Private Information and Market Making in Secondary Mortgage Markets

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ABSTRACT

This paper examines whether underwriters of prime mortgage-backed securities exploit private information when trading in the secondary market. While underwriters bid on more than 83 percent of their own tranches, the tranches they avoid bidding on have fewer bidders and exhibit worse-than-average ex-post performance. Most strikingly, when an underwriter declines to submit a bid at a secondary market sale, 30-day delinquent loans are about 3 times as likely to roll to 60-days delinquent in the next month compared to pools where the underwriter bids. The increased likelihood of missing the next payment only occurs in the next month, when data on such missed payments may be available to affiliates of the underwriter. Underwriters also avoid bidding on securities that have lower payoff rates in the four months after the auction. Instead of acting as unbiased market makers, underwriters appear to exploit private information and better models to their own advantage. These results suggest a lemons problem in secondary mortgage markets that might help explain some of the recent turmoil in the CDO market and why investment banks have moved towards vertical integration in the MBS market.

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1 Introduction

Financial institutions are increasingly using securitization to fund new and existing loans. According to Federal Reserve Flow of Funds data, private securitization issuance has grown from approximately $125 billion in 1985 to over $3.4 trillion at the end of 2006 (Table L126). Residential mortgages represent the largest portion of the securitization market, with total mortgage backed securities (MBS) issuance nearing $2 trillion. Many mortgage originators rely exclusively on the securitization market to fund the origination of mortgages (Bruskin, Sanders et al. 2001).

Securitization presents many benefits to the financial system, allowing lenders to diversify their risks across a larger base of borrowers and recycle scarce capital to make new loans. In addition, securitized lending markets are seemingly more transparent, potentially increasing liquidity of MBS relative to the more limited resale market for whole loans.

Nonetheless, the separation of mortgage origination, servicing (managing payments and delinquencies), underwriting, and investing raises the potential for conflicts between disparate parties. (See Figure 1) Some parties may exploit private information to the disadvantage of other parties in the securitization. For example, commentators have recently alleged that securities issuers misled investors about the poor quality of subprime mortgages originated in the last two years. In some cases, these potential conflicts are reduced by vertical integration between parties that perform multiple functions of the securitization. In other cases, such vertical integration can exacerbate conflicts between the various parties. A recent paper shows that servicers who own part of the securitization may adjust how quickly they foreclose on a property to maximize the value of their part of the securitization to the disadvantage of other investors (Mayer and Gan 2006).

In this paper we examine the role of underwriters in the securitization process. As with initial public offerings of equities, underwriters serve as the middle-man in debt securitization markets, collecting and distributing information to potential investors, setting initial prices of securities, and providing post-issuance price support. These roles provide the potential for conflicts of interest. Underwriters either own or work quite closely with mortgage originators and servicers in the pools that they represent and thus possess non-public information about the quality of the ecollateral underlying the securitization and sometimes about the pool's subsequent performance. For example, originators have access to detailed information about the borrower that is not typically disclosed to investors, such as the number of points paid at origination and the payment-to-income ratio of the borrower. Servicers receive payments from borrowers before these payments are reported to investors. Borrowers also call servicers to discuss possible problems that may disrupt their ability to make a payment (unemployment or a medical crisis) or to check the mortgage balance. This information could potentially allow the originators and servicers better predict prepayments, delinquencies, and defaults.

Despite potentially having access to better information about a securitization than other market participants, debt underwriters are often called upon to provide post-origination price support for their securities, with the possibility of using their inside information when bidding on securities. This conflict is rarely present when the securities are originated, as the underwriter typically sells off all securities to third party investors, at least for the type of debt securities we examine in this paper. However, some underwriters also operate trading desks that participate in subsequent sales of their own and other MBS securities. While there are no explicit prohibitions against using internal private information in bidding for securities, at least that we know of, reputation and the potential for future underwriting income might discipline underwriters.

Below, we examine this potential conflict of interest by looking at the bidding strategy of underwriters for their own securitizations. We consider two alternative, but not necessarily mutually exclusive hypotheses: first, underwriters provide valuable support in the secondary market for their own issuances, bidding for less-liquid deals when others are unwilling to; and second, that underwriters use private information to inform their secondary market bidding for their own MBS versus MBS issued by other parties.

We utilize a unique proprietary dataset of prime MBS to examine these hypotheses. Prime MBS are backed by high-quality mortgages (that is, mortgages for borrowers with relatively low loan-to value ratios and with very good credit scores) that typically exceed the maximum limits for participation by government-sponsored entities (GSE's) Fannie Mae and Freddie Mac. An anonymous investor in prime MBS provided us with bidder names and bid amounts on all bids for 241 secondary auctions of MBS tranches from 2002-2005 in which a vertically-integrated bank underwrote securities. In all cases, these securities represent the "first-loss" positions for prime MBS. The first-loss tranches are ideal for our study as their value is highly sensitive to any adverse events like defaults or delinquencies, giving a bidder with private information a large advantage. We match bidding data with commonly available information on mortgage performance before and after the auction.

The results provide mixed evidence about the price support hypothesis. On one hand, integrated underwriters bid much more frequently for their own issuances relative to other underwriter's securities (83% versus 53%). Conditional on bidding, underwriters also win their own securities 19.9% of the time, about twice the rate as they win auctions for others' securities (9.2%) or as trading-only firms win auctions (10.3%). That said, underwriters choose not to submit bids at auctions for the subset of their own securities that are apparently the least liquid. The average number of other bidders at auctions in which the underwriter bids is 8.8, while the underwriter avoids bidding at auctions with an average of only 6.6 bidders.

The evidence is much stronger in favor of the informed bidder hypothesis, in which underwriters appear to exploit inside information to their advantage. Underwriters avoid placing bids for their own securities when the ex-post performance of these securities in the months after the auction date is much worse than average. We divide the securities into three groups: those in which the vertically integrated underwriter avoids bidding, those in which it bids and loses, and those that it wins. Observable characteristics of the underlying mortgages are quite similar for securities in all three groups. Yet loans in pools in which the underwriter does not submit a bit convert from 30 to 60 days delinquent immediately after the auction at nearly four times the rate as loans in pools in which the underwriter bids (20.1% versus 5.3%).

Next we run logit regressions to control for other factors like pool composition, differences across underwriters, interest rates, and timing that might impact bidding. The coefficients shows that when the underwriter bids, the estimated likelihood of a loan becoming delinquent falls by 7.9%, well over half of the univariate difference. Finally we examine the timing in more detail. The underwriters only avoid bidding in pools that have a higher rate of missed payments in the exact month when the servicer might already know that a second payment was missed, although this information has not yet been reported to outside investors due to lagged reporting. In other months before and after the auction, the underwriters bidding appears unrelated to the likelihood of missing a payment, suggesting that better models to predict future payment patterns are unlikely the explanation.

We examine a second outcome variable, the likelihood that a loan pays off early, an event that is typically associated with higher profits for owners of first-loss positions. As above, underwriters bid on securities that have a much higher prepayment rate in the four months after the auction (9.2% payoff rate when they bid vs. 5.3% when the underwriter does not bid). These results are also large and statistically significant when we run a logit specification with pool characteristics and underwriter fixed effects. However, unlike with defaults, the prepayment rates remain higher for at least four months after the auction, suggesting that underwriters are more likely to have better models of prepayment, rather than just earlier information about payoffs. Finally, we show that the winning bid of the underwriter appears to predict future performance in a way that the winning bid of a non-underwriter does not, further buttressing the view that underwriters are uniquely able to model the future behavior of their own pools. Nonetheless, we cannot distinguish the extent to which better access to information feeds those models or underwriters have some other modeling advantage for their own pools.

Below we provide details of this analysis. The next section lays out the empirical setting and details our hypotheses. Section three describes the data. The fourth and fifth sections go thru the empirical results on bidding and ex-post mortgage performance. Finally, we conclude with a policy discussion and avenues for future research.

2 Empirical Setting and Hypotheses

2.1 Background on First-Loss Positions

Securitization helps convert illiquid assets like mortgages or student loans into marketable securities. In a typical mortgage securitization (Figure 2), a large number of mortgages are grouped together in a pool and sold to a separate legal entity known as a special purpose vehicle (SPV). The SPV isolates the collateral so that investors only have claims on the cash flows in the SPV, and not against the assets of the underwriter or originator.[1] MBS Pools often include mortgages originated in various parts of the country, helping to diversify idiosyncratic risk associated with individual mortgages.

[1] Gorton & Soules (2005) have a more complete discussion of special purpose vehicles and their role in securitization. Ayotte and Gaon (2007) demonstrate the importance of bankruptcy remoteness in asset-backed securitizations.

Mortgage securitizations are usually divided into two broad categories: conforming and non-conforming. Borrowers with strong credit histories and mortgages with a balance under a pre-specified limit ($417,000 in 2006 and 2007) usually take out conforming mortgages—so named because they are eligible for purchase by government-sponsored entities, Fannie Mae and Freddie Mac.[2] Non-conforming loans include mortgages with large balances (aka, "jumbo" loans) and loans to especially risky borrowers, making up more than half of residential MBS origination in 2005 (Vallee 2006).

We examine securitizations of prime mortgages, which usually involve jumbo loans made to borrowers with good credit and collateralized by houses with relatively low loan-to-value ratios. This category does not include the oft-discussed subprime mortgages (made to borrowers with poor credit, properties with high loan-to-value ratios and other high-risk attributes) and the intermediate group of so-called Alt-A loans. This limitation is mostly based on the availability of the auction data. However, prime mortgages are relatively homogenous and have less asymmetric information compared to securities backed by more risky and variable sub-prime mortgages. To the extent that we identify an impact of information asymmetries in this market, it is likely to understate the role of these imperfections for securitizations with heterogeneous assets.

Claims to the cash flow from the pool are sold as securities based on a strict priority system. A more senior tranche will not absorb any losses until all securities that are junior to that tranche have been entirely wiped out. By "tranching" the securities, the underwriter is able to sell relatively safe securities to investors who will pay a premium to minimize credit risk, while selling higher-risk MBS to investors willing to accept the additional risk in return for a higher yield.[3] In recent years, MBS representing over 85% of the value of a typical pool have received AA-AAA ratings, often being purchased by insurance companies, money managers, bank conduits, and managers of collateralized debt obligations (CDOs). The mezzanine pieces (BBB-A ratings) account for around 10% of the security and are used primarily in CDOs. The remaining 5% or less of the pool is either junk rated or unrated and is generally purchased at origination by hedge funds and other institutional investors (Sinha 2007).[4] While non-

[2] See Downing, et. al. (2005) for a discussion of mortgage securitization by government-sponsored entities.
[3] Demarzo (2005) and Plantin (2006) discuss theoretical models on pooling and tranching.
[4] In some types of securitized assets, the underwriter / servicer owns the first-loss piece in order to provide incentives to effectively monitor borrowers and handle delinquencies and defaults [Pennacchi (1988), Gorton and

investment grade tranches comprise a small fraction of the par value in the overall securitization, these tranches contain the vast majority of the credit risk.

We examine the sale of the lowest priority tranches, the so-called “first-loss” positions. These positions are extraordinarily risky. In our sample, the most junior position represents just 0.2% of the collateral value in the pool, but retains 100% of the credit risk in the pool. Any information that can help predict even a small number of delinquencies is likely to be extremely valuable to investors and traders of first-loss positions.

The value of low rated tranches is primarily affected by two performance measures: (i) serious delinquencies/defaults; and (ii) prepayments. Even a very small number of serious delinquencies and defaults can quickly destroy the value of first-loss MBS tranches. The effect of prepayments on MBS values is more complicated. MBS investors in the highest quality (lowest yielding) securities are usually hurt when borrowers prepay their mortgages. Prepayment speeds tend to increase when interest rates decline, so these investors must reinvest the prepaid principal at a lower prevailing rate. However, investors in the low-rated tranches receive securities that are generally priced at a deep discount to par. Greater prepayment speeds increase the likelihood of receiving payment of principal at par value, usually outweighing any possible reinvestment costs [Hayre (2001)]. Sometimes rating agencies will even upgrade low-rated securities in deals with faster than anticipated prepayments without losses. As a result, early payoffs enhance the value of low-rated tranches.

2.2 Auction Description and Hypotheses

We examine secondary market auctions of low-rated prime MBS tranches. Figure 3 provides a timeline. We obtain data from an investor who purchases MBS either at origination or in the secondary market. At some point, the investor will attempt to resell these securities in an over-the-counter secondary market.[5] In the typical sale, the owner provides potential buyers with a security ID number that allows them to examine the security using widely available databases and a final date to submit a bid. Sales are usually in blind, first-price auctions. Bidders do not know which other institutions are participating in the auction or the value of their

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Pennacchi (1995), and Gan and Mayer (2006)]. According to our discussions with market participants, institutional investors nearly always buy the first-loss piece for prime securitized mortgages.

[5] For our sample, tranches are held by the investor for between 3 and 24 months, with an average holding period of 13 months (Table 2).

competitors' bids. All of the institutions have access to mortgage-level data that, when used in conjunction with prepayment and loss assumptions, allows buyers to project future cash flows and impute a price for the tranche. The seller can choose whether or not to sell the MBS to the highest bidder.

Table 1 provides the identities of the secondary market bidders in our data, who include many of largest commercial banks, investment banks, and bond traders such as Goldman Sachs, Lehman Brothers, Morgan Stanley, Citigroup, Countrywide, and Cantor Fitzgerald. We classify bidders into two categories: (i) underwriters, who are integrated banks that both securitize mortgages in the primary market and trade MBS in the secondary market; and (ii) traders, who do not underwrite MBS.[6] The critical distinction between integrated banks and traders is that integrated banks may bid for tranches that they also underwrote. Below we consider the potential tradeoffs inherent in underwriting and bidding on the same MBS.

Price support hypothesis: A commonly held view of integrated banks is that they are expected to provide price support for their own underwritten MBS. This is a well-documented feature of other markets, such as equity initial public offerings [e.g., see Hanley et. al. (1993), Schultz and Zaman (1994) and Ellis et. al. (2000)]. By building a reputation for supporting its securities, an underwriter can implicitly guarantee that less informed investors do not suffer major losses [Smith (1996)]. While it can be costly to buy poorly performing or illiquid tranches, price support can benefit underwriters in the long run by facilitating the continued sale of first-loss positions at reasonable prices in the primary securitization market. According to the price support hypothesis, integrated banks underwriters should bid on and win observably risky, opaque, and poorly performing tranches. We would also expect to find that underwriters do not avoid bidding in auctions that have fewer participants.

Informed bidder hypothesis: Of course, integrated banks may also have access to proprietary information that could allow a more accurate prediction of future performance. While commonly available information on the mortgage collateral is extensive, it is far from complete. For example, some key predictors of delinquencies and prepayments are not listed in databases, such as "points" paid (fees the borrower pays the lender at origination), the combined

[6] Among the traders, Credit Suisse First Boston, Lehman Brothers, Morgan Stanley, and Merrill Lynch securitize sub-prime mortgages. We classify these banks as "traders" because the tranches in our sample are backed by prime mortgages, so the securities are never underwritten by these banks.

loan-to-value ratio of all mortgages on the borrower's property (including so-called "piggyback loans"), and the actual property address.[7] Even more valuable, the underwriter may have proprietary access to on-going information from servicing activities that serve as immediate predictors of serious delinquencies or prepayments. For example, when a mortgage becomes 30 days delinquent, servicers often contact the borrower to determine the seriousness of the problem. On the prepayment side, borrowers may signal their intent to pay-off a mortgage by contacting the servicer to obtain a precise payoff amount. Finally, servicers may simply have more timely information on payoffs and delinquencies because market participants receive updates only on a monthly basis.

The most direct test of the informed bidder hypothesis is to examine the performance of MBS immediately following the auction, when the underwriter's potential information advantage is the most valuable. Of course, integrated banks have two margins to use in exploiting their information, depending on the type of information that they possess. They can choose not to bid (or submit low bids) on the least favorable MBS based on their private information or they can submit high bids on the most valuable MBS, or both. The former (low/no bid) is most likely if the underwriter's information is primarily about the likelihood of a loan transitioning into serious delinquency status. In this case, informed bidders might be well-informed about which securities to avoid, but have no advantage in choosing among the remaining securities. The latter (high bids on good tranches) would occur if integrated banks had an advantage in predicting prepayment rates and defaults on a longer-term basis.

Potential buyers must submit a bid through a qualified trading desk. It is impossible to know whether a bidder is trading for their own account or on behalf of other third-party buyers. To the extent that underwriters bid for third party buyers instead of their own account, we would expect to see evidence that favors neither of the two hypotheses. Instead, integrated banks bidding behavior would closely resemble that of other unaffiliated bidders.

[7] Brueckner (1994), LeRoy (1996) and Stanton and Wallace (1998) present models of mortgage choice in which points are a strong predictor of future prepayment.

3 Data and Descriptive Statistics

3.1 Data Sources and Sample Selection

Much of our data comes from an institutional investor that buys and sells first-loss positions in prime MBS. The institution has requested anonymity. This investor specializes in the purchase of junior tranches in prime securitizations and does not participate in any other part of the securitization process. All tranches are sold via first-price, sealed bid auctions. Bids, bidders, and sale prices in secondary markets are strictly proprietary. Our data are more complete than the data available to any other bidder or trader, who only knows his own bid and whether or not his bid was the winning bid in past auctions.

The institutional investor has provided us with complete information on all 394 auctions of low-rated prime MBS tranches that it held between December 2002 and December 2005. Of those, we limit our sample to the 241 auctions in which the deal was underwritten by an integrated bank that also operates a trading desk. The remaining deals were underwritten by banks that do not participate in secondary market bidding for MBS. The final data set consists of 106 first-loss tranches, 99 second-loss tranches, and 36 third-loss tranches. In all cases, if the institutional investor owns higher priority tranches, it also owns the corresponding lower priority tranches.

A critical aspect of this data is that it allows us to identify when the underwriter of the underlying tranche also participates in the auction as a bidder. For each auction, the data includes a security ID for the tranche put up for sale, the name of the underwriter, and the identity and actual bid of each institution that submits a bit. Bids are characterized as a percentage of par value of the security. We convert bids into yields so that we can compare bids across auctions.[8]

To examine the characteristics of the tranches, we collect information on individual mortgage contracts that are the collateral for the MBS tranches from *LoanPerformance*, a division of First American Real Estate. *LoanPerformance* provides the industry's largest and most comprehensive mortgage securities database, tracking collateral default, prepayment and

[8] See Appendix A for more details.

credit risk since 1992. *LoanPerformance* has mortgage-level data on over 8,500 active private-issue securities, which it claims covers over 90% of the outstanding jumbo mortgage pools.[9]

Using the security ID, we link the *LoanPerformance* mortgage data to the auction data. We obtain a total of 280,086 mortgages that act as collateral for the 241 mortgage backed securities. Of these mortgages, 219,955 have positive balances (i.e. have not paid off) at the end of the month before the auction date. For each mortgage, *LoanPerformance* provides many details such as the name of the originator, security underwriter, and servicer, the loan-to-value ratio (LTV), the borrower's FICO score, the type of property, whether the interest rate is fixed, floating, or hybrid, the purpose of the mortgage, whether the owner reports occupying the home, whether income has been verified, the mortgage term, and the origination mortgage balance. In addition to the static contract details, *LoanPerformance* provides monthly updates for each mortgage on payments and delinquencies, allowing us to create measures of ex-ante and ex-post performance that we use in the empirical tests, below. Appendix A provides a detailed description of all variables used in this study.

3.2 Descriptive Statistics

Table 2 provides descriptive information on the 241 MBS tranches at the auction date. Overall, the mortgages that serve as collateral for the MBS are relatively safe, consistent with the securities being backed by prime mortgages. The median tranche is backed by mortgages where the borrowers have an average FICO score of 739 on a scale of 300 (worst credit risk) to 850 (best possible credit score). The tranche with the lowest average FICO score still has a healthy value of 713. In addition, the median tranche is backed by mortgages with an average loan-to-value (LTV) ratio of 65% and had fewer than two percent of loans that were at least 30-days delinquent in any of the six months prior to the auction date. The vast majority of tranches are backed by fixed-rate mortgages on single family, owner occupied first-homes where the borrower provides at least some income documentation. These types of mortgages are generally considered safer than mortgages that back non-owner occupied homes, are structured as hybrid-ARMs, or have no documentation [Bendt, Ramsey et al.(2001)].

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[9] To check the completeness of data, we compared security balances, payoffs, and delinquencies against an independent source of this information – remittance reports. Of the 158 remittance reports that were publicly available, we found a greater than 0.9 correlation between the *LoanPerformance* and remittance report data at the auction date for balance, payoffs, and delinquencies. The discrepancies are typically due to small differences in reporting dates and are not material for our analysis.

Despite the relatively safe underlying collateral, the median winning yield is 12.25%, suggesting that there is still substantial risk in these junior tranches. In fact, only a few delinquencies can have a dramatic effect on the value of the tranches. The median par value of the tranches is just over $787,000, which represents only 0.2% of the median collateral value. Given that the typical mortgage is $539,723, if even four mortgages were to default with fifty percent recovery, the tranche would be worthless. This suggests that access to private information that can help predict the probability of serious delinquency or default is likely to be extremely valuable to investors and traders.

As noted above, investors in junior tranches of MBS prefer early payoffs because this can reduce the number of mortgages at risk of default. The data in Table 2 indicates that there is considerable variation in the payoff rates of the securities, with a range from one percent to sixty-seven percent of mortgage balances being paid off during the six months prior to the auction date. Given the wide range in payoff rates across tranches and the general difficulty in predicting payoffs [Hyre and Young (2001)], any informational advantage that can help a bidder to predict payoffs may increase profits.

4 Bidding at the Auctions

In this section, we examine the bidding behavior of underwriters banks and traders. Do underwriters bid more frequently when their own securities are sold by the investor? Do underwriters win their own securities more often? To what extent are observable differences in the securities associated with underwriters bidding on and / or winning the auctions for their own securities? Answers to these questions will allow us to determine whether underwriters are active market makers in their own securities and also provide insight into their reasons for bidding or abstaining from the auction.

The secondary market auctions are quite active. On average, 9.3 institutions place bids, including the underwriter when it bids. Given the potential for the underwriter to have superior information, it may seem that the less informed institutions should not bid because they are at a disadvantage. Some market participants reported their belief that the integrated bank has only a slight informational advantage, or that information does not flow between the servicing/origination and trading divisions. However, even if the underwriter were better informed than other bidders, having only a single bidder would not be an equilibrium outcome. If the informed bidder correctly anticipates that less informed institutions will not bid, its optimal response would be to bid slightly more than zero. Of course, the less informed institution could bid slightly more, win the auction, and earn positive profits, on average. This indicates that the less informed parties should use mixed strategies that force the informed institution to consider the possibility that it will lose the auction if it bids too low. By following a mixed strategy, an institution that only has access to public information will make zero expected profits when the item has common value to all participants [Wilson (1967), Engelbrecht-Wiggans, et. al. (1983), and Hendricks and Porter (1988)]. If the non-underwriters have access to some private information, even if not as valuable as the most informed bidder, they can also earn positive expected profits in equilibrium [Kagel and Levin (1999)].

Of course, the above discussion assumes a common value framework. In fact, a private value framework might be more appropriate for these prime MBS. In some cases, a given institution might have a higher value for a particular MBS if it provides a hedge for its pre-existing portfolio of securities. In other cases, the bidder might not be the final holder of the security, but instead is purchasing the MBS to include in a subsequent securitization, called a CDO (collateralized debt obligation). In a CDO, the manager or underwriter forms a pool with a large number of diversified debt securities and sells claims to that pool in a similar manner to a straight MBS offering. CDO managers prefer to avoid the risk of warehousing securities on their balance sheet for too long. As a result, when a CDO underwriter already owns a variety of securities, it will often have a high willingness-to-pay for securities that would allow it to close the CDO securitization. In a private value auction, extensive participation by seemingly less informed buyers is not a puzzle.

One of the complications we face in this analysis is how to treat very low bids at auctions. Throughout the paper, we define a non-bid as the case where an institution: (i) does not explicitly place a bid; or (ii) places a bid where the yield is more than 60% higher than the winning (lowest) yield. Bids where the yield is more than 60% higher than the lowest yield account for approximately 10% of the total sample of bids. Given the relatively tight distribution of most bids at the auctions, such bids are seemingly outliers that were not intended to win the auction. In some cases, institutions report submitting such low bids to satisfy the pressure to bid for a security that they do not want to purchase. Our results are robust to not including these observations as “no bids”.

In Table 3 we compare the bidding behavior of underwriters on their own securities with the bids of other underwriters and the bids of unaffiliated traders. The analysis in Panel A indicates that underwriters are substantially more likely to bid on securities where they are the underwriter. Underwriters bid in 52.7% of auctions where they are not the underwriter vs. 83.4% of auctions where they are the underwriter (Z-statistic = 12.10). On an individual bank basis, this fact is true for eight of the nine banks. Panel B shows that traders who do not underwrite securities are much less active, bidding at only 39.5% of auctions.

Not only do the underwriters bid more frequently, they also win at nearly twice the rate as other bidders on their own securities. Conditional on bidding, underwriters win 19.9% of the auctions of their own tranches as opposed to winning only 10.2% of the auctions of their competitors’ tranches (Z-statistic = 3.33). This finding is true individually for seven of the nine banks. Interestingly, conditional on bidding, traders win 9.3% of the auctions, a similar winning percentage as underwriters when bidding on other banks’ securities. These findings are consistent with the price support hypothesis.

Yet other evidence is more ambiguous. If underwriters are providing price support for difficult deals, we would expect to find that integrated traders might bid in auctions that have fewer other participants. This is not supported by the data. The results displayed in Table 4 show that underwriters bid in auctions that have more participants (8.8 bids by other bidders) than the auctions that they choose not to submit a bid (6.6 bids), a difference that is highly statistically significant. While underwriters do not know the number or identities of the potential buyers when placing a bid, the finding is still inconsistent with underwriters placing bids when other institutions are less willing to buy their securities in the secondary market.

Table 4 shows that other observable characteristics are mostly similar across the three potential outcomes of the auction. By some dimensions, underwriters bid on deals with more risk, for example deals that have a higher proportion of no documentation mortgages and a somewhat lower the average loan-to-value ratio (66.9 if wins vs. 65.3 if loses vs. 63.9 if does not bid). By other indicators, underwriters also bid on safer tranches, such as those that have a much lower percentage of loans without a FICO score and pools backed by relatively safe single family homes. Put together, there is no clear pattern from the observable characteristics suggesting that the primary purpose of underwriters bidding is to provide price support for illiquid or opaque securities.

5 Bidding, Private Information, and Ex-Post Performance

We now examine the extent to which underwriters use private information to avoid bidding on securities that will perform poorly and/or win securities that are strong performers. To do so, we examine the ex-post outcomes of securities based on whether integrated underwriters bid and win at the auction. We consider two principal types of private information: origination information that is unavailable to other market participants and more timely servicing data on payoffs and the seriousness of delinquencies. Better information, or better models, would allow underwriters to more accurately predict their own security performance relative to securities issued by other underwriters.

5.1 Delinquencies: 30-day to 60-day roll rates

Our first measure of ex-post performance is the proportion of loans that progress to 60-days delinquent immediately after the auction conditional on being 30-days delinquent at the auction date (the so-called "roll rate"). We examine this measure for two reasons. First, 60-day delinquencies signal a strong likelihood of a default and can have a major effect on the value of the low-rated tranches in our sample.[10] As discussed in Section 3, the default of only a few mortgages can make a first-loss position worthless. Second, while the typical pool has many thousands of mortgages, we expect market participants to focus their attention on the smaller number of loans that are already potentially in trouble. However, 30-day delinquencies themselves are a very imperfect measure of trouble. Borrowers may miss a payment for innocuous reasons (they were on vacation or just forgot) or for more serious reasons such as a job loss or a health problem. Only about 8 percent of 30-day delinquencies miss their next payment. Of course, the servicer has more timely access to information on the delinquency severity. If the servicing division shares this information to the trading desk in an integrated

[10] Many mortgage analysts focus on 90-day instead of 60-day delinquencies as a measure of seriously delinquent. We focus on 60-day delinquencies because the timing of missing the next payment is the most precise measure of inside information by the underwriter. In previous versions of the paper, we created Tables 5, 6 and 7 with 90-day delinquencies as the dependent variable. Marginal effects were smaller in size because 90-day delinquencies are less frequent, but the economic and statistical significance remained strong. These results and the previous version of the paper are available upon request.

bank, then underwriters may adjust their strategy to avoid bidding on the worst securities or bid more aggressively on the best MBS.

Table 5 provides summary statistics on loans that are 30-days delinquent at the auction date and the percentage of these loans that progress to 60-days delinquent. The sample has 1,381 loans that are 30-days delinquent at the auction date, or an average of 5.7 loans per tranche. The limited number of delinquent loans supports the view that informed bidders can feasibly collect detailed information on each of the delinquent loans. However, uninformed bidders have a little ability to collect such information. Loan level delinquencies are reported by *LoanPerformance* only with a delay of several months. Instead, uninformed bidders contemporaneously observe at most the dollar value of delinquent loans through monthly trustee reports.

The data strongly suggest that underwriters use private information when bidding on securities. Mortgages that back tranches where the underwriter does not bid have a roll rate of 20.1% versus a roll rate of only 5.3% when the underwriter bids on its own tranche. A t-test rejects equality at the one percent level. This result is not driven by any single bank, as four of the five largest underwriters (based on number of loans at risk) have roll rates that are considerably lower when they bid in the auction. This indicates that underwriters avoid bidding on tranches that perform worse, *ex post*.

The table also shows that roll rates are similar when the integrated underwriter wins at the auction relative to when the underwriter loses the auction conditional on bidding. This evidence suggests that private information may give underwriters an advantage of to avoid bidding for tranches that perform poorly, but that underwriters do not appear more likely to win the very best tranches. This result might be explained by the asymmetric importance of the private information when investing in low-rated MBS tranches. Since only a few bad loans can cause great losses and a few extra good loans have little effect on returns, private information is likely to be more valuable in limiting the downside risk.

Of course, these securities may differ in many observable characteristics, so we use a logit model to try to control for any factors that may be correlated with the roll rate. The dependent variable equals one if a mortgage becomes 60-days delinquent in the next month, conditional on being 30-days delinquent on the auction date. There are two key independent variables: whether the underwriter bids on a tranche that is backed by the mortgage and, conditional on bidding, whether the underwriter wins.

The empirical models include various controls that may be important determinants of the roll rate including borrower, property, and mortgage contract characteristics.[11] Borrower characteristics include the FICO score, an indicator for mortgages where the FICO score is unavailable, and an indicator for whether the borrower provides documentation. Property characteristics include dummy variables for single-family residences, an owner-occupied primary residence, and the loan-to-value ratio. Previous research shows that high LTV mortgages have greater delinquency and foreclosure rates [Avery et. al. (1996)]. Contract characteristics include the current mortgage balance, loan age, time to mortgage maturity, whether the mortgage is for home purchase or refinancing, and the type of interest rate (fixed, floating, or hybrid). We also include auction year fixed effects in order to control for differences in the economic environment. Finally, following common industry practice, we include an interest rate control which equals the difference between the current mortgage rate and the coupon rate that the borrower pays, as long as that difference is positive. This variable controls for the possibility that rising interest rates from mortgage origination may be associated with increased delinquencies. All specifications we include underwriter fixed effects to control for differences across underwriters in originating or servicing loans.[12]

Finally, we must account for the fact that these are loan level regressions, although bidders are attempting to value tranches with multiple loans. We address this issue in two ways. First, in our primary regressions, we weight each observation by the inverse of the number of loans in the security. We also cluster standard errors at the security-level to correct for potential correlation in the errors within loans from the same MBS. Second we re-run all specifications using a Tobit regression with the dependent variable that is the dollar-weighted percentage of 30-day delinquent mortgages in the MBS at the auction date that progress to 60-day delinquency.

[11] See Bendt et. al. (2001) for a more complete discussion of rating agency models and borrower and contract characteristics.

[12] Including underwriter fixed effects reduces the number of mortgages from 1,381 to 1,302. This occurs because none of Bank F and G's 79 mortgages roll to 60 days delinquent, thus causing the Bank F and G's fixed effect to be a perfect predictor of the outcome.

Neither the magnitude nor the statistical significance varies appreciably from the findings reported below using the loan level data.[13]

The results in Table 6 confirm the univariate finding that the underwriters choose not to bid on pools with mortgages that are much more likely to become seriously delinquent in the future. All coefficients are reported as marginal effects. In the sample, about 20.1% of mortgages roll from 30 to 60 days delinquent in deals that the underwriter avoids. The marginal effects in the first column show that the roll rate falls by 7.5% to 12.4% on deals that the underwriter avoids. This difference is both statistically and economically significant, given the large impact that even a single delinquency has on the value of a first-loss tranche. Including underwriter fixed effects (column 2) has little effect on either the statistical or economic significance. That is, integrated underwriters are not necessarily better at predicting roll rates for all tranches, only for their own tranches. These results are consistent with the view that the underwriter uses private information to avoid bidding on tranches where the mortgages are likely to have more unexpected delinquencies.

The estimations also reveal that while the underwriter seems able to identify deals to avoid, that this skill does not necessarily extend to winning deals with a slower-than-average roll rate, conditional on bidding. While negative, the coefficient on underwriter winning (conditional on bidding) is relatively small in magnitude and never close to being statistically different from zero at conventional levels.

Other control variables have the anticipated signs, but are only occasionally statistically significant. Of greatest importance is LTV, which is always positive and statistically significant. This finding is consistent with previous literature showing that LTV is one of the most important predictors of delinquency and default.

To further explore the role of information, modeling, and servicing, we examine whether the seeming ability of the underwriter to avoid bidding on the worst tranches is unique to the month immediately following the auction. To do so, we combine the data from nine consecutive months, including the four months prior to the auction, the auction month, and the four months after the auction. We run a pooled logit that parallels the logit regression in Table 6, except that it includes nine months of data. We include dummy variables for each of the months in the

[13] These results were presented in previous versions of the paper, but were cut for brevity. They are available from the authors upon request.

sample, as well as the interaction of those monthly dummy variables with dummy variables for the underwriter bids and wins. We exclude the monthly dummy variable and interaction variables for the month of the auction, so the interpretation of all auction variables is relative to the auction month. The primary coefficients of interest are those of the bid and win interactions after the auction date, but the inclusion of the interactions in the months prior to the auction allows us to consider the possibility that the underwriter might be following a pattern of data prior to the auction that might not be based on inside information.

The results in Table 7 suggest that the advantage the underwriter has in predicting the 60-day roll rate is most important for the month immediately following the auction, and much less valuable in subsequent months. The top panel includes a single pooled logit with monthly interactions with bid. The coefficients are reported as marginal effects. In column 2, the only interaction with bidding that is statistically different from zero is in the month after the auction. The estimated marginal effect of a 6.0 percent decline in the likelihood of rolling from 30 to 60-days delinquent is close to the marginal effect of 7.4 percent from Table 6. The other interactions of bid with the subsequent months (2 to 4 months after the auction) range from -0.8 to -2.4 and are never statistically different from zero. The coefficients on other covariates are not reported in Table 7, but are typically of expected signs.

Panel B reports interactions of bid and win with the monthly dummies. The results are somewhat more suggestive, relative to Table 6, of an additional effect of the underwriter winning pools with lower roll rates. Yet the evidence here is still fairly weak. While several of the coefficients on underwriter winning are negative and statistically different from zero after the auction, those interactions are also negative and statistically different before the auction as well. It is possible that the baseline date, the auction month, was one in which the pools the underwriter won had an abnormally high roll rate. The coefficients on the interactions with underwriter bids are quite similar to those in panel A.

5.2 Early Payoffs

Our second measure of ex-post performance is the proportion of loans that payoff (or "prepay") their mortgage during the six months after the auction date ("payoff rate"). As discussed in Section 2, early payoffs are value-enhancing for first-loss position holders because the earlier return of principal outweighs reinvestment risk. If the underwriter and uses private information on payoffs when bidding on tranches, we would expect that underwriters would avoid bidding on tranches that have worse than expected payoffs, *ex post*. Further, underwriters may be able to win auctions of their own underwritten tranches that have better than expected ex-post payoffs.

Table 8 displays the number of loans that have a positive outstanding balance at the auction date and the percentage of these loans that payoff within 4 months after the auction date. The results indicate that there are significant differences in the payoff rate based on whether the underwriter bids in the auction. In aggregate, the ex-post payoff rate is 5.3% for loans where the underwriter does not bid on its own tranche and 9.2% for loans where the underwriter bids on its own tranche (p-value = 0.01). This pattern holds individually for four of the five underwriters where such a comparison can be made. Similar to our findings for the delinquency roll rates, underwriters avoid bidding on tranches that perform worse during the four months after the auction date.

The table also reveals that the average payoff rate on tranches that the underwriter wins is higher than the payoff rate for tranches that the underwriter bids on but loses (10.4% vs. 8.9%), although that difference has a p-value of 0.06. The difference between the payoff rates of the bidder depending on whether they win of lose is mainly driven by Banks C and G, where both institutions appear to win their own tranches when they strongly outperform the average tranche. The difference is either small of the wrong sign for most other underwriters. The fact that Bank C was also one of the banks that avoided bidding on deals with high roll rates suggests that some banks are more willing than others to take advantage of their superior information.

As with roll rates, we estimate logit regressions that allow us to control for observable characteristics that are available to all bidders. The mortgage-level payoff model uses the 219,955 mortgages that have positive balances at the auction dates. We use logit estimation and weight each mortgage by the inverse of the number of loans in the security in order to recognize that loans from smaller pools are likely to have a larger impact on the value of the tranche. The dependent variable indicates that the mortgage has paid off in full within four months after the auction date. We include an independent variable that indicates the underwriter bids on a tranche that is backed by the mortgage. Based on the univariate results, we expect to find a positive relationship between the underwriter bidding and mortgage payoffs. A second variable indicates that the underwriter wins the auction for the tranche that is backed by the mortgage. Due to potential correlation in the errors within loans from the same MBS, standard errors are clustered at the security-level.

The model includes economic, borrower, and mortgage variables that are likely to be related to home sales and refinancings, which are the primary drivers of payoffs. We include the same variables that were used in the delinquency roll rate models.[14] Conventional wisdom in the industry suggests that the ex ante pool-level payoff rate is a strong predictor of the ex post payoff rate. On the contract terms, anecdotal evidence from originators suggests that borrowers who select floating rate loans often expect to move again soon, leading to an increase in payoffs (Hayre and Young 2001).

Results of the mortgage-level models are displayed in Table 9 and are consistent with the observation that underwriters avoid bidding for the lowest payoff-rate deals (coefficients are reported as marginal effects). In all specifications, the control variables have the anticipated signs and are usually significant. The estimations show that the underwriter's decision not to bid is associated with avoiding mortgages that are less likely to payoff in the four months after the auction date. Results in the first column show that the payoff rate increases by 1.4% when the underwriter bids, relative to a mean payoff rate of 5.3 percent when the underwriter does not bid. The inclusion of covariates reduces the size of the effect by almost two thirds versus the univariate difference of 3.9 percent. This is mostly driven by the inclusion of underwriter fixed effects, as Banks B and C exhibit an especially large increases in payoff rates in their pools when these banks bid. The results are consistent with underwriters using private information to avoid bidding on tranches that unexpectedly perform poorly.

The estimations also reveal that there is not a statistically significant relationship between the underwriter winning the auction and mortgage payoffs. As above, the underwriter fixed effects reduce the impact of Banks C and G who appear to disproportionately win auctions of their best ex-post performing tranches.

[14] In robustness tests, we included two additional variables related to the interest rate environment at the auction date and possible heterogeneity in the likelihood of prepayments across pools: (i) an indicator that equals one when the current 30-year fixed mortgage rate is more than 120 bps lower than the 5-year rolling average and (ii) the payoff rate in the previous 4 months for that pool. Both variables have been found to impact the payoff rate of mortgage pools in previous research. The inclusion of these variables does not affect the economic size or the statistical significance of the main independent variables. We excluded these variables from the current regressions for space and to allow comparison between the payoff and roll rate regressions.

To further examine the bidding behavior of seemingly better-informed integrated underwriters, we add two additional independent variables: (i) the winning yield minus the second lowest yield ("winning margin"); and (ii) the winning margin interacted with an indicator for the underwriter winning the auction. In this case we would like to examine whether the information content of the underwriters' bids is more valuable when they win relative to when another bidder wins. We subtract the second highest bid from the winning bid in all cases to control for information available to all bidders and to scale the results across auctions. A positive coefficient on the winning margin would be consistent with the winning bidder having access to information or models that better predict default relative to other bidders. Similarly, a positive coefficient on the interaction between winning margin and the integrated underwriter winning the auction would be consistent with the integrated underwriter being able to predict performance better than other winning bidders. A comparison of the bidding outcomes shows that the underwriter appears to win with a greater margin than non-underwriters (1.6% mean winning margin for underwriters versus 0.9 % winning margin for other bidders), possibly suggesting that underwriters are more aggressive bidders for the pools they want to win.

The results support the view that the underwriter is much better than other winning bidders at predicting the likelihood of payoffs relative to the second highest bidder, although the marginal effect is of moderate size. In the third column, the coefficient on the winning margin variable is negative and statistically insignificant, but the coefficient on the underwriter winning interacted with winning margin is positive and statistically significant (15.7). The coefficients show that underwriters bid more aggressively relative to other winning bidders for the best performing pools (those with the highest payoff rates). A one standard deviation increase in the winning margin for the underwriter (2.4 percent) is associated with a 0.4% higher payoff rate in the coming four months (compared to a 1.5% increase in the payoff rate associated with the underwriter bidding).

Finally we examine the payoff rate for the four months before and after the auction in Table 10. As with Table 7, we utilize a pooled logit approach. The dependent variable is an indicator that equals one if the loan pays off in the current month, conditional on the loan being in the pool at the beginning of the month. Notice that the number of observations declines with time as more loans payoff. Each logit regression is a fully saturated model, controlling for fixed effects for each month and the interaction of the month fixed effects with underwriter bids, underwriter wins, winning margin, and winning margin when the underwriter wins. Here we look for structural breaks before versus after the auction in how the underwriter bids and/or wins, controlling for any structural breaks at the auction date (the excluded month). As with the earlier regressions, we also control for a vector of loan, borrower, and collateral characteristics, as well as issuer and year fixed effects.

While the results confirm our findings, above, that the underwriter bids for pools with higher payoff rates, the findings suggest a broader advantage for the underwriter than might be evident in the month immediately after the auction. The underwriter bids on pools whose monthly payoff rate is about 0.5 to 1.5 percentage points higher *per month*, compared to a monthly payoff rate of 2.5 percent.[15] This effect grows with the number of months after the auction, peaking four months after the auction. Given that the lead time for direct information on payoffs could be valuable for only one to two months after the auction, it appears that the underwriter is able to create good models to predict subsequent payoffs.

Notice also that the sum of these payoff coefficients when the underwriter bids is much larger than the 4-month payoff coefficient for the underwriter bidding in Table 9. One possibility is that the auction month was an unusually low payoff month. This is also consistent with smaller, but still positive and sometimes statistically significant coefficients on underwriter bids in the four months prior to the auction.

The evidence as to the underwriter winning better-than-average tranches is similar to that in Table 9. In Panel B, the coefficients on underwriter winning when included as a dummy variable interacted with the monthly dummy variables are always small and never close to being statistically different from zero at conventional levels. However, the results continue to show that underwriters bid more aggressively relative to the second highest bidder (second lowest yield) for pools with the lowest payoff rates. As above, this effect is most pronounced in the fourth month after the auction date. The sum of the coefficients is larger than the coefficient in Table 8, but, as above, some of the underwriter wins*winning margin are significant prior to the auction. While the evidence suggests that the underwriter's bid is somewhat more informative

[15] The monthly payoff rate is very high for this time period given the sharp decline in interest rates between 2002 and 2005. The regressions contain year dummies and a control for the interest rate environment to control for any aggregate interest rate or macroeconomic effects.

when the underwriter wins than when a trader wins, the effect is moderate, at best, and is certainly not disproportionately large in the month or two after the auction.

6 Conclusion

The results in this paper suggest that underwriters exploit information advantages when bidding in the secondary market for their securities. Instead of bidding on the most illiquid and unattractive pools, underwriters instead bid on relatively liquid pools with a larger number of bidders. Ex-post, the pools that underwriters do not bid on have much worse performance, exhibiting especially high roll rates of loans from 30 to 60 days delinquent and lower payoff rates. When we examine more detailed data on timing of serious delinquencies, the evidence suggests that integrated underwriters avoid bidding for pools in which 30-day delinquent borrowers are more than three times more likely miss the next payment to become 60 days delinquent. Data on such missed payments are only available to the servicer, who is typically affiliated with the underwriter, but not to any outside parties. This effect appears primarily in the month following the auction, but not in any subsequent months, so it is unlikely that the underwriters exploit better models that can predict future serious delinquencies. Finally, underwriters appear to be successful in better modeling the likelihood that a loan pays off early for at least 4 months following the sale of their securities. They bid more aggressively relative to the second highest bidder for pools with greater payoff rates. These findings suggest that the underwriters use superior models, possibly because of their access to better data, to predict pool outcomes and take advantage of these models when bidding for their own securities.

These results suggest many avenues for future research. First, it is important to understand whether these results are confined to the prime MBS market, or whether underwriters more generally exploit their inside information in subsequent trading of securities after an IPO. Second, these results suggest that parties performing various roles in a securitization appear to act in their own interest, as opposed to maximizing the value of the entire structure. Other agency conflicts within the securitization structure are worth exploring.

Our findings suggest that role of underwriters is much more limited than has been suggested in other research. While underwriters may initially enhance the liquidity of mortgages through the issuance of MBS, their actions appear to make secondary trading more difficult by exploiting their inside information when bidding. Our conversations with the anonymous institution who provided access to this data and other market participants suggests that the extent to which underwriters exploit inside information may not be fully known in the marketplace. Given that this market is still relatively new, it is possible that traders do not fully account for adverse selection (the winner's curse) when placing bids. However, it is impossible to test this theory without better data on the value of the securities to the bidders, especially CDO buyers. However, one might speculate that, to the extent that CDOs were the marginal buyers of securities in this market, lemons problems may have contributed to the recent the well-publicized problems in the CDO market. The ability of vertically-integrated underwriters to exploit inside information might also help explain why investment banks have been purchasing originators and servicers in the securitization markets in recent years.

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Appendix A: Variable Construction

Variable	Description
Delinquency 30	Consider the subset of loans that have a positive balance for the duration of a month. This variable is one if the loan is 30 days past due on its 1st of the month payment at the end of the month and zero otherwise.
Delinquency Roll 30 to 60	Consider the subset of loans that is marked 30 days past due. This variable is one if the loan subsequently rolls to 60 days past due on the same payment and zero otherwise.
Four Month Payoff	Consider the subset of loans that has a positive balance. This variable is one if that loan pays off during the subsequent four months and zero otherwise.
Month vs. Auction Month	This variable denotes the number of months between an observation and the Auction Month. For example, if a trade occurs in Oct. then the August observation will be marked *Month vs. Auction Month* = -2.
Underwriter Bids	An indicator that equals one if the underwriter of the tranche bids in the auction and the yield is less than 60% higher than the winning (lowest) yield
Underwriter Wins	An indicator that equals one if the underwriter of the tranche places the highest bid (lowest yield) in the auction
Winning Yield	The highest bid (i.e. lowest yield) among all bids in a given auction. Yield (y) solves the following equation $$P_0 = \sum_{t=1}^{T} \frac{CF_t}{(1+y)^t}$$ Where P_0 is the dollar bid for the tranche and CF_t are the projected future cash flows for each tranche, assuming the industry-standard public securities association (PSA) prepayment rate of 300 for securities backed by fixed rate mortgages and constant prepayment rate (CPR) of 25 for securities backed by hybrid and floating rate mortgages
Winning Yield Margin	This variable denotes the spread between the lowest yield and the second lowest yield. This variable is always negative.
Underwriter Winning Yield Margin	This variable equals *Winning Yield Margin* if *Underwriter Wins* = 1 and zero otherwise.
Property Type Fixed Effects	Dummy variables that indicate the property type is a *Single-Family Residence*, or *Other*. *Single-Family Residence* includes all single-family residences, including those in planned urban developments. *Other* includes condos, co-ops, 2+ family residences, townhouses, manufactured housing, and other
Mortgage Purpose Type Fixed Effects	Dummy variables that indicate the purpose is for *Home Purchase* or *Refinance*
Rate Type Fixed Effects	Dummy variables that indicate the rate type is *Fixed*, *Floating*, or *Other*. *Other* includes hybrid ARMs, negative amortization mortgages, interest only mortgages, and other exotic mortgages
Documentation Status Fixed Effects	Dummy variables that indicate *Full Documentation, Low Documentation, or No Documentation*
LTV	Loan-to-value ratio of the mortgage at mortgage origination
FICO Score	The FICO score for the borrower at mortgage origination
No FICO	An indicator that equals one if no FICO score is provided
Balance	The mortgage balance at auction date, divided by one-hundred thousand
Current Mtg. Rate is X% Below Coupon Rate	This variable represents the point spread between the current 30yr. fixed mtg. rate the coupon rate. A positive value indicates a current mtg. rate below the contracted coupon rate.
Underwriter Fixed Effects	Dummy variables corresponding to the underwriter of the tranche
Loan Age Controls	Three variables. The first, *Age*, is a non-negative integer representing the number of months since the loan was originated. The second two controls are *Age* squared and cubed respectively.
Auction Year Fixed Effects	Dummy variables corresponding to the auction year for the tranche

Table 1
Identities of Underwriters (Integrated Banks) and Traders

Underwriters	Traders
Bear Stearns	Barclays
Bank of America	Cantor Fitzgerald
J.P. Morgan / Chase	Credit Suisse First Boston
Citigroup	Descap Securities
Countrywide	Greenwich Capital
Deutsche Bank	Lehman Brothers
Goldman Sachs	Morgan Stanley
UBS	Merrill Lynch
Washington Mutual	

Table 2
Summary Statistics at Auction Date

This table provides a summary of key attributes of the 241 mortgage-backed security (MBS) tranches at the time of the auction. *Collateral size* is the total dollar amount of mortgages that are collateral for a given MBS. *Tranche size* is the par value of tranche. Appendix A contains full descriptions for the remaining variables. Tranche means weighted by the share of the total value for each mortgage. Statistics for *FICO Score* exclude 37 tranches that do not report FICO scores for all mortgages.

	Mean	Median	Min	Max
Collateral size	$438,000,000	$340,000,000	$63,700,000	$2,060,000,000
Tranche size	$1,141,972	$787,305	$82,598	$1.25e+07
Mortgage Terms				
Balance	$483,626	$479,104	$371,646	$697,477
Age (Months)	13.1	13.2	3.2	24.1
Time to Maturity (Months)	295.0	344.9	155.5	357.7
LTV	65.7	66.7	47.2	74.8
FICO Score	737.2	739.1	703.8	750.5
No FICO (%)	16.6%	0.0%	0.0%	100.0%
Property Type (%)				
Single-Family Residence	92.4%	93.7%	79.6%	100.0%
Other	7.6%	6.3%	0.0%	20.4%
Rate Type (%)				
Fixed	72.9%	100.0%	0.0%	100.0%
Floating	12.8%	0.0%	0.0%	100.0%
Other	14.2%	0.0%	0.0%	94.8%
Occupancy Type (%)				
Owner, First-Home	94.8%	95.2%	71.3%	100.0%
Other	5.2%	4.8%	0.0%	28.7%
Documentation Status (%)				
Full Documentation	94.8%	95.2%	71.3%	100.0%
Low Documentation	5.2%	4.8%	0.0%	28.7%
No Documentation	19.8%	0.0%	0.0%	100.0%
Mortgage Performance 4-months before Auction Date				
Delinquency Rate (30 Day)	1.8%	1.7%	0.5%	4.7%
Payoff Rate	10.0%	5.9%	1.9%	43.3%
Mortgage Performance 4-months after Auction Date				
Delinquency Rate (30 Day)	1.8%	1.7%	0.4%	5.3%
Payoff Rate	9.3%	5.8%	1.8%	48.8%
Auction Characteristics				
# Bids	9.27	10	1	13
Winning Yield	16.81%	12.25%	6.03%	75.27%
Winning Yield Margin	1.34%	0.59%	0.00%	10.74%

Table 3
Bid and Win Frequencies for Underwriters and Traders

This table summarizes the bidding behavior of underwriters (Panel A) and traders (Panel B). *Underwriters* underwrite mortgage-backed securities (MBS) and also operate a MBS trading desk. *Traders* do not underwrite MBS, and only operate a MBS trading desk. *# Auctions* is the number of auctions of tranches in securities underwritten by the integrated bank listed in the first column. *% Bid On* is the percentage of auctions in which the institution bids for an MBS tranche. We only count bids as valid if they have a yield that is less than 60% higher than the winning (lowest) yield. *Of Bid On, % Won* is the percentage of auctions that the institution wins, conditional on bidding on the tranche. *Own* indicates that the auction is for a tranche in which the institution is also the underwriter. *Other* indicates that the auction is for a tranche in which the institution is not the underwriter. By definition, traders only bid on *Other* tranches.

Panel A: Underwriters	**# Auctions**	**% Bid On**		**Of Bid On, % Won**	
		Own	**Other**	**Own**	**Other**
Bank A	3	100.0%	52.1%	66.7%	4.0%
Bank B	47	93.6%	56.3%	15.9%	9.7%
Bank C	42	54.8%	62.1%	8.7%	9.9%
Bank D	11	63.6%	47.7%	14.3%	14.3%
Bank E	74	87.8%	47.9%	21.5%	11.1%
Bank F	6	100.0%	51.0%	0.0%	12.2%
Bank G	4	100.0%	9.3%	100.0%	0.0%
Bank H	5	100.0%	47.5%	20.0%	10.5%
Bank I	49	89.8%	54.2%	20.5%	9.4%
Total	**241**	**83.4%**	**52.7%**	**19.9%**	**10.2%**
Difference in Probabilities (Z-Statistic)		12.10		3.33	

Panel B: Traders	**# Auctions**	**% Bid On**	**Of Bid On, % Won**
Total	**241**	**39.5%**	**9.3%**

Table 4
Summary Statistics by Bid Status of the Informed Bidder

This table provides summary statistics for tranche and auction characteristics based on whether the informed underwriter bids at auction and wins the tranche. Appendix A contains full descriptions for each variable. Each variable is constructed at the tranche level. Means for each tranche are computed as weighted averages with weights proportional to each mortgages' proportion of the total par value of the pool, at the date of the auction. The column *No Bid* includes auctions where the underwriter either does not explicitly place a bid or the underwriter places a bid where the yield is more than 60% higher than the winning (lowest) yield. The column *Bid, Lose* includes auctions where the underwriter bids on the tranche but does not enter the highest bid. The column *Bid, Win* includes auctions where the underwriter bids on the tranche and enters the highest bid. Tests for differences in means and percentages are conducted at the security-level. ** and * indicate significantly different than zero at the 5%, and 10% level respectively.

	No Bid	Bid, Lose	Bid, Win	Test Statistic: No Bid ≠ Bid	Test Statistic: Bid, Lose ≠ Bid, Win
Mortgage Terms					
Balance	$489,132	$486,964	$476,546	0.41	0.96
Age (Months)	13.8	13.5	11.7	0.7	2.05
Time to Maturity (Months)	269.1	295.0	312.0	-2.21**	-1.29
LTV	64.7	66.0	67.5	-1.77*	-1.68*
FICO Score	735.5	737.8	735.8	-0.96	1.25
No FICO (%)	48.1%	10.1%	6.3%	6.76**	0.75
Property Type (%)					
Single-Family Residence	90.6%	92.7%	92.0%	-2.62**	0.88
Other	9.4%	7.3%	8.0%	-2.62**	0.88
Rate Type (%)					
Fixed	78.9%	73.1%	62.1%	1.04	1.38
Floating	8.0%	15.4%	9.3%	-1.26	1.16
Other	12.7%	12.1%	29.4%	0.55	2.55**
Occupancy Type (%)					
Owner, First-Home	94.0%	94.8%	94.6%	-1.23	0.41
Other	6.0%	5.2%	5.4%	-1.23	0.41
Documentation Status(%)					
Full Documentation	65.0%	42.6%	41.5%	3.97**	0.18
Low Documentation	29.9%	36.8%	38.4%	-1.35	-0.27
No Documentation	5.0%	20.5%	20.0%	-2.33**	0.06
Mortgage Performance 4-months before Auction Date (%)					
Delinquency Rate (30 Day)	2.0%	1.8%	1.6%	1.35	1.23
Delinquency Rate (60 Day)	0.2%	0.2%	0.2%	-0.06	-0.25
Payoff Rate	10.1%	9.1%	11.8%	0.34	-1.59
Auction Characteristics					
# Bids (including the underwriter)	6.63	10.09	8.65	5.33***	2.47**
Winning Yield	19.09%	15.78%	18.71%	1.24	1.50
Winning Yield Margin	2.43%	0.99%	1.64%	2.62***	1.59
# Auctions	40	161	40		

Table 5
30 to 60 Day Delinquency Roll Rate at Auction Date

This table provides the number of loans that are 30-days delinquent at the auction date and the percentage of these 30-day delinquent loans that roll to 60-days delinquent (*Delinquency Roll 30 to 60*). The column *No Bid* includes auctions where the underwriter either does not explicitly place a bid or the underwriter places a bid where the yield is more than 60% higher than the winning (lowest) yield. The column *Bid, Lose* includes auctions where the underwriter bids on the tranche but does not enter the highest bid. The column *Bid, Win* includes auctions where the underwriter bids on the tranche and enters the highest bid. ** and * indicate significantly different than zero at the 5%, and 10% level respectively.

	# Loans 30 Days Delinquent at Auction Date			% Roll to 60 Days Delinquent		
Integrated Bank	No Bid	Bid, Lose	Bid, Win	No Bid	Bid, Lose	Bid, Win
Bank A	9	150	37	0.0%	2.7%	5.4%
Bank B	17	25	4	29.4%	8.0%	0.0%
Bank C	38	279	57	21.1%	9.7%	14.0%
Bank D	0	0	0	.	.	.
Bank E	106	86	6	20.8%	2.3%	0.0%
Bank F	0	0	48	.	.	0.0%
Bank G	0	5	26	.	0.0%	0.0%
Bank H	0	0	0	.	.	.
Bank I	29	422	37	17.2%	4.3%	0.0%
Total	199	967	215	**20.1%**	**5.4%**	**5.2%**
		Tranche-Level T-tests				
		No Bid ≠ Bid		3.29**		
		Bid, Lose ≠ Bid, Win		0.26		

Table 6: Logit Regressions
30 to 60 Day Delinquency Roll Rate at Auction Date

The sample is all mortgages that are 30 days delinquent at the time of the auction. This table presents the marginal effects in percentages for three separate Logit models. All variables are described in Appendix A. The dependent variable, *Delinquency Roll 30 to 60*, equals 1 if the mortgage becomes 60 days delinquent (e.g., the borrower also misses the next payment) and zero otherwise. For continuous variables, results are reported as the marginal effect of moving one standard deviation. For discrete dummy variables, results are reported as the marginal effect of moving from 0 to 1. The excluded category is underwriter does not bid. Standard errors are clustered at the security-level. ** and * indicate significantly different than zero at the 5%, and 10% levels respectively.

	(1)	(2)
Underwriter Bids	-7.5**	-7.9**
	(3.06)	(3.03)
Underwriter Wins		1.1
		(0.71)
Single-Family Residence	-4.0*	-4.0*
	(1.70)	(1.72)
Home Purchase	-0.2	-0.2
	(0.23)	(0.22)
Fixed Rate	0.4	0.4
	(0.20)	(0.22)
Floating Rate	1.1	1.2
	(0.54)	(0.58)
Full Documentation	0.9	0.8
	(0.30)	(0.27)
Low Documentation	-1.2	-1.2
	(0.40)	(0.42)
LTV	0.1**	0.1**
	(2.29)	(2.30)
FICO Score	-0.02	-0.02
	(1.56)	(1.58)
No FICO	-5.8	-5.8
	(1.30)	(1.32)
Origination Amount	0.3	0.3
	(0.76)	(0.77)
(Coupon rate - prevailing mrg rate) *	3.4**	3.4**
(Coupon rate - prevailing mrg rate>0)	(1.98)	(1.99)
Pseudo R-squared	0.17	0.17
# Observations	1,302	1,302
Auction Year Fixed Effects	Yes	Yes
Underwriter Fixed Effects	Yes	Yes
Loan Age Fixed Effects	Yes	Yes

Table 7: Logit Regressions
30 to 60 Day Delinquency Roll Rate
Four Months Before and After the Auction

This table presents the marginal effects in percentages for three separate Logit models. The sample includes all mortgages that are 30 days delinquent in any of the four months before or after the auction. The variables are described in Appendix A. For continuous variables, results are reported as the marginal effect of moving 1 standard deviation. For discrete dummy variables, results are reported as the marginal effect of moving from 0 to 1. Standard errors are clustered at the security-level. ** and * indicate significantly different than zero at the 5%, and 10% levels respectively. Coefficients for various control variables are not reported to save space and are available upon request.

Panel A: Dependent Variable is *Delinquency Roll 30 to 60*

Model includes month dummy variables and the interaction of month dummy variables with *Underwriter Bids* and *Underwriter Wins,* plus loan characteristics, loan age, and underwriter and auction year fixed effects.

	Dummy Variable	Underwriter Bids
Dummy Variable		-0.1
		(0.05)
4 months prior to auction	0.2	0.3
	(0.06)	(0.07)
3 months prior to auction	-1.0	2.4
	(0.37)	(0.71)
2 months prior to auction	-0.2	0.4
	(0.08)	(0.10)
1 month prior to auction	-2.5	1.5
	(0.83)	(0.38)
1 month after auction	13.5**	-6.0**
	(2.50)	(3.05)
2 months after auction	2.9	-1.4
	(0.81)	(0.48)
3 months after auction	3.7	-2.8
	(1.12)	(1.20)
4 months after auction	3.3	-0.8
	(0.89)	(0.27)
Pseudo R-squared		0.07
# Observations		11,970

Panel B: Dependent Variable is *Delinquency Roll 30 to 60*

Model includes month dummy variables and the interaction of month dummy variables with *Underwriter Bids* and *Underwriter Wins,* plus loan characteristics, loan age, and underwriter and auction year fixed effects.

	Dummy Variable	Underwriter Bids	Underwriter Wins
Dummy Variable		-0.8	3.4*
		(0.29)	(1.78)
4 months prior to auction	0.3	1.1	-3.1**
	(0.08)	(0.27)	(1.99)
3 months prior to auction	-0.9	2.7	-1.5
	(0.34)	(0.81)	(0.74)
2 months prior to auction	-0.2	1.1	-2.6
	(0.06)	(0.27)	(1.09)
1 month prior to auction	-2.5	1.7	-0.3
	(0.83)	(0.42)	(0.11)
1 month after auction	13.3**	-5.6**	-3.3
	(2.48)	(2.73)	(1.64)
2 months after auction	2.9	-0.7	-2.9
	(0.80)	(0.21)	(1.27)
3 months after auction	3.6	-2.0	-3.7**
	(1.11)	(0.79)	(2.05)
4 months after auction	3.2	-1.2	1.7
	(0.88)	(0.40)	(0.56)
Pseudo R-squared		0.07	
# Observations		11,970	

Table 8
Payoff Rate Following the Auction

This table provides number of loans with non-zero balances at the auction date and the percentage of these loans that payoff in the next four months. The column *No Bid* includes auctions where the underwriter either does not explicitly place a bid or the underwriter places a bid where the yield is more than 60% higher than the winning (lowest) yield. The column *Bid, Lose* includes auctions where the underwriter bids on the tranche but does not enter the highest bid. The column *Bid, Win* includes auctions where the underwriter bids on the tranche and enters the highest bid. ** and * indicate significantly different than zero at the 5%, and 10% level respectively.

	# Loans at Auction Date			% Payoff in the next 4 months		
Underwriter	No Bid	Bid, Lose	Bid, Win	No Bid	Bid, Lose	Bid, Win
Bank A	2,075	32,622	6,951	12.8%	10.1%	10.7%
Bank B	2,246	4,153	805	3.4%	8.0%	8.2%
Bank C	6,270	40,937	8,509	7.5%	7.8%	18.1%
Bank D	0	721	1,442	.	8.3%	8.3%
Bank E	14,320	14,544	1,006	3.3%	6.3%	3.0%
Bank F	0	0	11,640	.	.	6.9%
Bank G	0	5,941	511	.	6.3%	47.0%
Bank H	0	1,683	0	.	5.9%	.
Bank I	5,620	47,918	10,041	5.9%	10.5%	7.3%
Total	30,531	148,519	40,905	**5.3%**	**8.9%**	**10.4%**
	Tranche-Level T-tests					
	No Bid ≠ Bid			2.46**		
	Bid, Lose ≠ Bid, Win			1.82*		

Table 9: Logit Regressions
Payoff Rate Following the Auction

The sample includes all mortgages with a non-zero balance that at the time of the auction. This table presents the marginal effects in percentages for three separate Logit models. All variables are described in Appendix A. The dependent variable, *Four Month Payoff*, equals 1 if the mortgage pays off in the four months following the auction and zero otherwise. For continuous variables, results are reported as the marginal effect of moving one standard deviation. For discrete dummy variables, results are reported as the marginal effect of moving from 0 to 1. The excluded category is underwriter does not bid. Standard errors are clustered at the security-level. ** and * indicate significantly different than zero at the 5%, and 10% levels respectively.

	(1)	(2)	(4)
Underwriter Bids	1.4**	1.4**	1.5**
	(2.17)	(2.06)	(2.26)
Underwriter Wins		0.2	
		(0.26)	
Winning Yield – 2nd Lowest Yield			-7.1
			(-1.06)
Winning Yield – 2nd Lowest Yield *Underwriter wins			15.7*
			(1.96)
Single-Family Residence	0.7**	0.7**	0.7**
	(2.06)	(2.06)	(2.06)
Home Purchase	-0.9**	-0.9**	-0.9**
	(2.45)	(2.45)	(2.45)
Fixed Rate	-4.7**	-4.7**	-4.7**
	(3.84)	(3.79)	(3.83)
Floating Rate	4.4**	4.4**	4.3**
	(4.61)	(4.54)	(4.57)
Full Documentation	0.9	0.9	0.9
	(1.04)	(1.04)	(0.97)
Low Documentation	1.4	1.4	1.4
	(1.60)	(1.59)	(1.54)
LTV	0.1**	0.1**	0.1**
	(5.53)	(5.54)	(5.52)
FICO Score	-0.01**	-0.01**	-0.01**
	(2.89)	(2.89)	(2.87)
No FICO	-5.4**	-5.4**	-5.3**
	(2.77)	(2.78)	(2.74)
Origination Amount	0.3**	0.3**	0.3**
	(3.29)	(3.29)	(3.29)
(Coupon rate - prevailing mrg rate) * (Coupon rate - prevailing mrg rate>0)	9.4**	9.4**	9.4**
	(10.13)	(10.09)	(10.21)
Pseudo R-squared	0.08	0.08	0.08
# Observations	219,955	219,955	219,955
Auction Year Fixed Effects	Yes	Yes	Yes
Underwriter Fixed Effects	Yes	Yes	Yes
Loan Age Fixed Effects	Yes	Yes	Yes

Table 10: Logit Regressions
Payoff Rate
Four Months Before and After the Auction

This table presents the marginal effects in percentages for three separate Logit models. The sample includes all mortgages with a non-zero balance in any of the four months before or after the auction. The variables are described in Appendix A. For continuous variables, results are reported as the marginal effect of moving 1 standard deviation. For discrete dummy variables, results are reported as the marginal effect of moving from 0 to 1. Standard errors are clustered at the security-level. ** and * indicate significantly different than zero at the 5%, and 10% levels respectively. Coefficients for various control variables are not reported to save space and are available upon request.

Panel A: Dependent Variable is *Four Month Payoff*

Model includes month dummy variables and the interaction of month dummy variables with *Underwriter Bids,* plus loan characteristics, loan age, and underwriter and auction year fixed effects.

	Dummy Variable	Underwriter Bids	Underwriter Wins
Dummy Variable		-0.2	
		(0.70)	
4 months prior to auction	0.1	0.4	
	(0.28)	(0.93)	
3 months prior to auction	-0.3	0.9**	
	(0.98)	(2.36)	
2 months prior to auction	-0.2	0.5*	
	(0.89)	(1.76)	
1 month prior to auction	-0.1	0.2	
	(0.54)	(0.60)	
1 month after auction	-0.5*	0.5*	
	(1.93)	(1.67)	
2 months after auction	-0.8**	1.4**	
	(3.61)	(3.41)	
3 months after auction	-0.9**	1.4**	
	(3.46)	(3.59)	
4 months after auction	-1.1**	1.5**	
	(3.21)	(2.74)	
Pseudo R-squared		0.06	
# Observations		1,992,104	

Panel B: Dependent Variable is *Four Month Payoff*

Model includes month dummy variables and the interaction of month dummy variables with *Underwriter Bids* and *Underwriter Wins,* plus loan characteristics, loan age, and underwriter and auction year fixed effects.

	Dummy Variable	Underwriter Bids	Underwriter Wins
Dummy Variable		-0.2	-0.03
		(0.68)	(0.14)
4 months prior to auction	0.1	0.4	0.02
	(0.27)	(0.89)	(0.06)
3 months prior to auction	-0.3	0.8**	0.1
	(0.99)	(2.26)	(0.31)
2 months prior to auction	-0.2	0.6**	-0.3
	(0.90)	(1.99)	(1.20)
1 month prior to auction	-0.1	0.1	0.2
	(0.54)	(0.40)	(0.67)
1 month after auction	-0.5*	0.5	0.1
	(1.93)	(1.52)	(0.22)
2 months after auction	-0.8**	1.3**	0.1
	(3.61)	(3.14)	(0.37)
3 months after auction	-0.9**	1.4**	0.02
	(3.46)	(3.57)	(0.11)
4 months after auction	-1.1**	1.5**	-0.1
	(3.21)	(2.81)	(0.23)
Pseudo R-squared		0.06	
# Observations		1,992,104	

Table 10: Logit Regressions (Continued…)
Payoff Rate
Four Months Before and After the Auction

Panel C: Dependent Variable is *Four Month Payoff*

Model includes month dummy variables and the interaction of month dummy variables with *Underwriter Bids* and *Underwriter Wins,* plus loan characteristics, loan age, and underwriter and auction year fixed effects.

	Dummy Variable	Underwriter Bids	Winning Yield Margin	Underwriter Winning Yield Margin
Dummy Variable		-0.1	-0.8	-6.7*
		(0.50)	(0.28)	(1.74)
4 months prior to auction	0.3	0.3	0.8	11.6*
	(0.64)	(0.64)	(0.16)	(1.69)
3 months prior to auction	-0.3	0.9**	-2.6	7.5
	(1.10)	(2.44)	(0.79)	(1.19)
2 months prior to auction	-0.1	0.4*	1.0	4.0
	(0.36)	(1.68)	(0.52)	(1.21)
1 month prior to auction	0.1	0.03	5.8**	-1.5
	(0.32)	(0.12)	(2.12)	(0.32)
1 month after auction	-0.3	0.4	3.0	6.5*
	(1.16)	(1.48)	(0.97)	(1.70)
2 months after auction	-0.7**	1.2**	2.9	5.6
	(3.05)	(3.56)	(0.68)	(1.03)
3 months after auction	-0.9**	1.4**	-2.0	8.4
	(3.12)	(3.40)	(0.43)	(1.58)
4 months after auction	-1.0**	1.5**	-2.5	19.0**
	(3.00)	(2.81)	(0.69)	(4.11)
Pseudo R-squared	0.06			
# Observations	1,992,104			

The following control variables are included in the 3 regressions above: *Single-Family Residence, Home Purchase, Fixed Rate, Floating Rate, Full Documentation, Low Documentation, LTV, FICO Score, No FICO, Origination Amount, Current Mtg. Rate is X% Below Coupon Rate at Trade Date, Age,* Age^2, Age^3; as well as *Underwriter Fixed Effects* and *Auction year Fixed Effects*.

Figure 1
Separation of Origination / Servicing from Credit Risk

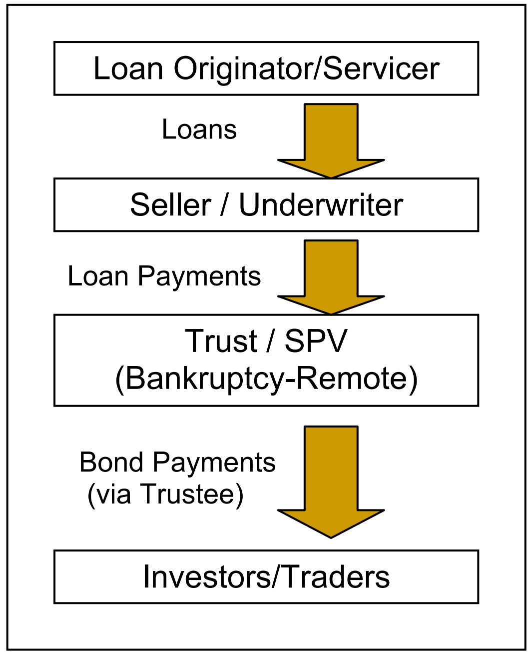

Figure 2
Pooling and Tranching

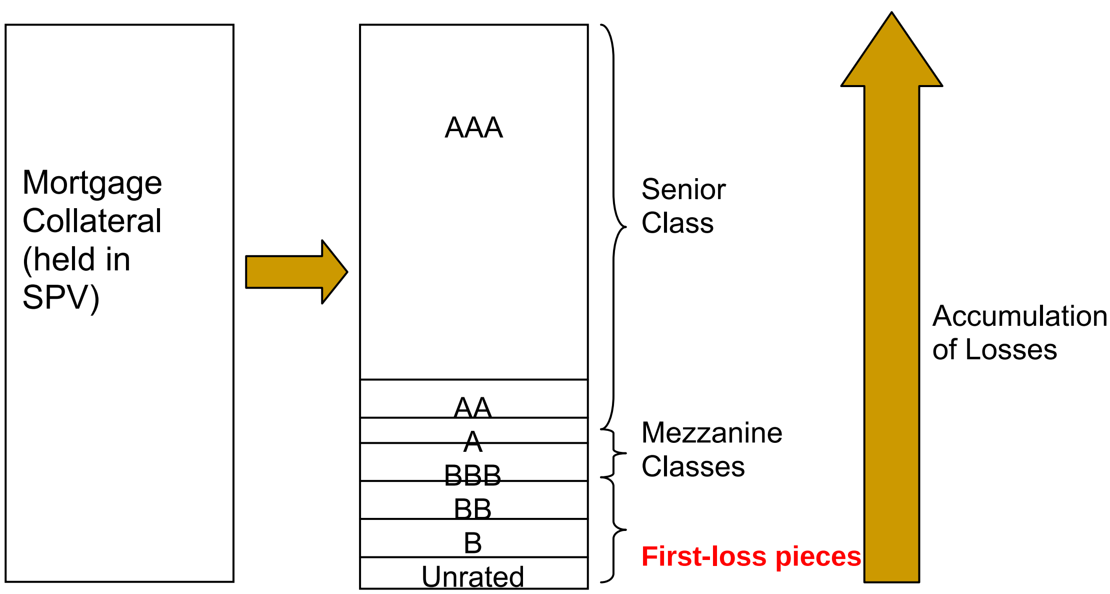

Figure 3
Time Line: From Origination to Secondary Market Trading