Differential returns to securitization: Evidence and Impact*

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Abstract

This paper studies market power along the supply chain of mortgages by leveraging a unique data set that provides information on prices at each link on the chain. We document large and systematic differences in expected loan duration across issuers. Conditional on borrower and contract attributes, *high quality* issuers manage portfolios of loans that are significantly less exposed to prepayment risk, while *low quality* issuers produce securities that are more likely to prepay early. Moreover, those differences in expected duration allow some issuers to sell loans at a premium in the secondary market by issuing customized securities with higher expected cash flows rather than selling them in multi-issuer pools where investors do not observe the characteristics of the individual loans. We find that issuers with systematically better pools (in terms of expected duration) indeed receive higher prices on average in the secondary market. We then examine whether these returns are passed through to the wholesale market and ultimately to borrowers. Our findings suggest that there is little pass-through, implying that customization generates market power for those issuers able to customize their securities.

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1 Introduction

The funding of U.S. mortgages is heavily reliant on securitization, such that less than 10% of "conforming" loans are kept on banks' balance sheets (Buchak et al. 2018, 2024*a*,*b*).[1] Under this *originate-to-distribute* (OTD) funding model, conforming loans are pooled into agency mortgage-backed securities (MBS) that feature a government-backed credit risk guarantee. In this environment, the process of issuing an MBS involves three stages: origination, aggregation, and servicing. At the origination stage, borrowers can either engage with a vertically integrated lender that performs all three of these tasks (this is the *retail channel*), or with a correspondent lender that sells the entire loan, including servicing rights, in a *wholesale* market to an aggregator for securitization.[2] In both cases, the MBS issuers earn profits by servicing loans, and by selling newly created securities in the secondary market to investors, such as deposit institutions, central banks and pension funds. Crucially, secondary market loan sales are a key source of internal liquidity, allowing issuers to fund new loan origination in the retail and wholesale markets with limited dependence on external financing such as deposits or wholesale lines of credit.

The resale value of a loan in the secondary market is primarily determined by two interconnected risks: interest rate risk and prepayment risk.[3] Depending, on their assessments of these risks, issuers can choose to pool loans either in a *To-Be-Announced* (TBA) eligible security or in a *custom pool* security (also known as *specified pool*). The TBA market is a highly liquid, forward market with low transaction costs in which a seller and a buyer agree to trade a volume of loans satisfying a coarse set of characteristics (e.g., 30-year fixed rate mortgage paying a coupon of 3% interest) at a given price and future date.[4] Importantly, under a TBA contract, securities are delivered on a "cheapest-to-deliver" (CTD) basis and the price reflects the characteristics of the average security expected to be delivered (Vickery & Wright 2013). In contrast, the custom pool market is less liquid and involve substantial price uncertainty, but investors observe the characteristics of the individual loans in the pool when the trade is made. Therefore, issuers have an incentive to sell worse loans (those with high pre-payment risk) in the TBA market, and loans with larger expected cash-flows in custom-pool markets at higher prices. Importantly, custom securities are also differentiated along fixed/pre-specified characteristics (hence the name "spec-pools"). In the market that we study, the

[1] Between 2013 and 2020, roughly 70% of new mortgages were securitized under one of the agency offering government-backed credit guarantees to investors: Freddie Mac, Fannie Mae and Ginnie Mae. The rest include loans that are for the most part above the conforming size limit (or "Jumbo" loans) held in banks' portfolio, and a small fraction that are privately securitized.

[2] Roughly 10% of loans are produced by brokers who originate loans on behalf of an aggregator who then services and securitizes it. The retail and correspondent segments have roughly equal shares.

[3] Interest tate risk is the general risk that the market value of a fixed-income security, such as a bond or an MBS, will fall due to a subsequent rise in overall market interest rates (or vice-versa). Prepayment risk is the risk specific to securities backed by loans (like mortgages) that the borrower will repay the principal earlier or later than expected, altering the projected stream of cash flows. The prepayment risk magnifies the interest rate risk for an MBS, leading to the phenomenon known as negative convexity. In addition, the price of securities incorporate smaller adjustments for liquidity, model risk (i.e. errors in the prepayment model), and housing turnover.

[4] See Bessembinder et al. (2013) for a discussion of transaction costs.

primary dimension of segmentation is loan size, and nearly all loans above $200K are pooled in multi-issuer securities.

In this paper, we investigate how issuers' customization strategies create rents, and how these rents are distributed along the supply chain of mortgages. While a growing literature studies the extent and consequences of adverse selection associated with pooling decisions (see for example Gao et al. 2017; Fusari et al. 2022; Huh & Kim 2023; and An et al. 2025), our contribution is to highlight the existence of important asymmetries across issuers in access to the spec-pool market. In our sample, 20% of loans are pooled in custom securities, but the median issuer sells only 1.5% of its portfolio in the spec-pool market.

We relate these differences to economies of scale in securitization and differences in prepayment-risk profiles across issuers, and investigate whether these asymmetries generate market power. Most of the literature has assumed symmetric banks and perfect competition, and indeed, if the wholesale and retail markets were competitive, the rents earned from higher resale values would be competed away, and banks with and without access to custom pools would be equally profitable. In this case, eliminating the adverse selection problem would lead to a transfer from consumers with longer expected durations (e.g., small-loan borrowers) to those with shorter expected durations (i.e., eliminating customization would be regressive).

Symmetry is a potentially reasonable assumption for loans pooled in TBA-eligible securities, since the expected revenue is easy to predict and independent of the size and characteristics of issuers' portfolios. For loans that can be transacted in the spec-pool market, across-bank heterogeneity in the value of securitization, stemming from differences in bank size and ability to acquire longer-duration loans, translates into differences in willingness-to-pay for new mortgages. Heterogeneity in the ability to customize securities can therefore lead to higher concentration and cause market power distortions in the retail and wholesale markets. In this case, eliminating the adverse-selection problem would lead to a transfer between banks, and make markets more competitive.

Understanding how the rents from customization are distributed is important. The objective of securitization is to convert illiquid/differentiated assets into homogeneous tradable securities, enabling originators to (i) diversify funding sources, (ii) transfer risk, (iii) improve capital efficiency. The implication is that securitization should homogenize returns across borrowers and lenders, and facilitate entry of mortgage specialists. But if there are differential returns to securitization, this may affect market concentration and industry fragility. Since access to custom pools depends largely on the size and quality of loans portfolios, many smaller non-bank lenders with more exposure to lower-quality loans may earn lower rents. Moreover, incomplete pass-through from issuers to (primarily non-bank) mortgage originators can raise the cost of financial intermediation and amplify vulnerabilities faced by these institutions This can increase risks to the mortgage market and to overall financial stability (see Kim et al. 2018, Financial Stability Oversight Council 2024).

Empirical analysis of how rents are distributed across borrowers, originators, and issuers requires

data covering the entire lifespan of a loan: from origination, to possible sale in the wholesale market, to sale in the secondary market, and, finally, to borrower repayment (history and duration). Until now, such data have been unavailable to researchers, but we have obtained access to three data sources that, once combined, allow us to construct the full history of a loan and characterize market power along the supply chain. A unique feature of our study is the use of proprietary data on loan acquisition by auction from the FinTech company Optimal Blue (OB), which operates one of the largest loan exchange platforms. To this we add data from (i) eMBS.Inc, which provides information on all agency MBS and their component loans permitting us to measure loan performance, (ii) TRACE, which provides us with information on the prices of securities in custom pools, (iii) Bloomberg, which provides us with TBA prices, and (iv) the Home Mortgage Disclosure Act, which provides information on retail prices (i.e., mortgage transactions).

We study this question in the context of loans securitized under the FHA and VA programs managed by Ginnie Mae. This segment represents roughly 25% of new mortgage origination, and is dominated by non-banks servicing over 80% of loans (Kim et al. 2018). We select this segment for our study due its relative simplicity relative to the securitization process under the two Government Sponsored Enterprises (GSEs). For each loan, Ginnie Mae issuers must select between a multi-issuer TBA security or a custom single-issuer security option (typically differentiated by loan size), with the restriction that they generally have no choice over the bond's coupon rate (unlike GSE issuers). Moreover, also unlike with the GSEs, issuers are directly involved in making securitization choices irrespectively of their size. This allows us to study heterogeneity in the return to securitization across issuers.

We begin by developing a framework for understanding loan acquisition and customization choice. The first stage of the model lays out the optimal customization problem. It highlights the role of firm asymmetries, and the tradeoffs between loan duration, liquidity, and transaction costs. The key prediction from this stage is that there is an adverse selection problem, with loans pooled in multi-issuer securities (TBA) having shorter duration and smaller expected cash flows. The model also predicts that selection is not just based on loan size, but also on borrower and issuer characteristics. Size, portfolio quality, and need for liquidity explain heterogeneity in returns from customization. Turning to the acquisition side and the pass-through of the higher returns along the supply chain, we predict that in the wholesale market there is full pass through of TBA prices, but incomplete pass through of spec-pool prices when banks are not symmetric. The fact that the willingness-to-pay function is additively separable in the security price implies that the bid function is additively separable in the TBA price. Competition forces every bidder to adjust its bid by the amount of the TBA price. On the retail side, information frictions and originator heterogeneity can generate market power. More specifically, it has been well-documented that there is limited consumer search in the mortgage retail market, such that they are generally unaware of resale values (see for instance Allen et al. 2014, 2019; Agarwal et al. 2024; Alexandrov & Koulayev

2017; Bhutta et al. 2025). In principle there are only small gains for collecting multiple quotes for consumer whose loan is pooled in TBA-eligible securities, and limited search is not costly. On the other hand, for a custom loan, the gains from search are large due to heterogenous returns to securitization, which potentially increase market-power rents in the retail market and lead to incomplete pass-through.

Next, we test the predictions from the model. To test that bank heterogeneity in size and loan duration drives securitization decisions, we must establish that banks with high quality loans do in fact obtain a higher return. We do this in two ways. First, we adopt a *revealed preference* approach that illustrates that banks with unobserveably good loans are more likely to supply securities in the custom pool market. To assess the importance of adverse selection in the secondary market, we construct a test that is commonly used in the insurance literature (Chiappori & Salanie 2000). Our approach relates to the "unused" observables adversed selection test developed by Finkelstein & Poterba (2004, 2014) to study adverse selection in the annuity market.

Specifically, we test whether the 12-month survival rate is higher for loans placed in custom pool securities than in TBA securities. The results strongly support the hypothesis of adverse selection. We find that roughly half of the difference in survival between loans pooled in custom vs TBA securities is due observable borrower characteristics that correlate with prepayment risk. More importantly, we find that the remaining difference is explained by systematic differences in expected loan duration across issuers. In other words, issuers with long duration portfolios (i.e. high quality) are significantly more likely to create custom securities. This in turns lead to differential returns to customization across issuers. Our data do not allow us to separate identify the demand vs supply factors that explain these large differences in "productivity" across issuers.

To quantify the importance of issuer asymmetries on loan resale value, we leverage a matched sample of eMBS and TRACE data to examine the degree of heterogeneity in custom pool prices for different banks. We find substantial residual dispersion in transaction prices across securities, consistent with the presence of important trading frictions. Focussing on the cross-section distribution of prices, we find that 15% of the variance is explained by differences in borrower characteristics across securities, and 13% is explained by issuer fixed-effects. This confirms that issuers earn very different returns from the custom-pooled market, even when we focus on issuers that regularly participate in this market. Furthermore, we find that issuers with systematically better pools (in terms of expected duration) receive higher spec-pool prices on average.

Next, we examine whether these higher custom pool prices are passed through to the wholesale and retail markets. This will inform us as to whether, and to what extent, rents are shared amongst issuers, originators, and borrowers. The literature (see for instance Fuster et al. 2024 and Westphal 2024) has shown that changes in the TBA prices are reflected in the closing cost and interest rate that consumers pay. However, because the return to customization varies across issuers, variation in spec-pool prices is likely passed through at a lower rate to correspondent lenders and ultimately

consumers. Following Westphal (2024), we quantify the pass-through rate of the "spec-pool pay-up" by exploiting discontinuities in prices around commonly-employed loan size cut-offs used to determine the characteristics of spec-pool securities. We leverage our auction data to separately identify a pass-through rate in the wholesale and retail markets.

Consistent with the theory, we find near complete pass-through of TBA prices to wholesale prices and incomplete pass-through of spec-pool pay-ups. In particular, we find that a dollar increase in the spec-pool pay-up (i.e., the difference between the security price and the TBA) leads to \$0.44 increase in the wholesale price that correspondent lenders receive. In contrast, we find a pass-through rate of 0.88 for the TBA price. Also consistent with the theory, we find much lower pass-through rates in the retail market. Conditional on the interest rates chosen by consumers, we find that a \$1 increase in the TBA price leads to a \$0.33 reduction in the closing costs for consumers, and that changes in the wholesale price associated with the customization result are uncorrelated with changes in the retail price of the loan. Similarly, we reject the hypothesis that consumers pay lower interest rates when their loans are pooled in custom securities (despite much higher returns for originators).

In a final step, we investigate the impact of eliminating the option to pool some loans in custom pools. More precisely, our objective is to measure the change in profit per loan from eliminating customization, holding fixed the allocation of loans to banks. Doing so has the effect of eliminating adverse selection in multi-issuer pools, since under the counterfactual all loans will be directed there. We simulate counterfactual multi-issuer pool prices. Our exercise requires two assumptions. First, that there is a constant allocation of loans and interest rates, and second that pass-through is linear. Under these assumption the MSR and the fixed component of issuer profits cancel out, allowing us to quantify the change in profit as simply the sum of the difference in resale value and the difference in acquisition price, which we observe.

Our findings suggest that eliminating adverse selection (i) benefits small borrowers (opposite to the finding under perfect-competition), (ii) benefits lenders who have limited access to customization because of the quality of their portfolio or their size, and (iii) reduces market power in the wholesale market, and therefore the cost of intermediation.

Related literature: This paper contributes to several important literatures at the intersection of Industrial Organization and Finance. First, most of the literature studying the mortgage market has focused on the retail (origination) segment in which financial intermediaries acquire loans from borrowers (e.g., Allen et al. 2014, 2019; Agarwal et al. 2024; Alexandrov & Koulayev 2017; Bhutta et al. 2025; Benetton et al. 2025; Aguirregabiria et al. 2025).[5] According to the traditional banking model, financial institutions fund mortgages using deposits and then keep the resulting loans on their balance sheets. Retail margins capture the difference between the interest rate on loans and the marginal cost of attracting deposits. The literature has focused on two main sources of

[5]See Clark et al. (2021) for a review of this literature.

dispersion in this segment: cost differences and heterogeneous search frictions. Our pass-through results are consistent with the idea that consumers face high search cost when negotiating contract terms, but offers a novel mechanism that explains retail market power and price dispersion: because MBS issuers earn different returns from securitization, consumers need to search a large number of lenders in order to obtain competitive quotes.

We also contributes to a growing literature on the MBS market, specifically those articles considering pooling choices and market structure. Fuster et al. (2022) and Fabozzi (2016) survey the literature on MBS. Gao et al. (2017), Fusari et al. (2022), Huh & Kim (2023), and An et al. (2025) study the parallel trading environment. Huh & Kim (2023) evaluate the impact of eliminating custom pools, but assume symmetric issuers and perfect competition. As a result, they predict that removing the custom pool option is regressive – surplus is transferred from small-loan (those with longer duration loans) to big-loan borrowers (shorter durations). Only An et al. (2025) recognizes the existence of issuer heterogeneity, but they do not consider its impact on market power or rent distribution.

More generally, we are related to the literature on product design in decentralized markets that stretches back at least to DeMarzo & Duffie (1999) and DeMarzo (2005). More recently, Brancaccio & Kang (Forthcoming) study product design in the context of the US municipal bond market.

Stanton et al. (2014) describe the structure of the markets at each level of the mortgage supply chain. Fuster et al. (2024) study pass-through of TBA prices to retail prices and show that it is essentially complete. Westphal (2024) builds on this to investigate whether custom pool prices are also fully passed through and finds that they are not, which he attributes to information frictions.

Our adverse selection results contribute to a large literature measuring the importance of adverse selection in financial and insurance markets. Closely related papers include the work of Agarwal et al. (2012) and Downing et al. (2009). See Einav et al. (2010) for a review of the insurance literature. We are especially related to papers studying the interaction of market power and selection such as Mahoney & Weyl (2017), Crawford et al. (2018), and Cuesta & Sepulveda (2021). See Einav et al. (2021) for a summary. We are also related to the literature in health insurance on *risk selection*, including papers by Aizawa & Kim (2018), Shepard (2022), and Serna (2024).

We also contribute to a large and growing literature on competition and fragility in the financial sector that includes such papers as Egan et al. (2017) and Corbae & Levine (2019). Vulnerabilities faced by nonbank mortgage companies have been pointed out by Kim et al. (2018), and these are of growing concern in light of the rising importance of these institutions (Buchak et al. 2018, 2024*a*,*b*).

2 Institutional Details

2.1 Supply Chain of Mortgages in the US

Figure 1 illustrates the supply chain for mortgages, focusing on the originate-to-distribute segment. In the retail market, *originators* (lenders, namely banks and mortgage specialists) provide loans to borrowers seeking to buy a home or refinance an existing mortgage. Borrowers are presented with a rate sheet of note rates and upfront payments, known as "discount points," that specify the amount that the borrower would need to pay at closing to lower the note rate (Fuster et al. 2013). Based on these rate sheets, the borrower selects a lender and a note rate. The originator must then decide whether to keep the loan on its books (traditional banking), sell the loan to another lender in the wholesale market, or securitize the loan and sell it in the secondary market. Loans sold on the wholesale market are purchased by *issuers* (servicers) and then securitized.

We refer to banks that originate loans and then securitize them directly as being *vertically integrated* and say that they operate in the *retail channel*, and contrast this situation with the *wholesale channel* in which banks, referred to as *correspondent lenders*, sell the loans they originate in the wholesale market to issuers, who then securitize the loans.[6]

Some banks such as Quicken Loans or Bank of America rely almost exclusively on the retail channel to acquire loans. In contrast, several large shadow-banks such as PennyMac originate a very small quantity of loans directly, and rely on the wholesale market to acquire loans. However, most banks and shadow banks manage a diversified portfolio of retail and non-retail loans. As originators in the retail market, these lenders have to decide whether to keep a loan or sell it in the wholesale market and, as buyers in the wholesale market, they have to set lock prices in the posted-price market and submit bids in the auction market.

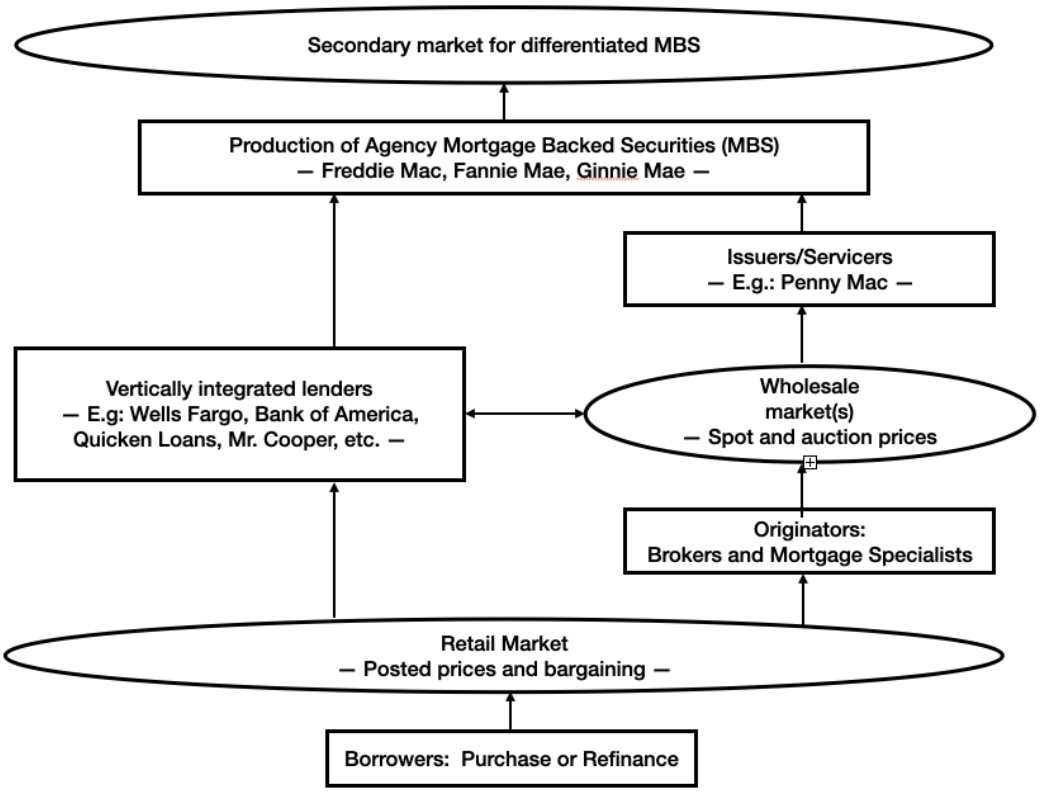
The production of mortgage backed securities (MBS) is done mostly by one of the three housing agencies: Fannie Mae, Freddie Mac, or Ginnie Mae.[7] The two government-sponsored enterprises (Fannie Mae and Freddie Mac) actively purchase conforming loans from banks. Although they are not guaranteed, these loans have implied government support against default. In contrast, Ginnie Mae guarantees MBS issued by approved lenders, backing loans insured by federal agencies such as the Federal Housing Administration (FHA) and Veterans Affairs (VA). Ginnie Mae insures these loans against default risk, but does not issue securities directly.[8]

[6] More specifically, a correspondent lender is a mortgage specialist or bank that underwrites and funds the mortgage at closing and then sells it to an issuer (typically) a few days after the closing date. The origination market also features *brokers*, who match a borrower to a bank that underwrites and funds the loan at closing. In our sample of Ginnie Mae loans, which covers the period from 2013 to 2022, roughly 50% of all securitized loans were originated by correspondent lenders, and 10% by brokers. The remaining 40% of loans were originated by vertically integrated lenders.

[7] There are also nonagency MBS issed by private financial institutions that are not guaranteed. For further discussion, see (Fuster et al. 2022).

[8] The largest subsidy category is FHA loans. These loans increased in popularity after the financial crisis, replacing privately securitized sub-prime loans, because the FHA program allows borrowers with low credit-scores and/or high

Figure 1: Supply chain of mortgages in U.S.



The securitization process involves pooling many different loans and issuing a mortgage-backed security (MBS) backed by these loans. The security is then sold (in tranches) to investors such as foreign banks, hedge funds, and pension funds. Banks are responsible for delivering and managing loan packages, subject to Ginnie's underwriting rules. In both cases, the banks typically retain the servicing rights to the loans. They collect the interest payment from the borrower each month, pay the MBS coupon to investors and the guarantee fee to the agency (to insure timely payment of principal and interest), and keep the difference, known as the *service income*. Both investors and banks bear the risk of loan prepayment.

Secondary market: Most agency MBSs are sold in the multi-issuer To-Be-Announced (TBA) market. TBA trades are forward contracts: a seller and buyer agree to trade a volume of loans (par value) of agency MBS at a specified price and future date (settlement date). The time between the date of the trade and date of the settlement is typically several weeks. When the trade is made, the mortgages in the MBS are not known, in part because they often do not yet exist. Instead, the two parties agree upon the issuer (agency guarantor), coupon, and maturity of the loans. In selecting

LTV ratios to access the mortgage market (although they do incur higher insurance payments over the life of the contract).

the pool of loans, the seller has an incentive to deliver loans that are more likely to default or be refinanced. However, according to Vickery & Wright (2013), the buyer understands this incentive, anticipates that loans will be adversely selected, and prices accordingly.[9] In principle, the market could unravel, but the lack of loan information makes the market more homogeneous and liquid, and the liquidity premium more than offsets the adverse selection discount (see Vickery & Wright 2013). An important benefit of the TBA market for lenders in the primary and wholesale markets is that it locks in a resale price for the loans that they originate or buy.

Banks with large volumes of loans can choose instead to sell their loans in another, less liquid, securities market, known as the "specified-pool" or "custom-pool" market, because the characteristics of the loans in the agency MBS are known when the trade is made. These securities are differentiated based on loan size and typically sell at a *payup* relative to the TBA. During our sample period, roughly 20% of the securitized loans were pooled in custom TBA-eligible securities.

The security customization decision amounts to deciding between going to the TBA market or to a custom pool, which reflects a trade-off between custom-pool premiums and transaction costs, and making a coupon choice based on a trade-off between liquidity and future cash-flows. How firms weigh these tradeoffs depends on their (i) size, and (ii) ability to acquire low prepayment risk loans. Small issuers do not have the scale to customize securities, and issuers with low-duration portfolios earn lower resale prices.

Wholesale market: Traditionally, correspondent lenders always sold their loans in a posted-price market. Buyers post wholesale rate sheets daily that specify the prices they were willing to pay for loans. These prices are known as *lock* prices because they vary with the lock-in period, which can be 0, 30, 60, or 90 days. They are also seller-specific, and contingent on a very coarse binning of loan characteristics.[10] More recently, online platforms such as *Optimal Blue* (OB) have provided correspondent lenders with the option to sell their loans individually in online auctions. Buyers in the auction have the same loan information they would have in the posted-price market. However, the auction allocation is likely to be more efficient (i.e., the buyer with the highest valuation is more likely to get the loan), since the bids that buyers submit are a continuous function of loan characteristics. The auction may also be less costly, because only the seller incurs holding costs.[11]

[9] This price is known in the finance literature as the "cheapest-to-deliver" price.

[10] Given these characteristics and a lock-in period, the correspondent lender selects a buyer, and that buyer then agrees to buy the loan shortly after closing. With this sales mechanism, both the seller and the buyer incur holding costs. They also bear the risk of "fall-out," which occurs when loan applications do not end up closing, either because the borrower does not qualify or because they turn down the offer.

[11] The OB auction is a first-price, sealed-bid auction that lasts one to two hours. The seller usually invites all the buyers in its network of buyers (typically 8 to 15 buyers) to submit bids, called *bulk* bids, for the loan. For more specialized loans, the seller may invite fewer buyers. The set of potential bidders varies across lenders, but only very little over time. Forming a relationship is costly because it involves both parties conducting due diligence as to the reliability and underwriting standards of their counter-party. In most auctions, nearly all invited bidders submit bulk bids, because bidding is essentially costless and is a way of maintaining the relationship with the seller. A bidder can always submit a low bid if it does not want to purchase the mortgage. An unusual feature of the auction is that the seller can always choose to sell the loan at the buyer's lock price if this price is higher than its bulk bid. Thus, from the seller's perspective, each buyer's actual bid is the maximum of its lock price and bulk bid, and the winning bid

The data do not allow us to distinguish between posted-price sales and auction sales, but auction sales represent a growing segment of the wholesale market. Specifically, auction sales accounted for over 75% of loan sales on the OB platform in 2019.

The value of each bid corresponds to the wholesale price for a \$100 loan. A bid of \$100 corresponds to paying the par-value of a loan. The mortgages are typically securitized and sold on the TBA MBS market and the MBSs fetch prices above the par value of the loan (loans generate interest). The TBA MBS price effectively acts as a floor on the bids that the seller will accept since it knows that buyers will get at least that price when they securitize the loan. From a bidder's perspective, the TBA MBS price corresponds to an observable reserve price.[12]

2.2 Distribution of rents

Here we characterize the additional rents earned from putting a loan in a custom pool rather than in the TBA. Let the value of a security i in a spec pool be given by V_i and its value in the TBA V_i'. Then, we can define the return to customization, or *payup*, as the difference: $V_i - V_i'$. We are interested in how these rents are distributed across issuers, originators, and borrowers, that is how the payup from placing a loan in a custom pool rather than in the TBA is passed-through from issuers to originators, and from originators to borrowers, or in the case of vertically integrated banks, directly from issuers to borrowers. In the wholesale channel, the pass-through of the payup to orginators is given by $\mu^w(V_i - V_i')$, where μ^w is the rate of wholesale pass-through. Similarly, pass through to retail is given by $\mu^p(1-\mu^w)(V_i-V_i')$, where μ^p is the rate of retail pass-through. In the vertically integrated channel since there is no wholesale transaction, the pass through to retail is given by $\mu^p(V_i - V_i')$. This is summarized in Table 1.

Table 1: Distribution of customization rents

	Wholesale channel			Vertical integration		
	Spec	TBA	Pass-through	Spec	TBA	Pass-through
Secondary	V_i	V_i'	$V_i - V_i'$	V_i	V_i'	$V_i - V_i'$
Wholesale	W_i	W_i'	$\mu^w(V_i - V_i')$			
Retail	P_i	P_i'	$\mu^p(1 - \mu^w)(V_i - V_i')$	P_i	P_i'	$\mu^p(V_i - V_i')$

is the maximum of the bulk bids and lock prices. The other unusual feature of the auction is that, after observing the bids, the seller can decide not to sell the loan, in which case it either resells the loan in a later auction or sells it in the secondary market. This event is common for conforming loans, but not for Ginnie Mae loans, since the seller of these loans bears the costs of securitization.

[12] There are some cases in which the seller accepts a price that is below the TBA MBS price and near the loan's par value. This can occur for loans that have an expected short duration (high prepayment risk) that will yield limited buyer interest. However, this does not imply that sellers lose money on these loans, since consumers typically pay upfront fees to the mortgage originators.

2.3 Ginnie Mae Loans

The Ginnie Mae guarantee program provides a government guarantee on payments to investors in the event of borrower default. While investors are protected, issuers still exposed to risk stemming from delinquency. The program supports high loan-to-value (LTV) lending, such as FHA loans with up to 97.5% LTV and VA loans that allow for zero down-payment. Notably, Ginnie Mae does not itself securitize loans; instead, banks or issuers assemble loan packages and bear the associated securitization costs. The program is dominated by non-bank issuers, who account for over 80% of participation.

Because Ginnie Mae guarantees loans with higher LTV ratios, borrowers tend to be riskier (both in terms of default and prepayment). FHA borrowers in particular are often first-time home-buyers who eventually transit to conventional products after building enough equity. As a result, these loans cannot be sold to the GSEs, Fannie Mae and Freddie Mac, which implies that this segment operates more or less independently of the other segments. The other reason for focusing on Ginnie Mae loans is that Ginnie Mae does not discriminate between lenders when setting its guarantee fee. It is fixed exogenously and the same for all lenders.[13] In this market, lenders and servicers make the securitization decisions. However, there are limitations, such as restrictions on coupon selection. Additionally, Ginnie Mae charges a uniform guarantee fee of 6 basis points to all lenders, regardless of risk or volume. Overall, Ginnie Mae accounts for approximately 25% of agency loan originations.

3 Data and descriptive statistics

In this section, we describe the data used in the empirical analysis and present statistics summarizing the data. Our focus is on 30-year fixed-rate mortgages insured by Ginnie Mae issued between October 2013 to December 2019 that had at least six months of performance data.[14]

3.1 Data

Wholesale and Retail: Information on the wholesale price is available through the mortgage auction data provided by *Optimal Blue* (OB). The dataset contains information at the loan-level based on a first-price, sealed-bid auction. For each mortgage, we (and the bidders) observe the following characteristics: original principal balance, loan-to-value ratio (LTV), note rate, loan type (purchase, refinance, etc.), property type, number of units, and zip code. Each mortgage is associated with an auction for which we observe the following variables: auction date, a seller ID,

[13] The GSE's also charge a fixed, monthly g-fee, but they allow the lender to "buy down" the fee by converting the flow into an upfront payment or, alternatively, to "buy up" the fee and receive an upfront payment from the GSE (see Fuster et al. (2013)).

[14] The 30-year fixed-rate mortgage is the most common, accounting for 93% of the loans in our data. The remainder is divided between fixed rate mortgages with different maturities (6%) and adjustable rate mortgages (1%).

the number of invited bidders, the value of each submitted bulk bid if it is above the bidder's lock price and the lock price if it is not, and the associated bidder ID. The sellers and bidders have unique identifiers, but we can infer their identities from eMBS and our dataset on the origination market. These data are available from January 2018 to August 2022, but we cut the sample earlier because of Covid, yielding a sample containing approximately 70,000 loans/auctions.

Retail prices are available from the *Home Mortgage Disclosure Act* (HMDA) dataset, which contains information on the near universe of new mortgage transactions (including rejections), as well as key demographic characteristics of borrowers such has race, gender and income. The key variable is the upfront lender fee (available since 2018), which can be thought of as the retail price. The sample up until the start of Covid sample contains roughly 60,000 loans.

To match HDMA loans with OB auction loans, we conduct a strict match on the following loan characteristics: sponsoring agency, loan term, property location (zip code and county), note rate, occupancy status, number of units, a dummy variable for whether the loan was a home purchase, and a dummy variable for whether the loan was an adjustable-rate mortgage. We then perform a fuzzy match on the continuous characteristics: loan amount, yearly income, DTI ratio and CLTV ratio. Doing so, we were able to match approximately 85% of auction loans to a unique loan in HMDA. We employ similar procedures to match OB auction loans to loans in eMBS issuances and HMDA originations to loans in eMBS issuances. We are able to match nearly 60% of HDMA originations with a unique loan in eMBS and match over 91% of auctioned loans with a unique loan in eMBS.

Securities and loan performance: *eMBS.Inc* provides detailed information on all mortgage backed securities insured by one of the three agencies and issued between January 2013 and the present, along with their component loans. Most importantly, this dataset provides information on the pooling choice. The MBS characteristics contained in the dataset include the CUSIP (security identifier), coupon rate, issuance date, issuer and servicer identity, maturity, and par amount. The loan characteristics include the CUSIP with which it is associated, the subsidizing agency, the loan type (purchase, refinance, etc.), original principal balance, note rate, loan-to-value (LTV), debt-to-income ratio, FICO score, number of units on the property, state, origination type (retail or non-retail), and the identity of the issuer, which, in the case of Ginnie Mae, is the servicer. For each component loan, we observe the unpaid principal balance on a monthly basis until it has either been paid off or defaulted. We use the unpaid balance for each loan in March 2022 to measure the loan duration until full payment. We use the above information to infer the service income earned each month by the servicer. The dataset contains approximately 14 million loans.

We get the daily TBA prices from Bloomberg. Bloomberg sources its pricing data from Trade Reporting and Compliance Engine (TRACE), which is a database of trades maintained by Financial Industry Regulatory Authority (FINRA). This database contains the universe of TBA bond trades for which one of the parties was registered with FINRA. TBA MBS trades are typically made with

Table 2: Variance decomposition table from TRACE prices

	Variance decomposition	
	(1) SD	(2) %
Pay-up deviations	0.81	1.00
Borrower characteristics (X)	0.32	0.15
Issuer	0.30	0.13
Covariance: X and Issuer	-0.01	-0.02
Residual	0.69	0.73
Observations	62626	62626

Dep. variable: Pay-up deviation within week and segment (date, size and coupon). Standard-deviations are weighted by the size of spec-pools.

a FINRA registered dealer so TRACE should contain nearly all trades (see Gao et al. 2017). The daily price of a TBA security corresponds to the last observed trading price as of that date.

We use the TRACE dataset to obtain transaction prices for spec-pool MBS in the OTC market. We perform a fuzzy match between TRACE and Ginnie-Mae securities. The resulting sample contains 767,695 loans and 52,675 securities. Our eMBS dataset ends in July 2022, and we drop observations after this date to make the analysis more comparable with our adverse-selection sample.

Since each security is small (on average 16 loans), and is purchased by a single buyer (e.g. an investment bank), and since TRACE does not report CUSIP-level transactions, we impute spec-pool prices using a hedonic regression at the security j level:

$$V_j(c) = \underbrace{\bar{X}_j\beta + \text{Issuer FE} + \text{Segment FE}}_{\hat{V}_j(c)} + \text{Week FE} + \text{Error}.$$

The segment is at the level of coupon x loan size category x issue date. Results are presented in Table 2. The R^2 of the hedonic is 83%, with (i) 15% of the cross-sectional dispersion explained by borrower characteristics, (ii) 13% by the issuer fixed effects, and (iii) 73% being residual dispersion.

3.2 Descriptive statistics

Using data from HMDA, we find that the wholesale market is highly concentrated, with the top four banks purchasing more than 45% of all agency loans. The retail market is less concentrated, with the top four originators acquiring less than 20% of the mortgages. This difference highlights the importance of scale when selling loans in the secondary market, and the lack of scale when selling loans in the wholesale market. Large issuers can acquire a diversified pool of loans in the retail and wholesale markets, enabling them to produce higher value securities and to achieve lower servicing

Table 3: Summary statistics on issuers in Ginnie Mae MBS

	Full Sample				
	mean	sd	p10	p50	p90
Loan Interest Rate	3.82	0.41	3.35	3.82	4.28
Service Income	0.43	0.06	0.36	0.43	0.50
Loan Amount (x100K)	2.28	0.53	1.64	2.27	2.95
Loan-to-Value	93.43	3.87	88.96	94.29	96.64
Credit Score	682.42	24.82	660.21	684.49	708.46
Debt-to-Income	40.87	3.13	37.67	41.28	43.94
1(DTI > 42)	0.55	0.14	0.38	0.56	0.70
1(VA-Backed)	0.32	0.21	0.04	0.29	0.56
1(Retail)	0.70	0.37	0.04	0.94	1.00
1(Correspondent)	0.19	0.32	0.00	0.01	0.80
Survival: 12-month	0.91	0.06	0.84	0.92	0.98
Survival: 36-month	0.59	0.15	0.41	0.58	0.77
1(Custom)	0.11	0.18	0.00	0.02	0.34
1(TBA)	0.89	0.18	0.66	0.98	1.00
1(High Coupon)	0.93	0.08	0.82	0.96	1.00
Log average monthly loan volume	4.63	1.84	2.32	4.67	7.14
Observations	371				

Reports the summary statistics of issuers in Ginnie Mae.

costs. By contrast, the barriers to entry in the retail market are much lower. Originators need only to invest in local networks of loan officers and real-estate agents, and they require relatively little liquidity to operate when they can sell loans at competitive prices in the wholesale market. Thus, the emergence of the online auction market has generated potentially important gains from trade: economies of scale upstream and geographic segmentation downstream.

Table 3 presents summary statistics on the issuers in our sample. The key takeaway is that the average level of customization across issuers is 11%, but there is considerable dispersion. At the 10th percentile the level of customization is 0%, while the 90th percentile is 34%. We can also see that there is heterogeneity in the survival probability of issuer loans. The average 12-month survival is 91%, but it is 84% at the 10th percentile and 98% in the 90th. Issuers also differ tremendously in their loan volume. Log monthly volume is 2.32 at the 10th percentile compared to 7.14 at the 90th.

Table 4 provides summary statistics on the characteristics of the loans in our sample. Note rates are typically quoted on a 1/8 percentage points (p.p) grid. The note rate varies between 3% and 5% and averages 4%. The average loan size is $240K, but there is considerable variation. The loans typically have a very high LTV, with 58% having values between 95 and 100. Moreover, the FICO scores of the borrowers are a relatively low 689, which is just above 670, the cutoff between

Table 4: Summary statistics on mortgages in Ginnie Mae MBS

	Full Sample		Coupon Choice		No Coupon Choice	
	mean	sd	mean	sd	mean	sd
Loan Interest Rate	3.80	0.77	3.67	0.81	3.88	0.74
Service Income	0.43	0.16	0.33	0.18	0.49	0.10
Loan Amount (x100K)	2.37	1.20	2.42	1.24	2.33	1.18
Loan-to-Value	93.05	11.18	91.88	12.11	93.76	10.51
Credit Score	689.34	57.16	693.58	58.20	686.56	56.30
Debt-to-Income	41.28	9.72	41.01	9.82	41.44	9.65
1(DTI $>$ 42)	0.58	0.49	0.60	0.49	0.58	0.49
1(VA-Backed)	0.40	0.49	0.44	0.50	0.37	0.48
1(Retail)	0.44	0.50	0.44	0.50	0.43	0.50
1(Correspondent)	0.44	0.50	0.42	0.49	0.45	0.50
Survival: 12-month	0.88	0.33	0.88	0.33	0.88	0.32
Survival: 36-month	0.51	0.50	0.53	0.50	0.51	0.50
1(TBA)	0.81	0.39	0.82	0.39	0.80	0.40
1(High Coupon)	0.94	0.25	0.84	0.37	1.00	0.00
Observations	13140947		5192985		7947962	

Reports the summary statistics of loans that entered Ginnie Mae 30 Year Fixed Rate MBS's issued between October 2013 and December 2019 that had at least 12 months of performance data. LTV, debt-to-income ratio, and FICO scores are missing for some of the mortgages in our dataset.

"fair" and "good" credit. The observed LTV and FICO scores make sense given the objective of the subsidy programs. The last two columns display statistics for a restricted sample that contains only those loans for which there is no coupon choice. We will mostly focus on this sample in our analysis.

As mentioned above, the vast majority of spec-pools are segmented simply by loan size, and the industry standard is to construct pools based on six maximum loan size thresholds:

$$k \in \{85K, 110K, 125K, 150K, 175K, 200K\},$$

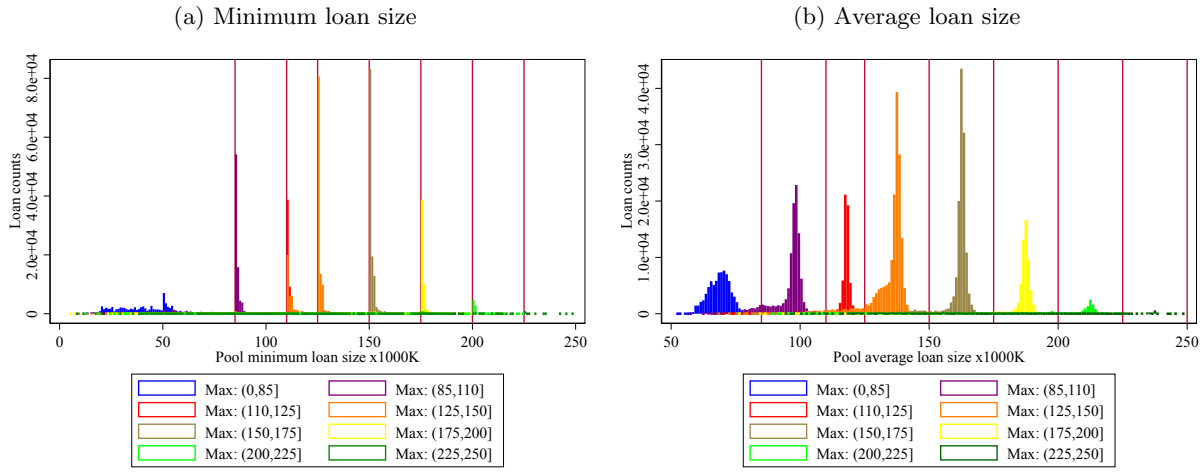
leading respectively to six spec pools plus one additional category (200K+) containing loans with unrestricted loan sizes:

$$(0, 85K], (85K, 110K], (110K, 125K], (125K, 150K], (150K, 175K], (175K, 200K], 200K + .$$

Figure 2 summarizes the loan-size distribution within custom securities of different types.[15] Each

[15]The last category includes securities with larger loans that might be differentiated along other dimensions (e.g. FICO $\geq$ 700, or New York state loans). Also, loans above the jumbo cutoff cannot be placed in the TBA and so must be customized. In our sample, only 15% of loans in custom pools belong to this category, and so we omit it from part of our analysis.

Figure 2: Distribution of loan size across spec-pools



histogram is weighted by the number of loans in each pool, so the y-axis is the number of loans in each size and security-type bin. The different colors correspond to the types of spec-pools. The "blue" securities are pools with maximum loan size less than 85K. The most common category includes the pools with max loan size between 125 and 150 (22%).

Figure 2a plots the distribution of minimum loans in each category (excluding the "other pool" category). If all spec pools with maximum loan size less than $250K were perfectly segmented, the distribution of the minimum would correspond to the maximum of the next lowest category. For instance, the yellow category shows that the vast majority of pools with max loan size between 175 and 200 have a minimum at 175, which means that the typical range is 25K. This corresponds to a pool exclusively with loans between 175 and 200. Although pools are not perfectly segmented, we see that most custom securities have a loan size range of 25K or 15K (except for the $85K pool). The segmentation is less clear for the 125K cutoff. This is because some issuers create a single pool category from 110-150, while others issue two types of pools 110-125 and 125-150.

Figure 2b plots the distribution in the average loan size per security. As we can see, securities are highly differentiated by size, and the average size distributions reveal very little overlap across categories. Importantly, securities are almost perfectly differentiated along the average loan size dimension, despite the fact that the distribution of the minimum loan size per pool exhibits a long left tail. Therefore, as a first-order approximation, the data suggest that firms bundle loans with loan sizes on a 25K grid (15K for loans between 110 and 125), consistent with our modeling assumption that loans "fit" in a single spec-pool. This suggests that spec-pools containing loans with similar sizes are more valuable than diversified pools with the same average loan size.

An implication of the high level of segmentation among custom securities is that the expected

Table 5: Summary stats spec pool prices TRACE-eMBS match

	Spec pool size categories							
	(1) 85K	(2) 110K	(3) 125K	(4) 150K	(5) 175K	(6) 200K	(7) 225K	(8) 250K
SP Pay-up	2.35	2.15	1.93	1.82	1.80	1.80	1.63	1.51
	1.63	1.65	1.59	1.51	1.53	1.54	1.49	1.58
Transaction Price	107.09	106.77	106.38	106.24	105.98	105.83	105.57	105.42
	2.42	2.35	2.27	2.21	2.18	2.27	2.26	2.36
WA Loan size	72.04	97.14	117.84	136.00	162.37	186.80	212.02	236.95
	5.96	5.48	3.13	5.51	4.88	5.14	5.69	6.37
WA Interest rate	4.33	4.24	4.20	4.20	4.12	3.96	3.83	3.84
	0.70	0.76	0.80	0.82	0.86	0.87	0.83	0.88
WA Credit score	672.76	670.28	669.80	668.40	668.60	670.67	673.94	677.41
	27.21	28.33	29.88	30.85	30.63	31.58	31.34	30.66
WA Loan size x Rate	3.10	4.10	4.93	5.69	6.68	7.39	8.11	9.11
	0.56	0.77	0.94	1.12	1.41	1.64	1.78	2.11
Trading date difference	21.68	20.60	20.09	20.19	19.82	19.55	18.67	19.87
	18.78	17.93	17.30	17.67	17.61	17.58	16.30	17.13
WTA DTI	29.15	26.92	25.44	24.73	21.34	16.38	13.04	12.55
	14.18	17.12	18.63	19.32	20.51	20.19	19.09	18.99
WA LTV	94.69	94.45	94.97	95.56	95.90	96.15	96.32	96.86
	4.97	5.13	4.53	4.10	3.89	3.90	3.92	3.30
Nb. loans in pool	21.36	17.15	14.62	14.91	13.53	13.25	11.95	12.36
	16.85	13.33	11.17	11.74	10.52	10.08	8.78	8.50
Observations	6356	9646	7291	11479	9586	6618	4169	2343

Each cell shows the mean (top) and standard-deviation (bottom).

xxxxx

resale value of mortgages in the secondary market is discontinuous in loan size. Our model of security pooling predicts that a discontinuity can arise from two sources. First, loans on the right side of a customization threshold can be less likely to be sold in the spec-pool market. Second, the average size of pools in which a loan is securitized is discontinuous in loan size.

Table 5 uses TRACE and eMBS data to characterize these pools. From the table we can see that pay-ups (and transaction prices) are decreasing in loan size. There is also considerable dispersion within pools. In contrast, there is very little dispersion in loan size within pools, since most loans are clustered at the minimum, as seen in Figure 2a. Trading takes place within the first month of issuance. We can also see that there are only 15-20 loans per pool.

Table 6 summarizes the main outcome variables in the auction data. The bids are typically above the par value of the loan and the highest bid is typically well above this amount. The money left on the table (highest bid less the second highest bid) is on average 0.20. Although this is a

Table 6: Summary of Bids

Variable	N	Mean	SD	Pctl10	Pctl90
# Bids in Auction	42,852	6.731	4.301	1	12
# Serious Bids in Auction[a]	42,852	6.192	4.264	1	12
Bid	288,454	104.214	1.487	102.325	105.780
Serious Bid	265,333	104.345	1.331	102.614	105.826
Highest Bid	42,779	104.765	1.450	102.869	106.436
Money on Table[b]	32,518	0.237	0.467	0.020	0.534
Money on Table (Auctions $\geq$ 2 Serious Bids)	31,259	0.212	0.300	0.020	0.491
TBA MBS Price Associated with Loan[c]	42,779	103.180	1.349	101.703	104.891
Bid - TBA MBS Price	288,454	1.070	0.994	0.109	2.040
Serious Bid - TBA MBS Price	265,333	1.248	0.632	0.440	2.069
Highest Bid - TBA MBS Price	42,779	1.586	0.759	0.710	2.487
Auction Reserve Price[d]	33,571	104.356	1.373	102.505	105.890
Bid - Reserve Price	231,768	−0.222	0.890	−0.875	0.460
Serious Bid - Reserve Price	212,977	−0.115	0.547	−0.703	0.470
Highest Bid - Reserve Price	33,571	0.397	0.572	−0.059	1.049
Reserve Price - TBA MBS Price	33,571	1.179	0.850	0.177	2.149

[a] Serious bids are those that are above the TBA MBS Price - 1/32.
[b] Money on Table is the highest bid less the second highest bid and is only computed for auctions with at least two bidders.
[c] If a mortgage can go into MBSs with two different coupons, we choose the price of the MBS with the higher coupon.
[d] Data on the reserve price were not available for a subset of the auctions.

small amount relative to the par value, it is a substantial portion of the bid once the MBS price is netted out. The bids are nearly always above the MBS price, which is consistent with the idea that it acts as an observable floor on the bids. In comparison, the lock price is effectively secret and it is common to see bids below the reserve.

4 A Model of Loan and Security Valuations

In this section, we develop a framework for measuring the willingness-to-pay for servicing/securitizing mortgages and for understanding how securitization decisions determine the resale price of a mortgage. The model illustrates tradeoffs between loan duration, liquidity, and transaction costs, and it highlights the role of firm asymmetries. Our first objective is to derive testable predictions related to the information structure generating securitization decisions that we will take to the data in Sections 5.2 and 5.3. The second objective of the model is to motivate the pass-through analysis performed in Section 5.4 by highlighting the fact that issuer asymmetries lead to incomplete pass-through of custom pool prices, but complete pass through of TBA price.

A mortgage generates two sources of income for a bank that retains servicing rights: (i) an upfront security price obtained from the sale of the loan in the secondary market, and (ii) monthly service income. The value of the servicing rights does not depend upon the type of security in which the loan is placed, but the resale price does. Importantly, this process is identical for loans originated and serviced by the same financial institution (i.e., *retail*) and for loans originated by correspondent lenders or brokers (i.e., *wholesale*). We focus primarily on loans acquired via auctions because our data come from a wholesale loan exchange platform, but our model of security valuations applies to both retail and wholesale loans.

We specify issuer willingness-to-pay for loan i as:

$$WTP = \underbrace{(r_i - c - g) \times \underbrace{\text{Loan duration}}_{\bar{M}_i}}_{\text{Mortgage servicing rights (MSR)}} + \underbrace{\text{Resale Value}}_{V_i} - \underbrace{\text{Cost+Retention option}}_{\text{Net fixed cost } (F)}, \tag{1}$$

where r_i is the note rate of mortgage i, c is the coupon that must be paid to investors, and g is the guarantee fee paid to the agency.

4.1 Security customization

After acquiring a portfolio of loans (either directly from consumers or indirectly from correspondent lenders), the issuer chooses for each loan whether to place it in a multi-issuer or a custom pool. We denote this pool choice as $k \in \{TBA, \bar{l}_i\}$, where $\bar{l}_i$ denotes the custom pool size segment of loan i.[16] The issuer's portfolio is summarized by $\{L_i, F_i\}$, $i = 1, .., Q$, where F_i represents the distribution of T_i given its characteristics and Q denotes the size of the portfolio. The portfolio's quality is characterized by higher expected cash flows conditional on the attributes. These quality differences across issuers are assumed to be observed by investors in the sense that issuers can develop reputations for issuing high- or low-quality loans.

Loans are segmented by size (based on the customization grid defined earlier) and coupon, and so we write that an issuer has Q_{ck} loans in its portfolio with coupon c and (maximum) size-segment k. These loans are essentially the same size, but are differentiated by other characteristics (e.g., FICO, state). We order them from highest to lowest based on their expected value to investors. This ordering is typically equivalent to ranking the loans based on their expected duration. We assume that an issuer takes the market's segmentation on loan size and quality as given when it makes securitization decisions.

Consider the pooling problem for loans in segment (c, k):

$$\max_{q_k \in [0, Q_{c,k}]} \quad q_k V_k(q_k; c) + (Q_{ck} - q_k) V_{tba}(c) - \kappa 1(q_k > 0), \tag{2}$$

[16] Banks also make a decision regarding the coupon rate. We focus here on the pooling decision by concentrating on loans without a coupon choice, and address the decision about which coupon to select in Appendix XX.

where κ is the cost of producing the security and $V_k(q_k, c)$ is the price that the investor pays for each loan in the security. If the spec-pool market is competitive, then this price is equal to the average expected revenues that an investor earns from the loans in the pool. More precisely, in a competitive equilibrium,

$$V_k(q_k, c) = \frac{1}{q_k} \sum_{i=1}^{q_k} L_i v_i(c), \tag{3}$$

where

$$v_i(c) = c \times E[M(T_i)|s_i] + E\left[\delta^{T_i} B_{T_i}|s_i\right],$$

is the expected value of loan i to investors. The first term is the coupon revenues from the loan and second term is the discounted repayment of the outstanding balance (B) when the loan terminates. Assuming an interior solution $q_k^* \in (0, Q_{c,k})$, one can use equation (3) to show that the solution to bank j's revenue maximization problem is to choose q_k^* such that the expected value of the marginal loan $v_{q_k^*}(c)$ is equal to $V_{tba}(c)$ (independent of k). This leads to a threshold strategy: all loans with expected values above $v_{q_k^*}(c)$ are placed in a spec-pool k, and loans with expected values less than $v_{q_k^*}(c)$ are pooled in the multi-issuer security. This threshold does not vary across issuers or loan-size bins.

However, two other solutions are also possible. The first is that $q_k^* = 0$. If an issuer has too few type k loans, then the gains from creating a type k spec security can be less than the costs κ. Even if it has a sufficient number of loans of type k, it might still fail to meet the threshold if these loans are of poor quality. In either case, the bank does not create a type k spec-security and allocates its type k loans to the TBA pool. The other possibility is that $q_k^* = 1$. In other words, *all* of the issuer's type k loans meet the threshold. In this case, the issuer allocates all loans to the spec-pool and none to the TBA pool. As we document in the next section, both of these events are common. Indeed, there are some issuers, typically the smaller banks, who always allocate their loans to the TBA pool.

The model implies the following predictions regarding customization:

Prediction 1. *The TBA is adversely selected, which implies that $V_k > V_{TBA}$ for all k, since the marginal loan is equal to V_{TBA}. Moreover because pre-payment risk is more severe for big loans, there should be a clearl ordering of spec-pool prices:*

$$\bar{V}_{85}(c) > \bar{V}_{110}(c) > \bar{V}_{125}(c) > \bar{V}_{150}(c) > \cdots > \bar{V}_{tba}(c)$$

.

Prediction 2. *Under the assumption that the custom market prices risk based on the characteristics of loans beyond just size, selection into the custom market will depend on all loan characteristics and not just size. In other words, selection into the custom market should depend on observed borrower and issuer attributes that correlate with pre-payment risk.*

Prediction 3. *Portfolio size and quality explain heterogeneity in the customization strategies across issuers.*

4.2 Implications for market power

Differences in resale value can lead to market power. In the wholesale market, competition at the auction depends on differences in resale value. Market power effects differ as a function of loan size. For small loans, heterogeneity in WTP increases markups and decreases pass-through of security prices. For large loans, symmetry in resale value decreases markups and increases pass-through of security prices. The pass-through of the TBA price will be one for loans that go to the multi-issuer pool. The key assumption is that willingness-to-pay is additively separable in the TBA price. Given this assumption, the bid function is additively separable in the TBA price. Intuitively, when the TBA price enters the bid function additively, then competition forces every bidder to adjust its bid by the amount of the TBA price. The pass-through rate of one then follows from the fact that the bidder's bid is measured in the same units (i.e., dollars) as the TBA price.

On the retail side, the combination of information frictions and originator heterogeneity can lead to market power. It has been well-documented that consumer search in the mortgage retail market is limited, such that borrowers are generally unaware of resale values (see for instance Allen et al. 2014, 2019; Agarwal et al. 2024; Alexandrov & Koulayev 2017; Bhutta et al. 2025). There are only minimal gains from searching for a consumer whose loan goes into TBA, but the market is competitive and so limited search is not costly.In contrast, for a custom loan, the gains from search are large, but it is hard to identify a lender offering potential gains because of important dispersion in valuations.

The model implies the following predictions regarding pass-through and market power:

Prediction 4. *TBA pass-through is higher in the wholesale market than in the retail market.*

Prediction 5. *Within the wholesale market there is incomplete pass-through of the spec-pool pay-up and complete pass-through of TBA prices.*

5 Empirical analysis

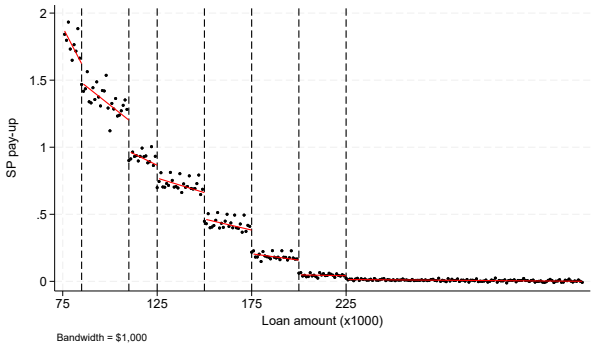
The objective of our empirical investigation is to document heterogeneity in the return from securitization across issuers and to understand the determinants of this heterogeneity. Our analysis is broken into three steps. In a first step we provide evidence of discontinuities in security prices (Prediction 1). Next we show that selection into the custom market depends on observed borrower and issuer attributes that correlate with pre-payment risk (Prediction 2). We then study the determinants of the return to customization across banks and consider the importance of screening, scale economies, and loan retention (Prediction 3). Finally, we measure pass-through of TBA and spec-pool pay-ups in the wholesale and retail markets (Predictions 4 and 5).

5.1 Evidence of discontinuities in security prices

Figure 3 provides evidence of discontinuities in security prices. Figure 3a displays the average security price minus $V_{tba}(c)$, while Figure 3b shows the average spec-pool price minus $V_{tba}(c)$. Both display obvious discontinuities at the loan-size cutoffs, confirming that there is a clear ordering of spec-pool prices.

Figure 3: Evidence of discontinuities in security prices

(a) Average security price - $V_{tba}(c)$



(b) Average spec-pool price - $V_{tba}(c)$

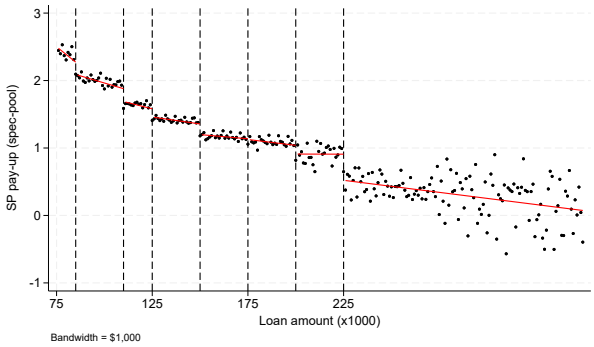


Figure 4 presents the distribution of spec-pool pay-ups across loan-size bins. It shows a clear relationship between the average loan size and the price of spec-pool securities. It also confirms that within each bin there is cross-sectional dispersion that remains. The pay-up over the TBA price is on average $2.63 for the smallest loan category, and essentially zero for spec-pools with average loan size above $300K.

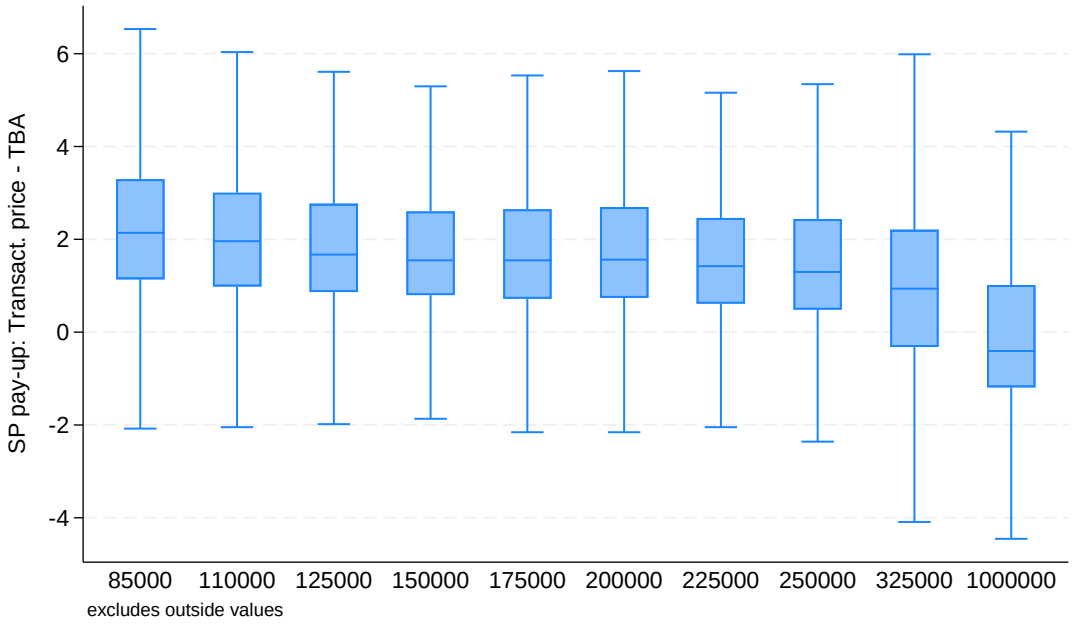
5.2 Adverse selection at the securitization stage

The value of security customization comes from the ability of banks to exploit their information advantage when assembling MBS pools We consider three sources of private information: (i) loan attributes (unpriced attributes in the TBA market), (ii) private signals from proprietary risk models, and (iii) systemic differences in loan duration across banks.

We test the hypothesis that there is adverse selection in the TBA market by comparing the performance of loans placed in multi-issuer and custom pools. In particular, if issuers securitize high-performing loans in custom pools (because the security price is increasing in loan duration), loans placed in multi-issuer pools should have lower survival probability. Specifically, we estimate the following linear regression model of early pre-payment risk:

$$100 \times 1(T_i > 12) \quad = \quad \lambda 1\left\{\text{Multi-issuer MBS}\right\} + FE_i + \gamma Z_i + \epsilon_i, \tag{4}$$

Figure 4: Distribution of spec-pool pay-up



where T_i is realized duration, FE_i is a Date x Rate fixed-effect, and λ measures the conditional expectation of the difference in survival probability for loans placed in multi-issuer and custom pools.

To identify the source of selection, we estimate λ varying the set of controls Z_i. The price of the TBA MBS securities is a function only of aggregate information available to investors at the trading date (typically a few weeks before the pool issuance date). Our baseline specification therefore compares the ex-post performance of eligible loans that are securitized on the same date. We do so by controlling for note-rate/issuance date fixed-effects (i.e., $r \times t$).

Next we also condition on the identity of the issuer (i.e., aggregator or retail originator) selling the loan. We do so by augmenting the fixed-effects to compare loans securitized on the same date, with the same note rate, and the same issuer. Finally, we also control for characteristics of the loans that are observed by the lender/issuer, but not by the investor buying the TBA security. This includes the financial attributes of the borrower, contract characteristics, as well as the origination channel. Note that the investor also does not observe the identity of the issuer.

Table 7 summarizes the results, and strongly confirm the hypothesis that loans placed in multi-issuer pools should have lower survival probability. The first row presents the estimate of λ across different sets of controls. Without conditioning on other loan or issuer characteristics, we find that loans placed in multi-issuer pools are 11% more likely to be pre-paid within the first year. Given

Table 7: Adverse selection test results – Security customization

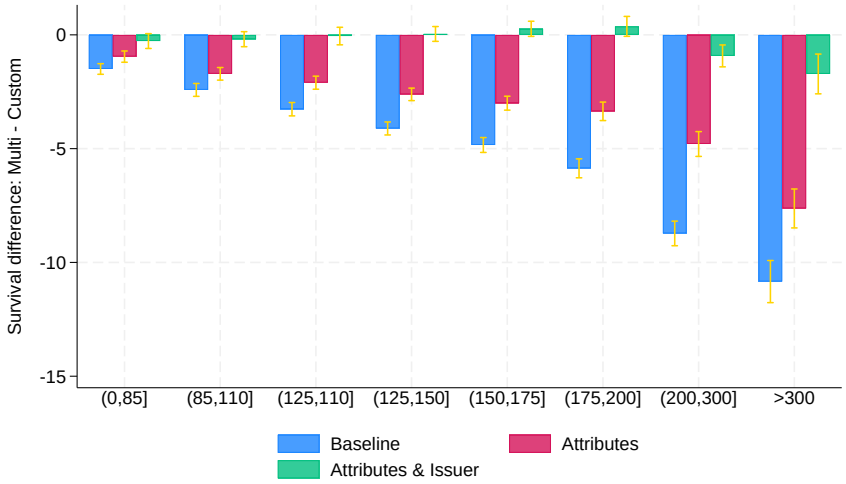
VARIABLES	(1)	(2)	(3)	(4)
1(Multi-issuer pool)	-11.0	-3.98	-2.03	-1.75
	(0.23)	(0.17)	(0.19)	(0.18)
Observations	10,856,333	10,856,333	10,856,331	10,817,280
R-squared	0.064	0.122	0.136	0.174
Loan characteristics	no	yes	yes	yes
Issuer FE	no	no	yes (+)	yes (x)
Latest issuance date	2021/2	2021/2	2021/2	2021/2
Fixed effects	Month x rate	Month x rate	Month x rate	Month x rate
Mean dep. var.	86.8	86.8	86.8	86.8
Fraction multi-issuer pool	0.82	0.82	0.82	0.82

that the average 12-month survival probability during our sample period was 87%, this difference suggests a very severe adverse selection problem. The difference is reduced to 4% when we condition on loan attributes, and is further reduced to 1.8% when we condition on the identity of the issuer. We therefore conclude that more than half of the adverse selection in the MBS market is due to observed characteristics of the loans. The identity of the issuer in particular is an important predictor of pool choice and loan survival.

Next, we measure the importance of adverse selection across loans of different sizes. In particular we estimate equation 4 separately by loan size categories: less than 85, 85-110, 110-125, 125-150, 150-175, and 175-200, 200-300, and greater than 300. Recall that the first six correspond to the standard cutoffs used to customize securities. Figure 5 plots the estimated coefficient $\hat{\lambda}$ obtained with and without loan and issuer characteristics. "Baseline" presents estimates from specification (1), "Attributes" corresponds to specification (2), and "Attributes and issuer" corresponds to specification (3). We interpret the difference between the first and second specifications as capturing adverse selection based on unused borrower observables (unused in the sense that they are not used to price TBA contracts, see Finkelstein & Poterba 2004, 2014). We interpret the difference between the second and third specifications as measuring the amount of private information about individual loans. As before the difference between the second and third measures the importance of issuer unobserved heterogeneity. The figure illustrates two important results.

First, the scope for adverse selection in multi-issuer pools is monotonically increasing with loan size. The survival-probability difference between loans in custom and multi-issuer pools is 10% for loans above $300K, compared to around 1% for loans less than $85K. Therefore, not only are smaller loans less likely to be prepaid early than large loans, but smaller loans are also significantly more homogenous in terms of expected duration. This is consistent with the idea that borrowers

Figure 5: Adverse selection and security customization by loan size bins



Period: August 2013 to December 2019. Control variables: FICO score, Loan size, single borrower, DTI, loan purpose, FHA/VA. Fixed-effects: (green) note-rate x month, (orange) note-rate x month x issuer, state. Standard errors clustered at the rate-date level.

with small loans have less to gain from refinancing when interest rates fall, which makes it more difficult for banks to predict the prepayment risk of individual borrowers. The repayment decisions of borrowers with small loans depend primarily on factors that are unobservable to banks, such as job relocation and divorce. In contrast, borrowers with large loans have more to gain from refinancing their mortgages, and banks can more easily distinguish between loans with higher or lower prepayment risk.

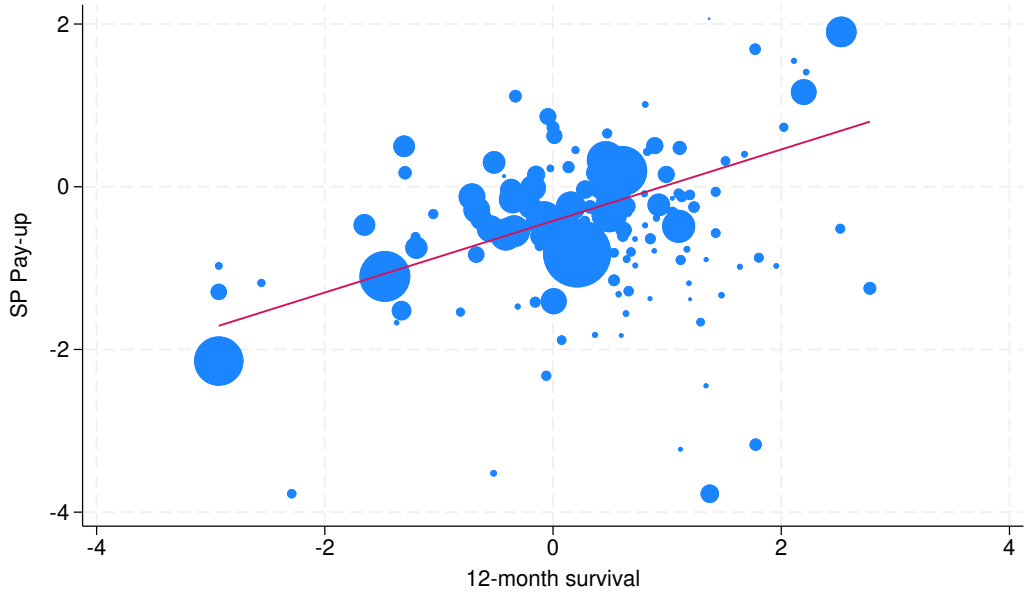
The second takeaway relates to the type of information that banks use to allocate loans across securities. For loans below $200K, the results show that the selection of custom securities is driven entirely by observable differences in loans and issuer characteristics. For large loans, roughly one third of the difference is attributable to private information that issuers have about the quality of individual loans, and most of the remaining differences are due to issuer unobserved heterogeneity.

Although it might be tempting to conclude that private information about loan duration is not the main driver of selection. We cannot conclude this from Figure 5 because most issuers put all or none of their loans in custom pools (i.e., there is a corner solution), especially for loans less than $200K. The regression specifications that control for coupon x date x issuer fixed effects therefore identify λ_k by comparing a relatively small number of issuers.

5.3 Heterogeneity in the returns to securitization

Figure 6 displays the relationship between the average spec-pool payup and loan duration (as measured by 12-month survival) across issuers (for those with at least 20 spec-pool securities). The

Figure 6: Relationship between average spec-pool pay-up and short-run survival across issuers



Issuers with at least 20 spec-pool securities.

figure shows that issuers with higher quality loans (loans with longer survival probability) receive higher spec-pool pay-ups. This is consistent with the fact that banks with longer duration loans are more likely to produce spec-pool securities. The correlation remains positive when we condition on other characteristics of banks (i.e. size, origination channel, retention rate, etc). The correlation is also stronger when we weight the data by Issuer size (measured by the total number of loans securitized between 2013-2022).

Having established that the return to customization differs across banks, here we investigate the sources of this heterogeneity, focusing on (i) loan screening (loan survival) and (ii) economies of scale and transaction costs. To do so we estimate the following regression:

$$\text{Customization issuer FE}_j \quad = \quad \beta_1 \text{Survival issuer FE}_j + \beta_2 \text{Log monthly volume}_j + e_j$$

We hypothesize that (i) $\beta_2 > 0$, i.e., that larger volume is associated with more customization (*selection*) and that (ii) $\beta_1 > 0$, i.e., return to customization is larger for banks with longer duration pools. Results are presented in Table 16 and they confirm the hypotheses. The return to customization depends on scale and loan quality. Regarding the former, banks need enough loans to justify transaction costs in the OTC market, but must acquire lower duration loans to increase volume. Regarding the latter, banks with systematically better pools are more likely to produce single-issuer pools. Servicers that invest in an *origination arm* are less likely to customize. These

Table 8: Determinants of heterogeneity in customization

VARIABLES	(1) Customization	(2) Customization	(3) Customization	(4) Customization
SP Pay-up				0.159*
				(0.0854)
Monthly volume (log)	0.288*	0.413***	0.311***	0.316***
	(0.162)	(0.0658)	(0.0643)	(0.0690)
Survival		0.385***	0.388***	0.309***
		(0.0566)	(0.0421)	(0.0468)
Retail origination			-0.154***	-0.172***
			(0.0553)	(0.0561)
Constant	-1.246**	-1.726***	-1.300***	-1.268***
	(0.596)	(0.260)	(0.270)	(0.280)
Observations	133	133	133	133
R-squared	0.090	0.534	0.582	0.598

Number of observations reports number of issuers. Observations are weighted the number of loans per issuer. SE clustered by issuer. *p<.1; **p<.05; ***p<.01. Weighted version. Figure xx in the Appendix shows the unweighted version. All variables are divided by the standard-deviation across issuers.

vertically integrated servicers typically have shorter duration loans since they have an incentive to reduce expected loan duration in order to collect closing fees – moral hazard. There is limited evidence that moral hazard affects the value of spec-pools. Finally, we can also see that there is a positive correlation between spec-pool pay-up and the propensity to customize.

5.4 Evidence of market power

In this section we test the hypothesis that customization leads to market power and investigate how customization rents are distributed. Since custom securities are associated with higher transaction costs, it is an empirical question whether or not customization leads to higher loan prices. Moreover, since banks have heterogeneous access to the spec-pool market, the pass-through of the spec-pool pay-up is not necessarily complete. Our analysis makes use of the OB-HMDA-eMBS matched dataset to perform the analysis.

Before discussing our measure of pass-through, we start by measuring the effect of customization on the dispersion of bids within auctions. Figure 8 displays wholesale price by pool type and within auction dispersion across loan-size bins. It illustrates that there is (i) limited uncertainty in customization decisions, and (ii) important heterogeneity in returns to customization. This provides our first evidence of market power. From our theoretical framework presented above, we know that customization is associated with market power if firms have differential returns (resale value) from custom loans. The fact that the dispersion of bids within an auction is decreasing in

loan size (up to the $225K customization cutoff) provides a test of this, and confirms the existence of heterogeneous returns. We observe a similar decrease in the difference between the highest and runner-up bid for loans below $225K (money left on the table), confirming that customization increases the dispersion in private values across the entire distribution. Figure 8b shows a similar pattern for the "money left on the table". The average difference between the 1st and 2nd bids is $0.18 for loans larger than $225K, and above $0.30 for loans smaller than $125K. Recall that a larger dispersion in private values (holding fixed the number of bidders) allows firms to shade their bids more, and therefore leads to more market power.

We next consider the following linear pass-through model:

$$W_i = f(Z_i) + \mu^w_{\text{pay-up}} \left[V_i - V_{tba}(c)\right] + \mu^w_{\text{tba}} V_{tba}(c) + \text{FE} + \text{Error}$$
$$P_i = g(Z_i) + \mu^r_{\text{pay-up}} \left[W_i - V_{tba}(c)\right] + \mu^r_{\text{tba}} V_{tba}(c) + \text{FE} + \text{Error},$$

where V_i is the security price and is equal to $V_{tba}(c)$ if multi-issuer or to $V_{j(i)}(c)$ if custom. The wholesale price is denoted W_i and is equal to Wholesale pay-up$+V_{tba}(c)$. The retail price is specified as $P_i = 100 -$ Lender fee $+$ Discounts.

Identification of $\mu_{\text{pay-up}}$ leverages discontinuities in the value of customization across loans sizes cutoffs (l_k). We also rely on an instrumental variable approach in which $IV_i = 1(L_i \in nbh_{k(i)}) \times 1(L_i > l_k)$. Finally, we include Loan-size category x Coupon diff. and Date x Coupon diff. fixed effects.

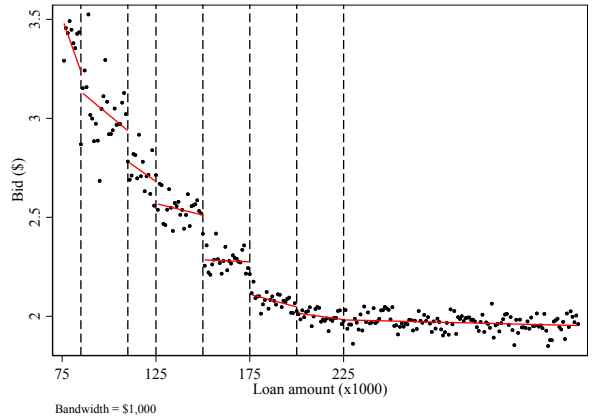
To see why the probability of customization can be discontinuous in loan size, recall that our model of pool selection under perfect competition implies a common cutoff for all pool types, defined in terms of expected loan value: $v(c, S_i) > V_{tba}(c)$ for all security types k. This implies that when issuers select a fraction between zero and one to pool in spec-pool k for all k (i.e., $q^*_k \in (0, 1)$), the probability of customization should be a smooth function of loan size in the $(0, 250]$ range, and should not exhibit any discontinuity. Moreover, the probability of placing a loan in a TBA-eligible pool should decrease in loan size because $v(c, S)$ is decreasing in l. When the optimal pooling strategy exhibits a corner solution (i.e., $q^*_k = 0$ or $q^*_k = 1$), the probability of placing a loan in a custom pool can be discontinuous across loan size categories. This is especially true if the quantity of loans with a value above $P^{tba}(c)$ is too small to justify paying the fixed cost of securitization.

Figure 7 displays wholesale prices (bids) from the OB data and retail prices by loan amount (as measured by lender fees) from HMDA. The figure shows clear evidence of discontinuities in the wholesale price and none for the retail price, suggesting that there is positive pass-through at auction and no pass-through to lender fees. Figure 7c repeat the same exercise for interest rates, and again we do not find any evidence of discontinuities.

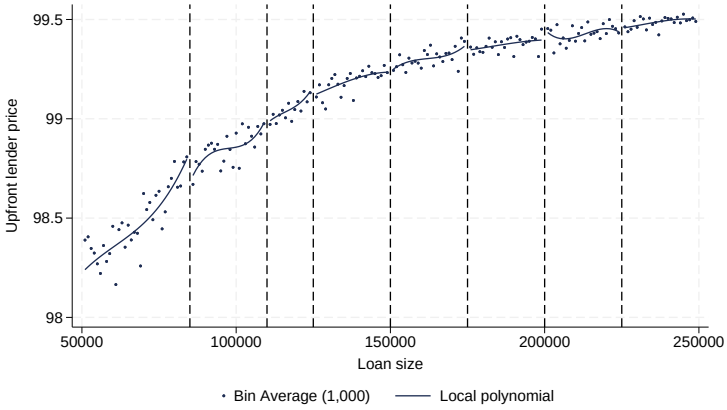
Table 9 presents results from the wholesale pass-through regression. The sample consists of loans sold in OB auctions between 2018 and 2019. The baseline specification includes Period x Note-rate fixed effects. In the MBS sample we control for Issuance month. In the auction sample

Figure 7: Evidence of discontinuity in wholesale and retail loan prices

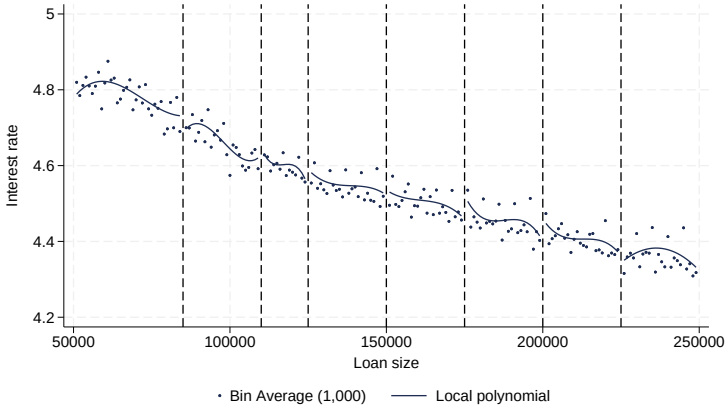
(a) Wholesale price: OB winning bid



(b) Retail price: HDMDA lender fee



(c) Retail price: Interest rate



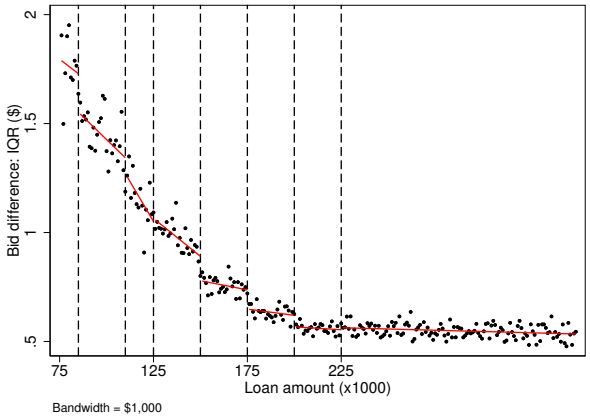
we control for the auction date. Loan attributes include loan size, FICO, LTV, Refi/Purchase, Income (auction), DTI, Agency (VA/FHA), Zip-code house value, County (Auction), and State (MBS). We also control for origination channel. In the auction sample we include Originator (Seller) fixed-effects, while in the MBS sample we have Channel, and Issuer fixed-effects.

The results show that in the wholesale market a dollar increase in the spec-pool pay-up leads to $0.44 increase in the wholesale price that correspondent lenders receive. In contrast, we find a pass-through rate of $0.88 for the TBA price. Consistent with the theory, we find near complete pass-through of TBA prices to wholesale prices and incomplete pass-through of spec-pool pay-ups.

Table 10 presents results from the retail pass-through regression. Also consistent with the theory, we find much lower pass-through rates in the retail market. Conditional on the interest

Figure 8: Within auction dispersion in bids across loan-size bins

(a) Within auction dispersion



(b) Difference between first and second highest bid

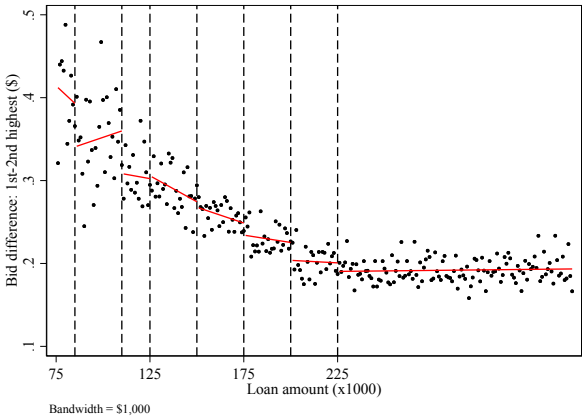


Table 9: Wholesale pass-through regression

	(1)	(2)	(3)	(4)
VARIABLES	Wholesale pay-up	Security pay-up	Wholesale price	Wholesale price
Security pay-up			0.39***	0.44***
			(0.019)	(0.073)
$1(L_i > l_k)$	-0.083***	-0.19***		
	(0.020)	(0.023)		
TBA price			0.86***	0.88***
			(0.030)	(0.035)
Observations	12,695	12,695	12,695	12,695
R-squared	0.754	0.833	0.927	0.791
Estimator	OLS	OLS	OLS	IV

Sample restrictions: No coupon-choice option and within 5000 of SP size cutoff.
Fixed effects: Auction date x High/Low Coupon and Loan size bin x High/Low Coupon.
Additional controls: Borrower characteristics.
SE clustered by Rate x Auction Month.
*p<.1; **p<.05; ***p<.01

rates chosen by consumers, we find that a $1 increase in the TBA price leads to a $0.32 reduction in the closing costs for consumers (recall that the retail price captures the revenues of consumers from selling the bond), and that changes in the wholesale price associated with the customization result

are uncorrelated with changes in the retail price of the loan. Similarly, we reject the hypothesis that consumers pay lower interest rates when their loans are pooled in custom securities (despite much higher returns for originators).

Table 10: Retail pass-through regression

	(1)	(2)	(3)	(4)
VARIABLES	Retail price	Wholesale pay-up	Retail price	Retail price
Wholesale pay-up			0.14***	-0.037
			(0.0064)	(0.048)
$1(L_i > l_k)$	0.0084	-0.12***		
	(0.0091)	(0.020)		
TBA price			0.34***	0.32***
			(0.0080)	(0.013)
Observations	19,219	19,219	19,219	19,599
R-squared	0.864	0.553	0.963	0.647
Estimator	OLS	OLS	OLS	IV

Sample restrictions: No coupon-choice option and within 5000 of SP size cutoff.
Fixed effects: Auction date x High/Low Coupon and Loan size bin x High/Low Coupon.
Additional controls: Borrower characteristics.
SE clustered by Rate x Auction Month.
*p<.1; **p<.05; ***p<.01

5.5 Takeaways from our empirical analysis

First, there are significant returns to customization and important heterogeneity in prices across securities. Second, loans placed in multi-pools are 10% more likely to get pre-paid. Third, 80% of adverse selection is due issuer heterogeneity in duration and other loan characteristics. Fourth, there is near complete pass-through of TBA prices to wholesale prices, but incomplete pass-through of spec-pool pay-ups. Moreover, spec-pool prices are heterogeneous across issuers, while TBA prices are common and predictable. Finally, there is incomplete pass-through in the retail market: zero pass-through of customization returns and limited pass-through TBA prices.

6 Counterfactual: Eliminating custom pools

In this section, we study the impact of eliminating the option to allocate certain loans into custom pools. Specifically, our objective is to measure the change in profit per loan resulting from the removal of this customization option. To do so, we simulate counterfactual loan prices in a setting

where the custom pool market no longer exists.

More specifically, we are interested in constructing counterfactual multi-issuer pool prices:

$$V_{tba}^{cf}(c) = \frac{1}{Q_c}\left[V_{tba}(c)q_{M,c} + \sum_j q_{j,c}V_j(c)\right],$$

and then quantifying the size of the adverse selection effect: $\Delta V_{tba} = V_{tba}^{cf}(c) - V_{tba}(c) > 0$. Doing so hinges on three key assumptions. First, we assume that there is a constant allocation of loans and interest rates. Second, we assume that pass-through is linear. Third, we assume that the cost of securitization F_i is unaffected by customization. These three assumptions allow us to quantify the effect of adverse selection of the distribution of prices across the three levels of the supply chain, without explicitly modeling competition and the production of securities. The third assumption likely overstates the profit loss from eliminating customization for issuers that have access to the spec-pool market.

Under these assumptions, we can measure the change in profits along the supply chain from the elimination of custom pools. Recall that issuer profits are given by:

$$\pi_i^{\text{Issuer}} = \begin{cases} (r-c-g)\bar{M}_i + V_i(c) - F_i - W_i & \text{in the correspondent channel,} \\ (r-c-g)\bar{M}_i + V_i(c) - F_i - P_i & \text{in the retail channel.} \end{cases}$$

We cannot calculate this directly, because we do not observe F_i. However, we can use the auction data to predict the bid conditional on characteristic and customization choices, and do the same with closing cost using HMDA. We then assume that all loans go to the TBA, which implies updating the TBA price and the acquisition price. Based on our findings above, we assume complete pass-through of the TBA price. This allows us to calculate the range in profit. Both the fixed cost and the MSR will cancel out. The change in profit is then just the sum of the change in resale value, and the change in loan acquisition cost. We then aggregate across banks to measure the change in profit across banks.

Specifically, we can write the change in issuer profits as follows:

$$\Delta\pi_i^{\text{Issuer}} = \begin{cases} (1-\mu_{payup}^w)\Delta\text{Pay-up} + (1-\mu_{tba}^w)\Delta V_{tba}(c) & \text{in the correspondent channel,} \\ (1-\mu_{payup}^r)\Delta\text{Pay-up} + (1-\mu_{tba}^r)\Delta V_{tba}(c) & \text{in the retail channel,} \end{cases}$$

where $\Delta\text{Pay-up} = 0 - \left(\hat{V}_{j(i)}(c) - V_{tba}(c)\right)$. This allows us to calculate the change in the borrower's upfront price as :

$$\Delta P_i = \begin{cases} \mu_{payup}^r\mu_{payup}^w\Delta\text{Pay-up} + \mu_{tba}^r\mu_{tba}^w\Delta V_{tba}(c) & \text{in the correspondent channel,} \\ \mu_{payup}^r\Delta\text{Pay-up} + \mu_{tba}^r\Delta V_{tba}(c) & \text{in the retail channel.} \end{cases}$$

Note that for both channels, the first terms cancel out.

6.1 Results from the counterfactual simulation

Table 11 displays the impact of elimination of custom pools on retail prices. Everyone benefits, but especially consumers who used to fit in TBA pools. The pass-through of spec pool prices to origination cost is practically zero, while the literature finds that the retail pass-through of the TBA price is close to one.

Table 11: Distribution of retail price changes

Loan	$\Delta P_i = P_i^{\text{cf}} - P_i^{\text{obs}}$			
Size	mean	sd	p10	p90
85000	0.107	0.112	0.001	0.265
110000	0.092	0.106	-0.001	0.224
125000	0.083	0.102	-0.001	0.202
...				
250000	0.053	0.085	-0.004	0.147
325000	0.048	0.081	-0.004	0.139
1000000	0.035	0.069	-0.004	0.112
Total	0.061	0.091	-0.004	0.155

The impact of the elimination of custom pools on bank profits is presented in Table 12. Without conditioning on customization (column 1) the main factor explaining profit change is the quality of banks' loan pools, captured by loan survival. Banks with better quality loans experience a profit decrease from the elimination of the custom pool option. In column 2, we condition on customization and find that banks that do a lot of customization, the change in resale value is negative. They used to receive the spec pool price (net of cost) and now are receiving the TBA price. For banks that do not do customization, they are now receiving a higher TBA price.

We also find that banks that are less vertically integrated experience a negative change in resale value. This is a somewhat surprising result at first glance, since one might expect vertically integrated lenders to benefit from the elimination of the custom pool via a double marginalization effect. However, there is a second force arising through the fact that elimination of customization makes the auctions more competitive and non-integrated (correspondent) lenders benefit from this.

Finally, size also plays a role, although this somewhat hard to see given that size is correlated with the other variables. To get a sense of its true importance, Table 13 displays summary statistics by issuer size groups. From this table we can clearly see that banks issuing large volumes of loans are particularly harmed by the elimination of custom pools.

Table 12: Beneficiaries of the elimination of customization

VARIABLES	(1) Profit change	(2) Profit change
Retail origination	0.066***	0.066***
	(0.025)	(0.020)
Survival	-0.090***	-0.041
	(0.030)	(0.026)
Servicer retention rate	-0.029**	-0.033**
	(0.014)	(0.015)
1(Zero servicer retention)	0.099**	0.083**
	(0.046)	(0.038)
Customization		-0.17***
		(0.041)
Monthly volume (log)	0.00028	0.068**
	(0.024)	(0.027)
Constant	-0.030	-0.30***
	(0.094)	(0.11)
Observations	115	115
R-squared	0.211	0.496

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6.2 Takeaways

Our counterfactual analysis yields the following takeaways regarding the impact of eliminating the custom pool option. Doing so removes adverse selection and thereby (i) benefits small borrowers (opposite under perfect-competition), (ii) benefits lenders who have limited access to customization because of the quality of their portfolio or their size, and (iii) reduces market power in the wholesale market, and therefore the cost of intermediation.

7 Conclusion

This paper highlights a new source of market power in the mortgage market, stemming from heterogeneity in the returns to securitization across issuers that are only pass-through in small part to consumers (likely due information frictions). To do so, we are the first to leverage detailed data from all along the supply chain of mortgages. Our findings suggest that customization raises the cost of financial intermediation with implications for industry turnover and concentration. Specifically, lower productivity issuers face more competitive wholesale markets, and suffer from

Table 13: Summary statistics by issuer size groups

	Issuer size groups			
	(1)	(2)	(3)	(4)
	1-10	11-50	51-100	100+
Change in issuer profits (bps)	-0.08	-0.06	-0.06	0.06
	(0.11)	(0.12)	(0.23)	(0.20)
Change in issuer profits per loan	-172.12	-122.12	-72.04	164.05
	(259.99)	(252.80)	(429.49)	(390.88)
Fraction custom securities	0.27	0.25	0.29	0.08
	(0.15)	(0.20)	(0.24)	(0.19)
Fraction vertical integration	0.45	0.61	0.82	0.84
	(0.37)	(0.39)	(0.31)	(0.32)
Issuer size (/1000)	126.24	27.67	4.89	0.51
	(73.62)	(16.21)	(1.83)	(0.57)

Standard-deviation in parenthesis.

adverse selection leading them to be more exposed to downturns in refinancing activity.

Follow-up work should address why issuers have different exposure to pre-payment risk and determine what are the main secondary market frictions limiting access to the spec-pool market. Finally, our findings raise questions as to whether competition between Fannie/Freddie alleviates market-power friction in the conventional loan segment.

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8 Appendix

8.1 Coupon choice

8.1.1 Model

Aside from choosing the type of security, issuers can also choose the coupon for loans with note rates that end in 0.25 or 0.75. In the finance literature, this problem is described as the "best execution" of an MBS. The choice of coupon depends on the security price $P(c)$ and the bank's beliefs about the loan duration (M_i). Since $P(c)$ is increasing in c, the tradeoff that banks face in choosing the coupon is between a higher price versus lower service income. The rules for coupon choice are the same for each type of security.

Recall that Ginnie Mae charges a fixed g-fee of 0.06 p.p. for all banks and restricts the coupon choice such that the spread $(r - c)$ is between 0.25 and 0.75. This effectively imposes a minimum and maximum markup on banks. Since note rates are typically quoted on a 1/8 p.p. grid, it implies that for most loans, banks do not face a coupon choice. However, for note rates ending with 0.25 or 0.75, lenders can choose a high or low coupon security. For instance, a 4.25 note rate mortgage can be pooled in a 4% coupon security (high) or in a 3.5% coupon security (low). In the latter case, the bank earns a servicing income of $r - c - g = 0.69$ p.p., compared to 0.19 p.p. with the 4% coupon, but receives a lower upfront payment from selling the loan.

Define $\overline{M}_i = E[M(T_i)]$ as the expected duration of loan i. Since Ginnie does not collect other upfront payments from banks, the optimal coupon for eligible loans is a binary discrete choice problem:

$$c_i = \begin{cases} c_L & \text{If } \bar{M}_i > \frac{P(c_H)-P(c_L)}{(c_H-c_L)} \\ c_H & \text{If } \bar{M}_i < \frac{P(c_H)-P(c_L)}{(c_H-c_L)}. \end{cases} \tag{5}$$

where c_L and c_H denote the low and high coupons available for loan i, and $P(c_L) < P(c_H)$ are the associated security prices. Equation 5 implies that only high-duration loans are placed in the low-coupon option, with the threshold determined by the difference in the security prices relative to the difference in coupons.

The empirically testable prediction of our coupon choice model is that loans in "high-coupon" securities are adversely-selected. Specifically, banks will select a low coupon if they believe a loan is likely to survive for a long time, and a high coupon if they believe the loan will be pre-paid early.

Prediction 6. *The duration of loans pooled in "low-coupon" securities is on average longer than the duration of loans pooled in "high-coupon" securities.*

As in the case of security choice, issuers are not homogenous. Some issuers, typically the smaller banks, appear to have preferenences for liquidity since they always choose the high coupon. Issuers who value upfront cash payments more than service income (lower δ) are more likely to choose the high-coupon option, which could mitigate the adverse selection problem.

8.1.2 Empirical analysis of adverse selection in coupon choice

The value of security customization comes from the ability of banks to exploit their information advantage when assembling MBS pools We consider three sources of private information: (i) loan attributes (unpriced attributes in the TBA market), (ii) private signals from proprietary risk models, and (iii) systemic differences in loan duration across banks.

The adverse selection test for the coupon choice is based on the following empirical discrete choice model. Recall that banks select the low-coupon security if:

$$\bar{M}(S_{ij}) > \frac{P(c_H) - P(c_L)}{(c_H - c_L)} = 2\Delta P_i. \tag{6}$$

where $c_H - c_L = 0.5$ by construction.

We test the hypothesis that banks have private information about loan duration by estimating the following linear regression model of early pre-payment risk, $Y_i = 100(T_i > 12)$,

$$Y_i = Z_i\beta + \lambda 1(c_i = c_h) + \text{Fixed effects} + e_i. \tag{7}$$

where $\lambda = E[Y_i|Z_i, \bar{M}(S_{ij}) < 2\Delta P_i] - E[Y_i|Z_i, \bar{M}(S_{ij}) \geq 2\Delta P_i]$ measures the conditional expectation of the difference in survival probability for loans pooled in low vs high coupon securities. Since $\bar{M}(\cdot)$ is a monotonic transformation of the expected duration, this difference is negative if banks have private information (beyond Z_i) about the distribution of T_i.

The ability of banks to select the coupon leads to adverse selection if the selection is driven by private information about loan duration. Selection can be *advantageous* if the factors entering the prices for high and low coupon securities are negatively correlated with duration. This can arise for instance if the security prices are set after the MBS pool is assembled, or if a bank's private benefit from assembling a diversified pool outweighs the benefit of placing a longer-duration loan in a low coupon. To minimize the importance of these factors, we focus on loans that are pooled in TBA-eligible multi-issuer securities. Recall that the TBA price reflects the expected composition

Table 14: Adverse selection test results – Coupon choice

VARIABLES	(1)	(2)	(3)	(4)
1(High coupon)	-5.23	-3.20	-1.64	-1.26
	(0.36)	(0.29)	(0.36)	(0.37)
Observations	2,175,394	2,175,394	2,175,389	2,165,179
R-squared	0.104	0.142	0.157	0.197
Loan characteristics	no	yes	yes	yes
Issuer FE	no	no	yes (+)	yes (x)
Latest issuance date	2021/2	2021/2	2021/2	2021/2
Fixed effects	Month x rate	Month x rate	Month x rate	Month x rate
Mean dep. var.	82.1	82.1	82.1	82.1
Fraction High Coupon (eligible)	0.83	0.83	0.83	0.83

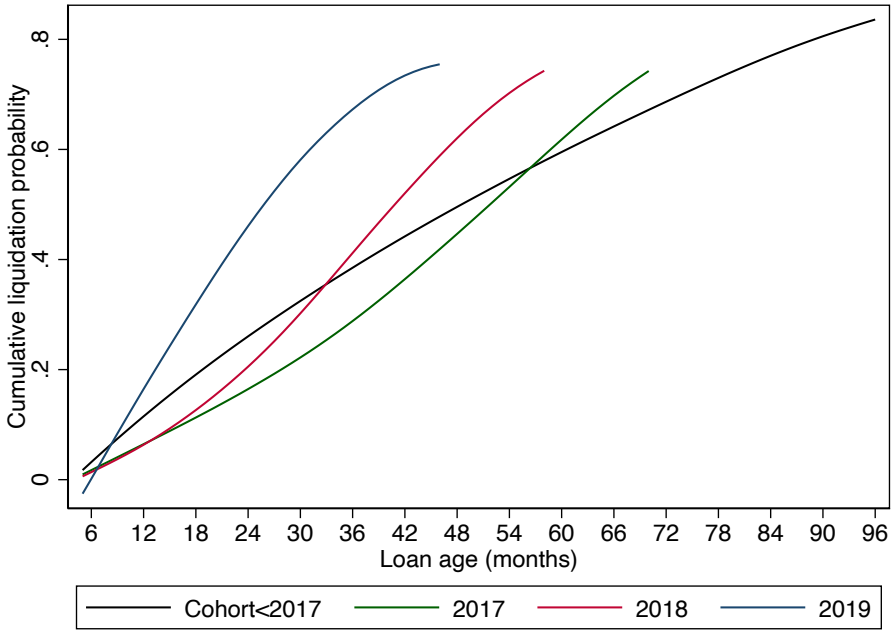
of fully diversified pools, and is therefore unaffected by the decision to include or not an individual loan.

We estimate the model on loans that are eligible for a coupon choice (i.e., note rates ending in .75 or .25 digits) and that are sold in multi-issuer pools. To identify the source of selection, we estimate λ varying the set of controls Z_i. The price of the TBA MBS securities is a function of only aggregate information available to investors at the trading date (typically a few weeks before the pool issuance date). Our baseline specification therefore compares the ex-post performance of eligible loans that are securitized on the same date. We do so by controlling for note-rate/issuance date fixed-effects (i.e., $r \times t$).

Next we also condition on the identity of the issuer (i.e., aggregator or retail originator) selling the loan. We do so by augmenting the fixed-effects to compare loans securitized on the same date, with the same note rate, and the same issuer. Finally, we also control for characteristics of the loans that are observed by the lender/issuer, but not by the investor buying the TBA security. This includes the financial attributes of the borrower, contract characteristics, as well as the origination channel. Note that the investor also does not observe the identity of the issuer.

Table 14 summarizes the results. The first row presents the estimate of λ across different sets of controls. The last two columns compare the estimate for loans acquired through the retail and wholesale channels. The results confirm that the coupon choice reflects issuer's beliefs about loan duration. Loans placed in high-coupons are 5% less likely to survive the first year, compared to loans sold on the same date and with the same note rate. This difference is reduced to 3.38% when we condition on loan attributes, and is further reduced to 1.8% when we condition on the identity of the issuer. We therefore conclude that more than half of the adverse selection in the MBS market is due to observed characteristics of the loans. The identity of the issuer in particular

Figure 9: Evolution of pre-payment risk across cohorts



is an important predictor of the coupon choice and loan survival. We find that a large fraction of issuers never select the low coupon option when it is available, and those lenders on average sell loans that are more likely to be pre-paid early.

Since consumers can exercise the option to pre-pay their loan early or default, very few loans last until maturity. Figure 9 quantifies this risk for the cohorts of Ginnie Mae loans originated between 2013 and 2019. The pre-2017 cohorts faced relatively stable interest rates. On average, 70% of these loans were pre-paid within the first six years, and about 10% were pre-paid within the first year. The risk of early pre-payment increased substantially for loans originated in 2018 and 2019, due to the dramatic decline in mortgage interest rates observed between 2019 and 2021. This affected especially the 2019 cohort. Nearly 50% of their loans were prepaid within the first 18 months, and 30% of loans were pre-paid during the first year. Since our data on auctioned loans cover the 2018-2020 period, we use the risk of early pre-payment as our primary measure of loan performance.

8.2 Additional tables and figures

Table 15: Survival probability regression

VARIABLES	(1) $1(T > 12)$	(2) $1(T > 36)$	(3) $1(T > 12)$	(4) $1(T > 12)$
Note rate	-9.53	-15.4	-10.1	-11.4
	(0.21)	(0.31)	(0.31)	(0.60)
Loan amount (x100K)	-6.24	-18.0	-9.11	-11.4
	(0.26)	(0.45)	(0.42)	(0.76)
Loan amount squared (x100K)	0.79	3.54	1.21	1.83
	(0.066)	(0.11)	(0.10)	(0.24)
1(VA)	-6.58	-5.55	-11.7	-14.2
	(0.29)	(0.29)	(0.40)	(0.64)
1(Second lien)	5.85	10.9	6.56	1.06
	(0.37)	(0.56)	(0.43)	(1.05)
LTV	0.044	0.12	0.070	0.25
	(0.0062)	(0.0092)	(0.011)	(0.032)
Credit score groups = 2, 630-690: Fair	-0.30	-1.11	-0.72	-2.20
	(0.14)	(0.21)	(0.25)	(0.56)
Credit score groups = 3, 690-720: Good	-0.87	-1.79	-1.95	-3.75
	(0.18)	(0.27)	(0.32)	(0.71)
Credit score groups = 4, 720-850: Excellent	-0.73	-0.91	-2.32	-4.37
	(0.19)	(0.29)	(0.34)	(0.71)
Loan type = 2, Refi: Not Streamlined, Not Cash Out	-4.05	-5.05	-5.08	-3.21
	(0.23)	(0.33)	(0.47)	(0.97)
Loan type = 3, Refi: Cash out	-6.26	-8.00	-7.10	-5.95
	(0.20)	(0.26)	(0.33)	(0.75)
Loan type = 4, Refi: Streamlined	-3.82	-3.20	-8.86	1.67
	(0.36)	(0.64)	(0.81)	(2.29)
1(DTI > 40)	-1.00	-1.89	-1.37	-2.00
	(0.074)	(0.12)	(0.15)	(0.33)
1(Retail)	0.35	1.10	-1.41	6.73
	(0.18)	(0.25)	(0.33)	(5.87)
1(Correspondent)	0.53	0.27	-0.57	-1.33
	(0.15)	(0.22)	(0.28)	(1.04)
Constant	140	140	147	139
	(1.48)	(1.95)	(2.29)	(4.40)
Observations	748,612	631,127	273,303	48,551
R-squared	0.128	0.194	0.152	0.160
Pool date FE	yes	yes	yes	yes
State FE	yes	yes	yes	yes
Issuer FE	yes	yes	yes	yes
Sample	2013-18	2013-18	2018-19	Matched
Mean dep. variable	89.1	57	83.1	82.3

The sample in columns (1-3) correspond to a 10% random sample of Ginnie Mae loans issued between 2013 and 2019. Robust standard errors in parentheses. Standard errors are clustered at the note-rate/issuing date level.

Table 16: Issuer heterogeneity – unweighted

VARIABLES	(1) Customization	(2) Survival	(3) Survival	(4) Survival
SP Pay-up				0.245**
				(0.109)
Monthly volume (log)	0.332***	-0.223*	-0.355***	-0.378***
	(0.0638)	(0.117)	(0.106)	(0.106)
Customization			0.474***	0.319**
			(0.116)	(0.127)
Survival	0.236***			
	(0.0568)			
Retention rate	-0.0166	-0.467***	-0.407***	-0.369***
	(0.0696)	(0.108)	(0.0962)	(0.0961)
Retail origination	-0.0313	0.331***	0.309***	0.261***
	(0.0733)	(0.113)	(0.103)	(0.0930)
1(Zero retention)	-0.129	-0.650**	-0.516**	-0.545**
	(0.157)	(0.253)	(0.246)	(0.252)
Constant	-1.351***	1.451***	1.930***	2.038***
	(0.240)	(0.382)	(0.347)	(0.351)
Observations	133	133	133	133
R-squared	0.228	0.246	0.331	0.363

Figure 10: Evidence of discontinuity in interest rates

