The Real Effects of Secondary Market Trading Structure: Evidence from the Mortgage Market

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Abstract

A vast majority of mortgages in the U.S. are securitized into agency mortgage-backed securities (MBS), many of which are traded in the to-be-announced (TBA) forward market. By allowing different MBS to be traded based on a limited set of characteristics, TBA market generates liquidity, with the aggregate daily trading volume second only to the U.S. Treasury market. In this paper, we quantify the effect of the unique secondary market trading structure on individual borrowers' mortgage rates, demand for mortgages, and consumer spending. With a simple model, we show that the benefit of access to the TBA market is higher for loans with less desirable prepayment characteristics. Then, exploiting sharp discontinuities in the probability of a loan to be included in an MBS eligible for TBA delivery, we estimate that TBA eligibility reduces mortgage rates by 10–40 basis points, depending on the prepayment risk of the loan. Furthermore, we also provide evidence that TBA eligibility affects borrowers' refinancing decisions and subsequent durable consumption.

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1 Introduction

Do financial markets matter for the real economy? More specifically, does liquidity and trading structure of the secondary market matter? One may argue that trading structure in the secondary market only affects the investors in those markets and that it does not impact the economy more broadly.

From a theoretical perspective, better liquidity in the secondary market would result in better prices in the primary market, leading to lower costs of capital for those raising funding. If investors value liquidity, assets with better liquidity would have higher prices, and thus, investors would be willing to pay higher prices in the primary market as well. A few recent studies (Brugler et al., 2018a,b; Davis et al., 2018) use the introduction of post-trade transparency in the corporate bond market and the change in trading rule at NASDAQ to show that secondary market trading structure impacts the cost of capital for the firms issuing corporate bonds or seasoned equity.

In this paper, we focus on the market for agency mortgage-backed securities (MBS), which are secured by mortgages in pools guaranteed by government-sponsored enterprises (Fannie Mae and Freddie Mac) or the U.S. government (Ginnie Mae). Specifically, we study the impact of liquidity and trading structure of the agency MBS market on mortgage rates for individual borrowers, demand for mortgages, and consumer spending. The mortgage market is different from the markets studied by the aforementioned papers in that it impacts a large set of population directly. In fact, a vast majority of mortgages, particularly after the 2008 financial crisis, end up in agency MBS. Also, although it has not been studied as much in the academic literature, the agency MBS market is the second most actively traded fixed-income market.

The unique feature of the agency MBS market is the to-be-announced (TBA) market, through which 90% of the trading is done. A TBA trade is a forward contract for a future delivery of MBS, where parties do not specify the CUSIP but agree only on six parameters at the time of the trade: agency (Fannie, Freddie, or Ginnie), coupon, maturity, price, par amount, and settlement date. Thus, if an MBS meets the six parameters specified in the TBA trade and the eligibility criteria for TBA delivery set by the Securities Industry and Financial Markets Association, then the TBA seller can deliver any of such MBS. As a result, the TBA trading structure concentrates trading of MBS with heterogeneous prepayment risks into a handful of TBAs and makes the market liquid. Although the TBA trading structure is a vital part of the MBS market, no studies so far have quantified the impact of TBA trading on mortgage borrowers in the primary mortgage market.

The goal of this paper is to quantify the impact of this unique trading structure on mortgage rates for individual borrowers, demand for mortgages, and the real economy, exploiting cutoffs that determine the probability that a loan is included in an MBS eligible for TBA delivery (i.e., TBA-eligible MBS). Given the uncertain future of the TBA market due to a potential housing finance reform, some argue that the TBA market structure should be preserved, citing its benefit for mortgage borrowers.[1] This paper provides quantitative evidence on how much the TBA market

[1] For example, see Bright and DeMarco (2016).

matters for individual mortgage borrowers.

TBA eligibility provides a number of benefits for an MBS investor. First, TBA eligibility gives an MBS access to a more liquid market with a large investor base. A TBA-ineligible MBS must be traded in the much less liquid specified pool (SP) market, where the individual CUSIP is specified at the time of trade.[2] Moreover, TBA pricing only depends on six parameters, thus is relatively simple; this simplicity increases the investor base for TBA trades. Second, TBA eligibility decreases downside risks for the MBS holder. All agency MBS, including TBA-eligible ones, can be traded in SP in principle. In fact, despite the high SP trading cost, TBA-eligible MBS with better prepayment characteristics often trade as SP to receive prices higher than the cheapest-to-deliver TBA prices. However, having the option to trade in TBA shields such MBS from the risk of not being able to find an buyer in the SP market. As a result, even an SP trade for TBA-eligible MBS is found to be more liquid than that for TBA-ineligible MBS (Gao et al., 2017). These benefits may fully or partially be passed down to primary market mortgage borrowers as lower mortgage rates.[3]

We begin our analysis with a simple model that describes the decision problem of an MBS seller that can sell an MBS as TBA or SP. If traded as TBA, the seller receives the cheapest-to-deliver price that does not depend on the prepayment risk of the MBS. If traded as SP, the seller receives the price that reflects the prepayment risk at the expense of a stochastic trading cost, which can be potentially very high. Thus, an implication of the model is that the option to easily sell the MBS as TBA protects the seller from the downside risk of having a very large realized SP trading cost. However, the value of TBA eligibility will depend on the prepayment risk of the MBS. An MBS with lower prepayment risk is more likely to be traded as SP despite high trading costs, and thus the option value of TBA trading will be lower for MBS. Moreover, loans with better prepayment characteristics tend to be pooled together into the same MBS empirically. Thus, TBA eligibility will be more valuable for loans with higher prepayment risks.

With these implications of the model in mind, we then estimate the impact of TBA eligibility on the mortgage rate. Our empirical strategy exploits two cutoff-based rules that determine the probability that a loan is included in a TBA-eligible MBS. An important difference between the two cutoffs is that they affect TBA eligibility for loans located in the opposite ends of the prepayment risk distribution. The model predicts that the estimated impact of TBA eligibility will be higher for the cutoff that is more relevant for loans with higher prepayment risks. Moreover, estimating the value of TBA eligibility at the two cutoffs will give us the range of TBA-eligibility benefit for the mortgages in between.

The first cutoff is the national conforming loan limit (CLL), which determines the maximum loan size that the government-sponsored enterprises (GSEs) can purchase and securitize. The GSEs can securitize only "conforming" mortgages, whose sizes are not greater than the CLL. Starting in

[2]Bessembinder et al. (2013) find that the trading cost of TBA and SP trades are 1 basis points and 40 basis points, respectively.

[3]The TBA market also positively impacts TBA-ineligible MBS because investors price TBA-ineligible MBS based on TBA prices and may also hedge with TBAs. Hence, the effect we measure here is a lower bound of the total impact of the TBA market.

2008, the GSEs began purchasing "high-balance" loans, which are larger than the national CLL but still not greater than the high-cost CLL.[4] The high-cost CLL, which became effective in 2008, is an increased loan limit for counties with high home prices. If an MBS contains more than 10% of its pool value in high-balance loans, the MBS is ineligible for TBA delivery. Indeed, we find that the probability to be included in a TBA-eligible MBS drops discontinuously from almost 100% to around 65% for a loan securitized by the GSE with the size just above the national CLL. We also find that a GSE loan with the size around the national CLL tend to have higher prepayment risks than a majority of other loans securitized by the GSEs, most of which are smaller than the national CLL. This is because a borrower with a larger loan usually has higher incentive to refinance because the same decrease in interest rates would result in larger savings.

The second cutoff is the loan-to-value ratio (LTV) of 105. A TBA-eligible MBS is not allowed to include even a single loan with LTV greater than 105. Thus, all loans with LTVs greater than 105 are included in TBA-ineligible MBS. Loans with such high LTVs were originated and sold to the GSEs under the Home Affordable Refinance Program (HARP) in 2009. Because a borrower can take advantage of HARP only once, and because the high LTV makes it difficult for such a borrower to refinance without such a special government program, loans with LTVs around 105 empirically exhibit lower prepayment risks than a majority of other loans securitized by the GSEs.

Using an empirical strategy that exploits discontinuities at the two cutoffs, we find that TBA-eligibility reduces mortgage rates by 40 basis points for loans around the national CLL and 10 basis points for loans with LTVs around 105, respectively. The large difference in the estimated magnitudes for the two cutoffs is consistent with the prediction of the model. Loans around the national CLL tend to have higher prepayment risks than loans with LTVs around 105. Thus, the option value of TBA will be more valuable for the former than the latter, thereby resulting in a greater magnitude of the estimated benefit from TBA eligibility for the former.

The fact that we estimate the impact on the mortgage rate with the two cutoffs is important not only for testing the prediction of the model but also for estimating the upper and lower bounds of the value of TBA eligibility. A common criticism against research designs estimating local treatment effects based on discontinuities is that the resulting estimate can be very different from the true effect for the entire population. This concern would apply to our setup if we estimated the impact on the mortgage rate using only one of the two cutoffs. In fact, the two cutoffs result in very different magnitudes, and it would be difficult to apply any one of these estimates to loans with different prepayment risks. However, the two cutoffs affect loans near either end of the spectrum of prepayment risks. Thus, the estimated impact on the mortgage rates with the two cutoffs are likely to be close to the upper and lower bounds, and we expect that the benefit of TBA eligibility will fall between our two estimates for loans with prepayment risks toward the middle of the distribution of prepayment risks.

Next, we estimate the impact of TBA eligibility on demand for mortgages. Because TBA

[4] High-balance loans are often also referred to as jumbo-conforming or super-conforming loans. These loans are different from jumbo loans, which the GSEs are not allowed to securitize.

eligibility impacts mortgage rates, we would expect that it also impacts the demand for mortgages. Specifically, we investigate how much TBA eligibility affects refinancing decisions of borrowers with remaining loan balances around the national CLL.[5] Studying refinancing decisions is important because of their implications for monetary policy transmission and the real economy. In fact, there is a growing literature on the refinancing channel of monetary policy transmission, where lower interest rates induce mortgage borrowers to refinance and subsequently increase their consumption.[6] Using the data that link each mortgage to the borrower's credit record, we are able to identify whether a borrower refinances a mortgage and how much the mortgage balance increases after refinancing. We find that the monthly probability of plain refinancing, which does not involve a significant increase in the loan balance, discontinuously increases by 0.25 percentage points (50% of the unconditional mean) when remaining mortgage balance reaches the national CLL from above. This finding suggests that borrowers delay refinancing in order to refinance into a TBA-eligible mortgage. A borrower slowly pays off the remaining principal according to the amortization schedule, waiting until his balance reaches the national CLL. Once the borrower's balance reaches the national CLL, the borrower quickly refinances into a loan below the national CLL. Moreover, this waiting can be quite long. The average borrower in our sample would need to wait for 17 (32) months to pay down $10,000 ($25,000) to reach the national CLL.

Finally, we study whether the delay of refinancing stemming from TBA eligibility affects real economic outcomes outside the mortgage market. Specifically, we investigate how a borrower's durable consumption changes upon refinancing. Our data allow us to identify new auto loan originations, from which we can infer whether and when an individual purchases a new automobile. Among borrowers who refinance when their remaining balances are close to the national CLL, we find that the probability of a new auto sale sharply increases immediately after refinancing. Consistently, we also find that a borrower's auto new loan origination increases right after a borrower's remaining mortgage balance reaches the national CLL from above. At that point, a borrower is much more likely to refinance his mortgage and then purchase a new car with a new auto loan. Thus, when a borrower delays refinancing in order to refinance into a TBA-eligible loan, the borrower's durable consumption is also delayed. This finding implies that the unique trading structure of agency MBS also matters for monetary policy transmission and real economic outcomes by affecting borrowers' refinancing and subsequent durable consumption.

Literature Review This paper adds to the literature on the real effects of financial markets.[7] A few papers in this literature study the effect of secondary market trading structure and liquidity on firms' borrowing costs and investments. Both Brugler et al. (2018b) and Davis et al. (2018)

[5] We do not consider a refinancing decision of a borrower with updated LTV close to 105 because we do not observe the updated house value that would be used in underwriting a borrower refinance application.

[6] For examples, see Abel and Fuster (2018), Agarwal et al. (2017), Beraja et al. (2018), Di Maggio et al. (2016), Greenwald (2018), and Wong (2018).

[7] Bond et al. (2012) provides a survey of theoretical and empirical literature on the real effects of financial markets. A majority of papers in this area study the effect that financial markets have on firms' decisions because of the information or the incentives that financial markets provide.

show that the introduction of post-trade transparency in the secondary corporate bond market has decreased cost of capital in the primary market. Field et al. (2018) also use the same variation to show that that firms with greater bond liquidity engage in more merger and acquisition activities. Brugler et al. (2018a) study a specific rule change in NASDAQ that moved the market from a dealer-oriented market towards a more centralized one and argue that this rule change decreased the underpricing of seasoned equity offerings.

However, only a few papers in this literature study consumer financial markets. Fuster and Vickery (2014) show that there are fewer fixed-rate mortgages when securitization is difficult. Benmelech et al. (2016) find that the collapse of the asset-backed commercial paper market reduced automobile purchases by decreasing the auto loan supply from nonbank auto lenders that depended on the funding market. We contribute to this literature by showing how the trading structure of the secondary market affects the primary mortgage market and consumer spending.

This paper is also related to a small number of papers that study the trading structure and liquidity of the secondary market for agency MBS, with a particular focus on TBA and SP trading. Vickery and Wright (2013) provides a comprehensive overview of the institutional details of TBA market and discusses how TBA market generates liquidity and how TBA trades are used. They also argue that TBA market liquidity would likely impact the pricing in the primary market for mortgages. However, given that their paper mostly focuses on the secondary market, they only provide preliminary evidence that TBA eligibility affects mortgage rates and caution the readers that differences in prepayment risks are not controlled for. In this paper, we look at narrow bands around TBA-eligibility cutoffs and use discontinuity tests to tease out the impact of TBA eligibility.

In addition, Bessembinder et al. (2013) studies trading costs in structured credit products and finds that trading costs in TBA trades are very small (1 bp) while that of SP trades are much higher (40 bps). Gao et al. (2017) argues that TBA eligibility affects trading costs for SP trades because dealers can more easily hedge SP inventory for TBA-eligible MBS with TBA trades. Schultz and Song (2018) studies the impact of post-trade transparency in the TBA market.

This paper also contributes to the literature that studies monetary policy transmission through the mortgage market. A number of papers study the refinancing channel of monetary policy transmission; for example, see Abel and Fuster (2018), Agarwal et al. (2017), Beraja et al. (2018), Di Maggio et al. (2016), Greenwald (2018), and Wong (2018). Moreover, Di Maggio et al. (2017) studies consumption and deleveraging of borrowers with adjustable-rate mortgages, whose mortgage rates would be automatically decreased by an accommodative monetary policy. We add to this literature by showing that the secondary mortgage market trading structure is an important factor that affects refinancing, which is an important part of monetary policy transmission.

This paper is also related to studies that estimate the spread in mortgage rates between conforming and jumbo loans such as Passmore et al. (2005), Sherlund (2008), Kaufman (2014), and DeFusco and Paciorek (2017). These papers measure how much the GSEs subsidize the mortgage market by comparing mortgage rates of conforming loans just under the CLL and jumbo (not high-balance) loans just above the CLL. Because jumbo loans cannot be sold to the GSEs, the spread reflects not only the value of TBA eligibility but also the value of credit guarantees from the GSEs. In our empirical strategy, in contrast, we compare GSE loans around the national CLL to estimate the value of TBA eligibility.

2 Institutional Details

2.1 Basic Facts about the TBA Market

TBA Eligibility A vast majority of mortgages in the U.S. are securitized and packaged into agency MBS. Most of agency MBS are backed by mortgages in pools guaranteed by Fannie Mae, Freddie Mac, or Ginnie Mae. Thus, these mortgages carry either implicit or explicit credit guarantees from the U.S. government.

TBA trade is in essence a forward contract where two parties agree on a price today for a future delivery of agency MBS. Moreover, instead of agreeing upon a specific CUSIP at the onset of the trade, parties only agree on six general parameters: agency (Freddie Mac, Fannie Mae, and Ginnie Mae), coupon, maturity, price, par amount, and settlement date. Only 48 hours before the delivery date, the seller is required to notify the buyer of the specific CUSIP(s) that he will deliver. Because the seller chooses what to deliver, there is a cheapest-to-deliver pricing for TBA trades. Given the large number of individuals CUSIPs in the agency MBS market and the relative homogeneity, this structure concentrates the trading into a handful of TBAs and generates liquidity. According to Vickery and Wright (2013), TBA trades account for 90 percent of trading volume in the agency MBS market.

However, not all MBS are allowed to be delivered for TBA settlement. There are largely three reasons why an MBS is not eligible for TBA settlement. First, MBS that include any loans with the original LTV greater than 105 are not TBA-eligible. Mortgages with such high LTVs are usually very difficult to be sold to the GSEs if not impossible. The GSEs began to buy and securitize these loans under the Home Affordable Refinancing Program (HARP). This program was set up in March 2009 to help refinancing for existing mortgage borrowers with depreciated home prices due to the housing market crisis at that time. With a very large decrease in home prices, many borrowers found themselves having remaining mortgage balances more than their the market values of their homes. In other words, their updated LTVs were greater than 100, which would have made it impossible for these borrowers to refinance into new loans to take advantage of historically low interest rates at that time. However, HARP made it possible for borrowers meeting its eligibility criteria with very high LTVs to refinance into a GSE loan.[8] Initially, HARP excluded loans with updated LTVs greater than 125, but the LTV limit was removed in December 2011. As for TBA eligibility of HARP loans, only HARP loans with LTVs up to 105 were allowed to be included in TBA-eligible MBS. Thus, any HARP loans with LTVs greater than 105 must be included in TBA-ineligible MBS.

Second, MBS that have more than 10 percent of the pool value in high-balance loans are not

[8] A borrower is eligible for HARP if he originated a mortgage sold to a GSE before May 31, 2009 and if he had not missed a mortgage payment for past 12 months.

eligible to be delivered for TBA settlement. High-balance loans refer to mortgages with loan size greater than the national conforming loan limit (CLL) but not greater than the county-specific high-cost CLL.[9] The GSEs are only allowed to purchase "conforming" loans that are not greater than the CLL. Until February 2008, the CLL was national except for Alaska, Guam, Hawaii, and Virgin Islands. For example, with the national CLL equal to $417,000 in 2007, the GSEs were able to buy only loans with size up to $417,000. In March 2008, however, Congress passed the Economic Stimulus Act (ESA) in response to the ongoing financial crisis, which raised the CLL in counties with high home prices. The new CLLs for the high-cost counties under the ESA were set equal to the greater of $417,000 and 125 percent of the county-level median home price with the ceiling of $725,750.[10] As a result, the ESA made it possible for the GSEs to buy and securitize high-balance loans. Initially, there was uncertainty about whether MBS including high-balance loans will be eligible for TBA settlement. Eventually, the SIFMA set the rule in August 2008 such that MBS with more than 10 percent of the pool value in high-balance loans are TBA-ineligible.

Lastly, MBS with greater than 15 percent of pool value in loans with other non-standard features such as co-op share loans, relocation loans, and loans with significant interest rate buydowns are not eligible for TBA delivery. As will be discussed in Section 2.2, only very few agency MBS are TBA-ineligible based on this criterion. Thus, we do not study the loans with these non-standard features in this paper.

Specified-Pool Market In a specified pool (SP) trade, parties agree and trade on the specific CUSIP, and each CUSIP is thinly traded. As a result, a SP trade usually has a higher trading cost than a TBA trade. In fact, Bessembinder et al. (2013) find that the trading cost of TBA and SP trades are 1 basis points and 40 basis points, respectively. Agency MBS that are not eligible for TBA delivery must be traded in the specified-pool (SP) market. TBA-eligible CUSIPs may also trade in the SP market; they may do so especially when the value of the CUSIP is high, that is, when the prepayment risk is low compared to other TBA-eligible CUSIPs.

2.2 TBA-Ineligible Pools

Figure 1 shows the evolution of dollar-weighted shares of loans (among 30-year fixed-rate mortgages sold to the GSEs) included in new agency MBS that are not eligible for TBA settlement. We categorize TBA-ineligible MBS into three broad groups: high-balance MBS, high-LTV MBS, and other TBA-ineligible MBS. First, high-balance MBS consist of high-balance loans only.[11] Thus, high-balance MBS are not eligible for TBA settlement. Second, high-LTV MBS consist of HARP loans with LTVs greater than 105. Because a TBA-eligible MBS cannot include any loan with the LTV greater than 105, such loans are packaged together into a high-LTV MBS. Third, other

[9] These loans are sometimes referred to as super-conforming or jumbo-conforming loans.

[10] The national CLL was $417,000 until the end of 2016. It was increased to $424,100 in 2017 and then to $453,100 in 2018.

[11] Note that not all high-balance loans are included in high-balance MBS. Because a TBA-eligible MBS is allowed to have up to 10% of its pool value in high-balance loans, many high-balance loans are still packaged into TBA-eligible MBS. We will discuss this in more details in Section 3.2.

TBA-ineligible MBS include various MBS that are not eligible for TBA settlement because loans in the MBS have other non-standard features such as co-op share loans, relocation loans, and loans with significant interest rate buydowns.

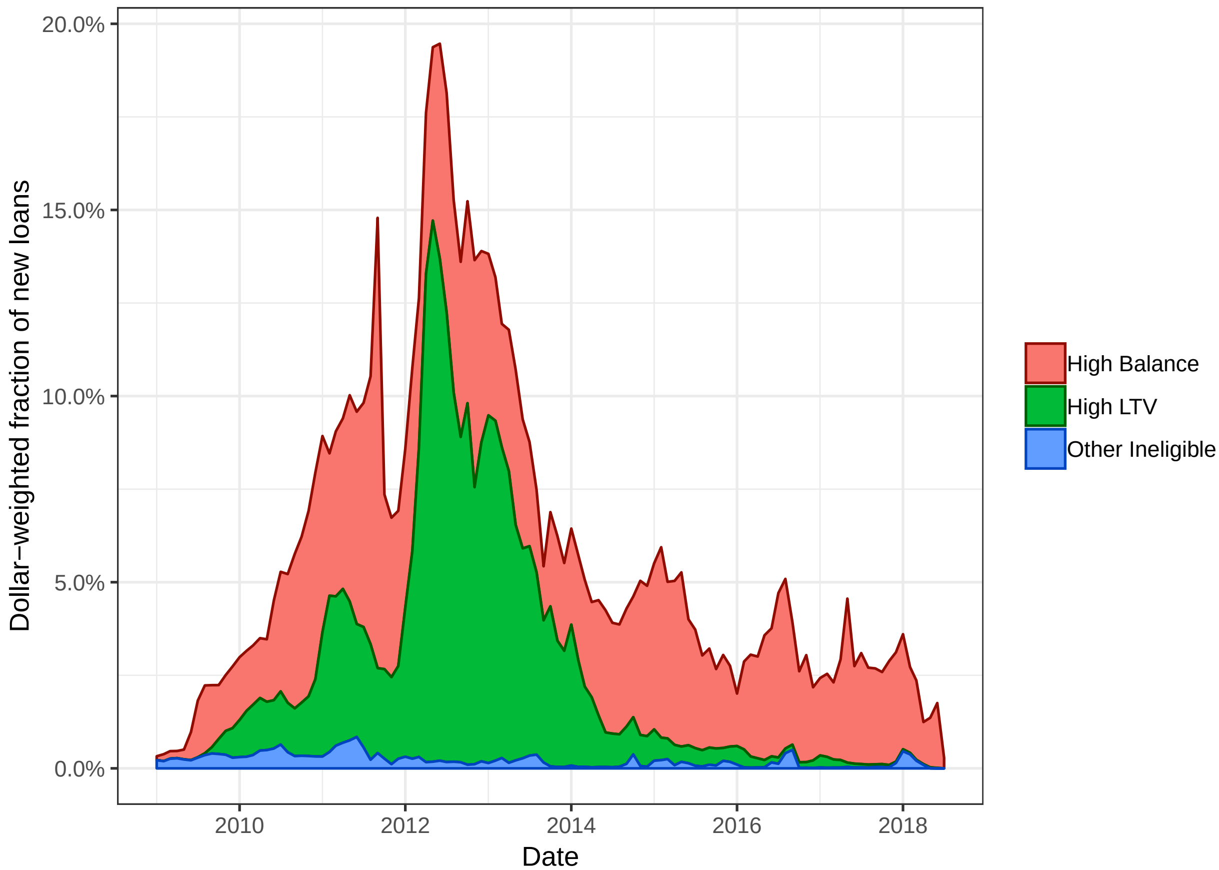
There are two main takeaways from Figure 1. First, the main reason why a loan is included in a TBA-ineligible MBS during the sample period is either because the loan has the original balance greater than the national CLL (a high-balance MBS) or because the LTV of the loan is greater than 105 (a high-LTV MBS). Most TBA-ineligible MBS are either high-balance or high-LTV MBS except in early 2009, although shares of the two types of MBS vary over time.

Second, the total share of TBA-ineligible MBS is not negligible during our sample period. In early 2009, the total share of TBA-ineligible MBS was close to zero, which means that all loans in the sample were included in TBA-eligible MBS. However, the share of loans in TBA-ineligible MBS grew substantially in the next few years, reaching close to 20% in mid-2012. The increase was mainly due to increasing originations of loans included in high-balance and high-LTV MBS.

The large shares of high-balance and high-LTV MBS in mid-2012 were in part because of a large refinance volume driven by historically low mortgage rates at that time. Many high-balance loan originations were due to refinancing by borrowers with jumbo mortgages that were originated pre-crisis (Bond et al., 2017). As mortgage rates continued to decrease in years after the 2008 financial crisis, many such borrowers refinanced into high-balance mortgages. The low interest rate environment, together with the slump in house prices, also resulted in a large number of mortgages being refinanced into HARP loans. In addition, a new version of HARP was implemented in December 2011 (called HARP 2.0) to increase the take-up of the program. Among many changes brought by HARP 2.0 to encourage borrowers to refinance into HARP loans, even a borrower with LTV greater than 125% were allowed to refinance into HARP mortgages without private mortgage insurance.

As mortgage rates increased in recent years, the refinancing volume decreased, and the shares of the high-balance and high-LTV MBS also decreased. In particular, there are barely any new issuances of the high-LTV MBS in 2018 as many borrowers eligible for HARP already took advantage of the program. Because the program is only available for borrowers who took out loans sold to the GSEs by early 2009, the number of borrowers eligible for the program will only decrease over time. Moreover, the house price appreciation in recent years has left very few borrowers with very high updated LTVs.

Figure 1: **Share of Mortgages in TBA-Ineligible MBS**: This figure plots the dollar-weighted share of loans in TBA-ineligible MBS, among 30-year fixed-rate mortgages in MBS securitized by the GSEs, that were originated in the period from 2008 to August 2018. Each month refers to the month of loan origination. The red area represents the share for loans in high-LTV MBS, which contain only loans with LTVs greater than 105. The green area represents the share for loans in high-balance MBS, which contain only high-balance loans. However, there are also high-balance loans included in TBA-eligible MBS. The blue area represents the share for loans in other TBA-ineligible MBS. The source of the data for this figure is eMBS.



2.3 Two Cutoff Rules

In our empirical analyses, we focus on two main TBA-eligibility cutoffs: loan size of national CLL and LTV of 105.[12] For both loan size and LTV dimensions, the probability that a loan is included in a TBA-eligible MBS changes discontinuously around the cutoffs, which we will show in Section 3.2. Our empirical strategies hinges on the discontinuities at the two cutoffs. For instance, to control for other characteristics that affect mortgage rates, we compare loans with sizes just under and above the national CLL. Similarly, we also compare loans with LTVs just under and above the threshold of 105.

[12]As discussed earlier, high-balance mortgages are greater than the national CLL but not greater than high-cost CLL.

3 Data and Summary Statistics

3.1 Data Description

We use multiple data sources to estimate the effect of TBA eligibility on the primary market. First, we use the eMBS data, which provides various information on agency MBS and mortgages underlying each of agency MBS. From this data, we obtain information on MBS-level characteristics such as coupon rate, issuer, pool issue amount, pool issue date, product type, TBA eligibility, prepayment history, the distribution of loan-level characteristics within an MBS, etc. The loan-level eMBS data provides information about loan-level characteristics and prepayment history. Moreover, the loan-level data provide a link between a loan and the CUSIP of the MBS that includes the loan. This information is crucial in correctly estimating the benefit of TBA eligibility on mortgage rates because some high-balance loans can be included in TBA-eligible pools, as discussed in Section 2. The eMBS loan-level data to which we have access covers loans in Fannie Mae pools that are issued in or before October 2013 and loans in Freddie Mac pools that are issued in or before August 2018. Thus, we are missing mortgages sold to Fannie Mae for for the period after late 2013.

The second data is the loan-level data from Fannie Mae and Freddie Mac. They provide a publicly available single family loan-level performance data for fixed-rate mortgages originated between between January 1, 1999 and September 30, 2017. Importantly for this paper, they also provide loan-level data for HARP mortgages and a link between a HARP mortgage and the original loan. With this link, we can track performance of an original loan and a HARP loan, which is crucial for our empirical test using the LTV cutoff.

We use the first two data sets for our analysis of the impact on mortgage rates. In our sample, we only keep 30-year fixed-year-mortgages originated in or after 2009 that are sold to the GSEs. In addition, we only keep loans originated for single-family houses to keep the sample relatively homogeneous. We also use different subsamples for different cutoffs to only compare loans near each cutoff. The subsample selection will be explained in more details in Section 5.

The third data set we use is Equifax Credit Risk Insight Servicing and Black Knight McDash Data (CRISM), which links loan-level mortgage data to each borrower's credit records from Equifax. We use this data to analyze the impact on refinancing and subsequent durable consumption through new auto loan originations.

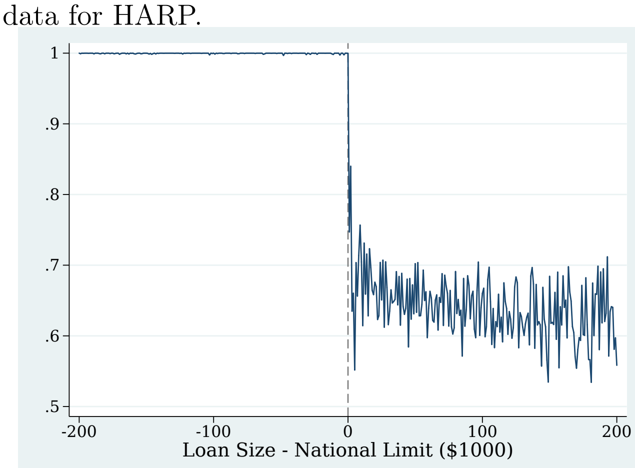
3.2 Summary Statistics

Figure 2 shows that the fraction of loans (among 30-year fixed-rate mortgages sold to the GSEs) that are included in TBA-eligible MBS changes substantially and discontinuously at the two cutoffs. In panel (a), the fraction is one for loans with size below the national CLL. However, the fraction decreases to around 0.6 for loans right above the CLL. This fraction does not decrease all the way to zero because high-balance loans can still be included in a TBA-eligible MBS as long as their share does not exceed 10%. In panel (b), the fraction decreases sharply to zero once the LTV exceeds 105 because any of such loans cannot be included in TBA-eligible MBS.

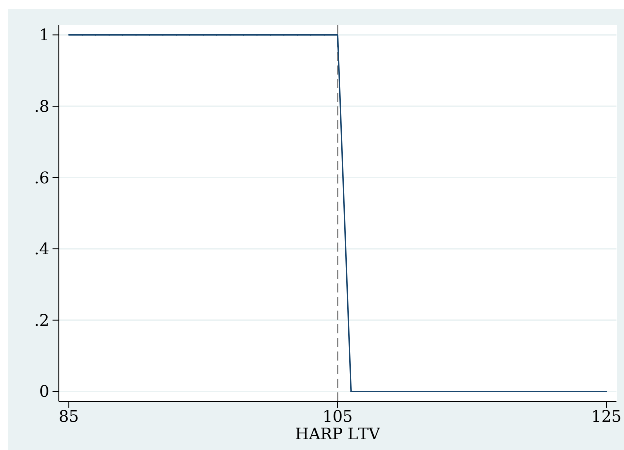
Note that these figures are created using only GSE loans. Consequently, jumbo loans, which are greater than the high-cost CLLs and thus cannot be securitized by the GSEs, are excluded from the data sample, and loans greater than the national CLL in the figure are high-balance loans that are securitized by the GSEs. Therefore, the fraction of loans included in TBA-eligible MBS decreases at the national CLL not because loans above the national CLL cannot be sold to the GSEs but because there is a limit on how much high-balance loans can be part of TBA-eligible MBS.

This is the main difference from papers that estimate spreads between jumbo and conforming loans in the period before the ESA introduced the high-cost CLLs in 2008 (e.g. Passmore et al. (2005); Sherlund (2008); Kaufman (2014); DeFusco and Paciorek (2017)). These papers aim to estimate how much the GSEs reduce mortgage rates by comparing loans that are eligible and ineligible for the GSE securitization. The effect of GSE eligibility will capture not only the value of having access to the TBA market, which is only available for agency MBS, but also the value of mortgage credit guarantees for GSE loans. In contrast, our data sample consists only of loans securitized by the GSEs, so we can estimate the effect of TBA-eligibility controlling for the effect of mortgage credit guarantees from the GSEs.

Figure 2: **Probability to Be Included in TBA-eligible Pools around the Cutoffs**: These figures plot the probability for a loan to be included in TBA-eligible MBS. Panel (a) plots the probability against the loan size. In the x-axis of this panel, the loan size is measured relative to the national CLL in thousand dollars. The source of the data for Panel (a) is eMBS. Panel (b) plots the probability against the LTV of a HARP loan. The source of the data for Panel (b) is loan-level data for HARP.



(a) Loan Size - CLL ($1000)

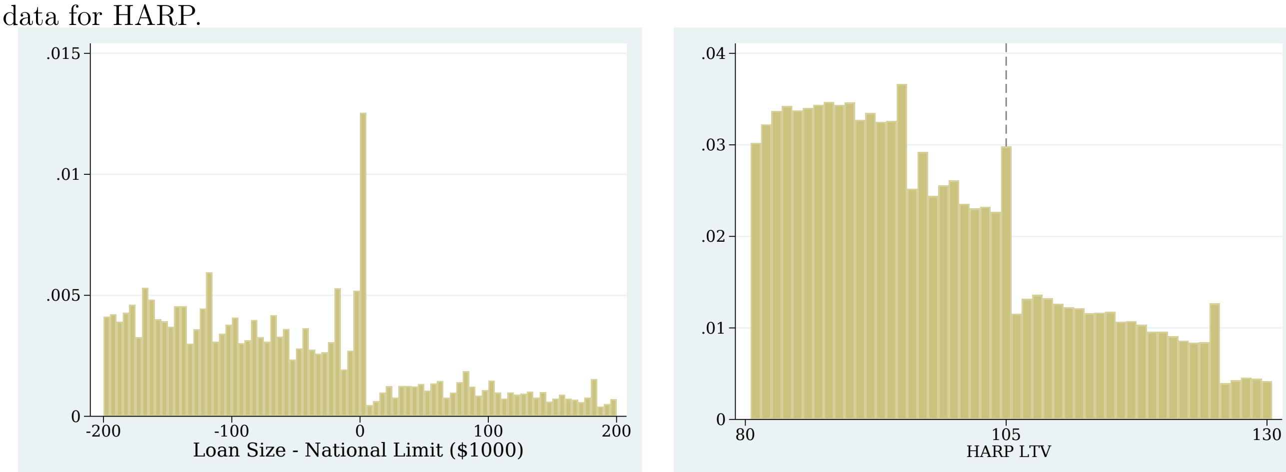


(b) Loan-To-Value

Figure 3 presents loan-level density around the two cutoffs. Bunching at the cutoffs shown in both panels is indicative of pricing differentials between loans below and above the cutoffs, possibly because of TBA eligibility. If mortgage rates are lower for loans that are more likely to be included in TBA-eligible MBS, borrowers that are slightly above the cutoff could to adjust the mortgage (e.g., by putting higher downpayments) to be at or below the cutoff. Previous papers that estimate the rate spread between jumbo and conforming loans also report a pattern similar to panel (a) at the national CLL before 2008; the pattern there is driven by pricing differential between loans securitized by the GSEs and loans that are not.

At the same time, the bunching at the cutoffs also poses challenges to estimation of the rate spreads at the cutoffs because those who bunch might have different unobserved characteristics from those who originate loans just above the cutoffs. If that is the case, then at least some of the rate spreads may be accounted for by the potential difference in unobserved characteristics of borrowers. We discuss how we address this challenge in Section 5.

Figure 3: **Bunching at the Cutoffs**: These figures plot loan-level density. Panel (a) plots the density against the loan size. In the x-axis of this panel, the loan size is measured relative to the national CLL in thousand dollars. The source of the data for Panel (a) is eMBS. Panel (b) plots the density against the LTV of a HARP loan. The source of the data for Panel (b) is loan-level data for HARP.



(a) Loan Size - CLL ($1000)

(b) Loan-To-Value

4 Simple Model

We write down a simple model that describe the value of TBA eligibility for an MBS. Consider a risk-neutral originator (or Fannie Mae or Freddie Mac) that is selling an MBS with fundamental value m. The fundamental value m would mostly be driven by prepayment risk. If the MBS is TBA-eligible, the originator has two options. First is to sell in the TBA market at price P_{tba}. Because of the cheapest-to-deliver pricing in TBA trades, this price does not depend on m. Second is to sell in the SP market at price $P_{sp}(m) + \epsilon$, where $\epsilon \sim \mathcal{N}(\mu, \sigma^2)$. The expected SP price, $P_{sp}(m)$, is an increasing function in m. The noise term ϵ can be thought of as coming from a random liquidity shock to the SP market or the difference in private valuation (or preferences) of the buyers. We assume that the originator observes ϵ before choosing which market to sell the MBS at.

The originator sells in the TBA market if $P_{sp}(m) + \epsilon < P_{tba}$. The expected value of this MBS is:

$$V(m) = \rho(m)P_{tba} + (1 - \rho(m))\mathbb{E}\left[P_{sp}(m) + \epsilon | \epsilon > P_{tba} - P_{sp}(m)\right] \tag{1}$$

where $\rho(m)$ is the probability that this MBS trades in the TBA market. The above equation illustrates that TBA eligibility decreases downside risk. When ϵ is low, that is, when the price that one can receive by selling in the SP market is low, one can sell the MBS in the TBA market and get a better price. This optionality in effect allows one to always sell the MBS at reasonable prices and makes the MBS more liquid (Gao et al., 2017).

We can rearrange Equation (1) to more clearly show the value of TBA eligibility. Given that the expected value of an MBS that is not TBA eligible is simply $P_{sp}(m)$, the value of TBA eligibility is:

$$V(m) - P_{sp}(m) = \rho(m)\mathbb{E}\left[P_{tba} - P_{sp}(m) - \epsilon | \epsilon < P_{tba} - P_{sp}(m)\right]. \tag{2}$$

From this expression, it can be easily seen that this value is always positive.

Given the simple structure of the model, we can solve for $\rho(m)$ and $V(m) - P_{sp}(m)$.

Lemma 1.

$$\rho(m) = 1 - \Phi\left(\frac{P_{sp}(m) - P_{tba}}{\sigma}\right)$$
$$V(m) - P_{sp}(m) = -\left\{1 - \Phi\left(\frac{P_{sp}(m) - P_{tba}}{\sigma}\right)\right\}(P_{sp}(m) - P_{tba}) + \sigma\phi\left(\frac{P_{sp}(m) - P_{tba}}{\sigma}\right)$$

where Φ is the standard normal CDF, and ϕ is the standard normal PDF.

We can easily show the following properties using Equation (1) and Lemma (1).

Proposition 1. *Probability of trading in the TBA market, $\rho(m)$, and the value of TBA eligibility, $V(m) - P_{sp}(m)$, have the following properties:*

(i) $\rho(m)$ is a decreasing function in m: Probability of trading in the TBA market is higher for MBS with higher prepayment risks.

(ii) $V(m) - P_{sp}(m) > 0$: The value of TBA eligibility is positive.

(iii) $-1 \leq \frac{\partial(V(m) - P_{sp}(m))}{\partial P_{sp}(m)} \leq 0$: The value of TBA eligibility is higher for MBS with higher prepayment risks.

These results and the interpretations are fairly intuitive. MBS with higher prepayment risks have lower value ($P_{sp}(m)$ and m are lower), and thus are more likely to be traded through the TBA market. Hence, the value added from TBA eligiblity is also higher for those MBS. Lastly, the value of TBA eligiblity is positive because TBA eligiblity gives an option to trade in the TBA market. Although we currently take $P_{sp}(m)$ to be exogenous, we can easily extend the model to make it endogenous. Proposition 1 still hold in the extended model. In rest of this paper, Proposition 1(iii), namely that the value of TBA eligibility is higher for MBS with higher prepayment risks, will be important. Lastly, while we do not model how the value of TBA eligibility, $V(m) - P_{sp}(m)$, gets passed to individual loans in the pool, we expect that it would fully or partially get passed down to the mortgage borrowers in the primary market.

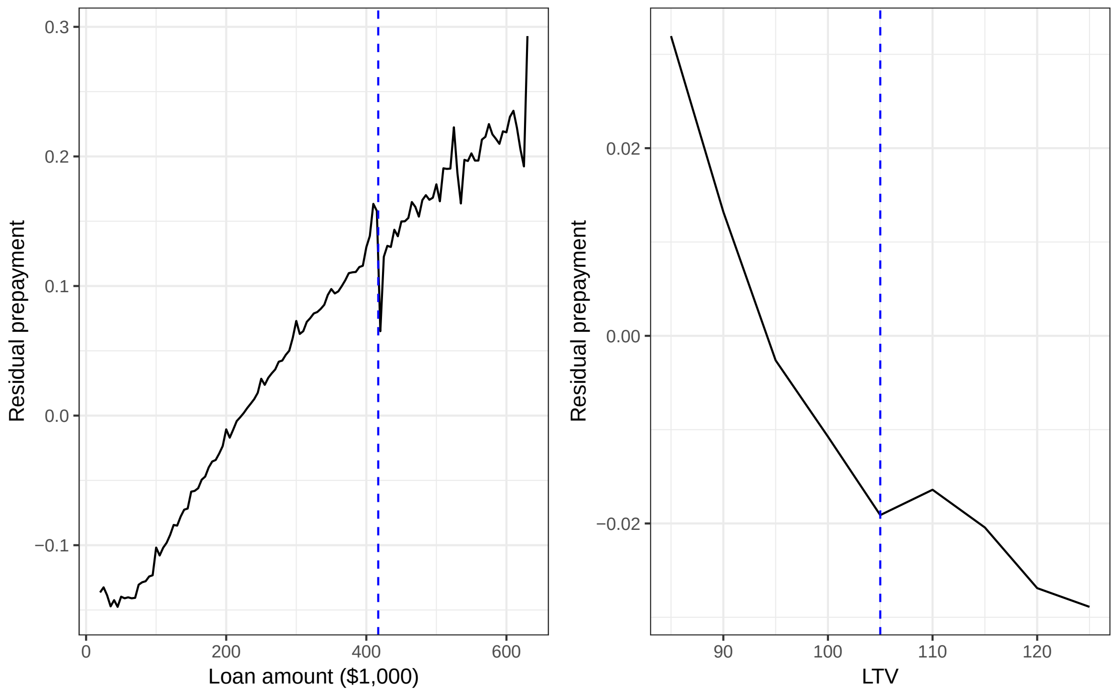
Value of TBA-eligibility and Prepayment Risks So far, we have shown that the value of TBA eligibility is greater for MBS with higher prepayment risks. What does this imply for the value of TBA-eligibility and loan-level prepayment risks? By definition, MBS with better prepayment characteristics (or lower prepayment risks) should have a larger share of loans with better prepayment characteristics than others. Moreover, we find that mortgage lenders tend to pool loans with better prepayment characteristics into the same MBS and trade the MBS in the SP market. Thus, loans with better prepayment characteristics will end up in MBS with better overall prepayment characteristics, and the value of TBA-eligibility will be also lower for such loans.

How is the relationship between prepayment risks and the value of TBA eligibility applied to our empirical setting? Figure 4 plots the relationship between ex-post prepayments and loan amounts (left panel) and between ex-post prepayments and LTVs (right panel). Ex-post prepayments in the figure are measured in terms of whether a loan was paid off completely by 36 months after the loan origination. Of course, this is a very specific measure of prepayments, but the pattern remains qualitatively unchanged when we use other loan ages. To control for the potential interactive effect of mortgage rates and interest rate path on prepayments, we consider residual prepayments, which are calculated by removing variation accounted for by the origination month $\times$ mortgage rate fixed effects.

The left-hand-side figure shows that prepayment risks and loan amounts are positively correlated. The vertical line is drawn at \$417,000, which is the national CLL until the end of 2016. Combined with the fact that a vast majority of loans are smaller than the national CLL as shown in Figure 3, this prepayment pattern suggests that loans around the national CLL have higher prepayment risks than a vast majority of loans securitized by the GSEs. Because the value of TBA eligibility will be higher for loans with higher prepayment risks, it is likely that the value of TBA eligibility for loans around the national CLL is close to the upper bound of the value of TBA eligibility.

On the other hand, the right-hand-side figure shows that prepayment risks and LTVs are negatively correlated. The vertical line is drawn at LTV 105, which is another cutoff used in the empirical analysis. Although the figure shows prepayments only for LTVs greater than 85, the prepayments for LTVs below 85 are higher than prepayments for LTVs greater than 85. This implies that loans with LTVs around 105 have lower prepayment risks than a vast majority of loans securitized by the GSEs. Thus, it is likely that the value of TBA eligibility for loans with LTVs around 105 is close to the lower bound of the value of TBA eligibility.

Figure 4: **Ex-post Prepayments by Loan Age 36 Months**: This figure displays the relationship between ex-post prepayment risks and loan amounts (on the left) and LTV (on the right). Vertical lines refer to the two cutoffs used in our empirical analysis: the national CLL (on the left) and LTV of 105 (on the right). Ex-post prepayments in the figure are measured in terms of whether a loan was paid off completely by loan age 36 months since origination. To control for potentially different prepayment behaviors depending on when a loan is originated and other loan characteristics, we consider residual prepayments, which are calculated by removing variation accounted for by the origination month $\times$ mortgage rate fixed effects.



5 Effects on Mortgage Rates

To quantify the benefit of TBA eligibility at the loan level, we would ideally compare interest rates between two identical loans, one of which is included in a TBA-eligible MBS while the other is included in a TBA-ineligible MBS. We can get close to the ideal situation by exploiting the rules that determine whether an MBS is eligible for TBA, which result in the discontinuities in the probability that a loan is included in TBA-eligible MBS around the cutoff values. We use the two cutoffs discussed earlier: the national CLL and LTV of 105.

5.1 High-Balance Loans

As shown by panel (a) in Figure 3, a high number of loans bunch at the national CLL although loans larger than the national CLL can be sold to the GSEs. This bunching poses a challenge to an identification strategy that utilizes the discontinuity in the probabilities for a loan to be included in TBA-eligible pools. Borrowers who bunch might have different unobserved characteristics from those who take out loans just above the cutoff. In that case, the rate spreads could be due to the potential difference in unobserved characteristics of borrowers.

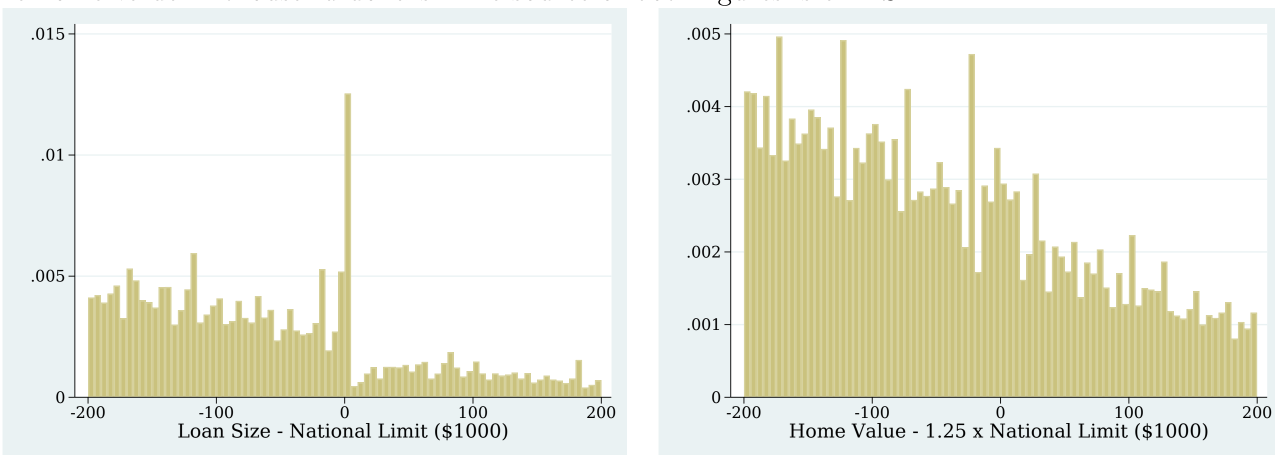
We overcome this challenge using an instrument variable strategy used by previous papers which estimate the impact of GSE purchase eligibility on mortgage rates in the period before the high-cost CLL was introduced.[13] The main idea of this empirical strategy is to utilize an alternative cutoff based on the home appraisal value instead of the loan size. The GSEs usually requires a borrower with less than a 20% down payment to have a mortgage insurance. In fact, a significant fraction of borrowers (36%) make exactly 20% down payments in our data. With this ubiquity of the 20% down payment, a borrower purchasing a home with the appraisal value not greater than 125% of the national CLL would most likely take out a conventional conforming mortgage. In contrast, a borrower purchasing a home with the appraisal value greater than 125% of the national CLL would take out a high-balance mortgage with a greater probability. Therefore, the probability of a loan to be included in a TBA-eligible MBS will change discontinuously depending on whether the home value is greater than 125% of the national CLL.

For this analysis, we impose the following additional sample selection criteria to keep the sample relatively homogeneous. First, we only keep purchase loans because our identification strategy is the most relevant for such loans. In fact, a majority of new originations with original LTV of 80 are purchase loans. Second, we exclude any loans with second mortgages (by comparing combined LTV and original LTV) or any loans with mortgage insurance (original LTV greater than 80).

The alternative cutoff based on the home value leads to a smooth density around the cutoff. Figure 5 shows differences in sorting patterns around the two different cutoffs. It is very clear that whereas panel (a) exhibits bunching at the national CLL, panel (b) shows a relatively smooth density around the cutoff based on the home appraisal value.

[13]Examples of such papers are Adelino et al. (2012); Kaufman (2014); DeFusco and Paciorek (2017). Another related paper that used the identification strategy is Vickery and Wright (2013), which studies how securitization affects availability of fixed-rate mortgages.

Figure 5: **Sorting around the Cutoffs**: These figures plot loan-level density. Panel (a) plots the density against the loan size. In the x-axis of this panel, the loan size is measured relative to the national CLL in thousand dollars. Panel (b) plots the density against home value associated with each loan. In the x-axis of this panel, the home value is measured relative to the cutoff based on the home value in thousand dollars. The source of both figures is eMBS.



(a) Loan Size - CLL ($1000)

(b) Appraisal Value - CLLx1.25 ($1000)

Regression Specification To estimate the effect of TBA eligibility on mortgage rates using the IV strategy, we start with the following first-stage regression:

$$NoTBA_i = \alpha 1[h_i > h^*_{t(i)}] + g^-(h_i;\theta_0) + g^+(h_i;\theta_1) + Z_i\gamma + \xi_{s(i)\times l(i)\times t(i)} + \epsilon_i. \tag{3}$$

The dependent variable, $NoTBA_i$, is a dummy variable that equals one if loan i is included in a TBA-ineligible MBS. On the right hand side, h_i represents the house appraisal value associated with loan i, and $h^*_{t(i)}$ is the 125 percent of the national CLL that is effective for the year corresponding to the origination year-month $t(i)$ for loan i.[14] Thus, $1[h_i > h^*_{t(i)}]$, which is our instrument, is a dummy variable that is equal to one if the house appraisal value associated with loan i is greater than 125 percent of the national CLL. Based on Figure 5, we expect that the coefficient estimate for α is negative.

Next, $g^-(h_i;\theta_0)$ and $g^+(h_i;\theta_1)$ represent polynomials of the running variable h_i for values not greater than $h^*_{t(i)}$ and values greater than $h^*_{t(i)}$, respectively. Both θ_0 and θ_1 are the coefficients of the polynomials and will be estimated. We experiment with different degrees of polynomials to see how sensitive the estimate for the main coefficient, α, is.. Vector Z_i contains other loan and borrower characteristics relevant for loan pricing: credit score, loan-to-income ratio, whether a loan is originated by a broker, and whether a loan is originated by a correspondent lender. The next term $\xi_{s(i)\times l(i)\times t(i)}$ refers to the fixed effects for a combination of state $s(i)$, the lender $l(i)$, and origination year-month $t(i)$. With these fixed effects, we can flexibly control for any differences across states, mortgage lenders, and origination months.

[14]During our sample period, the national CLL was set at \$417,000 from 2009 to 2016, \$424,100 in 2017, and \$453,100 in 2018. Thus, the cutoff is \$521,250, \$530,125, and \$566,375, respectively.

Once we estimate the first stage regression, we estimate the following second stage regression:

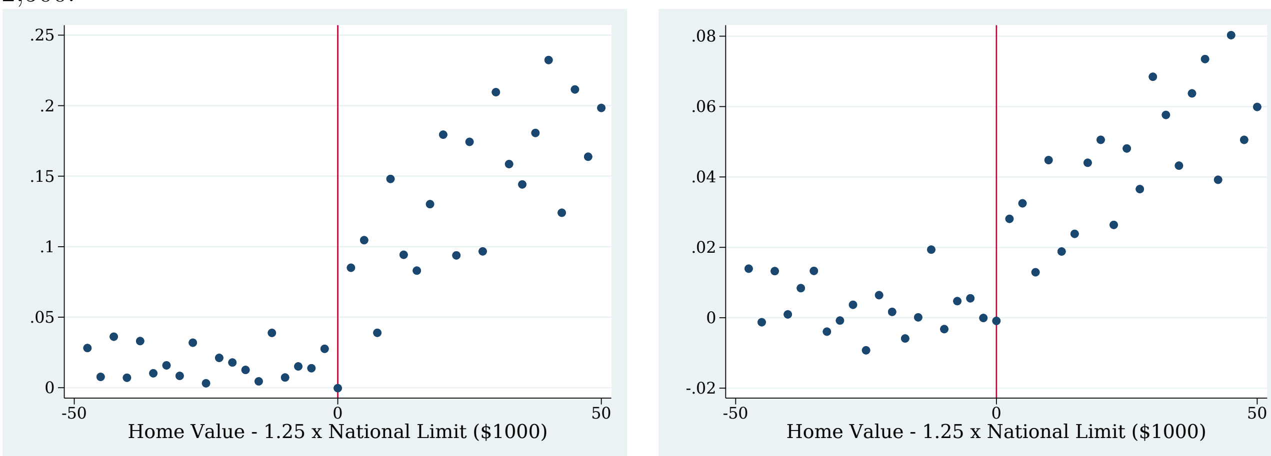
$$Rate_i = \beta \widehat{NoTBA}_i + g^-(h_i; \phi_0) + g^+(h_i; \phi_1) + Z_i\delta + \chi_{s(i)\times l(i)\times t(i)} + \omega_i \tag{4}$$

Based on the estimates of the first-stage regression, we calculate predicted value of the probability that loan i is not included in a TBA-eligible MBS ($\widehat{NoTBA}_i$). Then we use this variable in place of $1[h_i > h^*_{t(i)}]$ from Equation (3). The coefficient on $\widehat{NoTBA}_i$, β, estimates the impact of TBA eligibility on loan rates.

Graphical Examination of Discontinuities Before estimating the regressions, we first investigate whether there are visible discontinuities at the home appraisal value cutoff with respect to the probability of being included in TBA-ineligible MBS and mortgage rates. To precisely examine the relationship of the two variables and the home appraisal value, we remove variation in the two variables accounted for by the control variables Z_i and the fixed effects $\xi_{s(i)\times l(i)\times t(i)}$. For this purpose, we estimate a regression described by Equation (3) with the two variables ($NoTBA_i$ and $Rate_i$) as dependent variables, using the sample of loans with corresponding home values within the window of \$50,000 around the cutoff. Then by subtracting the estimate of $Z_i\gamma + \xi_{s(i)\times l(i)\times t(i)}$ from the dependent variable, we calculate the residual value of the dependent variable. We plot the residual dependent variable against the difference between the home appraisal value and 125 percent of the national CLL in Figure 6.

Discontinuities at the cutoff are clearly visible for both $NoTBA_i$ and $Rate_i$. Moreover, both panels have very similar patterns in terms of not only the jump at the cutoff but also the change in the slope. In both panels, the residual dependent variables do not change very much as the home appraisal value approaches to the cutoff from below. At the cutoff, both residual dependent variables increase discretely, and they increase as the home appraisal value moves upward from the cutoff. This similarity in the patterns shown in both panels indicates that TBA eligibility reduces mortgage rates.

Figure 6: **Probability to Be in TBA-ineligible MBS and Mortgage Rates (Cutoff 1)**: The figures plot the residual probability to be included in TBA-ineligible MBS (panel (a)) and the residual mortgage rate (panel (b)) against home values. The residual values are obtained by removing variation accounted by observable loan characteristics (Z_i) and the fixed effects ($\xi_{s(i)\times l(i)\times t(i)}$) after running regressions given by Equation (3) with $NoTBA_i$ and $Rate_i$ as dependent variables. Each dot in the plot represents the average value of each residual variable for each bin of the size of \$2,500.



(a) NoTBA

(b) Mortgage Rate

IV Regression Results First, we estimate the first-stage regression described by Equation (3). Table 1 presents estimates of α, which measure the difference in the probability of being included in a TBA-ineligible MBS between loans just above the cutoff and loans just below the cutoff. Columns (1)–(3) display estimates with a subsample with loans for home values within the window of \$50,000 around the cutoff. For instance, until 2016, this sample covers home values ranging from \$471,250 to \$571,250 with the national CLL equal to \$417,000. Columns (4)–(6) display estimates with an even smaller subsample with the window of \$25,000 around the cutoff. Until 2016, this sample covers home values ranging from \$496,250 to \$546,250. For each subsample, we experiment with different maximum numbers of polynomials for functions g^- and g^+ in Equation (3).

The table shows that loans just above the cutoff are more likely to be included in TBA-ineligible MBS than loans right below the cutoff. Although magnitudes of estimates are slightly different across specifications, the estimates show that borrowers purchasing homes just above the cutoff are more likely to originate high-balance loans, some of which will be included in TBA-ineligible MBS. With our preferred specification (column (3)), the probability to be included in TBA-ineligible MBS increases by 6 percentage points for loans just above the cutoff. This result is consistent with panel (a) of Figure 6, which shows a discrete jump in the probability by a similar magnitude at the cutoff.

Table 1: **First-Stage Results for Loans near Cutoff 1**: This table display estimates of coefficient α in Equation (3). Columns (1)–(3) are for the subsample of loans with home values within the window of $50,000 around the cutoff. Columns (1)–(3) are for specifications with up to first-, second-, and third-degree polynomials, respectively. Columns (4)–(6) are for the subsample of loans with home values within the window of $25,000 around the cutoff. Columns (4), (5), and (6) are for specifications with up to first-, second-, and third-degree polynomials, respectively. All specifications include State x Lender x Month Fixed effects and control variables described in the main text. Standard errors are clustered at the level of State x Lender x Month.

	Home Value: 1.25xCLL±$50K			Home Value: 1.25xCLL±$25K		
	(1) Polynomial=1	(2) Polynomial=2	(3) Polynomial=3	(4) Polynomial=1	(5) Polynomial=2	(6) Polynomial=3
$1[h_i > h^*_{t(i)}]$	0.059***	0.040***	0.060***	0.026***	0.061***	0.088***
	(17.52)	(9.08)	(10.02)	(5.98)	(8.89)	(9.64)
STATExMONTHxSELLER FE	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N. Obs.	78,535	78,535	78,535	37,891	37,891	37,891
Adj. R^2	0.22	0.22	0.22	0.16	0.16	0.16

Next, Table 2 displays the result from the second-stage regression. The table shows that the estimated effects of TBA eligibility on the mortgage rate are mostly similar across specifications. Our preferred estimate (Columns (3)) shows that TBA eligibility reduces the mortgage rate by around 40 basis points for loans near the national CLL. With the first-stage regression, we found that the probability to be included in TBA-eligible MBS increases by 6 percentage points for loans just above the cutoff. Then the second-stage estimate of 40 basis points implies that mortgage rates are higher for loans just above the cutoff by 2.4 basis points than loans just below the cutoff, which is consistent with the magnitude of the discrete jump shown in panel (b) in Figure 6.

Note that the estimate of 40 basis points does not measure the difference in mortgage rates between conventional conforming loans (not larger than the national CLL) and high-balance loans. Figure 2 shows that the about 65 percent of high-balance loans are still included in TBA-eligible MBS. Thus, the average rate spread between conventional conforming loans and high-balance loans should be about 14 basis points (= 0.35 × 40 basis points).[15]

[15]The actual spread between the two types of loans is time-varying. In fact, Vickery and Wright (2013) report that the spread was around 30 basis points in the beginning of 2009 and decreased to around 10 basis points by 2011. Our estimate of 14 basis points for the spread is the average across our sample period, which ranges from 2009 to mid-2018.

Table 2: **Second-Stage Results for Loans near Cutoff 1**: This table display estimates of coefficient β in Equation (4). Columns (1)–(3) are for the subsample of loans with home values within the window of $50,000 around the cutoff. Columns (1)–(3) are for specifications with up to first-, second-, and third-degree polynomials, respectively. Columns (4)–(6) are for the subsample of loans with home values within the window of $25,000 around the cutoff. Columns (4), (5), and (6) are for specifications with up to first-, second-, and third-degree polynomials, respectively. All specifications include State x Lender x Month Fixed effects and control variables described in the main text. Standard errors are clustered at the level of State x Lender x Month.

	Home Value: 1.25xCLL±$50K			Home Value: 1.25xCLL±$25K		
	(1) Polynomial=1	(2) Polynomial=2	(3) Polynomial=3	(4) Polynomial=1	(5) Polynomial=2	(6) Polynomial=3
$\widehat{NoTBA}$	0.310***	0.275**	0.398***	0.521***	0.321**	0.321***
	(6.02)	(2.51)	(3.74)	(2.83)	(2.57)	(2.69)
STATExMONTHxSELLER FE	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N. Obs.	77,898	77,898	77,898	37,565	37,565	37,565
Adj. R^2	0.87	0.87	0.86	0.86	0.87	0.87

Differences in Prepayments An important identifying assumption in our IV strategy is that unobserved characteristics correlated with mortgage rates are smooth at the cutoff. There is no direct way to test whether this assumption is true, but our data allow us to test it indirectly with ex-post prepayments. Because mortgages in our sample are guaranteed by the GSEs, default risks are viewed just as a source of prepayment risks from an MBS investor's perspective, and our ex-post prepayment measures include prepayments due to defaults.

We measure the ex-post prepayment by whether a loan was paid off, from an MBS investor's perspective, by the n-th month since the origination for $n \in \{24, 36, 48, 60, 72, 84\}$. Using these dummy variables as dependent variables, we estimate regressions similar to Equation (3) but with realized prepayment as the dependent variable. Because the loans in our sample are originated in 2009 or later, we only consider prepayment outcomes up to the 84th month since origination. Moreover, when considering whether a loan was paid off by the n-th month, we estimate the regression only with loans that could reach the loan age of n months without being paid off as of September 2018, when the latest prepayment data are available. For example, for $n = 48$, we exclude loans originated after September 2014 because the maximum loan age for such a loan would be 47 in September 2018, when the most recent performance data are available.

After estimating the regression for each n, we calculate the residual rate of prepayment by loan age n by removing variation accounted for by $Z_i\gamma + \xi_{s(i)\times l(i)\times t(i)}$. We then plot the residual rate of prepayment against the difference between the home value and the national CLL in Figure 7. The figures show no systematic changes in prepayment at the cutoff across all prepayment measures. Compared with the two panels in Figure 6, whose patterns lined up with each other, the patterns shown in Figure 7 do not seem to have any systematic relationships with the change in the probability of being included in a TBA-ineligible MBS shown in panel (a) of Figure 6. Therefore, this finding indicates that the discontinuity in mortgage rates at the cutoff is unlikely to be driven by changes in unobserved characteristics at the cutoff.

Figure 7: **Prepayment Probabilities around Cutoff 1**: These figures plot the residual probability that a loan is completely paid off by different loan ages in terms of months since origination. The x-axis represents the home value associated with each loan relative to the cutoff in thousand dollars. The residual variables are obtained by removing variation in corresponding original variables accounted by observable loan characteristics after running regressions given by Equation (3) with the original variables as dependent variables ($Z_i\gamma + \xi_{s(i)\times l(i)\times t(i)}$). Each dot in the plot represents the average value of each residual variable for each bin of the size of $2,500.

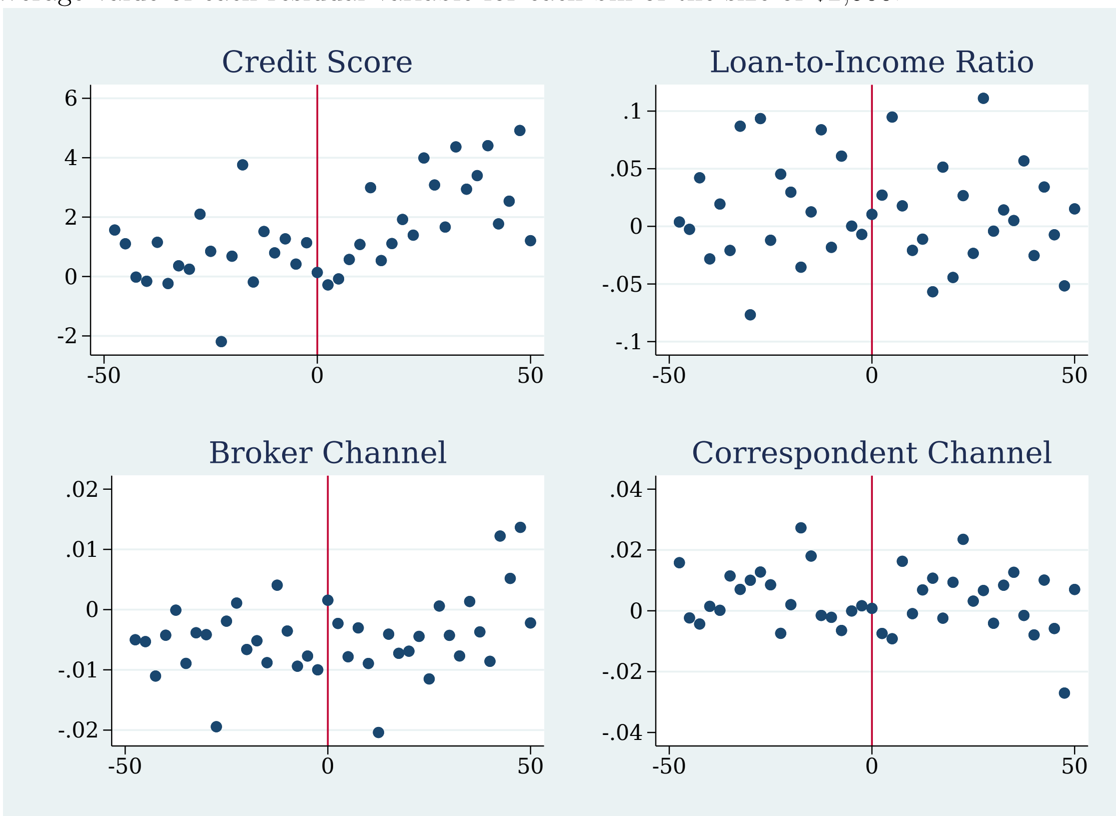
In addition, regression estimates reported in Table 3 show that there are no discontinuities in ex-post prepayments at the cutoffs. In the Appendix, Figure 16 and Table 10 show similar patterns with an alternative measure of ex-post prepayments, which is the ratio of original balance paid off by loan age n. This measure captures partial payoffs, whereas the original measure only captures complete payoffs. This set of evidence suggests that the estimated impact on the mortgage rate is unlikely to reflect differences in unobservables around the cutoff.

Table 3: **Regression Results for Prepayment Probabilities (Cutoff 1)**: This table displays the estimates of the regression similar to Equation (3), but where dependent variables are the dummy variable that is equal to one if a loan is completely paid off by loan age n for $n \in \{24, 36, 48, 60, 72, 84\}$. The maximum degree of polynomials included in the regressions are two for each regression. For all columns, we used the subsample of loans with corresponding home values within the window of $50,000 around the cutoff. For each column, we further restricted the subsample to loans that were originated at least n months before the most recent month available in the data (2018m9). All specifications include State x Lender x Month Fixed effects and control variables described in the main text. Standard errors are clustered at the level of State x Lender x Month.

	(1) By Age 24	(2) By Age 36	(3) By Age 48	(4) By Age 60	(5) By Age 72	(6) By Age 84
$1[h_i > h^*_{t(i)}]$	-0.005	-0.020	-0.011	-0.034	-0.050	-0.021
	(-0.27)	(-0.86)	(-0.41)	(-1.20)	(-1.59)	(-0.69)
h_i	-0.000	0.004**	0.003	0.000	0.000	0.000
	(-0.16)	(2.11)	(1.24)	(0.16)	(0.19)	(0.21)
$1[h_i > h^*_{t(i)}] \times h_i$	0.001	-0.004	-0.002	0.003	0.007	0.001
	(0.29)	(-0.89)	(-0.54)	(0.53)	(1.31)	(0.22)
STATExMONTHxSELLER FE	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N. Obs.	35,443	29,761	25,066	20,564	15,614	12,434
Adj. R^2	0.14	0.20	0.24	0.25	0.20	0.09

Exogenous Variables around the Cutoff An identifying assumption with the regression discontinuity design is that the sample is selected randomly around the cutoff. A way to test for a random selection is to test whether exogenous variables exhibits any discrete jumps at the cutoffs. Figure 8 plot the residual values of exogenous loan characteristics against the difference between the home appraisal value and 125 percent of the national CLL. We consider exogenous loan characteristics included in Z_i in Equations (3) and (4). The figure shows that there is no noticeable jump in any of the four variables. In appendix, Table 11 also confirms that there is no statistically significant jump at the cutoff for any of the four variables.

Figure 8: **Exogenous Variables around Cutoff 1**: The figures plot the residual values of exogenous loan characteristics against home values. The residual values are obtained by removing variation accounted by the fixed effects ($\xi_{s(i)\times l(i)\times t(i)}$) after running regressions given by Equation (3) with the exogenous loan characteristics as dependent variables. Each dot in the plot represents the average value of each residual variable for each bin of the size of \$2,500.



5.2 Loan-To-Value 105

In the previous section, we showed that TBA eligibility reduces mortgage rates for loans near the national CLL. In this subsection, we similarly estimate the effect of TBA eligibility on mortgage rates for loans with LTVs near 105.

As shown by panel (b) in Figure 3, there is bunching at LTV of 105, and origination shares for LTVs above 105 seems to be discretely lower than origination shares for LTV right below 105. This discontinuity in the distribution of LTV at origination poses a challenge to an identification strategy that utilizes the cutoff of LTV 105. Those who originate loans at or right below the LTV 105 might have different unobserved characteristics from those who originate loans just above the cutoffs. Thus difference in the mortgage rates around the cutoff may be accounted for by the potential difference in unobserved characteristics.

We also address this problem with an instrument variable strategy, which utilizes an alternative cutoff based on the ending balance of the original loan that preceded the refinanced HARP loan. When refinancing into a HARP mortgage, the borrower needs to pay a closing cost. This cost varies across lenders and can be thousands of dollars. A borrower can roll the closing cost into the new balance, which can make the new loan balance higher than the ending balance of the preceding loan. Freddie Mac imposes a limit on how much of the closing cost can be included in the balance of the new HARP loan: the lesser of 4% of the balance of the preceding loan and \$5,000.[16] This rule restricts the size of the HARP loan to a limit that depends on the ending balance of the preceding loan. As a result, the maximum LTV of the new HARP loan is a function of the ending balance of the preceding loan:

$$PredLTV_i \equiv \frac{\min\{PrevBalance_i \times 1.04, PrevBalance_i + 5000\}}{UpdatedHomeValue_i} \times 100 \geq LTV_i.$$

We argue that $PredLTV_i$ predicts the probability that a HARP loan would be included in a TBA-ineligible MBS. If $PredLTV_i \leq 105$, then we expect that the LTV of a new HARP loan securitized by Freddie Mac is likely to be not greater than 105. Otherwise, the probability that the LTV of a HARP loan is greater than 105 will increase as $PredLTV_i$ increases beyond 105. Because any HARP loan with the LTV greater than 105 must be included in a TBA-ineligible MBS, we expect that the relationship between $PredLTV_i$ and the probability of being included in a TBA-ineligible MBS changes discontinuously at $PredLTV_i$ of 105.

Loan-level data from Freddie Mac allow us to calculate $PredLTV_i$ for each HARP origination. $UpdatedHomeValue_i$ can be obtained by multiplying the new LTV and the new loan amount for each HARP origination. Since the data provide a link between each HARP loan and its preceding loan, we obtain $PrevBalance_i$ by looking at the outstanding balance of the preceding loan in the month right before HARP refinancing.

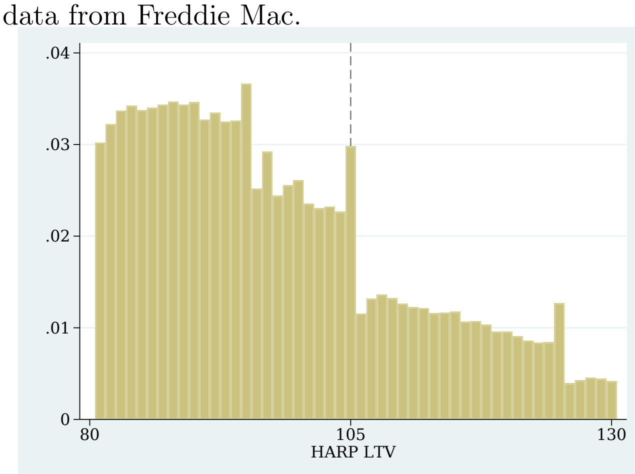
For this analysis, we impose the following additional sample selection criteria to keep the sample relatively homogeneous. First, we only keep HARP loans securitized by Freddie Mac because Fannie Mae did not have similar restrictions on closing costs. Second, we keep only the loans for owner-occupied single-family houses as we did for our analysis for loans near the national CLL in Section 5.1. Moreover, we exclude any loans with second mortgages (by comparing combined LTV and original LTV) or any loans with mortgage insurance.[17]

Figure 9 suggests that the density of $PredLTV_i$ is smooth at the cutoff of 105 (panel (b)) unlike the density of LTVs of HARP loans (panel (a)). The smooth density of $PredLTV_i$ suggests that there is no systematic manipulation of $PredLTV_i$, which satisfies a key condition for identification.

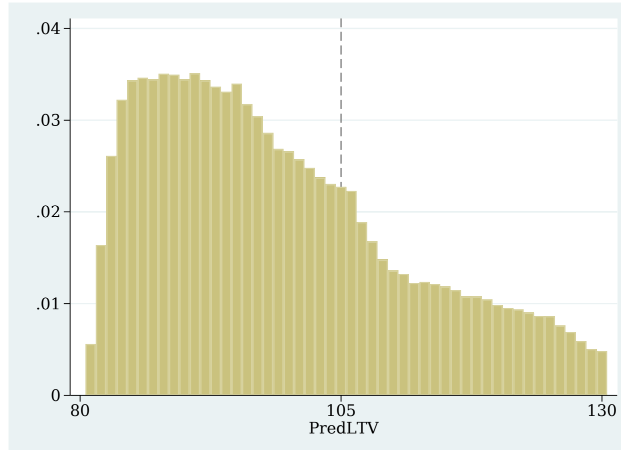
[16] This information on the limit on how much the closing cost can be included in the new balance is provided on page 15 of the evaluation report by the Office of Inspector General of the Federal Housing Finance Agency on the HARP program. The link to the report is: https://www.fhfaoig.gov/Content/Files/EVL-2013-006.pdf.

[17] HARP allowed borrowers to refinance without mortgage insurance although their updated LTVs are greater than 80. However, there are a small group of HARP borrowers who still had mortgage insurance.

Figure 9: **Sorting around the Cutoffs**: These figures plot loan-level density for HARP originations securitized by Freddie Mac. Panel (a) plots the density of the LTV at origination for a HARP loan. Panel (b) plots the density of $PredLTV_i$. The data source of both figures is the loan-level data from Freddie Mac.



(a)HARP LTV



(b) PredLTV

Graphical Examination Panel (a) of Figure 10 displays the relationship between $PredLTV_i$ and the probability of being included in a TBA-ineligible MBS. As before, we calculate the residual probability of being included in a TBA-ineligible MBS with the following regression:

$$NoTBA_i = \alpha 1[PredLTV_i > 105] + g^-(PredLTV_i; \theta_0) + g^+(PredLTV_i; \theta_1) \\ + Z_i\gamma + \xi_{zip3(i)\times l(i)\times t(i)} + \epsilon_i \tag{5}$$

The dependent variable, $NoTBA_i$ is a dummy variable that is equal to one if loan i is included in TBA-eligible MBS. Note that in this setting, a HARP loan with the initial LTV above 105 is not allowed to be included in TBA-eligible MBS. The dummy variable, $1[PredLTV_i > 105]$ is equal to one if a HARP loan i's $PredLTV$ is above 105. Similarly to the analysis for loans near the national CLL, we include up to the third-degree polynomials of $PredLTV_i$ interacted with $1[PredLTV_i > 105]$,which are captured by the two functions g^- and g^+. Next, Z_i include other loan characteristics: credit score, whether a loan is originated by a broker, whether a loan is originated by a correspondent lender, and the mortgage rate for the previous loan. Lastly, [18] $\xi_{zip3(i)\times l(i)\times t(i)}$ refers to the fixed effects for a combination of first three digits of zipcodes, mortgage lenders, and loan origination months.

After estimating Equation 5, we calculate the residual value of $NoTBA_i$ by removing variation in the probability accounted for by loan characteristics Z_i and fixed effects. The figure shows that

[18] Loan characteristics in Z_i in Equation 5 are not exactly the same as loan characteristics included for the analysis for loans near the national CLL. This is in part because different data sets are used for the analyses for loans near the national CLL and HARP loans. For example, a borrower's income is missing for the data set for HARP loans, whereas we can infer a borrower's income in the data set for loans near the national CLL. Thus, we do not include the loan-to-income ratio in Equation 5.

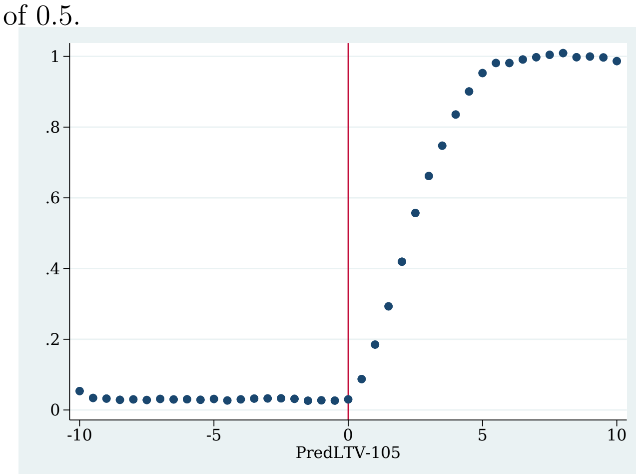
although there is no jump at the cutoff, the slope changes discontinuously, which results in a kink at the cutoff. As $PredLTV_i$ approaches to 105 from below, the slope of the graph is almost flat. In contrast, as $PredLTV_i$ moves away from the cutoff value, the slope of the graph becomes suddenly much steeper, indicating that the same amount of an increase in $PredLTV_i$ makes the LTV of HARP loan much more likely to be greater than 105. Based on this pattern, it is evident that there is a kink at the cutoff in the relationship between $PredLTV_i$ and the probability of being included in a TBA-ineligible MBS.

Panel (b) of Figure 10 displays the relationship between $PredLTV_i$ and residual mortgage rates of HARP loans. As in panel (a), we calculate the residual rate by removing variation in mortgage rates accounted for by loan characteristics Z_i and the fixed effects $\xi_{zip3(i)\times l(i)\times t(i)}$. As in panel (a), there is also a kink in the relationship between $PredLTV_i$ and the residual mortgage rate at the cutoff, which suggests that the change in the relationship with the residual mortgage rate at the cutoff is correlated with TBA eligibility.

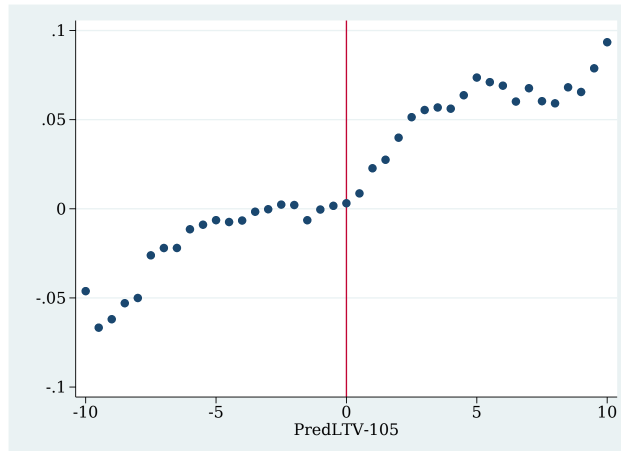
An important pattern shown by Figure 10 is that there is a kink instead of a jump at the cutoff, whereas there is a jump at the cutoff for loans near the national CLL (displayed in Figure 6). The main reason for the pattern is that $PredLTV_i$ is calculated based not on actual closing costs but on the largest possible closing costs that can be rolled into a HARP balance. In contrast, the appraised home value, which is the IV used for the analysis for loans near CLLs, is the actual home value, not the maximum possible home value. If closing costs for HARP ends up being smaller than the upper limit, then LTVs for new HARP loans will be below $PredLTV_i$. Thus, if closings cost are usually below the upper limit, then actual LTVs for HARP loans will not be very different regardless of whether $PredLTV_i$ is below or above the cutoff of 105. In that case, there would not be a jump at the cutoff as shown in Figure 10. However, as $PredLTV_i$ increases away from the cutoff, even closing costs smaller than the upper limit will be more likely to result in actual LTVs for HARP loans higher loan 105, which will lead to the upward slopes for $PredLTV_i$ above 105 as shown in Figure 10.

Another notable pattern is that the relationships between $PredLTV_i$ and the two variables are non-linear for values of $PredLTV_i$ away from the cutoff. For example, the slope for the mortgage rate in panel (b) also seems to changes for $PredLTV_i$ near -5. Thus, it is important to control for these non-linear relationship by including higher-degree polynomials especially when using a subsample with nonlinearity. That is because the linear terms by themselves with the larger subsample cannot estimate the change in the slopes in the relationship between $PredLTV_i$ and the mortgage rate at the cutoff.

Figure 10: **TBA-eligible Probabilities and Mortgage Rates (Cutoff 2)**: The figures plot the residual probability to be included in TBA-ineligible MBS (panel (a)) and the residual mortgage rate (panel (b)) against $PredLTV_i$. The residual variables are obtained by removing variation in corresponding original variables accounted by observable loan characteristics after running regressions given by Equation (5) with the original variables as dependent variables ($Z_i\gamma + \xi_{zip3(i)\times l(i)\times t(i)}$). Each dot in the plot represents the average value of each residual variable for each bin of the size of 0.5.



(a) NoTBA



(b) Mortgage Rate

Regression Specifications Figures 10 suggests that the standard regression discontinuity design will not work well in this setup because there is no jump in the probability of being included in a TBA-ineligible pool at the cutoff. Instead, we use the regression kink design, which estimates the treatment effect by estimating changes in the slopes at the cutoff in the relationship between a running variable and dependent variable. In this empirical design, we run a two-stage-least-square regression with the first- and second-stage regressions as follows:

$$\begin{aligned} NoTBA_i = {} & \alpha_0 PredLTV_i + \alpha_1 PredLTV_i \times 1[PredLTV_i > 105] & (6) \\ & + g^-(PredLTV_i;\theta_0) + g^+(PredLTV_i;\theta_1) + Z_i\gamma + \xi_{zip3(i)\times l(i)\times t(i)} + \epsilon_i \\ Rate_i = {} & \beta_0 PredLTV_i + \beta_1 \widehat{NoTBA}_i & (7) \\ & + g^-(PredLTV_i;\phi_0) + g^+(PredLTV_i;\phi_1) + Z_i\delta + \chi_{zip3(i)\times l(i)\times t(i)} + \omega_i \end{aligned}$$

In this empirical design, Equations (6) and (7) are the first- and second-stage regressions, respectively. In Equation (6), α_1 measures the change in slopes at the cutoff. The variable $PredLTV_i \times 1[PredLTV_i > 105]$, which only shows up in Equation (6), serves as an IV. The coefficient β_1 measures the treatment effect of being included in a TBA-ineligible MBS.

IV Regression Results First, we estimate the first-stage regression described by Equation (6). Table 4 presents coefficient estimates for the first stage with six different specifications, which measure how much slopes between $PredLTV_i$ and the probability to be included in TBA-ineligible

MBS changes at the cutoff. Columns (1)–(3) present estimates with the subsample with loans with $PredLTV_i \in [95, 115]$, which has the window size of 10 around the cutoff of 105. Columns (4)–(6) present estimates with the subsample with loans with $PredLTV_i \in [100, 110]$, which has the window size of 5 around the cutoff of 105. For each subsample, we experiment with different maximum numbers of polynomials for functions g^- and g^+ in Equation (6).

The table shows that the slope is more positive for $PredLTV_i$ above 105, which is consistent with Figure 10. These estimates shows that a marginal increase in $PredLTV_i$ is much more likely to result in a HARP loan with the LTV above 105 if $PredLTV_i$ is above 105. This result is consistent with panel (a) of Figure 10, which shows a kink in the probability.

Table 4: **First-Stage Results with Cutoff 2**: This table display estimates of coefficients in Equation (6). Columns (1)–(3) are for the subsample of loans with $PredLTV_i \in [95, 115]$. Columns (1)–(3) are for specifications with up to first-, second-, and third-degree polynomials, respectively Columns (4)–(6) are for the subsample of loans with $PredLTV_i \in [100, 110]$. Columns (4), (5), and (6) are for specifications with up to first-, second-, and third-degree polynomials, respectively. All specifications include Zip3 x Lender x Month Fixed effects and control variables described in the main text. Standard errors are clustered at the level of Zip3 x Lender x Month.

	$PredLTV$: [95,115]			$PredLTV$: [100,110]		
	(1)	(2)	(3)	(4)	(5)	(6)
	Polynomial=1	Polynomial=2	Polynomial=3	Polynomial=1	Polynomial=2	Polynomial=3
$PredLTV$	0.014***	-0.005***	-0.023***	0.002	-0.014***	0.032***
	(37.75)	(-4.01)	(-8.22)	(1.36)	(-3.11)	(2.95)
$1[PredLTV > 105] \times PredLTV$	0.107***	0.284***	0.329***	0.205***	0.249***	0.089***
	(138.22)	(114.31)	(45.86)	(79.25)	(23.12)	(3.52)
ZIP3xMONTHxSELLER FE	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N. Obs.	67,466	67,466	67,466	26,473	26,473	26,473
Adj. R^2	0.76	0.82	0.82	0.63	0.63	0.63

The second-stage regression results are reported in Table 5. Note that because the relationship between $PredLTV_i$ and the mortgage rate are highly non-linear, the estimate can be misleading withjust up to the first-degree polynomials. In Column (1), our point estimate is negative (but statistically insignificant) although Figure 10 is indicative of at least a positive coefficient. Our estimates become consistent with the figure as we include higher-degree polynomials (Columns (2) and (3)) or as we use a narrower sample window (Columns (4)–(6)). When we use the smaller sample window and include up to the third-degree polynomials (Column (6)), the point estimate of the impact of TBA eligibility on mortgage rates is the largest but statistically insignificant because the standard error of the estimate becomes very large with the third-degree polynomials with a relatively small number of observations with the second subsample. Our preferred estimate (Columns (3)) shows that TBA eligibility reduces the mortgage rate by 10 bps for HARP loans with LTVs around 105.

Table 5: **Second-Stage Regression Results with Cutoff 2**: This table display estimates of coefficients in Equation (7). Columns (1)–(3) are for the subsample of loans with $PredLTV_i \in [95, 115]$. Columns (1)–(3) are for specifications with up to first-, second-, and third-degree polynomials, respectively Columns (4)–(6) are for the subsample of loans with $PredLTV_i \in [100, 110]$. Columns (4), (5), and (6) are for specifications with up to first-, second-, and third-degree polynomials, respectively. All specifications include Zip3 x Lender x Month Fixed effects and control variables described in the main text. Standard errors are clustered at the level of Zip3 x Lender x Month.

	$PredLTV$: [95,115]			$PredLTV$: [100,110]		
	(1) Polynomial=1	(2) Polynomial=2	(3) Polynomial=3	(4) Polynomial=1	(5) Polynomial=2	(6) Polynomial=3
$\widehat{NoTBA}$	-0.005	0.079***	0.075***	0.061***	0.067**	0.148
	(-0.74)	(7.73)	(4.31)	(5.14)	(2.20)	(0.73)
ZIP3xMONTHxSELLER FE	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N. Obs.	66,632	66,632	98,754	26,107	39,900	39,900
Adj. R^2	0.85	0.85	0.84	0.86	0.85	0.85

Differences in Prepayments To check whether there is a kink at the cutoff for the relationship between $PredLTV_i$ and unobserved characteristics, we investigate whether the relationship between $PredLTV_i$ and the ex-post prepayment changes at the cutoff. Similar to Figure 7, we also measure the ex-post prepayment by whether a borrower paid off the loan by the n-th month since the origination for $n \in \{24, 36, 48, 60, 72, 84\}$. Using these dummy variables as dependent variables, we estimate regressions similar to Equation (5). Similarly to the earlier analysis for high-balance loans, moreover, we also estimate the regression only with loans that could reach the loan age of n months without being paid off as of September 2018, when the latest prepayment data are available. After estimating the regression for each n, we calculate the residual rate of prepayment by loan age n by removing variation accounted for by loan characteristics Z_i and the fixed effects.

Table 6: **Regression Results for Prepayment Probabilities (Cutoff 2)**: This table displays the estimates of the regression similar to Equation (3), where dependent variables are the dummy variable that is equal to one if a loan is completely paid off by loan age n for $n \in \{24, 36, 48, 60, 72, 84\}$. The maximum number of polynomials included in the regressions are three for each column. For all columns, we used the subsample of loans with $PredLTV_i$ between 100 and 110. For each column, we further restricted the subsample to loans that were originated at least n months before the most recent month available in the data (2018m9). All specifications include Zip3 x Lender x Month Fixed effects and control variables described in the main text. Standard errors are clustered at the level of Zip3 x Lender x Month.

	(1) By Age 24	(2) By Age 36	(3) By Age 48	(4) By Age 60	(5) By Age 72	(6) By Age 84
$1[PredLTV > 105]$	0.004	-0.005	0.003	0.002	-0.009	-0.024
	(1.51)	(-1.54)	(0.74)	(0.27)	(-0.80)	(-1.12)
$PredLTV$	-0.002	-0.002	-0.002	-0.003	-0.002	0.022**
	(-1.16)	(-1.09)	(-0.64)	(-0.72)	(-0.25)	(2.17)
$1[PredLTV > 105] \times PredLTV$	0.001	0.004	0.004	0.003	0.012	-0.019
	(0.41)	(1.41)	(1.20)	(0.56)	(1.08)	(-0.93)
ZIP3xMONTHxSELLER FE	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N. Obs.	61,744	54,914	44,277	23,311	11,282	3,481
Adj. R^2	-0.02	0.01	-0.00	0.00	-0.03	-0.06

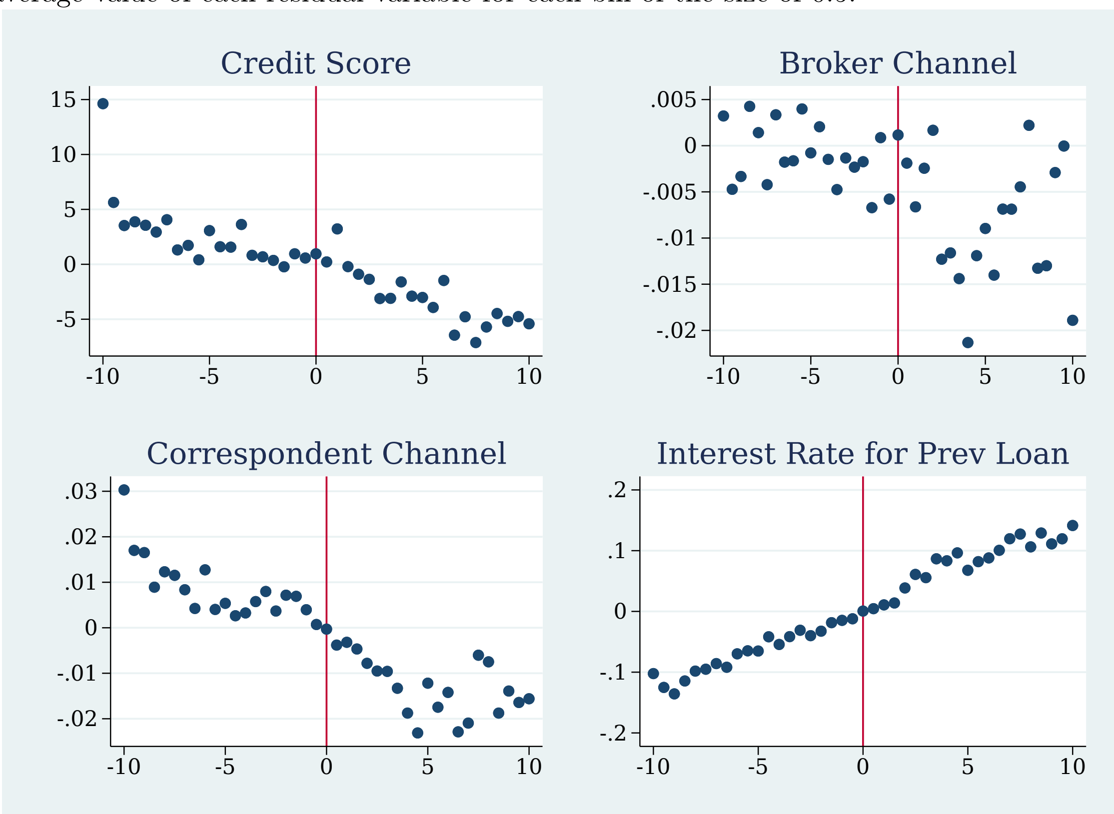
The regression estimates are reported in Table 6, and we also plot the residual rate of prepayment against $PredLTV_i$ in Figure 11. The table shows that any changes in the slopes are not statistically significant. The figure is consistent with the results displayed by the table. It is apparent that no systemic changes in the relationship between the ex-post prepayment and $PredLTV_i$ at the cutoff for all measures of prepayment we considered. Therefore, this finding indicates that the discontinuity in mortgage rates at the cutoff is unlikely to be driven by changes in unobserved characteristics at the cutoff.

Figure 11: **Prepayment Probabilities around Cutoff 2**: These figures plot the residual probability that a loan is completely paid off by different loan ages in terms of months since origination. The residual variables are obtained by removing variation in corresponding original variables accounted by observable loan characteristics after running regressions given by Equation (5) with the original variables as dependent variables ($Z_i\gamma + \xi_{zip3(i)\times l(i)\times t(i)}$). Each dot in the plot represents the average value of each residual variable for each bin of the size of 0.5.

In the Appendix, Figure 17 and Table 12 show similar patterns with an alternative measure of ex-post prepayments, which is the ratio of original balance paid off by loan age n. This measure captures partial payoffs, whereas the original measure only captures a complete payoff. This set of evidence suggests that the estimated impact on the mortgage rate is unlikely to reflect difference in unobservables around the cutoff.

Exogenous Variables around the Cutoff We also test for a random selection with respect to exogenous variables. Figure 12 plot the residual values of exogenous loan characteristics against $PredLTV_i$. We consider exogenous loan characteristics were included in Z_i in Equations (5). The figure shows that there is no noticeable pattern in any of the four variables. In appendix, Table 13 report estimated coefficients for each dependent variable. Although the coefficient for the interaction between $1[PredLTV_i > 105]$ and $PredLTV_i$ is significant, the pattern is not robust to different specifications. In fact, the corresponding figure suggests that there is no noticeable pattern for loans very close to the cutoff. In an alternative specification with only up to first- or second-degree polynomials of $PredLTV_i$ or the smaller subsample, the coefficient becomes statistically insignificant even at the 90% level.

Figure 12: **Exogenous Variables around Cutoff** 2: The figures plot the residual values of exogenous loan characteristics against $PredLTV_i$. The residual values are obtained by removing variation accounted by the fixed effects ($\xi_{zip3(i)\times l(i)\times t(i)}$) after running regressions given by Equation (5) with the exogenous loan characteristics as dependent variables. Each dot in the plot represents the average value of each residual variable for each bin of the size of 0.5.



5.3 Discussion

We have estimated the effect of TBA-eligibility on the mortgage rate, exploiting the two cutoffs that determine TBA-eligibility. We found that TBA eligibility reduces the mortgage rate by 40 basis points for loans near the national CLL and by 10 basis points for loans with LTVs near 105. The difference in magnitudes of the estimates is consistent with the prediction from our model that the option to trade in the TBA market is more valuable for loans with higher prepayment risks because they are less likely to trade in SP.

A common criticism against empirical designs based on discontinuities estimating local treatment effects is that the resulting estimate might be difficult to be extrapolated to the rest of the population. This concern would apply to our setup if we estimated the impact on the mortgage rate using only one of the two cutoffs. However, the two cutoffs used in our empirical analysis are at opposite ends of the spectrum of prepayment risks. Thus, the estimated impact on the mortgage rates with the two cutoffs are likely to be close to the upper and lower bounds. Moreover, given the model prediction that the benefit of TBA eligibility is higher for loans with higher prepayment risks, we expect that the benefit of TBA-eligibility will fall between our two estimates for a majority of loans, which are likely to have prepayment risks toward the middle of the distribution of prepayment risks.

6 Effects on Refinancing Behavior and Consumer Spending

In the previous section, we have established that loans included in TBA-eligible pools have lower interest rates. Because TBA eligibility impacts the price, we expect that it would impact the quantity, or in other words, borrowers' demand for mortgages. In this section, we specifically investigate whether TBA eligibility affects borrowers' refinancing behavior. Previous research such as Agarwal et al. (2017) and Abel and Fuster (2018) find that refinancing is important for monetary policy transmission because consumer spending increases subsequent to refinancing. Thus, we also investigate how TBA eligibility affects consumer spending as well.

For this analysis, we focus only on refinancing behavior of borrowers with remaining loan balances near the national CLL. We do not investigate refinancing behavior with LTVs near 105 because of data limitations. Our data provides exact information about evolution of a borrower's loan balance over time. In contrast, we do not have good information about the evolution of updated LTV. Because our analysis hinges on differences in borrowers' behavior at the cutoffs, it is important to observe any differences in a borrower's decision to refinance depending on whether his updated LTV is above or below the cutoff. However, our data only allows us to observe updated LTVs only when a borrower refinances into a HARP loan, and we do not observe updated LTVs for borrowers who do not refinance at a given time.

6.1 Refinancing and National CLL

The period after when the GSEs were allowed to purchase and securitize high-balance loans (since March 2008) has experienced historically low interest rates, which resulted in a refinancing boom. We investigate whether TBA eligibility affects the refinancing decision of a borrower with a remaining loan balance near the national CLL after 2008 when the GSEs purchased high-balance loans. As in the earlier analysis on mortgage rates, we do not consider 2008 because there was significant uncertainty regarding TBA eligibility of high-balance loans.

A borrower seeking to refinance with a remaining balance above the national CLL faces the following trade-off: refinancing now into a high-balance loan with a higher rate versus refinancing later into a conventional conforming loan with a lower rate.[19] Having the trade-off in mind, we

[19] A borrower could always refinance into a conventional conforming loan if he makes a sufficient lump-sum mortgage payment. However, this possibility is not very likely.

investigate whether the refinancing probability increases for borrowers with remaining loan balances right below the national CLL relative to those with remaining balances right above the cutoff. We will interpret the difference in the refinancing probabilities as demand response to the spread in mortgage rates around the cutoff.

Another possibility is that a borrower cannot refinance into a high-balance loan because a higher rate associated with a high-balance loan makes debt-to-income (DTI) ratio binding. A DTI ratio is calculated as the monthly mortgage payment divided by a borrower's income. Thus, the larger mortgage rate is, the higher DTI is. Thus, even if a borrower would like to refinance into a high-balance loan, a lender might not be willing to extend a loan to the borrower because of the binding DTI. In this case, we would also expect an increase in the refinancing probability when a borrower's remaining balance decreases to right below the national CLL because of higher rates associated with high-balance loans. For our purpose, it is not very important to distinguish different reasons why refinancing volumes increase abruptly when the remaining mortgage balance reaches the national CLL, as long as the increase is due to the rate differential between conventional conforming and high-balance loans.

Sample Selection and Data For this analysis, we restrict the sample to pairs of a loan and a month with 30-year FRMs that were originated in 2007 or later with remaining balances greater than the national CLL at any point in March 2009 or later. Many of these loans in the sample were not securitized by the GSEs, including jumbo loans and loans kept on lenders' portfolios, unlike our analysis on mortgage rates in Section 5. Moreover, we only consider borrowers in high-cost counties where the Economic Stimulus Act of 2008 increased the CLL at least by $50,000. This geographical sample restriction is important because we would like to study a borrower's trade-off between a conventional conforming loan and high-balance loan, the latter of which is available only in high-cost counties.

We further restrict the sample to loan-month pairs with remaining balances within $50,000 around the national CLL at some point in our sample period (January 2009 or later). We exclude borrowers with adjustable-rate mortgages (ARMs) because their incentives to refinance are different from those with FRMs. ARM borrowers often refinance to avoid higher rates after the end of the initial period with fixed teaser rates, whereas FRM borrowers refinance to take advantage of lower current rates. Moreover, we only consider loans originated in 2007 or later because loans that were originated earlier and remain in the sample in our sample period may cause a selection bias.

For this analysis, we use the CRISM data, which provide loan-level mortgage performance information matched to borrower-level credit records. The main advantage of using CRISM over a typical loan-level performance data is that CRISM allows us to tell apart different reasons for a voluntary payoff of a mortgage such as plain refinancing, cash-out refinancing, moving to a different home, etc. Moreover, the data also provide information about a borrower's other credit activities such as auto financing, etc. In investigating the effects on consumption, we will focus on auto financing, which is used to purchase a car.

Another desirable feature of the CRISM data is that the data provide information for loans that are not securitized by the GSEs. Because GSEs were allowed to purchase high-balance loans starting in 2008, many loans with remaining balance above the national CLL in 2009 or later are jumbo loans originated before the high-cost loan limits were introduced and were not able to be purchased by GSEs. Hence, our sample includes many cases where the original loans were not securitized by the GSEs and were either packaged into private-label mortgage securities or kept on lenders' balance sheets.

Empirical Design We estimate the following regression:

$$y_{it} = \alpha 1[bal_{it} \leq CLL_t] + g^+(bal_{it}; \theta_0) + g^-(bal_{it}; \theta_1) + Z_{it}\gamma + \xi_{zip(i)\times t} + \epsilon_i. \tag{8}$$

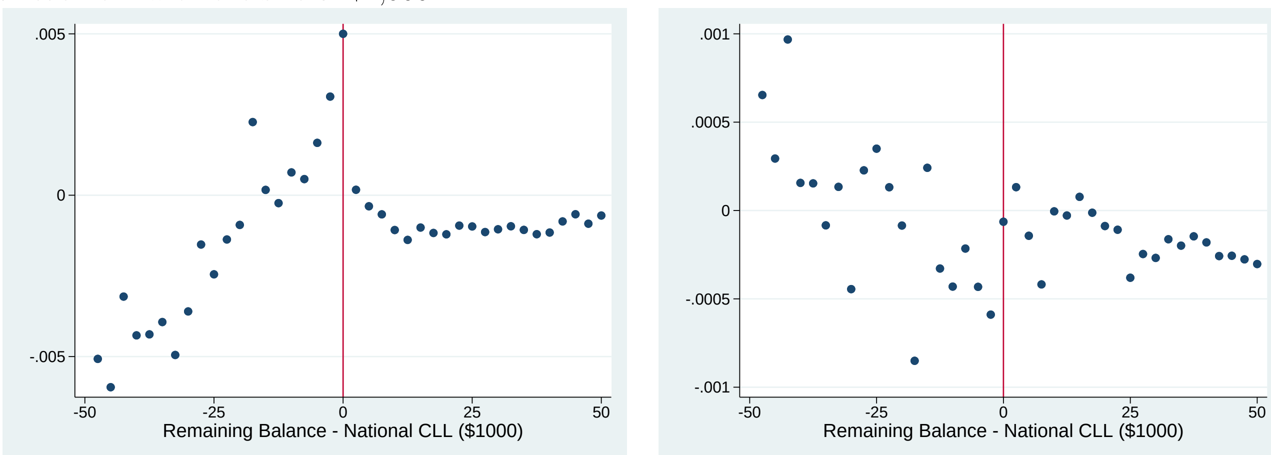
Equation (8) looks quite similar to Equation (3), which was used for earlier analyses. Whereas the unit of analysis is a loan at the time of its origination in the previous analyses, the unit of analysis here is a loan-month pair. Thus, the dependent variable y_{it} has two subscripts: i for each loan and t for each month. On the right hand side, bal_{it} refers to the remaining balance of loan i as of time t, and $1[bal_{it} \leq CLL]$ is a dummy variable that is equal to one if the remaining balance of loan i in time t is not greater than the national CLL at that time. Functions g^+ and g^- give polynomials of bal_{it} depending on whether or not bal_{it} is greater than CLL_t, respectively. Vector Z_{it} includes the following loan characteristics: loan age, the purpose of the loan (refinance or purchase), whether a loan is kept on a lender's balance sheet, whether a loan is securitized by a GSE, updated estimated LTV, the fraction of the initial balance paid off as of time t, original loan balance, updated credit score, mortgage interest rate, LTV at origination, whether the loan is a first mortgage, whether the borrower is an owner-occupant, whether there is a prepayment penalty, whether the prepayment penalty period expired by time t, whether there is a delinquency in last twelve months, whether the loan is an interest-only loan, and whether the interest-only period expired by time t. Lastly, $\xi_{zip(i)\times t}$ refers to the fixed effects at the level of loan i's zipcode and time t. Because the CRISM data do not provide identities of lenders or servicers, we are not able to include lender or servicer characteristics unlike in the previous analyses on mortgage rates.

The dependent variable, y_{it}, is an indicator variable that equals one if loan i is refinanced at time t. We consider the following two types of refinancing separately: plain refinancing and cash-out refinancing. Plain refinancing refers to refinancing without a significant increase in the loan balance. Since the loan balance could increase because of the closing cost of a new loan, we view refinancing as plain refinancing if the loan balance does not increase more than 5% of the ending balance of the previous loan. Cash-out refinancing is refinancing in which a borrower increases the loan balance by more than 5% of the ending balance of the previous loan. We expect that the probability of plain refinancing increases discontinuously when the remaining balance of a loan is right below the national CLL because a borrower can refinance into a conventional conforming loan without making additional mortgage payments. In contrast, we do not expect to see a similar pattern for cash-out refinancing because cash-out refinancing for a borrower with the remaining balance right below the national CLL will make the new loan balance greater than national CLL.

Graphical Examination Before presenting estimated coefficients, we first visually examine the relationship between the remaining loan balance and the probability of plain and non-plain refinancing. Similar to earlier analyses on mortgage rates, we also run the regression described in Equation (8) and calculate the residual probability of refinancing a loan by removing the variation in the dependent variable accounted for by loan characteristics Z_i and the fixed effects. Figure 13 displays the relationship between the remaining loan balance and the probability of plain and non-plain refinancing in panels (a) and (b), respectively. Panel (a) clearly shows that there is a jump in the probability of plain refinancing at the CLL. A borrower with a remaining balance just below the national CLL is about 0.50 pp more likely to plain-refinance than a borrower with a remaining balance slightly above the cutoff. Given that the average monthly probability to pay off the loan is 1.1 percent, the difference of 0.50 pp in the probability of plain refinancing at the cutoff is economically significant. As the remaining balance increases away from the national CLL, the probability does not change very much. In contrast, the probability decreases fast as the remaining loan balance decreases away from the national CLL. This pattern suggests that many borrowers wait for their loan balances to reach below the CLL to refinance into mortgages not greater than the national CLL. It also suggests that very few borrowers make extra mortgage payments to refinance into loans smaller than the national CLL.

In contrast, panel (b) shows that the probability of cash-out refinancing does not exhibit a similar pattern around the national CLL. Because cash-out refinancing of a loan with a remaining balance right below the cutoff will still make a borrower refinance into a high-balance loan, there is no reason for a discrete jump at the national CLL.

Figure 13: **Monthly Probability of Plain and Cash-out Refinancing around the National CLL**: This figure plots the relationship between the residual monthly probabilities of plain and cash-out refinancing and the remaining loan balance. The residual probability is obtained by removing variation in the original variable accounted for by observable characteristics Z_{it} and fixed effects $\xi_{zip(i)\times t}$ after running the regression given by Equation (8). Each dot represents the average value for each bin with the size of $2,500.



(a) Plain Refinancing

(b) Cash-out Refinancing

Regression Estimates Table 7 shows the results of regression (8) with plain refinancing as the dependent variable. Columns (1)–(3) show estimates with the sample consisting of pairs of borrower and months with remaining loan balances within the window of $50,000 around the national CLL. Columns (4)–(6) show estimates with the window of $25,000 around the national CLL. Regardless of the number of polynomials included and the size of the sample window, we find a statistically significant jump in the probability of plain refinancing at the cutoff. The coefficient estimates are around 0.50 pp, which is consistent with Figure 13.

Table 7: **Monthly Probability of Plain Refinancing around the National CLL**: The table displays the estimated coefficients of the regression given by Equation (8) with plain refinancing as the dependent variable. Columns (1)–(3) are for the subsample of loan-month pairs with remaining mortgage balances within the window of \$50,000 around the cutoff. Columns (1)–(3) are for specifications with up to first-, second-, and third-degree polynomials, respectively. Columns (4)–(6) are for the subsample of loan-month pairs with remaining mortgage balances within the window of \$25,000 around the cutoff. Columns (4), (5), and (6) are for specifications with up to first-, second-, and third-degree polynomials, respectively. All columns include the Zipcode × Month fixed effects and the control variables described in the main text. The standard errors are clustered at the level of Zipcode × Month.

	Larger Window			Small Window		
	(1)	(2)	(3)	(4)	(5)	(6)
	Polynomial=1	Polynomial=2	Polynomial=3	Polynomial=1	Polynomial=2	Polynomial=3
$1[bal_i \leq CLL]$	0.0048***	0.0048***	0.0051***	0.0040***	0.0048***	0.0058***
	(13.90)	(9.75)	(7.86)	(8.83)	(7.15)	(6.42)
bal_i	0.0000	-0.0001***	-0.0001**	-0.0001***	-0.0002***	-0.0003*
	(0.48)	(-3.28)	(-2.42)	(-4.78)	(-2.62)	(-1.67)
$1[bal_i \leq CLL] \times bal_i$	0.0002***	0.0004***	0.0007***	0.0003***	0.0008***	0.0016***
	(12.65)	(7.20)	(5.11)	(8.19)	(5.71)	(4.87)
ZIPxMONTH FE	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N. Obs.	3,684,465	3,684,465	3,684,465	1,422,031	1,422,031	1,422,031
Adj. R^2	0.013	0.013	0.013	0.025	0.025	0.025

Table 8 shows estimates for regressions with cash-out refinancing as the dependent variable. Regardless of the size of the sample window, the main coefficient becomes statistically insignificant with polynomials of degree two or higher.

Table 8: **Monthly Probability of Cash-out Refinancing around the National CLL**: The table displays the estimated coefficients of the regression given by Equation (8) with cash-out refinancing as the dependent variable. Columns (1)–(3) are for the subsample of loan-month pairs with remaining mortgage balances within the window of \$50,000 around the cutoff. Columns (1)–(3) are for specifications with up to first-, second-, and third-degree polynomials, respectively. Columns (4)–(6) are for the subsample of loan-month pairs with remaining mortgage balances within the window of \$25,000 around the cutoff. Columns (4), (5), and (6) are for specifications with up to first-, second-, and third-degree polynomials, respectively. All columns include the Zipcode × Month fixed effects and the control variables described in the main text. The standard errors are clustered at the level of Zipcode × Month.

	Larger Window			Small Window		
	(1) Polynomial=1	(2) Polynomial=2	(3) Polynomial=3	(4) Polynomial=1	(5) Polynomial=2	(6) Polynomial=3
$1[bal_i \leq CLL]$	-0.0004***	-0.0003	-0.0002	-0.0003*	0.0001	-0.0002
	(-2.77)	(-1.41)	(-0.77)	(-1.79)	(0.49)	(-0.65)
bal_i	-0.0000**	-0.0000	-0.0000	-0.0000	0.0001*	-0.0001*
	(-2.49)	(-0.83)	(-0.48)	(-0.42)	(1.90)	(-1.78)
$1[bal_i \leq CLL] \times bal_i$	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0002*
	(-1.54)	(0.62)	(0.95)	(0.04)	(0.06)	(1.70)
ZIPxMONTH FE	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N. Obs.	3,684,465	3,684,465	3,684,465	1,422,031	1,422,031	1,422,031
Adj. R^2	-0.008	-0.008	-0.008	-0.014	-0.014	-0.014

The relationship between the remaining loan balance and the probability of plain refinancing shows that a borrower typically wait until the remaining loan balance falls below the national CLL. As discussed earlier, that is either because a borrower would like to take advantage of a lower rate with a conventional conforming loan or because a higher mortgage rate with a high-balance loan makes the DTI binding.

How long would a borrower have to wait for the remaining balance to reach the national CLL? In our sample, a borrower with a remaining balance of the national CLL plus \$25,000 has to wait 32 months to reach the national CLL. For a borrower with a remaining balance of the national CLL plus \$10,000, it takes about 17 months to reach the national CLL. Even for a borrower with a remaining balance of the national CLL plus \$5,000, it takes about 11 months. This finding suggests that the rate spread between high-balance and conforming loans due to TBA-eligibility results in a significant delay in a borrower's refinancing.

6.2 Consumer Spending

Previous research such as Agarwal et al. (2017) and Abel and Fuster (2018) find that consumer spending increases subsequent to refinancing. In the previous subsection, we found that TBA eligibility delays a borrower's refinancing decision. Then a natural question is whether and how much a borrower's consumption behavior is affected by TBA eligibility. Although our data do not provide direct information about a mortgage borrower's spending, CRISM sheds light on part of consumption that typically involves financing such as an automobile purchase. For this reason, a number of papers have relied on consumer credit data and used new auto loan originations to study durable consumption.[20]

In this subsection, we first investigate whether borrowers in our sample increase their auto loan originations subsequent to refinancing. Then we investigate whether TBA eligibility affects auto originations by estimating how much auto originations increase once borrowers' remaining mortgage balances fall below the national CLL.

6.2.1 Consumer Spending Subsequent to Refinancing

To examine whether auto loan originations increase after refinancing, we construct our estimation sample in the following way. First, we include borrowers who ever plain-refinanced within the estimation sample used to study a borrower's refinancing decision in Section 6.1. We then follow the borrowers for twelve months: six months before and after plain refinancing.

With this estimation sample, we estimate the following regression:

$$NewAutoAmt_{it} = \Sigma_{t'=-6}^{5} \beta_{t'} 1[t = t_i^* + t'] + Z_{it}\gamma + \xi_{zip(i)\times t} + \epsilon_i. \tag{9}$$

The dependent variable $NewAutoAmt_{it}$ denotes a new auto loan amount. If borrower i does not originate a new auto loan in time t, then the variable is equal to zero. If he does, then the variable is equal to the origination amount. This variable measures changes not only in the extensive margin (whether a borrower originates a new auto loan) but also in the intensive margin (whether a borrower takes out a larger auto loan possibly to buy a more expensive car). CRISM does not tell directly whether or how much a borrower takes out a new auto loan in a given month. Instead, we observe each borrower's outstanding auto loan balances in each month. We assume that a borrower takes out a new auto loan if his outstanding auto loan balance increases by more than \$3,000 and if the number of outstanding auto loan accounts increases at the same time.[21]

On the right-hand side, $\beta_{t'}$ are the main coefficients of interest. The dummy variable $1[t = t_i^* + t']$ is equal to one if calendar month t is t' months after t_i^*, the month in which borrower i plain-refinanced. We normalize β_{-1} (the month right before refinancing) to zero. Next, Z_{it} refers to the same set of observed characteristics included in Equation (8). Moreover, we also include Zipcode $\times$ Month fixed effects ($\xi_{zip(i)\times t}$).

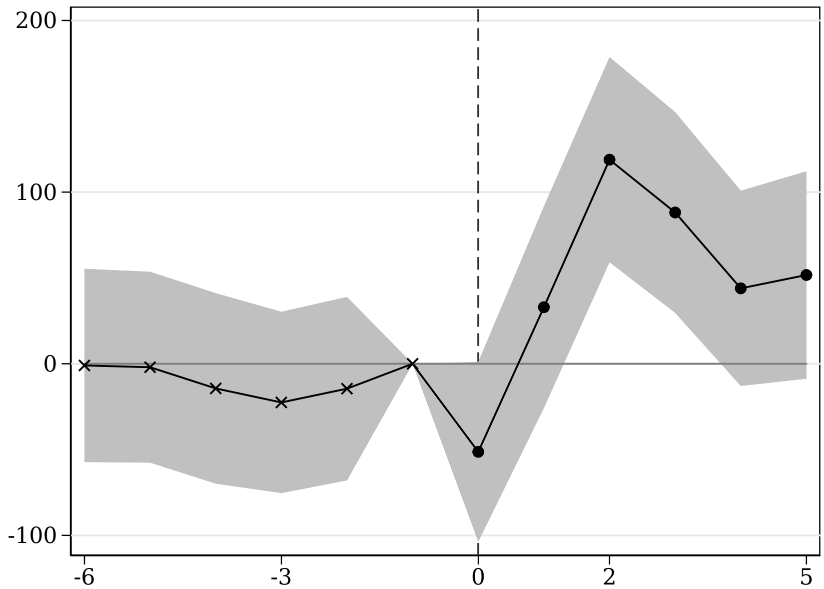
Figure 14 displays point estimates of $\beta_{t'}$ from Equation (9) and their 95% confidence intervals. We find that auto loan origination amounts increase after Month 0. The increases are especially high and statistically significant for for Months 2 and 3. Moreover, the increases in the two months are also substantial given that the average auto loan origination amount is \$300 in a month.[22] The figure also shows that the auto loan originations increases only after refinancing. We do not find any trends in new auto loan origination amounts before before Month 0.

[20] Examples of such papers are Agarwal et al. (2017), Di Maggio et al. (2017), and Abel and Fuster (2018).

[21] We also tried with a different threshold (\$5,000) to define an auto loan origination. The results are very robust to this alternative definition of auto loan originations.

[22] This number appears low because there are lots of borrowers who do not originate a new auto loan in a given month.

Figure 14: **Auto Loan Origination Amounts after Refinancing**: This figure plots point estimates of $\beta_{t'}$ from Equation (9) and their 95% confidence intervals. We normalize $\beta_{-1}$to zero. The dependent variable is a new auto loan amount. The regression includes the Zipcode $\times$ Month fixed effects and the control variables described in the main text. Standard errors for all specifications are clustered at the level of Zipcode $\times$ Month.



6.2.2 National CLL and Consumer Spending

Our findings so far suggest that TBA eligibility affects a borrower's refinancing decision, and those who refinanced increase their spending on automobiles after refinancing. Thus, we expect that TBA eligibility also affects a borrower's spending on automobiles.

In this subsection, we investigate whether a new auto origination amount increases for a borrowers with a remaining mortgage balance below the national CLL. We estimate the following regression, which is similar to Equation (8) but with $NewAutoAmt_{it}$ as the dependent variable. Our regression specification, including the set of variables included as controls and fixed effects, is exactly identical to the specification used in Section 6.1. The estimation sample is also identical.

$$NewAutoAmt_{it} = \alpha 1[bal_{it} \leq CLL_t] + g^+(bal_{it}; \theta_0) + g^-(bal_{it}; \theta_1) + Z_{it}\gamma + \xi_{zip(i)\times t} + \epsilon_i. \qquad (10)$$

We first graphically examine patterns of residual value of $NewAutoAmt_{it}$ around the cutoff in Figure 15. The auto loan origination amounts generally decreases as remaining mortgage balances decreases. Patterns for borrowers with remaining mortgage balances below the cutoff are noisier than those for borrowers with balances above the cutoff. Comparing values right below and above the cutoff, however, we find that auto loan origination amounts increase at the cutoff by \$50, which is about 13% of the unconditional average (\$300).

Figure 15: **Auto Loan Origination Amounts around the National CLL**: This figure plots the relationship between the residual value of new auto origination amounts and the remaining loan balance. The residual value is obtained by removing variation in the original variable accounted for by observable characteristics Z_{it} and fixed effects $\xi_{zip(i)\times t}$ after running the regression given by Equation (10). Each dot represents the average value for each bin with the size of \$2,500.

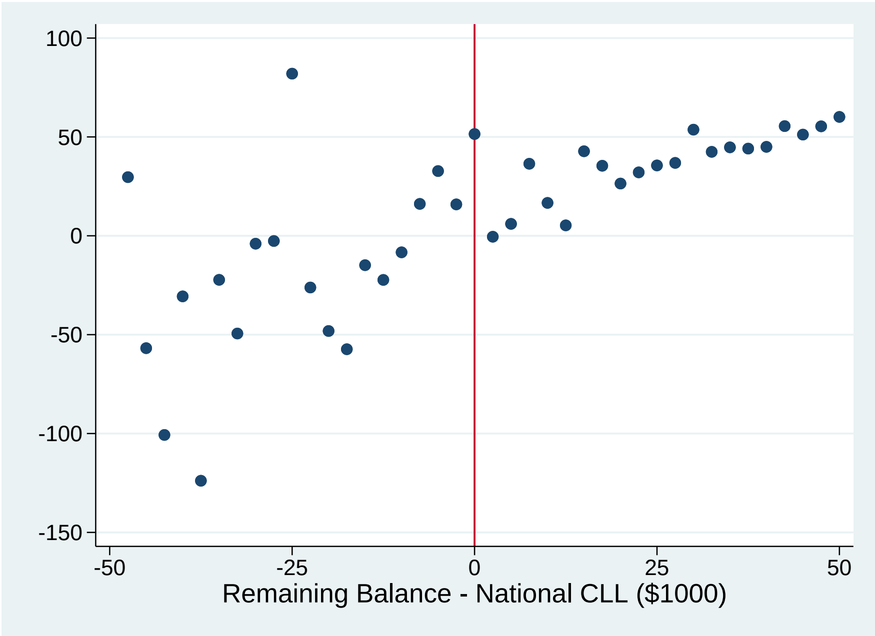


Table 9 provide regression estimates that are consistent with Figure 15. Although exact magnitudes are different, all estimates indicate that auto loan origination amounts increase at the cutoff. The estimate in Column (6) is not statistically significant, but its magnitude is quite consistent with other estimates. Additional polynomials seem to increase the standard error of the estimate very much.

Table 9: **Auto Loan Origination Amounts around the National CLL**: The table displays the estimated coefficients of the regression given by Equation (10) with new auto origination amounts as the dependent variable. Each column is different only with respect to the maximum number of polynomials. All columns include the Zipcode × Month fixed effects and the control variables described in the main text. The standard errors are clustered at the level of Zipcode × Month.

	Larger Window			Small Window		
	(1) Polynomial=1	(2) Polynomial=2	(3) Polynomial=3	(4) Polynomial=1	(5) Polynomial=2	(6) Polynomial=3
$1[bal_i \leq CLL]$	19.8052*	37.6581**	51.7643**	37.0721**	55.6822***	32.3898
	(1.82)	(2.42)	(2.57)	(2.54)	(2.59)	(1.15)
bal_i	0.9492***	1.4851**	2.8757*	1.0552*	3.2657	3.8933
	(5.63)	(2.24)	(1.72)	(1.96)	(1.57)	(0.73)
$1[bal_i \leq CLL] \times bal_i$	1.0813**	2.8484	3.8282	2.9645**	3.1970	-11.9429
	(1.99)	(1.59)	(0.94)	(2.52)	(0.74)	(-1.15)
ZIPxMONTH FE	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N. Obs.	3,684,465	3,684,465	3,684,465	1,422,031	1,422,031	1,422,031
Adj. R^2	0.004	0.004	0.004	0.002	0.002	0.002

The findings in this section show that TBA eligibility eventually affects a borrower's spending on automobiles through his refinancing decision. Facing a trade-off between refinancing now into a high-balance loan and refinancing later into a conventional conforming loan, many borrowers wait until their mortgage balances decrease to levels below the national CLL and then refinance into conventional conforming loans. As mentioned earlier, this waiting can be quite long. At the same time, a borrower's consumption spending is also tied to his refinancing decision. Durable spending, approximated by the new auto loan amount, typically increases in two or three months after refinancing. As a result, as a borrower waits for refinancing into a conventional conforming loan, his durable spending is also delayed.

This finding has an important implication for monetary policy transmission. One of the main channels for a lower interest rate to be translated into the real economy is through mortgage borrowers' refinancing (Agarwal et al., 2017; Abel and Fuster, 2018). Our finding suggests that liquidity of the secondary mortgage market, which is captured by eligibility for TBA delivery in our setting, is an important factor that affects how a lower interest rate is transmitted to the real economy. It also highlights that preserving the secondary market structure that improves liquidity of the market is important not only for welfare of borrowers but also for monetary policy transmission.

7 Conclusion

In this paper, we quantify the value of TBA eligibility for the mortgage borrowers. Being included in TBA-eligible pools reduces primary mortgage rates by 10–40 basis points, depending on the prepayment risk of the loan. Hence, the liquidity and trading structure of the secondary market can have direct impact on the primary market and in the real economy. Borrowers also delay refinancing in order to refinance into TBA-eligible loans. Given that refinancing is an important channel in which monetary policy affects the real economy, the discontinuity in TBA-eligibility and the associated delay in refinancing may potentially slow the transmission of monetary policy.

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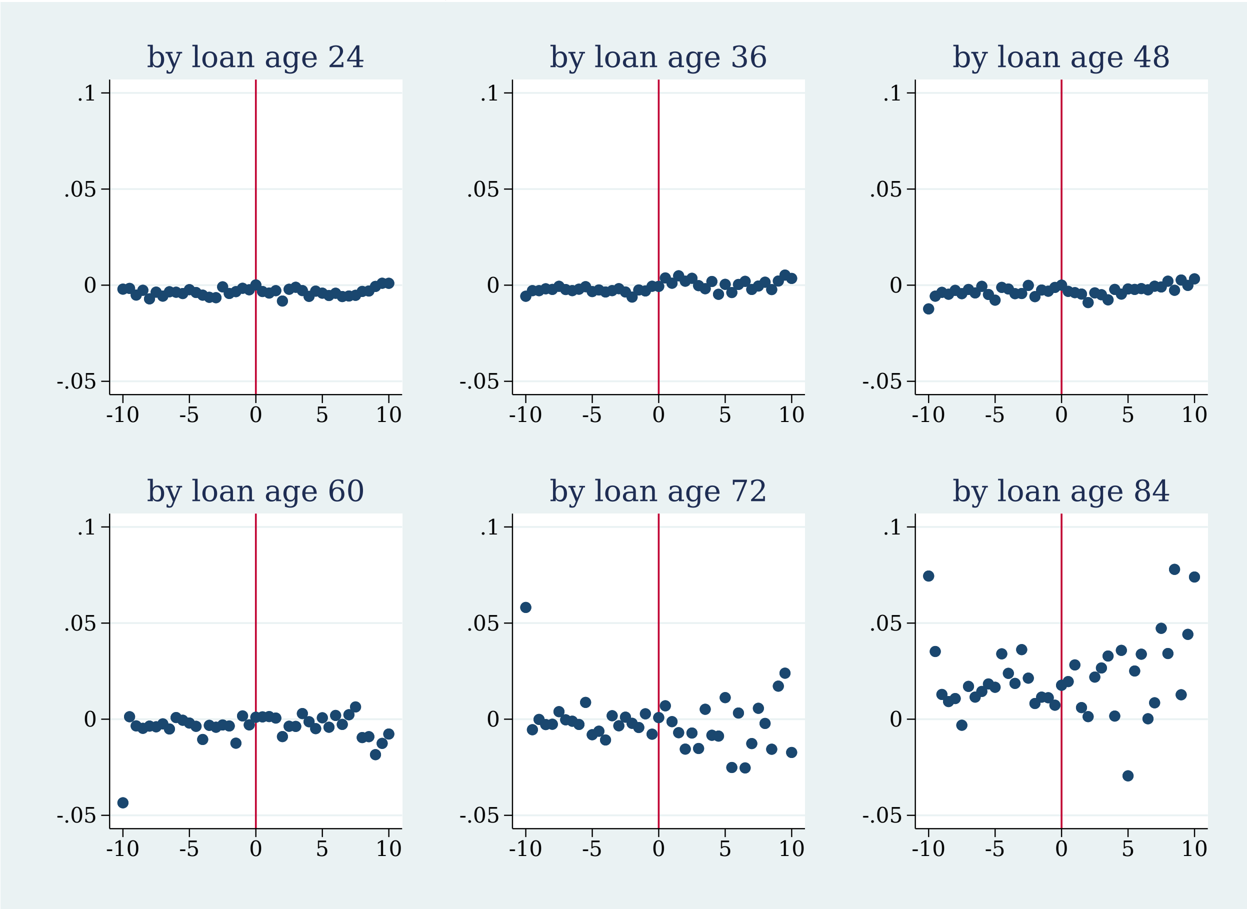
A Appendix: Extra Figures

Figure 16: **Ratio of the Remaining Balance to the Original Balance around Cutoff 1**: These figures plot the residual ratio of the remaining balance to the original balance as of different loan ages in terms of months since origination. The residual variables are obtained by removing variation in corresponding original variables accounted by observable loan characteristics (Z_i) and fixed effects ($\xi_{s(i)\times l(i)\times t(i)}$) after running regressions given by Equation (3) with the original variables as dependent variables. Each dot in the plot represents the average value of each residual variable for each bin of the size of $2,500.

Figure 17: **Ratio of the Remaining Balance to the Original Balance around Cutoff 2**
These figures plot the residual ratio of the remaining balance to the original balance as of different loan ages in terms of months since origination. The residual variables are obtained by removing variation in corresponding original variables accounted by observable loan characteristics (Z_i) and fixed effects ($\xi_{zip3(i)\times l(i)\times t(i)}$) after running regressions given by Equation (3) with the original variables as dependent variables. Each dot in the plot represents the average value of each residual variable for each bin of the size of 0.5.



B Appendix: Extra Tables

Table 10: **Regression Results for the Ratio of the Remaining Balance to the Original Balance (Cutoff 1)**: This table displays the estimates of the regression similar to Equation (3), where dependent variables are the ratio of remaining balance to the original balance as of loan age n for $n \in \{24, 36, 48, 60, 72, 84\}$. The maximum degree of polynomials included in the regressions are three for each column. For all columns, we used the subsample of loans with corresponding home values within the window of $50,000 around the cutoff. For each column, we further restricted the subsample to loans that were originated at least n months before the most recent month available in the data (2018m9). All specifications include State x Lender x Month Fixed effects and control variables described in the main text. Standard errors are clustered at the level of State x Lender x Month.

	(1) By Age 24	(2) By Age 36	(3) By Age 48	(4) By Age 60	(5) By Age 72	(6) By Age 84
$1[h_i > h^*_{t(i)}]$	0.006	0.023	0.013	0.030	0.049*	0.023
	(0.36)	(1.06)	(0.55)	(1.17)	(1.81)	(0.90)
h_i	0.000	-0.004**	-0.003	-0.001	-0.001	-0.001
	(0.10)	(-2.17)	(-1.43)	(-0.33)	(-0.50)	(-0.36)
$1[h_i > h^*_{t(i)}] \times h_i$	-0.001	0.003	0.002	-0.002	-0.006	-0.001
	(-0.40)	(0.73)	(0.59)	(-0.37)	(-1.28)	(-0.35)
STATExMONTHxSELLER FE	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N. Obs.	35,443	29,761	25,066	20,564	15,614	12,434
Adj. R^2	0.13	0.20	0.23	0.24	0.19	0.09

Table 11: **Regression Results for Exogenous Variables (Cutoff 1)**: This table displays the estimates of the regression similar to Equation (3) but with dependent variables are exogenous loan characteristics in Z_i. The maximum degree of polynomials included in the regressions are three for each column. For all columns, we used the subsample of loans with corresponding home values within the window of $50,000 around the cutoff. All specifications include State x Lender x Month Fixed effects and control variables described in the main text. Standard errors are clustered at the level of State x Lender x Month.

	(1) Credit Score	(2) Loan-to-Income Ratio	(3) Broker Channel	(4) Correspondent Channel
$1[h_i > h^*_{t(i)}]$	0.592	0.063	0.001	-0.008
	(0.43)	(1.20)	(0.09)	(-0.62)
h_i	-0.176	-0.005	0.001	-0.000
	(-1.57)	(-1.10)	(0.92)	(-0.01)
$1[h_i > h^*_{t(i)}]=1 \times h_i$	0.104	-0.007	-0.002	0.003
	(0.46)	(-0.75)	(-1.33)	(1.34)
STATExMONTHxSELLER FE	Y	Y	Y	Y
Other Controls	N	N	N	N
N. Obs.	78,683	78,589	78,737	78,737
Adj. R^2	0.06	0.11	0.48	0.43

Table 12: **Regression Results for the Ratio of the Remaining Balance to the Original Balance (Cutoff 2)**: This table displays the estimates of the regression similar to Equation (5), where dependent variables are the ratio of remaining balance to the original balance as of loan age n for $n \in \{24, 36, 48, 60, 72, 84\}$. The maximum degree of polynomials included in the regressions are three for each column. For all columns, we used the subsample of loans with $PredLTV_i$ between 100 and 110. For each column, we further restricted the subsample to loans that were originated at least n months before the most recent month available in the data (2018m9). All specifications include Zip3 x Lender x Month Fixed effects and control variables described in the main text. Standard errors are clustered at the level of Zip3 x Lender x Month.

	(1) By Age 24	(2) By Age 36	(3) By Age 48	(4) By Age 60	(5) By Age 72	(6) By Age 84
$1[PredLTV > 105]$	-0.005	0.004	-0.003	0.002	0.009	0.021
	(-1.61)	(1.28)	(-0.80)	(0.38)	(0.82)	(1.01)
$PredLTV$	0.002	0.003	0.002	0.003	0.003	-0.018*
	(1.35)	(1.32)	(0.94)	(0.79)	(0.41)	(-1.80)
$1[PredLTV > 105] \times PredLTV$	-0.001	-0.004	-0.004	-0.007	-0.017	0.013
	(-0.31)	(-1.30)	(-1.15)	(-1.26)	(-1.61)	(0.65)
ZIP3xMONTHxSELLER FE	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N. Obs.	61,744	54,914	44,277	23,311	11,282	3,481
Adj. R^2	-0.02	0.01	0.01	0.01	-0.01	-0.03

Table 13: **Regression Results for Exogenous Variables (Cutoff 2)**: This table displays the estimates of the regression similar to Equation (5) but with dependent variables are exogenous loan characteristics in Z_i. The maximum degree of polynomials included in the regressions are three for each column. For all columns, we used the subsample of loans with $PredLTV_i$ between 100 and 110. All specifications include Zip3 x Lender x Month Fixed effects and control variables described in the main text. Standard errors are clustered at the level of Zip3 x Lender x Month.

	(1) Credit Score	(2) Broker Channel	(3) Correspondent Channel	(4) Interest Rate for Prev Loan
$1[PredLTV > 105]$	1.511	0.003	0.000	-0.009
	(0.79)	(0.36)	(0.04)	(-0.52)
$PredLTV$	-0.777	0.003	-0.004	0.012
	(-0.69)	(0.79)	(-1.03)	(1.29)
$1[PredLTV > 105]{=}1 \times PredLTV$	-0.252	-0.013**	-0.003	0.021
	(-0.14)	(-1.99)	(-0.54)	(1.40)
ZIP3xMONTHxSELLER FE	Y	Y	Y	Y
Other Controls	N	N	N	N
N. Obs.	70,193	70,195	70,195	70,195
Adj. R^2	0.10	0.23	0.21	0.22