The Effect of Large Investors on Asset Quality: Evidence from Subprime Mortgage Securities

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Working Paper 2014-4
April 2014

Abstract: This paper examines how the government-sponsored enterprises (GSEs) Fannie Mae and Freddie Mac, the largest investors in subprime private-label mortgage-backed securities (PLS), influenced the risk characteristics and prices of the deals in which they participated. To identify the causal effect of the GSEs, we use the fact that PLS deals in which Fannie Mae and Freddie Mac purchased securities included separate mortgage pools: one specifically created for the GSEs and one or more others directed at other triple-A investors. Using within-deal variation, we find that the pools bought by Fannie Mae and Freddie Mac had similar ex-ante risk characteristics but performed much better ex-post relative to other mortgage pools in the same deals. These effects were concentrated in low-documentation loans and in issuers that were highly dependent on Fannie Mae and Freddie Mac. Our results extend the importance of disciplining effects of large claimholders beyond information-sensitive securities, such as equities and bank debt, to information-insensitive arm's-length debt.

JEL classification: G17, G21, G23

Key words: mortgage default, GSEs, securitization, private information

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For helpful comments and discussions, the authors thank Brent Ambrose, Andra Ghent, Laurie Goodman, Robert Hansen, Peter Niculescu, Larry Wall, and Paul Willen as well as seminar participants at the Kellogg Junior Finance Conference. They also thank Neil Desai for outstanding research assistance. Frame also thanks the Federal Reserve Bank of Richmond for financial support. This paper was previously circulated under the title "The Role of Blockholders in Debt Markets: Fannie Mae, Freddie Mac, and Subprime MBS." The views expressed here are the authors' and not necessarily those of the Federal Reserve Bank of Atlanta or the Federal Reserve System. Any remaining errors are the authors' responsibility.

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1. Introduction

Informational frictions and incentive conflicts between issuers of financial claims and the owners of those claims are central topics in financial economics. Previous work has argued that the presence of large concentrated claimholders can be a powerful mechanism for disciplining issuing managers, as in the case of equity blockholders who can directly intervene in the management of firms and indirectly exert influence through the threat of exit; or the case of banks who actively screen and monitor borrowers.[1] This paper explores the disciplining effect of large investors in arms-length debt on issuer behavior. Specifically, we study the role played by two government-sponsored enterprises (GSEs), Fannie Mae and Freddie Mac, as the largest investors in subprime private-label mortgage-backed securities (PLS) during the recent housing boom.[2] Fannie Mae and Freddie Mac together purchased roughly 30 percent of all subprime PLS volume (all rated triple-A) issued in 2003-2007, making them by far the largest single investors in this asset class.

We identify the causal effect of large investors in mitigating agency conflicts in securitized arms-length debt by exploiting a unique feature of the PLS market. By law, Fannie Mae and Freddie Mac are only allowed to acquire mortgages below the conforming loan limit. During the mid-2000s, this restriction prompted the creation of separate loan pools within many PLS deals made up exclusively of conforming mortgages, while other pools in the same deals had a mix of conforming and non-conforming loans. This design allows us to isolate the securities that were purchased by the GSEs and to implement an identification strategy that compares the risk characteristics of securities bought by the GSEs with those aimed at other investors within the same deals and rating class. Our analysis examines not only *ex-ante* observable risk characteristics at the time of deal issuance (as in Agarwal, Chang, and Yavas 2012 or Ambrose, LaCour-Little, and Sanders 2005), but also the *ex-post* performance of the underlying loans. By doing so, we are able to test

[1] See Shleifer and Vishny (1986), Burkart, Gromb, and Panunzi (1997), Brav, Jiang, Partnoy and Thomas (2008), and Morse (2013) for evidence of blockholder intervention in the management of firms; and Edmans (2009), McCahery, Sautner, and Starks (2008) and Parrino, Sias, and Starks (2003) on governance through exit. See Bhattacharaya and Thakor (1993) and Boot (2000) for surveys on the extensive literature on bank screening and monitoring; see Roberts and Sufi (2009) for more recent evidence.

[2] In addition to investing in PLS and other residential mortgage-related assets, Fannie Mae and Freddie Mac play a central role in the U.S. mortgage market through their "credit guarantee" businesses, whereby mortgage originators exchange pools of loans for securities that represent an interest in the same pool; and the GSEs agree to ensure timely payment of principal and interest on the securities in exchange for a monthly insurance premium ("guarantee fee"). This paper focuses solely on the GSEs' participation in the PLS market.

whether PLS issuers used private information about loan quality when sorting loans across GSE and non-GSE pools.[3]

We find that Fannie Mae and Freddie Mac purchased subprime PLS in deals that were ex-ante observably riskier, but that loans in GSE pools and non-GSE pools *within the same deals* have very similar ex-ante predicted default rates. Thus, it appears that the GSEs were seeking to invest (or were offered securities) in the riskiest subprime PLS deals during the run-up to the housing boom; but that in terms of observable risk characteristics there were no meaningful differences relative to other investors in the same deals.

When studying ex-post loan performance, a more subtle story emerges. Conditioning only on the year of issuance, loans in GSE pools performed worse on average compared to loans in non-GSE pools, consistent with the ex-ante risk results. However, the pattern reverses when we consider only within-deal variation in default rates, as we find that loans backing GSE pools performed significantly *better*. This superior within-deal performance of loans in GSE pools is robust to controlling for an extensive set of observable underwriting characteristics, which suggests an explanation involving within-deal unobserved heterogeneity. The fact that individual deals were split into GSE and non-GSE pools of loans allows us to exclude alternative explanations for our findings related to unobserved heterogeneity across PLS deals, including unobserved heterogeneity at the level of the issuer, originator, and servicer, since these entities were all shared by loans in the same deal. Additionally, the split between conforming and non-conforming pools of loans applied exclusively to the triple-A securities in these deals, while more junior tranches received cash flows from both pools and provided credit support for all senior securities (GSE and non-GSE triple-A alike). This removes any concern that differences in performance could be driven by differential levels of credit support or risk retention. We also show that results are unchanged when we include controls for whether loans are eligible for the GSEs' "underserved areas" housing goal, and when we exclude jumbo loans in the non-GSE pools from the estimation.

[3] Issuers are sometimes referred to as sponsors. The primary responsibility of an issuer is to create the mortgage pool(s) by acquiring loans from originators and then issuing securities backed by the pool cash flows. As discussed below, the issuer and originator are sometimes the same institution or affiliated institutions, but in many cases they are unaffiliated entities.

Two explanations are potentially consistent with our finding regarding the *ex-post* performance of GSE pools. First, Fannie Mae and Freddie Mac may have had better risk assessment models that led them to demand a different composition of loans than what was in non-GSE pools in the same deals. This seems plausible given the GSEs' centrality to the U.S. housing finance system and the breadth and depth of data they collected over time. A second explanation is that issuers may have used private information to choose safer mortgages for GSE pools because of reputational concerns and the importance of the GSEs as major investors in the deals, or because the GSEs might be more likely than other investors to trigger representation and warranties clauses.

Consistent with a private information story, we show that the difference in ex-post performance between loans in GSE and non-GSE pools primarily comes from low documentation loans, where soft information has been found to be especially important (Jiang Nelson Vytlacil, 2014a, 2014b; Keys, Seru, and Vig, 2012; Begley and Purnanandum 2013; Saengchote, 2013). The difference in default rates between GSE and non-GSE pools up to the end of 2008 is 3.9 percentage points, whereas the difference for full documentation loans is only 0.7 percentage points. This suggests that issuer sorting of mortgages across pools within a deal was the source of the higher quality mortgages in the GSE pools (i.e., a supply-side effect).

In order to further pin down the supply-side mechanism driving these differences in performance, we construct a measure of issuer dependency on the GSEs over time. To do this, we use information on the identity of subprime PLS issuers and compute the fraction of previous deals for each issuer that was designed for GSE participation and in which Fannie Mae or Freddie Mac purchased securities. The rationale for this measure is that issuers that have very frequent interactions with Fannie Mae and Freddie Mac are more likely to want to maintain good standing with the two GSEs, as they are more likely to be dependent on them for future business. We find that deals arranged by issuers that rely heavily on Fannie Mae and Freddie Mac as investors show significantly larger differences between GSE and non-GSE pool performance. The (within-deal) difference in overall ex-post loan performance across GSE and non-GSE pools is fully explained by the difference in low documentation loans and by the fraction of previous deals designed for GSE participation.

Finally, we find that the superior performance of low documentation loans in GSE pools and of loans securitized by issuers that were highly dependent on the GSEs is especially strong in deals where the issuer and the originator of the mortgages were affiliated. This again implies a supply-side interpretation by which issuers that were highly dependent on investment by Fannie Mae and Freddie Mac included unobservably higher quality loans in GSE pools in order to maintain a good reputation and their relationship. Consistent with the results related to issuer dependence on the GSEs, we find that the yields at origination of GSE pools are significantly higher than those on non-GSE pools, and that this difference is also fully explained by the frequency of previous interactions between issuers and the GSEs.

Our findings have important implications for understanding the extent to which large claimholders help to mitigate agency conflicts. The results suggest that even in the case of information- insensitive arm's length debt (in this case, triple-A rated securitized debt), where investors ostensibly have little incentive to learn about underlying asset quality, the presence of large claimholders can lead to significantly better performing securities.[4] This may be due to reputational concerns on the part of issuers (that may require capital in the future), or due to large investors' higher likelihood of enforcing certain contractual clauses, as they are more likely to internalize both the benefits and costs of ex-post monitoring.

This paper builds on a large literature that highlights the fact that the originate-to-distribute model of mortgage finance can give rise to a number of conflicts of interest (Ashcraft and Schuermann, 2008). Several studies have analyzed whether securitization gives rise to moral hazard in terms of originator screening incentives (Keys, Mukherjee, Seru, and Vig, 2010; Purnanandam, 2011; Keys, Seru and Vig, 2012; Bubb and Kaufman, 2014), as well as the observable risk characteristics of securitized loans and portfolio loans (Ambrose et al, 2005; Krainer and Laderman, 2009; Elul, 2011; Agarwal, Chang and Yavas, 2012; and Jiang, Nelson, and Vytlacil 2014b). Importantly, investors understand the misaligned incentives associated with securitization, and protect themselves from these frictions through contracting features (e.g., by requiring representations and warranties about loan quality), security design features (e.g., requiring higher subordination levels) or required risk premia (Begley and Purnanandum 2013). Issuers of securities, on the

[4] See, for example, Boot and Thakor (1993) for a discussion of the rationale for partitioning cash flows to create information-insensitive senior claims and information-sensitive junior claims.

other hand, have incentives to signal higher loan quality through risk retention (e.g., DeMarzo, 2005), vertical integration with originators (Demiroglu and James, 2013), and ultimately through reputation-building (Albertazzi, Eramo, Gambacorta, and Salleo, 2014). This paper investigates a related, but unexplored, role of concentrated claims of securities as another way of mitigating information frictions in this market.

The paper is organized as follows: Section 2 discusses models of differentially informed investors in securitized debt and which investors were known participants in this market. Section 3 describes the data and the empirical strategy. Section 4 presents the results and Section 5 concludes.

2. PLS Deal Structure and Identification Strategy

In general, it is difficult to associate individual investors with specific securities, especially in the context of arms-length debt issues. Some PLS deals, however, were specifically structured in a way to allow Fannie Mae and Freddie Mac to purchase triple-A-rated securities while meeting their requirement of only purchasing mortgages below the conforming loan limit (CLL).[5] This was done by using more than one collateral pool: one with only "conforming" mortgages and one or more others that included a mix of "conforming" and "non-conforming" loans. PLS issuers then created triple-A securities intended for the GSEs and other triple-A securities for all other investors. Remaining cash-flows from all pools in a deal accrued to the junior tranches (double-A and below). Figure 1 illustrates how a typical subprime PLS deal with GSE participation was structured.

There are a couple of potential reasons why Fannie Mae and Freddie Mac may have been interested in investing so heavily in the subprime PLS market. First, the GSEs benefitted from an implicit federal guarantee of their obligations that resulted in a significant funding advantage and little market discipline (e.g., Greenspan, 2005). Hence, Fannie Mae and Freddie Mac faced strong incentives to grow and acquire eligible mortgage-related assets with yields above their cost of funding. Second, mortgages funded through PLS deals

[5] The CLL for most single-family homes between 2006 and 2013 was $417,000. Single-family homes in certain high cost areas have higher limits. We refer the reader to the appendix for a list of single-family conforming loan limits during our sample period.

could be counted against the GSEs' affordable housing goals (in proportion to their investment).[6] Analysis by the U.S. Department of Housing and Urban Development illustrates the goal-richness of subprime PLS acquired by Fannie Mae and Freddie Mac in 2004 and 2005 (Bunce, 2007).

Based on this institutional feature of the subprime PLS market, we design a simple algorithm to identify mortgage pools that backed securities that were eligible to be purchased by either Fannie Mae or Freddie Mac between 2003 and 2007. We classify a pool as being a "GSE pool" if at least 99% of the loans in the pool are below the CLL at the time that securities in the deal are issued to investors.[7] Crucially for our identification strategy, the only reason why an issuer would structure a deal in this way would be to attract the GSEs as investors, as no other investors in the market are constrained by the CLL. In Section 3.2, we show that we are able to closely match the aggregate amount of purchases by the GSEs; and in the appendix we provide additional details about the algorithm, as well as perform a validation exercise that shows that we likely capture most of the relevant securities purchased by the GSEs. For example, of the 478 subprime PLS securities that were included in the series of lawsuits brought by the Federal Housing Finance Agency (FHFA) in 2011 alleging fraudulent marketing and sales materials for GSE-purchased PLS, 476 are captured by our algorithm as being "GSE" securities, while the other triple-A securities in those same deals are classified as "non-GSE".[8] This gives us confidence that our algorithm is not a significant source of type I error. The evidence using the lawsuit securities and the aggregate amount of purchases also indicates that the GSEs purchased most (if not all) of the pools that were created with these characteristics (i.e., those made up exclusively of conforming loans). In particular, if the GSEs were not the sole buyers of these pools, we would likely miss the total amounts purchased by a substantial amount, which is not the case.

[6] As Robert Levin, the former chief business officer of Fannie Mae, told the Federal Crisis Inquiry Commission, buying private-label mortgage–backed securities "was a moneymaking activity—it was all positive economics. . . . [T]here was no trade-off [between making money and hitting goals], it was a very broad-brushed effort" that could be characterized as "win-win-win: money, goals, and share", (FCIC, 2011). Ghent et al (2013) analyze a random sample of 100 prospectus supplements and argue that the affordable housing goals are unlikely to have strongly influenced those purchases.

[7] We also add a condition that less than 75% of loans in the pool are second liens (although the results are not sensitive to this additional condition). Since the vast majority of second lien mortgages have outstanding balances well below the conforming loan limit, the CLL tells us very little about whether or not the GSEs purchased securities collateralized by those loan pools.

[8] Details on the lawsuits are available on the FHFA website at fhfa.gov/webfiles/22599/PLSLitigation_final_090211.pdf

The buyers of triple-A securities with claims on the "non-GSE" pools are much more dispersed. According to Greenlaw, Hatzius, Kashyap, and Shin (2008, p.35), there were seven main groups of non-GSE investors in subprime PLS before 2007: Commercial banks, investment banks, insurance companies, hedge funds, finance companies, mutual funds, and pension funds. For various regulatory reasons, U.S. and foreign commercial banks, investment banks, and insurance companies were the most likely investors (on and off-balance sheet) in non-GSE triple-A subprime securities.

2.1 Empirical Specification

The analysis below focuses on three sets of issues for GSE and non-GSE mortgage pools. First, we consider the observable risk characteristics of the loans, summarized by their ex-ante default probabilities at issuance (we describe the method for obtaining ex-ante default probabilities in more detail in the next section). Second, we look at the ex-post performance of the mortgages, to evaluate whether there is evidence of the use of private information (by the GSEs or by the securities issuers) that was not observable in the initial mortgage pool characteristics. Finally, we analyze the yield spreads at issuance for evidence on preferential treatment of the GSEs relative to other investors.

Our main identification strategy relies on comparing the observable risk characteristics and ex-post performance of GSE and non-GSE mortgage pools *in the same deal*. This allows us to exclude all deal-level unobservable characteristics as drivers of our results, such as issuer, originator, and servicer, since these entities were all shared by loans in the same deal. This is a unique setting, in that we can isolate the impact of a specific investor (or class of investors) on the quality of the underlying assets and on the behavior of issuers. In fact, in any other corporate finance setting (equities, loans or corporate bonds) different investors either hold the same securities issued at the same point in time, or securities differ either in terms of the timing of issuance or in terms of security characteristics, or usually both.

Specifically, we estimate loan-level regressions of the form

$$LHS_{ijz} = \alpha + \beta_1 X_{ijz} + \beta_2 GSE_{iz} + \eta_j + \varepsilon_{ijz} \tag{1}$$

where *z* identifies each mortgage in pool *i* within deal *j*. LHS_{ijz} is a measure of either mortgage delinquency (described in more detail in the next section) or of the yield spreads at the time of security issuance . X_{ijz} is a vector of mortgage-level control variables that includes all relevant observable borrower and loan characteristics, and GSE_{iz} is an indicator variable that is equal to 1 for mortgages in GSE pools and 0 otherwise. The term η_j represents deal-level fixed effects. Note that by including deal-level fixed effects, η_j, we are accounting for very fine time fixed effects (effectively one fixed effect for each date that we observe an issuance).

3. Data and Summary Statistics

3.1 Data Sources

The data used in this paper comes from two main sources. All loan-level data comes from CoreLogic's private label securities database, which covers virtually the entire PLS market.[9] This dataset contains information on the underwriting characteristics of the loans underlying the mortgage-backed securities at origination (borrower credit score, first-lien and combined LTV, term of the loan, balance, documentation status, original interest rate, and indicators for adjustable and fixed-rate loans, interest-only loans, negatively amortizing loans, occupancy status and property type) and the performance of the loans from the month of origination through 2012. Importantly, this dataset includes an identifier for the mortgage pool that each loan belongs to, which allows us to construct pool-level variables using individual loan data (as opposed to datasets that just include the deal to which a loan belongs, which does not allow for the distinction between GSE and non-GSE mortgage pools that we use in this paper). In addition, the dataset contains security identifiers (CUSIPs) and deal identifiers.

The CoreLogic raw data sample includes 13,189,213 mortgages that backed subprime PLS issued between 2000 and 2007 (we exclude Alt-A and other PLS issues). We drop loans that are not first or second

[9] According to CoreLogic's website, the dataset contains information on mortgages that make up over 97 percent of outstanding non-agency MBS pool balances (http://www.corelogic.com/solutions/data-resources-for-capital-markets.aspx#rmbs).

liens (22,395 loans), loans that were seasoned more than 12 months at the time of issuance (813,901 loans), and loans originated in the U.S. territories of Puerto Rico and the Virgin Islands (126 loans).[10] This leaves us with 12,352,791 loans in 3,987 mortgage pools that collateralized 2,161 subprime deals issued between 2000 and 2007. In most of the empirical analysis we restrict attention to loans backing deals issued between 2003 and 2007 so that the majority of securities are not paid off (or close to being paid off) by the third quarter of 2007 when the crisis hits.

Additional information on the attributes of residential mortgage-backed securities was hand-collected from Bloomberg. The data fields include all of the security identifiers (including CUSIP and ticker), the issuer name, the date of issuance, the identification of the loan pool that the security has claims on, the spread at origination, and the weighted average life as advertised in the prospectus. The dataset we obtain from Bloomberg covers over 90 percent of all subprime PLS issued in the U.S. between 2000 and 2007. We are able to combine the two datasets by merging on individual security CUSIPs. Given that Fannie Mae and Freddie Mac only purchased triple-A PLS, we focus exclusively on the highest rated tranches.

In order to determine whether a loan is likely to be eligible to meet the GSEs' affordable housing goals, we match tract-level underserved areas goals (UAG) data obtained from the FHFA to the zip code associated with each mortgage using a population-weighted bridge provided by the Missouri Census Data Center. We use 1990 tract definitions for tract data up to 2002, and 2000 tract definitions for the later years.[11]

Finally, we obtain monthly unemployment rates at the county-level from the Bureau of Labor Statistics and monthly county-level house price indices from CoreLogic.

[10] We eliminate seasoned loans to avoid potential survivorship bias. More than 90 percent of the loans in the CoreLogic database were less than 12 months old at the time of securitization. Other studies that use similar datasets have adopted similar restrictions.

[11] A census tract in a metropolitan area is classified as an underserved area if the tract's median income is no greater than 90 percent of median income for the metropolitan area; or if minority households comprise at least 30 percent of the tract's population and tract median income is no greater than 120 percent of area median income. A similar definition, based on counties, is employed for nonmetropolitan areas.

3.2 Summary Statistics

Table 1 displays the aggregate dollar amount of subprime PLS issued each year over the period 2000—2008 (column 1) obtained from Inside Mortgage Finance's 2011 Mortgage Market Statistical Annual. The table shows the rapid growth in the market that took place during the housing boom and the steep decline that occurred at the onset of the financial crisis. In 2000, a little more than $52 billion subprime PLS was issued. Issuance peaked at $465 billion in 2005, remained roughly constant in 2006, and then dropped precipitously in 2007 to just over $200 billion. Since 2007 the subprime PLS market has virtually disappeared.

Unfortunately, there is no publicly available information on the exact dollar amount of subprime PLS purchased by Fannie Mae and Freddie Mac over the entire sample period. We were able to obtain this information for 2006—2008 from the FHFA's 2011 Annual Report to Congress, which we display in the second column of the table. But prior to 2006, the report does not break out PLS purchases by type of security (subprime, alt-a, prime) for Freddie Mac. In the third column of Table 1, we show estimates of the annual amount of subprime PLS purchased by Fannie Mae and Freddie Mac based on our algorithm. In order to obtain these totals, we sum over all triple-A securities we classify as being eligible for GSE purchase and that are included in Bloomberg. The numbers that we obtain for 2006—2008 are very close to the FHFA figures, which suggests that our algorithm is truly identifying mortgage pools backing subprime PLS purchased by the GSEs. The last column of the table displays the GSEs' combined subprime PLS market shares based on aggregate amounts derived from our algorithm.[12] In 2001 Fannie Mae and Freddie Mac purchased less than four percent of total subprime PLS issued, but in 2004 they bought almost 40 percent. Their market share of purchases fell slightly after 2004, but still remained quite high at around 25 percent through 2007.

[12] Note that the GSEs' market share of *triple-A* subprime PLS is higher than the percentages listed in the table. Since the triple-A tranches comprised about 80 percent of the typical subprime PLS deal, to obtain a rough estimate of the total amount of triple-A subprime PLS issued over the sample period, we would have to reduce the numbers in column 1 by 20 percent. This suggests that the GSEs' market share of triple-A subprime PLS was about 25 percent higher than the percentages listed in Table 1, so that in 2004 they purchased approximately 50 percent of all triple-A subprime PLS issued.

Table 2 shows detailed, loan-level summary statistics broken down by mortgages in GSE versus non-GSE pools. The top panel of the table shows information on the distributions of the continuous variables that we include in our mortgage performance regressions. There are some notable differences between GSE and non-GSE mortgage pools. For example, while the FICO distributions are both lower than those in the overall U.S. population, reflecting the fact that many subprime mortgage borrowers have poor credit histories, the distribution of loans in GSE pools is significantly lower than the distribution of loans in non-GSE pools (26 points lower on average). Average loan size appears to be similar for both pool types, although this masks important differences across the distributions. The distribution of loan size is much more dispersed in the non-GSE pools, as the top of the distribution is significantly higher due to the presence of non-conforming (jumbo) loans, which are not included in the GSE pools. The bottom of the non-GSE pool loan size distribution is also significantly lower (e.g., tenth percentile is $30,000 compared to almost $60,000 in the GSE pools). The distribution of cumulative loan-to-value ratios is significantly lower in the GSE pools (the median is about seven percentage points lower and the average is about four points lower), while the distribution of interest rates (at the time of origination) in the GSE pools is also significantly lower than the distribution in non-GSE pools (the median is approximately 60 bps lower and the average is almost 70 bps lower). Another interesting difference between the two pool types can be seen in the distribution of mortgage terms. Virtually all loans in GSE pools have 30-year maturities, while more than 25 percent of the loans in non-GSE pools have maturities less than 20 years. Loans in GSE pools were originated in counties with initially higher unemployment rates, but with slower growth in unemployment rates over the entire sample period. GSE pools are comprised of loans originated in counties in which house prices declined less on average over the crisis period.[13] The last line of the top panel of Table 2 shows that, on average, 49.4 percent of the mortgages in non-GSE pools were secured by properties located in areas identified as "underserved" for purposes of the GSEs' housing goals, whereas 52.4 percent of mortgages in GSE pools qualified towards the underserved areas goal. This difference is small, consistent with the affordable housing goals not having

[13] Loans in GSE pools were also in areas with slightly higher house-price appreciation over the 12 months preceding the date of issuance. This fact, combined with the observation that loans in GSE pools were in areas with higher unemployment, suggests that Fannie Mae and Freddie Mac may have used the these mortgage- backed securities to assist in meeting their affordable housing goals.

been a major driver of loan sorting for GSE and non-GSE pools.[14] See Ghent, Hernandez-Murillo, and Owyang (2013) for an analysis of the effect of the GSE housing goals on the PLS market.[15]

The bottom panel of Table 2 displays averages of the dichotomous variables that we include in our mortgage performance regressions also broken down by GSE and non-GSE pools. The most striking difference between the pool types in the panel is the difference in the share of adjustable-rate mortgages. Adjustable-rate loans account for 74 percent of the loans in GSE pools, compared to only 49 percent in non-GSE pools.[16] The GSE pools are also characterized by lower fractions of low documentation mortgages, interest-only loans, and loans with balloon payments at the time of maturity. A higher fraction of loans in GSE pools contained prepayment penalties. Loans in GSE pools were also much less likely to be purchase-money mortgages and much more likely to be cash-out refinances.

Finally, the lower part of the panel displays unconditional average default rates for mortgages in both GSE and non-GSE pools. We assume that a mortgage is in default if the borrower is at least two payments behind (60+ days delinquent).[17] Ex-ante default probabilities are calculated from a set of models that use only information before the issuance date of the corresponding deal. We calculate these for horizons of 12 months, 24 months, and 36 months, and describe the details of the empirical models in the next section. Ex-post default rates are calculated directly from the CoreLogic database using information on loan performance from the time of origination. We report ex-post default rates through the end of 2008, 2010, and 2012 (the end of our Corelogic data sample). It is clear from the table that ex-ante default probabilities associated with

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[14] There may be a variety of explanations for this finding. First, we are studying subprime loans which tend to be made to borrowers with weak credit, low down-payments, and/or moderate income. Second, the housing goals would be based on the proportion of the loan funded by the GSEs. So, if there were two triple-A securities (GSE and non-GSE) of equal size that accounted for 80 percent of the deal's capital structure, the GSEs would only receive housing goal credit of 0.4 per eligible mortgage. Finally, the GSEs' always met the underserved area goal by a wider margin than the other two housing goals.

[15] Other studies have examined the effect of the underserved area housing goals on the GSEs' credit guarantee businesses (Ambrose and Thibodeau 2004; Bhutta 2012).

[16] Virtually all adjustable-rate mortgages in subprime PLS pools were what the industry refers to as "hybrid-ARMs." These loans were typically characterized by a fixed interest rate for 2--3 years at which point the rate would reset to an adjustable-rate that was indexed to a market rate (typically the 6-month LIBOR).

[17] This is conventional in the literature and includes properties that are in the foreclosure process and bank-owned owned (REO). In the appendix we provide results for our main empirical specifications where we define default to be borrowers that are 90+ days delinquent rather than 60+ days delinquent.

GSE pools are higher than those associated with non-GSE pools. The average two-year predicted default probability is two percentage points higher for loans in GSE pools, while the average three-year predicted default probability is more than three percentage points higher. In contrast, average ex-post default rates associated with GSE pools are significantly *lower* than those associated with non-GSE pools (by approximately five percentage points for the 2010 and 2012 horizons). This pattern of higher ex-ante risk and lower ex-post risk associated with loans in GSE pools is one of the key empirical findings in the paper. As we show in the discussion of the regression results presented below, this pattern persists even when controlling for an exhaustive set of covariates, including deal-level fixed effects.

Table 3 displays summary statistics (from Bloomberg) for the triple-A securities that are collateralized by the loans in the CoreLogic database broken down by whether the securities are derived from GSE or non-GSE mortgage pools. For each year, the table shows the number of associated mortgage pools, the average size of the mortgage pools, the spread between the average coupon of the triple-A securities and the one-month LIBOR, and the weighted average expected life of the associated triple-A tranches using the sizes of each individual security as the weights. The last column in the table displays the differences in the summary statistics between the pool types and whether those differences are statistically different from zero. The average pool size is between $19 and $20 million for both GSE and non-GSE pools in each year of our sample. The average spread over the LIBOR rate on GSE triple-A securities was between two and six basis points higher than the average spread on the non-GSE triple-A securities in each year of our sample. Finally, the GSE and non-GSE pools have similar weighted average lives, where the life of each security is taken from the prospectus and is based on predicted prepayment behavior on the part of the borrowers.

3.3 Model of Ex-ante Default Probabilities

In order to determine whether Fannie Mae and Freddie Mac purchased triple-A subprime PLS backed by observably riskier loans than other investors, we construct ex-ante default probabilities for each of the subprime mortgages in our sample. The ex-ante default probability variable is constructed each quarter using all of the data available in CoreLogic and is done in the spirit of the model in Ashcraft, Goldsmith-Pinkham and Vickery (2010). The idea is to forecast subprime mortgage default using only performance information available at the time of issuance (i.e., from the past performance of loans in previous deals). For each loan in the sample, we determine the quarter in which the corresponding deal was issued. We then take all loans in pools that collateralized deals issued between 24 months and 12 months *before* that quarter, and track those mortgages over the subsequent 12 months, creating indicator variables that take values of one if the mortgage is 60 days delinquent, 90 days delinquent, in foreclosure or in REO (or any other liquidation status following foreclosure) at any point during the 12 month period, respectively.[18] We perform the same exercise for horizons of 24 and 36 months.[19] We then estimate three different discrete choice models using variables that are available in CoreLogic to predict the default variable: a linear probability model, a logistic regression, and a multinomial logistic regression that specifically accounts for the fact that mortgages can prepay as well as default. The regressions are estimated each quarter over the period 2003—2007 and include most of the variables in Table 2 as well as state fixed effects.[20] Specifically, the variables we use in the model are the combined loan-to-value ratio, the logarithm of the original loan balance, the original interest rate, the credit score, the original size of the loan, the original term, the number of months between origination and issuance (seasoning), indicator variables for low documentation, interest-only loans, first lien loan, negative amortization, residence status (owner-occupied, investor/vacation home), loan purpose (cash-out refinance, other refinance, purchase), property type (condominium, multi-family, single-family), and the existence of a prepayment penalty. We also include the level of the unemployment rate and the level of the house price index at the time of issuance, as well as the 12-month trailing house price appreciation at the county level and the 12-month trailing unemployment rate at the county level. Additional indicator variables are included whenever there are missing observations in any of the controls.

[18] For the 12-month predicted default variable we take loans that were originated between 24 months and 12 months before that quarter, so that we have a full 12 months of history for each loan.

[19] For the 24-month horizon we take all loans that collateralized deals issued between 36 months and 24 months before the quarter of interest and track those mortgages over the subsequent 24 months, while for the 36-month horizon we take all loans in deals issued between 48 and 36 months before the quarter of interest and track those loans over the subsequent 36 months.

[20] We also tried more disaggregated fixed effects at the county level, but this change had a trivial impact on the predicted default probabilities. Finally, we also tried estimating separate models for jumbo loans, second lien loans, and adjustable-rate loans. These variations, which are displayed in the appendix, also had little impact on the results.

We take the estimated coefficients from these loan-level credit risk models and apply them to the characteristics of the loans in deals issued in the current quarter to create the 12-month, 24-month, and 36-month loan-level default probabilities. This means that ex-ante default probabilities are created using only information available at the time in which the deals are issued.[21] The average ex-ante default probabilities are shown in the bottom panel of Table 2. According to the 24-month and 36-month measures, GSE pools were slightly riskier than the non-GSE pools. The correlation between the 24-month default probability (from the linear probability model) and the actual default rate experienced by the pools of loans through 2012:Q4 is 0.23 (not shown).

4. GSE Investment, Subprime PLS Collateral Characteristics and Mortgage Performance

4.1 Ex-ante Risk Characteristics

The first part of our analysis considers the riskiness of the mortgages underlying GSE and non–GSE pools based on the loan characteristics at the time that the deals were originated. This analysis tells us two things. First, it addresses the question of whether the GSEs chose to invest in more or less risky deals based on the observable characteristics of the underlying mortgages. Second, we can also assess whether, *within the same deals*, Fannie Mae and Freddie Mac were given safer pools at the time of issuance relative to other investors.

Table 4 shows the results from loan-level regressions of the 12-month, 24-month and 36-month ex-ante default probabilities on a dummy variable that is equal to one for GSE pools identified by our algorithm. As discussed above, we use three alternative models to compute the default probabilities at the loan level. Panels A, B, and C correspond to the linear probability model, logit model, and multinomial logit model, respectively, as the underlying models for constructing ex-ante default probabilities. In each of the panels and

[21] Most mortgages are seasoned only one or two months so that the month of origination closely corresponds to the month in which the deal is issued. In addition we eliminate mortgages seasoned more than 12 months, so the two months are never more than one year apart. We have estimated the credit risk models relative to the month of origination rather than issuance. The results are not significantly affected by this change.

for each of the horizons, we show OLS regressions both with and without deal fixed effects.[22] The specification without deal fixed effects captures both within-deal differences between GSE and non-GSE pools, as well as differences across deals (i.e. whether deals that include a GSE pool are more or less risky within the universe of subprime PLS).

The results in Table 4 show that without deal fixed effects, loans underlying GSE pools were riskier in terms of observable characteristics. This finding is robust across all horizons and model specifications. The point estimates range from 35 to 53 basis points higher ex-ante default probabilities at a one-year horizon all the way up to 250 to 320 basis points higher probabilities at a three-year horizon. However, once we include deal fixed effects, loans in GSE pools either do not look riskier or the magnitude of the difference in predicted default probabilities becomes significantly smaller. The linear probability model shows statistically insignificant and economically very small differences in the *ex-ante* riskiness of loans in GSE pools versus those in pools directed at other investors, whereas the logit and multinomial logit models suggest that there is a higher ex-ante default probability of 60-100 basis points at a two or three-year horizon (although there is no difference at the 12-month horizon), which is substantially smaller than the specifications without fixed effects.

Taken together, the results in Table 4 tell a very clear story: the GSEs purchased securities in deals that were observably riskier than other subprime PLS deals issued at the same time. However, if we compare the pools purchased by the GSEs and those purchased by other investors *in the same deals*, there is either no difference in the riskiness based on observable loan characteristics, or that difference is small. We should point out that a very large share of the variation in ex-ante mortgage risk can be explained by the deal fixed effects included in these regressions (R-squared goes from 1 percent to over 30 percent).

[22] In the appendix, we display results using a logit model rather than a linear probability model. In addition, we also show results for an alternative definition of default (90+ days delinquent). The results of both modifications are virtually identical to those reported in Table 4.

4.2 Ex-post Performance

We next turn to the ex-post performance of the loans included in GSE pools. We estimate linear probability models where the dependent variable is a 1 if a loan is in default between origination and the end of 2008, 2010 or 2012. We control for all observable loan characteristics and year of securitization fixed effects. In most specifications we also include deal fixed effects, so that identification comes from comparing loans in the same deal that are in GSE versus non-GSE pools.

Table 5 shows that, for all three horizons, the loans underlying GSE pools performed worse (on average) if we do not include deal fixed effects or any of the loan characteristics as controls. Loans in GSE pools have unconditional default rates that are 120 to 160 basis points higher depending on the horizon we consider. This is consistent with the ex-ante analysis, which showed that these loans also looked riskier at the time of securitization based on observable characteristics.[23]

Interestingly though, we see a reversal of this pattern once we include deal fixed effects in the regressions, thus focusing on within deal variation that compares loans in pools purchased by the GSEs with loans backing securities directed at other investors. Loans in GSE pools have 320 to 330 basis points *lower* default rates than loans in the same deals backing other securities. The magnitude is reduced to 150 to 190 basis points when we include all of the observable borrower and loan characteristics.[24] This is a striking result

[23] In the appendix we show results in which linear probability models are substituted with logit models, and default is defined as 90+ days delinquent. The results of both modifications are virtually identical to those reported in Table 5. In addition we present results for 24-month and 36-month default horizons (from the month of issuance), which are also very similar to those reported in Table 5.

[24] The covariate set includes the combined loan-to-value ratio, the logarithm of the original loan balance, the original interest rate, the credit score, the original size of the loan, the original term, the number of months between origination and issuance (seasoning), indicator variables for low documentation, interest-only loans, first lien loan, negative amortization, residence status (owner-occupied, investor/vacation home), loan purpose (cash-out refinance, other refinance, purchase), property type (condominium, multi-family, single-family), and the existence of a prepayment penalty. We also include the level of the unemployment rate and the level of the house price index at the time of issuance, as well as the 12-month trailing house price appreciation at the county level and the contemporaneous unemployment rate at the county level. In addition, we include the change in both the county-level unemployment rate and county-level house price index from the time of issuance through the end of the default horizon, as well as a full set of state-level fixed effects. Additional indicator variables are included whenever there are missing observations in any of the controls.

considering that we see either no difference or slightly *higher* default probabilities for these loans at the time of securitization, and yet they default much less than the observable characteristics would suggest.[25]

The observation that loans in GSE pools perform much better than their observable characteristics would predict indicates that they are different in unobservable ways relative to loans in non-GSE pools. There are a couple of potential explanations for this pattern. The first is that the GSEs had superior screening technologies (compared to other investors), which are unobservable to us, and this resulted in the loans in GSE pools performing better.[26] For example, it is possible that the GSEs chose to invest in specific mortgage pools based on superior credit risk models that were able to predict loan performance more accurately than other investors. A second possible explanation is that issuers used private information about the quality of the mortgages to give the GSEs higher quality loans within the same deal. Since Fannie Mae and Freddie Mac were such important investors in the market, PLS issuers would have had an incentive to maintain a good reputation with the two GSEs in order to ensure a stable source of demand for future business.

4.2.1 Low Documentation Loans

One natural place to examine whether issuer private information could explain the results is to look specifically at low documentation mortgages. The existing literature has argued that low documentation lending is the segment of the market where banks putting together the deals are most likely to have private information that could lead to systematically differential performance across mortgage pools that is not accounted for by observable loan characteristics (e.g. Keys, Seru and Vig, 2012; Saengchote, 2013; Begley and Purnanandum 2013; Jiang, Nelson and Vytlacil, 2014a, 2014b).

Returning to Table 5, we find that the difference in ex-post default risk between mortgages in GSE and non-GSE pools is significantly reduced (by 50 percent or more) once we add an interaction between the

[25] In our tables, in order to conserve space, we do not report the coefficient estimates associated with the set of control variables (borrower, mortgage, and geographic characteristics). However, in the appendix we do report these estimates for two of the regression specifications.
[26] Superior monitoring of borrowers on the part of servicers is unlikely to explain the performance differences since the inclusion of deal fixed effects eliminates variation in mortgage servicing. The same institution virtually always serviced all loan pools in a given deal.

GSE dummy and an indicator variable for low documentation mortgages to the regressions. This means that differences in ex-post performance are relatively small for full documentation loans across GSE and non-GSE pools, but that these differences are significantly amplified for low documentation loans. Specifically, we find that low documentation loans in GSE pools default by 2.6 to 3.2 percentage points *less* than low documentation loans in non-GSE pools. This evidence suggests that private information on the part of subprime PLS issuers explains the differences in ex-post performance between loans in GSE non-GSE pools. If the better ex-post performance between pools were driven by better risk assessment by the GSEs, it is not obvious why so much of the effect would be concentrated in low documentation loans. Figure 2 shows that the results are not driven only by one or two quarters, but rather that the effects of both the GSE dummy and the low documentation interaction are always below zero, and become especially strong after the first quarter of 2005.

4.2.2 Issuer Dependence on GSEs

While the low documentation results suggest that private or soft information is important in explaining differences in loan quality, they do not allow us to completely distinguish between who holds the informational advantage. In particular, it could still be the case that the GSEs are somehow better at identifying higher quality low documentation loans and demand that these loans be included in the pools that back their security purchases. In order to further test whether a supply (issuer-driven) or a demand (GSE-driven) effect is more likely to explain the differences in within-deal mortgage performance, we construct a measure of the frequency of interaction between the GSEs and issuers of subprime PLS. Specifically, for each deal issuer that we are able to identify in CoreLogic, we take the number of deals by that issuer that have a GSE pool and divide that number by the total number of deals issued by the issuer from the start of 2003 up until that quarter. We call this variable the "GSE deal fraction", so that a value of one means that all of the issuer's previous deals involved the GSEs, while a value of zero means that none involved the GSEs. Our contention is that this variable measures the extent of issuer dependency on the GSEs at a given point in time, such that an issuer with a high GSE deal fraction will have an incentive to supply the GSEs with higher quality loans in order to maintain a good reputation and continue doing business with the GSEs. If the difference in ex-post performance is largely explained by loans in pools arranged by issuers with high GSE deal fractions, then a supply story is the most likely explanation.

In Table 6, we show descriptive statistics of the GSE deal fraction variable for each year in our sample period. Some issuers almost exclusively created deals that included pools aimed at the GSEs (e.g., Fremont had a GSE pool in 100 percent of their deals, as did Wells Fargo, Barclays and Fieldstone in 2004 and 2005). But the average of this variable across all issuers is about 60 percent, suggesting that other issuers sold a significant fraction of deals without a pool specifically directed at the GSEs.[27] One notable observation from the table is that there is substantial variation in the GSE deal fraction variable both across issuers as well as over time for the same issuer.

In Table 7 we assess the extent to which prior deals with the GSEs affects our finding that within-deal mortgage performance was better for GSE pools -- particularly for low documentation mortgages. We add an interaction between the GSE deal fraction variable and the GSE dummy to the specification in Table 5. The first three columns in Table 7 display the estimation results for the three different default horizons. The coefficient estimate associated with the interaction term is negative and statistically significant, with a magnitude between 0.026 and 0.033 depending on the horizon. Thus, a loan in a GSE pool arranged by an issuer with a GSE deal fraction of one is approximately 2.6 to 3.3 percentage points less likely to default than a loan in a GSE pool arranged by an issuer with no prior experience with the GSEs (i.e. a GSE deal fraction of zero). The interaction between the GSE dummy and the low documentation dummy is largely unaffected, remaining negative and statistically significant. However, the addition of the new interaction term causes the sign of the GSE dummy coefficient to flip from negative to positive. This suggests that full documentation loans in GSE pools arranged by issuers with no prior experience with the GSEs are *more* risky than similar loans in non-GSE pools within the same deal. Thus, controlling for documentation status and previous

[27] Identifying the deal issuers was not completely straightforward. We obtained the identity of the issuer of many deals from Bloomberg. However for some deals, Bloomberg does not have information on the identity of the issuer. In these cases we took the ticker number, and cross-referenced it against the SEC database on company filings. In most cases we were able to obtain the pooling and servicing agreement (PSA) for the corresponding deal, which contains the identity of the deal issuer.

experience with the GSEs fully explains the ex-post performance differential between mortgages in GSE pools and non-GSE pools in the same deal.

4.2.3 Issuer-Originator Affiliation

The previous section showed that subprime PLS issuers with greater dependence on Fannie Mae and Freddie Mac (as measured by the frequency with which they structured deals with the GSEs) delivered unobservably better-quality low documentation mortgages into GSE pools. This is consistent with those issuers having private information and using it to sort loans into pools. A natural question is how PLS issuers might come by such information, since it is the originator rather than the issuer that directly interacts with borrowers and underwrites mortgages. There are a couple of possible ways in which private information could be transferred from originators to issuers. First, there are direct relationships between many issuers and originators in the subprime PLS market. In some cases the originator and issuer are the same institution, while in others they are part of the same vertically integrated corporation (in which case the originator is typically a subsidiary of the issuer). To the extent that issuers are more likely to obtain private information about loans that are underwritten by affiliated originators (an argument also made by Demiroglu and James, 2012; He, Qian, Strahan, 2012; and Furfine, 2014), we would expect to find stronger results for the sample of loans in which the issuer and originator are affiliated corporations. Second, it is also possible for private information to be transferred between unaffiliated originators and issuers. For example, an issuer may have sufficient experience with a group of originators to be able to identify those that are especially meticulous in their screening of loans (beyond what can be inferred from the set of observable borrower characteristics). Our hypothesis, however, is that it is likely easier to transfer private information when there is a direct affiliation.

Columns 4 through 9 of Table 7 replicates the first three columns in the same table, but it separates deals based on whether the issuer and originator were affiliated at the time that the deal was issued (either the same institution or part of the same vertically integrated corporation). Approximately two-thirds of the observations in the CoreLogic database (64.2 percent of our sample) contain information on the identity of the originator; and for this subset we are able to determine whether the originator and issuer are affiliated. The columns with issuer-affiliated originators include 396 deals where all loans are by affiliated originators, and the "unaffiliated" column has 695 deals where no loans are made by issuer-affiliated originators. This leaves out 85 deals that had a mix of both affiliated and unaffiliated issuers.[28] We find that within issuer-originator affiliated deals (columns 4 through 6), low documentation mortgages in GSE pools perform significantly better compared to those in non-GSE pools and that the fraction of previous deals made with the GSEs is strongly correlated with performance. For unaffiliated deals, we also obtain negative point estimates for both low documentation and GSE deal fraction variable interactions, but the results are statistically and economically weaker (especially for the 2010 and 2012 horizons). This is consistent with better transmission and use of private information within the same organization, and suggests that unaffiliated issuers were less likely to have private information that they could use to form mortgage pools.

4.2.4 Robustness Tests

There are two sources of potential differences between the GSE and non-GSE pools that are driven by institutional features of the GSEs. The first is directly related to the way we identify the GSE pools in the first place, namely that they do not contain jumbo loans. To the extent that jumbo loans might behave systematically worse due to unobserved characteristics, this could explain some of the results above. The second potential issue concerns the GSEs' percent-of-business affordable housing goals set by regulation. It could be the case that the GSEs demanded more loans in census tracts that qualified for the affordable housing goals, and that these census tracts are different along dimensions unobservable to us, which might explain the performance differences that we are finding.

We show in Tables 8 and 9 that our results are not affected by either explanation. Table 8 excludes jumbo loans from the estimation altogether. The first thing to note is that only a very small fraction of

[28] Approximately 40 percent (2.74 million out of 6.79 million) of the subprime PLS loans for which we have information on the originator's identity are in deals where the issuer and the originator for all loans in the deal are affiliated corporations. The 85 mixed deals are dropped due to our lack of confidence in the identity of the originator and/or our ability to identify a relationship between the issuer and originator (the raw data on originator identities in the CoreLogic database is somewhat messy, so we were forced to expend significant effort in cleaning and standardizing the names in order to integrate the information into our empirical analysis).

mortgages in the non-GSE pools are jumbos (about 680,000, or 6.5 percent of the whole sample). When we exclude them from the regressions, we obtain essentially the same estimates as in Tables 5 and 7, both for the GSE “main effect”, as well as for the interactions with low documentation and the GSE deal fraction variables.

Table 9 repeats the regressions in Tables 5 and 7 including a zip-code level variable that is a 0 if the zip code does not contain a census tract that is eligible for the underserved area goal, and is a 1 if the entire population in that the zip code is in goal-eligible census tracts. This variable takes intermediate values when only a fraction of the zip code’s population is in such tracts. We find that the results are virtually unchanged when we include these additional controls.[29]

4.3 Analysis of MBS Prices

We turn to the pricing of subprime MBS and we consider whether GSE and non-GSE pools were priced differently at the time of issuance. For our analysis that focuses on the yield spread of triple-A securities with claims on GSE and non-GSE pools, we focus exclusively on the subset of deals where all the triple-A securities were either floating rate tranches or inverse floaters. Focusing on floating rate tranches has two main advantages: First, because the yield on those tranches is always quoted as a spread over one-month Libor in our sample, we can cleanly aggregate the yield for multiple tranches in the same deal and construct a pool-level spread. Second, because these tranches have a very short duration, we can ignore interest rate risk and the negative convexity issue that arises with fixed-rate mortgage-backed securities. Including only floating rate pools drops 177 observations, leaving 3,290 unique pools that we use to run the regressions.

Table 9 reports the results of regressions of the at-issuance yield spreads of the securities in our sample (relative to Libor) on the GSE dummy variable, a control for the weighted average of the expected life of each security and pool-level loan characteristics. We find that the yield spreads on GSE-purchased

[29] In fact, we include a series of dichotomous variables rather than a single continuous variable. In the appendix, we describe how they are constructed and show the coefficient estimates associated with the underserved areas goal variables. We find that loans originated in zip codes with a higher fraction of the population in goal-eligible census tracts are characterized by higher default rates, ceteris paribus.

securities are, on average, three to six basis points higher than those purchased by non-GSE investors. This holds both with and without deal fixed effects, and also when we control for observable characteristics of the mortgages in each pool, which indicates that Fannie Mae and Freddie Mac were able to obtain higher yielding securities relative to other investors in the same deals buying similarly triple-A rated securities. It is important to remember that GSE pools looked similar on ex-ante characteristics (or perhaps slightly riskier), but that they performed significantly better ex-post. Hence, the GSEs seem to have gotten a better deal based on realized returns than other investors in the same deals.

In columns 3 and 6 we consider whether the spread difference between GSE and non-GSE pools co-varies with the "GSE deal fraction" variable. Indeed, we find that the whole spread difference can be explained by the interaction of the GSE dummy with this variable, suggesting that Fannie Mae and Freddie Mac got particularly good deals in terms of spreads at origination from issuers that frequently included GSE pools in their deals (and were likely to be more dependent on the GSEs as investors in their deals).

5. Conclusion

Fannie Mae and Freddie Mac have long played a central role in the U.S. housing finance system as both securitizers and investors in conforming prime mortgages. Moreover, during the recent U.S. housing boom, the GSEs were also the two largest investors in subprime PLS – a fact that has largely escaped academic attention.

In this paper we use a unique feature of the structure of subprime PLS deals to show that the loan pools that were eligible to be bought by Fannie Mae and Freddie Mac had similar (or slightly worse) ex-ante risk characteristics than those targeted at other investors, but they performed significantly better during the crisis. We document that this difference is concentrated in low documentation loans, which suggests that issuers were using private information to sort mortgages into GSE and non-GSE pools. Deals sold by issuers that frequently structured deals for Fannie Mae and Freddie Mac also exhibit larger differences in performance between GSE and non-GSE pools, especially when the issuer of the deals and the originator of the mortgages are affiliated institutions. This further supports the view that this was largely a supply-driven response by the issuers to the presence of these large investors in the subprime PLS market.

The implications of our findings for the overall quality of mortgages originated between 2002 and 2007 are ambiguous and are an important topic for further research. On one hand, the significant presence of Fannie Mae and Freddie Mac in this market may have increased credit supply and pushed originators further down the distribution of borrower quality. In this case, had GSE capital never found its way into subprime PLS, it is possible that the worst loans originated during this period would have not have been made. On the other hand, it may be that the capital provided by Fannie Mae and Freddie Mac to the subprime mortgage market would have otherwise been provided by other sources.

Taken together, our results imply that the presence of large investors in the subprime PLS market served as a disciplining device on deal issuers. Given that the securities that the GSEs purchased were always rated triple-A at issuance, this extends our current understanding of the role of blockholders in financial markets beyond corporate equity and bank debt. In fact, this paper shows that large claimholders can mitigate agency problems even in the case of information-insensitive arms-length debt, likely through reputation concerns on the part of issuers.

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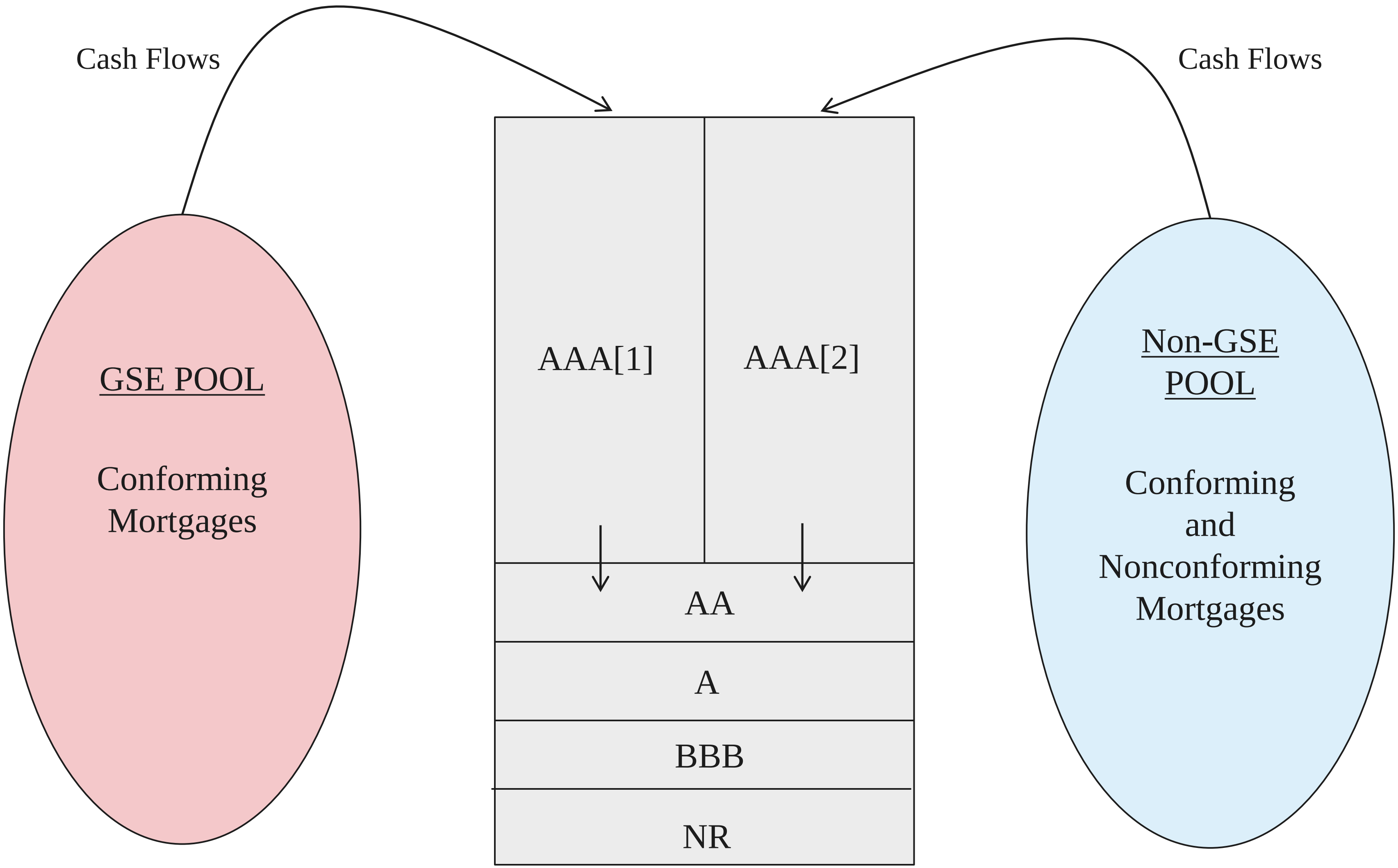
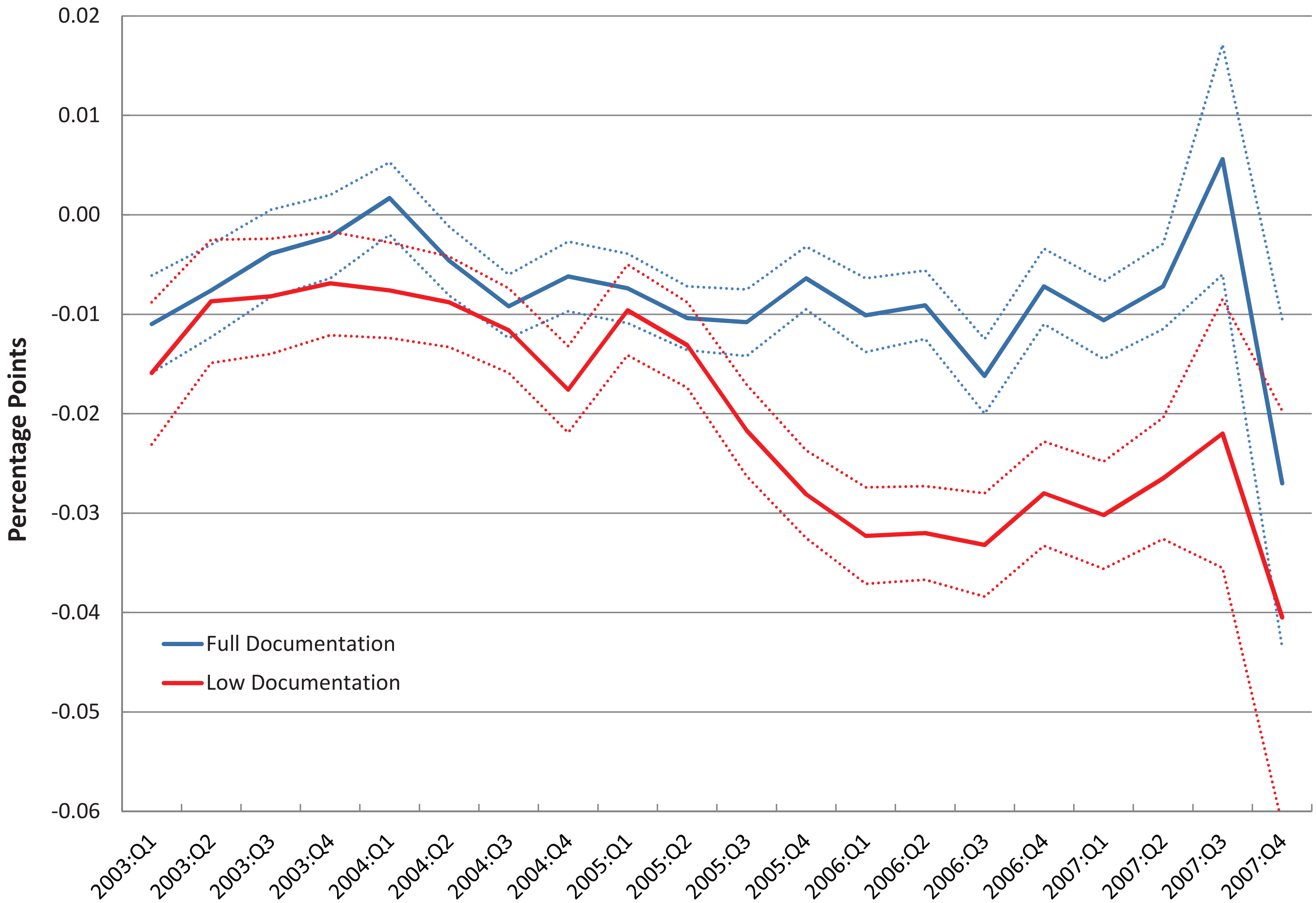
Figure 1: Typical Subprime PLS Deal Structure with GSE Participation



This figure displays the structure of a typical subprime PLS deal purchased by the GSEs. These deals involved more than one mortgage pool: one consisting of only conforming loans ("GSE pool") and at least one other pool made up of both conforming and non-conforming (jumbo) loans ("Non-GSE Pool"). The lower rated securities derived their cash flows from all pools, while the triple-A securities purchased by the GSEs derived their cash flows exclusively from the conforming pool and the triple-A securities purchased by other investors derived their cash flows from the other pools.

Figure 2: Evolution of Ex-Post Performance Difference between GSE and Non-GSE Mortgage Pools over Sample Period



Notes: This figure plots the coefficient estimates of the GSE dummy variable and the interaction of the GSE dummy and the low documentation dummy from a series of linear probability models estimated separately for each quarter of issuance over the sample period 2003–2007. The dependent variable is the ex-post default rate measured through 2008, where default is defined as a loan being 60 or 90 days delinquent, in foreclosure or REO. The model specification is identical to column 4 in Table 5, and is estimated separately for each quarter (of issuance) in the sample. The solid lines correspond to the point estimates from each linear probability model, while the 95 percent confidence intervals are given by the dashed lines.

Table 1: Subprime Private-label Securities Issuance (PLS): 2000–2008

Year	Subprime PLS Issuance ($ billions)	GSE Subprime PLS Purchases		
		Public Data ($ billions)	Proprietary Data ($ billions)	Market Share (%)
2000	52.5	.	.	.
2001	87.1	.	3.4	3.8
2002	122.7	.	14.6	11.9
2003	195.0	.	67.7	34.7
2004	362.6	.	141.0	38.9
2005	465.0	.	134.4	28.9
2006	448.6	110.4	106.0	23.6
2007	201.6	59.6	50.1	24.9
2008	2.3	0.7	.	.

Notes: Subprime PLS Issuance is obtained from the 2011 Mortgage Market Statistical Annual (volume II, page 31). Publicly available data on PLS purchased by the GSEs is obtained from the 2012 Federal Housing Finance Agency's (FHFA) Annual Report to Congress. The FHFA report only breaks out PLS purchases into subprime and Alt-A for Freddie Mac beginning in 2006. Proprietary data on PLS purchased by the GSEs is obtained from CoreLogic's Asset-Backed Securities database. The GSEs' market share of PLS purchases (column 5) is obtained by dividing GSE PLS purchases (column 4) by total subprime PLS issuance (column 2).

Table 2: Loan-level Summary Statistics: Corelogic Subprime PLS Issued 2003–2007

Continuous Variables	Non-GSE (N = 6,324,311)						GSE (N = 4,140,711)					
	Mean	10 perc.	25th perc.	Median	75th perc.	90th perc.	Mean	10 perc.	25th perc.	Median	75th perc.	90th perc.
FICO (Points)	642	558	600	641	684	729	616	538	574	615	653	692
Balance ($)	159,224	30,000	54,900	109,180	214,000	375,000	156,907	59,600	90,980	140,000	209,600	282,000
CLTV (P.Points)	88.8	70.0	80.0	91.8	100.0	100.0	84.4	65.0	78.8	85.0	95.0	100.0
Orig. Rate (P. Points)	8.64	6.44	7.20	8.33	9.90	11.45	7.94	6.25	6.88	7.75	8.75	9.95
Term (months)	314	180	240	360	360	360	350	360	360	360	360	360
Unemployment (P. Points)	5.09	3.40	4.10	4.90	5.80	6.90	5.39	3.60	4.30	5.20	6.20	7.20
Trailing 12-month unemployment change	-6.5%	-18.6%	-13.2%	-7.4%	-1.1%	7.0%	-5.3%	-17.6%	-12.4%	-6.4%	0.0%	8.6%
Unemployment change through 2012	54.7%	7.1%	25.7%	48.1%	79.2%	108.5%	47.1%	2.8%	20.0%	41.7%	66.7%	96.2%
Trailing 12-month HPA	12.1%	1.2%	4.4%	9.8%	18.9%	26.8%	12.3%	1.9%	4.8%	9.9%	18.7%	26.8%
HPA through 2012	-17.5%	-42.8%	-32.2%	-18.8%	-3.8%	8.4%	-13.8%	-39.5%	-28.1%	-14.6%	-0.4%	11.1%
UAG Zip Code Fraction	49.4%	0.0%	8.2%	49.9%	88.3%	100%	52.4%	0.0%	12.0%	55.7%	93.4%	100%

Indicator Variables	Non-GSE Mean	GSE Mean
Low Documentation (share)	0.412	0.347
Non-Owner Occupied (share)	0.083	0.084
Purchase Loan (share)	0.508	0.356
Cash-Out Refinance (share)	0.422	0.563
Interest-Only (share)	0.137	0.096
Balloon (share)	0.225	0.094
ARM (share)	0.489	0.744
Prepay Penalty (share)	0.616	0.719
12-m. Pred. Loan Default (P. Points)	0.119	0.123
24-m. Pred. Loan Default (P. Points)	0.150	0.171
36-m. Pred. Loan Default (P. Points)	0.163	0.195
Default Rate through 2008:Q4	0.338	0.315
Default Rate through 2010:Q4	0.421	0.376
Default Rate through 2012:Q4	0.444	0.393

Notes: This table shows summary statistics for the loans underlying the GSE and non-GSE triple-A subprime PLS securities in the Corelogic database issued between 2003 and 2007. GSE refers to mortgage pools made up of almost exclusively loans below the conforming loan limit, whereas non-GSE pools refer to mortgage pools made up of loans both above and below the conforming loan limit. The variables coincide with the covariate set included in the ex-ante and ex-post default regressions below. The mean, median, 10th, 25th, 75th, and 90th percentiles of the respective distributions of the continuous variables are displayed, while the mean of the dichotonomous variables is shown. FICO score is the credit score of the borrowers on the loan application; balance is the size of the loan at origination; CLTV is the size of all loans on the property relative to the price of the house (transaction price or appraisal amount, depending on whether it is a purchase or a refinance); original rate is the interest rate on the loan at origination; term is the original term of the loan; unemployment is measured at the county-level (from the BLS); HPA is the county-level house price appreciation (from CoreLogic); low-documentation is a 1 if the loan was either low documentation or no-documentation; non-owner occupant is a 1 if the property is for investment purposes or is a vacation/second home. The bottom of the table shows the 12-month, 24-month, and 36-month predicted default rates for each loan at the time of issuance using all information in the data for the previous two vintages of subprime PLS and defining default as being 60 or 90 days delinquent, in foreclosure or REO. In addition the realized default rates as of 2008:Q4, 2010:Q4, and 2012:Q4 are also displayed.

Table 3: Pool-level Summary Statistics: Corelogic Subprime PLS Issued 2003–2007

Year		Non-GSE	GSE	Difference
2003	# Pools	312	172	140
	Pool Size ($ millions)	19.34	19.83	0.49***
	Spread (bps)	36.96	38.83	1.87
	Average Life (years)	2.91	2.85	-0.07
2004	# Pools	419	297	122
	Pool Size ($ millions)	19.59	20.11	0.52***
	Spread (bps)	30.16	33.17	3.01***
	Average Life (years)	2.66	2.76	0.10*
2005	# Pools	511	316	195
	Pool Size ($ millions)	19.92	20.02	0.11**
	Spread (bps)	20.02	25.88	5.86***
	Average Life (years)	2.31	2.51	0.19***
2006	# Pools	537	314	223
	Pool Size ($ millions)	20.05	19.72	-0.32***
	Spread (bps)	13.46	16.44	2.98***
	Average Life (years)	2.15	2.30	0.15***
2007	# Pools	241	171	70
	Pool Size ($ millions)	19.90	19.58	-0.32***
	Spread (bps)	23.47	25.27	1.80
	Average Life (years)	2.20	2.18	-0.02
All	# Pools	2,020	1,270	750
	Pool Size ($ millions)	19.79	19.88	0.09***
	Spread (bps)	23.41	26.92	3.51***
	Average Life (years)	2.42	2.51	0.09***

Notes: This table shows summary statistics for triple-A subprime PLS issued between 2003 and 2007 broken down by whether the security was collateralized by GSE or non-GSE mortgage pools. GSE refers to mortgage pools made up of almost exclusively loans below the conforming loan limit, whereas non-GSE pools refer to mortgage pools made up of loans both above and below the conforming loan limit. The spread refers to the difference between the average coupon of triple-A subprime securities (weighted by the size of the tranche in each pool) and the one-month LIBOR. The average life refers to the average expected life for the tranches as advertised in the prospectus (where the average for the pools was weighted by the size of each tranche). Level of statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

Table 4: Ex-Ante Default Probabilities for Loans in GSE and Non-GSE Pools

Panel A: OLS (Linear Probability Model)

	12-month Horizon		24-month Horizon		36-month Horizon	
GSE (d)	0.0053*	-0.0064***	0.0200***	-0.0025	0.0251***	-0.0029
	(1.93)	(3.79)	(4.47)	(1.07)	(5.40)	(1.21)
Deal F.E.?	N	Y	N	Y	N	Y
# Loans	10,465,022	10,465,022	10,465,022	10,465,022	9,168,963	9,168,963
# Deals	1,809	1,809	1,809	1,809	1,571	1,571
R^2	0.00	0.37	0.01	0.31	0.01	0.30

Panel B: Logit

	12-month Horizon		24-month Horizon		36-month Horizon	
GSE (d)	0.0035	-0.0021	0.0222***	0.0063***	0.0322***	0.0071***
	(1.20)	(1.25)	(5.55)	(3.30)	(8.72)	(3.44)
Deal F.E.?	N	Y	N	Y	N	Y
# Loans	10,438,305	10,438,305	10,330,159	10,330,159	8,779,903	8,779,903
# Deals	1,809	1,809	1,807	1,807	1,556	1,556
Pseudo R^2	0.00	0.33	0.01	0.24	0.02	0.19

Panel C: Multinomial Logit

	12-month Horizon		24-month Horizon		36-month Horizon	
GSE (d)	0.0042	-0.0016	0.0214***	0.0077***	0.0315***	0.0103***
	(1.48)	(1.01)	(5.03)	(3.92)	(9.20)	(5.15)
Deal F.E.?	N	Y	N	Y	N	Y
# Loans	10,464,165	10,464,165	10,464,165	10,464,165	9,168,963	9,168,963
# Deals	1,809	1,809	1,809	1,809	1,571	1,571
Pseudo R^2	0.00	0.32	0.01	0.24	0.01	0.19

Notes: This table shows loan-level, OLS regressions where the dependent variables are the 12-month, 24-month, and 36-month predicted default rates at the time the loan is originated using all information in the data for the previous two years for the 12-month rate and three years for the 24-month and 36-month predicted rates. Default is defined as a loan being 60 or 90 days delinquent, in foreclosure or REO. The independent variable of interest is "GSE" which is a 0/1 indicator variable. GSE pools have claims on groups of mortgages made up of almost exclusively loans below the conforming loan limit, whereas non-GSE pools refer to mortgage pools made up of loans both above and below the conforming loan limit. In Panel A we compute ex-ante default rates using OLS regressions, while Panel B uses ex-ante default rates using logistic regressions, and Panel C uses ex-ante default rates using multinomial logistic regressions. Standard errors are heteroskedasticity-robust and clustered at the quarter of issuance level. The first row for each variable shows the regression coefficient, the second row shows t-statistics. Level of statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

Table 5: Effect of GSE participation on Ex-Post Default Rates

	Horizon through 2008:Q4				Horizon through 2010:Q4				Horizon through 2012:Q4			
GSE (d)	0.016***	-0.033***	-0.019***	-0.007***	0.014**	-0.033***	-0.016***	-0.006**	0.012**	-0.032***	-0.015***	-0.006
	(3.04)	(3.73)	(10.69)	(4.17)	(2.49)	(4.24)	(8.77)	(2.53)	(2.30)	(4.45)	(7.99)	(2.55)
Low Doc			0.057***	0.070***			0.060***	0.072***			0.058***	0.069***
			(8.22)	(10.04)			(8.94)	(10.77)			(9.58)	(11.60)
GSE*Low Doc				-0.032***				-0.029***				-0.026***
				(9.19)				(8.76)				(8.73)
Deal F.E. ?	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y
Covariates ?	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Issue Year F.E. ?	Y	.	.	.	Y	.	.	.	Y	.	.	.
# Loans	10,465,022	10,465,022	10,464,165	10,464,165	10,465,022	10,465,022	10,464,165	10,464,165	10,465,022	10,465,022	10,464,165	10,464,165
# Deals	1,809	1,809	1,809	1,809	1,809	1,809	1,809	1,809	1,809	1,809	1,809	1,809
Adjusted R^2	0.04	0.08	0.16	0.16	0.09	0.14	0.20	0.20	0.11	0.15	0.21	0.21

Notes: This table shows loan-level, OLS regressions where the dependent variable is the actual default rate of loans backing subprime PLS issued between 2003 and 2007 calculated at three different points in time: 2008Q4, 20010Q4 and 2012Q4. Default is defined as a loan being 60 or 90 days delinquent, in foreclosure or REO. The independent variable of interest is "GSE" which is a 0/1 indicator variable. GSE pools have claims on groups of mortgages made up of almost exclusively loans below the conforming loan limit, whereas non-GSE pools refer to mortgage pools made up of loans both above and below the conforming loan limit. Regressions with "covariates" include controls for a large number of borrower and loan characteristics. A full list of those controls is given in the text in Section 3. Standard errors are heteroskedasticity-robust and clustered at the quarter of issuance level. The first row for each variable shows the regression coefficient, the second row shows t-statistics. Level of statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

Table 6: List of Sponsors with Highest Values of “GSE Deal Fraction”

Sponsor	Average value of GSE Deal Fraction (%)						# Deals
	All Years	2003	2004	2005	2006	2007	(2003 - 2007)
Fremont	100	100	100	100	100	.	28
Fieldstone	98.3	.	100	100	94.1	91.7	13
Wells Fargo	94.4	.	100	100	87.4	63.6	11
Barclays	91.8	.	100	100	88.8	84.0	36
Washington Mutual	83.7	84.7	78.2	82.5	86.1	87.9	43
UBS	82.5	100	97.3	89.4	68.7	61.3	42
Morgan Stanley	80.4	75.3	79.5	83.5	81.8	78.6	111
National City	77.8	73.1	77.3	78.2	79.4	.	65
Goldman Sachs	77.3	100	91.3	78.0	70.9	69.0	65
Deutsche Bank	75.7	64.4	81.7	78.9	74.3	73.2	74
All Sponsors	59.7	43.1	59.8	62.4	61.4	58.1	1,751

Notes: This table displays the ten subprime PLS sponsors with the highest values of the “GSE Deal Fraction” measure used in the analysis. “GSE Deal Fraction” is a variable that is calculated quarterly for each deal sponsor that we are able to identify in the CoreLogic sample. It is calculated by taking the number of deals that include a GSE pool that the sponsor has issued up to each point in time and dividing that number by the total number of deals issued by the sponsor up until that quarter. Only sponsors involved in at least ten deals over the sample period (2003–2007) are included in the table.

Table 7: Ex-Post Default Rates, “GSE Deal Fraction,” and Issuer/Originator Affiliation

	All Deals			Affiliated Deals			Unaffiliated Deals		
Horizon	2008:Q4	2010:Q4	2012:Q4	2008:Q4	2010:Q4	2012:Q4	2008:Q4	2010:Q4	2012:Q4
GSE (d)	0.013***	0.012***	0.011***	0.026**	0.025***	0.024***	-0.005	-0.014**	-0.015**
	(3.59)	(4.03)	(4.21)	(2.43)	(2.91)	(3.01)	(0.78)	(2.24)	(2.45)
GSE*Low Doc	-0.032***	-0.029***	-0.026***	-0.034***	-0.025***	-0.022***	-0.032***	-0.009	-0.008
	(8.99)	(8.76)	(8.72)	(6.29)	(6.26)	(6.19)	(7.08)	(0.80)	(0.80)
GSE*“GSE Deal Fraction”	-0.033***	-0.027***	-0.026***	-0.052***	-0.051***	-0.050***	-0.005	0.009	0.010
	(5.73)	(4.56)	(4.43)	(3.21)	(3.58)	(3.70)	(0.58)	(1.00)	(1.14)
Deal F.E. ?	Y	Y	Y	Y	Y	Y	Y	Y	Y
Covariates ?	Y	Y	Y	Y	Y	Y	Y	Y	Y
# Loans	10,156,202	10,156,202	10,156,202	2,668,773	2,668,773	2,668,773	3,374,320	3,374,320	3,374,320
# Deals	1,724	1,724	1,724	396	396	396	695	695	695
Adjusted R^2	0.16	0.20	0.21	0.15	0.19	0.21	0.15	0.19	0.21

Notes: This table shows loan-level, OLS regressions where the dependent variable is the actual default rate of loans backing subprime PLS issued between 2003 and 2007 calculated at three different points in time: 2008Q4, 20010Q4 and 2012Q4. The first three columns display results for the sample of all deals, while columns 4-6 display results where the originator of all loans in a deal is affiliated with the issuer, while the last three columns display results for the sample of deals in which the originator of all loans in a deal is not affiliated with the issuer. Default is defined as a loan being 60 or 90 days delinquent, in foreclosure or REO. The independent variable of interest is “GSE” which is a 0/1 indicator variable. GSE pools have claims on groups of mortgages made up of almost exclusively loans below the conforming loan limit, whereas non-GSE pools refer to mortgage pools made up of loans both above and below the conforming loan limit. “GSE Deal Fraction” is a variable that is calculated quarterly for each deal sponsor that we are able to identify in the CoreLogic sample. It is calculated by taking the number of deals that include a GSE pool that the sponsor has issued up to each point in time and dividing that number by the total number of deals issued by the sponsor up until that quarter. Regressions with “covariates” include controls for a large number of borrower and loan characteristics. A full list of those controls is given in the text in Section 3. Standard errors are heteroskedasticity-robust and clustered at the quarter of issuance level. The first row for each variable shows the regression coefficient, the second row shows t-statistics. Level of statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

Table 8: Robustness Check: Conforming Mortgages Only

	Horizon through 2008:Q4			Horizon through 2010:Q4			Horizon through 2012:Q4		
GSE (d)	-0.022***	-0.010***	0.011***	-0.019***	-0.007***	0.011***	-0.018***	-0.007***	0.011***
	(10.67)	(5.69)	(2.87)	(8.81)	(3.07)	(3.48)	(8.04)	(2.94)	(3.66)
GSE*Low Doc		-0.034***	-0.033***		-0.032***	-0.033***		-0.030***	-0.030***
		(9.28)	(9.07)		(9.40)	(9.40)		(9.58)	(9.56)
GSE*"GSE Deal Fraction"			-0.034***			-0.029***			-0.028***
			(5.85)			(4.64)			(4.44)
Deal F.E. ?	Y	Y	Y	Y	Y	Y	Y	Y	Y
Covariates ?	Y	Y	Y	Y	Y	Y	Y	Y	Y
# Loans	9,783,310	9,783,310	9,495,412	9,783,310	9,783,310	9,495,412	9,783,310	9,783,310	9,495,412
# Deals	1,809	1,809	1,724	1,809	1,809	1,724	1,809	1,809	1,724
Adjusted R^2	0.15	0.15	0.15	0.20	0.20	0.20	0.21	0.21	0.21

Notes: This table shows loan-level, OLS regressions where the dependent variable is the actual default rate of loans backing subprime PLS issued between 2003 and 2007 calculated at three different points in time: 2008Q4, 20010Q4 and 2012Q4. Default is defined as a loan being 60 or 90 days delinquent, in foreclosure or REO. The independent variable of interest is "GSE" which is a 0/1 indicator variable. GSE pools have claims on groups of mortgages made up of almost exclusively loans below the conforming loan limit, whereas non-GSE pools refer to mortgage pools made up of loans both above and below the conforming loan limit. "GSE Deal Fraction" is a variable that is calculated quarterly for each deal sponsor that we are able to identify in the CoreLogic sample. It is calculated by taking the number of deals that include a GSE pool that the sponsor has issued up to each point in time and dividing that number by the total number of deals issued by the sponsor up until that quarter. Regressions with "covariates" include controls for a large number of borrower and loan characteristics. A full list of those controls is given in the text in Section 4. Standard errors are heteroskedasticity-robust and clustered at the quarter of issuance level. The first row for each variable shows the regression coefficient, the second row shows t-statistics. Level of statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Loans above the conforming loan limit (jumbo mortgages) are excluded from the sample.

Table 9: Robustness Check: Controlling for Affordable Housing Goal Effects

	Horizon through 2008:Q4			Horizon through 2010:Q4			Horizon through 2012:Q4		
GSE (d)	-0.019***	-0.008***	0.013***	-0.016***	-0.006***	0.011***	-0.015***	-0.006***	0.011***
	(11.13)	(4.73)	(3.29)	(9.54)	(2.87)	(3.67)	(8.61)	(2.83)	(3.67)
GSE*Low Doc		-0.032***	-0.032***			-0.029***		-0.026***	-0.026***
		(9.04)	(8.90)			(8.53)		(8.43)	(8.44)
GSE*“GSE Deal Fraction”			-0.032***			-0.027***			-0.026***
			(5.53)			(4.46)			(4.21)
Deal F.E. ?	Y	Y	Y	Y	Y	Y	Y	Y	Y
Covariates ?	Y	Y	Y	Y	Y	Y	Y	Y	Y
# Loans	9,823,431	9,823,431	9,554,443	9,823,431	9,823,431	9,554,443	9,823,431	9,823,431	9,554,443
# Deals	1,809	1,809	1,691	1,809	1,809	1,691	1,809	1,809	1,691
Adjusted R^2	0.16	0.16	0.16	0.20	0.20	0.20	0.21	0.21	0.21

Notes: This table shows loan-level, OLS regressions where the dependent variable is the actual default rate of loans backing subprime PLS issued between 2003 and 2007 calculated at three different points in time: 2008Q4, 20010Q4 and 2012Q4. In addition to the full list of those controls discussed in section 4 of the text, we include a series of indicator variables that measure the fraction of the population in a zip code that resides in census tracts which meet the qualifications for the underserved area affordable housing goal (UAG). Default is defined as a loan being 60 or 90 days delinquent, in foreclosure or REO. The independent variable of interest is “GSE” which is a 0/1 indicator variable. GSE pools have claims on groups of mortgages made up of almost exclusively loans below the conforming loan limit, whereas non-GSE pools refer to mortgage pools made up of loans both above and below the conforming loan limit. “GSE Deal Fraction” is a variable that is calculated quarterly for each deal sponsor that we are able to identify in the CoreLogic sample. It is calculated by taking the number of deals that include a GSE pool that the sponsor has issued up to each point in time and dividing that number by the total number of deals issued by the sponsor up until that quarter. Standard errors are heteroskedasticity-robust and clustered at the quarter of issuance level. The first row for each variable shows the regression coefficient, the second row shows t-statistics. Level of statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 10: Yield Spreads for GSE and Non-GSE Pools

	(1)	(2)	(3)	(4)	(5)	(6)
GSE (d)	2.71***	3.55***	-2.41	4.68***	6.36***	2.75
	(4.59)	(3.99)	(1.28)	(7.20)	(3.88)	(1.26)
Average Life	5.41***	6.99***	6.99***	4.52***	5.49***	5.50***
	(6.53)	(6.66)	(7.66)	(4.73)	(4.78)	
GSE * "GSE Deal Fraction"			9.61***			6.57**
			(3.29)			(2.03)
Pool Characteristics?				Y	Y	Y
Issue Quarter FE?	Y			Y		
Issue FE?		Y	Y		Y	Y
# Pools	3,290	3,290	3,290	3,290	3,290	3,290
R^2	0.56	0.79	0.79	0.62	0.84	0.84

Notes: This table shows pool-level, OLS regressions where the dependent variable is the pool-level average spread (in percentage points) over the one-month LIBOR rate. The average spread is calculated by weighting the spread on individual tranches included in each pool by their original dollar amount. The independent variable of interest is "GSE" which is a 0/1 indicator variable. GSE pools have claims on groups of mortgages made up of almost exclusively loans below the conforming loan limit, whereas non-GSE pools refer to mortgage pools made up of loans both above and below the conforming loan limit. Regressions with "Pool Characteristics" (columns 4,5, and 6) have pool-level controls for the loan characteristics in the pool. A full list of those controls is given in the text in Section 3. Pool-level average life is the average weighted expected life for the tranches in each pool as advertised in the prospectus where the average is weighted by the size of each tranche. The sample includes only triple-A floating rate tranches that are part of deals where all the triple-A tranches are either floating rate or inverse floaters. Standard errors are heteroskedasticity-robust and clustered at the quarter of origination level. The first row for each variable shows the regression coefficient, the second row shows t-statistics. Level of statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

Appendix (NOT FOR PUBLICATION)

A.1 Algorithm for Identifying GSE Pools

This section describes our algorithm for identifying pools of mortgages backing subprime PLS deals involving Fannie Mae and Freddie Mac.

As described in the text, we use a unique feature of the subprime PLS market to indirectly identify triple-A subprime PLS purchased by the GSEs. PLS deals involving Fannie Mae and Freddie Mac were split into conforming and nonconforming mortgage pools. This split was necessary to facilitate the GSEs' purchases of PLS since, by law, Fannie Mae and Freddie Mac are only allowed to securitize and/or invest in mortgages below the conforming loan limit. The GSEs would thus purchase triple-A securities that were backed by loans from the pool(s) of exclusively conforming mortgages, while other investors would purchase securities from the pool(s) that contained both conforming and non-conforming loans.

Based on this institutional feature of the PLS market, we design an algorithm to identify mortgage pools that backed securities purchased by either Fannie Mae and Freddie Mac between 2003 and 2007.[1] The algorithm is quite simple, with the following two conditions required for a pool to be categorized as a "GSE pool":

1. At least 99% of loans in the pool must be below the conforming loan limit at the time that securities in the deal are issued to investors.

2. Less than 75% of loans in the pool are second liens.

[1] Unfortunately this algorithm does not allow us to distinguish between mortgage pools backing securities purchased by Fannie Mae versus pools backing securities purchased by Freddie Mac.

Table A.1: Conforming Loan Limits: 2000–2007

Year	Conforming Loan Limit (Single Family Property)
2000	\$ 252,700
2001	\$ 275,000
2002	\$ 300,700
2003	\$ 322,700
2004	\$ 333,700
2005	\$ 359,650
2006	\$ 417,000
2007	\$ 417,000
2008	\$ 417,000

The first restriction is the most important. It is based on whether the loan lies above or below the conforming loan limit at the time that the deal is issued, rather than the time that the mortgage is originated.[2] Table A.1 shows the conforming loan limits for the period 2000–2007, which applied to all states within the continental U.S.

We allow up to 1 percent of the loan pool to be composed of non-conforming mortgages to take into account potential measurement error in the data. Specifically we are concerned with potential error stemming from two variables. First, there may be cases in which the outstanding balance reported in the CoreLogic database is incorrect. Second, there may be cases in which the variable that indicates whether a property is single-family or 2-4 family is incorrectly reported. The conforming loan limits for 2-4 family properties were significantly higher than those for single-family properties. Thus, if an observation is incorrectly categorized as pertaining to a single-family home instead of a 2-4 family property, then we would likely misclassify the observation as a non-conforming mortgage.[3]

[2]This distinction is potentially important because there are often seasoned loans in the mortgage pools so that the loan amount at origination can be higher than the outstanding balance at the time that the deal is issued.

[3]Note that our algorithm only considers single-family mortgages due to the fact that 2-4 family properties were subject to different conforming loan limits depending on the exact number of units, and CoreLogic does not distinguish between properties by the number of units (i.e. it groups 2, 3, and 4 family units

We impose the restriction on the proportion of second lien mortgages because the vast majority of them have outstanding balances below the conforming loan limit.[4] Hence, the conforming loan limit tells us very little about whether or not the GSEs purchased securities collateralized by those loan pools.[5]

A.2 Additional Validation of Algorithm

Table 1 in the paper compares annual, aggregate GSE purchases of subprime PLS as calculated using our algorithm with those listed in the 2011 FHFA Annual Report to Congress. In the table we were only able to compare numbers for 2006 and 2007 because the FHFA report does not break out Freddie Mac's purchases by the type of security (subprime versus Alt-A), whereas it does for Fannie Mae going back to 2003. Another source of information about the aggregate purchases of subprime securities by the GSEs is the Federal Crisis Inquiry Commission (FCIC) Report. In order to infer the annual purchases in 2003–2005 by Freddie Mac, we use a Figure in the FCIC report entitled "Buyers of Non-GSE Mortgage-Backed Securities" (see page 124 of the report). Of course, we cannot obtain precise numbers for Freddie Mac from the figure, but we are able to obtain approximate numbers. Table A.2 displays Fannie Mae's numbers from the FHFA Annual Report, as well as Freddie Mac's inferred numbers from the FCIC figure (as an interval, to allow for potential measurement error). We add these numbers to arrive at a total annual figure for GSE subprime PLS purchases from 2003–2007. In the last column of the table we show the annual purchases derived from our algorithm, which closely tracks the purchases derived from the public sources.

together).

[4] In our sample of pools backing securities issued between 2003 and 2007 there are 245 pools for which the share of second lien loans is greater than 75%.

[5] We also imposed the restriction that a GSE pool can only be associated with a deal that contained at least two mortgage pools. We did this because of our focus on deal-level fixed effects, however there is nothing that prohibited an issuer from structuring a deal with only a single conforming loan pool. There were only a handful of these deals in the CoreLogic database, so the restriction has no effect on the algorithm.

Table A.2: GSE Subprime PLS Annual Purchases: 2003–2007

	FHFA Report to Congress		FCIC Report	FHFA + FCIC Reports	Algorithm
	Total	Fannie Mae	Freddie Mac	Total	Total
2003	.	25.8	[44-48]	[69.8-73.8]	67.7
2004	.	67.0	[70-74]	[137-141]	141.0
2005	.	24.4	[112-116]	[136.4-140.4]	134.4
2006	110.4	35.6	[72-76]	[107.6-111.6]	106.0
2007	59.6	16.0	[37-41]	[53-57]	50.1

Although a complete list of PLS securities purchased by Fannie Mae and Freddie Mac is not publicly available, one source of information for validating our algorithm at the security-level is a disclosure by the Federal Housing Finance Agency (FHFA) announcing lawsuits against PLS issuers in September of 2011.[6]

In the lawsuits, the FHFA focuses on 718 securities that were purchased by the GSEs, and includes the associated tickers (e.g. "ABFC 2006-HE1 A1"). We attempt to match the 718 securities to subprime PLS tickers obtained from Bloomberg. We are able to identify 478 out of the 718 securities as being subprime, while another 226 have different collateral characteristics.[7] The face values of the 478 subprime securities included in the lawsuit were $37.3 billion in 2005, $80.7 billion in 2006, and $38.3 billion in 2007, vastly less than the total amount of subprime PLS purchased by the GSEs during those years.

We can use the 478 securities to partially validate our algorithm, as we are certain that these securities were purchased by the GSEs. When we match the securities to our GSE indicator variable we find that 476 out of the 478 subprime securities included in the lawsuit (99.6%)

[6] In this lawsuit, the FHFA sued 17 PLS issuers because it concluded that "some portion of the losses that Fannie Mae and Freddie Mac incurred on private-label mortgage-backed securities (PLS) are attributable to misrepresentations and other improper actions by the firms and individuals named in these filings." (FHFA, September 6, 2011, "Federal Housing Finance Agency Statement on Recent Lawsuits Filed").

[7] This leaves out 14 securities that we are not able to match to Bloomberg using the tickers provided in the lawsuit documents.

are classified as GSE, which translates into a type I error rate of 0.4%. We cannot use this test to evaluate the type II error in our algorithm, given that there are many securities purchased by Fannie Mae and Freddie Mac that are not part of the lawsuits.

A.3 Robustness Tables

This section contains tables of the robustness check results referred to in the main text. Tables A.3 and A.4 contain results that correspond to Tables 4, 5, and 7 in the text in which default is defined as 90+ days delinquent rather than 60+ days delinquent. The results are quite similar and suggest that they are not sensitive to the definition of default.

Tables A.5 and A.6 contain ex-ante predicted default probability results (corresponding to Table 4 in the text) in which predicted default probabilities are calculated using slightly different statistical models. Table A.5 uses separate models for first and second lien mortgages and separate models for conforming and non-conforming (jumbo) loans, while Table A.6 uses separate models for adjustable-rate and fixed-rate mortgages. The results are quite similar to those in Table 4, in which a single model was used to calculate all predicted default probabilities.

In Table A.7 we re-estimate our ex-post default rate regressions (Tables 5 and 7 in the text) using logistic models rather than linear probability models. The drawback of using logit models in the presence of fixed effects is the well-known incidental parameters problem. With small numbers of observations within groups, the incidental parameters problem can result in significant bias of the estimates of the slope parameters. Since most of the deals contain thousands of loans in multiple mortgage pools, this is likely not an important issue in our context. In fact, the results displayed in Table A.7 are virtually identical to the results in Tables 5 and 7.[8]

[8]We also considered the conditional logit estimator developed by Chamberlain (1980), which eliminates

Finally, we re-estimate our ex-post default rate regressions in Table A.8 over two different horizons (24 months and 36 months) measured relative to the month of security issuance rather than a specific point in (calendar) time. These horizons are consistent with the methodology used in estimating the ex-ante default probabilities. The estimates in Table A.8 are qualitatively and quantitatively similar to those in Tables 5 and 7 in the text.

the fixed effects from the likelihood function, and thus is not susceptible to the incidental parameters problem. However, with large numbers of observations within groups (in our case loans within deals), the estimator becomes difficult to implement computationally.

Table A.3: Predicted Default Probabilities for Loans in GSE and Non-GSE Pools: Alternative Default Definition

Panel A: OLS (Linear Probability Model)

	12-month Horizon		24-month Horizon		36-month Horizon	
GSE (d)	-0.0009	-0.0075	0.0085	-0.0067	0.0103	-0.0079
	(0.48)	(5.96)	(2.47)	(3.32)	(2.71)	(3.77)
Deal F.E.?	N	Y	N	Y	N	Y
# Loans	10,465,022	10,465,022	10,465,022	10,465,022	9,168,963	9,168,963
# Deals	1,808	1,808	1,808	1,808	1,570	1,570
R^2	0.00	0.40	0.00	0.33	0.00	0.30

Panel B: Logit

	12-month Horizon		24-month Horizon		36-month Horizon	
GSE (d)	-0.0033	-0.0050	0.0108	0.0024	0.0188	0.0039
	(1.39)	(2.88)	(3.35)	(1.55)	(7.14)	(2.36)
Deal F.E.?	N	Y	N	Y	N	Y
# Loans	10,438,305	10,438,305	10,330,159	10,330,159	8,779,903	8,779,903
# Deals	1,808	1,808	1,806	1,806	1,555	1,555
Pseudo R^2	0.00	0.34	0.00	0.24	0.01	0.17

Panel C: Multinomial Logit

	12-month Horizon		24-month Horizon		36-month Horizon	
GSE (d)	-0.0025	-0.0046	0.0106	0.0035	0.0186	0.0065
	(1.11)	(2.72)	(3.14)	(2.21)	(7.85)	(3.99)
Deal F.E.?	N	Y	N	Y	N	Y
# Loans	10,464,165	10,464,165	10,464,165	10,464,165	9,168,963	9,168,963
# Deals	1,808	1,808	1,808	1,808	1,570	1,570
Pseudo R^2	0.00	0.34	0.00	0.24	0.01	0.17

Notes: This table shows loan-level, OLS regressions where the dependent variables are the 12-month, 24-month, and 36-month predicted default rates at the time the loan is originated using all information in the data for the previous two years for the 12-month rate and three years for the 24-month and 36-month predicted rates. Default is defined as a loan being 90 days delinquent, in foreclosure or REO. The independent variable of interest is "GSE" which is a 0/1 indicator variable. GSE pools have claims on groups of mortgages made up of almost exclusively loans below the conforming loan limit, whereas non-GSE pools refer to mortgage pools made up of loans both above and below the conforming loan limit. Panel A computes predicted default rates using OLS regressions, while Panel B computes predicted default rates using logistic regressions, and Panel C computes predicted default rates using multinomial logistic regressions. Standard errors are heteroskedasticity-robust and clustered at the quarter of issuance level. The first row for each variable shows the regression coefficient, the second row shows t-statistics.

Table A.4: Ex-Post Default Rates for Loans in GSE and Non-GSE Pools: Alternative Default Definition

	Horizon through 2008:Q4			Horizon through 2010:Q4			Horizon through 2012:Q4		
GSE (d)	-0.019	-0.007	0.012	-0.016	-0.005	0.009	-0.015	-0.006	0.008
	(10.43)	(4.66)	(3.45)	(9.62)	(2.68)	(3.18)	(8.75)	(2.65)	(3.21)
GSE*Low Doc		-0.033	-0.033		-0.029	-0.030		-0.027	-0.027
		(9.88)	(9.66)		(8.91)	(9.07)		(8.76)	(8.95)
GSE*"GSE Deal Fraction"			-0.031			-0.023			-0.021
			(5.41)			(3.84)			(3.66)
Deal F.E. ?	Y	Y	Y	Y	Y	Y	Y	Y	Y
Covariates ?	Y	Y	Y	Y	Y	Y	Y	Y	Y
# Loans	10,464,165	10,464,165	10,156,202	10,464,165	10,464,165	10,156,202	10,464,165	10,464,165	10,156,202
# Deals	1,809	1,809	1,724	1,809	1,809	1,724	1,809	1,809	1,724
Adjusted R^2	0.15	0.15	0.15	0.21	0.21	0.21	0.22	0.22	0.22

Notes: This table shows loan-level, OLS regressions where the dependent variable is the actual default rate of loans backing subprime PLS issued between 2003 and 2007 calculated at three different points in time: 2008Q4, 20010Q4 and 2012Q4. Default is defined as a loan being 90 days delinquent, in foreclosure or REO. The independent variable of interest is "GSE" which is a 0/1 indicator variable. GSE pools have claims on groups of mortgages made up of almost exclusively loans below the conforming loan limit, whereas non-GSE pools refer to mortgage pools made up of loans both above and below the conforming loan limit. "GSE Deal Fraction" is a variable that is calculated quarterly for each deal sponsor that we are able to identify in the CoreLogic sample. It is calculated by taking the number of deals that include a GSE pool that the sponsor has issued up to each point in time and dividing that number by the total number of deals issued by the sponsor up until that quarter. Regressions with "covariates" include controls for a large number of borrower and loan characteristics. A full list of those controls is given in the text in Section 4. Standard errors are heteroskedasticity-robust and clustered at the quarter of issuance level. The first row for each variable shows the regression coefficient, the second row shows t-statistics. Level of statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A.5: Ex-Ante Default Probabilities for Loans in Conforming and Non-Conforming Pools: Alternative Model for Generating Predicted Default Rates

Panel A: OLS (Linear Probability Model)

	12-month Horizon		24-month Horizon		36-month Horizon	
GSE (d)	0.0006	-0.0034	0.0241	0.0096	0.0232	0.0104
	0.11	-1.07	6.25	3.31	8.72	2.55
Deal F.E.?	N	Y	N	Y	N	Y
# Loans	10,465,022	10,465,022	10,465,022	10,465,022	9,168,963	9,168,963
# Deals	1,809	1,809	1,809	1,809	1,571	1,571
R^2	0.00	0.35	0.01	0.22	0.01	0.19

Panel B: Logit

	12-month Horizon		24-month Horizon		36-month Horizon	
GSE (d)	0.0044	-0.0023	0.0212	0.0079	0.0213	0.0090
	(0.92)	(0.82)	(6.08)	(4.38)	(5.71)	(3.90)
Deal F.E.?	N	Y	N	Y	N	Y
# Loans	10,438,305	10,438,305	10,330,159	10,330,159	8,779,903	8,779,903
# Deals	1,809	1,809	1,807	1,807	1,556	1,556
Pseudo R^2	0.00	0.32	0.01	0.18	0.01	0.19

Panel C: Multinomial Logit

	12-month Horizon		24-month Horizon		36-month Horizon	
GSE (d)	0.0035	-0.0026	0.0211	0.0092	0.0189	0.0093
	(0.74)	(0.91)	(6.04)	(5.59)	(5.39)	(3.53)
Deal F.E.?	N	Y	N	Y	N	Y
# Loans	10,464,165	10,464,165	10,464,165	10,464,165	9,168,963	9,168,963
# Deals	1,809	1,809	1,809	1,809	1,571	1,571
Pseudo R^2	0.00	0.33	0.01	0.18	0.01	0.16

Notes: This table shows loan-level, OLS regressions where the dependent variables are the 12-month, 24-month, and 36-month predicted default rates at the time the loan is originated using all information in the data for the previous two years for the 12-month rate and three years for the 24-month and 36-month predicted rates. Predicted default rates are calculated by estimating separate regressions for first and second mortgages and separate regressions for conforming and non-conforming (jumbo) loans. Default is defined as a loan being 60 days delinquent, in foreclosure or REO. The independent variable of interest is "GSE" which is a 0/1 indicator variable. GSE pools have claims on groups of mortgages made up of almost exclusively loans below the conforming loan limit, whereas non-GSE pools refer to mortgage pools made up of loans both above and below the conforming loan limit. Panel A computes predicted default rates using OLS regressions, while Panel B computes predicted default rates using logistic regressions, and Panel C computes predicted default rates using multinomial logistic regressions. Standard errors are heteroskedasticity-robust and clustered at the quarter of issuance level. The first row for each variable shows the regression coefficient, the second row shows t-statistics.

Table A.6: Ex-Ante Default Probabilities for Loans in Conforming and Non-Conforming Pools: Alternative Model for Generating Predicted Default Rates

Panel A: OLS (Linear Probability Model)

	12-month Horizon		24-month Horizon		36-month Horizon	
GSE (d)	0.0017	-0.0038	0.0159	-0.0052	0.0045	-0.0092
	(0.55)	(1.75)	(3.82)	(2.53)	(0.84)	(3.85)
Deal F.E.?	N	Y	N	Y	N	Y
# Loans	10,465,022	10,465,022	10,465,022	10,465,022	9,168,963	9,168,963
# Deals	1,809	1,809	1,809	1,809	1,571	1,571
R^2	0.00	0.32	0.00	0.23	0.00	0.26

Panel B: Logit

	12-month Horizon		24-month Horizon		36-month Horizon	
GSE (d)	0.0038	-0.0018	0.0214	0.0064	0.0197	0.0057
	(0.89)	(0.84)	(4.91)	(2.77)	(4.86)	(2.42)
Deal F.E.?	N	Y	N	Y	N	Y
# Loans	10,438,305	10,438,305	10,330,159	10,330,159	8,779,903	8,779,903
# Deals	1,809	1,809	1,807	1,807	1,556	1,556
Pseudo R^2	0.00	0.33	0.01	0.17	0.01	0.17

Panel C: Multinomial Logit

	12-month Horizon		24-month Horizon		36-month Horizon	
GSE (d)	0.0038	-0.0023	0.0219	0.0054	0.0182	0.0046
	(0.90)	(1.04)	(6.56)	(2.28)	(4.79)	(1.84)
Deal F.E.?	N	Y	N	Y	N	Y
# Loans	10,464,165	10,464,165	10,464,165	10,464,165	9,168,963	9,168,963
# Deals	1,809	1,809	1,809	1,809	1,571	1,571
Pseudo R^2	0.00	0.34	0.01	0.14	0.00	0.17

Notes: This table shows loan-level, OLS regressions where the dependent variables are the 12-month, 24-month, and 36-month predicted default rates at the time the loan is originated using all information in the data for the previous two years for the 12-month rate and three years for the 24-month and 36-month predicted rates. Predicted default rates are calculated by estimating separate regressions for adjustable-rate and fixed-rate mortgages. Default is defined as a loan being 60 days delinquent, in foreclosure or REO. The independent variable of interest is "GSE" which is a 0/1 indicator variable. GSE pools have claims on groups of mortgages made up of almost exclusively loans below the conforming loan limit, whereas non-GSE pools refer to mortgage pools made up of loans both above and below the conforming loan limit. Panel A computes predicted default rates using OLS regressions, while Panel B computes predicted default rates using logistic regressions, and Panel C computes predicted default rates using multinomial logistic regressions. Standard errors are heteroskedasticity-robust and clustered at the quarter of issuance level. The first row for each variable shows the regression coefficient, the second row shows t-statistics.

Table A.7: Ex-Post Default Rates for Loans in GSE and Non-GSE Pools: Logit Model

	Horizon through 2008:Q4			Horizon through 2010:Q4			Horizon through 2012:Q4		
GSE (d)	-0.015	-0.004	0.016	-0.014	-0.005	0.013	-0.014	-0.005	0.012
	(10.70)	(2.56)	(4.56)	(9.09)	(2.53)	(4.15)	(8.91)	(2.87)	(3.81)
GSE*Low Doc		-0.030	-0.030		-0.027	-0.027		-0.025	-0.025
		(9.08)	(8.95)		(7.75)	(7.84)		(7.48)	(7.60)
GSE*"GSE Deal Fraction"			-0.032			-0.027			-0.026
			(5.82)			(4.55)			(4.32)
Deal F.E. ?	Y	Y	Y	Y	Y	Y	Y	Y	Y
Covariates ?	Y	Y	Y	Y	Y	Y	Y	Y	Y
# Loans	10,018,355	10,018,355	9,742,002	10,018,355	10,018,355	9,742,002	10,018,355	10,018,355	9,742,002

Notes: This table shows average partial effects from loan-level, logistic regressions where the dependent variable is the actual default rate of loans backing subprime PLS issued between 2003 and 2007 calculated at three different points in time: 2008Q4, 20010Q4 and 2012Q4. Default is defined as a loan being 60 days or more delinquent, in foreclosure or REO. The independent variable of interest is "GSE" which is a 0/1 indicator variable. GSE pools have claims on groups of mortgages made up of almost exclusively loans below the conforming loan limit, whereas non-GSE pools refer to mortgage pools made up of loans both above and below the conforming loan limit. "GSE Deal Fraction" is a variable that is calculated quarterly for each deal sponsor that we are able to identify in the CoreLogic sample. It is calculated by taking the number of deals that include a GSE pool that the sponsor has issued up to each point in time and dividing that number by the total number of deals issued by the sponsor up until that quarter. Regressions with "covariates" include controls for a large number of borrower and loan characteristics. A full list of those controls is given in the text in Section 4. Standard errors are heteroskedasticity-robust and clustered at the quarter of issuance level. The first row for each variable shows the average partial effects, the second row shows z-statistics. Level of statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

Table A.8: Ex-Post Default Rates for Loans in GSE and Non-GSE Pools: Alternative Horizons

Horizon	24 Months			36 Months		
GSE (d)	-0.016	-0.006	0.008	-0.016	-0.005	0.012
	(6.89)	(3.26)	(1.77)	(8.50)	(2.42)	(3.27)
GSE*Low Doc		-0.027	-0.028		-0.031	-0.031
		(6.78)	(7.08)		(9.39)	(9.41)
GSE*"GSE Deal Fraction"			-0.021			-0.027
			(2.83)			(4.46)
Deal F.E. ?	Y	Y	Y	Y	Y	Y
Covariates ?	Y	Y	Y	Y	Y	Y
# Loans	10,464,165	10,464,165	10,156,202	10,464,165	10,464,165	10,156,202
# Deals	1,809	1,809	1,724	1,809	1,809	1,724
Adjusted R^2	0.16	0.16	0.16	0.20	0.20	0.20

Notes: This table shows loan-level, OLS regressions where the dependent variable is the actual default rate of loans backing subprime PLS issued between 2003 and 2007 calculated over two different horizons relative to the month of security issuance: 24 months and 36 months. Default is defined as a loan being at least 60 days delinquent, in foreclosure or REO. The independent variable of interest is "GSE" which is a 0/1 indicator variable. GSE pools have claims on groups of mortgages made up of almost exclusively loans below the conforming loan limit, whereas non-GSE pools refer to mortgage pools made up of loans both above and below the conforming loan limit. "GSE Deal Fraction" is a variable that is calculated quarterly for each deal sponsor that we are able to identify in the CoreLogic sample. It is calculated by taking the number of deals that include a GSE pool that the sponsor has issued up to each point in time and dividing that number by the total number of deals issued by the sponsor up until that quarter. Regressions with "covariates" include controls for a large number of borrower and loan characteristics. A full list of those controls is given in the text in Section 4. Standard errors are heteroskedasticity-robust and clustered at the quarter of issuance level. The first row for each variable shows the regression coefficient, the second row shows t-statistics. Level of statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

A.4 Additional Analysis

In the first column of Table A.9 we display output from our main specification (Table 5) for (virtually) all covariates, in order to provide the reader with an idea of the quantitative magnitudes of the estimates associated with the control variables in our regressions. In the second column, we display a similar set of estimates from the regression specification that includes controls for the fraction of the zip code (in which the loan was originated) that lies in census tracts that are eligible for the underserved area affordable housing goal (UAG).[9] We specify the variable has a set of indicators that correspond to each decile. For example, the first variable is an indicator for whether the UAG zip code fraction is between 0 and 0.1, the second is an indicator for whether the UAG fraction is between 0.1 and 0.2, etc. We omit the indicator that corresponds to the highest UAG values (between 0.9 and 1). The estimation results show that loans originated in zip codes with higher UAG fractions are more likely to default, *ceteris paribus*.

Table A.9: Ex-post Default Rate Linear Probability Model Coefficient Estimates

	Horizon through 2008	
	Baseline Specification	Include UAG Controls
GSE (d)	-0.007	-0.008
	(4.17)	(4.73)
Low Doc (d)	0.070	0.068
	(10.04)	(10.16)
GSE*Low Doc	-0.032	-0.032
	(9.19)	(9.04)
Owner Occupant (d)	-0.047	-0.044

[9]Both regressions also include a full set of state fixed-effects, deal fixed-effects, and dummy variables that control for missing covariate values.

	(11.72)	(11.29)
Prepay Penalty (d)	0.047	0.046
	(9.47)	(9.49)
1-unit Single Family Prop. (d)	-0.004	-0.002
	(3.03)	(1.83)
Condominium (d)	-0.024	-0.019
	(10.71)	(9.00)
Balloon (d)	0.049	0.048
	(12.12)	(11.88)
# Months Seasoned	0.000	0.000
	(0.00)	(0.04)
ARM (d)	-0.003	0.031
	(0.08)	(0.88)
Interest-Only (d)	0.046	0.046
	(10.31)	(10.46)
Negatively Amortizing (d)	0.046	0.045
	(1.73)	(1.70)
First Lien (d)	0.037	0.024
	(2.54)	(1.56)
Purchase Loan (d)	0.012	0.012
	(3.23)	(3.41)
Refinance Cash-Out (d)	-0.017	-0.018
	(13.21)	(13.65)
LTV	0.002	0.002
	(8.53)	(8.28)
$70 \leq$ LTV < 80 (d)	0.023	0.024
	(5.04)	(5.11)

$80 < \text{LTV} < 90$ (d)	0.047	0.048
	(5.20)	(5.30)
$90 \leq \text{LTV} < 100$ (d)	0.074	0.075
	(6.37)	(6.49)
$\text{LTV} \geq 100$ (d)	0.130	0.131
	(8.24)	(8.32)
$\text{LTV} = 80$ (d)	0.026	0.025
	(6.78)	(6.62)
FICO	-0.001	-0.001
	(25.93)	(26.03)
$\text{FICO} < 580$	0.025	0.026
	(7.05)	(7.39)
$580 < \text{FICO} \leq 620$	0.022	0.023
	(5.90)	(6.12)
$620 < \text{FICO} \leq 660$	0.004	0.004
	(1.24)	(1.54)
$660 < \text{FICO} \leq 700$	-0.010	-0.009
	(4.32)	(4.12)
Interest Rate	0.030	0.029
	(17.04)	(17.29)
Log (Loan Balance)	0.020	0.027
	(2.27)	(2.90)
Term	0.000	0.000
	(8.73)	(8.55)
Jumbo (d)	0.023	0.025
	(4.85)	(5.37)
Unemp. Level at Origination	0.004	0.003

	(6.17)	(4.97)
Price Index Level at Origination	0.001	0.001
	(7.90)	(7.41)
Δ Unemp. through 2008	0.013	0.019
	(2.76)	(3.67)
HPA through 2008	-0.190	-0.191
	(4.30)	(4.38)
$0 \leq$ UAG Fraction < 0.10	.	-0.040
	.	(11.57)
$0.10 \leq$ UAG Fraction < 0.20	.	-0.038
	.	(11.31)
$0.20 \leq$ UAG Fraction < 0.30	.	-0.030
	.	(8.62)
$0.30 \leq$ UAG Fraction < 0.40	.	-0.029
	.	(10.60)
$0.40 \leq$ UAG Fraction < 0.50	.	-0.023
	.	(7.59)
$0.50 \leq$ UAG Fraction < 0.60	.	-0.026
	.	(9.04)
$0.60 \leq$ UAG Fraction < 0.70	.	-0.017
	.	(11.77)
$0.70 \leq$ UAG Fraction < 0.80	.	-0.014
	.	(7.04)
$0.80 \leq$ UAG Fraction < 0.90	.	-0.008
	.	(7.06)
Deal F.E. ?	Y	Y
State F.E. ?	Y	Y

# Loans	10,464,165	9,823,431
# Deals	1,809	1,809
Adjusted R^2	0.16	0.16