185***	0.169***	0.177***	0.202***
	(-6.56)	(-8.05)	(-5.04)	(-2.55)	(13.73)	(10.58)	(6.97)	(5.42)
Piggyback x CLTV=95	-0.317***	-0.367***	-0.312***	-0.388***	0.221***	0.127***	0.188***	0.186***
	(-10.68)	(-11.62)	(-5.30)	(-4.85)	(19.06)	(9.01)	(9.14)	(5.90)
Piggyback x CLTV=100	-0.318***	-0.454***	-0.527***	-0.413***	0.035*	0.088***	0.061*	0.211***
	(-11.00)	(-16.92)	(-12.28)	(-4.28)	(2.10)	(5.20)	(2.57)	(3.71)
Observations	1981015	1623658	711161	211358	1981015	1623658	711161	211358
Pseudo R2	0.042	0.036	0.042	0.063	0.013	0.013	0.014	0.022

C. Regressions by Market Competition

	(1)	(2)	(3)	(4)	(5)	(6)
		Default by Market Competition			Prepayment by Market Competition	
	High	Med	Low	High	Med	Low
Piggyback x CLTV=85	0.241	0.210	0.851	-0.073	0.131	0.212
	(0.98)	(0.65)	(1.13)	(-0.85)	(1.85)	(1.52)
Piggyback x CLTV=90	-0.266***	-0.042	-0.081	0.237***	0.193***	0.231***
	(-4.80)	(-0.55)	(-0.60)	(8.08)	(6.66)	(7.17)
Piggyback x CLTV=95	-0.299***	-0.040	-0.185	0.148***	0.199***	0.264***
	(-6.65)	(-0.70)	(-1.85)	(5.79)	(7.80)	(8.90)
Piggyback x CLTV=100	-0.318***	-0.027	0.043	0.064*	0.030	0.154*
	(-7.96)	(-0.55)	(0.31)	(2.26)	(1.07)	(2.54)
Observations	688215	491685	266613	688215	491685	266613
Pseudo R2	0.044	0.033	0.037	0.013	0.016	0.016

Table 7 Blinder-Oaxaca Decomposition of Differences in Default and Prepay Risks

	Default (PMI - Piggyback)			Prepay (PMI - Piggyback)		
	Difference	t-stat	%	Difference	t-stat	%
			Overall differences			
Endowment effect	(0.28)	(2.92)	-85%	0.004	3.65	-130%
Coefficient effect	0.90	4.97	276%	(0.007)	(4.57)	226%
Interaction effect	(0.30)	(4.23)	-91%	(0.000)	(0.23)	4%
Total	0.33	1.75	100%	(0.003)	(2.11)	100%
			Endowment effect			
Soft Information	(0.04)	(1.35)	-12%	0.001	1.12	-24%
CLTV	(0.14)	(4.14)	-44%	0.001	3.97	-29%
Economic Controls	(0.09)	(1.05)	-29%	0.002	2.63	-77%
			Coefficient effect			
Soft Information	(5.16)	(4.25)	-1580%	(0.014)	(1.00)	465%
CLTV	1.40	4.73	429%	(0.003)	(1.57)	87%
Economic Controls	0.25	2.91	77%	(0.002)	(1.98)	68%
Constant	4.41	3.66	1351%	0.012	0.86	-394%
			Interaction effect			
Soft Information	(0.16)	(3.33)	-48%	(0.000)	(0.98)	14%
CLTV	(0.12)	(2.94)	-36%	(0.000)	(2.96)	16%
Economic Controls	(0.03)	(0.90)	-8%	0.001	3.84	-26%

Figure 1 Home Price Appreciation and Origination of First and Second Liens

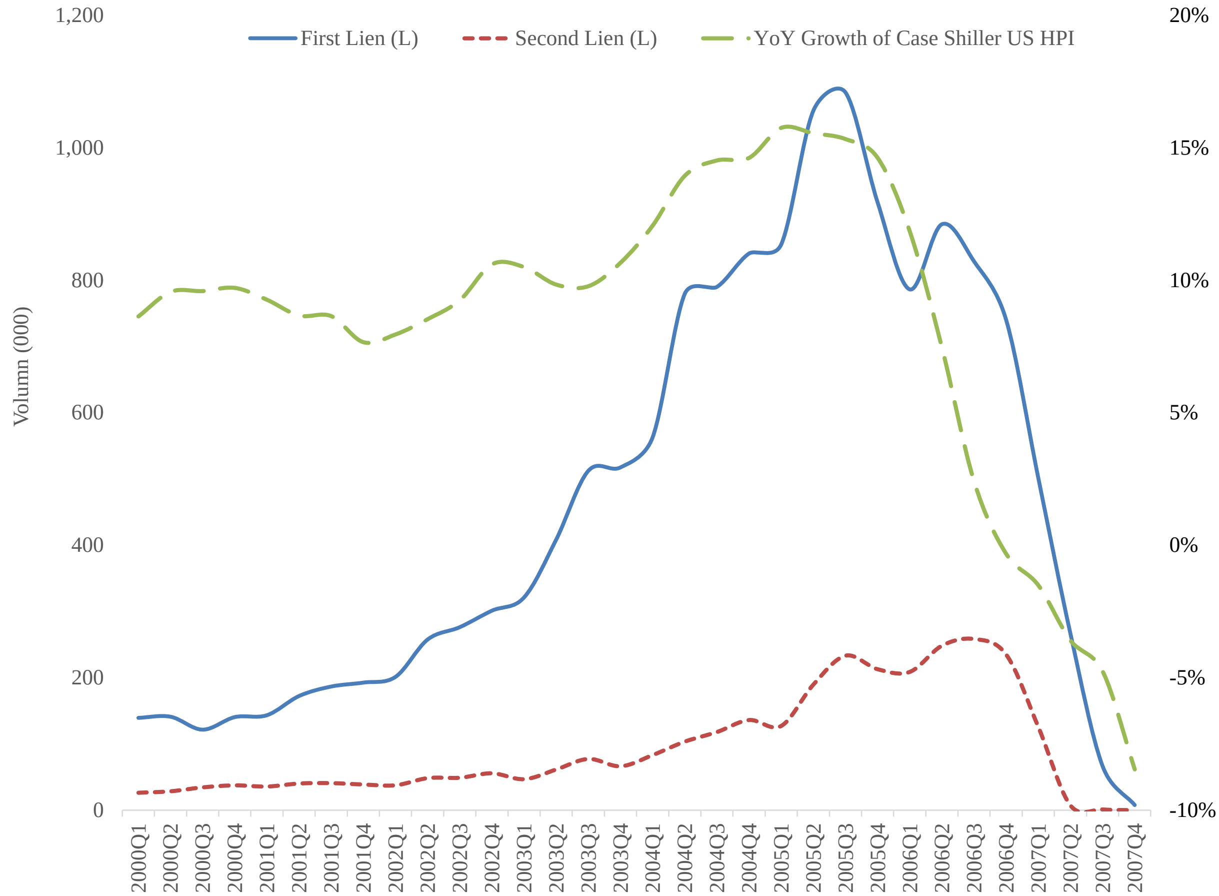

Figure 2 Time Series of Piggyback Selection by CLTV (unmatched sample)