# The Impact of the Adverse Market Refinance Fee: Estimating the Interest Rate Elasticity Using Mortgage Refinancing Notches

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**TABLE OF CONTENTS**

# Contents


**1 Introduction** **4**

**2 Policy Background** **10**

**3 Literature Review** **17**

**4 Data** **20**

**5 Empirical Strategy** **25**
- 5.1 The Case of Linear Interest Rates . . . . . . . . . . . . . . . . . . . . . . . . . . 25
- 5.2 Notched Interest Rates . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 27
- 5.3 Bunching . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 28
- 5.4 Optimization Frictions . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 30
- 5.5 Estimating Elasticities . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 30
- 5.6 Round Number Effects . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 31

**6 Results** **34**

**7 Robustness** **37**
- 7.1 The Channel Question . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 37
- 7.2 Simultaneously Changing Variables . . . . . . . . . . . . . . . . . . . . . . . . 38
- 7.3 Placebo Tests . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 43

**8 External Validity** **44**

**9 Discussion** **48**

**10 Conclusions** **51**

**11 References** **53**

**12 List of Figures** **57**

**13 List of Tables** **75**

**14 Appendix** **79**

**Abstract**

This paper examines the impact of a new policy implemented by the Federal Housing Finance Agency (FHFA) on December 1st, 2020, called the Adverse Market Refinance Fee (AMRF), equal to 0.5% of the value of a refinancing loan. The AMRF was instituted by the FHFA as a mechanism to mitigate losses incurred from forbearance defaults and to support the Government Sponsored Enterprises (GSEs) — Fannie Mae and Freddie Mac — in managing the increased risk associated with lending during the COVID-19 pandemic. This paper measures the degree of bunching in response to a jump in interest rates, using individual loan-level data by Fannie Mae. Specifically, I identify the effect of interest rates on borrower behavior by exploiting the exogenous variation in the relationship between loan size and interest rates that results from the threshold used by the new fee policy. The estimates suggest average bunching weights ranging from 0.19 to 0.56. Moreover, this paper also provides estimates of the interest rate elasticity of mortgage refinancing demand on the intensive margin ranging from 0.02 % to 0.8 %.

# 1 Introduction

Mortgage refinancing activity increased sharply during the COVID-19 pandemic. In 2020, it reached its highest annual total since 2003. It is estimated that there were $932 billion in single-family refinances in Q4-2020[1] alone. For the full year of 2020, there were about $3.01 trillion in inflation-adjusted refinance originations, more than double the volume in the prior year.[2] While there is certainly a significant increase in refinance originations during the onset of the pandemic, that still falls short of the refinance boom in 2003, when refinance originations volume reached $4.1 trillion in 2021 dollars.[3]

While major developments were happening in the mortgage refinancing markets, a new policy was implemented by the Federal Housing Finance Agency (FHFA). It was called the "Adverse Market Refinance Fee" (AMRF). The AMRF was instituted by the FHFA as a mechanism to mitigate losses incurred from forbearance defaults and to support the Government Sponsored Enterprises (GSEs) — Fannie Mae and Freddie Mac — in managing the increased risk associated with lending during the COVID-19 pandemic. This paper measures the degree of bunching in the treated group of borrowers, in response to a jump in interest rates resulting from the AMRF.

The pandemic had a significant impact particularly on the economy and financial markets, which, in turn, influenced mortgage rates. Mortgage rates during the COVID-19 pandemic were characterized by unprecedented lows, followed by a gradual climb as the economic situation evolved. The situation was dynamic, and rates were influenced by a wide range of economic and public health factors. These rates remained historically low throughout most of the pandemic, offering opportunities for homeowners interested in refinancing their loans. However, borrowers needed to remain vigilant and stay informed about the most up-to-date market conditions to make the most of the low-rate environment.

[1] According to Mortgage Bankers Association.

[2] In 2021, there were about $2.8 trillion in first-lien refinance originations, a 7.6% decline from 2020

[3] Freddie Mac Economic and Housing Research: https://www.freddiemac.com/research/pdf/202204-Note-Refinancing-04.pdf

Homeowners who decided to refinance their mortgages in 2020 and 2021 took advantage of historically low interest rates, setting themselves up for many years of cost-effective financing. Those who pursued a "rate refinance" strategy successfully reduced their monthly mortgage payments, therefore enhancing their available cash flow. Meanwhile, other homeowners – known as "cash-out" borrowers – leveraged the equity in their real estate assets to free up additional funds for their spending needs.

It was exactly in the face of these developements that the Federal Housing Finance Agency (FHFA) introduced the "Adverse Market Refinance Fee" (AMRF). To determine the extent to which pandemic-related developments in the housing market helped or harmed borrowers, I estimate the impact on refinance decisions of the AMRF. The AMRF introduced a fee that was implemented on December 1$^{st}$ 2020, and was equal to 0.5% of the value of the refinancing loan. The "Adverse Market Refinance Fee" (AMRF) stipulates those loans originated after December 1$^{st}$, 2020, that have a UPB (Unpaid Principal Balance) at or above $125,000 are subject to the increase equal to 0.5% of the total loan amount. The AMRF affected both standard and cash-out refinancing loans, while FHFA announced that loans under $125,000 as well as VA loans, FHA loans, USDA loans, and Jumbo loans would be exempt from the new refinancing fee. This created a discontinuity at the $125,000 mark for these loans.

I identify the effect of interest rates on borrower behavior by exploiting the exogenous variation in the relationship between loan size and interest rates that results from the threshold used by the new fee policy. This paper also provides estimates of the interest rate elasticity of mortgage refinancing demand. I investigate the notch in the inter-temporal budget constraint of households deciding how much mortgage refinance debt to incur and hypothesize that it is created as a result of the difference in interest rates caused by the "Adverse Market Refinance Fee". It is this difference in interest rates that gives incentives to some borrowers who would otherwise take out loans above the AMRF threshold to instead bunch right at the limit, or slightly below.

The literature on bunching methodology distinguishes between two different types of designs, “kinks” and “notches”. It is important to understand the difference between these two, when investigating the existence of bunching and implementing the empirical strategy. The former relates to a “kink” in the mortgage refinance consumption function, as only loans above the $125,000 threshold would have an increased interest rate, in our application. Technically, a kink is a sudden change in the slope of the budget set. In our scenario, this would correspond to an increase in interest rates above a loan amount threshold. Since theory suggests that a portion of the borrowers will then bunch right at the threshold, this increase in interest rates will cause borrowers who would have paid less above the threshold without the kink, to borrow less, now that the kink is presented. However, this increase in interest rates will have no effect on borrowers who would have otherwise borrowed a loan below the threshold. Moreover, the type of this increase in interest rates above the threshold is the deciding factor when identifying whether we are in a kink or a notch scenario. In a kink the interest rate would be gradually increasing the more we increased the loan amount, whereas in a notch the increase in interest rates is similar to a “lump-sum” increase that will be the same for all levels of loan amounts. A “notch” increases the interest rate liability on all loan sizes, leaving an interval where individuals are either strictly better off or given strong incentives to borrow below the threshold.

Having this one notch in my dataset, makes it possible to also identify the interest rate elasticity of mortgage refinancing demand. By using the measure of the excess mass of individuals — who bunch at the policy limit — I can accurately achieve identification using a bunching design developed by Saez (2010) and Chetty et al. (2011). Since the assumption pertains to having calculated what the density of borrowers would be without the notch, we would then know how far the marginal buncher shifted their loan size to reach the notch, which would tell us the interest rate elasticity of mortgage refinancing demand. Recall that estimating this counterfactual density is exactly what the bunching estimation does during the first step.

There are, undoubtedly, major implications regarding the magnitude of this elasticity.

One benefit is that it provides insight into the effects of monetary policy and how it influences borrowing behaviour. It does seem however, that a lack of exogenous variation when it comes to interest rates could be playing a role in the further development of this literature.

This paper contributes to the literature on empirical estimates of the elasticity of mortgage demand to interest rates, estimated as a result of bunching in the distribution of refinancing loan amounts. Currently, there exists limited evidence regarding this particular topic in the literature. For example, Glaeser and Shapiro (2003) investigate the elasticity of housing demand to interest rates by using state-level variation in the home mortgage interest deduction. They find that increases in subsidy cause the homeownership raise to increase, but the effect is slight and insignificant. A one percent increase in the subsidy rate causes homeownership to rise by .0009 percent.

This paper fills a gap in the literature by examining the impact of interest rates on refinance mortgage origination borrower decisions. It does so by investigating bunching in the distribution of refinancing loan amounts. Previous work by Best et al. (2015) exploits quasi-experimental variation in interest rates due to notched mortgage contracts in the UK which follow a step function of the loan-to-value (LTV) ratio. Examining bunching estimates at LTV breakpoints at the time of refinancing, Best et al. (2015) finds that the mortgage demand elasticity is about 0.3 on average and strongly heterogeneous. Best et al.'s (2015) study has important implications for the elasticity of intertemporal substitution, re-mortgagors are deciding how much consumption to give up now to lower interest payments in the future.

Additionally, this paper also makes use of the new non-parametric and semi-parametric identification assumptions on the distribution of agents presented by Bertanha et al. (2018). This methodology typically excludes (or "truncates") a region around the threshold, to estimate the extent of bunching. Bertanha et al. (2018) propose the use of multiple truncation windows instead of a single one. The idea is to estimate the bunching parameter for different sizes of the excluded region around the threshold. By looking at the 100% truncation window, I estimate an interest rate elasticity of mortgage refinancing demand of 0.21, which is lower than the 0.42 estimate obtained by the 10% truncation window. I explain the usage of this methodology in more detail under the "Empirical Strategy" section.

This paper also follows Chetty et al. (2011) in estimating the counterfactual scenario in which an interest rate applies both above and below a threshold within a certain distance surrounding the notch (the "bunching region"). This removes the notch within the region of study, and therefore removes the incentive to bunch. It also changes the marginal interest rate faced by those with loan sizes narrowly greater than the threshold.

To measure the amount of bunching, I compare the actual distribution of income with the predicted counterfactual distribution of income under the new interest rate. This counterfactual density, is then estimated using the Chetty et al.'s (2011) technique. Chetty et al. (2011) establish a well-recognized methodology of conducting this estimation across the optimal tax rate literature and the bunching literature in general. However, this paper applies it to the mortgage markets and the estimation of the interest rate elasticity of mortgage refinancing demand[4]. Calculating these kinds of elasticity values — especially those related to housing — is complicated.

One concern regarding the elasticity estimation is the existence of multiple channels through which an increase in interest rates could affect refinancing decisions. One channel is that of additional borrowing. Another channel through which interest rates could affect refinancing decisions is the decrease in the loan size. Finally, households can decide on shifting the timing of a refinance or not go ahead with refinancing altogether. I address these concerns in the robustness section and find that there is no shift away from mortgage refinancing, into other types of loans, by analyzing the major trends in this period, related to different borrowing channels available to borrowers. In general, studies facing similar challenges find that a rough estimate of the effect of these channels on the elasticity would be to scale down the elasticity estimates by a factor of one-third.

Another piece of information that is relevant to this study is the idea that we need to

[4]The Stata code I use to measure bunching is available online at http://www.rajchetty.com/utilities/

make the distinction between the effects of interest rates on purchase mortgages compared to refinance mortgages. This is especially true when considering the findings of Keys, Pope & Pope (2016). Using a random sample of outstanding US mortgages in December 2010, they find that approximately 20% of unconstrained households for whom refinancing was optimal had not done so. Therefore, behavioral biases also play a role when considering interest rate effects on refinancing decisions, which is why the findings of this paper may differ somewhat from those of studies considering only purchase mortgage originations. In that context, the findings in this study become much more relevant. For example, I estimate Interest Rate Elasticities of Mortgage Refinancing Demand ranging from ranging from 0.02 % to 0.8 %. . At first glance, these estimates can strike as being quite low when compared to other studies. For example, Follain & Dunsky (1997) estimate elasticities ranging from 0.015 to 0.035 while DeFusco & Paciorek (2017) find that a 1% increase in interest rate decreases mortgage refinancing demand by 2 to 3 percent in its size. This is consistent with elasticities ranging from 0.02 to 0.03. However, my estimates become much more reasonable in the context of the policy being studied (the AMRF), and the subset of loans this policy affects. Moreover, as suggested by Keys, Pope & Pope (2016), refinancing borrowers' demand themselves is expected to be much less elastic due to behavioral biases. I can only predict that these biases play an even greater role when we consider only borrowers taking loans in the low end of the UPB distribution.

The remainder of this paper is organized as follows. Section II presents the Policy Background and its components. Section III presents the Literature Review and the contributions this paper makes. Section IV describes the data and the summary statistics. Section V discusses the empirical strategy used in this paper. The main results are presented in Sections VI. Section VII, then, shows the different robustness checks. Section VIII discusses external validity while Section IX and X conclude by discussing the main points of the paper and exploring avenues for future research.

# 2 Policy Background

The AMRF was announced on the $12^{th}$ of August 2020 and was originally scheduled to take effect on September 1 2020 but the Federal Housing Finance Agency (FHFA) delayed its implementation until December $1^{st}$, 2020. This is a fee that was implemented by the FHFA and it is equal to 0.5% of the value of the Refinancing loan. The AMRF was introduced by the FHFA as a way to recoup losses from forbearance defaults and help the Government Sponsored Enterprises (GSEs)- Fannie Mae and Freddie Mac - manage the higher risk of lending during the pandemic.

There was a lot of criticism directed towards the GSE's when the AMRF was implemented. It was seen as a financial burden that was being placed on borrowers on top of the tough economic conditions brought upon by the COVID-19 pandemic. The critics of the AMRF argued that this fee would end up becoming a deterring factor in the refinancing capabilities of many borrowers as well as negating the positive effects of lower interest rates during that time period. Mortgage industry associations such as the Mortgage Bankers Association (MBA) and the National Association of Realtors (NAR) as well as lawmakers voiced strong opposition calling for the fee's delay or cancellation. This is also the reason that the AMRF's implementation was originally delayed for December 2020.

Following the implementation of the AMRF there were discussions regarding the scope of the role and responsibilities of the GSEs during times of economics uncertainties. The fact that smaller loans were exempt from the AMRF highlighted the importance of considering affordable borrowing options for low-income borrowers while balancing that with the need of managing risk by the GSEs. In line with that Fannie and Freddie reported that in the absence of the AMRF they would face losses of around $6 billion as a result of pandemic-related delinquencies forbearances and defaults. The AMRF affected both standard and cash-out refinancing loans while FHFA also announced that loans under $125000 as well as VA loans, FHA loans, USDA loans and Jumbo loans would be exempt from the new refinancing fee. When applied to the interest rate the fee is approximately one-eighth of a point meaning the rate will increase by about 0.125% for an average mortgage of $300000 if the lender chooses to apply the fee there. In short this means that for a $300000 refinancing loan borrowers incurred an additional cost of $1500.

On July 16th 2021 FHFA announced that they were eliminating the fee. This decision took effect on August 1st 2021 which means that the AMRF was essentially in place for 8 months during which time it affected refinancing costs for a large number of borrowers in the US. The fee was waived as a way to help families reduce their housing costs. FHFA stated that "their policies reduced the impact of the pandemic and were effective enough to warrant an early conclusion of the AMRF" (FHFA 2021).

The incidence of the "adverse market refinance fee" is another important detail. It seems like it was the borrowers who bored the weight of the half-point fee. Fannie Mae and Freddie Mac managed to collect an estimated $5.9 billion from them. On July 16 when FHFA announced it eliminated the fee at the end of the month the announcement said that this action "will help families take advantage of the low-rate environment to save more money" and that the FHFA expects lenders who were charging the fee to pass the cost savings back to borrowers. This detail is particularly important when thinking about how certain costs (taxes, fees etc.) are usually applied to one agent in the market (for example sellers of a good) but the actual weight of this cost is split between two or more agents. It seems like in the case of the AMRF the cost of the fee was entirely passed onto the borrower. One reason the lenders were able to do this could have been the historically low rates at the time of the implementation of the AMRF and the general perception that while this fee increased refinancing costs it was still financially reasonable to go through with a refinance. Using the pass-through mechanism that lenders employed to transmit the AMRF - an increase of 1/8th of a point in the interest rate - I compare two borrowers who decide to take a refinancing loan after the implementation of the AMRF in Table 1. Borrower A borrowed just below the $125000 threshold and borrower B just above. We see clearly now, that when rolling the AMRF into the interest rate, borrower B ends up with almost a $4000 increase in their borrowing costs.

To better understand the background of the AMRF it would also be beneficial to look at a compilation of the most important moving variables in and around this time period. Figure 2 does just that . Figure 2 shows that prior to the AMRF (January 2019–November 2020) there was a steady rise in refinancing activity from the beginning of 2019 to the end of the year with only slight variations over the course of the quarters. The pattern persisted during the first three months of 2020 with a noteworthy spike in refinancing activity in Q2 2020—possibly due to advantageous interest rates and a strengthening economy. Prior to the AMRF the refinance market was generally stable and growing.

Refinance activity fluctuated significantly during the period that the AMRF was effective (December 2020–August 2021) particularly in the quarters that followed the AMRF's implementation in December 2020. Refinancing originations increased in Q4 2020 which could be interpreted as borrowers rushing to lock in advantageous terms before the AMRF went into effect. Refinance activity did however decrease in Q2 and Q3 2021 which may have been due to changes made to the mortgage sector such as increasing interest rates rising prices etc. While lenders and borrowers adapted to the new rules and policies the refinance market was marked by uncertainty and volatility during the period that the AMRF was taking place as well as the period that followed.

Refinancing originations continued to drop after the AMRF was terminated in August 2021 ultimately reaching Q1 2019 levels indicating a long-lasting effect of the regulatory reforms on lender operations and borrower behavior. The refinance market saw a period of instability and adjustment during the period that the AMRF was effective as well as the period that immediately followed. Refinancing originations increased continually prior to the AMRF implementation but there was a steady decline following that. Ultimately around Q4 2022 and Q1 2023 refinancing originations reached pre-pandemic levels seen around Q1 and Q2 2019. Interest rates fluctuated from January to November 2019 within a relatively small range with weekly variations being observed. During this time the interest rates varied from roughly 4.31% to 3.49%. The general trend in the period that preceded the implementation of the AMRF was that of dropping interest rates. The decline was steady but continuous resulting in a 1.5% drop in interest rates approximately in the period from Q1 2019-Q1 2021. This coincides with a steep increase in refinancing originations. Following theory as well this seems to be one of the main components that would affect refinancing activity so it is safe to say that the steady drop in interest rates is an important factor that motivated the steep increase in refinancing originations.

Interest rates witnessed a decline from December 2019 to January 2021 followed by an increase in February 2021 and then a steady decline until the AMRF was abolished in August 2021 by which time the interest rates still stood at a higher level than they were at the implementation of the AMRF. This small increase in interest rates coincides with a steep decline in refinancing originations. While this would be expected i.e. higher interest rates would lead to a decline in mortgage originations and especially refinancing mortgages the magnitude of the increase in interest rates does not explain that of the decline in refinancing originations during the time when the AMRF was active.

Interest rates progressively started to rise after the AMRF was abolished indicating the changes in monetary policy around this time. Interest rates had an overall rising trend from September 2021 to February 2024 peaking at roughly 6.64% by that time. As the economy recovered from the effects of the pandemic this increase in interest rates reflects a turn towards normalizing monetary policy and tackling inflationary pressures. The increase in interest rates coincides with a further drop in refinancing originations. This time we could say that the magnitudes also align which could mean that one of the main factors that would explain the further drop in refinancing activity would be the steep increase in interest rates.

It is also interesting to note the way in which interest rates behave in response to the AMRF. In Figure 3, I plot average interest rates for refinance loans as well as for purchasing mortgages. It is interesting to witness the existence of the notch happening to the interest rate schedule, also displayed in the data. As expected, we see this notch at the $125000 threshold for refinancing mortgages, but not for purchasing mortgages, give that the AMRF was only applied to refinances. I further break down this notch by refinancing purpose (regular vs Cash-Out) and loan term (15 vs 30-year) in the appendix in Figure 1A and Figure 2A.

Going back to Figure 2, it is worth reminding the reader that prior to the AMRF in December 2020 the housing market in the United States operated under various mortgage financing options including fixed-rate mortgages and other adjustable-rate products. Home prices — as indicated by the HPI — were influenced by factors such as supply and demand dynamics, economic conditions and prevailing mortgage interest rates during this period, showing a steady rise throughout 2019 and 2020.

In Figure 2 I am using the Low-Tier HPI derived from the FRED data as this seems like the most relevant House-Price Index when considering that the AMRF exempted loans below $125000. This index becomes even more relevant when considering the range of loans this paper is analyzing. This increase in house prices seems to be accompanied by the steep increase in refinance mortgage originations that was mentioned above as well. Following theory it makes sense that these two would be correlated and that to an extent the magnitude of the increase in refinance originations could be happening as a result of the higher prices. When house prices go up there are two main effects that benefit the borrower of existing mortgages. Specifically with the higher home price the borrower gets to enjoy higher equity in terms of USD in his property as well as a lower LTV ratio. These would theoretically in turn give the borrower better terms when looking to refinance their mortgage. This could very well be a reason why prior to the AMRF we see such an increase in refinancing originations among other reasons discussed in this section as well.

The HPI during the period that the ARMF was effective reflects once again the increased demand for housing contributing to upward pressure on prices. This is shown as an even greater increase in the HPI. However this is not accompanied by an increase in refinancing originations but rather a decrease. The reasoning behind this could be the halt of the decreases in interest rates followed by a slight increase around mid-2021 as mentioned earlier.

After the termination of the ARMF in August 2021 the HPI trend reflects the broader housing market conditions including the impact of changes in mortgage financing options and other economic factors. After the ARMF was terminated the graph shows an even greater spike in the Price Index until around mid-2022 when the HPI starts to stabilize. This is accompanied by a further decline in refinancing originations which seems to suggest that home prices do not seem to be a main factor in borrowers' decision-making when considering refinancing their mortgage. It seems that there were more than one factor contributing to the unpredictable nature of the movements in refinancing activity. First, the rapidly changing interest rates seem to have played the main role in the direction of the refinancing activity but not always in the magnitude. As we see during the period that the AMRF is active interest rate movements are minimal while there are significant fluctuations in refinancing activity. Finally, the housing prices and other changing dynamics also affected refinancing activity though not always uniformly. While this paper is analyzing a small section of the refinancing loans around this period having this clear picture of moving variables is crucial.

So while there were major developments during this period it is necessary to have evidence that borrowers are responding as we expect them to, when presented with the incentives created by the AMRF. Is there any evidence that would point to the existence of bunching behaviour around the policy threshold?

The bunching evidence is provided in Figure 4, which serves as preliminary proof that we might be dealing with this phenomenon. This figure shows the fraction of all Refinance (both Standard and Cash-Out) loans in the sample that fall into any given $1,000 bin of the log of Original Unpaid Principal Balance -UPB (Loan Amount) relative to the AMRF threshold in effect at the date of origination. The red vertical line is drawn at ln(125,000) or 11.73, which is also where the discontinuity in the interest rates happens as a result of the AMRF.

Figure 4a shows Refinance loans originated in the 3 months before the implementation of the fee, while Figure 4b shows Refinance loans originated in the 3 months after. What is striking in the comparison between these two graphs, is the missing mass to the right of the red line that is happening because of bunching of loans under $125,000 in the period right after the implementation date. On the other hand, that missing mass is not visible in the period prior to the implementation. This is yet another sign that makes the existence of bunching behaviour an even more compelling argument.

An argument that is then made undoubtedly worth examining, when looking at Figure 5. Here I plot the ratio of the distribution of loan sizes for all refinancing mortgages during the period that the AMRF was effective, divided by the distribution of loan sizes for all refinancing mortgages exactly a year prior to the implementation of the AMRF. I further break down this ratio by refinancing purpose (regular vs Cash-Out) and loan term (15 vs 30-year) in the appendix in Figure 3A and Figure 4A. What is striking about this figures is that, consistently with bunching borrower behaviour, we see a marginal spike just below the $125000 threshold, followed by a missing mass in the distribution of loan sizes just above $125000. There is no reason to expect that this ratio would exhibit such discontinuity at the threshold, barring any loan size adjustment made by borrowers in an attempt to avoid the additional costs of the AMRF. These pieces of evidence serve to motivate the analysis and the findings further along in this paper.

# 3 Literature Review

In contrast with most recent work in the literature that looks at policies implemented around the time of the Great Recession and estimate borrowers' responses, this paper is concerned with a novel policy that has not been examined before. Another focal point of this paper is that unlike much of the recent literature that looks into policies designed to facilitate and promote refinancing during recessionary markets, this research investigates a policy that negatively affects borrowers' incentives to refinance during a period where it is otherwise profitable to do so.

Regarding elasticity estimates discussed in this paper, recent years have seen an increased focus on smaller interest rate elasticities in other consumer credit segments as opposed to mortgages, such as credit cards and auto loans, due to either variation in interest rates or data availability (Karlan (2014), Gross (2002)). This study contributes to the literature examining borrowers' responses to interest rate changes, which includes several natural experiment studies utilizing variation in after-tax interest rates created by taxes, subsidies, and regulations.

DeFusco and Paciorek (2017) estimate interest rate elasticities of mortgage demand ranging from -0.015 to -0.02. Martins and Villanueva (2006), employing triple difference estimators, find that the elasticity of the probability of obtaining a loan to changes in the interest rate lies between -0.028 and -0.013. Jappelli and Pistaferri (2007) find no detectable effect of the tax reform they examine on mortgage debt demand or the amount borrowed.

Glaeser, Gottlieb, and Gyourko (2012) focus on house prices rather than housing demand, finding that they are less responsive to interest rates than predictions made by the standard pricing model used in housing market analysis. They estimate that a 100-basis point decrease in real rates is associated with a 0.0683 log point increase in house values. Using this semi-elasticity estimate of -6.8, the authors find that the 190-basis point decline in real rates between 2000 and 2005 predicts a price increase of approximately 0.13 log points.

Fuster and Zafar (2014) attempt to measure housing demand sensitivity using a survey that assesses respondents' willingness to pay under various financing conditions, including different mortgage rates. They find that a two-percentage point increase in mortgage rates changes the willingness to pay for a home by only about five percent on average.

Lo (2017) demonstrates that both the intensive and extensive margins of demand for mortgages are sensitive to interest rates and are economically significant. The study finds that a 25-basis point decrease in mortgage rates for high-FICO individuals is associated with a 50% increase in the likelihood of a potential borrower demanding a loan and an increase in loan size of approximately $15,000, or about 10% of the average origination volume.

In terms of broader trends in the elasticity of demand for loans to interest rates, Karlan and Zinman (2013) run an experiment in Mexico in which the researchers exogenously impose lower interest rates. The researchers find that the price elasticity of demand for credit is quite elastic: outstanding loan balances and the number of loans each increase by more than 10 percent from the 10-percentage point reduction in the interest rate (on a base of roughly 100 percent APR).

This paper also contributes to literature studying the Adverse Market Refinance Fee. To my knowledge, Ahsin (2023) is the only other paper investigating the Federal Housing Finance Agency's 2020 Adverse Market Refinance Fee (AMRF). Using high-frequency rate-lock data in a difference-in-differences framework, the study finds full (100%) pass-through of the fee to borrowers - more than 60% via higher interest rates. This highlights how policy-induced cost increases, hinder refinancing by amplifying market frictions. These results also support my study, proving that the high degree of pass-through to borrowers, highly incentivizes the bunching behavior in the intensive margin, making it's investigation even more relevant.

Other contributions of this paper are in the recent bunching literature in public economics, which has mostly focused on static contexts and reduced-form estimation. Papers like (Kleven(2016)),(Saez(2010), Chetty(2011) and Kleven(2013) have developed methods for estimating behavioral responses to nonlinear incentives in similar settings.

In order to recover primitive parameters, bunching estimators have been developed and have been largely applied in economics (Saez(2010), Chetty(2011), and Kleven(2013). The main idea behind these estimators is that the larger the mass point, the higher the response capacity of the agents. Bunching estimators have also been used in papers including fuel economy regulations (Sallee(2012)), electricity demand, labor regulations (Garicano(2016)), education (Dee(2019)), and minimum wage (Jales(2018)), (Cengiz(2019)). Another related paper is by Agarwal et al. (2020), which quantifies the impact of HARP on mortgage refinancing activity and analyzes consumer spending and other economic outcomes among borrowers with fixed-rate mortgages.

This paper further contributes to the literature because of the quantitatively different segment of US mortgages that it studies. Earlier papers aiming to measure structural elasticities have generally looked at loans on the higher end of the spectrum with regards to Unpaid Principal Balance (UPB). DeFusco and Paciorek (2017) center their study around mortgages at the conforming loan limit — the maximum loan size eligible for purchase by Fannie Mae and Freddie Mac. Best et al. (2018) studies UK mortgages for which the interest rate jumps once the 80% LTV threshold is passed. The loans in my sample have a maximum UPB of $200,000, which is why this paper has the benefit of looking at loans for which the borrowers are at least theoretically expected to be different in the degree of responsiveness following an increase in mortgage-related costs.

# 4 Data

This paper makes use of two primary datasets. The first one is the Fannie Mae Single-Family Loan Performance dataset that offers detailed loan-level data on its 30-year and less, single-family, conventional fixed-rate mortgages. These are mortgages that Fannie Mae has purchased from US lenders. It covers acquisition and performance data, meaning it includes all details as origination and consequent changes in future quarterly updates. This dataset includes variables such as borrower credit scores, loan-to-value ratios, debt-to-income ratios, and prepayment performance. This dataset updates quarterly and provides the bulk of the data used in this paper. For relevance, in my analysis consider loans with an origination date starting from 2019 until December 2021 and with loan sizes (or as labeled in the data Unpaid Principal Balance-UPB) close to the AMRF threshold of \$125,000. For most analyses in this paper, I use a \$25,000 band around loans with an Unpaid Principal Balance (UPB) of \$125,000. Essentially, under the \$25,000 band, loans in my dataset have a UPB of \$100,000–\$150,000.

The second dataset used in this paper is the CoreLogic Mortgage Basic Dataset which provides comprehensive mortgage transaction data for primary and junior mortgages, equity lines of credit, and other mortgage types. It includes variables such as borrower names, lender details, loan types (e.g., conventional, FHA, VA) etc. I make use of this dataset mainly in my analysis looking at FHA & VA loans while focusing on the same years and loan sizes as with the Fannie Mae data.

An initial overview of the loans and borrowers in my dataset is given in Figure 6, which shows the credit score and LTV distribution for both Refinance and Cash-Out Refinance mortgages. Regarding credit scores, it looks like Cash-Out refinances have a smaller fraction of originated loans for which the main borrower has a credit score close to 800 when compared to standard Refinance loans. Regarding LTV (loan-to-value) ratios, it seems like Cash-Out Refinance loans have a higher fraction of borrowers with LTV ratios close to 80% when compared to standard Refinance loans, while it is also evident that some Refinance originations belong to borrowers with original LTV ratios higher than 80%. The same is not true for Cash-Out Refinance loans.

For each variable, I analyze around 2,616,000 observations. Table 2 presents summary statistics for the main variables in the dataset. Analyzing the differences among the categories gives valuable insight into the market situation both in terms of different time periods and in terms of the various loan types included in the data. There are some trends that are observable when analyzing the Original Interest Rate. Column 1 indicates a mean value of 3.287% with a standard deviation of 0.836, indicating significant variability around the mean. Column 2 — which only analyzes refinancing mortgages — exhibits a slightly lower average interest rate of 3.125% with a standard deviation of 0.679. Some reasoning behind this could include the idea that most borrowers looking to refinance do so after obtaining a decrease in their original mortgage. This would explain the small drop in interest rates. Moving on, columns 3 and 4 show a significant decrease in average interest rates with means of 2.914% and 2.863%, respectively, and smaller standard deviations — 0.423 and 0.416, respectively — indicating less variability. This is evidence of the fact that interest rates were falling sharply during the period that the AMRF was active (December 2020–August 2021). Furthermore, we see the slightly lower interest rates when comparing columns 3 and 4, which once again could be explained by the fact that borrowers look for better terms when considering a refinance.

When analyzing Unpaid Principal Balance (Loan size), column 1 indicates a mean value of $190,137.4 with a standard deviation of $62,205, indicating significant variability. Column 2 shows a slightly lower UPB at around $188,484.9 with a standard deviation of $61,893.51. This decrease goes in line with expectations. Usually, borrowers decide to refinance after spending a number of years paying their mortgage, thus decreasing the amount they need to pay off (UPB). Moving on to when the AMRF was in effect, there is a further decrease in average UPB during this period. The mean decreases to $188,124.4 (Column 3) and $186,292.7 (Column 4) with smaller standard deviations indicating less variability. One very important fact in this part of the analysis is the truncation that the dataset received. In the dataset used to produce these values, UPB was limited to a maximum of $300,000. This means that while there was significant refinancing activity going on in this period, especially for properties with a high UPB, that would not be represented in these values. Furthermore, the drop in means moving from columns 1 and 2 to columns 3 and 4 suggest a trend toward lower mortgage balances during the period that the AMRF was in effect for the portion of loans analyzed here, possibly due to these borrowers seeking to remain cautious in response to changing market conditions even in the presence of lower interest rates.

Regarding the term length for the loans in the sample, column 1 suggests a mean of 308.135 months with a standard deviation of 80.14 months, showing significant variability in loan term lengths for the full sample, while for refinances in column 2, we notice a slightly shorter average term of 289.48 months with a standard deviation of 86.103 months. The same trend persists during the period that the AMRF was effective, with a slightly further decrease in the mean to 302.483 months for column 3 and 286.466 months for column 4. This trend could be explained by borrowers choosing shorter loan terms during refinancing, trying to achieve their repayment sooner.

When analyzing Loan-to-Value ratios, column 1 gives a mean ratio of 67.705% with a standard deviation of 19.211%, whereas refinancing mortgages shown in column 2 exhibit a lower average LTV ratio of 61.141% with a standard deviation of 16.922%. This is to be expected, being that by the time borrowers decide to refinance, their equity situation should have improved compared to the start of the mortgage, so we should therefore expect lower LTVs when analyzing refinances. Furthermore, during the period of the AMRF, there's a decrease in the average LTV ratio to 65.920% in column 3 and 60.123% in column 4, which in part is explained by the significant increase in house prices happening during the period that the AMRF took place. These trends are in part similar to those for DTI (Debt-to-Income), a variable in which we see lower values for refinances when compared to the full sample across the board, as well as lower averages when looking at the period spanning the AMRF. Both these observations would be supported by theory — borrowers should experience lower DTIs once they refinance, at the very least due to their lower monthly payment, whereas lower DTIs during the period the AMRF was in effect make sense when recalling that this was a time period when interest rates were going down continuously and thus borrowers' monthly payments on all new debt would be expected to decrease. The difference in credit scores displayed in the table can be easily explained by one factor, and that is stricter lending requirements put in place after the COVID-19 pandemic, thus it makes sense that mean values in column 3 and 4 would be greater than those in columns 1 and 2. Looking at mortgage insurance, we can conclude that borrowers, whether refinancing or not, may have experienced slightly lower mortgage insurance rates during the period of the AMRF.

Ultimately, I also analyze a different set of loans through the usage of a well-constructed dataset from CoreLogic. They include FHA & VA refinancing loans originated from January 2020 until March 2021. The CoreLogic Mortgage Basic_V2 data provides detailed data on residential properties across the U.S. It contains detailed loan-level data on mortgage characteristics and provides variables related to the origination and performance of mortgage loans. The information in this dataset includes Origination Characteristics like UPB, Interest Rate at Origination, LTV ratio, etc. It also includes Property and Geographic Information, Borrower Information, Loan Performance Information, etc. While this dataset is a great resource, it is different from the Fannie Mae data in two very important limitations: The data in the Mortgage Basic_V2 dataset only provides information on the initial origination of the loan and do not follow the loan over time. While the information provided is very useful, this does pose some limitations to my strategy. This, coupled with the second limitation of this dataset, is the reason it is used as part of the placebo test, which purpose it serves much better rather than to inform the main results of this study. The other limitation is that the data sample I have access to, spans until March 2021. This makes it impossible for this dataset to provide a clear picture of the borrower behavior during and after the implementation of the AMRF. I describe how I use the Mortgage Basic_V2 dataset from

CoreLogic in the Placebo Test section under Robustness Checks.

Another important analysis is that of the pre-AMRF trends that the data follows. To give a better idea of that, I constructed the balance table in Table 3 describing some key loan and borrower variables. We see here that Interest Rate, Loan-to-Value (LTV), Debt-to-Income (DTI), and Credit Score have negligible, inconsequential differences, that are also in line with the theoretical expectations between what would hypothetically be the control and treatment group if the AMRF were to be present during this period. Specifically, it makes sense that loans in the treatment group would have slightly higher LTV, DTI and Credit Score, due to these values being exactly the standard used by most lenders to approve a loan application, thus the slightly higher loan sizes in the treatment group exhibit such higher values for these variables. The Unpaid Principal Balance (UPB) has an expected difference of $9000-$10000 being that the opposing sides of the threshold each cover a $10000 fascia of loan sizes. The Original Term is also behaving as expected, with both the treatment and control groups having no clear significant difference in the term of the loan (the treatment group having a slightly longer term of around two months). It seems like the two sides of the $125,000 threshold behave similarly during the pre-period when it comes to loans in the region of $115,000-$135,000, while we saw differences in the post-implementation period. After also examining other occurring policies and changes in the economic climate and concluding that none of those would affect the opposite sides of our threshold differently, this reaffirms the belief that any change in the post-period would come as a result of the AMRF.

Moreover, even with the negligible differences in the two groups, the methods applied to this analysis include controls for the different loan and borrower characteristics which does add to the reliability and confidence in the results.

# 5 Empirical Strategy

This section presents the theoretical framework and empirical strategy of this study, which in its entirety can be simplified in two steps. First, I calculate measures of bunching and "missing mass"- which is based on the difference between the empirical distribution of refinancing mortgages in my dataset and the estimated counterfactual distribution. The second step will be to use excess bunching and this missing mass to identify several structural parameters, amongst which the interest rate elasticity of mortgage refinancing demand. I also include the estimation of excess bunching while accounting for round numbers, explained later in this chapter.

The bunching methodology used in this paper begins by considering a simple two-period model of mortgage choice (Brueckner (1994)); Chetty et al. (2011); Chetty, Friedman, and Saez (2013); Saez (2010)). The model starts with linear interest rate schedules and afterwards the notch in this interest rate schedule is introduced. I further explain how the bunching statistics are then estimated below.

## 5.1 The Case of Linear Interest Rates

Households in this model live for two periods. The first assumption is that each household has purchased one unit of housing in the first period, and has chosen to finance their purchase with a mortgage- $m'$, that may not exceed the total value of the house. I limit housing units to one, this way the focus can be on the quantity of debt households choose when refinancing their loan, and not on the quantity of housing units.

Households can refinance their housing purchase with a new mortgage- $m''$, which can be either smaller, equal or greater than $m'$. Therefore, by definition $m'' = m' + x$ where $x = 0$ for strict rate refinances. For cash-out refinance $x = C_o - C_i$ where $C_o$ is the Cash-Out dollar value and $C_i$ is the decrease in the Cash-Out payment needed to bunch at the threshold. Finally for strict rate refinances where $m'$ is greater than the quantity needed to bunch at the threshold, $x = -C_i$ and $m'' = m' - C_i$

The interest rate on the refinancing mortgage is given by $r$ and does not depend on the mortgage amount.

In the second period, housing is liquidated, the refinancing mortgage is paid off, and households consume all of their remaining wealth.

The household's problem is thus to maximize lifetime utility by choosing non-housing consumption in each period, denoted by $c'$ and $c''$ and also $C = c' + c''$ equals life-time consumption. In general, the household solves:

$$\begin{gathered} \text{Max}_{c',c''}\{U(c',c'') = u(c') + \delta u(c'')\} \\ \text{s.t.} \quad c' + m' = y + m'' \\ c'' = m' – (1+r)m'' \\ 0 \leq m'' \end{gathered}$$

where $\delta \in (0,1)$ is the discount factor which is distributed normally and $y$ is income in the first period. Finally, preferences are governed by a constant elasticity function $u(c) = \frac{1}{1-\epsilon}c^{1-\epsilon}$ while the density function is given by $f(\delta)$. We can thus solve for mortgage refinancing demand as:

$$m''^{*} = \frac{m' - (\delta(1+r))^{1/\epsilon}(y - m')}{(\delta(1+r))^{1/\epsilon} + (1+r)} \tag{1}$$

## 5.2 Notched Interest Rates

I first introduce a notch in the interest rate schedule at threshold of \$125,000 - $\bar{m''}$. Loans above this threshold are subject to a higher interest rate because of the AMRF. This leads to an interest rate schedule of

$$r(m'') = r + \Delta r \cdot 1(m'' > \bar{m''})$$

Here, $\Delta r$ is the difference in interest rates between the treatment and control groups and $1(m'' > \bar{m}_2)$ is an indicator for a loan being part of the treatment group. A lifetime budget constraint would then be

$$C = y - m' \cdot [r + \Delta r \cdot 1(m'' > \bar{m}'')]$$

where $C = c' + c''$ is lifetime consumption and $y$ is first period income. By indexing households in the Original UPB distribution, the number of households bunching at the \$125,000 threshold is given by

$$B = \int_{\bar{m''}}^{\bar{m''}+\Delta\bar{m''}} f(m')dm' \approx f(\bar{m''})\Delta\bar{m''}$$

where on the bunching interval $(\bar{m''}, \bar{m''} + \Delta\bar{m''})$, the counterfactual no-notch distribution is constant, and $f(\bar{m''})$ is the density when a notch exists.

To estimate the quantity of bunching and the counterfactual mass at the limit I begin by centering loans in my dataset at the \$125,000 threshold. This way, a value of zero represent a loan size equal to the policy threshold-\$125,000. I then create bins – $m''_i$ where I group these loans and where $i = -I, \ldots, L, \ldots, 0, \ldots H, \ldots, I$. The number of loans in each bin is $n_i$. This means that I can fit the following regression to the number of loans in each bin:

$$n_i = \sum_{j=0}^{P} \beta_j (m''_i)^z + \sum_{k=L}^{U} \mu_k 1(m''_k = m''_j) + \epsilon_i \tag{2}$$

Bunching is then estimated as the difference between the observed and counterfactual bin counts in the excluded region at and to the left of the \$125,000 threshold

$$\hat{B} = \sum_{i=L}^{0}(n_i + \hat{n}_j) = \sum_{i=L}^{0}\hat{\mu}_i \tag{3}$$

While missing mass due to bunching would be

$$\hat{M} = \sum_{i>0}^{U}(n_i - \hat{n}_j) = \sum_{i>0}^{U}\hat{\mu}_i \tag{4}$$

My preferred specification uses \$1000, and \$2000 bins, a seventh-degree polynomial, chosen using the Bayesian Information Criteria (BIC) method (following Bosch et al. (2020)) and $m_L$ = -\$1000 and -\$2000 depending on the bin width.

## 5.3 Bunching

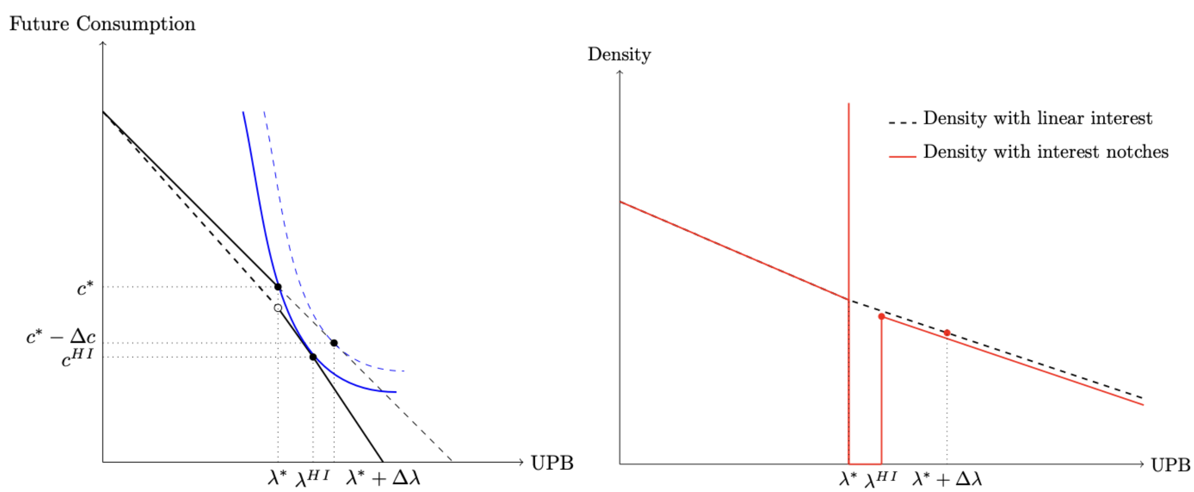


Figure 1: Budget Set Diagram

In Figure 1 above, I am presenting the case of bunching in a "perfect world". The left panel is showing a budget set diagram in which Unpaid Principal Balance (UPB, $\lambda$) is located on the horizontal axis while consumption in the future is on the vertical axis. This panel represents the notch happening in the budget constraint as a result of the increase in the interest rates and represents the "perfect" case of what a notching bunch density distribution looks like. At any UPB value greater than $\lambda^*$-\$125000, we see that because of the jump in interest rates due to the AMRF, the borrower “jumps” away from his previous budget constraint into a lower one, which decreases his future consumption $c^*$.

The panel on the left provides the rational borrower’s loan value-UPB density distribution. Given the right incentives, such as those introduced after the implementation of the Adverse Market Refinance Fee (AMRF), the marginal household decides to bunch at a UPB of \$125000, denoted by $\lambda^*$. This, in turn, creates the missing mass we observe between $\lambda^*$ and $\lambda^{HI}$, the latter being the upper limit on the bunching window, because borrowing any amount inside this window would not be rational, as it would lead to the borrower paying more in interest while having a lower future consumption.

The marginal household is indifferent between bunching at the notch and borrowing $\lambda^*$ or a point $\lambda^{HI}$, located within the higher interest rate bracket. However, any Unpaid Principal Balance (loan size) between $\lambda^*$ and $\lambda^{HI}$ becomes undesirable due to the higher interest rate these loans face after the introduction of the AMRF when accounting for future consumption. The indifference curves in the graph belong to this type of household.

These graphs represent the choices faced by a refinancing household presented with a notched interest rate schedule. If the household has a UPB choice $\lambda^*$, this means that its future consumption is $c^*$, as demonstrated in the left panel. This represents the trade-off between choosing a higher UPB for the loan versus saving that money for future consumption. The solid black line is the budget constraint, where the interest notch occurs at UPB $= \lambda^*$ which for this policy is \$125000 , and the slope of the budget constraint is $R$ below $\lambda^*$ and $(R+\Delta R)$ above $\lambda^*$. In the case of the AMRF, $R$ consists of the interest rate the refinancing loan faces when its UPB falls under $\lambda^*$- the \$125000 threshold, whereas $(R+\Delta R)$ is the interest rate after UPB passes the \$125000 threshold where $(\Delta R)$ is 0.125% or 1/8th of a point for the average loan. This is also the interest rate “notch” I use for my estimations in this paper, in an attempt to provide conservative estimates, however, as reported by the Mortgage Bankers Association (MBA) the AMRF led to interest rate increases as high as 0.375%.

## 5.4 Optimization Frictions

An important detail related to the marginal buncher is that the ability to manipulate the UPB of their refinancing loan is not always going to be costless. This is where the idea of optimization frictions comes into play. Chetty et al. (2011) prove the existence of this phenomenon when they show that kinks or notches that lead to larger changes in prices, produce higher elasticity values that come as a result of the significant increase in the bunching incentives even with the existence of these costs. For this study in particular, that simply means that a high enough interest rate would cause the marginal buncher to ignore the fixed costs and actually bunch at the USD125000 level. This means that, without a significant enough policy change, we could see optimization frictions that would prohibit some borrowers who might find it optimal to bunch at the threshold, but don't because of the fixed costs. In this case, the observed number of bunching households is then:

$$B = \int_{\bar{m_2}}^{\bar{m_2}+\Delta\bar{m_2}} (1-\alpha) f(m') dm' \approx (1-\alpha) f(\bar{m''}) \Delta\bar{m''}$$

where $(1-\alpha)$ is the proportion of individuals who would optimize by bunching at $\bar{m''}$ but cannot due to the fixed cost associated with modifying their loan size. The bunching estimation then takes this observation under consideration when calculating the bunching mass for all calculations

## 5.5 Estimating Elasticities

I start by using the same optimization setup as in Kleven & Waseem (2013). Under a notch for the purposes of my example I show that there is an interest rate schedule where above a given threshold $\bar{m_2}$, the interest rate increases from $r_0$ to $r_1$ but applies to all loan levels, not just those falling in the new bracket (as it would under a kink). In other words, instead of the marginal interest rate changing (as it would under a kink), the average interest rate changes. This can be analyzed using the same optimization setup as with kinks, the only difference being that the interest rate function is now given by

$$r(m'') = m''(r_0 + (r_1 - r_0)1(m'' > \bar{m}''))$$

Here $1(m'' > \bar{m}'')$ is an indicator for a loan being part of the treatment group. To estimate the interest rate elasticity of mortgage refinancing demand, I use a reduced-form approximation based on Kleven & Waseem (2013) and Kleven (2018).

I start by converting the average interest rate into an implicit marginal interest rate that results in what would be an equivalent bunching response under a hypothetical kink for the marginal buncher. Note that in this case we are dealing with a notch which explains the need to convert the interest rate in such a manner.

I denote this marginal interest rate $r^*$ Next, I use the trapezoid rule to approximate the region under the previous function to get this approximation:

$$r^* \approx r + \left(2 + \frac{\Delta \bar{m}''}{\bar{m}''}\right) \frac{\bar{m}'' \Delta r}{\Delta \bar{m}''}$$

where $\Delta \bar{m}''$ stands for the reduction in loan size made by the borrower in order to bunch at the \$125000 threshold-$\bar{m}''$. Solving further I end up with the following reduced form elasticity:

$$e = \frac{\Delta \bar{m}''/\bar{m}''}{\Delta r^*/(1-r^*)} \approx \frac{1}{2 + \Delta \bar{m}''/\bar{m}''} \cdot \frac{(\Delta \bar{m}_2/\bar{m}'')^2}{\Delta r/(1-r)}$$

## 5.6 Round Number Effects

Observing the data, it becomes clear that one of the major issues that could negatively affect the bunching estimation are the round number effects. Just like in a large percentage of studies making use of the bunching methodology, or just simply ones that observe individuals' choices once they are presented with a large number of incrementally increasing consumption or borrowing levels, this paper suffers from borrowers self-selecting into loans with amounts represented by round numbers. This phenomenon is even more prevalent in this study, given that borrowers are making choices as opposed to scenarios where the bunching methodology in used to investigate tax reports from wage-earners, whose income might be reported by third parties. Round number bunching follows a certain pattern making it so that some round numbers end up being more prominent than others (or rounder than others). For instance, while excess clustering occurs at any borrowing level that is a multiple of USD1000, it is more pronounced at multiples of USD5000, USD10000 and so on. In the case of this study, it seems like the "rounder numbers" are multiples of USD1000 and USD5000. There are two key points to consider regarding round-numbers. First, I observe that notches are typically positioned at prominent round numbers, applying specification (3) without accounting for rounding would mix true notch bunching with round-number bunching, leading to an overestimation of borrowing responses to the notch. Second, it is possible to account for this phenomenon happening at the notches we are observing by using the excess bunching at 'similar round numbers' that are not notches as a counterfactual. Visually, in my estimations, the counterfactual will appear to feature spikes at round numbers that are multiples of \$1,000 and \$5,000, accounting for the fact that we would have observed such a distribution with bunching masses even in the absence of a notch. Constructing a set of round number fixed effects, I am able to account for the effect of round numbers. The regression specification I consider is the following:

$$n_i = \sum_{j=0}^{P} \beta_j (m''_i)^z + \sum_{r \in R} \rho_r 1(m''_i / r \in N) + \sum_{k=L}^{U} \mu_k 1(m''_k = m''_j) + \epsilon_i \tag{5}$$

where N is the set of natural numbers, $R = \{USD1,000, USD5,000\}$ is a vector of round-number multiples that capture borrower loan size rounding whereas the estimate of the counterfactual distribution is defined as the predicted values from regression (3) omitting the contribution of the dummies around the notch, but not omitting the contribution of round-number dummies.

This paper also implements the non-parametric approach similar to Bertanha et al (2018) under the "bunching" package to estimate the interest rate elasticity of mortgage refinancing demand through two distinct methods. The first method, implemented through bunchbounds, observes that when a policy or fee threshold is introduced, borrowers tend to bunch just below the threshold to avoid additional costs. The bunching method relies on the probability density function (PDF) of borrower heterogeneity. Specifically, it assumes a limit to the slope of this PDF. The number of borrowers that bunch at the threshold can be interpreted as the area under the PDF across an interval, the length of which depends on the unknown elasticity. By imposing a maximum slope on the PDF, I can derive bounds on this interval, which correspond to upper and lower bounds on the elasticity estimate. Essentially, the more pronounced the bunching behavior, the more elastic demand appears, and this method offers a straightforward way to quantify this elasticity.

The second method, implemented using bunchtobit, approaches the problem from a different angle by treating bunching behavior as a middle-censored regression model. In this framework, borrowers who would typically take out loans above the threshold are effectively "censored" because they adjust their borrowing amounts to avoid the added cost. This model introduces an important innovation by controlling for observable heterogeneity such as individual characteristics like income or creditworthiness that influence refinancing decisions. By controlling for these factors, bunchtobit allows for a more refined estimate of elasticity, as it accounts for the variability in borrower behavior that might otherwise obscure the true effect of interest rates on refinancing demand. Together, these two methods provide a comprehensive approach to estimating the interest rate elasticity of mortgage refinancing demand. Bunchbounds offers a clear and interpretable bound on elasticity, while bunchtobit enhances precision by controlling for individual-level differences in borrower characteristics. This combined approach leads to a deeper understanding of how borrowers respond to changes in interest rates, especially in the context of policies like the AMRF.

# 6 Results

Figure 8 shows the bunching results using a methodology similar to Chetty et al. (2011). The increments on refinancing mortgages are reported in $1,000 intervals which also motivates the selection of the bin size equal to $1000. The model appears somewhat more accurate with this selection as shown by the elasticity standard errors, and it makes more sense in the context of this study. Figure 8 shows the bunching output for the basic specification. Here, I am not accounting for round number bunching. Thus, the bunching weight which is giving the density of agents at the threshold compared to a counterfactual smooth distribution is significantly over-estimated at 1.359. So is the elasticity value, measured at approximately 0.046. Due to the over-estimated response because the model fails to account for the round number behaviour, the refinancing demand also appears much more elastic compared to when the model does account for these irregularities.

In Figure 9, I show the bunching output for the specification where I am accounting for round number bunching. In this specification, the bunching estimator drops significantly as the bunching happening due to the round number loan sizes is eliminated. The bunching estimator is 0.363. The elasticity estimates also fall in this specification; Figure 9 gives us an elasticity of around 0.003, meaning that a 1% (or 100 basis points) increase in interest rates will lead the marginal buncher to lower their loan size by about 0.3%. This means that for this increase in interest rates, the bunching household right at the threshold is decreasing their loan size by about $375. There could be a list of reasons why this elasticity might be lower than previous estimates from similar studies. First, it is already well-established, that at least in 20% of the cases, borrowers that might find it optimal to refinance do not do so, with the main reason being poor financial literacy(Keys,Pope & Pope(2016)). Thus, it is to be expected that even when some borrowers do refinance, they might not optimally do so, mainly for the same reasons, forgoing further savings in the process. Second, this idea is reinforced when considering that the loan sizes analyzed in this study are small enough to assume that these borrowers are not particularly well-off, and thus do not possess the means or financial literacy needed to benefit from maneuvers such as bunching below the AMRF threshold. Third, as we covered in the beginning, for a refinance borrower right above the threshold at \$126000, he would incur an extra \$4000 as a result of the AMRF across the life of the loan, typically 30 years, and that might just be tolerable enough that most refinancing borrowers would just ignore the savings resulting from bunching below the threshold, even if they had the financial literacy needed to bunch.

Even so, we can understand a bit more as we take a look at different subsamples of the Fannie Mae data when investigating bunching behaviors. In Figure 10 and Figure 11 I estimate bunching parameters for regular refinances and then cash-out refinancing loans respectively. What I find, goes in line with theoretical predictions. Borrowers taking cash-out refinances, have lower optimization frictions when bunching because they have the option to just lower their cash-out payment and thus fall under the \$125000 threshold. This is also supported by Table 4, where we see ($\alpha$) for column 4 is greater than column 3 ( meaning a lower $(1-\alpha)$, which gives average optimization frictions to bunching). This partially explains what I find regarding the bunching statistic and the elasticity measure, where cash-out refinancing borrowers appear more elastic and thus have larger estimates for both these variables.

Similarly in Figure 12 and Figure 13 I am showing the bunching chart and main statistics when looking at the subsamples including only refinancing loans with terms around 15-years and 30-years respectively. In this case the 15-year refinancing borrowers display larger elasticity, manifesting as higher bunching statistic as well as higher elasticity estimates. This, once again is partly explained by the lower optimization frictions faced by 15-year refinancing borrowers, supported by the higher ($\alpha$) in Table 4.

Figure 14 shows the results obtained by implementing the non-parametric approach similar to Bertanha et al (2018) under the "bunching" package. The `bunchbounds` method partially identifies the elasticity. More specifically, the length of the interval where agents bunch, under the heterogeneity PDF depends on the unknown elasticity. Selecting a maximum slope magnitude of the PDF will then imply the existence of upper and lower bounds for PDF values inside this interval, which means there will be upper and lower bounds on the size of the bunching interval. This, in turn, corresponds to lower and upper bounds on the elasticity. This figure also gives the results generated by `bunchtobit`. The `bunchtobit` command estimates the elasticity for ten different subsamples by default and it is a semi-parametric method that rewrittes bunching as a middle-censored regression model. This method yields a mid-censored Tobit model. It does this by using truncation windows that make use of smaller and smaller sample sizes centered around the policy threshold. Thus, the first truncation window uses all the data ie. 100%; the second uses 90% of the data around the kink, and so on. Each subsample is truncated symmetrically with 5% of the data being from the notch and the other 95% divided equally above and below the notch. `bunchbounds` graphs the non-parametric bounds for different maximum slope magnitudes of the unobserved heterogeneity PDF. Figure 14 also shows the different slope magnitudes along with their corresponding bounds and it shows how the upper bound increases and the lower bound decreases as the maximum slope increases. The vertical lines at 0.66 and 83.11 are the minimum slope for the existence of the bounds and the maximum slope for a finite upper bound. The intersection denotes the point identified elasticity using the trapezoidal approximation. The results generated by `bunchtobit` are also given, which produces a best-fit graph for each subsample and a graph of the elasticity estimate for all subsamples. Each of these panels presents a histogram of the log value of a particular bin minus the log of $125,000 and the estimate of the truncated Tobit model. The smaller the truncation window around the kink, the stronger is our conviction that the estimate of the elasticity is consistent. Figure 14 shows the elasticity estimates along with the 95% confidence intervals according to the percent of data that was used for the estimation. There is clearly a difference in the magnitude of these elasticity estimates as opposed to the ones produced by the reduced form approximation. It seems like the poor fit of the distribution of refinancing loans to the Tobit regression used by the Bertanha et al.'s (2018) "bunching" package is the major difference and seems to be playing a huge role. While useful, it must be noted that this methodology is not accounting for round-number bunching. I believe this to be a main reason for the over-estimation of elasticities. Nonetheless, these estimates serve as a ”right tail extreme” when considering interest rate elasticities of mortgage refinancing demand.

# 7 Robustness

## 7.1 The Channel Question

One concern regarding the elasticity estimation is the existence of multiple channels through which an increase in interest rates could affect refinancing decisions. One channel is that of additional borrowing. In this scenario, households can choose to take out an additional separate loan to make up for the forgone savings due to the AMRF. The idea here is that since a marginal household had a set level of borrowing that would maximize their utility with respect to the trade-off between borrowing and future consumption, now that they had to bunch at a lower UPB due to the AMRF, they will seek to supplement their borrowing demand with a different type of loan. In other words, household will want to keep the same level of borrowing they set out with. This is an issue that can be addressed by looking at different types of borrowing around this period. If there is an increase in applications for personal loans or other types of borrowing, this can be an indicator of the usage of this channel. This is exactly what is represented in Figure 15. What we can discern from this figure are two things: First, since the “additional borrowing” channel would only apply to the marginal buncher and since the marginal buncher would at most lower their loan size by about $5,000, the only additional borrowing that would make sense for a borrower in these circumstances would either be that of Credit Cards or the “Other Loan” category given that “Automobile Loans” are usually much higher in value than $5,000. Second, the additional borrowing would most likely take place around the time when the AMRF was implemented since that is when the marginal buncher had to adjust his borrowing demand, given the extra cost imposed by the AMRF on mortgage refinancing demand. What we see in Figure 15 is that first, Credit Card loans experienced a decrease in the first 4 months after the implementation of the AMRF. Second, the other two categories do not seem to experience any significant jump during the first months when the AMRF was implemented. Clearly, this evidence is not conclusive, but it does provide some insight into whether there is a large shift away from mortgage refinancing into other loans, and Figure 15 does not seem to suggest that.

Ultimately, following literature related to this issue, DeFusco & Paciorek (2017) find that a rough estimate of the effect of this channel on the elasticity would be to scale down the elasticity estimates by a factor of one-third. I believe that could also be applicable in this case. Another channel through which interest rates could affect refinancing decisions is the decrease in the loan size. Households can choose to pay down to the $125k threshold, which is what the bunching method assumes as well.

Finally, households can decide on shifting the timing of a refinance or not go ahead with refinancing altogether. This is a channel that can be investigated further and is briefly and non-conclusively covered in Figure 5A of the appendix.

## 7.2 Simultaneously Changing Variables

There were a lot of changes happening simultaneously in the period that encompassed the COVID-19 pandemic. One important concern to my particular methodology is the threat of confounding factors when studying the different responses to the AMRF on the two different sides of the $125,000 UPB (Unpaid Principal Balance) threshold. It does seem, however, that while significant changes were happening amongst many different variables during this period, it was only the AMRF that used this threshold to separate borrowers that would be affected by the fee from borrowers that wouldn't. There is no evidence that seems to suggest any other development was affecting the two sides of this threshold in different ways. Initially I discuss the various smoothness tests in Figure 7, and the I take a close look at the various policies that were enacted as a response to the COVID-19 pandemic, that could have influenced the refinance loans close to the threshold being analyzed.

In Figure 7, I plot the three main borrower characteristics, before and during the AMRF, to show that there is no difference in trends around the $125000 threshold in these two time periods. Specifically, I plot Loan-to-Value ratios, borrower FICO scores and Debt-to-Income ratios and find very similar trends around the $125000 threshold in both periods. This suggests that any differences in loan value selection or interest rates face by borrowers are potentially due to the primary (interest rate hikes) and secondary (bunching response) effects of the AMRF.

Next, focusing on concurrent policies, a very important one passed during this time was the CARES Act which had three main areas of focus. It provided direct payments to eligible individuals and families. It supplemented existing state unemployment benefits by a fixed $600 payment, and it established the Paycheck Protection Program (PPP), offering forgivable loans to small businesses to help them retain their employees and assist the overall economy. If the loans were used to aid in maintaining employee payroll (i.e. usually the requirement was set at around 60% of the funds) these loans were usually forgiven. PPP loans went through multiple rounds because of the dynamic economic environment of those times and faced different adjustments each time.

While the Cares Act was largely influential during the COVID-19 pandemic, it doesn't seem like any of its intended goals would in any way interfere with refinancing loans in the threshold we are studying or otherwise. The unemployment benefit supplement helped families and individuals tremendously during this period, but as far as we know, it had no discontinuous effect around the $125000 threshold on refinancing loan demand. The same could be said for the direct payments made as part of the Cares Act. As for the Paycheck Protection Program (PPP), theory doesn't suggest that there would be any effect on refinancing loans being that PPP loans were offered to businesses. Admittedly, Unemployment benefits as well as income rebates could have increased the likelihood that the household would qualify for a refinance since their DTI's would now be lower. This could in turn increase mortgage refinancing demand, however, what is important in this case is that there is no evidence of a discontinuity at the threshold of $125,000. Another policy enacted during this period was the Families First Coronavirus Response Act (FFCRA). FFCRA introduced Paid Sick Leave during the pandemic for individuals impacted by COVID-19. It also expanded family and medical leave to provide additional leave for parents dealing with school closures or other COVID-19-related issues. Clearly, this is a policy that could not have any effect on refinancing loan demand, at least not directly, and definitely, not around the threshold of the loan sizes this study is looking at. Eviction Moratoriums were another policy that was largely used during the COVID-19 pandemic. These federal moratoriums protected renters from being evicted from their residences as long as they fulfilled specific criteria. In addition to the moratoriums, there were also some financial assistance measures implemented to help both renters and landlords during this period.

Yet again, the theory doesn't suggest that the eviction moratoriums would have any sort of effect on the threshold of refinancing loans studied here or otherwise. Another evident change that happened during the COVID-19 recession was the stark increase in house prices. Comparing the pre-pandemic trend that house prices were following with that of the COVID-19 recession it is clear that these were times when house prices were reacting in an unusual manner. There are different reasons as to why this happened. Amongst the most important ones, we could mention the limited supply of houses and the easing in the lending standards from banks. At the peak of the house price increase in July of 2021, the FHFA house price index recorded a jump of 19.3 percent year to date. This contrasts the pre-pandemic period where we would usually see an average annual rate increase of about 5 percent. To reiterate, the concern with these statistics is whether or not there exists similar movement above and below the $125,000 threshold.

Figure 16 displays the percent change from a year ago for 2 different Tiers of Home-Price indices covering three of the biggest metropolitan areas in the USA. Looking at this figure we can see three different charts. The first one represents the Low and Mid-Tier S&P CoreLogic Case-Shiller for Los Angeles. We can see in this chart that both these indices are moving very similarly throughout the COVID-19 recession as well as during the period that immediately preceded it and the period right afterwards. This means that we don't expect these house price changes to have a different effect on the opposite sides of the $125,000 threshold for Los Angeles. The situation for Miami is slightly different, being that during the recession the Low-Tier index is showing a slight increase when compared with the Mid-Tier one. The opposite is true for New York, where the Low-Tier index is decreasing while the Mid-Tier one is going up. Considering the different trends for these three major metropolitan areas we can rule out the possibility that there is a common trend throughout the country that would be affecting the two sides of our threshold differently. The surge in mortgage refinancing, which we witnessed from the second quarter of 2020 through the fourth quarter of 2021, was initiated by a substantial drop in mortgage interest rates, amounting to nearly 200 basis points, stretching from November 2018 to November 2020. A similar 200 basis point decline in rates also catalyzed the refinance boom of 2003, along with a smaller-scale boom in 2013. However, there are three key characteristics that set the recent refinancing boom apart from its predecessors. First, during the pandemic years of 2020 and 2021, interest rates reached historically low levels, enticing numerous homeowners to capitalize on these favorable rates through means like extracting equity, reducing monthly obligations, or shortening their loan terms. Second, the rebound in mortgage interest rates following this historic low was exceptionally swift, putting a prompt end to the surge in refinancing activity. Last, home equity was at an all-time high prior to the pandemic, and as home values continued to rise, many borrowers found themselves with ample home equity they could access.

While we discussed the concern that the decline and the subsequent rebound in interest rates might have affected the loans on different sides of the $125,000 threshold differently, we do need to point out here that there is no indication, and neither should we expect that home equity throughout the US might somehow look different for loans above $125,000 compared to those below this threshold. In the discussion of self-selection, I do anticipate a connection between the outstanding mortgage balances and the likelihood of refinancing. Refinancing tends to be a more sensible choice when the mortgage balance is substantial because the potential benefits from refinancing are directly linked to the amount being refinanced. This is precisely what I depict in Figure 17 using data from the New York Fed Consumer Credit Panel. For instance, for mortgages with balances less than $100,000 as of the first quarter of 2020, refinancing occurred in less than 10 percent of cases. In contrast, almost half of mortgages with balances ranging from $400,000 to $500,000 were refinanced. Notably, the propensity to refinance begins to decrease after the $500,000 mark. Once again it seems that while the size of the loan has some correlation with the decision to refinance, we do not see any indication that the precise $125,000 threshold leads to any kind of separation in these incentives when comparing both sides of this threshold. This piece of information is very informative to this paper, as well as this particular discussion. While we did see self-selection when it came to the decision on how much to borrow it seems like we don't see a clear cut-off, around the $125,000 when it comes to the decision on whether to refinance. This means that the AMRF was influential around that $125,000 threshold on borrowers' decision on how much to refinance, but it did not ultimately affect the decision on whether to refinance or not.

When I examine the investor category of mortgages using data from the New York Fed Consumer Credit Panel [5], we see that around 25 percent of GSE mortgages underwent refinancing, with an equal proportion for both Fannie Mae and Freddie Mac. This uniformity is unsurprising, possibly due to the potential for GSEs to interchange these loans. FHA borrowers exhibited a lower inclination to refinance at 22 percent, even though the FHA offers a 'streamline refinance' program. In contrast, VA mortgages demonstrated the highest likelihood of being refinanced. Approximately 38 percent of VA mortgage accounts that were active as of the first quarter of 2020 had undergone refinancing by the end of 2021.

[5] More information is available at: https://libertystreeteconomics.newyorkfed.org/2023/05/the-great-pandemic-mortgage-refinance-boom/

As we just discussed above there is a higher likelihood of refinancing for mortgages with larger balances which is why the percentage of total balances refinanced is greater for these loans. During this period, approximately 35 percent of the balances for GSE mortgages, 29 percent for FHA mortgages, 46 percent for VA mortgages, and 29 percent for other mortgage types experienced refinancing. Throughout all of these figures, we don't expect to see any difference between the opposite sides of the threshold. There is no evidence that within any of these different loan types, there is a higher probability to refinance for loans below or above $125,000. We expect this to also be true prior to the implementation of the AMRF. Obviously, since we do not see an impact that is different on the two sides of the threshold besides that coming as a result of the AMRF, we think that in its absence the parallel trends hypothesis would hold true, and the two sides of the threshold should behave somewhat similarly in the pre-period. To give a better idea of that I constructed the balance table listed under Table 3 describing some key loan and borrower variables, and discussed earlier in this paper.

Ultimately, it is evident that while the period during which the AMRF was in effect was subject to different policies and changes in some key variables, these did not have a discontinous effect on the different sides of the $125000 threshold.

### 7.3 Placebo Tests

Next, I analyze another set of loans which will serve as the basis for a placebo test for my strategy. As I covered earlier, the AMRF exempted FHA & VA loans from its structure. This means that loans very similar to the 30-Year FRM in my initial investigation went unaffected by the increased interest rate that was introduced by the AMRF. So essentially, loans that would have otherwise been affected mostly by the same factors are now different in one major way and that is the additional 0.5% interest rate charged on regular loans vs. the FHA & VA loans. This makes FHA & VA loans the perfect candidate to analyze and investigate in order to draw conclusions regarding the behavior of the borrowers taking out these loans. In theory, if we assume these loans would behave similarly in the absence of the AMRF and that the bunching behavior exhibited in the Fannie Mae dataset comes as a result of the AMRF, then we should be able to verify that, being that that same behavior will not be exhibited when investigating the FHA & VA dataset. And ultimately, this is what the data reveal. Looking at in Figure 18, I am conducting the same bunching estimations as with the Fannie Mae data, and there doesn't seem to be any convincing evidence to show that there is any bunching taking place at the $125000 UPB threshold. I account for round numbers as well as optimization frictions. The elasticities and bunching statisticsestimated are quite small and insignificant as shown in Figure 18 . It seems like in the absence of the AMRF, the bunching behavior around the $125000 threshold is not exhibited. There are limitations to my findings here, however, due to the number of months that I have access to the CoreLogic data, which is used to conduct this analysis. As far as the period after the implementation of the AMRF, I only have data for the first 4 months—up to March 2021. Nonetheless, as demonstrated in the main bunching specification, for the 30-year FRM, the largest number of bunching borrowers originate their loans exactly in the first few months after the AMRF is implemented. Thus, if we extrapolate these findings, we can assume the same trend holds true and conclude that the bunching estimates for the 30-year FRM hold true and maintain their relevancy in the context of this policy and similar ones.

# 8 External Validity

One concern regarding this study is the extent to which the findings can be generalized and applied in a broader context. While we could notice certain borrower behaviors in a specific time, under specific circumstances, external validity needs to be addressed for these results to carry weight outside of these circumstances. In the external validity discussion, it is very important to clearly recognize the characteristics of the population being studied. The Fannie Mae data used throughout this paper are made up of loans for single family homes that are part of the Fannie Mae portfolio. Obviously, not all loans in the US are part of that portfolio. However, a very strong argument could be made that these loans are representative of the broader US loan market for single family homes. As of 2023, Fannie Mae and Freddie Mac support around 70% of the US mortgage market, with Fannie Mae holding the larger share, as reported by the National Association of Realtors. The majority of the loans purchased by the two GSE's (Government-Sponsored-Enterprises) are conventional, and so we can confidently claim that the Fannie Mae data are representative of US conventional mortgages in general, and any results achieved by using these datasets could be generalized to the broader US conventional mortgage markets. VA, FHA and other types of non-conventional loans are not part of the Fannie Mae datasets, and they are also excluded from the AMRF. Therefore, results of this paper should not be generalized when considering non-conventional and non-conforming loans. As far as other characteristics regarding the loan population, the loans being studied are FRM (Fixed-Rate Mortgages) so the results could be generalized for that mortgage category. Since ARMs (Adjustable-Rate Mortgages) and other types of mortgages are not included in this study any results would not be applicable to these categories of loans. However, it needs to be said that ARMs usually account for a much smaller percentage of the mortgage markets when compared to FRM. For example, in April 2023, ARMs accounted for 18.6% of the dollar volume for mortgages, up from 4% in 2021, as reported by the Mortgage Bankers Association. Regarding other borrower and loan characteristics such as FICO score, LTV or DTI ratios, Original Interest Rate etc., loans included in the Fannie Mae dataset display a healthy distribution along all of these variables, as shown in the balance table and summary statistics. Therefore, it is expected that the results of this paper could be generalized to loans with similar borrower and loan characteristics.

In the external validity discussion, it is also crucial to analyze the time period that is being studied and all moving variables that come with it. In light of this, the fact that the AMRF was set in place during the COVID-19 pandemic, becomes highly important. In the US, COVID-19 had a major effect on mortgage borrower behavior that had an impact across all sectors in the market. As a response to the economic crisis brought on by the pandemic, the Federal Reserve reduced interest rates, which increased the appeal of refinancing for existing mortgages with higher rates. Refinancing applications skyrocketed as a result, giving borrowers the chance to potentially reduce their monthly payments. In addition, due to lockdowns and remote work, homeowners spent more time at home and reviewed their living arrangements. As a result, refinancing became more popular among those looking to consolidate debt, access more finances, or renovate already-owned properties.

Thus, it would not be sensible to generalize the results of this study to periods with opposite borrower incentives in place, i.e. any results this paper lands on, in terms of refinancing mortgage demand elasticity or refinancing decisions and bunching behaviors should not be generalized during periods with constantly increasing interest rates or otherwise periods when refinancing would be counterintuitive for most borrowers.

One trend that could be observed during the during the pandemic's early phases, was that as a result of job losses and unstable employment some prospective homeowners put off applying for mortgages because they were worried about their capacity to repay the loan.

In response to this, the government established forbearance programs that let homeowners who were having trouble making their mortgage payments temporarily stop or lower them. This slowed down the general activity of the mortgage market while also assisting in preventing defaults and foreclosures. While this does represent an example of an unusual situation tied to the COVID-19 pandemic, it is also true that the uncertainty only lasted for a few months and was followed by a boom in mortgage activity, and especially in refinancing mortgages. It is also a fact that the AMRF was put in place almost 7-8 months after the COVID-19 pandemic started, so the impact of these developments should be inconsequential in our analysis.

Another important development during this time is that lenders grew more cautious and tightened lending standards and credit score requirements following the economic unpredictability. This might have made it harder for certain consumers to get approved for mortgages. However, on the other hand, other borrowers found this time period to be full of opportunity due to other developments such as lower interest rates etc. In general, refinancing activity surged in the market, but there were also delays in loan applications and borrower profile modifications. This means, that in the context of these developments, results generated by this paper should in most cases be generalized and used to characterize borrower behaviour in the context of refinancing mortgage demand.

The adoption of the Adverse Market Refinance Fee (AMRF) by the Federal Housing Finance Agency (FHFA) in December 2020, along with the notable increase in mortgage refinancing activity seen in 2020 and 2021, had a substantial impact on borrower behavior and housing market policies. The results of this research highlight how crucial it is to comprehend how policy interventions, like the AMRF, affect the choices made by borrowers in the housing market. The possible effects of regulation changes on mortgage refinancing activity and borrower welfare must be carefully considered by policymakers.

In light of the offered empirical results, policymakers should reevaluate how well the AMRF and other comparable regulatory measures accomplish their stated goals. In times of economic uncertainty, it is crucial to find a balance between protecting the housing market from systemic dangers and making sure that borrowers can obtain credit at reasonable rates.

Considering this it would make sense for there to be a discussion regarding the effects of the AMRF specifically in the context of welfare outcomes, which could be an avenue worth pursuing as a future study, and it would add significant further understanding of the policy ramifications of the AMRF, and how it affects mortgage refinancing activity. At this point in time however, it remains important to highlight that even with all the unusual market activity happening around the period that the AMRF took place, this study holds significant value in the discussion of bunching behavior and refinancing mortgage demand elasticity.

# 9 Discussion

One important area meriting discussion is the multitude of factors affecting mortgage rates around 2020. As the pandemic started – in March 2020 – there was a quick reaction by the Federal Reserve, cutting the federal funds rate to a range of 0-0.25%. This, in turn, led to a significant drop in mortgage interest rates for all loan types. Moreover, the Fed expressed a commitment for the foreseeable future to counteract the negative effects of the pandemic. This commitment did provide stability to mortgage rates. A popular benchmark, the 30-year fixed rate mortgage slipped – at one point – below 3%. These fluctuations in interest rates, obviously had a huge impact on refinances as borrowers were trying to take advantage of the low rates.

While it is true that while the Fed was trying to combat the effect of the pandemic, economic stability concerns were putting upward pressure on interest rates. First, remote working and increased loan volumes put pressure on lenders also due to the increased demand for refinances during this period. This is one of the reasons why the pass-through of the Fed's policies might have not been as direct and swift as was hoped – particularly during the first few months of the pandemic. Another reason that might have caused unpredictable fluctuations in mortgage rates is the fluctuations in the Mortgage-Backed-Securities (MBS) markets, caused by increased demand for MBS as well as challenges related to operational capacity.

Fluctuations also arose due to economic data and vaccine news. Positive developments were partially responsible for incremental upticks in mortgage rates, while the opposite was also true. Inflation concerns as well as inflation data also had an effect. As the pandemic continued, concerns about inflation emerged due to significant government stimulus spending, which also, in turn, led to higher interest rates, partially translating to higher mortgage rates.

Later in 2020, and 2021, mortgage rates began a steady increase that was due to these inflation concerns as well as economic recovery expectations. The Fed further fueled this belief as they indicated they would start to reassess their monetary policy and focus more on inflation control. During this period, there was also regional and geographical variation which is also true during normal economic environments. Local economic conditions, housing market dynamics, and lender policies all affected mortgage rates and were also affected by the COVID-19 pandemic.

Looking at all major developments happening in this period regarding interest rates in the mortgage markets we still do not see any evidence that these fluctuations affected loans on opposite sides of the $125,000 threshold differently. As the Fed decreased the federal funds rate – leading to a drop in mortgage rates – we cannot say that these initial drops were substantially greater or smaller for loans on either side of the $125,000 threshold. There are a lot of factors that go into the particular mortgage rate that are assigned to a loan (LTV, DTI, FICO Scores, etc.), however, it seems like the AMRF is the only policy that affected the two opposite sides of this threshold differently. Later, when mortgage interest rates were increasing due to the factors that we mentioned above, once again we neither expected nor saw evidence of a difference between changes happening on one side of the threshold when compared to the other. The economic stability concerns in this period or the fluctuations in the MBS markets don't seem to affect loans under or over $125,000 differently from the opposite side of the threshold. And, neither did inflation concerns. While inflation became a central topic in the later stages of the COVID-19 pandemic its effect on interest rates came as the Fed focused more towards price stability and less towards low unemployment. The Fed started to increase the federal funds rate which as a result affected mortgage rates, which also started to go up. However, just like before when rates were decreasing, there was no evidence that these increases in mortgage rates affected loans below $125,000 differently from those above $125,000. Therefore, it should be noted that any discussion regarding mortgage rates around the period that the AMRF was in effect, did not – in any substantial way –affect the two sides of the $125,000 threshold discontinuously.

Other areas meriting discussion are the several estimates in this paper along with their representation, relevance, and context. The bunching statistics along with the elasticity estimates are informative when it comes to questioning the existence of bunching. It is clear that in this limited region of refinancing mortgages, there was a response from the borrowers to the policy introduced by the AMRF. Specifically, the best estimates of this response are gathered by the ones in Table 4. It is important to note that this table does not display the semi-parametric results from the method similar to Bertanha et al. (2016) which aims to fit the distribution of loans into a Tobit regression, as those results serve more as an upper bound of what the bunching statistic and elasticity could look like, as well as a way of confirming the initial estimates are in the right "neighborhood". In Table 4 the more elastic seems to be the demand of cash-out refinance borrowers (when accounting for round numbers) with the regular refinancing borrowers being the most inelastic. If we were to split even further, it is trivial to understand also that the cash-out, 15-year refinance borrowers would be even more elastic compared to all other subsamples.

It seems that the estimates of the interest rate elasticity of mortgage refinancing demand, provided by the traditional bunching methodology similar to Kleven & Waseem (2013), in this paper are more or less in line with previous papers' findings. Specifically, when not accounting for round number bunching the value is estimated at 0.046, and it decreases to 0.003-0.008 when accounting for this phenomenon (depending on the subsample). While smaller than the values provided by DeFusco & Paciorek (2017), it needs to be mentioned again that this study exclusively looks at refinances, which I believe accounts for a major part of that difference. The rest of that discrepancy could be explained by the limited segment of loans analyzed in this paper and the difference in loan sizes- this paper studies the 25000 threshold while DeFusco & Paciorek (2017) look at the Conforming Loan Limit(CLL)

# 10 Conclusions

In conclusion, this paper proves the existence of bunching behavior as a response to the AMRF. The bunching ratio ranges from 0.188 to 0.561, while the interest rate elasticity of mortgage refinancing demand ranges from 0.001 to 0.008. These values provide insight into the small positive response to the discontinuous change in interest rates for refinancing mortgages and are further verified by the placebo test carried on the FHA & VA mortgages. The semi-parametric bunching method serves as a ceiling for the elasticity measure at 0.21, however, this does not account for round number bunching which suggests that this ceiling should be even lower (as much as by a magnitude of 10 if the difference in the similar results from the traditional bunching methodology is to be considered as a benchmark). While lower than previous relevant studies, these estimates are reasonable considering the context of this study.

Though the response of borrowers is smaller than optimal, the ones that did change their loan size and bunch at the $125,000 threshold could have benefited from savings ranging from $3500-$4700 depending on the original size of the loan they intended to borrow. These numbers assume that the marginal buncher, at the best case, would be a borrower who would at most borrow $128,500 in the absence of the AMRF. The attractiveness of these savings would then become a subjective matter, which is one reason why a higher bunching statistic is not observed, i.e. these might be savings that are not providing a significant incentive that would lead borrowers to assume the costs associated with bunching.

As mentioned in the previous section, the bunching and elasticity estimates, however, could benefit from further investigation. Another avenue worth pursuing is the inclusion of the second discontinuity resulting from this policy. Being that Jumbo loans are not subject to the AMRF, there is a discontinuity in the interest rate given to loans above and below the Federal Conforming Loan Limit. The findings resulting from such an analysis could further inform the estimates of this paper, especially when trying to identify the interest rate elasticity of mortgage refinancing demand.

Furthermore, even more avenues of research are presented by the cancellation of the AMRF on August $1^{st}$, 2021 in terms of exogenous variation and I believe further investigation of this topic is warranted as more and more data encompassing this period becomes available. For example, as shown in Figure 1.A, in the appendix, households can avoid the AMRF not only by modifying their loan size but also by moving around their origination date. Future research can analyze this bunching channel and possibly provide relevant and informative elasticity measures.

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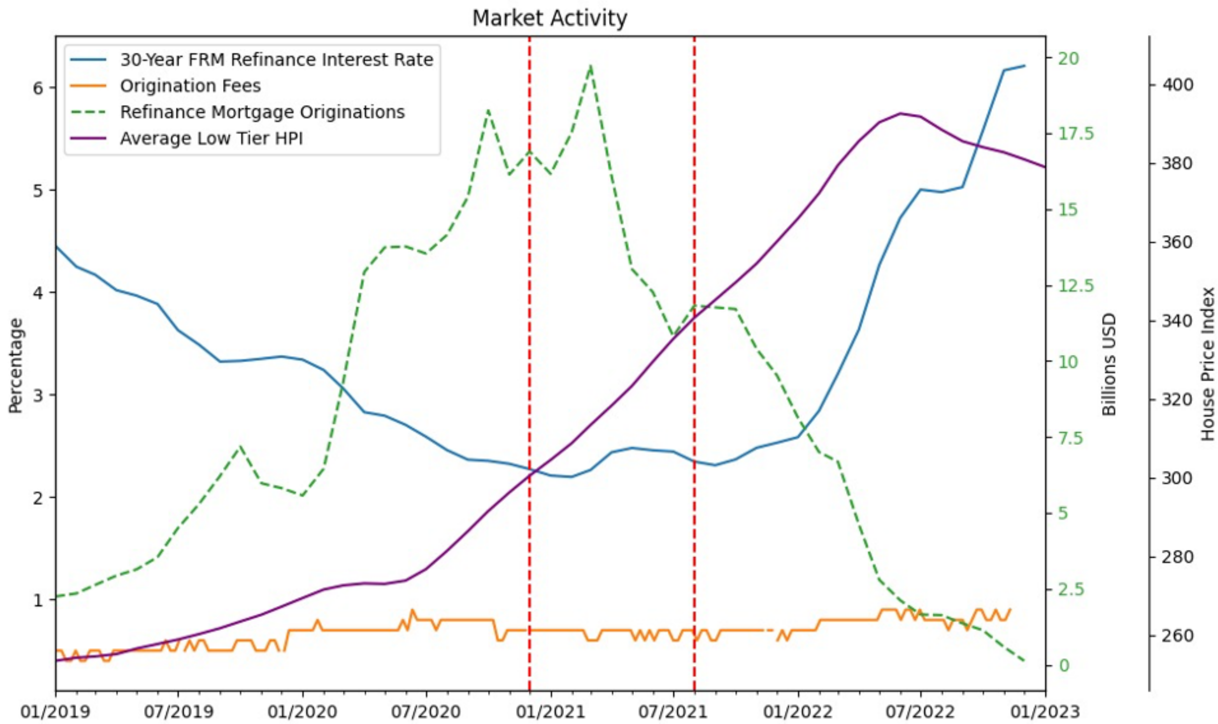
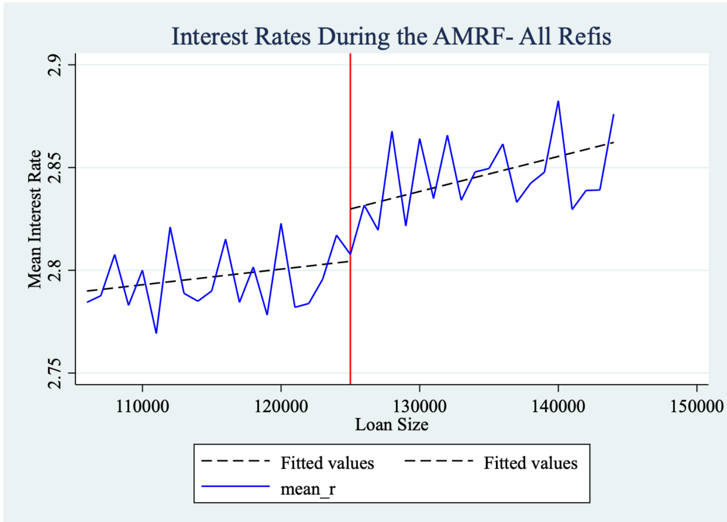
# 12 List of Figures

Figure 2: Relevant Variables

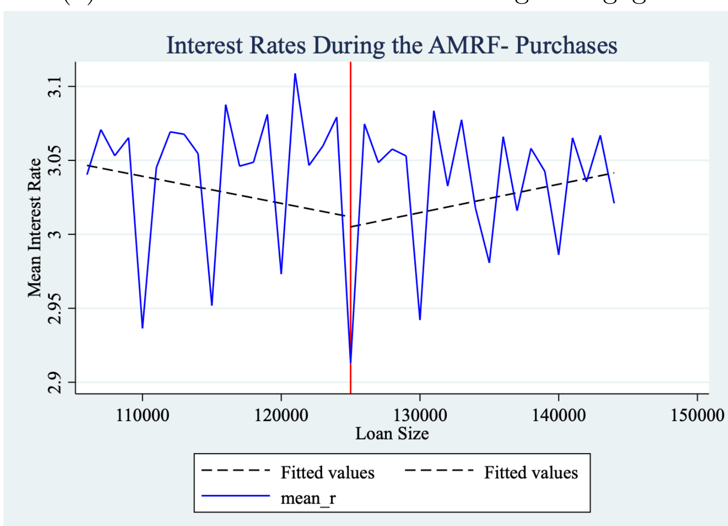



Notes: Figure 2 presents an overview of the most important moving variables during and around the period being analyzed in this study. The timespan on this graph covers the period from January 2019 until January 2023. Interest rates and Origination fees are reported as a percentage and as a percentage of the full values of the loan specifically (left vertical axis). Refinancing originations are reported in Billions of USD (First right vertical axis) while HPI as a value ranging from 100-400 (second right vertical axis). Interest rates pertain to all 30-year FRM. The two vertical dotted red lines represent the start and finish of the AMRF.

Figure 3: The Interest Rate Discontinuity during the AMRF (Notches)



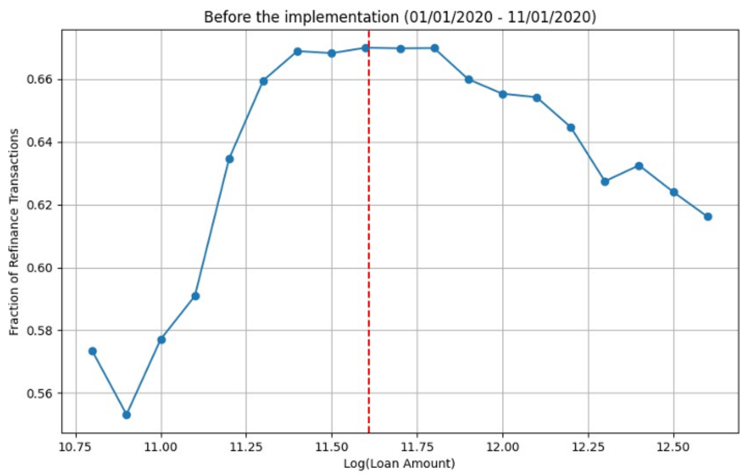

(a) Interest Rates for all Refinancing Mortgages



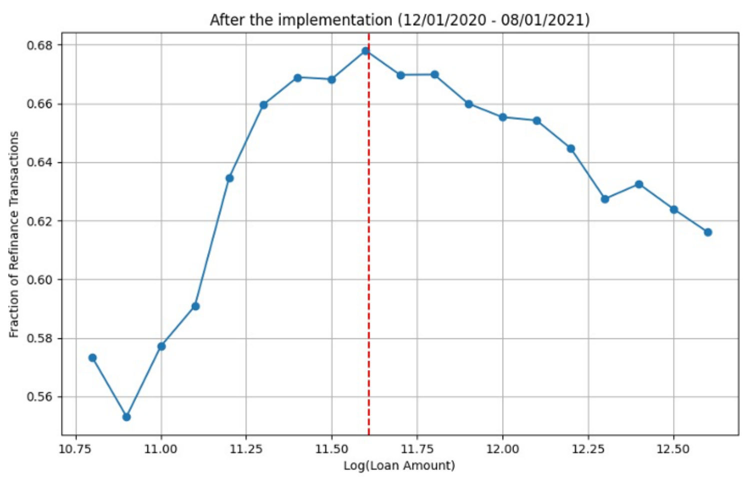

(b) Interest Rates for all new purchasing mortgages

Figure 3: Figure 3 shows the discontinuity at the \$125000 threshold for all refinance mortgages (plot a) and all purchase mortgages (plot b) purchased by Fannie Mae while the AMRF was in place (from December 2020 to August 2021)

Figure 4: Bunching Evidence (Pre vs Post-AMRF)



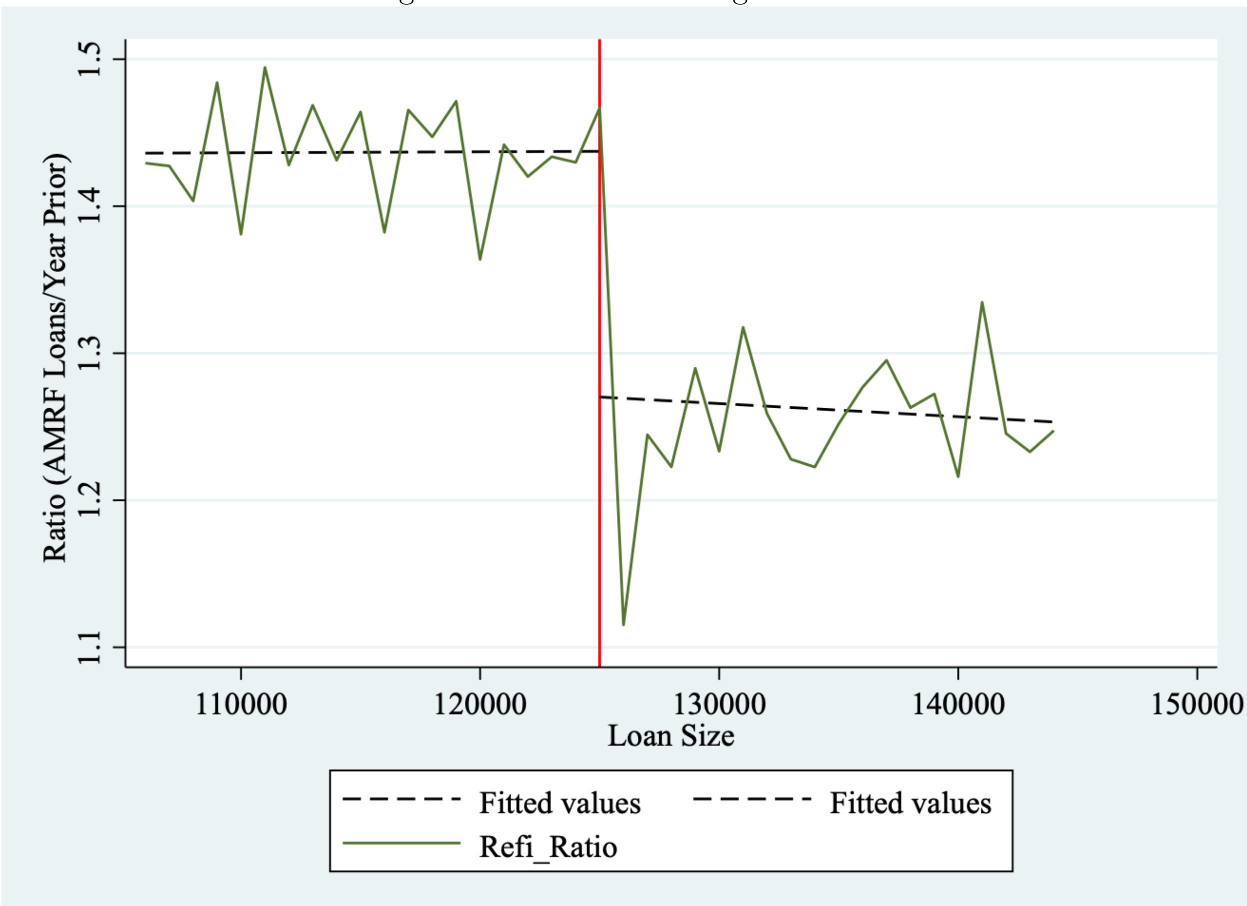

(a) Loan amount distribution (Pre-AMRF)




(b) Loan amount distribution (Post-AMRF)

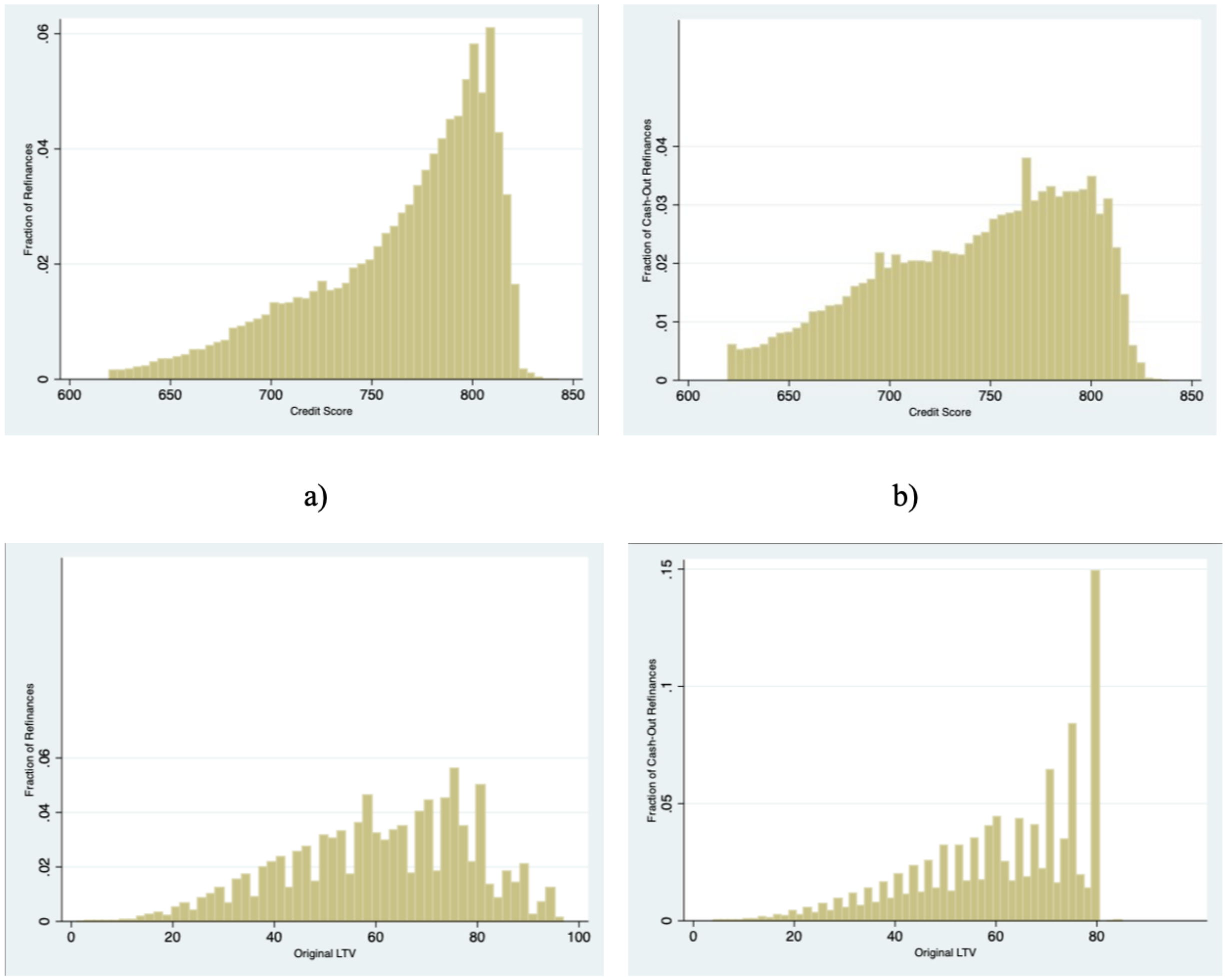
Figure 4: Figure 4 shows the fraction of all Refinance (both Standard and Cash-Out) loans in the sample that fall into any given $1,000 bin of the log of Original Unpaid Principal Balance -UPB (Loan Amount) relative to the AMRF threshold in effect at the date of origination. The red vertical line is drawn at the ln(125,000) or 11.73.

Figure 5: Further Bunching Evidence




Notes: Figure 5 shows the ratio of the distribution of loan sizes for all refinancing mortgages during the period that the AMRF was effective, divided by the distribution of loan sizes for all refinancing mortgages exactly a year prior to the implementation of the AMRF.

Figure 6: LTC and FICO Scores

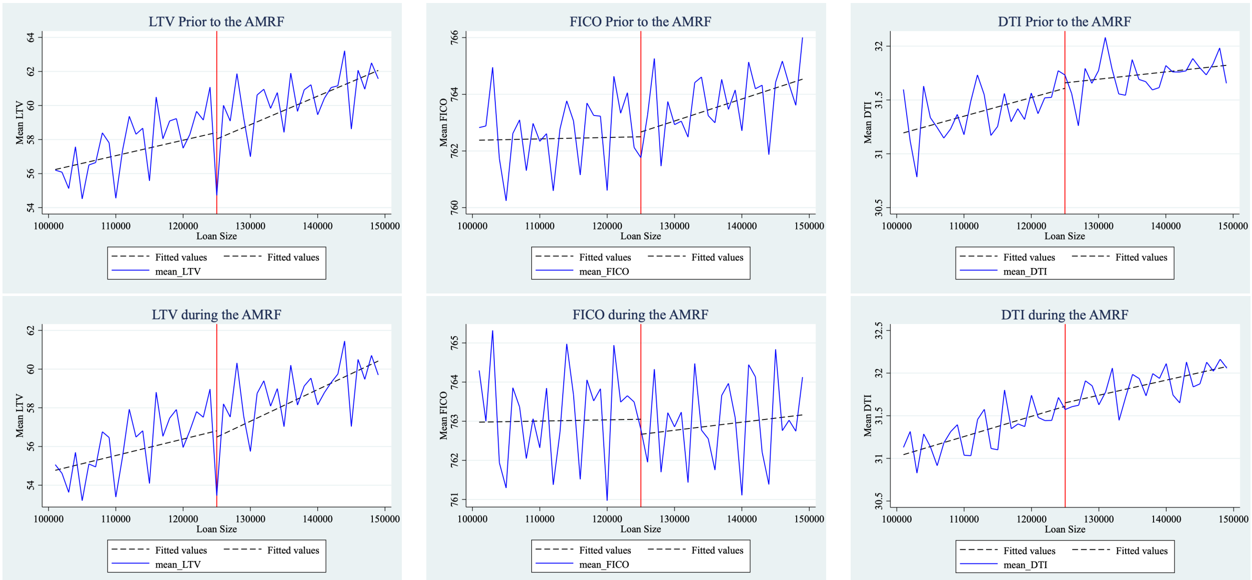



a) b)

c) d)

Notes: Distribution of the LTV and credit scores for Fannie Mae 30-year, fixed-rate, single-family refinancing mortgages originated from January 2019 to August 2021 with a UPB between \$100,000 and \$150,000. Panels a) and c) represent standard refinances, while panels b) and d) represent Cash-Out Refinances.

Figure 7: Smoothness of Borrower Characteristics Around the $125,000 Threshold



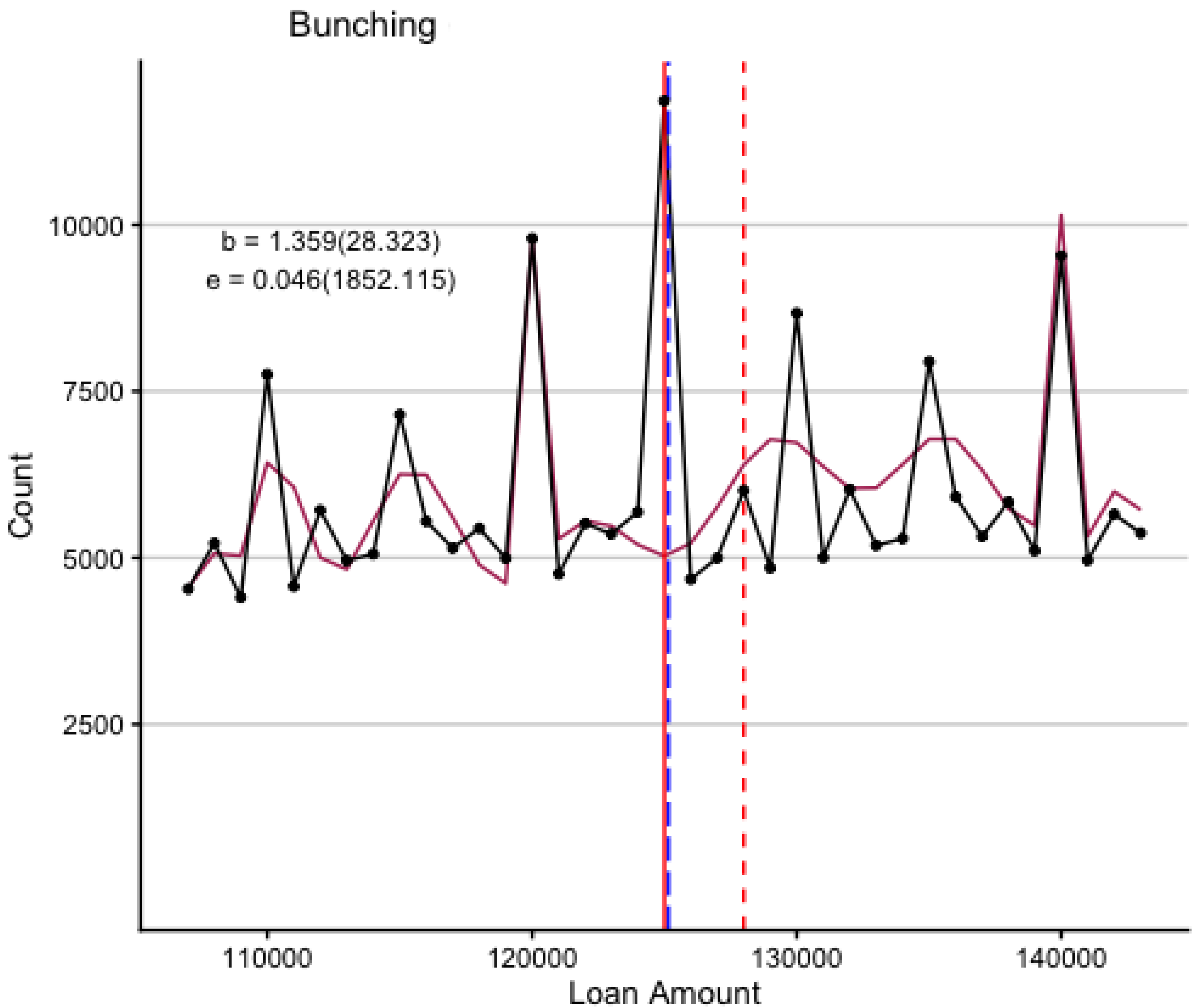

(a) Loan-to-Value Ratio

(b) FICO Credit Score

(c) Debt-to-Income Ratio

Notes: This figure examines the smoothness of borrower characteristics around the $125,000 AMRF threshold. The top panels show the pre-AMRF period and the bottom panels show the post-AMRF period. Each panel plots the mean value of the characteristic within loan size bins, with the vertical line indicating the $125,000 threshold. Smooth progression of characteristics across the threshold supports the validity of the bunching identification strategy.

Figure 8: Basic Bunching Specification




Notes: Figure 8 shows the bunching output for the basic specification. It does not account for round number bunching. Thus, the bunching weight is significantly over-estimated. The black line shows the distribution of refinancing loans from \$100,000-\$150,000, which represents the window of interest. The binwidth is set to \$1000. The red line gives the counterfactual, accounting for larger weights around loan sizes of \$120,000 and \$140,000. The vertical dotted red line represents the upper bunching region, calculated internally. The blue vertical line represents the upper bound of the dominated region.

Figure 9: Bunching with Round Numbers

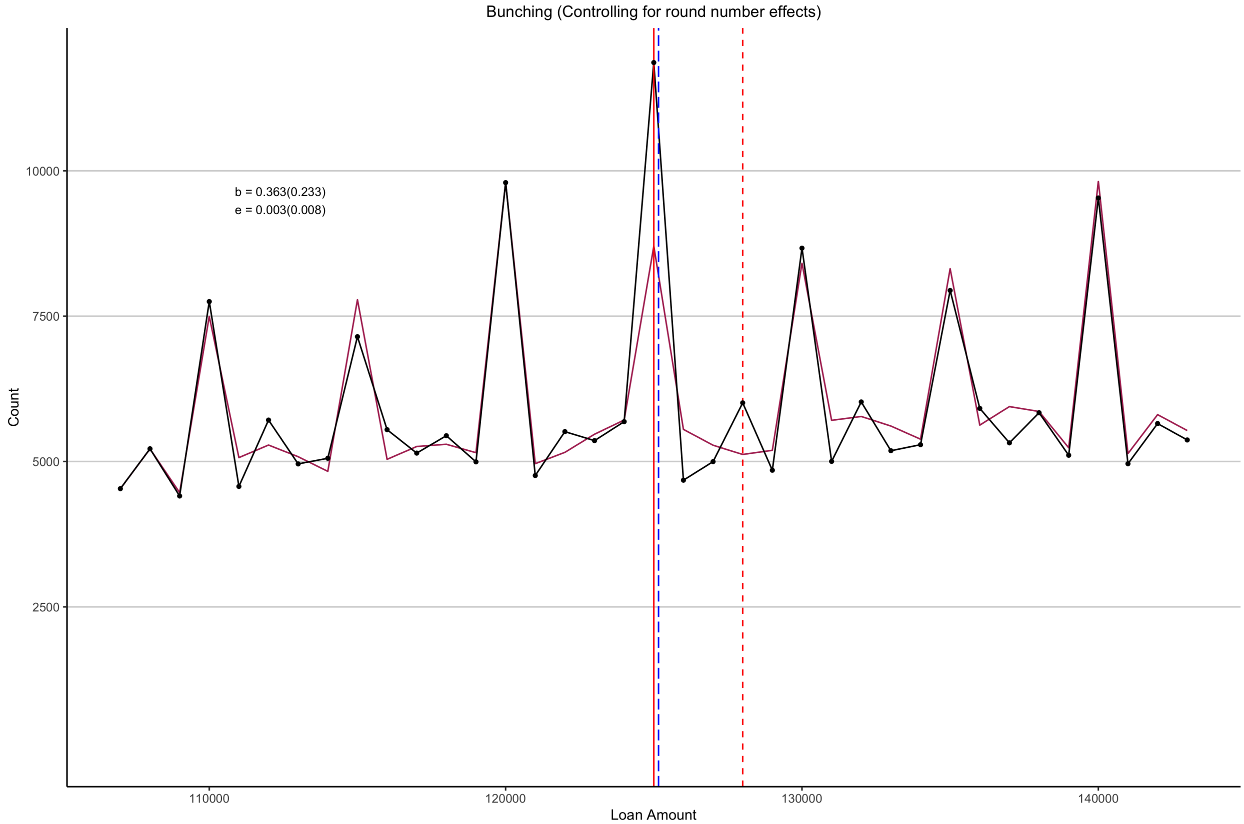



Figure 9 shows the bunching output for the specification where I am accounting for round number bunching. In this specification, the bunching weight drops significantly as the bunching happening due to the round number loan sizes is eliminated. The black line shows the distribution of refinancing loans from \$100,000-\$150,000, which represents the window of interest. The binwidth is set to \$1000. The red line gives the counterfactual, accounting for both round numbers and larger weights around loan sizes of \$120,000 and \$140,000.

Figure 10: Bunching for Regular Refinances

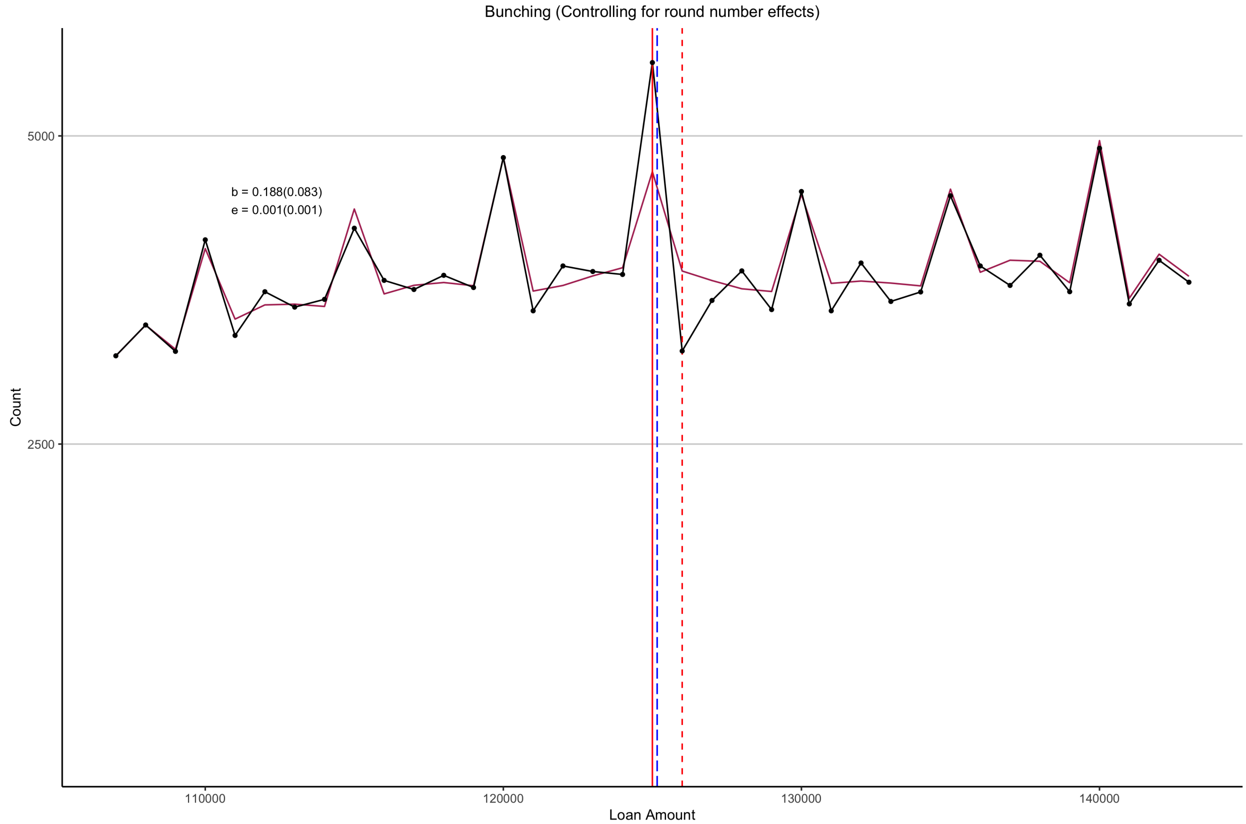



Figure 10 shows the bunching output for the specification looking only at regular refinances. The black line shows the distribution of refinancing loans from \$100,000-\$150,000, which represents the window of interest. The binwidth is set to \$1,000. The red line gives the counterfactual, accounting for both round numbers and larger weights around loan sizes of \$120,000 and \$140,000.

Figure 11: Bunching for Cash-Out Refinances

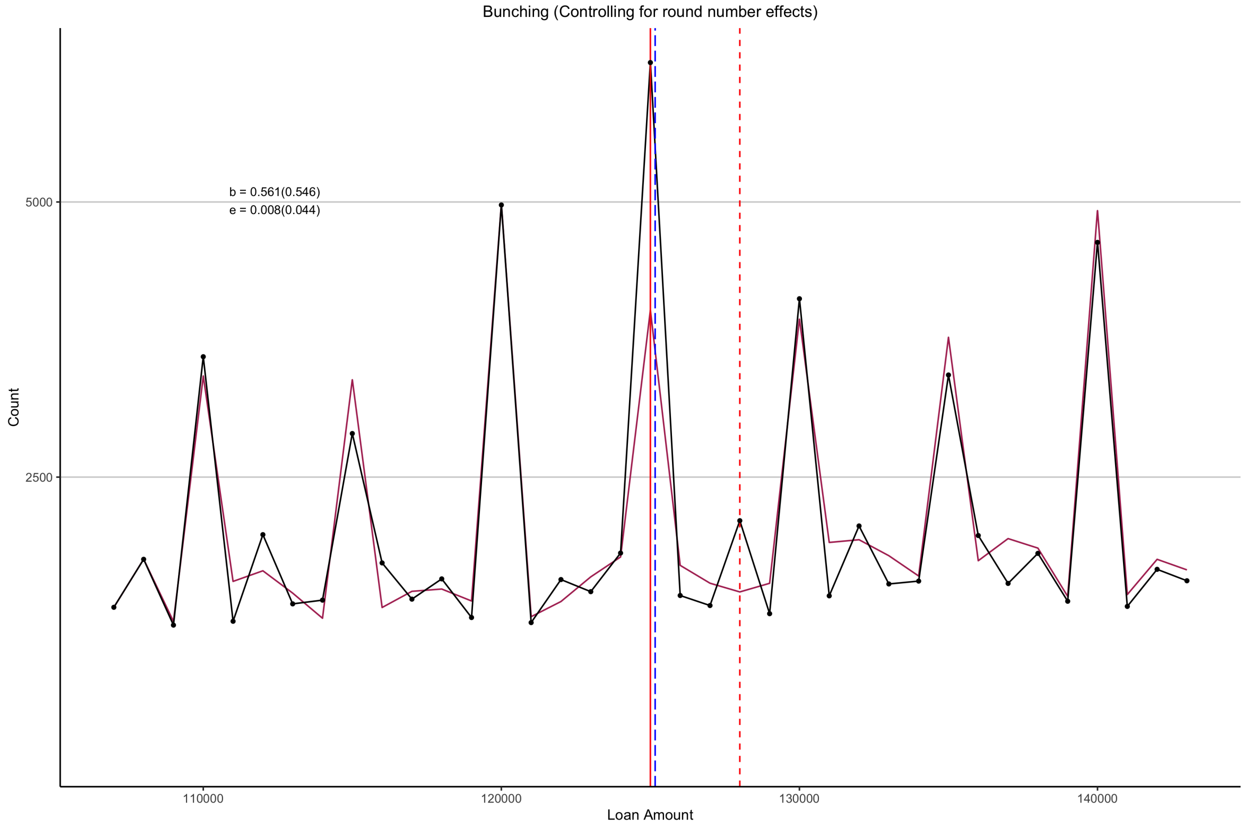



Figure 11 shows the bunching output for the specification looking only at cash-out refinances. The black line shows the distribution of refinancing loans from \$100,000-\$150,000, which represents the window of interest. The binwidth is set to \$1,000. The red line gives the counterfactual, accounting for both round numbers and larger weights around loan sizes of \$120,000 and \$140,000.

Figure 12: Bunching for 15-Year Refinances

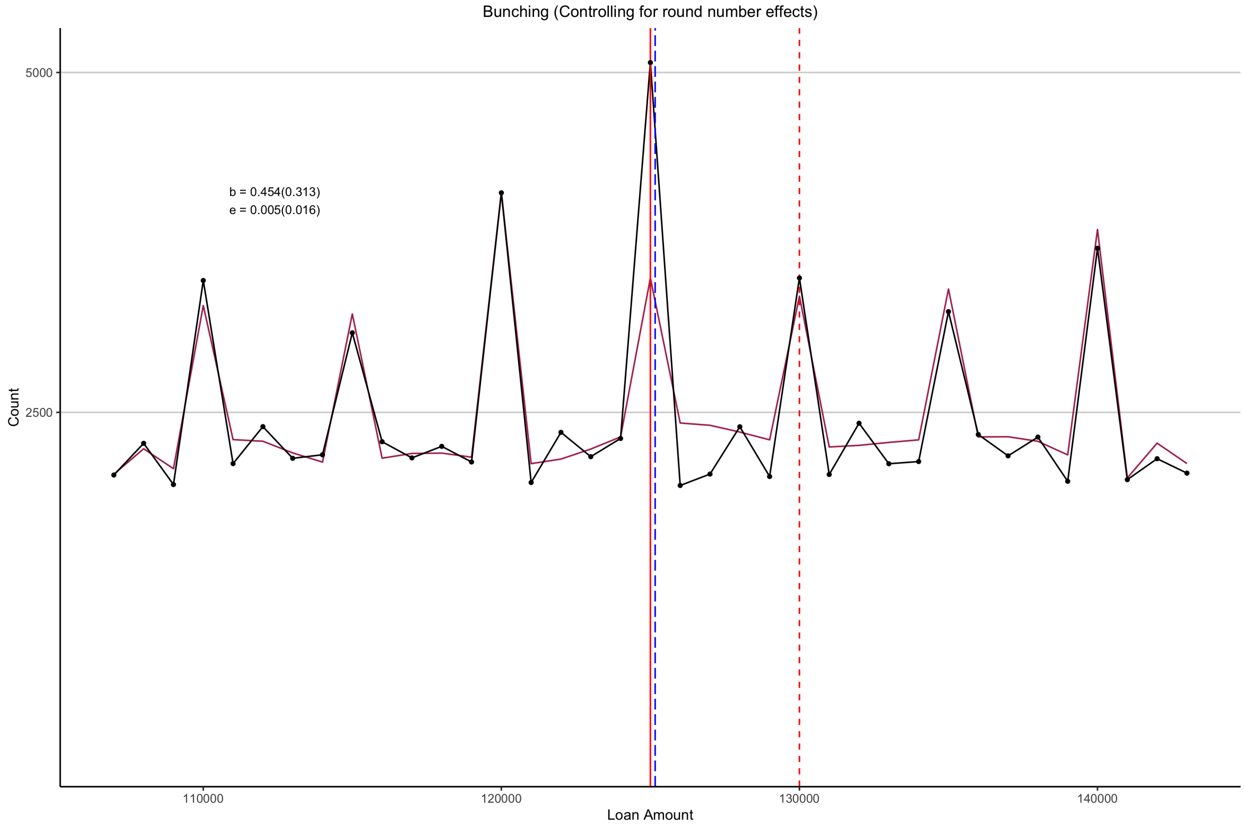



Figure 12 shows the bunching output for the specification looking only at 15-Year refinances. The black line shows the distribution of refinancing loans from \$100,000-\$150,000, which represents the window of interest. The binwidth is set to \$1,000. The red line gives the counterfactual, accounting for both round numbers and larger weights around loan sizes of \$120,000 and \$140,000.

Figure 13: Bunching for 30-Year Refinances

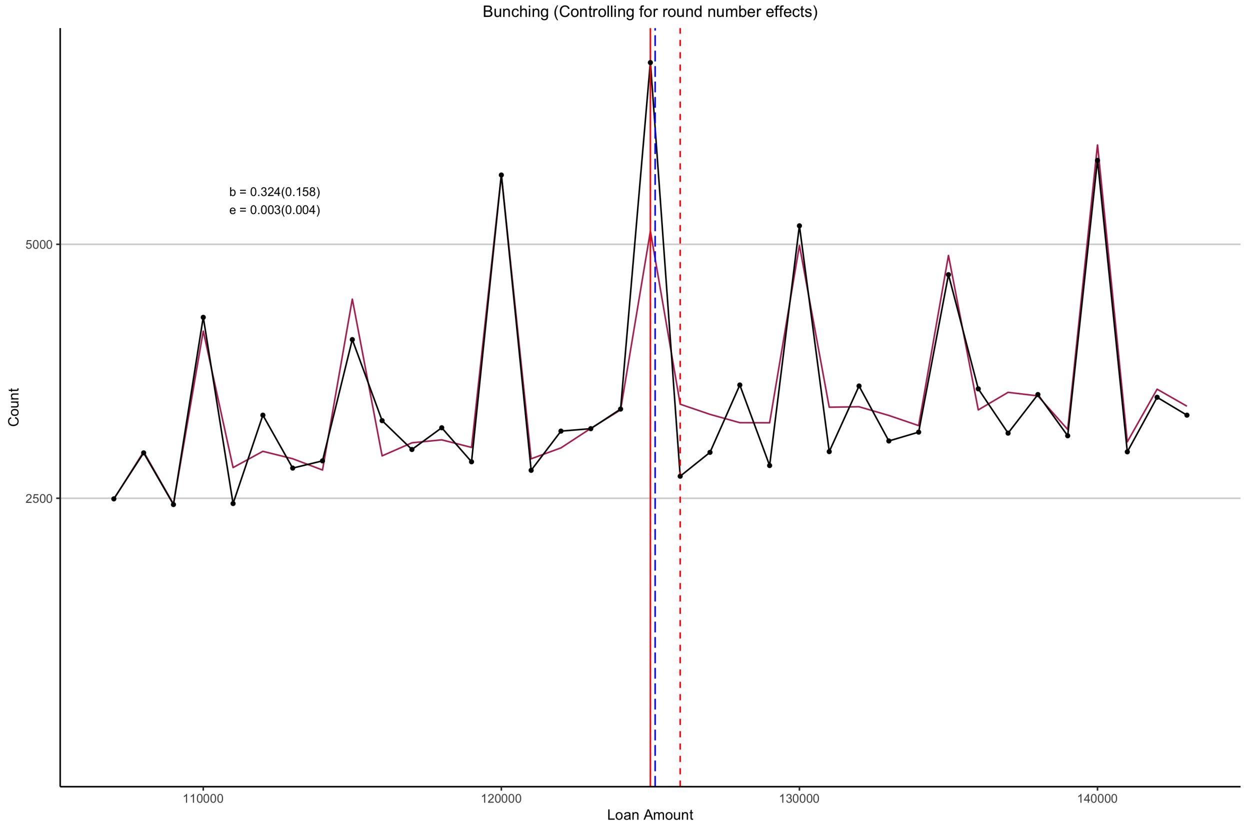
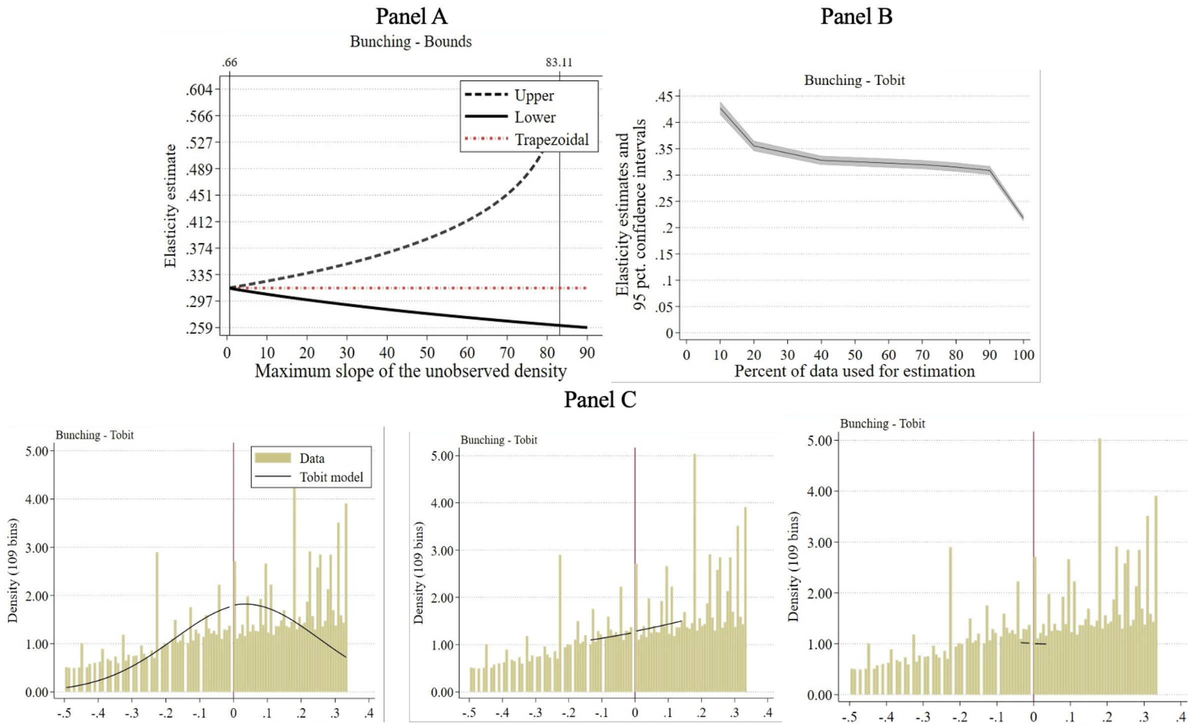


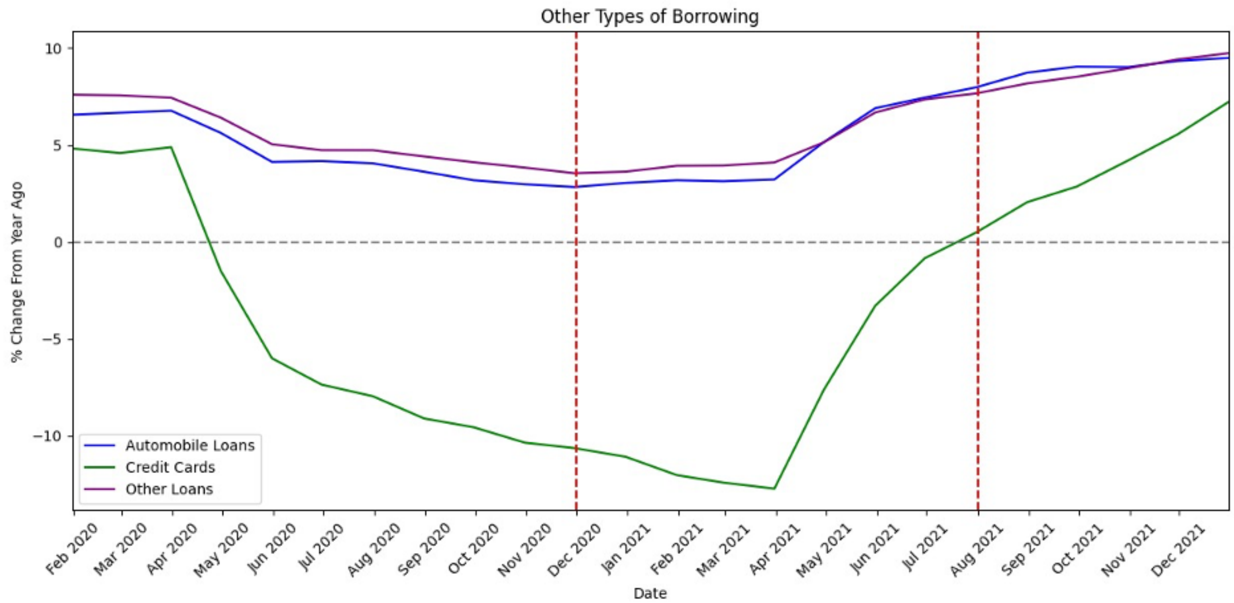

Figure 13 shows the bunching output for the specification looking only at 30-Year refinances. The black line shows the distribution of refinancing loans from \$100,000-\$150,000, which represents the window of interest. The binwidth is set to \$1,000. The red line gives the counterfactual, accounting for both round numbers and larger weights around loan sizes of \$120,000 and \$140,000.

Figure 14



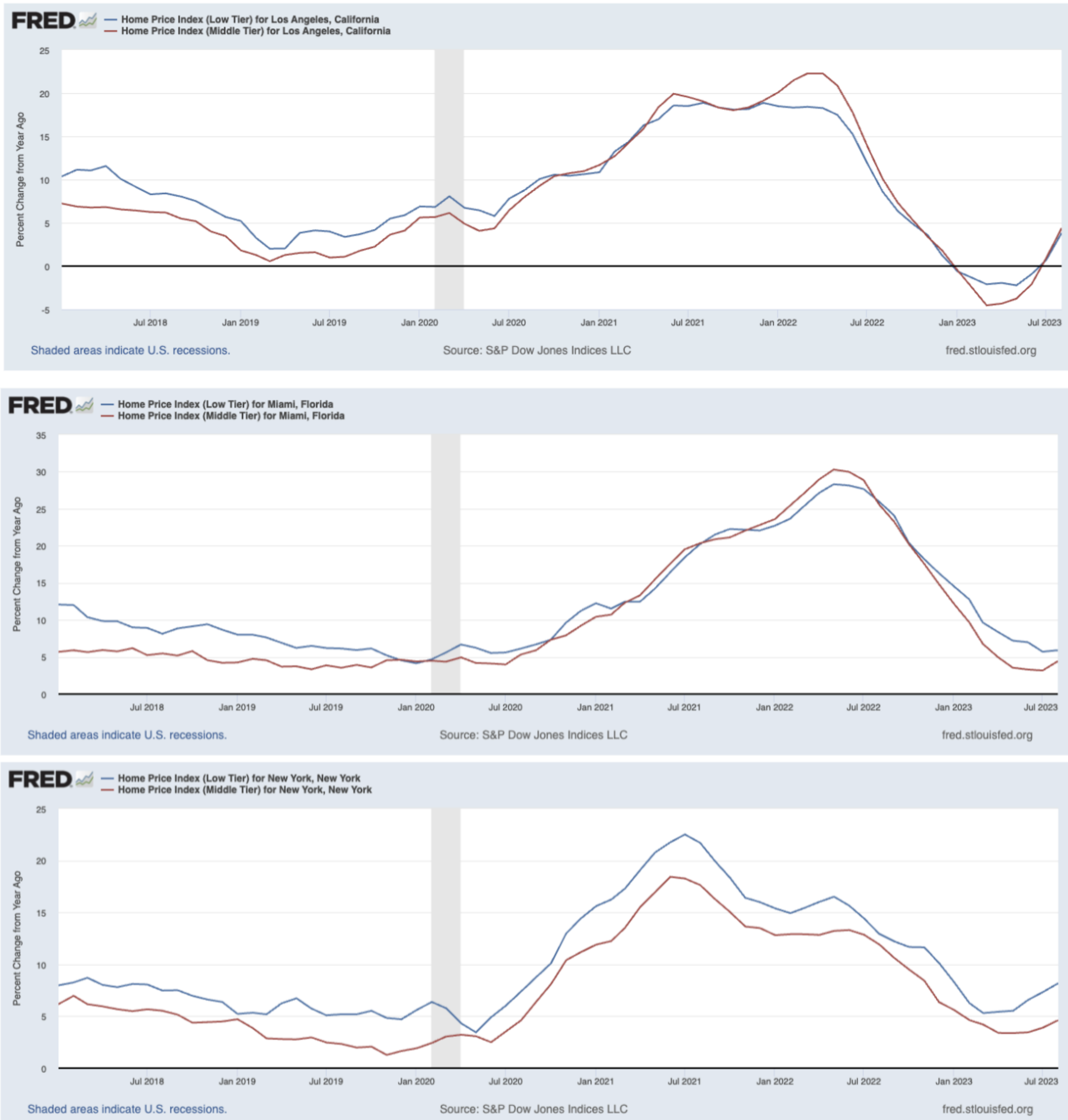

Notes: Panel A graphs the non-parametric bounds for different maximum slope magnitudes of the unobserved heterogeneity PDF using the bunchbounds command. Panel B gives the elasticity estimates along with the 95% confidence intervals according to the percent of data that was used for the estimation. Panel C gives the results generated by bunchtobit, which produces a best-fit graph for each subsample and a graph of the elasticity estimate for all subsamples. The first graph uses 100% of the data, the second 40% and the third 10%. The graphs from Panel C are the ones used to derive the estimates represented in Panel B.

Figure 15: The Additional Borrowing Channel




Notes: Figure 15 represents the percentage change from a year ago for three types of borrowing happening around the time that the AMRF was in place, Automobile loans, Credit Card loans, and the "Other Loans" category. The time period spans from February 2020 until December 2021. The two vertical red lines represent the implementation and termination of the AMRF. The data source is from the FRED website.

Figure 16

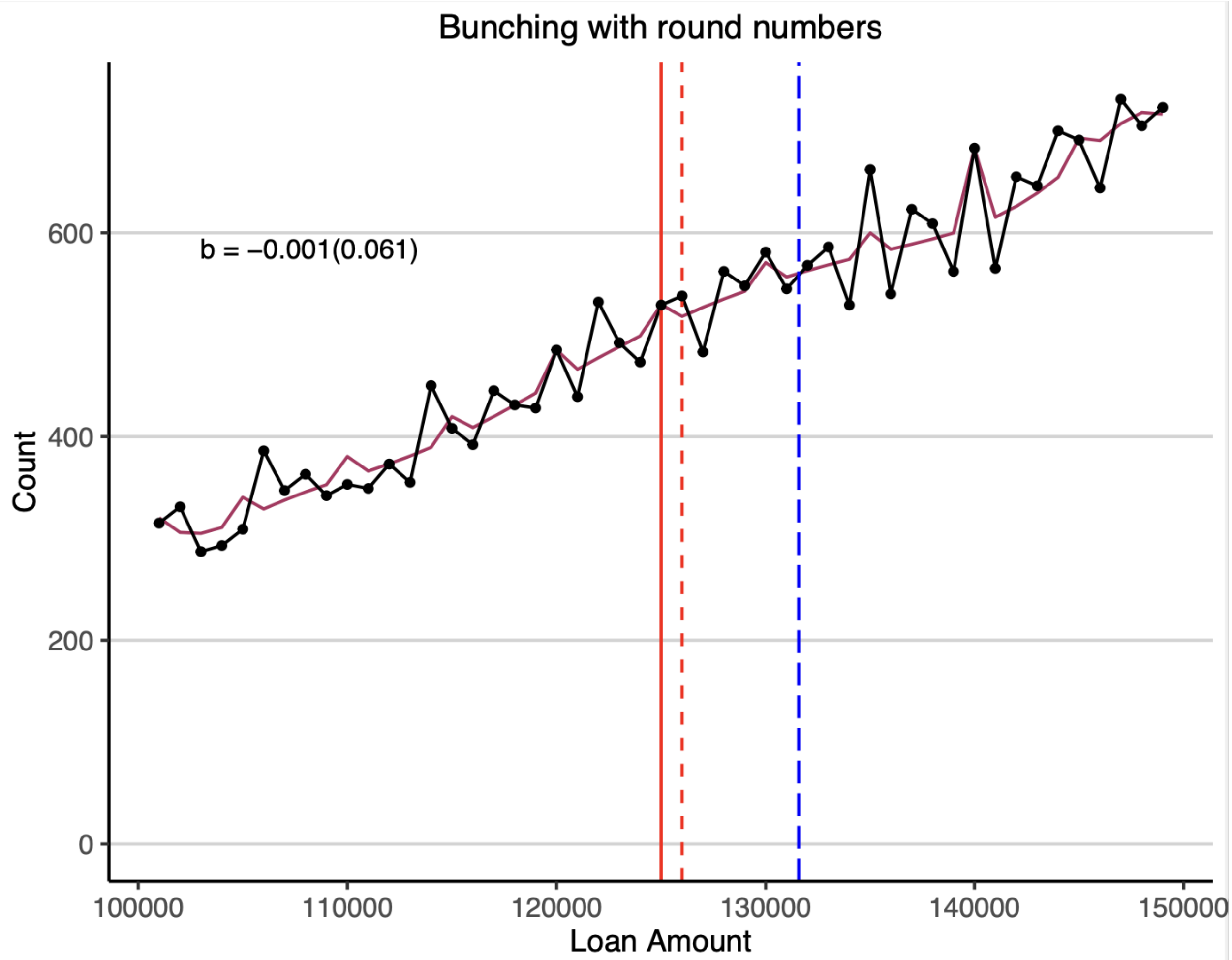



Notes: Figure 16 shows the percent change from a year ago for 2 different Tiers of Home-Price indices covering three of the biggest metropolitan areas in the USA. The graphs show the Low and Middle of the Samp;P CoreLogic Case-Shiller U.S National Home price index for Los Angeles, Miami, and New York. The reporting period goes from January 2018 to July 2023. The indices are all seasonally adjusted and the graph is imported from the FRED website.

Figure 17: Percent of loans refinanced in terms of the remaining balance on the mortgage

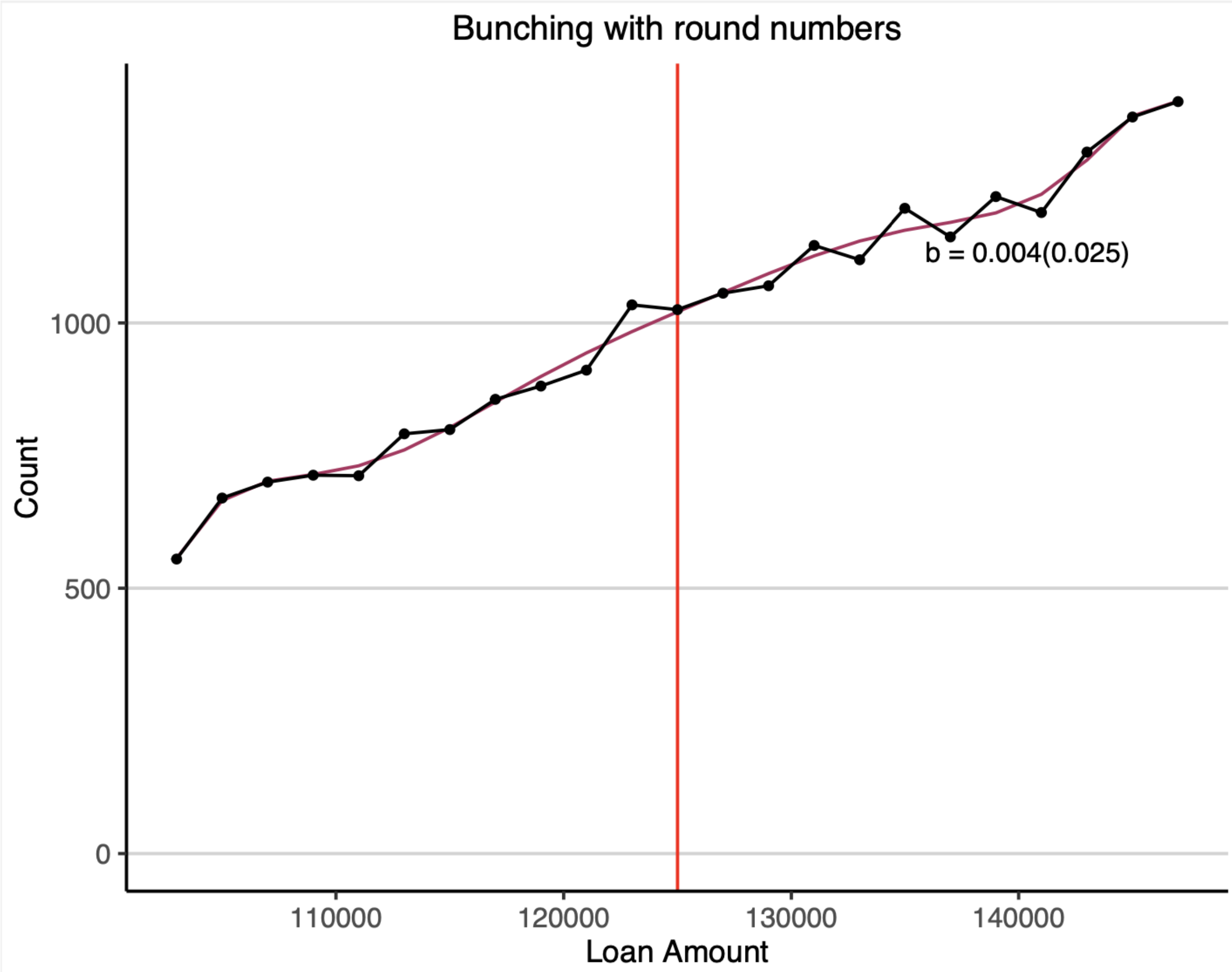

Notes: The horizontal axis shows the remaining balance in March 2020, in thousands. The time frame is between the Q2 of 2020 and Q4 of 2021.
Source: New York Fed Consumer Credit Panel / Equifax.

Figure 18A: Placebo Tests (FHA & VA Refinances)




Notes: Figure 18 shows the bunching output for the specification where I am accounting for round number bunching, for the FHA & VA dataset. In this specification, any bunching happening due to round numbers is eliminated. The black line shows the distribution of refinancing loans from \$100,000-\$150,000, which represents the window of interest. The binwidth is set to \$1,000 for Figure 13A and \$2,000 for Figure 13B. The red line shows the counterfactual. The vertical dotted red line represents the upper bunching region, calculated internally. The blue vertical line represents the upper bound of the dominated region.

Figure 18B: Placebo Tests (FHA & VA Refinances)




Notes: Figure 18 shows the bunching output for the specification where I am accounting for round number bunching, for the FHA & VA dataset. In this specification, any bunching happening due to round numbers is eliminated. The black line shows the distribution of refinancing loans from $100,000-$150,000, which represents the window of interest. The binwidth is set to $1,000 for Figure 13A and $2,000 for Figure 13B. The red line shows the counterfactual. The vertical dotted red line represents the upper bunching region, calculated internally. The blue vertical line represents the upper bound of the dominated region.

# 13 List of Tables

Table 1: Example of the Impact of the AMRF after Implementation

| | **Borrower A** | **Borrower B** |
|---|---|---|
| Loan Size ($000s) | 124 | 126 |
| Interest Rate (%) | 2.65 | 2.775 |
| Monthly Payment ($) | 500 | 516 |
| Total of 360 Payments | 179,883.04 | 185,779.41 |
| Total Interest | 55,883.04 | 59,779.41 |

Notes: This table presents the impact of the Adverse Market Refinance Fee (AMRF) for GSE-conforming 30-year refinance loan. Interest rates are shown as percentages, loan sizes in thousands of dollars, and monthly payments in dollars. Sample includes loans originated between December 2020 and August 2021. Borrower B decides to roll the $630 cost of the AMRF into the interest rate.

Table 2: Summary Statistics

| | Full Sample (2020-2022) | | AMRF Effective | |
|---|---|---|---|---|
| | All Loans | Refinances | All Loans | Refinances |
| | (1) Mean/sd | (2) Mean/sd | (3) Mean/sd | (4) Mean/sd |
| Original Interest Rate | 3.287 (0.836) | 3.125 (0.679) | 2.914 (0.423) | 2.863 (0.416) |
| Original UPB | 190137.4 (62205) | 188484.9 (61893.51) | 188124.4 (62191.14) | 186292.7 (61936.96) |
| Original Term | 308.135 (80.14) | 289.48 (86.103) | 302.483 (83.025) | 286.466 (87.399) |
| Original LTV | 67.705 (19.211) | 61.141 (16.922) | 65.920 (19.198) | 60.123 (16.915) |
| Number of Borrowers | 1.43 (0.508) | 1.448 (0.504) | 1.434 (0.507) | 1.450 (0.504) |
| DTI | 33.34 (9.929) | 32.562 (9.986) | 32.813 (10.003) | 32.203 (10.062) |
| Credit at Origination | 758.779 (44.914) | 760.524 (45.451) | 761.146 (44.415) | 763.297 (44.459) |
| Number of Units | 1.016 (0.166) | 1.015 (0.158) | 1.016 (0.162) | 1.015 (0.156) |
| Mortgage Insurance (%) | 25.156 (7.228) | 19.449 (8.124) | 24.879 (7.369) | 18.850 (7.975) |

Notes: Table 2 presents summary statistics for the main variables in the Fannie Mae dataset. The data is initially split into two categories: "Full Sample" which includes the data from January 2020 until December 2022 and "AMRF Effective" which only includes the period when AMRF was effective. Each category is further split into: "All Loans" which includes both purchases and refinances and "Refinances" which only includes refinancing mortgages. All data cover loans with a size ranging from $50,000 to $150,000.

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Table 3: Balance Table

| | Control Mean/(SE) | Treatment Mean/(SE) | Pairwise t-test Mean Difference |
|---|---|---|---|
| Original Interest Rate | 3.044 (0.005) | 3.035 (0.004) | 0.009*** |
| Original UPB | 120,000 (11.369) | 129,000 (12.289) | -9,375.945*** |
| Original Term | 267.298 (0.786) | 269.302 (0.728) | -2.004*** |
| Original LTV | 60.013 (0.424) | 60.534 (0.430) | -0.521*** |
| DTI | 30.979 (0.079) | 31.117 (0.079) | -0.138** |
| Credit at Origination | 767.587 (0.417) | 768.539 (0.374) | -0.951*** |
| N/Clusters | 1,154,471 (877) | 1,461,901 (876) | 2,616,372 (884) |

Notes: Table 3 shows the Balance table containing some of the key loan and borrower variables in my dataset. The table is constructed using only data from January 2019 up until the implementation of the AMRF (December $1^{st}$, 2020). Data is separated based on AMRF treatment and TREATMENT=0 means that loans in that group have a UPB less than $125,000 while TREATMENT=1 means that loans in that group have a UPB greater than 125,000. All loans used to generate this table are limited to having a UPB between $115,000 to $135,000. Errors are clustered at *Zip_Short*, a variable indicating a 3-digit ZIP CODE generated by Fannie Mae.

Table 4: Bunching Estimates-Fannie Mae Loans

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Number of Bunchers (sd) | 6,834 (1,953) | 3,159 (1,156) | 886 (323) | 2,252 (790) | 1,585 (554) | 1,661 (570) |
| Bunching Weight (sd) | 1.359 (28.323) | 0.363 (0.233) | 0.188 (0.083) | 0.561 (0.546) | 0.454 (0.313) | 0.324 (0.158) |
| Elasticity (sd) | 0.046 (1852.115) | 0.003 (0.008) | 0.001 (0.001) | 0.008 (0.044) | 0.005 (0.016) | 0.003 (0.004) |
| $Z^d$ | 125,160 | 125,160 | 125,160 | 125,160 | 125,160 | 125,160 |
| Marginal Buncher (sd) | 138,179 (28,323) | 127,307 (233) | 126,132 (83) | 128,475 (546) | 127,394 (313) | 126,565 (158) |
| Alpha (sd) | 0.897 (17.455) | 0.843 (0.291) | 0.834 (0.064) | 0.839 (3.637) | 0.810 (0.566) | 0.793 (0.133) |

Notes: Table 5 gives the main parameters estimated by the bunching methodology. Rows 1-6 are specifically results for the following subsamples during the period the AMRF was in effect: 1-All Refinances without accounting for round numbers ; 2-All Refinances accounting for round numbers ; 3-Only Regular Refinances accounting for round numbers ; 4-Only Cash-Out Refinances accounting for round numbers ; 5-Only 15-year Refinances accounting for round numbers ; 6-Only 30-year Refinances accounting for round numbers. Bunching Weight is the additional concentration of borrowers at or near the 125,000 threshold attributable to the AMRF. Elasticity entries report estimated interest rate elasticities of mortgage refinancing demand with standard deviations in parentheses. $Z^d$ is the upper bound of the dominated region. Marginal Buncher is the loan size of the last borrower willing to adjust the loan amount. Alpha is the estimated relocation fraction: the share ($\alpha$) of the "missing mass" that reappears as excess mass (bunchers). Standard deviations are shown in parentheses next to each estimate.

# 14 Appendix

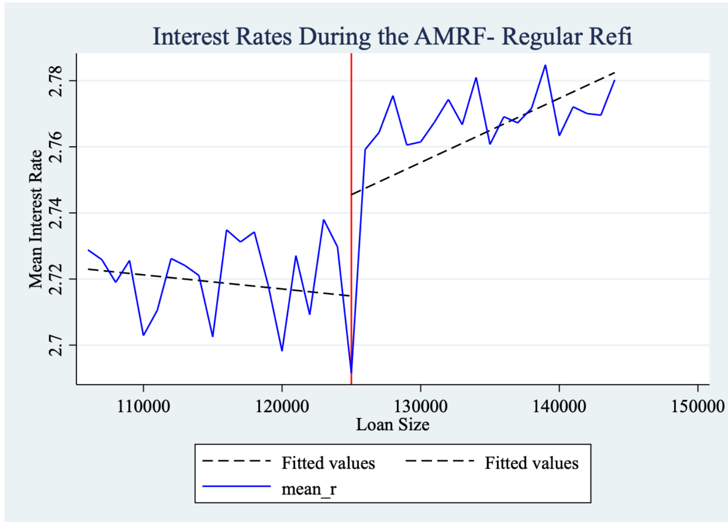
In Figure 1.A, I analyze bunching happening on another level. While households can avoid the AMRF by modifying their loan size, they can also do that by moving around their origination date. Theory suggests that only the most financially responsible would make use of this channel, and even then, there could be numerous reasons why this could prove difficult to pull off. What we do know, however, is that the AMRF received some, but not a lot of, media attention even months before the actual implementation, also due to its postponement from August 2020 to December 2020. This could also be the reason why there is a significant bunching weight of around 0.435 in October 2020. At the same time, the number of bunchers in this case is much less than that in the Loan size channel. It seems that the findings in this case align with the theory once again. We expect there to be a number of households, who bunch during the months prior to the implementation of the AMRF. This seems to be especially pronounced during October 2020, represented as 10 in the graph. Further analysis of this topic will be covered in the second paper of this project.

Table 1.A: The effect of nominal Interest Rates

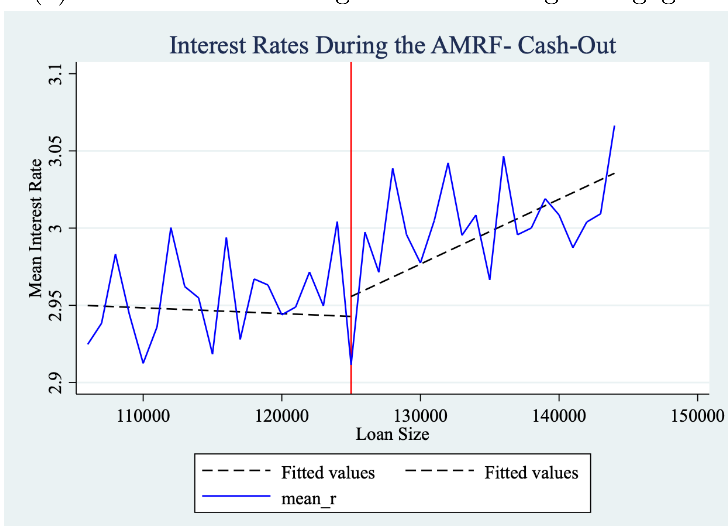
| Investigator | Dependent Variable | Loan Parameter | Elasticity |
|---|---|---|---|
| MPS 1956:3-1972:2 | Value of single family starts | Mortgage Rate | -.5 (Long Run) -1.00 (Short Run) |
| Brady 1960:3-1970:2 | Conventionally financed single family starts | Mortgage Rate | -2.78 |
| Brady 1960:3-1970:2 | All Starts | Mortgage Rate | -2.02 |
| Huang 1953:2-1965:4 | Starts FHA (demand) | Mortgage Rate | -2.36 |
| Rosen 1962:4-1972:4 | Single family starts (demand) | Mortgage Rate | -1.33 |
| Kearl-Rosen 1962:4-1972:4 | All starts (demand) | Mortgage Rate | -1.52 |
| Maisel 1952-1965 | Starts | Mortgage Rate | -.56 |
| Swan 1958:1-1965:4 | Starts (demand) | Mortgage Rate | -1.92 |
| Follain & Dunsky 1997 | Mortgage demand | Mortgage Rate | -1.5 to -3.5 |
| DeFusco & Paciorek 2017 | Refinancing demand | Interest Rate | -2 to -3 |
| Bhutta & Ringo 2017 | Refinancing demand | Interest Rate | Highly elastic |
| Campbell 2013 | Mortgage demand | Interest Rate | Moderately elastic |
| Lo 2017 | Mortgage demand | Interest Rate | 50% increase in demand per 25 basis point cut |

Notes: Table 1.A table shows elasticity values of similar relevant studies looking at the effect of nominal Interest Rates on different dependent variables.

Figure 1A: The Interest Rate Discontinuity during the AMRF (Notches)



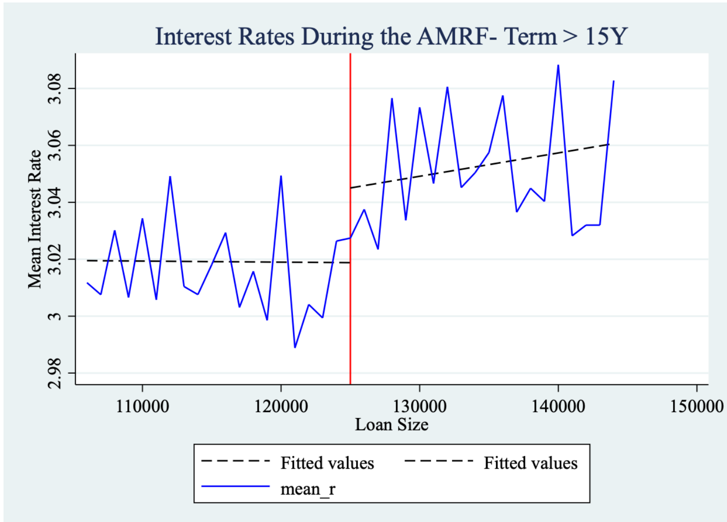

(a) Interest Rates for regular Refinancing Mortgages



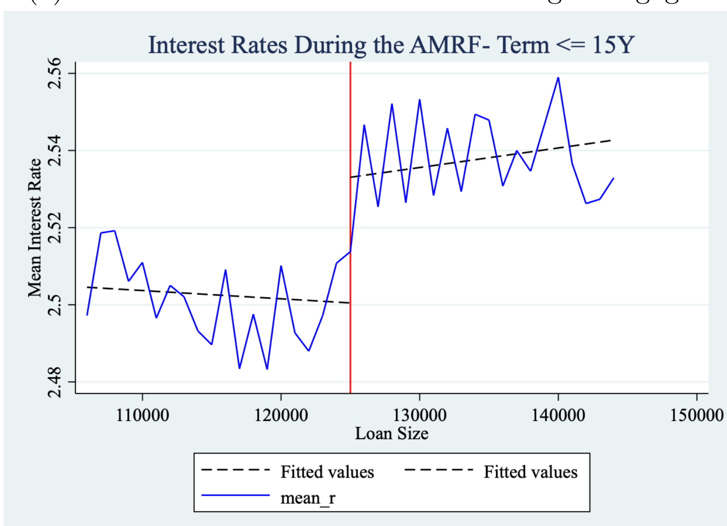

(b) Interest Rates for Cash-Out refinancing mortgages

Figure 21: Figure 1A shows the discontinuity at the \$125000 threshold for regular refinance mortgages (plot a) and cash-out refinance mortgages (plot b) purchased by Fannie Mae while the AMRF was in place (from December 2020 to August 2021)

Figure 2A: The Interest Rate Discontinuity during the AMRF (Notches)



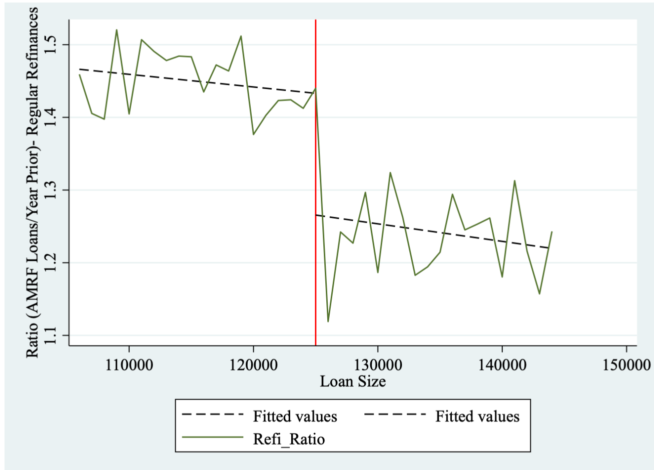

(a) Interest Rates for 30-Year Refinancing Mortgages



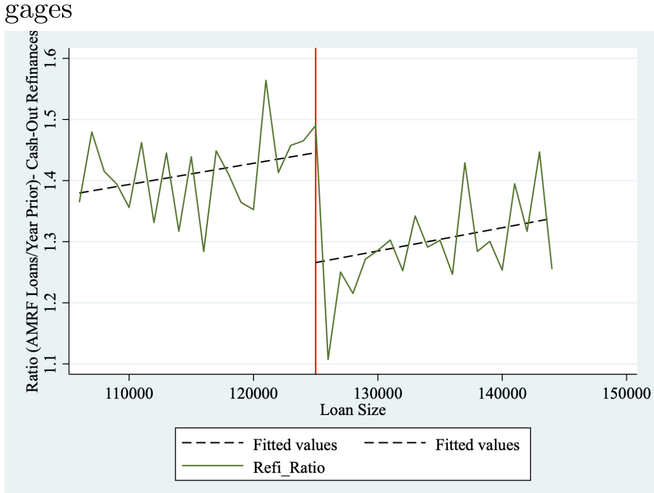

(b) Interest Rates for 15-Year Refinancing mortgages

Figure 22: Figure 2A shows the discontinuity at the $125000 threshold for 30-Year refinance mortgages (plot a) and 15-Year refinance mortgages (plot b) purchased by Fannie Mae while the AMRF was in place (from December 2020 to August 2021)

Figure 3A: Further Bunching Evidence (Continued)



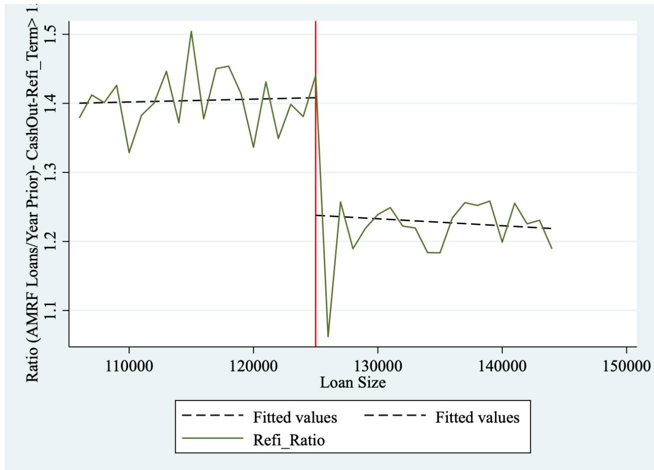

(a) Ratio of loan sizes for regular refinancing mortgages



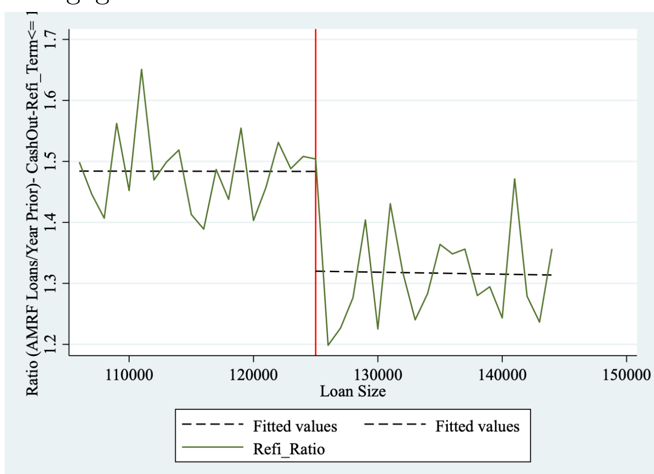

(b) Ratio of loan sizes for cash-out refinancing mortgages

Figure 23: Figure 3A shows the ratio of the distribution of loan sizes for refinancing mortgages during the period that the AMRF was effective, divided by the distribution of loan sizes for all refinancing mortgages exactly a year prior to the implementation of the AMRF. Plot a includes only regular refinancing mortgages while plot b includes only cash-out refinancing mortgages

Figure 4A: Further Bunching Evidence (Continued)



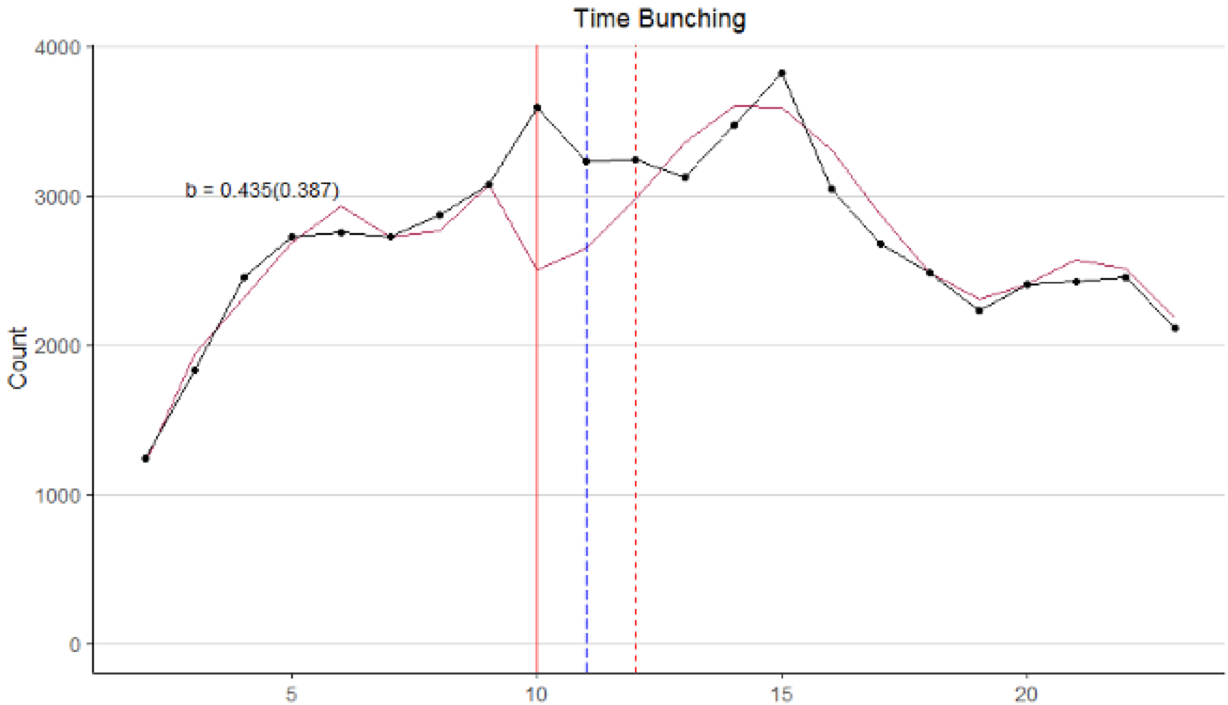

(a) Ratio of loan sizes for all 30-year refinancing mortgages




(b) Ratio of loan sizes for all 15-year refinancing mortgages

Figure 24: Figure 4A shows the ratio of the distribution of loan sizes for refinancing mortgages during the period that the AMRF was effective, divided by the distribution of loan sizes for all refinancing mortgages exactly a year prior to the implementation of the AMRF. Plot a includes all 30-year refinancing mortgages while plot b includes all 15-year refinancing mortgages

Figure 1.A: Time Bunching




Notes: Figure 5A shows the bunching output for the specification where I am analyzing bunching happening during the period prior to the AMRF implementation. The black line shows the distribution of refinancing loans with UPB $125,000-$130,000, from January 2020 until December 2021 which represents the window of interest. The binwidth is set to 1 month. The horizontal axis represents months, starting with January 2020 shown as 1, and ending with December 2021 shown as 24. The red line shows the counterfactual. The vertical dotted red line represents the upper bunching region, calculated internally. The blue vertical line represents the upper bound of the dominated region.