Mortgage Rates and Credit Risk: Evidence from Mortgage Pools*

Gaetano Antinolfi,† Celso Brunetti,‡ and Jay Im§

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Abstract

Beginning in the 1990s, the growth of mortgage lending was associated with a new set of mortgage-backed securities. We study the evolution of initial mortgage rates as a function of loan and borrower characteristics. We find that credit risk was historically priced similarly in all types of mortgage pools with the exception of subprime pools, for which credit risk became increasingly important. Results are robust across regions of the United States and the income distribution of borrowers. Finally, we show that loading factors on subprime rates are economically important and linked to delinquencies and house price dynamics.

Keywords: Securitization, mortgage rates, subprime mortgage pools.
EFM classification codes: 340, 780, 510, 530

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†Department of Economics, Washington University in St. Louis, One Brookings Drive, 63130. Tel. 314-935-7335. Email: gaetano@wustl.edu.

‡Board of Governors of the Federal Reserve System, 20th Street and Constitution Avenue N.W., Washington, DC 20551. Tel. 202-452-3134. Email: celso.brunetti@frb.gov.

§Duke University Fuqua School of Business, 100 Fuqua Drive, Durham, NC 27708. Tel. 919-660-7734 . Email: jay.im@duke.edu.

1 Introduction

The mortgage market in the United States experienced rapid growth in recent history, with household mortgage debt increasing from 28% of GDP in 1974 to a peak of 79% in 2009. Securitization played an important role in the evolution of this market. The process of mortgage debt securitization involves a transfer of the risks inherent to the individual loans. During the initial period of rapid growth of mortgage pools in the late 1970s and early 1980s, there was a substantial redistribution of interest rate risk and prepayment risk. As interest rate volatility subsided (see Figure 1) in the 1990s and 2000s, mortgage pools progressively became vehicles of redistribution of credit risk. The buildup of credit risk in mortgage pools and the subsequent increase in default rates during the financial crisis of 2008 has been well documented.[1]

The market for mortgage-backed securities (MBS) before the early 1990s consisted almost entirely of (in terms of volume traded) securities issued by government-sponsored enterprises (GSEs), mainly Fannie Mae and Freddie Mac. In the early- to mid-1990s, a market for privately issued MBS developed. The emergence of privately issued MBS introduced new financial products in the sense of risk-return tradeoffs. Privately issued MBS pooled mortgages that were typically higher in nominal value relative to those pooled by GSEs, which were restricted by regulation.[2] Moreover, privately issued MBS could pool mortgages issued to high-risk borrowers with low credit scores or borrowers with incomplete documentation. Thus, private mortgage pools consisted of mortgages that were issued in larger loan amounts or expected to have higher credit risk.

We study the interest rate at the time of issuance for mortgages belonging to different pools, and trace how these initial rates evolved over time as a function of the level of credit risk embedded in the loan. We consider four destinations for mortgage loans: securities issued by GSEs, securities issued by private institutions, which are divided into prime and subprime securities, and mortgages that are not securitized but remain on the balance sheet of the issuing institutions. For each of these loans, we model the interest rate premium over a reference rate (the federal funds rate or a Treasury bill rate) as a function of a set of characteristics of both the loan and the borrower. Specifically, we consider fixed- and variable-rate loans, 15- and 30-year loans, the loan-to-value ratio of the mortgage, and the credit score of the borrower. In total, our observations consist of 121 million loans issued between 1992 and 2015. We also separate the four groups of mortgages according to geography and income distribution. We do this by exploiting ZIP Code information on the mortgage loan and the availability of average household income at this level of disaggregation.

Our results deliver several clear features of the evolution of securitization. First, even

[1] For a survey focused on the period surrounding the 2008 financial crisis, see, Keys, Piskorski, Seru, and Vig (2013).

[2] The Conforming Limit is the maximum principal balance of mortgages which GSEs are allowed to purchase. The Federal Housing Finance Agency (FHFA) annually announces the limit, set at $417,000 for single-family housing for the majority of counties as of 2016. Some counties designated as high-cost have higher limits. The limit of $417,000 has been unchanged since 2006.

though mortgages are segmented through the creation of different pools (including mortgages on the balance sheet of issuers), all mortgages behave very similarly in terms of pricing, with the exception of subprime mortgage pools. Second, evidence indicates that, in the early stages of subprime mortgage securitization, high-risk mortgagors were treated approximately like the "traditional" population of borrowers. However, over time, the pricing of subprime mortgages increasingly diverged from the rest. Pricing of credit risk moved in the expected directions, where lower credit scores and high loan-to-value ratios commanded an increasing premium over time until the demise of the subprime market in 2008. Third, the evolution of the interest rate premium is different when the total amount borrowed is considered. We document an inverse relation between the interest rate and the amount borrowed, which indicates that the advantage to borrow larger amounts became stronger over time for mortgages securitized in subprime pools. In fact, starting in 2002, this effect is so strong as to reverse the interest rate premium of subprime mortgages. Finally, we show another important distinction between subprime loans and other classes of mortgages: the evolution of loading factors on initial mortgage rates is cointegrated with delinquencies and, to a lesser extent, house prices for subprime pools, whereas such co-evolution is not present for all other types of mortgages. The cointegration results highlight (i) the strong economic linkages between the evolution of ABS pricing and delinquency (see Mian and Sufi, 2009), and (ii) the increasing relative importance of subprime borrowers in the housing market. These results are robust across different regions of the United States and across different segments of borrowers' income distribution.

Our results are consistent with and complement many other studies. The financial crisis of 2008 has naturally generated an extensive literature studying the buildup of risk in mortgage loans around the crisis period.

Justiniano, Primicieri, and Tambalotti (2017) also study interest rates on mortgages. Their motivation is estimating the date at which mortgage interest rates start behaving differently from other rates—that is, when mortgage rates stop "following" the federal funds rate and deviate from the stance of monetary policy. They name this phenomenon the *mortgage rate conundrum* and estimate the date to be 2003. We find similar results, and interestingly, we also see this phenomenon in the number of mortgages issued (quantity rather than prices). The left panel in Figure 1 shows the interest on U.S. Treasuries and the number of mortgages issued. [3] The negative correlation between the two variables is clearly visible until 2003, at which point there is a spike—the refinancing boom documented by Justiniano et al. (2017)—and after 2003 the two variables appear to move together.

Keys, Seru, and Vig (2012) analyze the link between securitization and screening of borrowers during the years surrounding the crisis and find that unsound screening decisions are associated with securitization in the subprime market. Similarly, Keys, Mukherjee, Seru, and Vig (2010) find that the ease of securitization is associated with an increase in the probability of default. Mian and Sufi (2009) find that the expansion of credit is particularly strong in subprime ZIP Codes, even in periods in which these ZIP Codes experienced strong

[3] Shaded areas in all figures correspond to NBER recessions.

income contraction, breaking the typically positive correlation between income and credit growth, and replacing it with a new positive correlation between securitization and credit growth during a period of declining income.

Similar results are contained in Demyanyk and Van Hemert (2010), who find that the quality of loans fell steadily over the six years preceding the crisis, and that credit quality was, to some extent, known at the time the loans were securitized. This last point is consistent with our evidence of increasing loading factors. It is also consistent with our cointegration analysis, in which we show that defaults are cointegrated with loading factors on subprime loans but not with loading factors on other forms of mortgage lending. In fact, not only are our results consistent, but we also show that this phenomenon began many years before the crisis.

Nadauld and Sherlund (2013) find that the expansion of subprime mortgage credit is associated with higher default rates. Importantly, they find that the forces that drove the expansion of subprime lending were different from those that guided the expansion of lending in prime mortgage securitization. Again, this result is consistent with our analysis, in which pricing is different for subprime loans, where the classification of a mortgage as subprime was set by intermediaries at the time the loan was made, indicating that market segmentation was endogenous.

Our results are also consistent with evidence about credit expansion and house prices. Favara and Imbs (2015) find that credit expansion is an independent cause of increasing housing demand, supply, and house prices. Our results indicate that house price dynamics were linked to interest rates on subprime loans more directly than to interest rates on other classes of mortgage loans.

There is also a theoretical literature that studies optimal mortgage contracts as a function of the environment in which they are issued (see Piskorski and Tchistyi, 2010 and 2011). The results are consistent with the evidence that increases in mortgage lending are associated with higher credit risk. In particular, these papers explain the increase in credit risk (in part) with expectations about house-price dynamics. We find that delinquencies for high-risk mortgages and house prices share similar dynamics with loading factors on subprime loans.

In the next two sections, we present the data set and summary statistics. Cross-sectional regression analysis is presented in section 4. Cointegration analysis is presented in Section 5. Section 6 concludes and lays out some directions for future research.

2 Data

Our analysis is based on two large loan-level data sets that cover a substantial portion of the U.S. residential mortgage market in all standard types of mortgages. Data on privately securitized loans are collected by CoreLogic in the Loan Performance (LP) database, which contains almost all the privately securitized mortgages in recent years. The LP data set is separated into two categories, MBS and ABS. MBS covers privately securitized prime

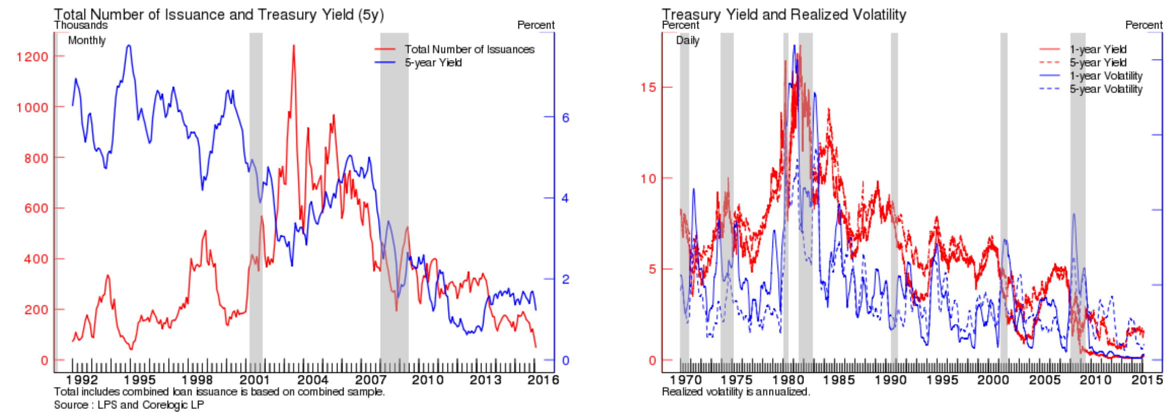

Figure 1: Interest Rates, Mortgage Loans, and Interest Rate Volatility

and prime jumbo loans, and ABS contains subprime and alt-A loans.[4] The second data set, the Lender Processing Services (LPS) database, now maintained by McDash Analytics, provides observations on mortgage loans backed by GSEs and loans that are not securitized but remain on intermediaries' balance sheets. The LPS data set is comprised of servicing portfolios of the 12 largest residential mortgage servicers in the United States.[5] LPS covers about two-thirds of all installment-type loans in the U.S. residential mortgages market. Because LPS coverage is based on information collected by the largest mortgage servicers in the United States, the universe of mortgages covered includes a subset of privately securitized loans as well. We use LPS observations only for mortgages securitized by the GSEs and discard information on privately securitized mortgages from LPS, as LP coverage is more comprehensive for privately securitized mortgages. For LPS data, we look at loans at the time of first appearance to determine whether they are securitized by GSEs or held on the balance sheet of an intermediary (that is, these loans are not securitized).

We divide all observations into four mutually exclusive sets: privately securitized prime and prime jumbo loans (LP-MBS), privately securitized subprime and alt-A loans (LP-ABS), GSE guaranteed loans (LPS-GS), and portfolio-held loans (LPS-PO). Our analysis applies to each of the four aggregates separately.

LPS and LP are structured similarly in many aspects.[6] Both LPS and LP data sets provide detailed information at a monthly frequency dating back to 1992 on loan specification, borrower characteristics, collateral information, and payment histories. LPS and LP both provide time-invariant characteristics of loans at the time of issuance (such as originated amount and closing date), as well as time-varying variables such as current: interest rate, payment, and delinquency information. Even though LPS and LP contain a rich set of loan

[4]Alt-A is a classification of mortgages for which the risk profile of the borrower is between the safest and riskiest classifications—that is, between prime and subprime.

[5]The exact number of servicers coverage has changed over time due to mergers.

[6]Initial data processing was done by Risk Assessment, Data Analysis, and Research (RADAR) of the Federal Reserve Bank of Kansas City. RADAR aligned two different data sets in a similar format and we thank them for this great effort.

	LPS-GSE	LPS-PO	LP-ABS	LP-MBS	Total
15-yr FRM	8.0	6.0	0.7	0.3	15
30-yr ARM	4.0	6.0	9.9	1.1	21
30-yr FRM	30	30	4.6	1.6	66
Total	42	42	15.2	3.0	102

Table 1: Sample Size (millions)

characteristics, coverage for each variable is not uniform, especially in the early part of the sample. For this reason, we use only loan characteristic variables for which a large number of observations are reported.

We exclusively look at the most common types of mortgage contracts. In particular, we limit our analysis to 15-year and 30-year term mortgages.[7] The 15-year and 30-year term mortgages constitute more than 90% of the total mortgages in our data. Moreover, we find that 15-year adjustable rate mortgages (ARMs) are issued rarely, so we exclude them from the analysis.[8] We further limit our analysis to purchases and refinance loans only. Finally, in both LPS and LP data sets, there are records of loans that originated before 1992 as long as a single payment information was received after 1992. However, we discard pre-1992 observations because we cannot determine information about the loan at the time of origination.[9] We also drop loans that originated in Alaska or Hawaii, as these states have different conforming limits.

3 Summary statistics

Our sample period, which covers January 1992 through April 2015, contains 121 million mortgages. Table 1 contains the total number of loans in the LPS and LP data sets that we could employ in our statistical analysis. In total, we employ 102 million mortgages. The large majority of loans have a 30-year maturity and a fixed rate for LPS-GS and LPS-PO and an adjustable rate for LP-ABS. Figure 2 reports estimates of the coverage of our samples as a percentage of the respective populations: our data sets have an excellent coverage of private labels but less so for portfolio held loans. In what follows, we report a series of figures that describe the data in some detail.

Figure 3 displays the number of issuances by mortgage type during our sample period. Observations on GSEs are very volatile during our sample and exhibit the largest number of issuances, which spikes in 2002-03, though these features could be due to data limitations.

[7] We define N-year term mortgage as mortgages having the last payment date 10 months within the N-year from the closing date.

[8] The number of 15-year ARM issuances constitutes around 0.2% of the sample.

[9] In particular, the LPS data set does not report initial interest rates in the static data set, unlike LP. Hence, the initial rates have to be collected from the first payment record from the dynamic data set. The first dynamic values are not available for pre-1992 loans, which implies that we cannot determine initial rates on the ARMs issued prior to 1992. We should also add as a general observation that there are well-known data limitations up to the mid-nineties.

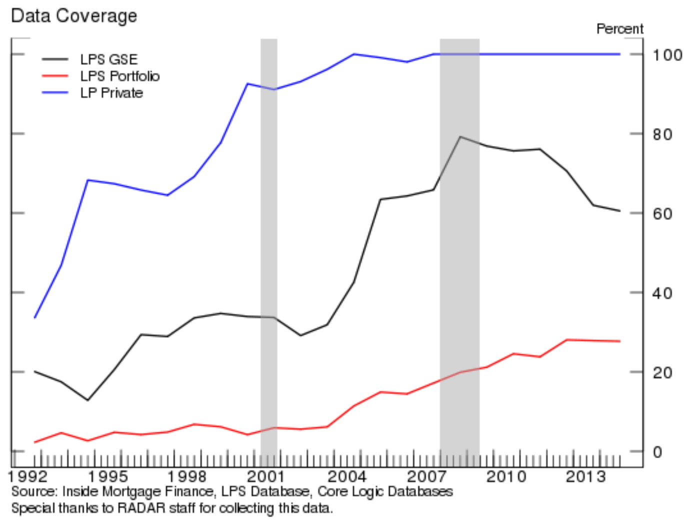

Figure 2: Estimated Sample Coverage

Issuance of LP-ABS increases substantially from 2000 to 2005. The crisis marks the end of the LP-ABS market. LP-MBS issuances are small and, similar to the LP-ABS market, disappear after the crisis. LPS-PO mortgages increase steadily in the pre-crisis period. After the crisis, LPS-GS and LPS-PO remain steady until 2012 and then decrease.

Figure 4 shows the monthly average interest rates by mortgage type (the top-left panel refers to all mortgages in our sample). Notice that, with the exception of 15-year fixed rate mortgages, the interest rate on subprime loans is similar to other mortgages at the beginning of the sample until 1995, at which point it starts to diverge. However, the spread between interest rates on subprime and other kinds of mortgages is not constant. In particular, it first increases, and then decreases after the year 2000 until the crisis; whereas, interest rates on other types of mortgages move together. We will see that this phenomenon is an important aspect of our results: subprime mortgage pools were treated differently from other pools, reflecting a different pricing of credit risk starting a few years after the emergence of such pools.[10] These developments occurred in a macroeconomic context in which the level of interest rates was declining, and the variability of interest rates was declining as well, as documented in Figure 1. The standard deviation of initial mortgage rates is displayed in Figure 5.[11] Notice that the variability of initial interest rates on subprime loans is the highest, and it begins to diverge from that of other mortgages in 2003.

Figures 6 and 7 depict the upper and lower quantiles of the interest rates of various mortgage pools.

[10] We add here that another limitation of the data sets is that they do not contain information about the fees that make up part of the mortgage cost. In particular, they do not provide information about interest rate points possibly purchased by borrowers at the time of issuance. However, it seems unlikely that this missing piece of information had a systematic effect on the analysis, given that the evidence generally partitions mortgage pools into two groups, ABS on one side and all other categories on the other.

[11] For brevity, we report results for all mortgages without separating by maturity and interest rate types.

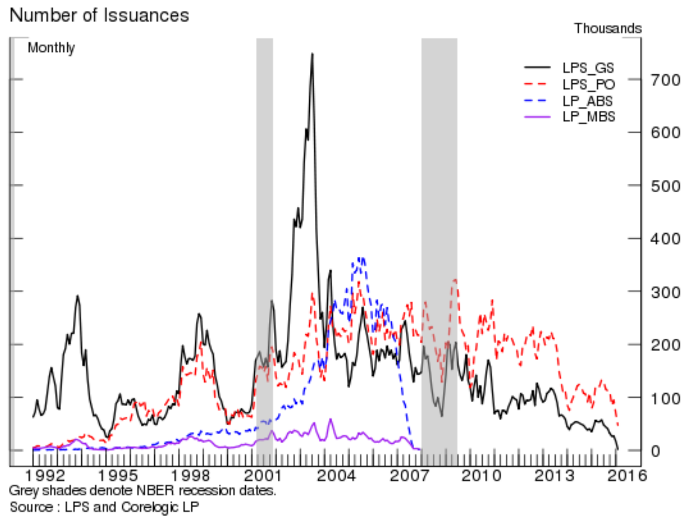

Figure 3: Number of Issuances

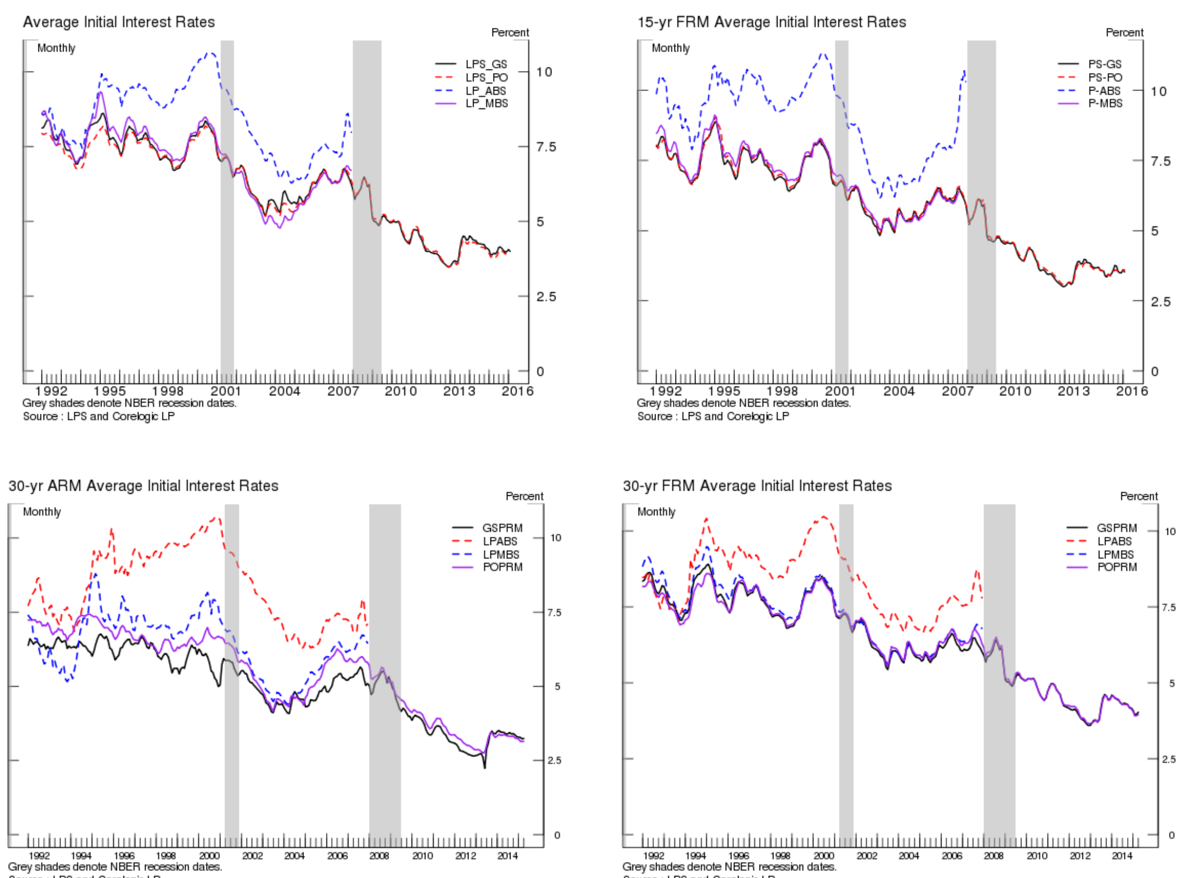

Figure 4: Initial Interest Rates

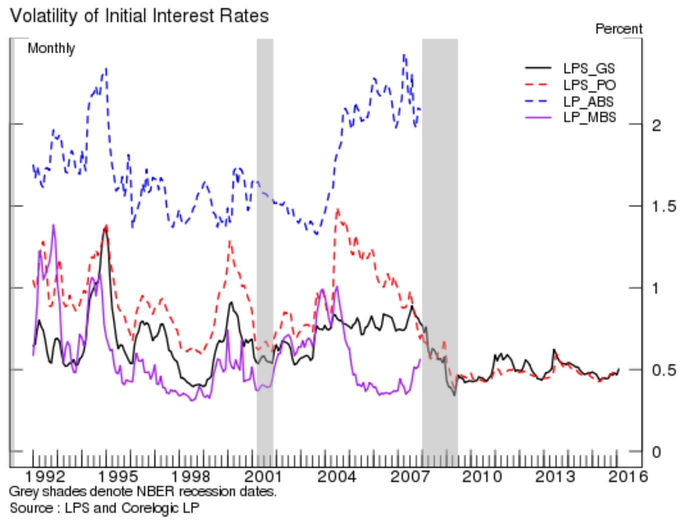

Figure 5: Volatility of Initial Interest Rates

Notice that all mortgage classes behave similarly, but that the premium for borrowers in the upper quantile of the subprime group is substantial, even in the mid-1990s, reflecting the higher credit risk of ABS pools.

Figure 8 shows the average loan-to-value ratio by mortgage type. From the beginning of the sample to 2001, LP-ABS pools have a positive trend, indicating that, for a given house value, LP-ABS mortgagors increase borrowing over time. As a result, counterparty risk is increasing. Also, notice that during the 1993-2000 period, LPS-GS and LPS-PO mortgages are characterized by a loan-to-value ratio higher than LP-ABS mortgages. After 2000 and until the beginning of the crisis, ABS mortgages have the highest loan-to-value ratio. The timing is consistent with results in Antinolfi and Brunetti (forthcoming) where the growth of the MBS market is associated with a reduction in the volatility of real variables (such as GDP) until approximately 2000, but with an increase in volatility of economic activity starting at the beginning of the new millennium. The results in Antinolfi and Brunetti (forthcoming) discuss the possibility that such soaring volatility was linked to a substantial increase of credit risk in the subprime MBS market.

Another indication of the gradual and steady increase in counterparty risk is portrayed in Figure 9, which depicts the average debt-to-income (DTI) ratio by mortgage type. The positive trend indicates that mortgagors increased loan size relative to their income over time.[12]

Figures 10 and 11 report the arithmetic average and the standard deviation of the natural logarithm of the amount borrowed by mortgagors. LP-MBS mortgages are characterized by the largest amount borrowed, as expected, since prime jumbo loans can be securitized only in LP-MBS pools.

[12]We do not report DTI for LP-ABS and LP-MBS pools because data on DTI are often missing from the sample.

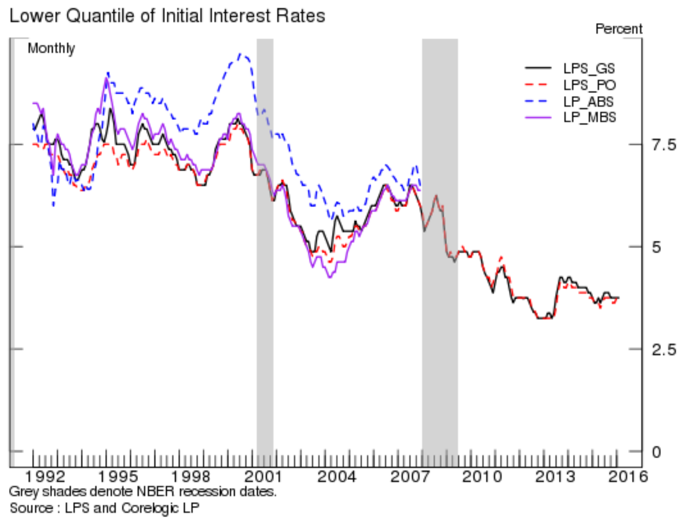

Figure 6: Lower Quantile of Initial Interest Rates

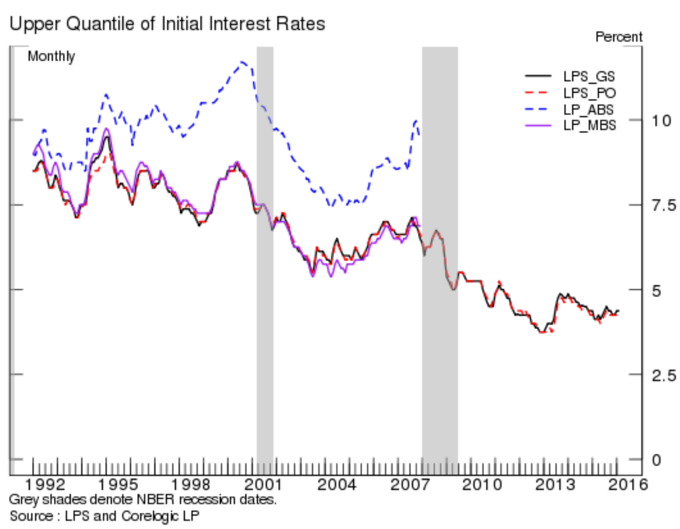

Figure 7: Upper Quantile of Initial Interest Rates

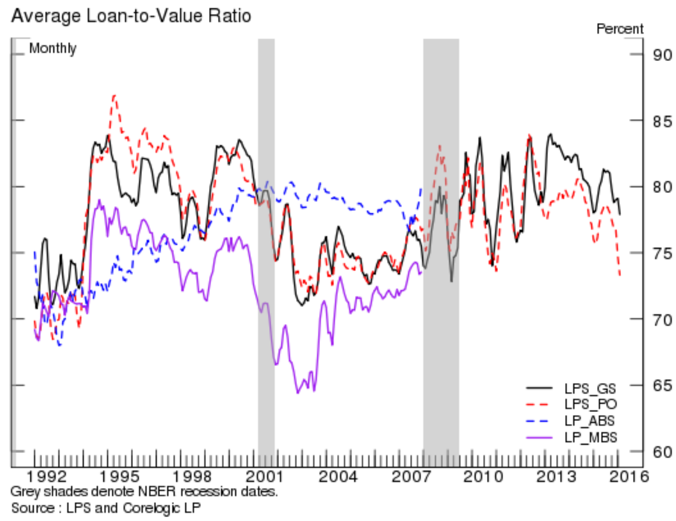

Figure 8: Loan-to-Value Ratio

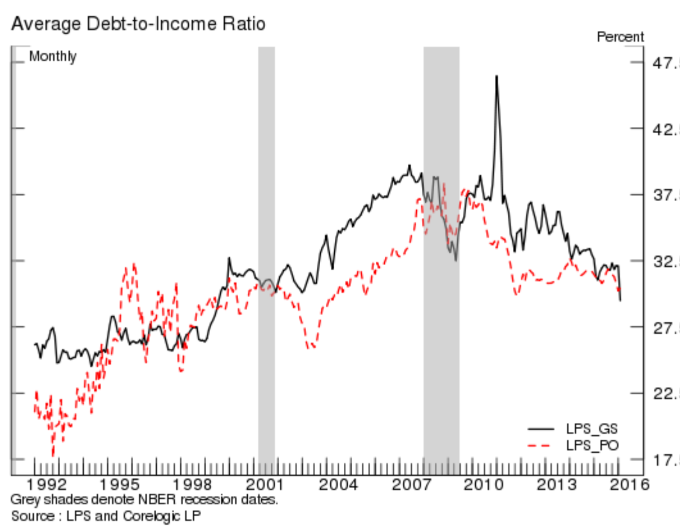

Figure 9: Debt-to-Income Ratio

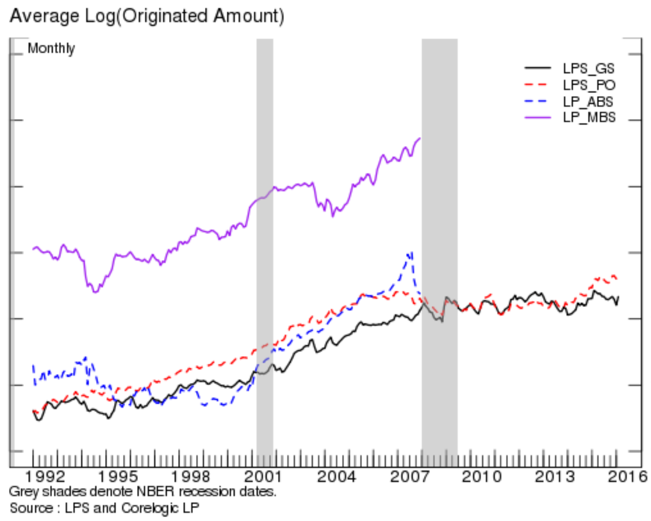

Figure 10: Log(Originated Amount)

LP-ABS, LSP-GS, and LPS-PO have similar average behavior. In other words, LP-ABS and LPS-GS mortgagors borrowed similar amounts (until the crisis). All mortgage amounts exhibit a positive trend. Figure 11 shows that LP-ABS is very volatile, perhaps indicating, once again, the high diversity of mortgages in LP-ABS pools. Volatility of the amount borrowed on LP-ABS pools spikes dramatically before the crisis.

Another measure of credit risk is the FICO score of mortgagors. This statistic is depicted in Figure 12. LP-ABS FICO scores are, on average, lower than those of other mortgage types, as expected. However, in the first part of our sample, from 1993 to 2000, the average FICO score for ABS is very volatile and exhibits an overall decrease. ABS FICO scores increase from 600 in 2000 to 680 before the crisis. The large majority of LP-ABS mortgages have a FICO score below 680 for most of the sample. LPS-GS, LPS-PO, and LP-MBS have similar average FICO scores, although LP-MBS exhibits a somewhat higher average. Portfolio FICO scores are the highest after the crisis, possibly indicating that banks/issuers responded to the crisis by keeping mortgages with the lowest counterparty risk on their balance sheets.

3.1 Summary statistics by region

Housing finance is national rather than regional, whereas the housing market is regional. An important exercise is to verify whether there is variability in regional financial conditions for different groups of mortgagors. Figures 13, 14, and 15 reproduce some of the evidence previously presented by grouping mortgages into four regions: northeast, midwest, south, and west.[13]

[13]Northeast: ME, NH, VT, MA, CT, RI, NY, PA, NJ, DE, MD, DC. Midwest: WI, MI, OH, IN, IL, MN, IA, MO, ND, SD, NE, KS. South: WV, NC, VA, SC, GA, FL, KY, TN, AL, MS, AR, OK, LA, TX. West: AK, HI, WA, OR, CA, MT, ID, WY, NV, UT, CO, AZ, NM. We followed regional divisions as defined by the U.S. Census Bureau except for three states: MD, DC, and DE. We added these states to the northeast.

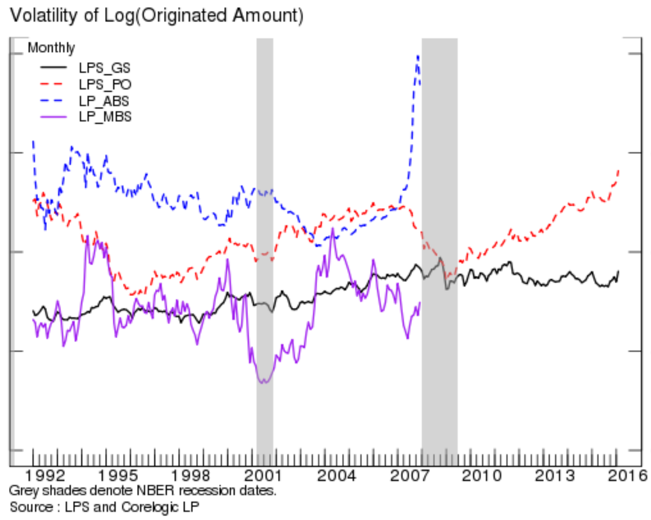

Figure 11: Volatility of Log(Originated Amount)

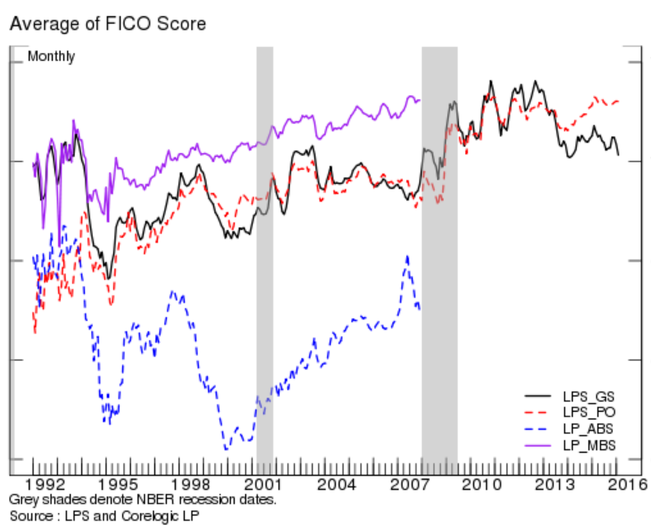

Figure 12: FICO Score

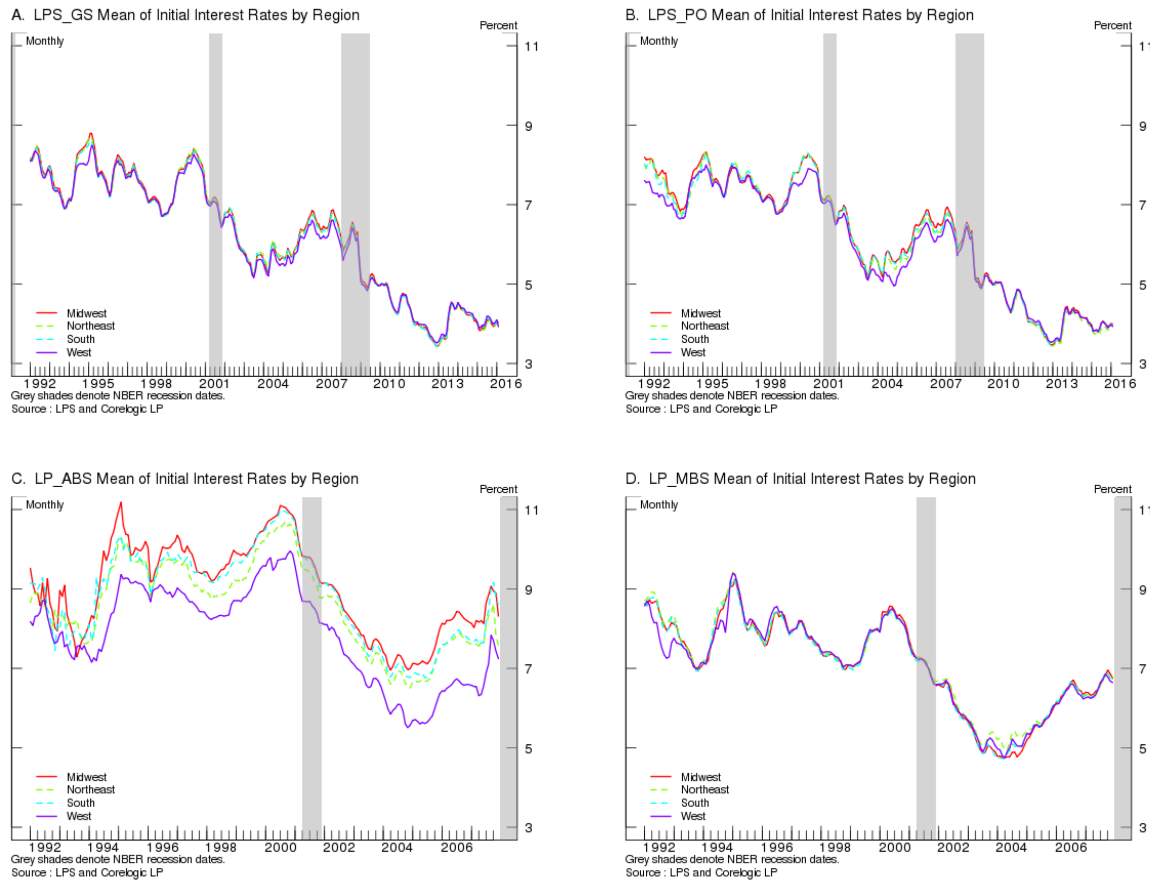

Figure 13: Initial Interest Rates by Region

For the case of the initial interest rate, Figure 13 shows that conditions on "traditional" mortgages are largely independent of geography, which is not the case for subprime loans. Notice that subprime loans in the west tend to have lower interest rates, while those in the midwest have higher rates. We do not report results on the standard deviation of interest rates, as there is no material difference across regions.

Figure 14 shows the monthly average loan-to-value ratio by region for the four mortgage pools. Notice that the loan-to-value ratio for ABS pools is lower in the northeast and the west, which is possibly related to the price dynamics in Figure 13. Loan-to-value ratios also reflect cross-regional price dynamics. DTI ratios do not exhibit any regional difference. Hence, we do not report them.

Figure 15 shows the arithmetic average of the natural logarithm of the amount borrowed by mortgagors in each region. Mortgagors in the northeast and west regions borrowed larger amounts relative to those in the midwest and south regions. FICO scores do not exhibit any regional differences.

The regional summary statistics suggest two observations. First, for subprime borrowers, the mortgage market is "less national" than for other classes of borrowers.

In particular, subprime borrowers in the west, and to some extent in the north-east,

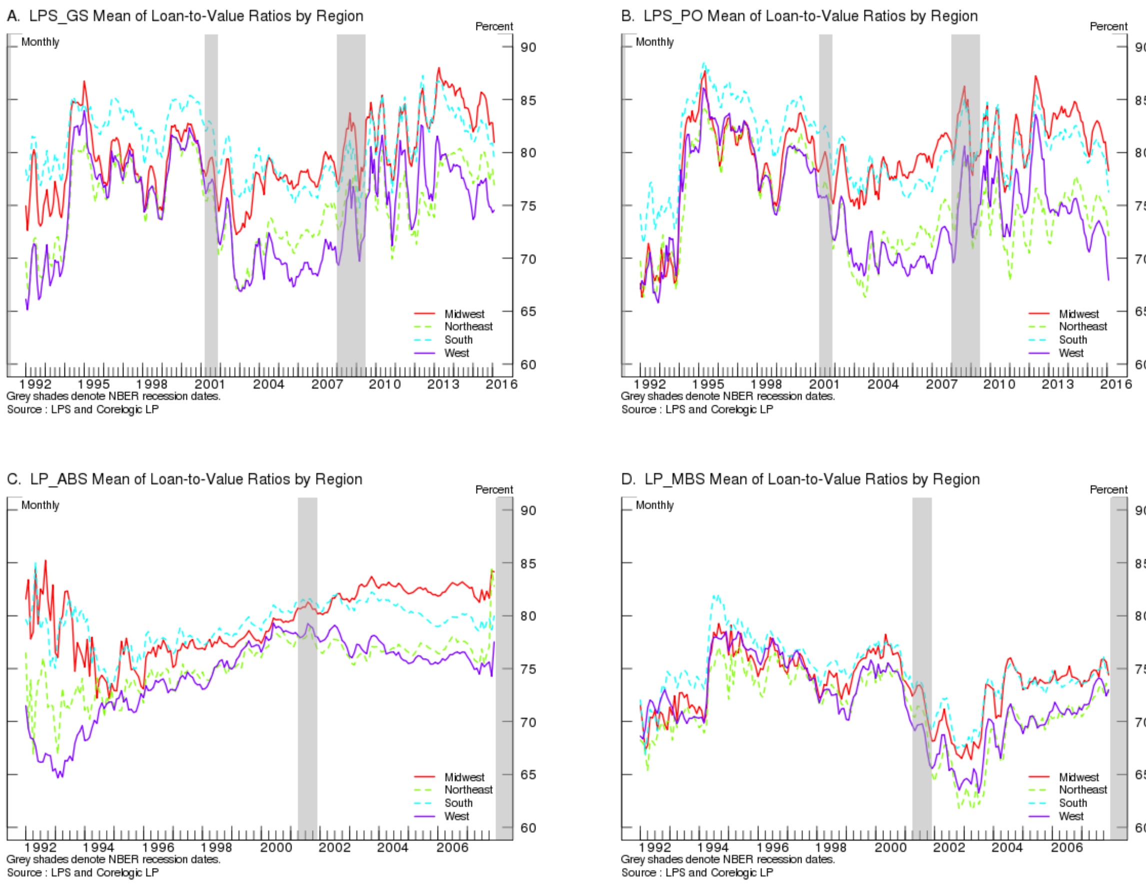

Figure 14: Loan-to-Value Ratio by Region

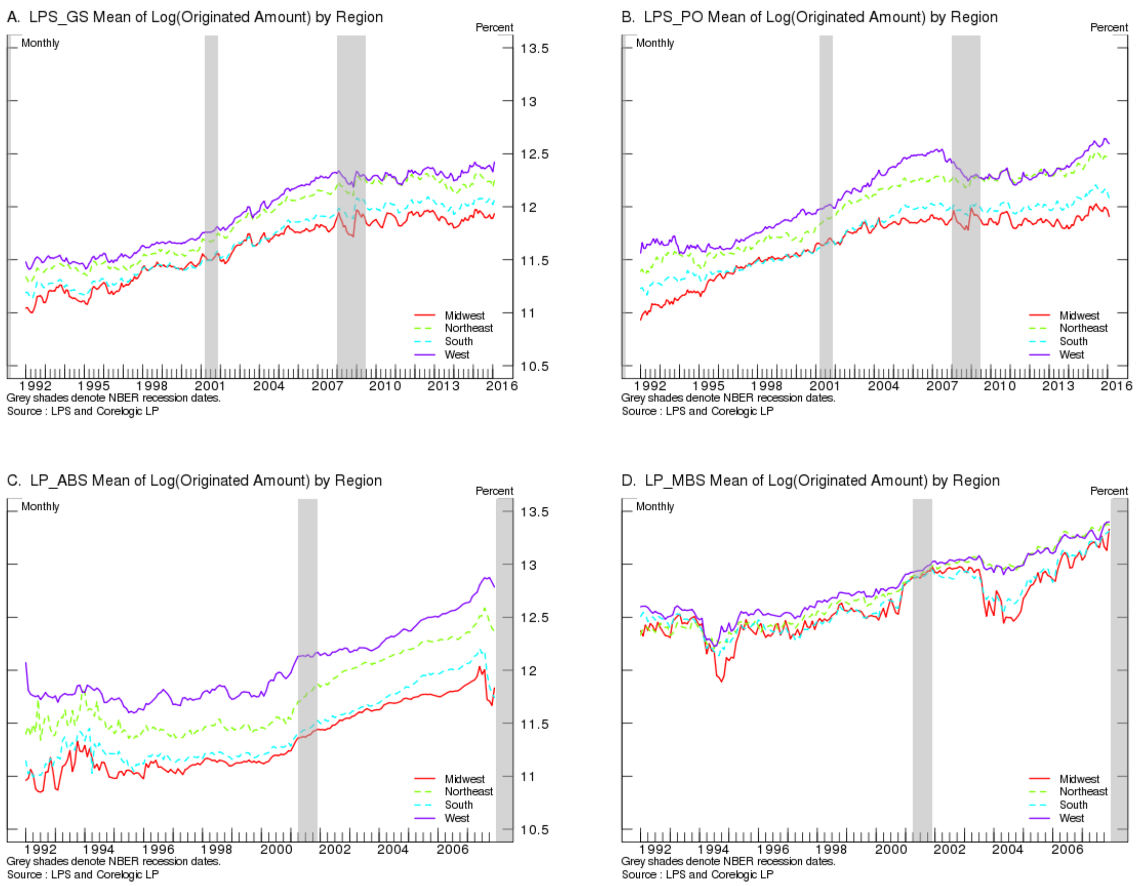

Figure 15: Log(Originated Amount) by Region

tend to pay lower interest rates than subprime borrowers in other regions. They also tend to get bigger loans in absolute amount, but contribute with a higher down payment (loan to value ratios are reversed region-wise relative to nominal amounts borrowed). Second, this piece of evidence points to the relevance of subprime borrowers in regions where house prices grew most: the west and the northeast. Lower interest rates combined with higher loan amounts and lower loan-to-value ratios seem to indicate that the mortgage market was supporting purchases by subprime borrowers moving to more expensive houses, with monthly payments curbed by favorable interest rates and increasing house prices.

3.2 Summary statistics and income distribution

We use information about the ZIP Code where each mortgage in the sample is located and merge this information with ZIP Code level Income Tax Statistics produced by the Internal Revenue Services. For each mortgage type, we construct three data buckets: i) mortgages in areas where household income is equal to or below the 50th percentile of national income; ii) mortgages in areas where household income is above the 50th percentile but equal to or below the 80th percentile; iii) mortgages in areas where household income is above the 80th percentile. Of course, it is not always the case that the ZIP Code of the property and the ZIP Code of the borrower are the same, as people purchase investment properties in different location from their main residence. Nonetheless, we believe that it is informative to look at different income brackets, and in this section we present the same summary statistics of the previous sections to assess whether income has an effect on financing conditions for the different kinds of mortgage pools.

Figure 16 depicts the number of issuances across the three income groups for each mortgage type. The highest number of loans, beginning in the late 90s and through the crisis, are issued to borrowers with incomes below the 50th percentile. This fact is particularly true for LP-ABS pools starting in the early 2000s. The only exception is for LP-MBS pools, for which the highest number of new mortgages goes to high-income households. This phenomenon is to be expected, as mortgages in this pool are mainly prime jumbo loans.

Figure 17 depicts the average interest rate across the three income groups for each mortgage pool. Mortgage interest rates for LPS-GS, LPS-PO, and LP-MBS do not exhibit substantial differences along the income distribution. However, LP-ABS shows that income matters: the higher the income, the lower the interest rate of the mortgage. Notice that, especially for LP-ABS mortgagors, low income is associated with relatively higher interest rates before recessions.

Figure 18 displays the loan-to-value ratio by income group for the four mortgage types. Notice that households in lower-income groups tend to borrow larger amounts for a given house value. Also, notice that the only loan-to-value ratio with a clear trend is the one associated with LP-ABS mortgages.

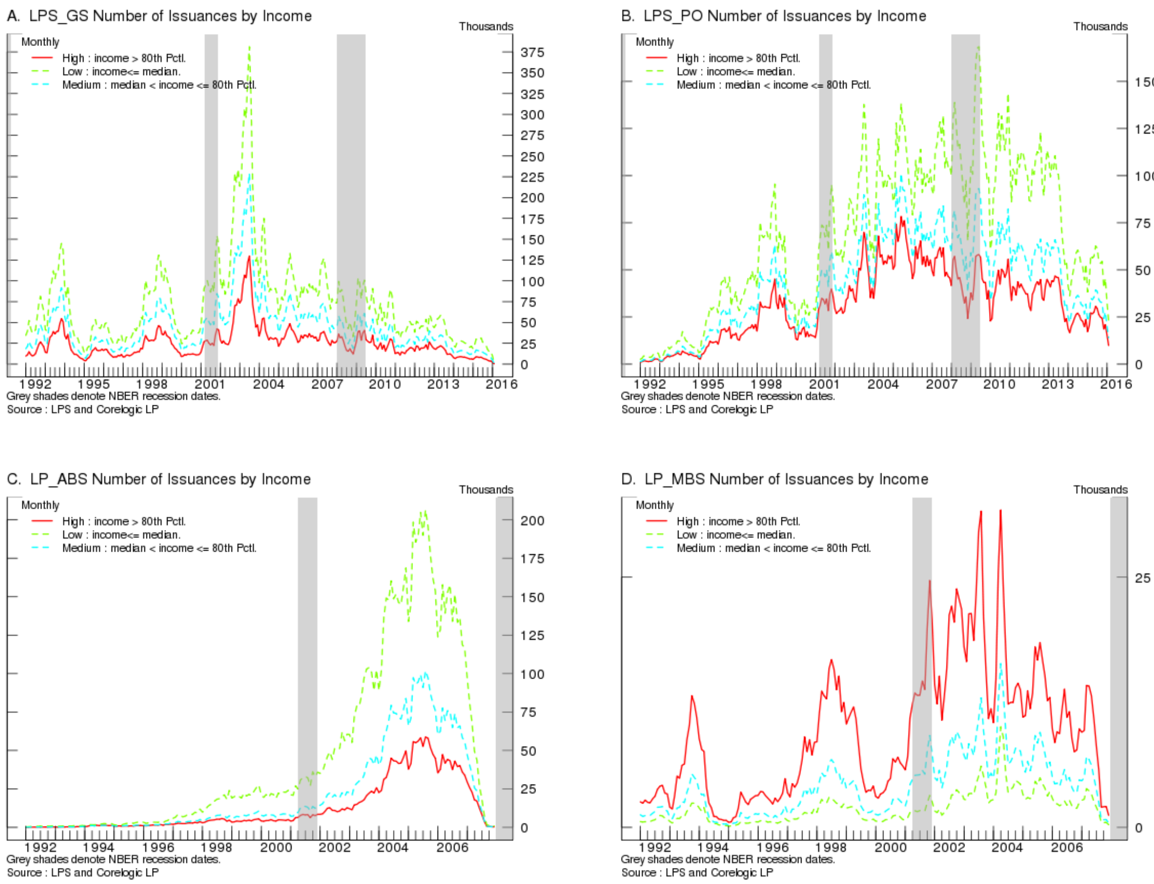

Figure 16: Number of Issuance by Income

Figure 17: Initial Interest Rates by Income

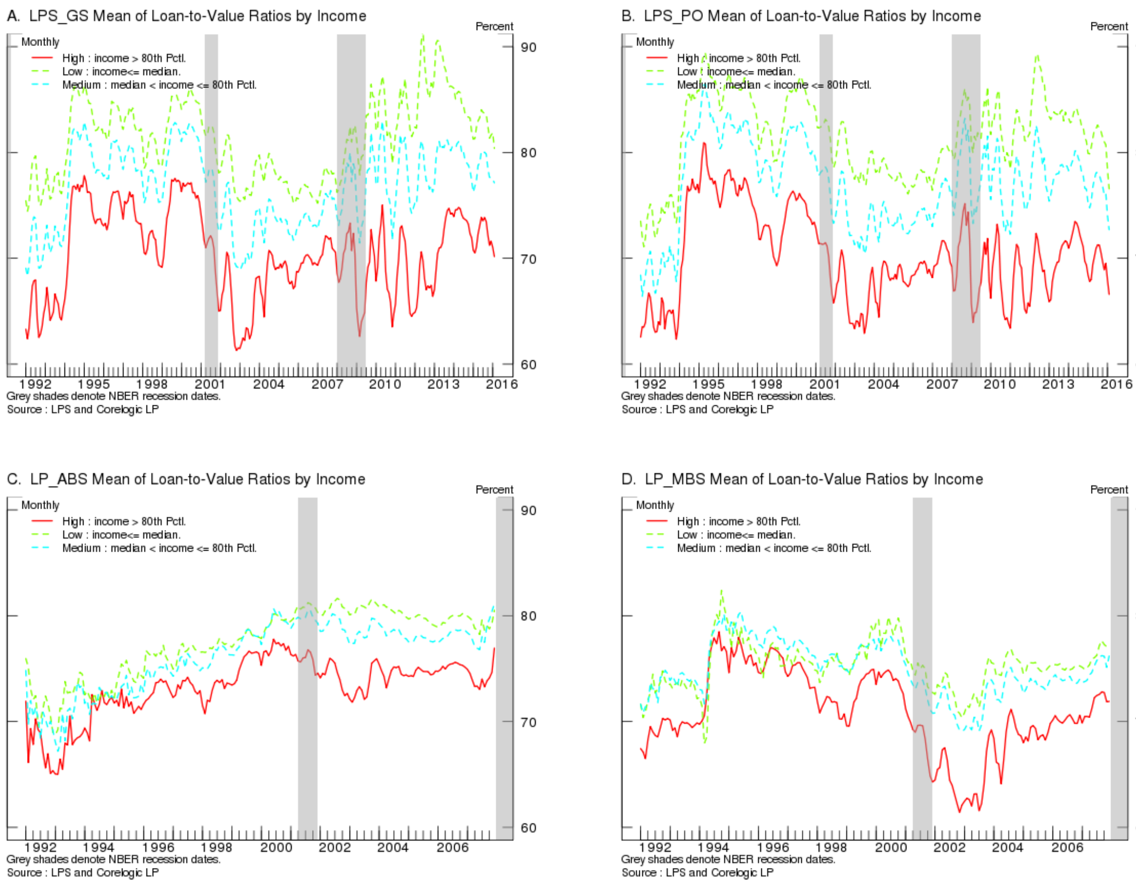

Figure 18: Loan-to-Value Ratios by Income

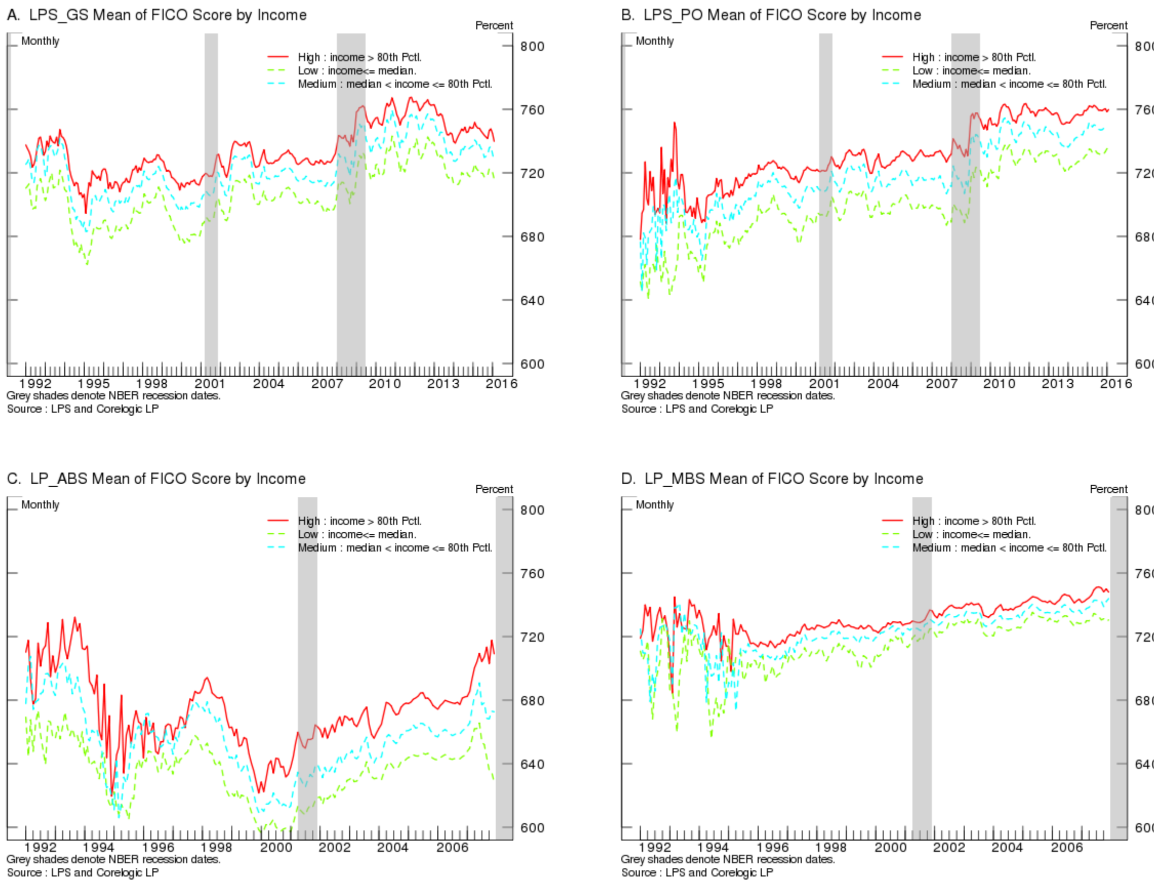

Figure 19: FICO Score by Income

Figure 19 depicts the FICO score at origin for the three income groups for each mortgage type. High-income borrowers tend to have higher FICO scores. Of note, all types of mortgages show a positive trend in the FICO score starting in the mid-1990s. The only exception is, once again, represented by LP-ABS mortgages, for which the positive trend begins in 2000.

4 Evidence from initial interest rates

To study the pricing of mortgages for each of the four pools, we regress the initial interest rate for a mortgage on a set of explanatory variables that measure the amount of credit risk inherent in the mortgage. Specifically, the hypotheses we would like to test are:

- H_0^1 : Is the pricing of counterparty risk similar across the four segments of the mortgage market?
- H_0^2: Is the pricing of counterparty risk constant over time?

The pricing model includes the loan-to-value ratio, the FICO score of the mortgagor, the dollar amount borrowed, and two dummy variables that capture whether a mortgage is a fixed-rate loan, and whether it is a 30-year loan or a 15-year loan. We concentrate on newly issued mortgages in each month including new purchases and refinancing loans.[14] Finally, we use a benchmark interest rate to account for a measure of the "cost of funds" for the lender. In particular, we use as benchmarks the federal funds rate and the 1-year, 10-year, and 30-year Treasury rates. The results are consistent across the different rates. For brevity, we only report results for the mortgage premium based on the federal funds rate.

We use monthly observations and run cross-sectional regressions. This approach allows us to trace the evolution over time of the loading of different risk factors and provides robust estimations. For each month of the sample, and each different pool of mortgages, we estimate the following regression:

$$r_i - r_{ff} = \alpha_0 + \alpha_1 LTV_i + \alpha_2 FICO_i + \alpha_3 log(Amount_i) + \beta_1 ARM_i + \beta_2 MAT_i + u_i, \quad (1)$$

where LTV_i refers to the loan-to-value ratio of the mortgage, $FICO_i$ is the FICO score of the mortgagor, $Amount_i$ is the amount of the mortgage, ARM_i is a dummy variable equal to one when mortgage i is characterized by a variable rate, and MAT_i is a dummy variable that is equal to one when the maturity of the mortgage is 30 years. As previously described, we estimate equation (1) for LPS-GS, LP-ABS, LP-MBS, and non-securitized loans for every month in the sample. Because this process delivers over 5,000 estimated coefficients and over 1,000 error terms, we report results graphically—that is, in all figures below, each estimated coefficient represents a point, and for each month we report four points corresponding to the four separate mortgage pools. Each parameter is estimated utilizing at least 100 monthly observations, though there is a lot of variation in the number of observations available for different mortgage pools over time. The vast majority of estimates are statistically significant at the 5% level.[15]

Figure 20[16] reports the monthly estimates of the constant, $\hat{\alpha_0}$. LP-ABS is characterized by a larger (conditional) mortgage premium, while LPS-GS, LPS-PO, and LP-MBS have very similar patterns; LP-MBS mortgages have the lowest premium from 2000 to 2006 despite the fact that this segment of the market includes jumbo loans.

Figure 21 shows the coefficients of loan-to-value ratios, $\hat{\alpha}_1$. We expect a positive relation between the mortgage premium and LTV_i—*ceteris paribus*, the higher the amount borrowed for a given house value, the higher the counterparty risk. LP-ABS mortgages show a

[14] We also consider new purchases only; see Section 4.1.

[15] We estimate equation (1) for each mortgage pool, for a total of 6960 estimated coefficients. At the 5% significance level, the number of coefficients that are not significant is: 58 for LPS-GS, 131 for LPS-PO, 209 for LP-ABS, and 240 for LP-MBS. At the 10% significance level the number of coefficients that are not significant is: 43 for LPS-GS, 107 for LPS-PO, 176 for LP-ABS, and 222 for LP-MBS. At the 20% significance level the number of coefficients that are not significant is: 34 for LPS-GS, 77 for LPS-PO, 143 for LP-ABS, and 192 for LP-MBS.

[16] Note that in Figures 20-24, the reported estimates of the coefficients associated with LP-ABS pools end in the middle of 2007. These estimates tend to become erratic in the last few months of the sample. The reason is that new issuances of subprime pools decrease markedly in the months preceding the complete collapse of this market.

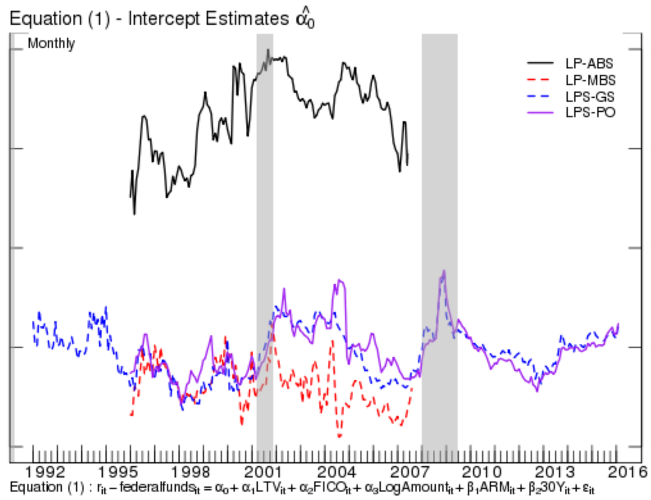

Figure 20: Regression Model (1) - Intercepts

positive trend in $\hat{\alpha}_1$, indicating that over time, LTV_i became a more important factor in the determination of ABS mortgage rates. Just before the crisis, $\hat{\alpha}_1$ for LP-ABS stabilizes at 0.03, which means that, for example, given an average value of LTV_i of about 80%, the LP-ABS mortgage premium was 2.4%. Again, $\hat{\alpha}_1$ is relatively stable for LPS-GS, LP-MBS, and LPS-PO and only marginally significant from an economic point of view.

The coefficients for the FICO score, $\hat{\alpha}_2$, are reported in Figure 22. For LPS-GS, LP-MBS, and unsecuritized mortgages, as expected, there is a negative relation between the FICO score and the interest premium paid by the mortgagor. However, this premium does not vary much over the sample period. The same is not the case for LP-ABS mortgages, for which $\hat{\alpha}_2$ is characterized by a strong negative trend from 1996 to 2000, followed by a relatively stable period that lasted until 2003, and again a strong negative trend until the crisis, when this trend rapidly changed sign. During the sample period, FICO scores became more important factors in LP-ABS mortgage rates. Notice that, once again, LP-ABS pools depart from the other pools around 1996, and their different behavior continues relatively regularly until the crisis.

Figure 23 depicts the time series of $\hat{\alpha}_3$. For LP-ABS, this coefficient is always negative and economically significant: the higher the amount borrowed, the lower the interest rate charged by the issuer of the mortgage. Just before the crisis, $\hat{\alpha}_3$ for LP-ABS became even more negative. We conjecture that the mortgage issuers were incentivizing mortgagors to borrow more at lower interest rates. Interestingly, $\hat{\alpha}_3$ is relatively stable for LPS-GS, LP-MBS, and unsecuritized mortgages. The same is not true for LP-ABS mortgages, for which the interest rate discount for large loans is substantial.

Time series for $\hat{\beta}_1$ and $\hat{\beta}_2$ indicate that variable interest rates ($\hat{\beta}_1$) and longer maturities ($\hat{\beta}_2$, 30-year) reduce the interest rate for all mortgage types.[17]

[17]To limit the already large number of graphs, we do not report the results.

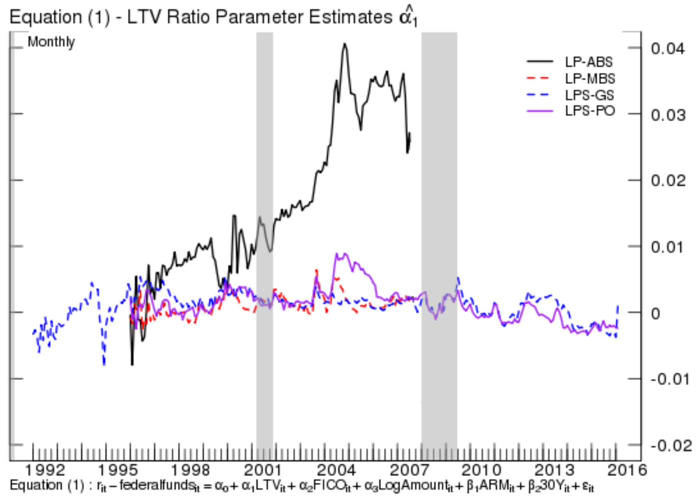

Figure 21: Estimated Parameters on Loan-To-Value Ratio

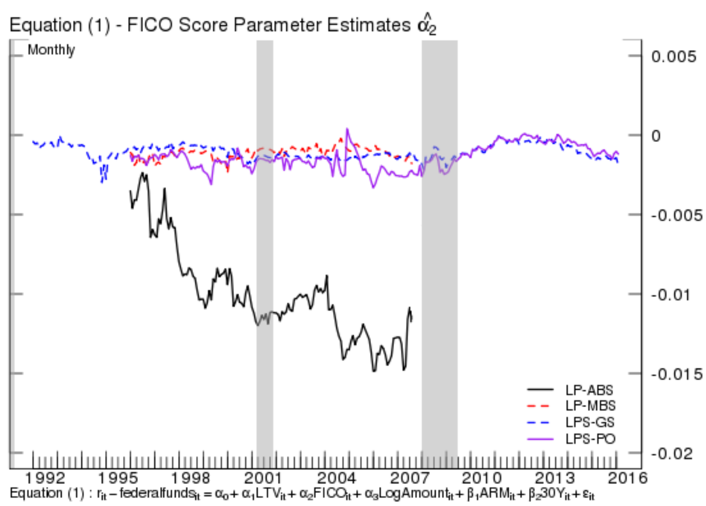

Figure 22: Estimated Parameters on FICO Score

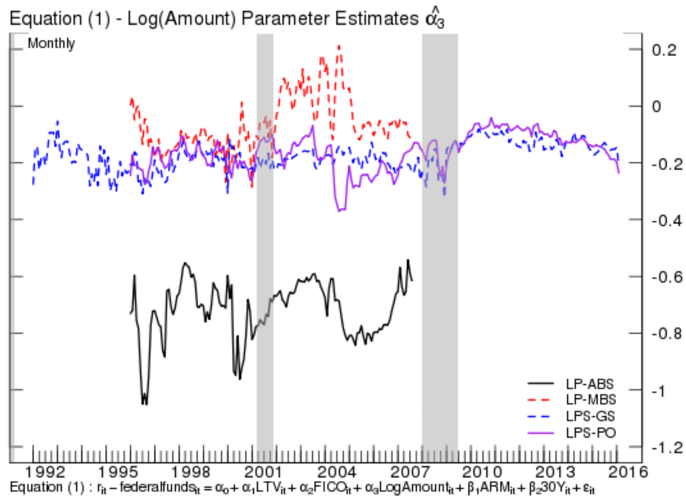

Figure 23: Estimated Parameters on Log(Originated Amount)

An important variable in our data is the DTI ratio.[18] Unfortunately, this field is sparsely available in the data set, so we estimate equation (1) adding to the right-hand side the DTI ratio only for the mortgages where this data field is available. Figure 24 depicts the time series of the estimated parameters. For LP-ABS mortgages, this parameter is very volatile: it increases dramatically in 2003 and again in 2005. However, this result again confirms that the interest rate (price) of LP-ABS mortgages accounts for different risk factors in ways that evolve over time. At the opposite end, we have LPS-GS pools, which are characterized by very stable parameters throughout our sample.

The results presented in this section indicate that LP-ABS pools evolved differently from other pools of mortgages, hence, we reject the hypothesys that the pricing of counterparty risk is similar across the four segments of the mortgage market. Moreover, our estimates show that the pricing of LP-ABS changes over time and displays a clear pattern, thus rejecting our second hypothesys. Initially, when the market for LP-ABS pools was very young, the credit risk inherent in subprime borrowers was scarcely priced into the mortgage's initial interest rate. As the market developed, credit risk became increasingly important, whether one looks at indicators such as loan-to-value ratios or FICO scores, by then the "accepted sufficient statistics" for credit risk.[19] A different story is told by the amount borrowed, where the the estimated coefficients suggest that LP-ABS mortgagors were encouraged to borrow larger amounts. These phenomena are not visible for LPS-GS, LP-MBS, and non-securitized loans, for which the loading factors remain relatively stable throughout our sample. It seems legitimate to suppose that the underwriting of risky loans

[18] Also known as as the *front-end ratio*, it indicates the percentage of income that goes toward housing costs, which for renters is the rent amount and for homeowners is PITI—mortgage principal and interest, mortgage insurance premium (when applicable), hazard insurance premium (when applicable), property taxes, and homeowners' association dues (when applicable).

[19] On this point, see Rajan, Seru, and Vig, (2015); Keys, Piskorski, Seru, and Vig (2012).

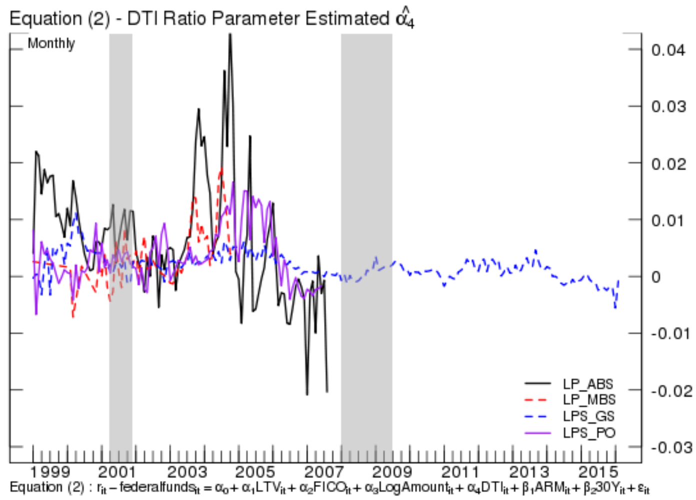

Figure 24: Estimated Parameters on Debt-to-Income Ratio

and the pooling of credit risk through LP-ABS pools was a conscious decision to start a new market to expand the extent of counterparty risk in mortgage loans (probably motivated by the profitability of the securitization process, which until then was dominated by GSEs).

Interest rate levels are a measure of ex-ante perceived credit risk. In Section 5, we look at an ex-post measure of credit risk, delinquencies, in the various mortgage pools. Before that, we briefly discuss how the regression results are affected by some variations of the model.

4.1 Alternative models

We consider several additional specifications of equation (1). In particular, we consider a dummy variable that is equal to one when the FICO score is above 620 to capture a possible regime shift linked to low FICO scores—an approach not too distant from Mian and Sufi (2009). Alternatively, we consider a dummy variable that is set to unity when the FICO score is between 615 and 625. We also estimate variations of equation (1) separately for fixed rates and variable rates, for 15-year and 30-year maturities, and for new purchases loans only. Finally, we estimate the same pricing equations for different intervals of the LTV ratio to account for possible non-linearities. Specifically, we estimate equation (1) using dummies to divide LTV ratios in four intervals: below 60%, between 60% and 80%, between 80% and 90%, and between 90% and 100%. We always obtain results very similar to those previously described.

4.2 Analysis by region and income distribution

We also estimate equation (1) to account for local and regional differences. We do so in two ways. First, we compute a set of dummy variables based on the ZIP Code of the mortgage. In particular, a ZIP-dummy is equal to 1 when the first three digits of the ZIP Code are the same.[20] Second, we adopt the same regional classification of Section 3.1 and run the analysis for each region and for each market segment.[21] There are no substantial local and or regional differences in the estimated parameters. In particular, the evolution of $\hat{\alpha}_1$and $\hat{\alpha}_2$ for LP-ABS is largely the same as those depicted in Figures 21 and 22.

Finally, we also consider the income distribution described in Section 3.2–i.e. we run the models described above for each of the three income brackts for each market segment. The main result from the income analysis is that the intercept, $\hat{\alpha}_0$, is higher for lower incomes. This result holds for all mortgage types and is to be expected. Another interesting result refers to the FICO score for LP-ABS mortgages for incomes below the median. Until the late 1990s, the FICO score did not matter for these mortgages, as $\hat{\alpha}_2$ was close to zero and statistically unimportant.[22] This result is counterintuitive, since we would expect FICO scores to be more important for lower-income levels and less important for higher-income levels.

4.3 Model (mis)specification

The speficiations in equation (1) and in the alternative models are dictated by data availability. As a consequence, it is possible that the estimated parameters may suffer from omitted variable bias.

It is unlikely that an omitted variable bias would result in the parameters' patterns presented above. However, it is important to further investigate such a possibility. In this setting, a possible omitted variable candidate could be the level of documentation associated with a subprime loan. If the prevalence of loans with no or low documentation grew through time, which was the case in the subprime market, the bias would grow through time as well. Some of the LP-ABS mortgages in our data contain information about the level of documentation. Therefore, we construct a dummy variable which is equal to one for mortgages with no or low documentation and zero otherwise. In several cases the information about documentation is missing, which does not imply that there is no documentation. In fact, the sample used for this excercise is significantly smaller than that adopted in the above sections.[23]

For LP-ABS mortgages with information about the level of documentation, we estimate the model in equation (1) with and without the documentation dummy. Then, we run the likelihood ratio test, the Wald test, and the Lagrange Multiplier test between the two models. The null hypothesis for all three tests is that the smaller model (without documentation) is the "true" model. We only report results of the Lagrange Multiplier test (it is the most efficient of the three) but results are consistent across the three tests. Our main goal is to show that the omitted variable bias, if present, is not the driver of the parameters' patterns presented in Figures 20-23.

[20]The aggregation of the ZIP-dummy to the third digit is necessary to allow for feasible estimations.

[21]For each region, we also run all the alternative models described in Section 4.1 and obtain similar results.

[22]To conserve space we do not report these results.

[23]Several months are completely misssing the information about documentatiton.

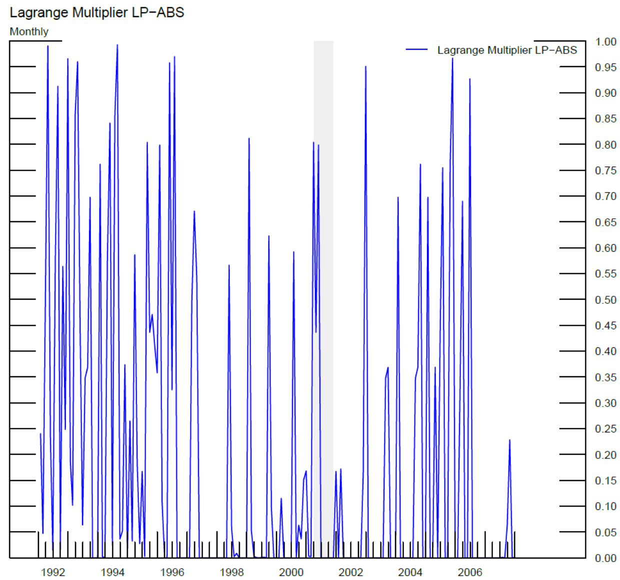

Figure 25: Lagrangian Multiplier (LM) - p-values

Figure 25 shows the p-values of the Lagrange Multiplier test. It is clear that there is no regular pattern in the test results. This means that there are instances where the "true" model is the restricted model (without documentation) and others where documentation matters. From Figure 25, it is difficult to think that the omitted variable bias, when present, is the driver of our results.

We further investigate this issue by looking at the estimated parameters of the unrestricted model (with documentation dummy). Recall that for this excercise we are using a smaller sample, nevertheless the estimated parameters still present the patterns depicted in Figures 20-23.

5 Estimated coefficients, delinquencies, and house prices

The results of the previous sections indicate that LP-ABS mortgages behaved differently from the other mortgage types. In particular, the parameters in equation (1) evolve over time, indicating some adjustment of the risk factors accounted for in mortgage rates. To further investigate these phenomena, we look at the relationship between the time series of the estimated parameters, $\hat{\alpha}_1$ and $\hat{\alpha}_2$, from the model in equation (1) and

1. Delinquency rates by mortgage type;
2. Major house price indices.

The analysis of the previous sections contains cross-sectional monthly evidence on mortgage pricing. Monthly estimates display a clear evolution over time of the parameters associated with LP-ABS pools. Hence, the rationale of this section is to investigate whether the evolution of interest-rate premia associated with available measures of credit risk is linked with the evolution of other important variables.

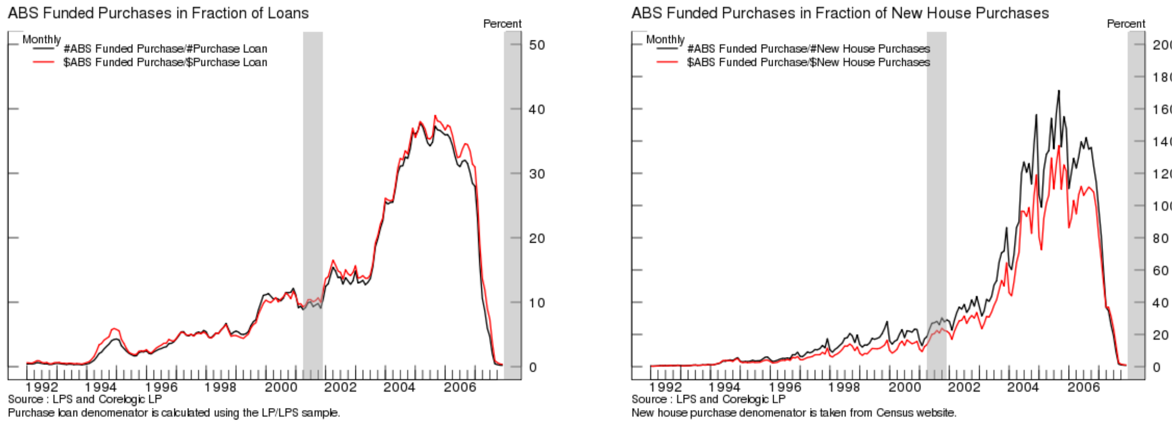

Figure 26: LP-ABS Pools Share of Mortgage Debt and Sales of Newly Constructed Houses

Default rates are an approximate measure of actual counterparty risk, whereas house prices represent the value of the collateral for a mortgage loan and, as a consequence, are also directly related to credit risk. The last consideration is particularly important because the historical price dynamics of the collateral asset gives an alternative measure of risk, which is independent, in part, of the credit rating of the borrower. An additional reason to consider house prices is the growing importance over time of the demand for housing of LP-ABS mortgagors. The importance of LP-ABS pools for the housing market can be gauged by looking at their evolution in relation to total new construction (Figure 25).

5.1 Delinquency

The hypothesis we would like to test is:

- H_0^3 : Does the price of LP-ABS evolve with delinquency rates?

The test of this hypothesis provides information about the co-evolution of mortgage conditions and delinquency rates, which is important for understanding the mutual relation between interest rates and defaults in this market. For every month, we compute the number of terminations that caused some loss to the lender[24] and normalize this number by the total number of terminations (excluding servicer changes and missing information). This variable captures the percentage of delinquencies in each mortgage pool class and is depicted in Figure 26. We are interested in assessing how the delinquency rate is linked to the time series of loading factors $\hat{\alpha}_1$ and $\hat{\alpha}_2$ of loan-to-value ratios and FICO scores. In Section 4, we noticed that loan-to-value ratios and FICO scores became more important over time and here we investigate whether this phenomenon is linked to delinquencies. Because the number of newly issued mortgages in LP-ABS collapsed during the crisis, we restrict our

[24]These terminations include a real estate owned sale, short payoff, payoff out of foreclosure, payoff out of bankruptcy and serious delinquency, liquidation to termination, and third-party sale.

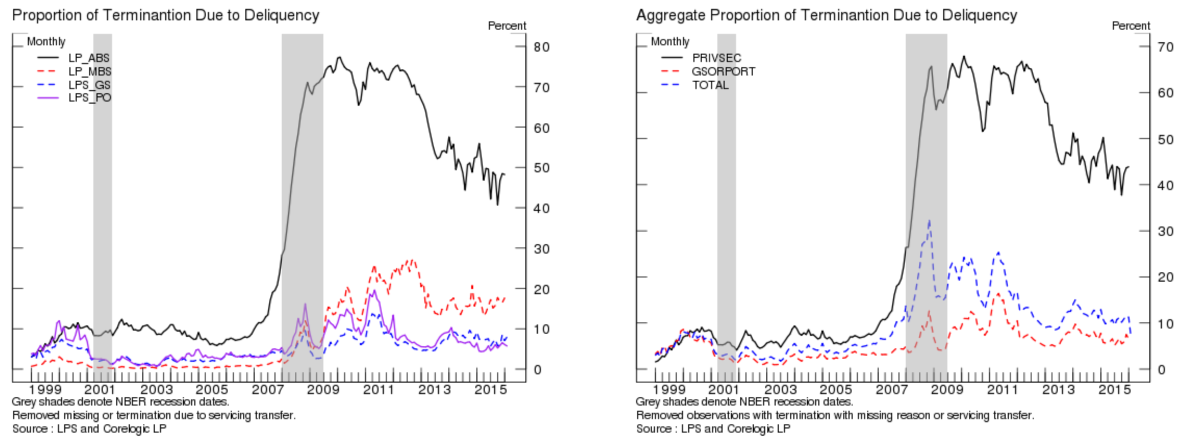

Figure 27: Delinquencies that Caused Losses to Lenders

analysis to the period from January 1992 to December 2006. (This observation also holds for the analysis in Section 5.2.)

For ABS, we run a cointegration analysis of delinquency and $\hat{\alpha}_{1,t}$ and $\hat{\alpha}_{2,t}$. Table 3 reports the Johansen cointegration rank test (trace) results (with deterministic trend). The first column indicates the number of cointegrating relations under the null hypothesis, the second column reports the eigenvalues, and the third column shows the 5 percent critical values followed by the p-values. These variables are not stationary, and we find that there are three cointegrated vectors. This result implies that $\hat{\alpha}_{1,t}$ and $\hat{\alpha}_{2,t}$ are cointegrated with delinquency (and between themselves), hence failing to reject H_0^3. The results are robust to the lag-length specification[25] and state that the pricing of LP-ABS mortgages evolved with delinquency rates: higher delinquency rates were accompanied by higher loading factors that captured credit worthiness of LP-ABS mortgagors. The results imply a co-evolution of the three variables. The evidence is important: it is possible that loading factors increased as a result of increasing delinquencies. Alternatively, increases in delinquencies and increasing loading factors might have been the result of the same underlying process: an increase in the risk profiles of borrowers. The present analysis of course can only generate this question, but does not allow us to provide an answer, which will require more research and a different framework.

The estimated parameters $\hat{\alpha}_1$ and $\hat{\alpha}_2$ for GSE, private MBS, and Portfolios are stationary, and they do not seem to be correlated with delinquencies over the sample period.

[25]We also run the maximum eigenvalue statistics and obtain similar results.

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value (5%)	Prob.
None	0.126	43.12	29.80	0.000
At most 1	0.108	23.94	15.49	0.002
At most 2	0.030	5.074	3.841	0.024
Unrestricted Cointegration Rank Test (Trace). Prob. refers to the MacKinnon-Haug-Michelis (1999) p-values.				

Table 2: Delinquency - Cointegration Tests

5.2 House prices

The last hypothesys we would like to test is:

- H_0^4: Is the pricing of PL-ABS linked to house price dynamics? Put differently, is the evolution of LP-ABS pricing economically important for the entire housing sector?

Figure 27 depicts two major house price indices. The first index is published by the U.S. Federal Housing Finance Agency and is known as HPI. The index is a monthly broad measure of the movement of single-family house prices, and is a weighted, repeat-sales index, meaning that it measures average price changes in repeat sales on the same properties in 363 metropolitan areas. This information is obtained by reviewing repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac since January 1975. As the index only includes houses with mortgages within the conforming amount limits, the index has a natural cap and does not account for jumbo mortgages.[26] The second major house price index is the Case-Shiller index, which is measured monthly and also tracks repeat house sales. The index adopts a weighted-repeat sales methodology and is able to adjust for the quality of the homes sold. We are interested in assessing how the two price indices are linked to the time series of loading factors $\hat{\alpha}_1$ and $\hat{\alpha}_2$ of loan-to-value ratios and FICO scores for LP-ABS mortgages.

Table 3 reports the results of the cointegration analysis for $\hat{\alpha}_{1,t}$ and $\hat{\alpha}_{2,t}$ for LP-ABS pools and the house price indices. The results indicate some evidence of a cointegrating relationship between the house price indices and $\hat{\alpha}_1$ and $\hat{\alpha}_2$. For the HPI index, the cointegrating relationship exists at a 15% significance level. Hence, the relationship between the time series of loading factors of loan-to-value ratios and FICO scores for ABS and the price indices is weaker than the one for delinquencies. The estimated parameters $\hat{\alpha}_1$ and $\hat{\alpha}_2$ for GSE, private MBS, and Portfolios are stationary and do not seem to be linked to house price indices. Also, in this case, we fail to reject H_0^4.

These results provide evidence of a co-evolution between house prices, loan-to-value ratios, and FICO scores for ABS pools, but do not explain the reasons for such links.

It is possible that the increase in risk associated with new borrowers profiles was the result of an increase in housing demand.

[26] The HPI was developed in conjunction with the former Office of Federal Housing Enterprise Oversight's (now FHFA) responsibilities as a regulator of Fannie Mae and Freddie Mac. It is used to measure the adequacy of their capital against the value of their assets, which are primarily home mortgages. On July 30, 2008, the Office of Federal Housing Enterprise Oversight became part of the new Federal Housing Finance Agency (FHFA). The index is now termed the FHFA HPI.

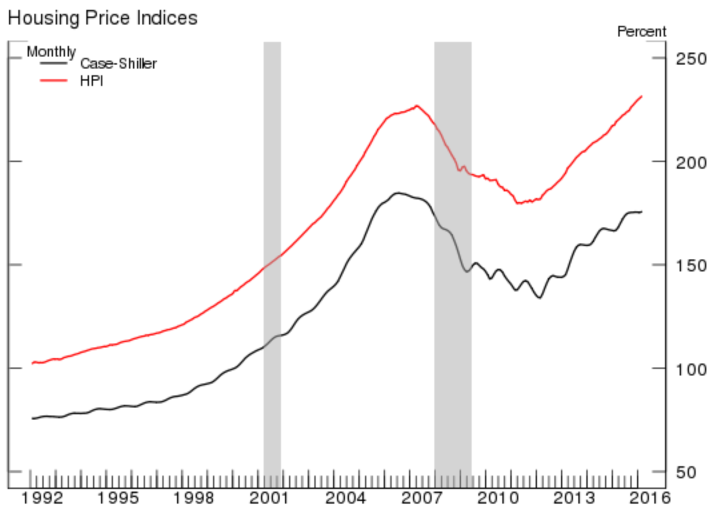

Figure 28: House Prices

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value (5%)	Prob.
	HPI			
None	0.052	20.51	24.28	0.139
At most 1	0.044	11.72	12.32	0.0628
At most 2	0.025	4.220	4.130	0.047
	Case-Shiller			
None	0.188	50.11	42.92	0.008
At most 1	0.176	27.60	25.87	0.030
At most 2	0.061	6.740	12.52	0.372

Unrestricted Cointegration Rank Test (Trace). Prob. refers to the MacKinnon-Haug-Michelis (1999) p-values.

Table 3: House Price Indices - Cointegration Tests

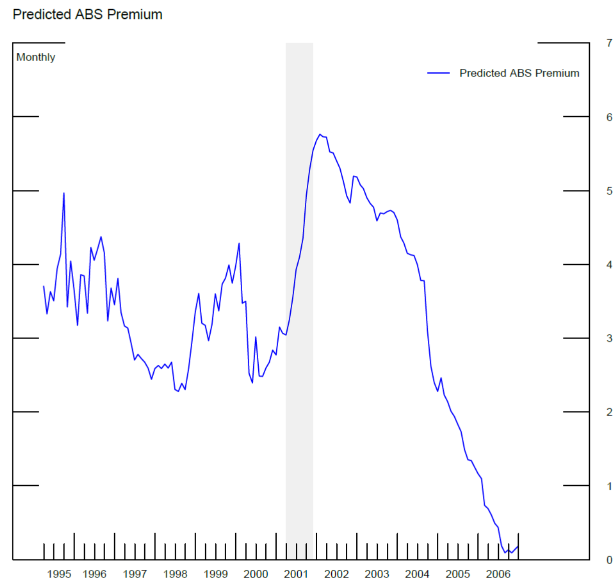

Figure 29: Predicted interest rate premium on a subprime loan

It is also possible that loading factors and house prices increased at the same time as a result of house price expectations, in the sense that house price increases (and the expectation that they would persist) became an important variable in the provision of credit to high-risk borrowers.

6 Discussion and Concluding Remarks

Figure 28 shows the fitted interest rate premium over a reference rate associated with a typical mortgage in a subprime pool using the estimated coefficients.[27] The premium displays no trend until the early 2000s, when it starts increasing for the successive two years, and then begins a rapid descent until the onset of the crisis. The important observation is that even though intermediaries adjusted the risk premium over time, see for example Figure 22 for the FICO score, overall the risk premium decreased monotonically after 2002. Coupled with the evidence on number of issuances in Figure 3, the pattern of subprime lending is consistent with a substitution, in the early 2000s, of "quantity for quality:" borrowers with safer profiles collectively borrowed increasing amounts until 2003, but then the number of issuances declined and was in part substituted by issuances of subprime loans (notice the amount of total mortgage lending continues increasing until 2009). The pattern in Figure 28 also indicates that decreasing interest rates on on larger loans supported progressively larger amounts of subprime borrowing. This finding is consistent with regional evidence (see Figure 13), which indicates that in the western region, where home prices increased faster, interest rates were lower than in other regions.

[27]Specifically, we take as an example a 15-year fixed-rate mortgage, a 0.8 loan to value ratio, a FICO score of 650, and a house value of \$168,000 in 2009 dollars.

In sum, we presented evidence that starting in the early 1990s, as interest rate volatility was dwindling, there was a clear shift toward credit risk, possibly aided by the potential of diffusing this risk through securitization. Our results indicate that intermediaries gradually but constantly adjusted the pricing of risky loans to account for credit risk. In the early 2000s, amounts borrowed through subprime loans increased rapidly, and increasing borrowed amounts commanded a substantial price discount.

These results raise several questions. First, it will be important to investigate whether the interest rate on risky mortgages was changing over time because the willingness of intermediaries to accept more credit risk was changing over time or because the market was learning about how to price a new class of loans. By comparison, no such dynamics are visible in the more traditional mortgage pools, where credit risk is limited. Second, results show that the evolution of loading factors on initial mortgage rates are cointegrated with delinquencies and, to a lesser extent, house prices for subprime pools, whereas, again, such co-evolution is not present for all other "classes" of mortgages, whether securitized or not. The important question is whether (and how) intermediaries were reacting to market conditions in setting contractual terms, or whether they were just relying to house price dynamics, so that in essence the borrower became less important over time than the collateral.

Finally, the time horizon of our analysis goes from 1992 to 2015. The reason for focusing on a long time horizon is the attempt of understanding when intermediaries allowed for an increase in credit risk in the mortgage market. The process of creation of mortgage pools works as a choice about the inherent credit risk profile of a group of loans. The selection and performance of LP-ABS pools indicate that there was an attempt to price credit risk soon after the market reached a relatively substantial size in the mid 1990s. Of course, there is evidence that, around 2003, a bubble phenomenon developed. A rich literature has emerged to study this aspect of the mortgage market, and our results are consistent with it. However, bubbles tend to emerge on a trend of real economic growth, and it would be reductive to think of the evolution of securitization only in light of the crisis. There is potentially a macroeconomic effect of the evolution of mortgage markets that spans a much longer period, and that is important to analyze as well.[28] Understanding the industrial organization of intermediation, regulatory framework, economic policy, and more generally the macroeconomic context in which the segmentation of mortgage pools emerged in the early 1990s and then grew so rapidly remains a very important research agenda.

[28]Some examples are Antinolfi and Brunetti (forthcoming) and Fuentes-Albero (2018).

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