Are Lemons Sold First? Dynamic Signaling in the Mortgage Market*

Manuel Adelino
Duke University

Kristopher Gerardi
Federal Reserve Bank of Atlanta

Barney Hartman-Glaser
UCLA

October 3, 2016

Abstract

A central result in the theory of adverse selection in asset markets is that informed sellers can signal quality and obtain higher prices by delaying trade. This paper provides some of the first evidence of a signaling mechanism through delay of trade using the residential mortgage market as a laboratory. We find a strong relation between mortgage performance and time-to-sale for privately-securitized mortgages. Additionally, deals made up of more seasoned mortgages are sold at lower yields. These effects are strongest in the "Alt-A" segment of the market where buyers had less hard information about mortgages.

*Manuel Adelino, manuel.adelino@duke.edu, Fuqua School of Business, 100 Fuqua Drive, Durham, NC 27708. Kris Gerardi, kristopher.gerardi@atl.frb.org, Federal Reserve Bank of Atlanta, 1000 Peachtree St NE, Atlanta, GA. Barney Hartman-Glaser, bhglaser@anderson.ucla.edu, Anderson School of Management, 110 Westwood Plaza, Los Angeles, CA 90095. For helpful comments and discussions we would like to thank Brendan Daley, Joseph Mason, Anthony Pennington-Cross, Tim Riddiough, Hongfei Tang, Nancy Wallace, Paul Willen, and Basil Williams as well as seminar participants at the 2015 Southern Finance Association Conference, 2016 AREUEA National Conference, and 2016 FIRS Conference. We thank Valeria Vargas-Sejas for outstanding research assistance. This paper was previously circulated under the title "A Test of Dynamic Signaling Models: Evidence from Mortgage Securitization"

1 Introduction

One of the most widely studied market settings in economics is that of a seller with private information about the quality of an asset facing less informed buyers. In the presence of such an adverse selection problem, sellers can take actions to reveal their private information as in the classic signaling model of Spence (1973). This notion of signaling has been successfully applied in theoretical models of financial markets to explain a variety of phenomena from the optimality of debt (DeMarzo and Duffie (1999)) to the fragility of over-the-counter markets (Daley and Green (2012)). There is, however, remarkably little empirical evidence that agents actually engage in costly signaling to overcome informational asymmetries. This paper begins to fill this gap in the literature, by presenting empirical evidence that is consistent with the existence of costly signaling in the U.S. mortgage mortgage.

We present a simple model of mortgage sales to motivate our empirical tests. In the model, sellers of high quality mortgages face a lower cost of waiting because their mortgages have a lower probability of default. The seller privately observes mortgage quality and we assume that default is publicly observable and extinguishes the possibility of sale. A separating equilibrium emerges in which time-to-sale perfectly reveals the seller's information, a relation often referred to as the skimming property.[1] The idea that sellers delay trade to signal higher asset quality and obtain higher prices is a central and general prediction of dynamic signaling models.

This paper uses data on the U.S. mortgage market to test these predictions. The mortgage market serves as a unique laboratory for testing the skimming property for two reasons. First, mortgages are durable assets characterized by an objective measure of quality based on the probability of default. There is detailed micro data available to investors, originators, and the econometrician on the observable characteristics of borrowers and mortgage

[1] The skimming property is one of the properties derived from the Coase (1972) analysis of pricing by a durable-goods monopolist (Coasian dynamics). Many recent studies have found that the skimming property can emerge in dynamic adverse selection models of financial markets, see for example Daley and Green (2012), Fuchs and Skrzypacz (2013), Fuchs et al. (2015).

contracts, which together serve as a good proxy for observable mortgage quality at the time of the sale. At the same time, while outcomes are not known at the time of sale, they are known to the econometrician *ex post*. This provides a source of *unobserved* heterogeneity in asset quality that is (i) known privately by the seller, as shown in previous studies of the mortgage market,[2] (ii) unknown to potential buyers, and (iii) known to the econometrician. The distinction between observable and unobservable asset characteristics is central to our tests, and one of the main reasons dynamic adverse selection models are particularly hard to test empirically.[3] In fact, most models predict that assets that are observably better should trade faster, not slower.

Second, during the middle of the last decade there was an active secondary market for mortgages where investors in mortgage-backed securities (the buyers) purchased claims on large portfolios of mortgages. While there is a chain of intermediaries between the originators of mortgages and the buyers of the securities (as shown in Stanton et al. (2014) and Stanton and Wallace (2015)), we are able to measure time-to-sale from the creation of the asset (when the mortgage is originated) to the sale of the securities that ultimately receive cash flows on those mortgages. The fact that there may be more than one transfer of a mortgage along this chain biases our tests *against* capturing the role of signaling in transmitting information.

We concentrate the majority of our empirical analysis on the relation between delay of trade and mortgage quality. We also present evidence on how the pricing of mortgage-backed deals varies with average mortgage time-to-sale. As we discuss in the model section, the loan-level default results allow us to distinguish signaling from other alternative hypotheses more sharply than the deal-level pricing results, which is why the former are the main focus of the paper.

Using data on mortgages securitized in the non-agency, private-label securitization (PLS)

[2]See, for example, Demiroglu and James (2012a), Jiang et al. (2014b), Griffin and Maturana (2016), and Piskorski et al. (2015).

[3]Fuchs et al. (2015) find evidence consistent with the skimming property in the IPO market.

market, we find a clear negative relationship between time-to-sale and the component of mortgage performance that is not explained by observable mortgage characteristics. In our baseline specifications we find that, after conditioning on all underwriting characteristics, PLS loans sold five months or more after origination are approximately 5 percentage points less likely to default relative to loans sold immediately after origination. This is an economically meaningful difference, as it is approximately 30 percent of the average default rate in our sample (16 percent).

The results on *ex post* default are in contrast to those using *ex ante* measures of credit risk. Specifically, we construct predicted probabilities of default using only information available to mortgage investors at the time that mortgages are sold into PLS deals. We then ask whether *ex-ante* observable credit risk is related to time-to-sale. We find no relation between *ex-ante* observable risk and time-to-sale despite the fact that this measure is highly correlated with *ex post* performance. Put differently, while unobserved quality is related to delay of trade, observable risk measures are not.[4]

In addition, we show that in contrast to the findings in the PLS segment of the market, we find no evidence of a negative relationship between time-to-sale and mortgage default in a large sample of loans sold to the Government Sponsored Enterprises (GSEs), Fannie Mae and Freddie Mac. We argue that this is consistent with the institutional features of the GSE market, where automated underwriting and the credit guarantee provided by the agencies likely mitigates the role for asymmetric information about mortgage credit quality (though not necessarily about prepayment risk) between investors in GSE securities and originators.

We then turn to a secondary source of detailed loan-level data (CoreLogic) to implement a series of cross-sectional tests. Using this dataset we find that the results are strongest in

[4] The lack of relation between observable risk and time-to-sale speaks to the interpretation of our results in the case that the buyers of mortgages (the issuers) have more information than we do as the econometrician. In fact, the validity of our tests does not rely on observing *all* information that is common to buyers and sellers in the market. Our tests require a weaker assumption, namely that credit quality as we measure it be an unbiased estimate of quality measured by issuers using their full information set. If this is the case, the results using our observable risk measure provide a good approximation of the unobserved relation between credit risk (as measured by issuers) and time-to-sale.

the "Alternative-A" (or "Alt-A") segment of the market, which is comprised of a majority of low documentation loans or loans with risk characteristics that prevent them from being securitized in the conforming market. While the subprime segment of the market is riskier than the Alt-A segment, subprime mortgages are more homogeneous in their (potentially unobserved) risk characteristics. The previous literature has found private information to be especially important among low documentation mortgages, which lends further credence to an adverse selection, signaling interpretation.[5]

An additional virtue of the CoreLogic dataset is that it contains information on the identities of originators for a large subset of loans. This allows us to include originator fixed effects in our regressions, which helps address the concern that funding sources (in particular very short term warehouse loans and repo agreements) might prevent a signaling mechanism from taking place. By estimating within-originator regressions, any variation that comes from systematic differences across originators in funding differences is absorbed by the fixed effects. To the extent that certain types of originators (in particular independent mortgage companies, as pointed out in Stanton et al. (2014) and Ganduri (2015)) relied almost exclusively on these types of funding sources, that variation is accounted for in these specifications. We find similar results to the baseline specifications that do not control for the originator.

As a final test on the quality dimension, we separately estimate the correlation between time-to-sale and default for issuers and originators that are affiliated entities (as in Demiroglu and James (2012a) and Furfine (2014)). This helps distinguish signaling behavior from "unilateral" concerns about warehousing loans on the part of the seller. If our results simply reflected originator reluctance to hold on to bad loans without an intention to signal unobserved quality to buyers, we would expect no differences across affiliated and unaffiliated entities. Instead, we find a significantly weaker negative correlation between time-to-sale and default risk for the sample of mortgages in which the issuer and originator

[5] See for example, Jiang et al. (2014a), Jiang et al. (2014b), Begley and Purnanandam (2014), and Saengchote (2013)

are affiliated with each other.

We then turn to the pricing dimension to determine whether prices rise with time-to-sale as predicted by the signaling model. Data on prices paid for individual mortgages does not exist (to our knowledge), so we conduct an analysis of mortgage-backed security (MBS) prices. Since MBS derive their cash flows from pools of individual mortgages, if signaling plays an important role in the market, then we should expect to see a positive relationship between average time-to-sale at the pool level and MBS prices. Using data on floating-rate, triple-A, PLS yield spreads at origination, we find that securities made up of loans that take longer to sell (more seasoned loans) are sold at lower yields.[6] Consistent with the evidence on mortgage performance, the pricing results are non-linear in seasoning and are strongest in the Alt-A segment of the market.

This paper relates to the literature on adverse selection and signaling. The seminal work of Akerlof (1970) first identified that markets can break down when some participants have valuable, private information. In related work, Spence (1973) shows informed agents can take actions to credibly reveal their private information that lead to a separating equilibrium. This insight was first applied to financial markets by Leland and Pyle (1977) who showed the issuers of IPO's can signal information by retaining an equity stake in the IPO. DeMarzo and Duffie (1999) use the equilibrium relationship between retention and asset quality to show that debt minimizes the costs associated with the separating equilibrium and is hence an optimal security design. DeMarzo (2005) builds on this idea to show that it is optimal to first pool assets to minimize adverse selection and then create tranches to minimize signaling costs.

While retention is a common signaling device pointed out in the above literature on adverse selection, delay of trade serves the same function in a dynamic setting. Janssen and Roy (2002) show that, in a durable goods market in which sellers have private information, a

[6] We do not observe security prices at origination, so we use yield spreads as our measure of pricing (consistent with, among others, **?**, **?**, and **?**). The assumption is that floating rate securities were almost always issued at par.

market mechanism emerges in which prices and the quality of goods increases over time. This property of market equilibrium is the so-called *skimming property.* This property has been shown to be a general feature of equilibrium in dynamic models of adverse selection. For example, Daley and Green (2012) consider a model in which an informed party sells an asset to a market of uninformed agents. When news about asset quality arrives over time, sellers with high value assets wait to trade allowing market participants to infer that delayed trade is associated with higher value assets.

This paper also contributes to the empirical literature on the effects of asymmetric information. The seminal work of **?** finds weak evidence of adverse selection in the used car market. Another important paper in this literature is Garmaise and Moskowitz (2004) who use commercial real estate transactions to test a number of theories of asymmetric information, including the prediction that securities issuers retain a stake to signal their information. In contrast to our paper, they find no evidence that informed sellers of commercial real estate signal their information through retention. Downing et al. (2009) also look at retention and find that mortgages sold to special purpose vehicles (SPVs) tend to be of lower quality than mortgages not sold to SPVs. Agarwal et al. (2012) find no systematic difference between subprime mortgages sold in the secondary market and those retained on banks balance sheets. Closest to our setting, **?** find that higher levels of equity tranches in PLS deals (a measure of retention) are associated with lower delinquency rates and higher prices.

2 A Model of Signaling Through Delayed Trade

To motivate our empirical tests, we present a simple model of adverse selection and delayed trade in the secondary market for mortgages. Time is infinite, continuous, and indexed by t. The model consists of a mortgage originator and a competitive market of mortgage investors. All agents are risk neutral. At time $t = 0$, the seller originates a mortgage for potential sale to the market. This mortgage produces a cash flow of c dollars per unit of time until it defaults at some a random time τ. The default time τ is an exponential random variable with parameter λ distributed on the compact interval $[\lambda_\ell, \lambda_h]$ according to the continuous density $f(\lambda)$. While $f(\lambda)$ is common knowledge, the seller privately observes λ at the origination of the mortgage. As is common in such settings, we refer to λ as the seller's type.

While both the seller and potential investors are risk neutral, there are gains from trade generated by a difference in discount rates used by the two classes of agents. Specifically, the seller discounts cash flows at a rate γ, while the investors discount cash flows at rate $r < \gamma$. This difference in discount rates proxies for a difference in the investment opportunity set between the seller and the investors. Indeed, the seller has the technology to originate mortgages, while investors can only purchase mortgages in a competitive market once they have already been originated. We note that modeling these gains from trade as a difference in discount rates is convenient for the analysis that follows, but not necessary. As long as there are gains from trade between the seller and investors that are monotonic in the seller's type, λ, the predictions of the model will be qualitatively unchanged.

We assume that default is publicly observable, so that if a mortgage defaults before the seller has sold it to the investors, no sale will occur. In choosing when to sell the mortgage, the seller will take some market price function $P(t)$ as given. Note that the lowest possible value of a mortgage to investors is

$$p_h = E\left[\int_t^\infty e^{-r(s-t)}\mathbb{1}(s \leq \tau)cds|\lambda_h\right] = \frac{c}{r+\lambda_h},$$

while the highest possible value is

$$p_\ell = E\left[\int_t^\infty e^{-r(s-t)}\mathbb{1}(s \leq \tau)cds|\lambda_\ell\right] = \frac{c}{r+\lambda_\ell},$$

so that $P(t) \in [p_h, p_\ell]$.

An outcome of this game is a triple $(\lambda, t, p) \in [\lambda_\ell, \lambda_h] \times [0, \infty) \times [p_h, p_\ell]$, where λ is a realization of the seller's type and t and p correspond to the time and price at which trade takes place if the mortgage has not defaulted by time t. The value for the seller of an outcome of the game is then given by

$$\begin{aligned} U(\lambda, t, p) &= E\left[\int_0^t e^{-\gamma s}\mathbb{1}(s \leq \tau)c ds + e^{-\gamma t}\mathbb{1}(t \leq \tau)p \big| \lambda\right] \\ &= \frac{c}{\gamma+\lambda}\left(1 - e^{-(\gamma+\lambda)t}\right) + e^{-(\gamma+\lambda)t}p. \end{aligned}$$

An important feature of the seller's payoff function is the so-called single-crossing property; fixing a price p, delaying trade is less costly for better (lower default risk) type sellers. Intuitively, the lower the default risk, the greater the private value of the cash flows that accrue to the seller from the mortgage prior to the sale, and the greater the probability that the mortgage will remain current so that it can be sold at some future date. This feature of the model gives rise to the common *skimming property*, which is present in much of the literature on dynamic trading and adverse selection,[7] and is more broadly related to the literature on costly signaling with adverse selection.[8] In our model, the skimming property can be expressed as follows: For a given price function $P(t)$, better sellers will wait (weakly) longer to trade, and thus a delay in trade can act as a signal of quality.

A perfect Bayesian equilibrium of the game is a pair of functions (T, P) where $T(\lambda)$ is the time at which a seller of type λ trades and $P(t)$ is the price for a mortgage sold at time t such that the following conditions hold:

1. Seller optimality:

$$T(\tilde{\lambda}) \in \arg\max_t U(\tilde{\lambda}, t, P(t),)$$

[7] See, for example, the early literature on sequential bargaining models with one-sided incomplete information (Fudenberg and Tirole (1983), Sobel and Takahashi (1983), Cramton (1984), Fudenberg et al. (1985), Gul et al. (1986), Gul and Sonnenschein (1988), Ausubel and Deneckere (1989)), Evans (1989) and Vincent (1989). It is also present in dynamic auction models with private information (Vincent (1990)) and competitive markets models of durable goods with private information (Janssen and Roy (2002)).

[8] For example, Spence (1973) and Leland and Pyle (1977)

2. Zero profit for the investors:

$$P(T(\tilde{\lambda})) = E\left[\frac{c}{r+\tilde{\lambda}} | T(\tilde{\lambda})\right].$$

We call an equilibrium separating if $P(T(\tilde{\lambda})) = \tilde{\lambda}$.

We will focus on characterizing a separating equilibrium. Although other equilibria, for example pooling equilibria, may exist, they are eliminated by standard refinement criteria, such as the D1 refinement of Cho and Kreps (1987). The following proposition characterizes the unique separating equilibrium of the game:

Proposition 1. *The unique separating equilibrium of the game is given by*

$$T^*(\lambda) = \frac{\log(r+\lambda_h) - \log(r+\lambda)}{\gamma - r} \qquad\qquad P^*(t) = p_h e^{(\gamma-r)t}. \tag{1}$$

The method to derive the equilibrium of Proposition 1 is as follows. First, fix some candidate price function $P(t)$ and take a first order condition for the seller's problem

$$c - (\gamma + \tilde{\lambda})P^*(t) + \frac{d}{dt}P^*(t) = 0. \tag{2}$$

Next, use the fact that for any separating equilibrium

$$P^*(T(\tilde{\lambda})) = \frac{c}{r+\tilde{\lambda}}$$

and substitute into equation (2) to get the following ordinary differential equation for $P^*(t)$

$$\frac{d}{dt}P^*(t) = (\gamma - r)P^*(t). \tag{3}$$

Finally, because the highest default risk type does not benefit from delaying trade in a separating equilibrium, we must have $T^*(\lambda_h) = 0$ and hence $P^*(0) = p_h$. The functions given Proposition 1 solve equations (2) and (3) with this initial condition.

To connect the equilibrium given in Proposition 1 to our empirical analysis, it is useful to consider how the type of seller changes with time-to-sale. We let $\lambda^*(t)$ denote the seller type that chooses to sell at time t. Applying Proposition 1 we have:

$$\lambda^*(t) = (r + \lambda_h)e^{-(\gamma - r)t} - r. \tag{4}$$

Our empirical results relate to the following key properties of the functions $\lambda^*(t)$ and $T^*(\lambda)$.

1. The default risk of the mortgage decreases with time-to-sale, that is

   $$\frac{d}{dt}\lambda^*(t) < 0.$$

   This means that adverse selection creates a negative relationship between time-to-sale and default risk.

2. The price of the mortgage increases with time-to-sale

   $$\frac{d}{dt}P^*(t) > 0.$$

   This means that adverse selection creates a positive relationship between price and time-to-sale.

3. The maximimum time to sale for a mortgage is increasing in the difference in default risk between the safest and riskiest mortgage

   $$\frac{d}{d(\lambda_h - \lambda_\ell)}T^*(\lambda_\ell) > 0.$$

   This means that a more severe adverse selection problem, i.e. when the uncertainty about mortgage default risk is greater, leads to longer delays in trade.

Although the separating equilibrium we detail above is the unique equilibrium selected by D1, a discussion of other possible equilibria is in order. In particular, there can exist many pooling equilibria in which all seller types sell at the same time. For example, if investors believe that any mortgage sold after time $t = 0$ is the riskiest type, then all seller types will find it optimal to sell their mortgages at $t = 0$, since delaying the sale only leads to forgone gains from trade and does not increase the sale price. However, imposing D1 refinement will eliminate this equilibrium. If investors observe an off equilibrium path action, i.e., if a seller delays trade when investors expect immediate sale, then D1 requires that they only place positive weight on those seller types who would gain from deviating given largest set of prices. This set will always be largest for sellers of the least risky mortgages, since delaying trade is less costly for them than any other seller type. As such, D1 requires that investors must believe that the seller is the least risky type if she delays trade even a very small amount. These beliefs then imply that sellers of the least risky type have a profitable deviation, eliminating the simple pooling equilibrium. Thus, we focus our empirical analysis on the separating equilibrium we detail above.

2.1 Random Delay, Default, and Prices

To provide further discipline on our empirical analysis, we now consider a plausible variation to our model in which a correlation between delayed trade and ex-post performance need not be the signature of dynamic signaling or adverse selection. Intuitively, if trade is randomly delayed, then some higher risk mortgages may default before they can be sold. As a result, mortgages that take longer to sell will be positively selected (i.e., they are of higher quality than those that could not be sold). This selection mechanism would then lead to a positive correlation between time-to-sale and ex-post performance (negative correlation between time-to-sale and default rates). In addition, this implies that investors who understand this selection issue, will believe that mortgages that sell after a longer period of seasoning are higher quality and thus, prices will increase with seasoning. Importantly, this effect does not arise from signaling, as mortgages are sold randomly into pools by assumption, but rather through a learning process. As such, a simple model of randomly delayed trade and the associated selection mechanism may appear observationally equivalent to our signaling model of delayed trade. This is a key difficulty in bringing models of asymmetric information to the data–they often have similar predictions to models with symmetric information. We can overcome that difficulty in our setting by observing that the selection mechanism can be undone by conditioning the analysis on mortgages that do not subsequently (after sale) default up to a pre-specified period.

To make this intuition precise, suppose that the mortgage seller detailed above has the same information as potential investors. Specifically, she knows that the mortgage she wants to sell has an exponential default time with an intensity $\tilde{\lambda}$ uniformly distributed on $[\lambda_l, \lambda_h]$. When she chooses to sell the mortgage, there is a delay from the point at which she lists the mortgage for sale and the moment at which the transaction is recorded, which is exponentially distributed with parameter μ. If the mortgage defaults before the transaction can be recorded, no sale will take place. Thus, observing that the mortgage transacts at time t reveals that the mortgage did not default prior to t. Thus, the expected quality of a mortgage that transacts at time t is given by the following expression:

$$\begin{aligned} E\left[\tilde{\lambda}|\text{sold at time } t\right] &= E\left[\tilde{\lambda}|\tau > t\right] \\ &= \lambda_h + \frac{1}{t} - \frac{\lambda_h - \lambda_l}{1 - e^{-t(\lambda_h - \lambda_l)}}, \end{aligned}$$

which is increasing in the sale time t. Thus, randomly delayed trade will be associated with a negative correlation between time to sale and ex-post default outcomes as well as ex-ante prices. These predictions are essentially the same as properties 1 and 2 of the signaling model that we described above, which means that in order to test the predictions of the signaling model in the data, we need to find a way to overcome this selection effect.

One simple way of accounting for this selection effect is to condition the analysis on loans that do not default until some exogenously specified time s, where s needs to be after the period of sale, t . To see this, note that for loans that do not default before s, the event that the mortgage was sold at time $t < s$ does not contain any additional information about the default risk of the mortgage. Indeed, the expected quality of a mortgage that has not defaulted by time s and is sold at time $t < s$ is given by the following expression:

$$\begin{aligned} E\left[\tilde{\lambda}|\text{sold at time } t < s \text{ and } \tau > s\right] &= E\left[\tilde{\lambda}|\tau > s\right] \\ &= \lambda_h + \frac{1}{s} - \frac{\lambda_h - \lambda_l}{1 - e^{-s(\lambda_h - \lambda_l)}}, \end{aligned}$$

which is independent of the time of sale t. Thus, in a model with random delay and no signaling mechanism, there will be no correlation between time-to-sale and ex-post default outcomes if we condition on a sample of mortgages that do not default before s, where $s > t$. This is in stark contrast to our model of signaling through delayed trade in which time-to-sale always reveals information about ex-post default risk. We will explore whether such a model can explain our results in our empirical tests below.

3 Background on U.S. Mortgage Market

Our primary focus in this paper is on loans that were sold and then securitized by private financial institutions (or issuers). This segment of the market, often referred to as the PLS (private-label securitization) market, was the source of the initial mortgage foreclosure crisis in 2007, which led to the broader financial crisis and Great Recession. The PLS market grew rapidly during the housing boom of the mid-2000s, reaching a peak share of approximately 56% of the securitization market in 2006, before completely shutting down in the summer of 2007 when subprime mortgage defaults dramatically increased.

The PLS market is split into three broad segments, according to the degree of credit risk. The three segments are referred to as "subprime", "alternative-a" (or "Alt-A"), and "prime jumbo." The collateral in prime jumbo PLS is made up of large loans to borrowers with typically very good credit scores that exceeded the conforming loan limits and were thus not eligible to be securitized by the GSEs in the agency market.[9] The "Alt-A" PLS segment, also commonly referred to as "near prime," is typically characterized by loans to borrowers with slightly lower average credit scores than prime jumbo (but comparable to average credit scores in agency pools), and in which borrower income and/or assets are less than fully documented (i.e. low documentation mortgages). These loans were also more likely to finance investor or vacation home properties. Alt-A PLS included a mix of loans above and below the conforming loan limit. Finally, the collateral underlying subprime private-label securities is made up by loans usually below the conforming loan limit given to borrowers with low credit scores, and includes a large fraction of cash-out refinance mortgages. The majority of subprime PLS loans did not meet the underwriting standards in the agency market, and were broadly viewed as low quality mortgages by market participants. Our primary dataset (from Lender Processing Services, described in more detail below) includes loans from all three segments of the PLS market, while our secondary source of data (CoreLogic's LoanPerformance database, also described below) includes loans from the subprime and Alt-A segments of the market.

There is significant variation in the funding and operational models of mortgage originators in the PLS space, including independent mortgage companies, affiliated mortgage companies and others. We refer the reader to Stanton et al. (2014) and Ganduri (2015) for detailed descriptions of the structure of the market. Stanton et al. (2014) show that repurchase agreements and warehouse lines of credit with very short maturities were a large funding source in the PLS market. This limits the ability of originators to delay the sale of mortgages. For the purposes of our tests, we require that either originators of mortgages or issuers of PLS (or both) have the ability to hold on to mortgages and delay trade, even if some were limited by contractual features due to their funding sources.[10]

[9] In order to be securitized by the GSEs, a mortgage must have a principal balance below the conforming loan limit, a loan-to-value ratio at or below 80%, or else have equivalent credit enhancements (e.g., private mortgage insurance).

[10] Even though we find that the majority of loans in the PLS market were securitized within the first two months after origination, consistent with the evidence provided in Stanton et al. (2014) that warehouse loans and repurchase agreements had 30 to 45 days maturity, the variation that is most relevant for our

We focus on loans sold into the PLS market for two reasons. First, there are many recent papers in the literature that have documented a significant amount of private information in these markets, especially in the population of low documentation mortgages, and that originators were at least partially aware of unobserved quality.[11] In contrast, private information about credit quality plays a much less important role in the agency securitization market, where the GSEs provide specific parameters regarding the underwriting criteria that they will accept, and agree to purchase (usually through an automated process) all loans that satisfy those criteria.

Second, our PLS data are very similar in scope to the data used by many participants in the institutional PLS market to produce valuations and to monitor performance after issuance. In fact, some of the data we use originates from the trustees' reports provided to PLS investors in the market. Thus, our data closely matches the set of underwriting characteristics that PLS issuers and investors used to make real-time purchasing decisions. This is central to the implementation of our empirical tests described below.

4 Testing for Dynamic Adverse Selection Using Mortgage Data

We implement empirical tests of predictions 1 and 2 of the signaling model developed in section 2. Prediction 1 says that there should be a positive correlation between time-to-sale and mortgage quality, and hence a negative correlation between time-to-sale and ex-post default rates, while prediction 2 tells us that there should be a positive correlation between time-to-sale and mortgage prices. In section 2.1 we showed how it is difficult to empirically distinguish between models of asymmetric information with signaling and models with symmetric information. We showed that it is not possible to do so with only data on prices, but that it is possible with data on ex-post default rates as long as one conditions

tests are sales past this time period (up to 9 months after origination).

[11] For example, see Demiroglu and James (2012a) and Jiang et al. (2014b).

on loans that do not default before an exogenous time s where s should be greater than the maximum time-to-sale t.[12] For this reason, the bulk of our empirical analysis focuses on the relationship between time-to-sale and ex-post default rates. We also provide some evidence on the relationship between time-to-sale and pricing after our performance results, but interpret them with caution due to the inability to distinguish between signaling and random delay with learning with pricing data as well as a lack of such data at the individual mortgage level.

4.1 Time-to-Sale and Mortgage Default

A key issue in implementing an empirical test of the skimming property is distinguishing between observable and unobservable asset quality. Signaling models in general, and the skimming property in particular, refer specifically to quality that only the seller is informed about but is unobservable to the buyer.

We implement a strategy similar to Adelino et al. (2014) that uses conditional measures of loan performance to isolate aspects of loan quality that are unobservable to investors at the time of purchase, but are correlated with the originators' (and possibly the issuers') information set (and, by virtue of the passage of time, become observable to the econometrician). Specifically, we condition performance on a large set of loan and borrower characteristics used in mortgage underwriting models that were readily available to issuers and institutional investors in the MBS market. Our empirical specifications take the following general form:

$$Default_{ijt} = \alpha + \beta_1 * \text{Months-to-Sale}_{ij} + \beta_2 * X_{ijt} + \epsilon_{ijt} \tag{5}$$

where i indexes the individual mortgage, j indexes the the geographic area in which each mortgage is originated, and t indexes the horizon over which we calculate default rates. X_{ijt} is a vector of mortgage-level control variables that includes relevant observable borrower, loan, and geographic characteristics, including detailed fixed effects. $Months-to-Sale_{ij}$

[12] In other words, one must use variation in default rates occurring after time-to-sale, but not before.

is a variable that measures the time between when a mortgage is originated and when it is sold into the secondary market and securitized.

The existence of private information and signaling in the mortgage market predicts that $\beta_1 < 0$. This is a joint test of two hypotheses, namely that (i) the seller's private information, I_{seller}, is correlated with loan quality after accounting for underwriting characteristics, i.e.

$$Corr[(E(Default_i|X_i, I_{seller}) - E(Default_i|X_i)), Default_i)] \neq 0 \tag{6}$$

and (ii) that sellers signal asset quality by delaying trade.

It is important to note that our tests do not require that we observe the full information set of the buyers. Instead, the tests require a weaker condition, namely that our measure of ex ante default risk be an unbiased estimate of "true credit risk. Additionally, we assume that $X_i \subseteq I_{buyer} \subset I_{seller}$, i.e. both buyers and sellers information sets include the mortgage characteristics we observe, and sellers have some private information about the loans that is correlated with default. In such a setting, we can measure the relation between time-to-sale and credit risk using our measure of risk (which is assumed to be unbiased). To the extent that credit risk is the only variable that is systematically related with time-to-sale, the additional information in I_{buyer} is simply providing more precision for measuring credit risk, but should not change the direction of that relation. Put differently, if we find no relation between observable risk and time-to-sale for our (very comprehensive) measure that buyers and sellers also have available, our assumption is that this relation would not change if the public signal became more precise. This is a weaker condition than requiring that the buyers' information set I_{buyer} only includes the publicly available mortgage underwriting data we use in the regressions.

4.1.1 Default Measurement and Controls

We consider two different default horizons, 36, and 60 months, in our primary specifications, measured relative to the month of loan origination.[13]. We also consider a mortgage to be in default if the borrower is either two payments behind (60+ days delinquent) or three payments behind (90+ days delinquent) at any point between origination and each default horizon. We use 60-day and 90-day delinquency cutoffs rather than the initiation of foreclosure proceedings so that our default definition reflects borrower behavior that is not confounded by the decisions of mortgage servicers.

X_{ijt} in equation 5 above accounts for a large subset of the information held by the buyers of mortgages at the time of the sale. According to Stearns (2006), all issuers and most PLS investors had access to detailed information at the loan-level including data fields such as FICO score, combined LTV ratio, documentation type, occupancy type, loan purpose (refinance or purchase), property type, loan size, amortization schedule, interest rate type (ARM vs. FRM), and information on the geographic location of the property.[14] We choose our vector of control variables to include these variables, as well as some variables that measure ex-post conditions in the local housing market, which likely influence ex-post loan performance.

Specifically, our covariate set includes the combined loan-to-value (LTV) ratio, the original loan balance, the original interest rate, the borrower's credit score, the original maturity of the loan; and indicator variables for low documentation loans, interest-only loans, balloon loans, negative amortization loans, 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.[15] We also

[13]We have also tried a shorter horizon of 24 months, which did not make a material difference.

[14]This contrasts with the agency market, as the GSEs, in part due to the fact that they absorb all credit risk, do not disclose as much detailed information about the mortgages that back their securities. According to Stearns (2006), "Non-agency investors have access to a wealth of data–all at the loan level– that agency investors can only dream of."

[15]We estimate a fairly saturated model by including many categorical variables for the continuous variables in our covariate set like credit scores and LTV ratios. The appendix contains a list of the exact variables

include the county-level unemployment rate and the level of the house price index at the time of origination (normalized by setting the index value for January 2000 to 100 for each county), as well as the changes in these series from the time of issuance through the end of the default horizon. In addition we include a full set of state-level fixed effects, and fixed effects corresponding to the year-quarter of origination as well as the year-quarter of loan sale.[16] Additional indicator variables are included whenever there are missing observations for any of the controls.

4.2 Time-to-Sale and Mortgage Spreads

Unfortunately, we do not have access to data on individual mortgage prices.[17] As a result we are forced to conduct our pricing analysis at the security level. While we also lack explicit data on security transaction prices at the time of issuance, we are able to construct a good proxy using yield spreads. Specifically, we focus on the average spread (quoted as a spread over the one-month LIBOR rate) of floating rate triple-A mortgage-backed securities in the PLS market. We calculate a weighted average spread at the deal-level, where we weight by the face value of the triple A securities.[18] Since we do not have information on the actual prices paid for the securities, restricting the analysis to floating rate securities virtually eliminates the possibility that securities were not issued at par. In addition, these floating rate securities have very short duration, so we can ignore interest rate risk and the negative convexity problem that arises with fixed-rate mortgage-backed securities.

Our empirical analysis looks at the relationship between average yield spreads and mortgage seasoning. The seasoning variable, calculated as the average months-to-sale in the pool,

that we include in our covariate set.

[16]We have also experimented with a specification that includes zip code level fixed effects to absorb any effects of unobserved geographic shocks at a very fine geographic level, and found that the results were largely unaffected. Since including such a large number of fixed effects becomes very computationally demanding, we use state fixed effects in all of the tests in the paper.

[17]To our knowledge, such data simply do not exist.

[18]Whenever a given PLS deal is made up of more than one pool of mortgages, and triple-A securities have claims to cash flows from only one of the pools, the average spread and all controls are calculated at the pool level (rather than at the deal level). This follows the approach in Adelino et al. (2014), who compare outcomes across pools sold to different investors.

and all controls are constructed from loan-level data and aggregated to the pool level. Our specifications take the following form:

$$Spread_i = \alpha + \beta_1 * \text{Seasoning}_i + \beta_2 * X_i + \epsilon_i \quad (7)$$

Where i represents a pool, and X_i includes pool averages of all relevant loan and borrower characteristics used in the loan-level tests and described in detail below, as well as quarter of issuance fixed effects. Our model of adverse selection and signaling predicts that we should find a negative relationship between average seasoning and mortgage spreads, i.e. $\beta_1 < 0$.

4.3 Data

In this section we describe the two loan-level datasets used in this paper as well as our data on yield spreads. While both loan-level datasets are similarly structured panels that contain detailed information about contract characteristics and monthly loan performance, there are important differences in the scope of their coverage and in some of the underlying variables that produce advantages and disadvantages in the context of our analysis.

The pricing data at the individual security level was obtained from Bloomberg. The data fields include security identifiers (including CUSIP and ticker), issuer name, issuance date, the identification of the loan pool that the security has claims on, the spread over one-month Libor 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 2002 and 2007. We are able to combine the CoreLogic and Bloomberg datasets by merging on individual security CUSIPs.

4.3.1 Lender Processing Services Data

Our primary dataset comes from Lender Processing Services (LPS). The LPS dataset covers between 60 and 80 percent of the U.S. mortgage market, and contains detailed information on the characteristics and performance of both purchase-money mortgages and refinance mortgages. It includes mortgages from all segments of the U.S. mortgage market: PLS or non-agency securitized loans; loans purchased and securitized by the GSEs; and loans held in lenders' portfolios. The LPS dataset is constructed using information from mortgage servicers, financial institutions that are responsible for collecting mortgage payments from borrowers. Each loan is tracked at a monthly frequency from the month of origination until it is either paid off voluntarily or involuntarily via the foreclosure process. We focus on loans originated during the housing boom, from January 2002 through December 2007.

Importantly for the purposes of this study, the dataset includes a time-varying variable, "investor type," which identifies whether a mortgage is held in a bank's portfolio, is privately securitized, or is securitized by the GSEs. This variable makes it possible to explicitly identify if and when a loan is sold to a PLS issuer or to a GSE to be securitized. Since the purpose of this paper is to test for whether there is a positive correlation between the quality of an asset (observable only to the seller) and the time that it takes to sell the asset, we focus only on loans that are sold. Thus, we focus on loans that we identify as being transferred from a banks' portfolio to a PLS issuer or to one of the GSEs. Many loans in our LPS sample of sold mortgages begin in the portfolio of the mortgage originator and then are sold to a PLS issuer or GSE at some point after origination. In contrast, many loans in our sample are categorized by the "investor type" variable as being in a PLS or GSE security in the month of origination, in which case we assume they were immediately sold.

We adopt a few sample restrictions in our analysis of the LPS data. We consider only first lien mortgages originated in the 2002 – 2007 period that were sold to PLS issuers or to the GSEs.[19] We only keep loans originated in the 50 U.S. states, and restrict the sample to loans that enter the dataset in either the same month of origination or in the month following origination.[20] In addition to these sample restrictions, we also address outliers

[19]Thus, we eliminate loans kept in the portfolios of the mortgage originators and never sold. In addition, there were a small number of loans in the dataset that were sold to the Federal Home Loan Banks (FHLBs), which we also eliminate from the sample.

[20]That is, we throw out loans that is absent from the data more than the first month after origination.

in the data by winsorizing the distributions of credit scores, original loan balances, LTV ratios at origination, and interest rates at origination at the 1st and 99th percentiles of each respective distribution.[21]

The primary advantages of using LPS data to test the skimming property are the ability to precisely identify the month of sale, and the ability to look at sales to both PLS and the GSEs. However, there are also a few important drawbacks. The biggest problem with the LPS data in our context is the lack of information on the exact identity of the financial institution that originates the mortgage. Ideally, we would want to control explicitly for the identity of the originator, as this would eliminate potential heterogeneity in underwriting practices that is known to the PLS and GSE issuers, but not to us. In addition, there is some concern that the LPS dataset may under-represent the PLS market during our sample period. For these reasons, we also use data from Corelogic's LoanPerformance database discussed below.

4.3.2 CoreLogic Data

Our second source of mortgage data comes from CoreLogic's LoanPerformance (CL) PLS database, which covers virtually the entire subprime and Alt-A segments of the PLS market. Like the LPS dataset, CL contains detailed information on underwriting characteristics and monthly loan performance, but unlike LPS, CL does not have information on portfolio-held loans or loans securitized by the GSEs. One of the main advantages, however, of using CL data is its representativeness of the PLS market.[22]

The CL database includes virtually the same mortgage and borrower characteristics (at

We do this for two reasons. First, for these we are unable to determine the exact month in which they were sold. Second, since we do not observe the payment history of seasoned loans before they enter the dataset, we are unable to determine their default status in the months before they enter the dataset. The vast majority of LPS loans meet this criterion.

[21] We also tried trimming instead of winsorizing the data, and found that this change had little effect on the results.

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

the time of loan origination) as the LPS database, but, importantly, for a sample of CL loans (about 50% of the entire database) identity of the originating institution is provided, which allows us to examine the relationship between time-to-sale and ex-post performance using loans originated by the same lender. In addition to the identity of the originator, CL also provides information on the identity of the mortgage servicer, as well as information on security identifiers (CUSIPs) and deal identifiers, which allows us to obtain information on the identity of the securitizer (issuer) for most loans in the sample.

Unlike LPS, in CL we can distinguish between the subprime and Alt-A markets.[23] We display the distribution of months-to-sale (Table 3) and the summary statistics (Table 4) for the subprime and Alt-A loans separately. The tables show that the sample of Alt-A loans in CL looks more similar to the LPS sample. The Alt-A distribution of months-to-sale more closely resembles the LPS distribution, as a higher fraction of Alt-A loans are sold immediately compared to subprime loans. In addition, the average loan size, interest rate, and FICO score in the Alt-A are closer to the LPS sample than the subprime loans.

The timing for when a loan enters each dataset is also different across the LPS and CL datasets. In LPS we observe most loans from the month of origination, and can directly observe the month in which they are sold out of banks' portfolios to PLS issuers or the GSEs. In CL we compute time-to-sale as the difference between the date of issuance of the mortgage-backed security in which the loan is included and the reported month of origination of the mortgage.[24] In most cases, loans are transferred from the warehouse into the special purpose vehicle at the time of issuance, and so the date of issuance is a good proxy for when the mortgage credit risk is transferred from the originator to the issuers.

[23] There is a servicer-provided field in LPS that distinguishes Grade "A" loans and Grade "B" and "C" loans, with the grades supposedly corresponding to different levels of credit risk. We include the variable in our covariate set in the analysis. However, loans flagged as "B" and "C" in LPS do not appear to be similar to subprime loans in CL in terms of observable underwriting characteristics.

[24] Loans enter the CL dataset on the issue date, so we do not see the performance history of loans before they are securitized.

4.4 Summary Statistics

Table 1 displays the distribution of the number of months between origination and sale for our sample of PLS and GSE securitized mortgages in the LPS data. It is clear from the table that the majority of both PLS and GSE securitized mortgages are sold very quickly – either immediately or only one month after origination. However, there are some important differences between the PLS and GSE distributions. For example, very few GSE loans (about 7%) are sold more than two months after origination, but a non-trivial fraction of PLS loans are sold later in their lives (about 20% are sold more than 2 months after origination). While there are some sales that occur several months after origination, the number of sales drops off very quickly with time for both loan types. In implementing our tests, we would like to restrict our analysis to loans that are originated with the intent of being sold, and are concerned that the loans sold long after they were originated may not have been made with the intent of being sold (or are fundamentally different on some other dimension that is unobservable to us). Furthermore, the combination of the small number of loan sales in later months and the large number of control variables in the empirical models results in low statistical power. For these reasons, we impose one last sample restriction, which is a maximum threshold for the number of months between origination and sale. We base this threshold on the PLS sample, since that is our main focus in the analysis, and choose a threshold value of 9 months, based on the simple observation that approximately 97% of loan sales happen within 9 months in that market.[25] This leaves us with a sample of over 5 million loans sold to PLS issuers and over 11 million loans sold to the GSEs.

In Table 2 we display summary statistics for many of the control variables in the empirical models. The table displays statistics for both the sample of loans sold to PLS issuers and the sample of loans sold to the GSEs. In general, PLS loans are characterized by riskier attributes compared to GSE loans. For example, there were more interest-only loans, more adjustable-rate loans, more low documentation loans, more subprime loans, and more loans

[25] We have experimented with higher thresholds such as 12 months, with little affect on the estimation results.

that carried prepayment penalties in the PLS sample.

We apply the same sample restrictions to the Corelogic data that we applied to the LPS data. Table 3 displays the distribution of months-to-sale in the CL dataset, while Table 4 provides some basic summary statistics. The first notable observation is that there are many more PLS loans in CL compared to LPS.[26] The second thing to note is that the distribution of months-to-sale in CL is similar to LPS, although there are a few subtle differences. In both datasets over 90% of loans that end up in PLS are sold within 5 months of origination, but a lower fraction of loans are sold within the first 2 months in the CL database (45%) compared to the LPS database (56%). There are more dramatic differences in the summary statistics between the two datasets. The CL sample is characterized by significantly lower credit scores (FICOs), higher interest rates, and lower loan amounts. There is a much higher fraction of adjustable-rate mortgages and low documentation loans in CL. There also appears to be a large difference in the average LTV ratios, but this is likely due to the fact that the LTV ratio in CL incorporates second mortgages (i.e. piggybacks) while LPS only provides the LTV ratio based on the first lien. In addition, the average (unconditional) default rates are significantly higher in the CL sample. Overall, based on average underwriting characteristics, the sample of PLS loans in CL appears to be significantly riskier than the LPS sample.

Table 5 shows the summary statistics of all pool-level characteristics used in the pricing analysis. The average spread of triple-A securities in the data is 28 basis points, with a standard deviation of 23 basis points. This spread is computed as the pool-level average of all triple-A securities drawing cash flows from a given pool, and the sample is limited to pools with only floating rate triple-A securities. The average pool-level seasoning in the data is 3.3 months, and it is truncated at 9 months following the approach for the default analysis. About 97.5% of pools have an average seasoning below 9 months (Figure 5 shows

[26] The LPS sample size of 5.3 million loans listed in the tables understates the total number of PLS loans as there are some seasoned mortgages that we eliminate from the sample due to our sample restriction of only including loans for which we see a full history of performance. There are actually more than 7 million PLS loans originated between 2002 and 2007 (inclusive) in the LPS database.

the histogram and cumulative distribution of the pool-level seasoning variable). Pools are made up of 2,355 loans on average (the median is 1,911), with an average FICO score of 640 and combined loan-to-value ratio of 84%.[27] The Table lists means and other statistics for all other controls included in the pricing regression.

5 Results

In this section we present results on the empirical relationship between time-to-sale and loan quality as well as the relationship between time-to-sale and prices. We begin by presenting results based on conditional, ex-post default rates of both PLS loans and GSE loans in the LPS dataset. We then show results on the relationship between ex-ante, predicted default probabilities and time-to-sale using only information that mortgage investors had access to in real-time. Next, we present results using the CoreLogic data where we can account for time-invariant heterogeneity in originator practices and look at different segments of the PLS market. Following our analysis of default rates, we present results on the relationship between average PLS security spreads (our proxy for prices) and pool-level seasoning. Finally, we consider an alternative measure of mortgage quality based on prepayment risk rather than credit risk.

Because time-to-sale is the key variable of interest, we first implement tests using simple linear specifications (consistent with the prediction in the model), so that $\text{Months-to-Sale}_{ij}$ (for the loan-level default analysis) and $\text{Average Seasoning}_i$ (the pool-level average used in the pricing regressions) take values from 0 to 9 and enter linearly. We then add quadratic terms, $\text{Months-to-Sale}^2_{ij}$ or $\text{Average Seasoning}^2_i$, in order to determine if there is a non-linear relationship between the outcome variables and time-to-sale. Finally, for the loan-level

[27]Instead of simply including the pool-level averages of FICO and CLTV as covariates in our pricing analysis, we adopt a more flexible specification that allows for potential non-linear effects in those variables. Specifically we include variables that capture the average fraction of loans in the pool that fall into various FICO and CLTV categories. The categories are displayed in Table 5. In addition we include a variable corresponding to the fraction of loans in a pool that have an LTV ratio that is exactly equal to 80 percent in order to capture the potential importance of piggyback loans, which we do not directly observe.

tests of default we include separate indicator variables for each value of the months-to-sale variable.[28]

5.1 Default and Time-To-Sale

In this and the subsequent sections we turn to an analysis of mortgage quality (measured by default) as a function of time-to-sale. Panel A of Table 15 displays results for the linear and quadratic regression specifications estimated on our sample of loans in the LPS dataset. The panel displays estimation results for our variables of interest for two different default definitions (60+ DQ and 90+ DQ) and two different default horizons (36 months and 60 months relative from the month of origination).[29] The results show a negative, statistically significant relationship between default risk and time-to-sale. The magnitude of the coefficient in the linear specification is approximately -0.01, which implies that a one month increase in time-to-sale is associated with a 1 percentage point decrease in the average default rate. The results appear to be very consistent over the different horizons and default definitions.

The results for the quadratic specifications suggest that the relationship between time-to-sale and default rates is non-linear. The positive coefficient on the quadratic terms implies that for small values of time-to-sale the relationship is negative, but that for higher values of time-to-sale the relationship becomes significantly less negative and even turns positive.[30] We explore this non-linearity in greater detail in Table 7, where the results from the non-parametric specification are displayed. Columns 1-2 and 5-6 display the non-parametric results for the different combinations of the default definitions and horizons. The results suggest that average default rates are decreasing in time-to-sale until $\text{Months-to-Sale}_{ij} = 5$,

[28] Since we cannot distinguish between loans with values of 0 and 1 for months-to-sale, the omitted category for the regressions estimated on LPS data includes both.

[29] In the Appendix we display a set of regression results that includes the coefficient estimates for most of the variables in our covariate set. Most of the estimates are consistent with the previous literature on mortgage default.

[30] The quadratic term begins to dominate the linear term when time-to-sale reaches 10 months, which is beyond the highest value for time-to-sale in our sample (9 months).

at which point average default rates begin to moderately rise. Mortgages sold in the 5th month after origination have default rates that are approximately 6 percentage points lower than loans sold in either the month of origination or the month after origination, while mortgages sold in the 9th month after origination have default rates that are lower by 3 - 4 percentage points on average. Again, the estimation results are quite consistent across the alternative default definitions and horizons.

5.2 Accounting for "Mechanical" Effects from Random Delay

One potential concern in the default analysis above is the role of early payment defaults in generating a mechanical relationship between time-to-sale and ex-post default risk due to institutional features of the PLS market. We discuss this possibility in Section 2.1. Specifically, loans that are in delinquency are harder to sell into a securitized pool of loans. This could create a negative relationship between time-to-sale and default that is independent from a mechanism involving private information and signaling. Random delay would mean that loans sold quickly would be representative of the population of eligible loans in terms of default risk, whereas loans that take a longer time to sell would be of higher average quality than the population of eligible loans.

In order to address this issue, we implement a sample selection for loans that are sold early that mimics the selection they would suffer if they had taken longer to sell. Put differently, in this analysis we only include loans that are current by month 9. We refer to this sample that excludes all loans that became delinquent within 9 months of origination as the "restricted sample". This forces the sample of sold loans to be homogeneous in terms of early payment defaults across the time-to-sale distribution, and the results *cannot* be explained by the mechanical problem described above.

While this correction directly addresses the mechanical issue discussed above, there are a few drawbacks. First, loans that default early may still be sold, in which case the mechanical effect is not severe, and the correction would simply be throwing away information. Second, and more importantly, it may be that signaling that goes on in the market is precisely about the likelihood of early-payment default. That is, if most of the private information on loan quality concerns the likelihood of default within the first few months of origination, this "correction" to the sample effectively eliminates the variation we are most interested in. For this reason, we choose to display the correction as a robustness check rather than adopt it as our baseline specification.

Panel B of Table 15 and columns 3-4 and 7-8 in Table 7 display the same set of results for our restricted sample, where we throw out all loans that default within 9 months (inclusive) in order to address the potential sample selection bias that we discussed above. There is virtually no difference in the results for the linear specification of the Months-to-Sale$_{ij}$ variable, but there are a few subtle differences for the non-linear specifications. From the results of the non-parametric specification we see that this sample restriction slightly mitigates the negative relationship between time-to-sale and default for loans sold within 4 months. However, the sample restriction appears to have the opposite effect for loans sold later as the coefficient estimates associated with loans sold between 7 and 9 months after origination become slightly more negative. This pattern is confirmed in the quadratic specifications in Table 15 as the coefficients on the linear terms become less negative while the coefficients on the quadratic terms become less positive. Overall, the sample correction appears to have a very minor effect on the results, which suggests that sample selection bias is not an important issue.

In the top left panel of Figure 1 we plot the estimated relationship between time-to-sale and ex-post PLS default risk from the non-parametric specification in column (3) of Table 7 (60+ DQ, 36-month horizon, restricted sample). The plot includes 95% confidence intervals to show the precision of the estimates. There is a clear negative trend until month 6 at which point the coefficient estimates flatten out. The estimates associated with the first 4 months are much more precise compared to the last 5 months due to the much larger sample size of loans sold early in their lives. Overall, the results in Tables 15 and 7 provide evidence of a negative relationship between time-to-sale and (conditional) ex-post default risk, which supports the existence of a signaling motive in the PLS market. Furthermore the results are robust to potential sample selection bias generated by early payment defaults.

5.3 Default and Time-To-Sale – Agency Loans

Tables 8 displays results for our sample of loans sold to the GSEs. The table displays results for the linear and quadratic specifications and is structured in the same manner as Table 15, which displayed the PLS results.[31] There is very little evidence of any relationship between time-to-sale and ex-post default risk in the GSE segment of the market. We plot the estimated relationship from the non-parametric specification in the top right panel in Figure 1 (the same specification as the one used to construct the PLS graph in the top left panel). The first thing to note from the plot is the stark difference in the pattern relative to the one displayed in the PLS graph. While there is a clear downward trend in the PLS estimates that flattens out toward the end of the time-to-sale distribution, the GSE coefficients are basically zero until the very end of the distribution when they begin to fall. In addition, the GSE estimates are much more precise, on average, compared to the PLS results due to the much larger sample size. However, the PLS estimates are fairly precise for the low values of time-to-sale where the downward trend is the most pronounced, while the GSE estimates become much more imprecise toward the end of the time-to-sale distribution when the sample size becomes significantly reduced. In general, the GSE results are consistent with our hypothesis that private information is much less of an issue in the agency market compared to the PLS market.

[31] For the sake of brevity we do not include a separate table containing estimation results for the non-parametric GSE specifications.

5.4 Ex-Ante Analysis

In this section we attempt to estimate the empirical relationship between time-to-sale and *ex-ante* credit risk in order to compare and contrast it with our results above on the relationship between time-to-sale and *ex-post* credit risk that conditioned out the set of observable underwriting characteristics. To do this, we construct ex-ante default probabilities for each loan using all of the data available in LPS in a manner that is similar in spirit to the method used in Ashcraft et al. (2010). The idea is to forecast mortgage default using only performance information available at the time of origination (i.e., from the past performance of previously originated loans).

We choose a 36-month horizon to forecast defaults in order to maintain consistency with our results above. We begin by taking each loan in our LPS sample, and determining the quarter in which it was originated. We then take all loans that were originated between 48 months and 36 months before that quarter, and track those mortgages over the subsequent 36 months, creating indicator variables that take values of one if the mortgage ever becomes 60 days delinquent at any point during the 36 month period. We then estimate a discrete choice model (linear probability and logit) using variables that are available in LPS to predict the default variable. The regressions are estimated each quarter over the period 2002–2007 and include virtually the same set of covariates that were included in the ex-post default risk regressions described above. We take the estimated coefficients from these loan-level credit risk models and apply them to the characteristics of the loans originated in the current quarter to create 36-month, loan-level, default probabilities. This leaves us with a set of ex-ante default probabilities created using only information available at the time in which the loans were originated.

We then take those ex-ante default probabilities and substitute them into equation 5 in order to estimate the relationship between time-to-sale and *observable* default risk. We display the estimation results in the lower two panels in Figure 1. The lower left panel displays the relationship between time-to-sale and ex-ante, default risk for PLS loans, while the lower right panel displays the relationship for GSE loans. The PLS results suggest that loans sold later are slightly *more* risky based on observable underwriting characteristics. Loans sold in the 2nd, 3rd, and 4th months after origination have expected default probabilities that are approximately 2 - 3 percentage points higher than loans sold in the month of origination or the month immediately following origination. This difference moderates at the end of the time-to-sale distribution, with loans sold between 6 and 9 months having only slightly (about 1 percentage point) higher expected default probabilities, on average. This pattern is in stark contrast to the estimated relationship between ex-post default rates and time-to-sale in the PLS market (top left panel in Figure 1), and provides some reassurance that our ex-post conditional default measures are doing an adequate job in purging predictable default risk. The horizontal line displayed in the lower right panel in the figure implies that there is no relationship between predictable default risk and time-to-sale in the GSE market.

5.5 Default and Time-To-Sale Using Corelogic Sample

Table 10 displays the core set of results on the relationship between ex-post default risk and time-to-sale using the sample of PLS loans in CoreLogic. One of the main reasons for using CL data is the availability of the identity of the mortgage originator, which allows us to account for any variation generated by heterogeneity across originators. In Table 10 we present results corresponding to our parametric specifications of equation 5 and focus on a default horizon of 36 months and a default definition based on 60+ days delinquent. In Panel A we display results from a specification that does not control for originator heterogeneity, and thus, these are results are directly comparable to the LPS results displayed in Table 15. In Panel B, we include, for each specification, a full set of originator fixed effects. Information on the originator is available for slightly more than half of the loans in the CL dataset, so we focus our analysis on this subsample.[32]

[32]We do this even for the specifications that do not include originator fixed effects in order to isolate the impact of originator heterogeneity from the impact of changing the size and scope of the sample.

The estimation results reported in Table 10 show a statistically significant, but slight, negative relationship between ex-post default risk and time-to-sale, which is not very sensitive to the inclusion of lender fixed effects. According to the linear specification results (column 1) an increase in time-to-sale by one month is associated with 0.28 – 0.36 percentage point increase in average default rates. While the magnitudes are significantly smaller than the LPS results discussed above, the pattern is quite similar as evidenced by the estimates from the non-parametric specification, which are displayed in the top panel of Figure 2. Average ex-post default rates decline over the first half of the time-to-sale distribution and then flatten out over the second half of the distribution in a similar manner to the LPS results plotted in the upper left panel of Figure 1.

5.5.1 Alt-A PLS vs. Subprime PLS

In addition to the information on the identities of originators, an advantage of using CL data is the ability to analyze different segments of the PLS market. A priori, we may expect to see a larger role for signaling unobservable mortgage quality in the Alt-A segment of the PLS market, since this was largely comprised of low documentation mortgages. Table 4 shows that over 70 percent of Alt-A mortgages were less than fully documented compared to 35 percent of subprime loans.

Table 10 displays the parametric specification results from separately estimating regressions for the subprime and Alt-A segments of the PLS market (columns 3-6), and the bottom panels of Figure 2 plots the results for the non-parametric specifications. The differences between the subprime and Alt-A results are fairly striking, and help to explain where the differences between the LPS and CL results are likely coming from. There is essentially no relationship between ex-post default risk and time-to-sale among subprime PLS loans (Panel C), while there is a fairly significant, negative relationship among Alt-A loans (Panel B). The estimates from the Alt-A regression are monotonically decreasing in time-to-sale. A loan sold to an issuer of Alt-A PLS 9 months after origination is, on average, about 6 percentage points less likely to default compared to a loan sold immediately upon origination, which is very similar to the estimated magnitudes obtained in the LPS sample. As we discussed above, when we compare the summary statistics between LPS and CL (Tables 2 and 4) it appears as though the LPS sample of PLS loans is more similar to the Alt-A mortgage sample than the subprime sample in CL. This could rationalize the differences in the quantitative magnitudes of the estimates coming from each sample as the CL Alt-A magnitudes are quite similar to those obtained from LPS.

5.5.2 Documentation Results

We further explore the role of documentation standards by stratifying our PLS sample into loans with full documentation of income and assets and loans with less than full documentation ("low doc"). We stratify by documentation type for the full sample of PLS loans as well as for our subprime and Alt-A samples separately. The results are displayed in Table 11, with Panel A containing results for the parametric specifications and Panel B containing results for non-parametric specifications. Figure 3 plots the non-parametric results with 95 percent confidence intervals to provide a sense of the statistical significance between the low documentation and full documentation estimation results.

The results are mixed. In the sample of all PLS loans (subprime and Alt-A combined), there does appear to be a stronger negative relationship between time-to-sale and default for low documentation loans compared to full documentation loans. This negative relationship is approximately twice as large (in absolute value) in the sample of low documentation PLS loans (columns 1-2). However, Figure 3 shows that the difference in this relationship between the two types of loans is not statistically significant at conventional levels. Furthermore, based on the results displayed in Table 11 (columns 3-6) and Figure 3 (Panels B and C) there are essentially no differences between full documentation and low documentation loans within the subprime and Alt-A subsamples.

5.5.3 Affiliation Results

In this section we test whether an affiliation between the originator (seller) and issuer (buyer) plays a role in the relationship between time-to-sale and default risk. There are direct relationships between many issuers and originators in the 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). A priori, we might expect that the scope for private information between an originator and issuer who are affiliated is less than in the case of an originator and issuer who are independent entities.[33] Thus, if signaling is driving our results, we would expect a weaker negative relationship between time-to-sale and default risk for the sample of loans in which the issuer and originator are affiliated with each other.

We obtained information on the identity of the issuer from Bloomberg, and supplemented the Bloomberg data with hand-collected data from the pooling and service agreements (PSA) associated with the PLS deals.[34]. We focus on only loans that are in deals in which either all loans were made by affiliated originators or all loans were made by unaffiliated originators.[35] Table 12 and Figure 4 displays the results. As in our analysis of documentation status above, we stratify by affiliation status in our sample of all PLS loans as well as in our Alt-A and subprime samples separately. While the results are different for the three samples, overall, the negative correlation between time-to-sale and default risk does appear to be weaker when the originator and issuer are affiliated entities. In the full sample, the correlation is more than twice as large for unaffiliated compared to affiliated issuers and originators (columns 1 - 2 in Table 12). Panel A in Figure 4 shows that this difference is statistically significant for loans sold within the 4 months of origination.

[33] This is also an argument made by Demiroglu and James (2012b) and Furfine (2014)

[34] We pulled the PSAs from the SEC's EDGAR website: http://www.sec.gov/edgar/searchedgar/companysearch.html

[35] We decided to drop the "mixed" deals that included loans made by both affiliated and unaffiliated originators 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).

The difference in the relationship between time-to-sale and ex-post default risk for unaffiliated compared to affiliated issuers and originators is especially stark in the Alt-A segment of the market. Loans sold 6 months after origination by affiliated originators are approximately 3 percentage points less likely to default compared to loans sold in the month of origination (column 3 of Panel B in Table 12), while this effect increases to almost 9 percentage points for loans originated by unaffiliated originators. Panel B in Figure 4 shows that this difference is highly statistically significant over the entire distribution of time-to-sale. Finally, we find no differences between affiliated and unaffiliated originators in the subprime segment of the PLS market.

There is some uncertainty about whether the originator field in the CoreLogic database actually corresponds to the lender of record (i.e. the institution that underwrote and originated the loan) or to what is sometimes referred to as the "aggregator" or "seller", which is the institution that is in charge of purchasing loans from various lenders to fill the PLS mortgage pools, and then selling those loans to the issuer (Stanton et al. (2014)). This is a potentially important distinction because it may be more likely that private information is obtained by the lender of record since it has more interaction with the mortgage borrower.

To verify that the originator field in CoreLogic indeed corresponds to the lender of record, we match our CoreLogic mortgage data to a database of public mortgage filings that contains the identity of the lender of record. This database contains the universe of all residential mortgages in the state of Massachusetts during our sample period, and comes from county deed registries that record information on property transactions. We compare the lender of record with the originator listed in the CoreLogic database for the sample of matched Massachusetts mortgages. In unreported tables, we find that for 83% of the matched sample, the lender of record matched the CoreLogic originator field. The remaining 17% are either cases in which CoreLogic is reporting an entity other than the lender of record (most likely the aggregator) or are bad matches (there is the potential for significant matching error because we are not able to perform a precise match using loan account numbers or social security numbers). Thus, we view the 17% figure as an upper bound on the severity of the potential issue of misidentifying the true originator in the CoreLogic data.

5.6 Security Spreads and Time-To-Sale

We now present evidence on the empirical relationship between time-to-sale and security prices. The unit of observation for this analysis is a pool, i.e. a group of loans from which different triple-A securities in each PLS deal derive cash flows. Junior securities (those below triple-A) generally derive cash flows from all pools. If deals have only one pool of mortgages, the average spread corresponds to the weighted average spread of the triple-A securities in the deal.

Table 13 displays the results from regressing average pool-level spreads on average pool-level seasoning. Panel A shows results when we include only a linear term for average seasoning while panel B includes a quadratic term. The results on ex-post default rates discussed above were significantly different in the sample of mortgages that collateralized Alt-A securities compared to the sample of loans that backed subprime securities. Thus, in both panels we show results for the full sample of floating-rate, triple A securities(columns 1-3) as well as results for Alt-A (columns 4-6) and subprime (columns 7-9) securities separately, in order to see if similar patterns emerge on the pricing dimension.

In Table 13 we display results for three different regression specifications. The first specification includes only quarter of issuance fixed effects, but no other control variables. The second specification includes the list of pool-level controls displayed in Table 5 along with quarter of issuance fixed effects. The third specification, in addition to pool-level controls and month of issuance fixed effects, includes a full set of issuer fixed effects.

Column (1) in panel A shows that one additional month of average mortgage seasoning is associated with a 1.5 basis points lower yield spread, which is about 5 percent of the average spread in the sample (28 basis points). When pool-level controls and both issuer and month of issuance fixed effects are included (column (3)), the coefficient estimate declines slightly, but remains statistically significant. Similar to our findings in the default analysis above, we see in columns (4)-(9) that this effect is concentrated in the Alt-A sample. For Alt-A securities, one additional month of average mortgage seasoning is associated with a 2.4 basis points lower yield spread.

For the non-linear specification results reported in panel B, both the linear and the quadratic terms are significant in the full sample and the Alt-A sample. The linear terms are negative and the quadratic terms are positive, which implies a similar non-linear relationship between time-to-sale and security spreads as the relationship that we documented above between time-to-sale and mortgage default. Figure 6 displays the predicted security spreads as a function of average pool-level seasoning calculated using the estimation results from the specification reported in column (6) in panel B. The figure includes 95 percent confidence intervals calculated using the delta method. There are a few notable takeaways from the plot. First, the minimum spread as a function of average seasoning is achieved between 4 and 5 months. Second, after 5 months, the spread begins to increase in seasoning, however the confidence bands show that we begin to lose precision for seasoning greater than 5 months since there are so few securities in the dataset with high values of average seasoning (Figure 5).

5.7 Early Prepayment Analysis

Until this point we have used default as a proxy for loan quality. We believe that this is a reasonable strategy since default is an unequivocally negative outcome from the perspective of an MBS investor. However, there are other types of negative outcomes that may be relevant in our context, and in this section we will consider one of these alternatives, namely early prepayment risk. In addition to default, residential mortgages contain a prepayment option that allows borrowers to fully repay the outstanding principal balance of their loans before the loan reaches full maturity. Since the exercise of the prepayment option reduces the expected future cash flow of a mortgage, it also reduces the value of a mortgage security, and thus, can be considered a negative outcome from the perspective of the average MBS investor. Early prepayment risk was an important consideration for investors in the period before the housing bust and financial crisis, especially given the low levels of default rates that prevailed during that time period.

It is well known in the mortgage literature that interest rate movements largely drive the prepayment behavior of borrowers with fixed-rate mortgages. In contrast, prepayments of adjustable-rate mortgages are typically driven by life events that are unrelated to interest rate movements, such as new housing purchases driven by employment changes or changes in household size due to the birth of a child or death of a family member. In the PLS market however, in addition to responses to life events, prepayments of adjustable-rate mortgages were often driven by specific contractual features. In particular, the prepayment behavior of 2/28 and 3/27 hybrid ARMS, the most common types of PLS ARMs, was highly correlated with the duration of the period in which the interest rate was frozen: two years for the 2/28s and 3 years for the 3/27s. The 2/28 and 3/27 hybrid ARMs were characterized by this initial period in which the interest rate was fixed, after which the interest rate would reset to a new level and begin to fluctuate, tracking a market interest rate (such as the 6-month LIBOR or the 10 year Treasury rate). Since the interest rate typically reset to a higher level, many borrowers prepaid either right at or shortly after the reset period. In addition, many ARMs in the PLS market contained prepayment penalties that expired at the same time of the interest rate reset, which provided further incentive for borrowers to wait until the reset date to exercise their prepayment option.[36]

For these reasons, the expectations of market participants were that many 2/28 and 3/27 ARM prepayments would occur on or immediately after the reset date. Therefore, prepayments that occurred significantly before the reset date can be viewed as particularly

[36]For an excellent reference on the PLS market in general, and especially for empirical analyses on the prepayment and default behavior of various types of PLS loans, we refer the reader to Kramer and Sinha (2006).

negative outcomes. We focus on the sample of 2/28 and 3/27 ARMs that did not default, and define a negative outcome to be an ARM that prepaid several months before the interest rate reset month.[37] The 2/28 and 3/27 ARM products were by far the most popular adjustable-rate product in the PLS market, accounting for approximately 75% of all subprime and Alt-A PLS ARMs combined.[38] We consider two cutoffs of 6 months and 9 months before the reset date in defining our early prepayment indicator variables. The reason for these threshold choices is that the most common type of prepayment penalty associated with these mortgages was 6 months of interest on 80% of the principal amount prepaid. Thus, even an ARM that carried this prepayment penalty that prepaid more than 6 months before the reset date would generate lower cash flow levels compared to a loan that prepaid at the reset date, and thus can be considered as a negative outcome for a PLS investor.

Table 14 contains the results of the early prepayment analysis. Panel A displays estimation results that correspond to the parametric (quadratic) specifications while Panel B displays results for the non-parametric specifications. We show results for various corrections for the potential sample selection issue that we discussed above in the context of the LPS default analysis. Recall that our correction was to throw out all defaults that occurred within our sale period (up to 9 months after origination). We found that such a correction had a minimal impact on the results, however, the issue may be more problematic in the context of prepayment, since, by definition, a loan that is prepaid cannot possibly be sold. At the same time however, the bulk of our sample is comprised of 2/28 hybrid ARMs, which means that the early prepayment period that we are considering is often within 15 months and 18 months of origination, respectively. Therefore, throwing out all loans that prepaid in the first 9 months eliminates a significant amount of the early prepayment variation in our

[37]We eliminate defaults from our analysis in order to isolate voluntary prepayment risk. From our analysis above we already know that there is a negative correlation between time-to-sale and (conditional) default risk. By throwing out defaults, we ensure that the results are not driven by involuntary prepayments.

[38]These products were mostly found in the subprime segment of the market, although there were a non-trivial number originated in the Alt-A segment. Many (about one-third) of Alt-A ARMs had a one month "teaser" rate that reset to a higher adjustable rate in the second month, and thus did not have prepayment profiles driven by reset concerns. See Sengupta (2010) for a detailed discussion of the composition of loans in the Alt-A and subprime PLS markets.

sample, and to the extent that investors are especially concerned with prepayments within the first year or so of origination, such a restriction could serve to attenuate the true signaling effect rather than simply correcting sample selection bias. For this reason, we display results for both a 6 and 9 month early prepayment cutoff for various sample restrictions: no restriction in columns (1) and (2), a 3-month restriction (i.e. throwing out all loans that prepay within 3 months) in columns (3) and (4), a 6-month restriction in columns (5) and (6), and finally the full 9-month restriction in columns (7) and (8). Table 14 clearly shows a negative relationship between time-to-sale and early prepayment risk. As months-to-sale increases, the likelihood of early prepayment decreases in a relatively monotonic manner. Focusing on the first two columns in the table (no correction), PLS loans sold 6 months after origination are approximately 6-7% less likely to prepay early compared to loans sold immediately, while loans sold 9 months after origination are about 10-11% less likely to prepay early. The extent of the sample restriction does have a significant impact on the results. The negative relationship remains pronounced in the cases where we apply partial corrections and throw out all prepayments that occur within 3 months and 6 months of origination, respectively (columns (3) - (6)), but the most severe restriction (throwing out all prepayments that occur within 9 months of origination) significantly flattens the slope of the negative relationship between months-to-sale and early prepayment.

In general, we believe these results on the correlation between time-to-sale and early prepayment of hybrid ARMs in the PLS market are consistent with our default analysis above, and support the existence of a motive to delay the sale of loans in order to signal their higher quality to PLS issuers and investors. While PLS investors were likely concerned about significant credit risk in the case of a large downturn (which of course occurred), prepayment risk is present in both good and bad states of the world, and thus was an important consideration for mortgage investors.

6 Conclusion

A general feature of dynamic models of adverse selection is that the prices and (unobserved) quality of goods increases over time. This paper provides the first empirical evidence of this prediction in the context of the residential mortgage market. Using detailed, loan-level data on privately-securitized mortgages, we find a statistically significant and economically meaningful positive correlation between conditional, ex-post mortgage performance and time-to-sale. This finding is robust to different ways of measuring performance, and importantly, is not generated by the component of mortgage performance that is predicable by buyers using ex-ante, observable information on underwriting characteristics. Furthermore, the positive relationship between time-to-sale and mortgage performance is not present in the agency securitization market where adverse selection between originators and issuers is not as serious of a concern. This estimated correlation appears to be strongest in the "Alt-A" segment of the PLS market, where most loans were underwritten with less than full documentation of income and/or assets, and thus, is consistent with previous studies that have found an important role of private information among low documentation mortgages.

Taken together, we believe that the results both confirm the importance of private information in the non-agency securitization market, and provide evidence consistent with a signaling mechanism by which lenders in the market are able to reveal the quality of their loans by delaying trade.

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Table 1: Distribution of Months-to-Sale in LPS Sample

	PLS Loans		GSE Loans	
Months-to-Sale	# Loans	Cumulative %	# Loans	Cumulative %
0	1,607,434	29.28	1,630,348	14.14
1	1,496,668	56.55	5,369,181	60.73
2	1,261,872	79.54	3,700,677	92.83
3	518,156	88.98	471,520	96.92
4	191,413	92.47	128,404	98.04
5	84,131	94	58,619	98.55
6	56,610	95.03	29,598	98.8
7	41,849	95.79	18,733	98.96
8	30,881	96.36	16,243	99.11
9	24,969	96.81	14,203	99.23
10	20,283	97.18	11,916	99.33
11	18,535	97.52	10,353	99.42
12	16,356	97.82	8,881	99.5
13	13,858	98.07	7,086	99.56
14	9,098	98.24	5,823	99.61
15	5,132	98.33	3,732	99.64
16	3,961	98.4	2,898	99.67
17	2,847	98.45	2,464	99.69
18	2,366	98.5	2,506	99.71
19	1,690	98.53	2,456	99.73
20	1,468	98.55	2,028	99.75
21	1,479	98.58	1,948	99.77
22	1,883	98.62	1,577	99.78
23	1,655	98.65	1,736	99.8
24	1,463	98.67	1,549	99.81

Notes: This table displays the distribution of the # of months between the time of origination and the time of sale ("Months-to-Sale") for both privately-securitized mortgages (PLS) and mortgages acquired by the housing GSEs (Fannie Mae and Freddie Mac) in the LPS dataset. The LPS sample includes only first-lien mortgages originated between January 2002 and December 2007. The sample is further restricted to only mortgages seasoned less than two months (i.e. loans that entered the dataset in either the month of origination or the month following origination).

Table 2: Summary Statistics: LPS Sample

	PLS		GSE	
	Mean	SD	Mean	SD
Loan/Borrower Characteristics				
Term	354	49	333	63
Original Rate	5.96	1.97	6.17	0.77
Original Amount	299,218	204,952	176,680	90,235
LTV Ratio	73.1	15.0	74.0	18.3
FICO	700	68	713	63
Purchase (d)	0.440	.	0.432	.
Cash Out Refinance (d)	0.208	.	0.140	.
Arm (d)	0.519	.	0.127	.
Balloon (d)	0.008	.	0.003	.
Interest Only (d)	0.234	.	0.064	.
"B" or "C" Grade (d)	0.178	.	0.012	.
Jumbo (d)	0.296	.	0.005	.
Low Doc (d)	0.146	.	0.131	.
Prepay Penalty (d)	0.279	.	0.012	.
Primary Residence (d)	0.868	.	0.876	.
Single Family (d)	0.822	.	0.847	.
Geographic Characteristics				
Unemployment rate (county-level)	4.8	1.4	4.9	1.5
36 month unemployment growth (				
Price Index (county-level)	188	53	163	46
36 month HPA (%)	43.9	26.5	31.4	23.1
Default Rates				
60+ DQ, 36-month horizon	0.160	.	0.090	.
60+ DQ, 60-month horizon	0.225	.	0.133	.
90+ DQ, 36-month horizon	0.136	.	0.071	.
90+ DQ, 60-month horizon	0.204	.	0.111	.
# Loans	5,313,983		11,437,525	

Notes: This table displays summary statistics for both privately-securitized mortgages (PLS) and mortgages acquired by the housing GSEs (Fannie Mae and Freddie Mac) in the LPS dataset. The LPS sample includes only first-lien mortgages originated between January 2002 and December 2007. The sample is further restricted to only mortgages seasoned less than two months (i.e. loans that entered the dataset in either the month of origination or the month following origination). In addition, the sample only includes loans that were sold to either PLS issuers or the GSEs within 9 months of origination (inclusive). All of the variables in the table are included in the set of model covariates. For a full list of covariates, see the Online Appendix.

Table 3: Distribution of Months-to-Sale in CoreLogic Sample

	All PLS		Subprime PLS		Alt-A PLS	
Months-to-Sale	# Loans	Cumulative % of Sample	# Loans	Cumulative % of Sample	# Loans	Cumulative % of Sample
0	2,446,106	17.9	1,079,646	12.4	1,366,460	27.7
1	3,675,646	44.8	2,296,307	38.7	1,379,339	55.6
2	2,952,576	66.4	2,026,277	62.0	926,299	74.3
3	2,064,585	81.6	1,521,350	79.4	543,235	85.3
4	1,149,410	90.0	861,916	89.3	287,494	91.1
5	571,103	94.2	415,989	94.1	155,114	94.3
6	286,959	96.3	201,827	96.4	85,132	96.0
7	140,231	97.3	86,683	97.4	53,548	97.1
8	87,131	97.9	51,849	98.0	35,282	97.8
9	56,839	98.3	32,197	98.4	24,642	98.3
10	38,190	98.6	20,454	98.6	17,736	98.6
11	30,233	98.8	16,464	98.8	13,769	98.9
12	24,564	99.0	14,094	98.9	10,470	99.1
13	19,247	99.2	11,051	99.1	8,196	99.3
14	15,630	99.3	9,301	99.2	6,329	99.4
15	14,481	99.4	9,445	99.3	5,036	99.5
16	11,835	99.5	7,744	99.4	4,091	99.6
17	13,645	99.6	9,997	99.5	3,648	99.7
18	11,432	99.6	8,364	99.6	3,068	99.7
19	10,814	99.7	7,889	99.7	2,925	99.8
20	8,602	99.8	6,245	99.7	2,357	99.9
21	7,910	99.8	6,062	99.8	1,848	99.9
22	7,574	99.9	5,790	99.9	1,784	99.9
23	7,511	100.0	5,702	100.0	1,809	100.0
24	764	100.0	3,710	100.0	1,576	100.0

Notes: This table displays the distribution of the # of months between the time of origination and the time of sale ("Months-to-Sale") for privately-securitized mortgages in the CoreLogic dataset. The CoreLogic sample includes only first-lien mortgages backing subprime and Alt-A PLS that were originated between January 2002 and December 2007. The time of sale corresponds to the month in which the PLS security was issued.

Table 4: Summary Statistics: CoreLogic Sample

	All PLS		Subprime PLS		Alt-A PLS	
	Mean	SD	Mean	SD	Mean	SD
Loan/Borrower Characteristics						
Term	356	37	355	34	357	42
Original Rate	7.28	1.62	7.86	1.32	6.27	1.60
Original Amount ($ 1000)	223	157	187	123	285	188
LTV Ratio	82.8	14.7	83.8	14.0	80.9	15.7
FICO	650	72	617	60	709	50
Purchase (d)	0.416	.	0.367701	.	0.501	.
Cash Out Refinance (d)	0.472	.	0.549	.	0.335	.
Arm (d)	0.684	.	0.748031	.	0.571	.
Balloon (d)	0.055	.	0.081966	.	0.009	.
Interest Only (d)	0.213	.	0.120	.	0.376	.
Jumbo (d)	0.142	.	0.083789	.	0.246	.
Low Doc (d)	0.475	.	0.345177	.	0.704	.
Prepay Penalty (d)	0.621	.	0.740	.	0.400	.
Primary Residence (d)	0.855	.	0.917567	.	0.744	.
Single Family (d)	0.727	.	0.782	.	0.630	.
Geographic Characteristics						
Unemployment rate (county-level)	5.18	1.57	5.32	1.59	4.93	1.50
36 month unemployment growth (%)	4.7%	39.6%	9.0%	40.6%	-2.9%	36.6%
Price Index (county-level)	177	52	170	50	189	53
36 month HPA (%)	42.5%	26.5%	40.2%	26.3%	46.3%	26.4%
Default Rates						
60+ DQ, 36-month horizon	0.215	.	0.245	.	0.154	.
60+ DQ, 60-month horizon	0.269	.	0.294	.	0.227	.
90+ DQ, 36-month horizon	0.178	.	0.204	.	0.131	.
90+ DQ, 60-month horizon	0.238	.	0.255	.	0.207	.
# Loans	13,430,586		8,574,041		4,856,545	

Notes: This table displays summary statistics for loans backing subprime and Alt-A PLS in the CoreLogic dataset. The CoreLogic sample includes only first-lien mortgages originated between January 2002 and December 2007. In addition, the sample only includes loans that were sold to PLS issuers within 9 months of origination (inclusive). All of the variables in the table are included in the set of model covariates. For a full list of covariates, see the Online Appendix.

Table 5: Pricing Analysis Summary Statistics

	Mean	Standard Dev.	Minimum	25th Perc.	Median	75th Perc.	Maximum
Yield Spread	0.28	0.23	0.04	0.16	0.23	0.32	2.09
Months-to-Sale	3.3	1.4	0.3	2.2	3.1	4.2	9.0
# Loans	2,355	1,833	55	1,108	1,911	3,078	18,190
Log Loan Balance	12.2	0.4	11.0	11.9	12.1	12.4	14.9
FICO	640	43	413	609	624	682	764
FICO $<$ 580	0.20	0.15	0.00	0.01	0.22	0.31	0.87
580 $\leq$ FICO $<$ 620	0.19	0.12	0	0.05	0.22	0.27	0.67
620 $\leq$ FICO $<$ 660	0.23	0.08	0	0.19	0.24	0.28	0.68
660 $\leq$ FICO $<$ 700	0.18	0.09	0.01	0.11	0.15	0.25	0.72
FICO $\geq$ 700	0.20	0.21	0	0.06	0.10	0.35	0.92
CLTV	84	6	39	80	84	88	102
70 $\leq$ CLTV $<$ 80	0.15	0.07	0	0.10	0.14	0.19	0.49
80 $\leq$ CLTV $<$ 90	0.28	0.13	0	0.20	0.27	0.36	0.92
90 $\leq$ CLTV $<$ 100	0.24	0.10	0	0.18	0.23	0.29	0.97
CLTV $\geq$ 100	0.20	0.20	0	0.02	0.16	0.32	0.96
LTV = 80	0.16	0.12	0	0.08	0.12	0.20	0.91
Term	359	15	120	356	359	360	480
Purchase Loan	0.42	0.20	0	0.27	0.40	0.57	1
Cashout Refinance	0.48	0.19	0	0.33	0.50	0.62	1
Primary Residence	0.87	0.13	0	0.85	0.91	0.95	1
Single-Family Property	0.73	0.11	0	0.68	0.75	0.80	0.99
Condominium	0.08	0.04	0	0.05	0.07	0.09	0.36
ARM	0.83	0.18	0	0.76	0.85	1	1
Interest-Only	0.21	0.28	0	0	0.10	0.26	1
Negative Amortization	0.10	0.30	0	0	0	0	1
Low Documentation	0.47	0.23	0	0.31	0.41	0.61	1
Balloon	0.08	0.15	0	0	0	0.05	1
Jumbo	0.19	0.24	0	0	0.10	0.27	1
Prepayment Penalty	0.69	0.21	0	0.65	0.74	0.81	1
Fraction in CA	0.26	0.17	0	0.13	0.23	0.34	1
Unemployment Rate	5.14	0.61	1.73	4.66	5.06	5.63	6.83
Predicted WAL	2.59	0.61	0	2.23	2.52	2.90	6.61
Subordination	1.00	3.10	0	0.81	0.85	0.91	103.35
# Securities				3,532			

Notes: This table displays summary statistics for the variables included in the pricing analysis presented in section 5.6. All mortgage characteristics correspond to averages that are calculated at the pool-level in the sample of CoreLogic loans, which includes mortgages backing Subprime and Alt-A triple-A, floating rate securities issued between January 2002 and December 2007. Yield Spread is the weighted average spread over 1-month LIBOR of all triple-A securities with claims on cash flows for a given mortgage pool. Seasoning is the average age (# months) of all mortgages in a pool at the time of issuance. Predicted WAL is a model-based calculation of expected weighted average life. Subordination is calculated as the ratio of the total face value of all triple-A securities associated with a pool to the sum of the remaining principal balances of all loans in the pool in the month of issuance.

Table 6: PLS Results from Parametric Specification: LPS Sample

Panel A: Full Sample

Default Horizon:	36 Months				60 Months			
Default Definition:	60+ DQ		90+ DQ		60+ DQ		90+ DQ	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Months-to-Sale	-0.0107	-0.0246	-0.0110	-0.0246	-0.0112	-0.0266	-0.0122	-0.0272
	(5.79)	(8.10)	(5.88)	(8.19)	(6.75)	(8.59)	(7.23)	(9.75)
Months-to-Sale^2		0.0027		0.0026		0.0029		0.0029
		(7.37)		(7.13)		(7.74)		(8.61)
# Loans	5,313,951	5,313,951	5,313,951	5,313,951	5,313,951	5,313,951	5,313,951	5,313,951
Adjusted R^2	0.23	0.23	0.22	0.22	0.25	0.25	0.25	0.25
Orig Qtr FEs?	Y	Y	Y	Y	Y	Y	Y	Y
State FEs?	Y	Y	Y	Y	Y	Y	Y	Y
Sale Qtr FEs?	Y	Y	Y	Y	Y	Y	Y	Y
Lender FEs?	N	N	N	N	N	N	N	N
Other Controls?	Y	Y	Y	Y	Y	Y	Y	Y

Panel B: Restricted Sample (Only Defaults Occurring After 9 Months)

Default Horizon:	36 Months				60 Months			
Default Definition:	60+ DQ		90+ DQ		60+ DQ		90+ DQ	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Months-to-Sale	-0.0105	-0.0173	-0.0101	-0.0167	-0.0112	-0.0203	-0.0115	-0.0206
	(5.90)	(6.51)	(5.99)	(6.46)	(6.39)	(6.91)	(6.83)	(7.68)
Months-to-Sale^2		0.0013		0.0013		0.0018		0.0018
		(4.57)		(4.27)		(5.39)		(5.98)
# Loans	5,143,409	5,143,409	5,143,409	5,143,409	5,143,409	5,143,409	5,143,409	5,143,409
Adjusted R^2	0.20	0.20	0.19	0.19	0.23	0.23	0.22	0.22
Orig Qtr FEs?	Y	Y	Y	Y	Y	Y	Y	Y
State FEs?	Y	Y	Y	Y	Y	Y	Y	Y
Sale Qtr FEs?	Y	Y	Y	Y	Y	Y	Y	Y
Lender FEs?	N	N	N	N	N	N	N	N
Other Controls?	Y	Y	Y	Y	Y	Y	Y	Y

This table displays results from the estimation of equation 5 on PLS loans in the LPS dataset originated in the 2002 - 2007 period. The dependent variable is an indicator variable for loans that default over a 36-month horizon (columns 1-4) and over a 60-month horizon (columns 5-8). Default is defined as a loan that is 60+ days delinquent(columns 1-2 and 5-6) and 90+ days delinquent (columns 3-4 and 7-8). Months-to-Sale is defined as the number of months that elapse between origination and sale to a PLS issuer. All regressions include origination year-quarter fixed effects, state fixed effects, year-quarter of sale fixed effects, and the detailed list of covariates described in the text. The first row for each variable shows the regression coefficient, the second row shows t-statistics.Standard errors are heteroskedasticity-robust and are clustered by year-quarter of origination.

Table 7: PLS Results from Non-Parametric Specification: LPS Sample

	Full Sample		Restricted Sample		Full Sample		Restricted Sample	
Default Horizon:	36 Months				60 Months			
Default Definition:	60+ DQ	90+ DQ	60+ DQ	90+ DQ	60+ DQ	90+ DQ	60+ DQ	90+ DQ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Months-to-Sale = 2	-0.019	-0.019	-0.012	-0.012	-0.020	-0.020	-0.014	-0.014
	(5.12)	(5.01)	(3.82)	(3.82)	(4.60)	(4.88)	(3.07)	(3.34)
Months-to-Sale = 3	-0.038	-0.038	-0.026	-0.026	-0.040	-0.041	-0.030	-0.031
	(6.37)	(6.57)	(5.24)	(5.24)	(6.28)	(6.89)	(5.22)	(5.78)
Months-to-Sale = 4	-0.057	-0.058	-0.046	-0.046	-0.062	-0.066	-0.055	-0.055
	(7.91)	(7.93)	(6.74)	(6.74)	(8.75)	(9.52)	(7.53)	(7.88)
Months-to-Sale = 5	-0.058	-0.059	-0.052	-0.052	-0.062	-0.066	-0.059	-0.061
	(4.71)	(4.81)	(4.86)	(4.86)	(5.98)	(6.22)	(6.07)	(6.14)
Months-to-Sale = 6	-0.054	-0.054	-0.054	-0.054	-0.059	-0.064	-0.063	-0.065
	(3.56)	(3.61)	(4.49)	(4.49)	(4.32)	(4.54)	(5.31)	(5.32)
Months-to-Sale = 7	-0.044	-0.046	-0.049	-0.049	-0.047	-0.053	-0.054	-0.056
	(3.51)	(3.76)	(5.28)	(5.28)	(4.33)	(4.94)	(5.39)	(5.77)
Months-to-Sale = 8	-0.031	-0.034	-0.045	-0.045	-0.028	-0.036	-0.044	-0.047
	(2.03)	(2.38)	(3.48)	(3.48)	(2.04)	(2.49)	(3.09)	(3.29)
Months-to-Sale = 9	-0.036	-0.040	-0.049	-0.049	-0.031	-0.037	-0.045	-0.046
	(2.11)	(2.39)	(3.42)	(3.42)	(1.81)	(2.29)	(2.91)	(3.12)
# Loans	5,313,951	5,313,951	5,143,409	5,143,409	5,313,951	5,313,951	5,143,409	5,143,409
Adjusted R^2	0.23	0.22	0.19	0.19	0.25	0.25	0.23	0.23
Orig Qtr FEs?	Y	Y	Y	Y	Y	Y	Y	Y
State FEs?	Y	Y	Y	Y	Y	Y	Y	Y
Sale Qtr FEs?	Y	Y	Y	Y	Y	Y	Y	Y
Lender FEs?	N	N	N	N	N	N	N	N
Other Controls?	Y	Y	Y	Y	Y	Y	Y	Y

This table displays results from the estimation of equation 5 on PLS loans in the LPS dataset originated in the 2002 - 2007 period. The dependent variable is an indicator variable for loans that default over a 36-month horizon (columns 1-4) and over a 60-month horizon (columns 5-8). Default is defined as a loan that is 60+ days delinquent(columns 1-2 and 5-6) and 90+ days delinquent (columns 3-4 and 7-8). Months-to-Sale is defined as the number of months that elapse between origination and sale to a PLS issuer. All regressions include origination year-quarter fixed effects, state fixed effects, year-quarter of sale fixed effects, and the detailed list of covariates described in the text. The first row for each variable shows the regression coefficient, the second row shows t-statistics.Standard errors are heteroskedasticity-robust and are clustered by year-quarter of origination.

Table 8: GSE Results from Parametric Specification: LPS Sample

Panel A: Full Sample

Default Horizon:	36 Months				60 Months			
Default Definition:	60+ DQ		90+ DQ		60+ DQ		90+ DQ	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Months to Sale	-0.0001	-0.0005	-0.0010	-0.0014	-0.0002	-0.0020	-0.0012	-0.0030
	(0.11)	(0.35)	(1.60)	(1.07)	(0.19)	(1.14)	(1.72)	(1.94)
Months to Sale^2		0.0001		0.0001		0.0005		0.0005
		(0.41)		(0.39)		(1.58)		(1.65)
# Loans	11,437,522	11,437,522	11,437,522	11,437,522	11,437,522	11,437,522	11,437,522	11,437,522
Adjusted R^2	0.14	0.14	0.14	0.14	0.16	0.16	0.16	0.16
Orig Qtr FEs?	Y	Y	Y	Y	Y	Y	Y	Y
State FEs?	Y	Y	Y	Y	Y	Y	Y	Y
Sale Qtr FEs?	Y	Y	Y	Y	Y	Y	Y	Y
Lender FEs?	N	N	N	N	N	N	N	N
Other Controls?	Y	Y	Y	Y	Y	Y	Y	Y

Panel B: Restricted Sample (Only Defaults Occurring After 9 Months)

Default Horizon:	36 Months				60 Months			
Default Definition:	60+ DQ		90+ DQ		60+ DQ		90+ DQ	
Months to Sale	-0.0014	-0.0014	-0.0015	-0.0014	-0.0015	-0.0029	-0.0017	-0.0031
	(2.42)	(1.20)	(2.97)	(1.35)	(2.15)	(1.95)	(2.89)	(2.31)
Months to Sale^2		0.0000		0.0000		0.0004		0.0004
		(0.00)		(0.07)		(1.42)		(1.47)
# Loans	11,267,367	11,267,367	11,267,367	11,267,367	11,267,367	11,267,367	11,267,367	11,267,367
Adjusted R^2	0.13		0.12	0.12	0.15	0.15	0.15	0.15
Orig Qtr FEs?	Y	Y	Y	Y	Y	Y	Y	Y
State FEs?	Y	Y	Y	Y	Y	Y	Y	Y
Sale Qtr FEs?	Y	Y	Y	Y	Y	Y	Y	Y
Lender FEs?	N	N	N	N	N	N	N	N
Other Controls?	Y	Y	Y	Y	Y	Y	Y	Y

This table displays results from the estimation of equation 5 on GSE loans in the LPS dataset originated in the 2002 - 2007 period. The dependent variable is an indicator variable for loans that default over a 36-month horizon (columns 1-4) and over a 60-month horizon (columns 5-8). Default is defined as a loan that is 60+ days delinquent(columns 1-2 and 5-6) and 90+ days delinquent (columns 3-4 and 7-8). Months-to-sale is defined as the number of months that elapse between origination and sale to a GSE. All regressions include origination year-quarter fixed effects, state fixed effects, year-quarter of sale fixed effects, and the detailed list of covariates described in the text. The first row for each variable shows the regression coefficient, the second row shows t-statistics.Standard errors are heteroskedasticity-robust and are clustered by year-quarter of origination.

Table 9: Ex-Ante Default Risk Results: LPS Sample

Panel A: PLS Loans

Default Horizon:	36 Months				60 Months			
Default Definition:	60+ DQ		90+ DQ		60+ DQ		90+ DQ	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Months-to-Sale	0.0058	0.0197	0.0045	0.0150	0.0057	0.0186	0.0040	0.0112
	(5.20)	(7.24)	(5.20)	(7.01)	(4.40)	(8.65)	(3.45)	(6.61)
Months-to-Sale^2		-0.0028		-0.0021		-0.0026		-0.0015
		(8.51)		(8.15)		(10.03)		(9.58)
# Loans	3,672,426	3,672,426	3,672,426	3,672,426	3,672,426	3,672,426	3,672,426	3,672,426
Adjusted R^2	0.26	0.27	0.24	0.25	0.30	0.31	0.36	0.37
Orig Qtr FEs?	Y	Y	Y	Y	Y	Y	Y	Y
Sale Qtr FEs?	Y	Y	Y	Y	Y	Y	Y	Y

Panel B: GSE Loans

Default Horizon:	36 Months				60 Months			
Default Definition:	60+ DQ		90+ DQ		60+ DQ		90+ DQ	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Months-to-Sale	0.0004	0.0014	0.0002	0.0004	0.0021	0.0011	0.0013	0.0008
	(1.17)	(1.78)	(0.93)	(0.96)	(3.20)	(0.68)	(3.50)	(0.78)
Months-to-Sale^2		-0.0002		-0.0001		0.0002		0.0001
		(1.57)		(0.71)		(0.64)		(0.58)
# Loans	7,378,891	7,378,891	7,378,891	7,378,891	7,378,891	7,378,891	7,378,891	7,378,891
Adjusted R^2	0.29	0.29	0.30	0.30	0.52	0.52	0.56	0.56
Orig Qtr FEs?	Y	Y	Y	Y	Y	Y	Y	Y
Sale Qtr FEs?	Y	Y	Y	Y	Y	Y	Y	Y

This table shows loan-level, OLS regressions where the dependent variables are the 36-month, and 60-month ex-ante default rates at the time the loan is originated, where the ex-ante default rates are calculated using the extensive information in the data on loan and borrower characteristics at the time of origination for the previous three years for the 36-month ex-ante rates and five years for the 60-month ex-ante rates. Default is defined as a loan being 60 days and 90 days delinquent or more at any point since origination. The independent variable of interest is "Months-to-Sale" which is defined as the number of months that elapse between origination and sale to a PLS issuer or GSE. All regressions include origination year-quarter fixed effects, and year-quarter of sale fixed effects. 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 10: Baseline Parametric Results for Sample of CoreLogic PLS Loans

Panel A: No Lender Fixed Effects

Default Definition:	60+ DQ over 36 Months					
	All PLS		Alt-A		Subprime	
	(1)	(2)	(3)	(4)	(5)	(6)
Months-to-Sale	-0.0036	-0.0046	-0.0072	-0.0100	-0.0020	-0.0019
	(4.28)	(3.38)	(6.87)	(5.78)	(2.46)	(1.19)
Months-to-Sale^2		0.0002		0.0004		0.0000
		(0.93)		(1.85)		(0.05)
# Loans	7,860,499	7,860,499	1,895,618	1,895,618	5,964,881	5,964,881
Adjusted R^2	0.21	0.21	0.25	0.25	0.19	0.19
Orig Qtr FEs?	Y	Y	Y	Y	Y	Y
State FEs?	Y	Y	Y	Y	Y	Y
Sale Qtr FEs?	Y	Y	Y	Y	Y	Y
Lender FEs?	N	N	N	N	N	N
Other Controls?	Y	Y	Y	Y	Y	Y

Panel B: Lender Fixed Effects

Default Definition:	60+ DQ over 36 Months					
	All PLS		Alt-A		Subprime	
	(1)	(2)	(3)	(4)	(5)	(6)
Months-to-Sale	-0.0028	-0.0043	-0.0063	-0.01	-0.0015	-0.0005
	(3.80)	(3.96)	(5.61)	(6.73)	(2.08)	(0.48)
Months-to-Sale^2		0.0002		0.0006		-0.0002
		(1.93)		(4.09)		(1.10)
# Loans	7,860,499	7,860,499	1,895,618	1,895,618	5,964,881	5,964,881
Adjusted R^2	0.21	0.21	0.26	0.26	0.19	0.19
Orig Qtr FEs?	Y	Y	Y	Y	Y	Y
State FEs?	Y	Y	Y	Y	Y	Y
Sale Qtr FEs?	Y	Y	Y	Y	Y	Y
Lender FEs?	Y	Y	Y	Y	Y	Y
Other Controls?	Y	Y	Y	Y	Y	Y

Notes: This table displays results from the estimation of equation 5 on PLS loans in the CoreLogic dataset originated in the 2002 - 2007 period. The dependent variable is an indicator variable for loans that default over a 36-month horizon. Default is defined as a loan that is 60+ days delinquent. Months-to-Sale is defined as the number of months that elapse between origination and sale to a PLS issuer. All regressions include origination year-quarter fixed effects, state fixed effects, year-quarter of sale fixed effects, and the detailed list of covariates described in the text. Specifications in Panel B include a full set of originator fixed effects. The first row for each variable shows the regression coefficient, the second row shows t-statistics. Standard errors are heteroskedasticity-robust and are clustered by year-quarter of origination.

Table 11: Documentation Results for Sample of CoreLogic PLS Loans

Panel A: Parametric Results

Default Definition:	60+ DQ over 36 Months					
	All PLS		Alt-A		Subprime	
	Full Doc	Low Doc	Full Doc	Low Doc	Full Doc	Low Doc
	(1)	(2)	(3)	(4)	(5)	(6)
Months-to-Sale	-0.0027	-0.0063	-0.0103	-0.0091	-0.0011	0.0006
	(2.43)	(4.03)	(5.08)	(5.76)	(0.99)	(0.37)
Months-to-Sale^2	0.0001	0.0003	0.0006	0.0006	0.0000	-0.0004
	(0.94)	(2.36)	(2.49)	(3.60)	(0.29)	(2.37)
# Loans	3,261,827	2,605,838	378,607	1,035,183	3,842,498	2,092,603
Adjusted R^2	0.18	0.25	0.16	0.27	0.17	0.24
Orig Qtr FEs?	Y	Y	Y	Y	Y	Y
State FEs?	Y	Y	Y	Y	Y	Y
Sale Qtr FEs?	Y	Y	Y	Y	Y	Y
Lender FEs?	Y	Y	Y	Y	Y	Y
Other Controls?	Y	Y	Y	Y	Y	Y

Panel B: Non-Parametric Results

Default Definition:	60+ DQ over 36 Months					
	All PLS		Alt-A		Subprime	
	Full Doc	Low Doc	Full Doc	Low Doc	Full Doc	Low Doc
	(1)	(2)	(3)	(4)	(5)	(6)
Months to Sale = 1	-0.0023	-0.0103	-0.0113	-0.0166	0.0001	0.0028
	(0.74)	(2.66)	(3.80)	(5.34)	(0.04)	(0.79)
Months to Sale = 2	-0.0015	-0.0138	-0.0177	-0.0219	0.0025	0.0049
	(0.54)	(4.05)	(4.39)	(7.97)	(1.12)	(1.78)
Months to Sale = 3	-0.0057	-0.0175	-0.0285	-0.0274	-0.0014	0.0005
	(1.91)	(4.05)	(5.31)	(7.49)	(0.51)	(0.13)
Months to Sale = 4	-0.0095	-0.0203	-0.0348	-0.0308	-0.005	-0.0016
	(2.75)	(3.80)	(6.88)	(6.17)	(1.46)	(0.39)
Months to Sale = 5	-0.0111	-0.0272	-0.0362	-0.0293	-0.0079	-0.0118
	(2.16)	(4.61)	(5.12)	(5.22)	(1.68)	(1.99)
Months to Sale = 6	-0.0109	-0.0292	-0.0364	-0.0347	-0.0076	-0.0116
	(1.84)	(3.90)	(5.29)	(5.54)	(1.35)	(1.28)
Months to Sale = 7	-0.0134	-0.0326	-0.048	-0.0388	-0.0087	-0.0147
	(1.81)	(3.69)	(4.41)	(4.86)	(1.27)	(1.67)
Months to Sale = 8	-0.0078	-0.0318	-0.0489	-0.0518	-0.0007	-0.0043
	(1.02)	(3.18)	(4.80)	(5.20)	(0.09)	(0.48)
Months to Sale = 9	-0.0004	-0.0339	-0.0528	-0.0583	0.0082	-0.0057
	(0.03)	(3.61)	(4.35)	(7.91)	(0.61)	(0.47)
# Loans	3,261,827	2,605,838	378,607	1,035,183	3,842,498	2,092,603
Adjusted R^2	0.18	0.25	0.16	0.27	0.17	0.24
Orig Qtr FEs?	Y	Y	Y	Y	Y	Y
State FEs?	Y	Y	Y	Y	Y	Y
Sale Qtr FEs?	Y	Y	Y	Y	Y	Y
Lender FEs?	Y	Y	Y	Y	Y	Y
Other Controls?	Y	Y	Y	Y	Y	Y

Notes: This table displays results from the estimation of equation 5 on PLS loans in the CoreLogic dataset originated in the 2002 - 2007 period. The dependent variable is an indicator variable for loans that default over a 36-month horizon. Default is defined as a loan that is 60+ days delinquent. Months-to-Sale is defined as the number of months that elapse between origination and sale to a PLS issuer. All regressions include origination year-quarter fixed effects, state fixed effects, year-quarter of sale fixed effects, originator fixed effects, and the detailed list of covariates described in the text. "Full Doc" loans correspond to those in which the borrower's income and assets were not fully documented at the time of origination, while "Low Doc" loans correspond to those in which either the borrower's income or assets (or both) were not fully documented. The first row for each variable shows the regression coefficient, the second row shows t-statistics. Standard errors are heteroskedasticity-robust and are clustered by year-quarter of origination.

Table 12: Affiliation Results for Sample of CoreLogic PLS Loans

Panel A: Parametric Results

Default Definition:	60+ DQ over 36 Months					
	All PLS		Alt-A		Subprime	
	Affiliation	No Affiliation	Affiliation	No Affiliation	Affiliation	No Affiliation
	(1)	(2)	(3)	(4)	(5)	(6)
Months-to-Sale	-0.0049	-0.0121	-0.0080	-0.0194	-0.0028	-0.0073
	(3.42)	(5.57)	(3.92)	(8.36)	(2.27)	(2.97)
Months-to-Sale^2	0.0001	0.0010	0.0004	0.0011	0.0000	0.0006
	(0.61)	(4.49)	(1.83)	(6.08)	(0.12)	(2.28)
# Loans	2,384,156	2,606,571	453,075	551,994	1,931,081	2,054,577
Adjusted R^2	0.20	0.21	0.24	0.26	0.19	0.20
Orig Qtr FEs?	Y	Y	Y	Y	Y	Y
State FEs?	Y	Y	Y	Y	Y	Y
Sale Qtr FEs?	Y	Y	Y	Y	Y	Y
Lender FEs?	Y	Y	Y	Y	Y	Y
Other Controls?	Y	Y	Y	Y	Y	Y

Panel B: Non-Parametric Results

Default Definition:	60+ DQ over 36 Months					
	All PLS		Alt-A		Subprime	
	Affiliation	No Affiliation	Affiliation	No Affiliation	Affiliation	No Affiliation
	(1)	(2)	(3)	(4)	(5)	(6)
Months-to-Sale = 1	-0.0042	-0.0310	-0.0073	-0.0443	-0.0029	0.0039
	(1.32)	(3.80)	(3.43)	(7.54)	(1.07)	(0.82)
Months-to-Sale = 2	-0.0068	-0.0377	-0.0138	-0.0518	-0.0038	-0.0019
	(2.45)	(5.19)	(3.29)	(10.29)	(1.52)	(0.37)
Months-to-Sale = 3	-0.0140	-0.0422	-0.0253	-0.0645	-0.0086	-0.0064
	(4.40)	(5.50)	(3.29)	(10.75)	(2.92)	(1.05)
Months-to-Sale = 4	-0.0183	-0.0456	-0.0279	-0.0745	-0.0120	-0.0095
	(4.66)	(4.80)	(4.64)	(9.12)	(3.21)	(1.28)
Months-to-Sale = 5	-0.0250	-0.0490	-0.0250	-0.0770	-0.0187	-0.0132
	(4.55)	(4.76)	(4.16)	(9.70)	(3.37)	(1.68)
Months-to-Sale = 6	-0.0204	-0.0513	-0.0271	-0.0870	-0.0150	-0.0122
	(3.07)	(4.54)	(3.13)	(8.04)	(2.00)	(1.36)
Months-to-Sale = 7	-0.0297	-0.0535	-0.0308	-0.0957	-0.0294	-0.0105
	(3.66)	(4.71)	(3.46)	(7.56)	(3.00)	(1.08)
Months-to-Sale = 8	-0.0267	-0.0537	-0.0552	-0.1089	-0.0167	-0.0059
	(2.20)	(4.80)	(5.32)	(8.40)	(1.27)	(0.50)
Months-to-Sale = 9	-0.0157	-0.0482	-0.0527	-0.1185	-0.0020	0.0083
	(1.70)	(3.44)	(3.83)	(9.36)	(0.16)	(0.63)
# Loans	2,384,156	2,606,571	453,075	551,994	1,931,081	2,054,577
Adjusted R^2	0.2	0.21	0.24	0.26	0.19	0.2
Orig Qtr FEs?	Y	Y	Y	Y	Y	Y
State FEs?	Y	Y	Y	Y	Y	Y
Sale Qtr FEs?	Y	Y	Y	Y	Y	Y
Lender FEs?	Y	Y	Y	Y	Y	Y
Other Controls?	Y	Y	Y	Y	Y	Y

Notes: This table displays results from the estimation of equation 5 on PLS loans in the CoreLogic dataset originated in the 2002 - 2007 period. The dependent variable is an indicator variable for loans that default over a 36-month horizon. Default is defined as a loan that is 60+ days delinquent. Months-to-Sale is defined as the number of months that elapse between origination and sale to a PLS issuer. All regressions include origination year-quarter fixed effects, state fixed effects, year-quarter of sale fixed effects, originator fixed effects, and the detailed list of covariates described in the text. "Affiliated" PLS deals correspond to those in which the originator of all mortgages in the deal is affiliated with the issuer (either the same company or part of the same vertical corporation). The first row for each variable shows the regression coefficient, the second row shows t-statistics. Standard errors are heteroskedasticity-robust and are clustered by year-quarter of origination.

Table 13: Pricing Analysis Results

Panel A: Linear Specification

Dependent Variable: Pool-level Average Yield Spread (Triple-A Securities Only)

	All Securities			Alt-A Securities			Subprime Securities		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Seasoning	-0.015***	-0.003	-0.010***	-0.022*	-0.024*	-0.024*	0.002	0.002	0.002
	(0.004)	(0.003)	(0.003)	(0.013)	(0.014)	(0.014)	(0.002)	(0.002)	(0.002)
Pool Covariates?	N	Y	Y	N	Y	Y	N	Y	Y
Issue Qtr FE?	Y	Y	Y	Y	Y	Y	Y	Y	Y
Issuer FE?	N	N	Y	N	N	Y	N	N	Y
Observations	3,532	3,532	3,513	909	909	909	2,623	2,615	2,615
Adjusted R^2	0.17	0.33	0.45	0.09	0.16	0.16	0.67	0.71	0.71

Panel B: Non-Linear Specification

Dependent Variable: Pool-level Average Yield Spread (Triple-A Securities Only)

	All Securities			Alt-A Securities			Subprime Securities		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Seasoning	-0.095***	-0.051***	-0.035**	-0.177***	-0.169***	-0.169***	-0.003	-0.008	-0.009
	(0.019)	(0.018)	(0.014)	(0.047)	(0.052)	(0.052)	(0.006)	(0.007)	(0.008)
Seasoning^2	0.010***	0.006***	0.003**	0.020***	0.019***	0.019***	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.007)	(0.007)	(0.007)	(0.001)	(0.001)	(0.001)
Pool Covariates?	N	Y	Y	N	Y	Y	N	Y	Y
Issue Qtr FE?	Y	Y	Y	Y	Y	Y	Y	Y	Y
Issuer FE?	N	N	Y	N	N	Y	N	N	Y
Observations	3,532	3,532	3,513	909	909	909	2,623	2,615	2,615
Adjusted R^2	0.17	0.33	0.45	0.09	0.16	0.16	0.67	0.71	0.71

This table displays results from the estimation of equation 7. The sample includes triple-A, floating rate Subprime and Alt-A securities issued between January 2002 and December 2007. The dependent variable is the weighted average spread over 1-month LIBOR of all triple-A securities with claims on cash flows for a given mortgage pool. Seasoning is the average age (# months) of all mortgages in a pool at the time of issuance. All regressions include month-of-issue fixed effects. The set of pool-level covariates corresponds to the variables included in Table 5, which are all pool-level averages. The first row for each variable shows the regression coefficient, the second row shows t-statistics. Standard errors are heteroskedasticity-robust and are clustered at the deal-level. Statistical significance is denoted by stars, with the following mapping: *** p<0.01, ** p<0.05, * p<0.1

Table 14: Early Prepayment Results

Panel A: Parametric Specification

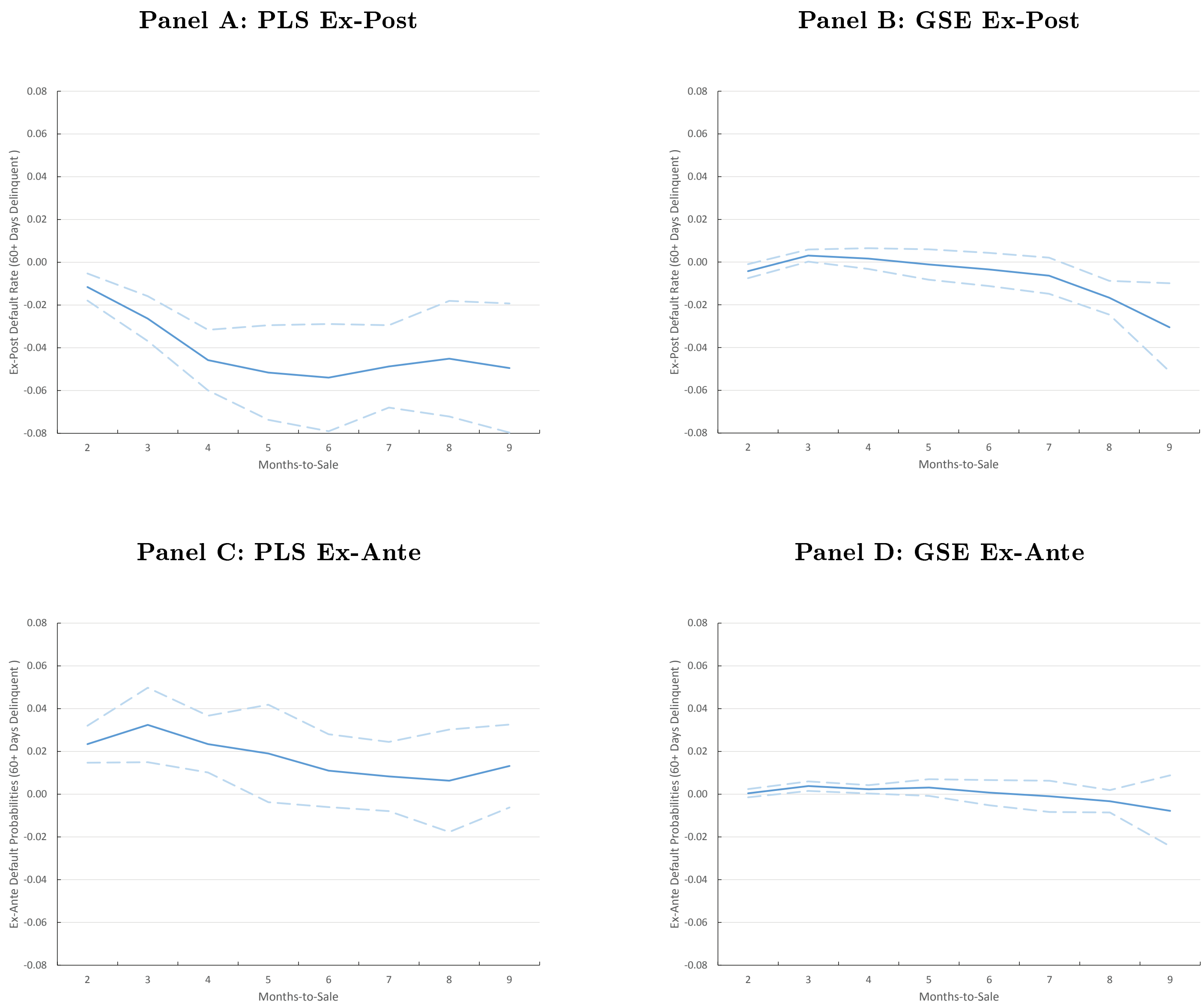
Correction:	None		≤ 3 months		≤ 6 months		≤ 9 months	
Reset Month - Prepay Month	≥ 6 Months	≥ 9 Months	≥ 6 Months	≥ 9 Months	≥ 6 Months	≥ 9 Months	≥ 6 Months	≥ 9 Months
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Months-to-Sale	-0.0129	-0.0152	-0.0089	-0.0105	-0.0111	-0.0131	-0.0144	-0.0169
	(6.20)	(6.28)	(4.11)	(4.15)	(4.76)	(4.75)	(5.66)	(5.57)
Months-to-Sale^2	0.0007	0.0009	0.0004	0.0005	0.0012	0.0015	0.0019	0.0023
	(2.56)	(2.83)	(1.36)	(1.58)	(3.75)	(4.03)	(5.07)	(5.36)
# Loans	4,024,361	4,024,361	3,968,227	3,968,227	3,701,607	3,701,607	3,302,260	3,302,260
Adjusted R^2	0.13	0.13	0.13	0.13	0.12	0.11	0.10	0.08
Orig Qtr FEs?	Y	Y	Y	Y	Y	Y	Y	Y
State FEs?	Y	Y	Y	Y	Y	Y	Y	Y
Sale Qtr FEs?	Y	Y	Y	Y	Y	Y	Y	Y
Lender FEs?	Y	Y	Y	Y	Y	Y	Y	Y
Other Controls?	Y	Y	Y	Y	Y	Y	Y	Y

Panel B: Non-parametric Specification

Correction:	None		≤ 3 months		≤ 6 months		≤ 9 months	
Reset Month - Prepay Month	≥ 6 Months	≥ 9 Months	≥ 6 Months	≥ 9 Months	≥ 6 Months	≥ 9 Months	≥ 6 Months	≥ 9 Months
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Months-to-Sale = 1	-0.024	-0.027	-0.023	-0.025	-0.024	-0.027	-0.025	-0.028
	(4.90)	(4.87)	(4.41)	(4.34)	(4.51)	(4.39)	(4.07)	(3.87)
Months-to-Sale = 2	-0.033	-0.038	-0.028	-0.032	-0.030	-0.034	-0.031	-0.035
	(6.90)	(6.88)	(5.70)	(5.63)	(5.81)	(5.69)	(5.17)	(4.98)
Months-to-Sale = 3	-0.039	-0.045	-0.030	-0.035	-0.032	-0.037	-0.034	-0.039
	(7.09)	(7.07)	(5.19)	(5.13)	(5.36)	(5.25)	(5.13)	(4.89)
Months-to-Sale = 4	-0.043	-0.049	-0.034	-0.038	-0.029	-0.033	-0.030	-0.033
	(7.24)	(7.48)	(5.36)	(5.47)	(4.51)	(4.53)	(4.50)	(4.38)
Months-to-Sale = 5	-0.049	-0.056	-0.040	-0.045	-0.026	-0.028	-0.028	-0.030
	(9.32)	(9.35)	(7.06)	(7.02)	(4.43)	(4.21)	(4.69)	(4.26)
Months-to-Sale = 6	-0.059	-0.066	-0.049	-0.055	-0.024	-0.024	-0.027	-0.027
	(8.59)	(8.93)	(6.93)	(7.15)	(3.03)	(2.88)	(3.24)	(3.02)
Months-to-Sale = 7	-0.064	-0.072	-0.054	-0.060	-0.027	-0.028	-0.014	-0.012
	(7.97)	(7.83)	(6.65)	(6.54)	(3.22)	(3.01)	(1.50)	(1.14)
Months-to-Sale = 8	-0.082	-0.090	-0.073	-0.078	-0.046	-0.047	-0.017	-0.011
	(10.65)	(11.38)	(8.99)	(9.56)	(5.57)	(5.63)	(1.91)	(1.22)
Months-to-Sale = 9	-0.096	-0.108	-0.085	-0.097	-0.059	-0.065	-0.011	-0.008
	(9.67)	(9.07)	(8.58)	(8.00)	(5.84)	(5.44)	(1.01)	(0.58)
# Loans	4,024,361	4,024,361	3,968,227	3,968,227	3,701,607	3,701,607	3,302,260	3,302,260
Adjusted R^2	0.13	0.13	0.13	0.13	0.12	0.11	0.10	0.08
Orig Qtr FEs?	Y	Y	Y	Y	Y	Y	Y	Y
State FEs?	Y	Y	Y	Y	Y	Y	Y	Y
Sale Qtr FEs?	Y	Y	Y	Y	Y	Y	Y	Y
Lender FEs?	Y	Y	Y	Y	Y	Y	Y	Y
Other Controls?	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table displays results from the estimation of equation 5 on adjustable-rate PLS loans in the CoreLogic dataset originated in the 2002 - 2007 period. The dependent variable is an indicator variable for loans that prepay more than 3 months or 6 months before the month in which the interest rate resets from a fixed rate to an adjustable rate. All loans that prepaid within 3 months of origination are eliminated from the sample. Months-to-Sale is defined as the number of months that elapse between origination and sale to a PLS issuer. All regressions include origination year-quarter fixed effects, state fixed effects, year-quarter of sale fixed effects, originator fixed effects, and the detailed list of covariates described in the text. The first row for each variable shows the regression coefficient, the second row shows t-statistics. Standard errors are heteroskedasticity-robust and are clustered by year-quarter of origination.

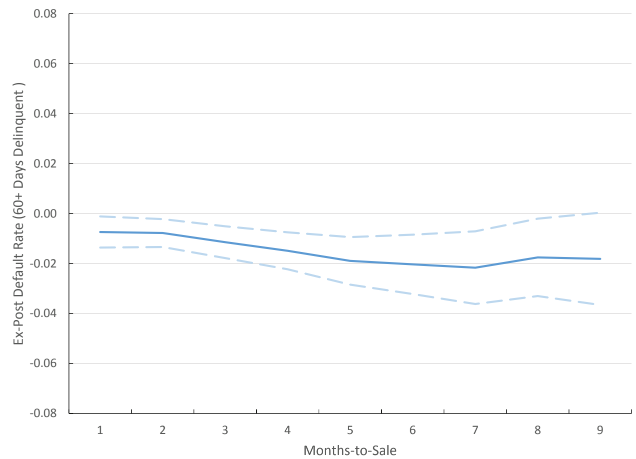
Figure 1: Ex-Ante vs. Ex-Post LPS Results



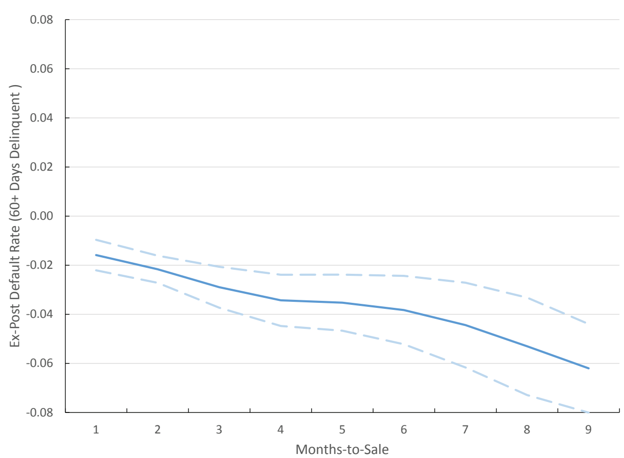
Notes: This figure displays results from the estimation of the non-parametric version of equation 5 for both PLS and GSE loans in the LPS dataset originated in the 2002 - 2007 period. Panels A and B correspond to ex-post default rates, while panels C and D correspond to ex-ante predicted default rates. Default is defined as a loan that becomes 60 days delinquent over a 36-month horizon measured from origination. Months-to-Sale is defined as the number of months that elapse between origination and sale to a PLS issuer. Dotted lines correspond to 90 percent confidence intervals.

Figure 2: CoreLogic PLS Results

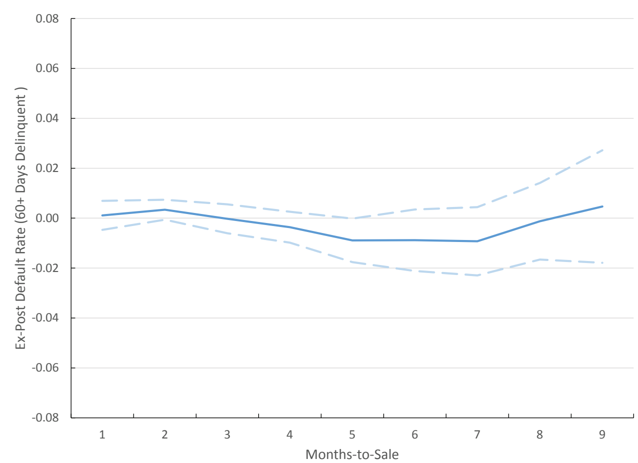
Panel A: All PLS



Panel B: Alt-A PLS



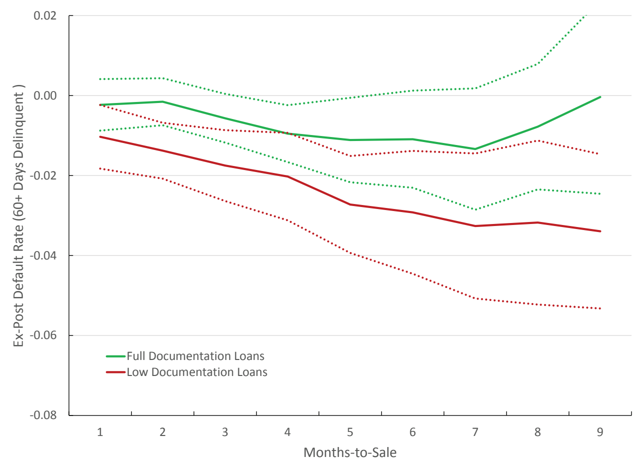
Panel C: Subprime PLS



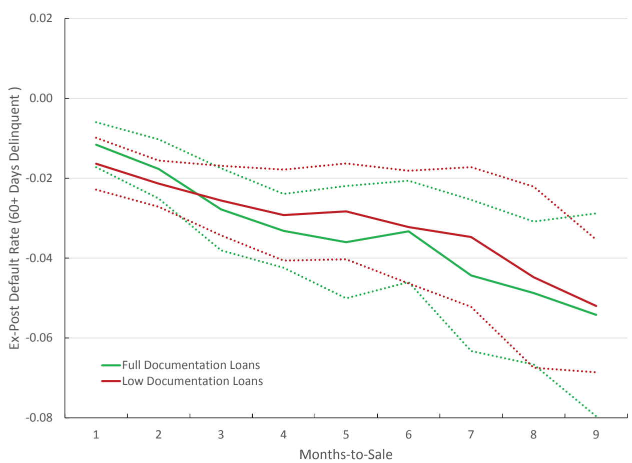
Notes: This figure displays results from the estimation of the non-parametric version of equation 5 for PLS loans in the CoreLogic dataset originated in the 2002 - 2007 period. Panel A corresponds to all PLS loans, while panels B and C correspond to Alt-A and Subprime loans, respectively. Default is defined as a loan that becomes 60 days delinquent over a 36-month horizon measured from origination. Months-to-Sale is defined as the number of months that elapse between origination and sale to a PLS issuer. Dotted lines correspond to 90 percent confidence intervals.

Figure 3: CoreLogic PLS Documentation Results

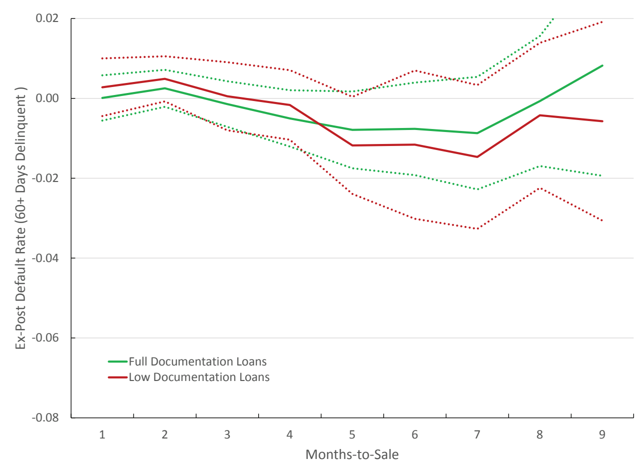
Panel A: **All PLS**



Panel B: Alt-A PLS



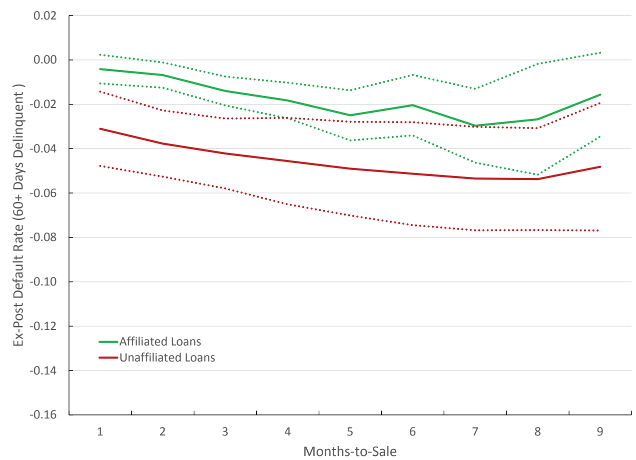
Panel C: Subprime PLS



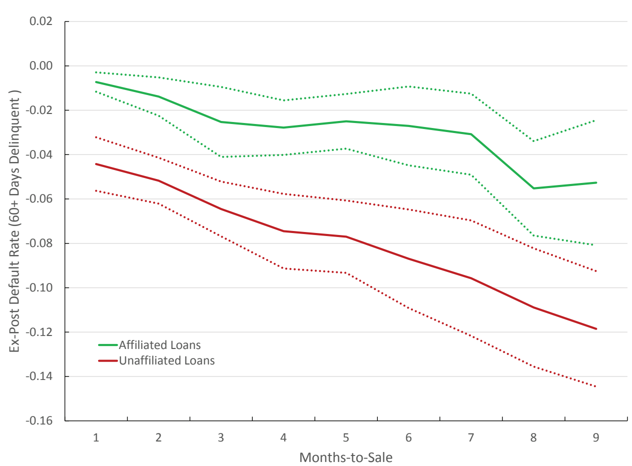
Notes: This figure displays results from the estimation of the non-parametric version of equation 5 for PLS loans in the CoreLogic dataset originated in the 2002 - 2007 period. Panel A corresponds to all PLS loans, while panels B and C correspond to Alt-A and Subprime loans, respectively. Default is defined as a loan that becomes 60 days delinquent over a 36-month horizon measured from origination. Months-to-Sale is defined as the number of months that elapse between origination and sale to a PLS issuer. Dotted lines correspond to 90 percent confidence intervals.

Figure 4: CoreLogic PLS Affiliation Results

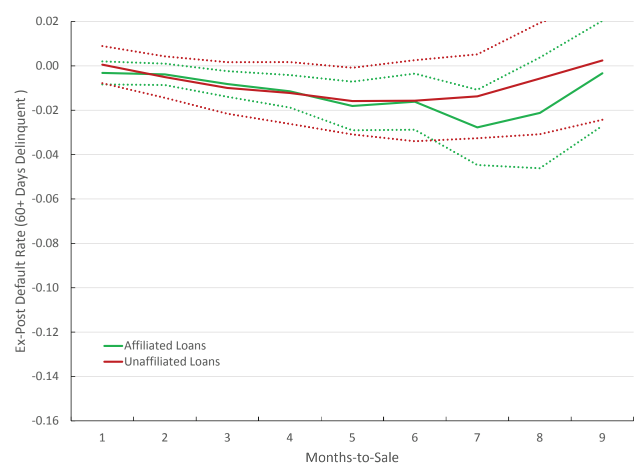
Panel A: All PLS



Panel B: Alt-A PLS

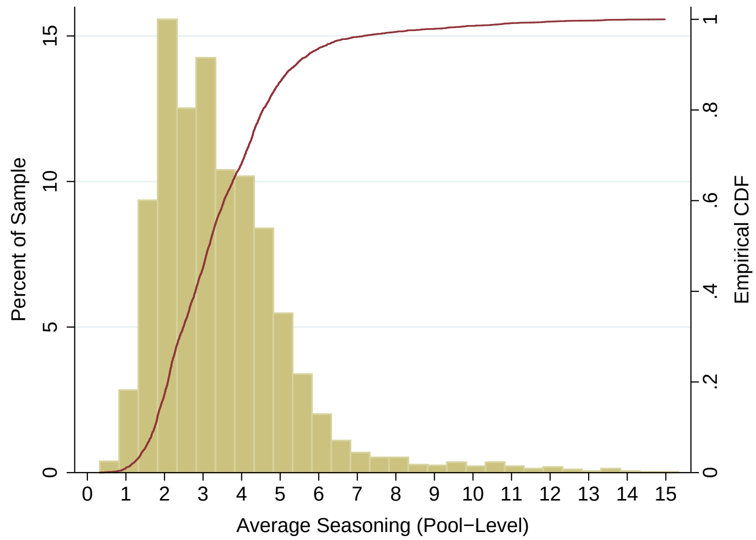


Panel C: Subprime PLS



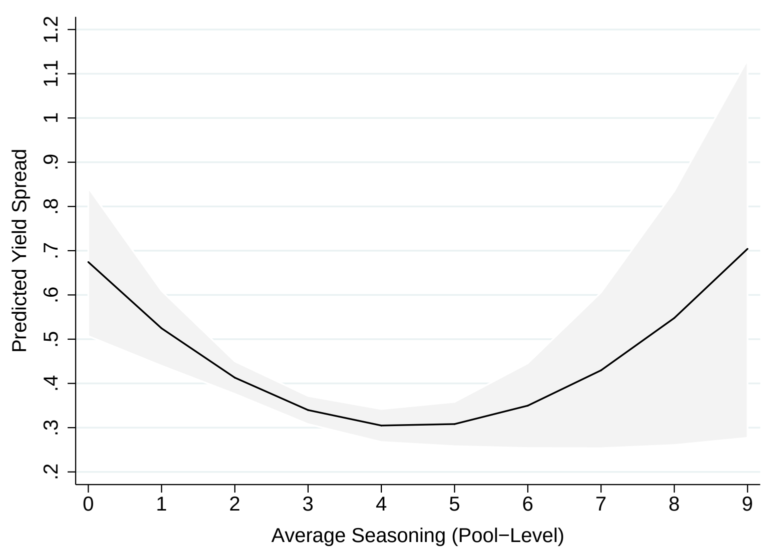
Notes: This figure displays results from the estimation of the non-parametric version of equation 5 for PLS loans in the CoreLogic dataset originated in the 2002 - 2007 period. Panel A corresponds to all PLS loans, while panels B and C correspond to Alt-A and Subprime loans, respectively. Default is defined as a loan that becomes 60 days delinquent over a 36-month horizon measured from origination. Months-to-Sale is defined as the number of months that elapse between origination and sale to a PLS issuer. Dotted lines correspond to 90 percent confidence intervals.

Figure 5: Distribution of Pool-Level Seasoning



Notes: This figure displays the density and cumulative distribution of average months of seasoning in the sample of floating-rate, triple-A, Subprime and Alt-A securities issued between January 2002 and December 2007 used in the pricing analysis in section 5.6.

Figure 6: Predicted Yield Spread as Function of Seasoning



Notes: This figure displays predicted security spreads (over the 1-month LIBOR) as a function of average pool-level seasoning calculated using the estimation results from the specification reported in column (6) in panel B of Table 13. The shaded area corresponds to 95 percent confidence intervals calculated using the delta method.

Appendix

Variable Definitions

ARM: An indicator variable that takes a value of 1 if the mortgage has an adjustable rate and 0 if it has a fixed rate.

Balance : The natural logarithm of the principal balance of the loan at origination.

Balloon: An indicator variable that takes a value of 1 if the mortgage is characterized by a balloon payment at the end of its term and 0 if it is fully amortizing mortgage.

Condo: An indicator variable that takes a value of 1 if the property is a condominium or a townhouse and 0 otherwise.

FICO: The credit score of the borrower at origination. All models include both the continuous FICO variable as well as a set of indicator variables corresponding to 5 FICO intervals: FICO $<$ 580, 580$\leq$FICO$<$620, 620$\leq$FICO$<$660, 660$\leq$FICO$<$700, FICO$\geq$700.

House Prices: County-level house price indices from CoreLogic. We include both the level of prices in the county in the month of origination as well as the cumulative growth in prices from the month of mortgage origination, calculated over the default horizon.

Interest-Only: An indicator variable that takes a value of 1 if the loan requires payments of only interest for a specified period of time and 0 otherwise.

Jumbo: An indicator variable that takes a value of 1 if the loan amount at origination exceeds the conforming loan limit set by statute that limits the size of mortgages eligible to be insured by the GSEs (during the vast majority of our sample period the limit was $417,000 for mortgages on single-family properties) and 0 otherwise.

Loan-to-Value (cumulative): The loan-to-value ratio at origination computed using information on the first lien and the second lien. All models include both the continuous LTV variable as well as a set of indicator variables corresponding to 5 LTV intervals: LTV $<$ 70, 70$\leq$LTV$<$80, 80$<$LTV$<$90, 90$\leq$LTV$<$100, LTV$\geq$100. An indicator variable for LTV ratios exactly equal to 80 is also included as a proxy for unreported second liens.

Low Documentation: An indicator variable that takes a value of 1 if the borrower's income and assets are not fully documented in the underwriting process and 0 if they are fully documented.

Month-to-Sale: The number of months after the date of origination in which a loan is sold to a PLS issuer or acquired by one of the GSEs. In the LPS dataset the variable is based on a field that is updated monthly and shows the current holder of the loan. In the CoreLogic LoanPerformance database, the variable is based on the length of time between the month of origination and the month in which the corresponding PLS security is issued.

Multi-family: An indicator variable that takes a value of 1 if the property is a 2-4 family house and 0 otherwise.

Negative Amortization: An indicator variable that takes a value of 1 if the loan requires payments of less than interest and principal for a specified period of time and 0 otherwise.

Prepayment Penalty: An indicator variable that takes a value of 1 if the mortgage contains a prepayment penalty and 0 otherwise.

Primary Residence: An indicator variable that takes a value of 1 if the property is the primary residence of the borrower and a value of 0 if the property is either an investment or a second home.

Purchase Loan: An indicator variable that takes a value of 1 if the loan is used to purchase the property and 0 otherwise.

Refinance (traditional): An indicator variable that takes a value of 1 if the loan is used to refinance previous mortgage debt without converting any equity into cash and 0 otherwise.

Refinance (cashout): An indicator variable that takes a value of 1 if the loan is used to refinance previous mortgage debt with a portion of equity converted to cash and 0 otherwise.

Single Family: An indicator variable that takes a value of 1 if the property is a detached single-family home and 0 otherwise.

Term: The maturity length of the mortgage in months.

Unemployment: County-level unemployment rates from the Bureau of Labor Services (BLS). We include both the level of rates in the county in the month of origination as well as the cumulative growth in the unemployment rate from the month of mortgage origination, calculated over the default horizon.

Table 15: Model Coefficient Estimates

Dependent Variable: Indicator for 60+ DQ within 36 months of origination	
Months-to-Sale	-0.0107
	(5.79)
Primary Residence (d)	-0.0012
	(0.49)
Prepayment Penalty (d)	0.0687
	(7.70)
ARM (d)	0.0281
	(2.24)
Balloon Payment (d)	0.0890
	(4.74)
Low Documentation (d)	0.0515
	(9.74)
Missing Documentation (d)	0.0119
	(1.80)
B or C Grade Mortgage (d)	0.1091
	(9.38)
Single Family Property (d)	-0.0010
	(0.69)
Missing Property Type (d)	0.0302
	(7.12)
Interest-Only (d)	0.0130
	(1.44)
Purchase Loan (d)	0.0015
	(0.22)
Refinance (cash-out) (d)	0.0141
	(3.04)
Missing Loan Type (d)	0.0141
	(3.04)
Term	0.0001
	(2.81)
LTV	0.0010
	(3.96)
Missing LTV (d)	0.1632
	(4.23)
$70 \leq$ LTV < 80 (d)	0.0352
	(4.19)
LTV $= 80$ (d)	0.0257
	(7.33)
$80 <$ LTV < 90 (d)	0.0443
	(4.75)
$900 \leq$ LTV < 100 (d)	0.0608
	(5.72)

LTV $\geq$ 100 (d)	0.0459
	(4.04)
FICO	-0.0011
	(8.59)
Missing FICO (d)	-0.8955
	(8.54)
FICO $<$ 580 (d)	-0.0614
	(3.22)
580 $\leq$ FICO $<$ 620 (d)	-0.0482
	(4.53)
620 $\leq$ FICO $<$ 660 (d)	-0.0149
	(5.86)
660 $\leq$ FICO $<$ 700 (d)	-0.0128
	(2.72)
Interest Rate (at origination)	0.0110
	(6.53)
Jumbo (d)	0.0217
	(2.55)
Unemployment Rate (at origination)	0.0041
	(7.63)
Cumulative Change in Unemployment Rate (36 months)	0.0244
	(5.75)
House Price Level (at origination)	0.0016
	(12.36)
Cumulative Change in House Prices (36 months)	-0.1583
	(7.65)
# Loans	5,313,951
Adjusted R^2	0.23
Orig Qtr FEs?	Y
State FEs?	Y
Sale Qtr FEs?	Y
Lender FEs?	N

Notes: This table displays the full set of results for the specification in Table 3, column (1). The dependent variable is an indicator variable for loans that default over a 36-month horizon. Default is defined as a loan that is 60+ days delinquent. Months-to-Sale is defined as the number of months that elapse between origination and sale to a PLS issuer. All regressions include origination year-quarter fixed effects, state fixed effects, year-quarter of sale fixed effects. The first row for each variable shows the regression coefficient, the second row shows t-statistics. Standard errors are heteroskedasticity-robust and are clustered by year-quarter of origination.