Gender Differences in Mortgage Bunching*

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Abstract

Accessing mortgage credit is the largest financial transaction most US households will undergo. Decisions at the time of mortgage origination can have important implications for both short- and long-term financial well-being. Using loan-level data on mortgage originations, we show that responses to pricing adjustments vary substantially based on borrower gender. We focus on a pricing adjustment that occurs based on loan amount and show that substantial bunching occurs within $1,000 of the limit. Our most robust estimates indicate single male borrowers are between 14.1% and 18.6% more likely to bunch than single female borrowers.

Keywords: bunching, mortgage markets, financial literacy

JEL Codes: G53, G51, G21, R30

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1 Introduction

Accessing mortgage credit is often the largest financial transaction that individuals will undertake in their lives. At the same time, housing wealth is typically the largest form of wealth within the household's portfolio. This means that decisions made by individuals at the time of mortgage origination can have important repercussions for both their short- and long-term financial well-being. Yet, the process of choosing and originating a mortgage loan is layered with complexity. Even the savviest of mortgage borrowers may lack certain data points which would increase their financial well-being. Motivated by existing research showing differences in financial literacy and sophistication across gender, this paper highlights behavioral responses to a mortgage pricing notch among female and male borrowers.

We use detailed loan-level data from the National Mortgage Database (NMDB) and Home Mortgage Disclosure Act (HMDA) to estimate bunching that results from a pricing discontinuity based on loan size (see Figures 1 and 2). The data includes information on borrower characteristics, namely borrower gender, which allows us to explore how bunching varies across this dimension. We show that single female borrowers are substantially less likely to take advantage of the pricing adjustment compared to single male borrowers and joint borrowers.

The primary contribution of this paper is documenting heterogeneity in bunching across borrower gender groups. Existing studies in the mortgage literature have not looked at this issue, even though single female borrowers account for 20 percent of mortgage originations in any single year. Our estimates inform how financial sophistication, or lack thereof, can create significant differences in financial well-being. We show that single women are less likely to bunch at the pricing notch and may be "losing out" on important savings. Furthermore, we explore various mechanisms that might explain this variation in bunching across gender.

Using the NMDB and HMDA data we estimate bunching at the national conforming loan-limit in counties designated as "high-cost". In these counties, a county-specific conforming loan limit exists that is greater than the national conforming limit. Loans that lie between the standard limit and the county-specific limit, also referred to as "high-balance", "super conforming", or "jumbo conforming" loans, are subject to a pricing adjustment of 25 basis points per year due to the government sponsored entities' (GSEs), Fannie Mae and Freddie Mac, guarantee fee schedule. We highlight the responsiveness of borrowers to this pricing discontinuity based on gender.

The advantage of this approach is that loans above and below the standard limit are conforming loans in these high-cost counties. Borrowers near this cutoff lie near the 75th percentile of the mortgage loan distribution, and loan characteristics at origination are similar above and below the high-balance limit. Earlier studies on mortgages notches have focused on the jumbo loan limit, which sits at the far-right tail of the mortgage loan distribution. Borrowers near the jumbo limit are likely not representative of the typical mortgage borrower. In addition, jumbo loans are not conforming and often require lower loan-to-value ratios at origination compared to conforming loans. Thus, loans just above and below the jumbo limit often have different characteristics at origination.

Our results show that excess bunching at the high-balance limit exists for all borrowers, with joint borrowers bunching the most and single-female borrowers the least. In our most robust specification the female-male bunching differential is near 0.3 percentage points. By contrast, the female-joint bunching differential is no longer significant when controlling for the full set of borrower, loan, geographic, and time of origination characteristics. We estimate an interest rate differential between high-balance and standard conforming loans of 8.0 basis points. This implies an interest rate pass through of roughly 32 percent. Combined with our bunching estimates, our results highlight the importance of pricing notches on the demand for mortgages. Compared to single male borrowers, single female borrowers appear to be losing out on importance savings by not carrying out as large an adjustment to loan size. In our most robust estimates single male borrowers are between 8.6 percent and 18.4 percent more likely to bunch than single female borrowers.

2 Literature Review

Our paper relates to two strands of the literature: one that makes use of the discontinuity in mortgage pricing associated with the conforming loan limit to analyze a variety of housing and mortgage outcomes, and another showing gender differences in financial transaction outcomes. On the former, authors have used the pricing discontinuity at the conventional loan limit to estimate interest rate elasticities of mortgage demand (DeFusco and Paciorek, 2017), impacts on house prices (Adelino et al. 2012), the availability of fixed rate mortgages (Fuster and Vickery, 2015), and the distribution of loan amount and pass through of fees to consumer mortgage rates (Alexandrov et al. 2019).

Using a sample of first-lien loan originations in California from 1997 to 2007, DeFusco and Paciorek (2017) show that in order to take advantage of a pricing notch, ranging from 12 and 16 basis points, borrowers reduce their mortgage demand (i.e., the size of their loan). Their results imply that a 1 percent increase in interest rates leads to a 2-3 percent decrease in first-lien mortgage amount. The authors also indicate that some borrowers increase the amount of second-lien mortgages in order to finance the gap between their down payment amount and the lower first-lien mortgage amount. Due to this behavior, the total mortgage demand, combining first- and second-lien mortgages, decreases by a smaller amount, of around 1-2 percent, in response to a 1 percent increase in interest rates. Alexandrov et al. (2019) show similar evidence of borrowers reducing their mortgage amount to be below the conforming loan limit using 2014 data for the entire United States. They highlight how this behavior differs by borrowers' credit scores.

Our research differs relative to the above set of papers since we don't use the pricing discontinuity associated with the conforming loan limit. Instead, we use the discontinuity at the national conforming limit in high-cost counties, where a higher limit applies. This is an important distinction since loans originated in high-cost counties are potentially eligible for GSE securitization on either side of the national conforming limit. By contrast, jumbo loans are not eligible for GSE securitization and are typically originated by lenders that specialize in such loans. Data from the 2018 HMDA show that only 0.6 percent of first-lien, single-family lenders had the majority of their originations be jumbo loans; while 88 percent of lenders originated more than 90 percent conforming loans and 13 percent did not originate a single non-conforming loan.[1] This emphasizes that borrowers may more easily adjust their loan amount above or below the national conforming loan limit in high-cost counties than they would switch between originating a conventional conforming or jumbo loan. The latter would likely involve switching to a different lender that might have different underwriting requirements. Our finding of loans bunching just below the conforming loan limit in high-cost counties support this.

Earlier literature on interest rate differences has focused on the jumbo-to-conforming limit. These estimates have ranged from 12 to 24 basis points in studies using data on loan originations (Sherlund, 2007; DeFusco and Paciorek, 2015) and as low as 5 basis points when looking at offered rates (Alexandrov et al, 2019). A recent study by Fisher et al. (2019) estimates the jumbo-conforming-to-conforming spread using data on loan originations since 2009. Their estimates range from 7-14 basis points depending on the sample period. We

[1] There were 3,085 HMDA-reporting lenders originating first-lien purchase or refinance loans for site-built 1-4 unit properties. Of these, only 18 (or 0.6 percent) had the majority of their originations be jumbo loans, 2,716 (or 88 percent) originated more than 90 percent conforming loans, and 386 (or 13 percent) did not originate any non-conforming loan.

report estimates of the jumbo-conforming-to-conforming spread of 8.0 basis points. We consider this to be a conservative estimate, given that it is closer to the lower end of the Fisher et al. estimates.

Our research also relates to the literature showing gender differences in financial transaction outcomes. Extensive research exists on gender differences in outcomes and attitudes toward negotiation in financial transactions; recent studies on the gender differences in housing transaction outcomes are the most closely related to our research. Using repeat sales data for the United States with information on the buyer and seller's names, Goldsmith-Pinkham and Shue (2019) show that women buy their properties for 1-2 percent more and sell their properties for 2-3 percent less than men. Additionally, differences in outcomes across genders are most pronounced when the transactions involve men on one side and women on the other. Among transactions that don't include couples, those where a woman buys and a man sells have the highest average price and those where a woman sells and a man buys the lowest.

Anderson et al. (2018) use repeat-sales data for Denmark and find that gender differences in transaction prices become insignificant when one more accurately accounts for differences in the property characteristics across genders. Harding et al. (2003), use American Housing Survey data to show that single women have less bargaining power than men, as evidenced by the fact that women on average pay a higher price when buying. Interestingly, Harding et al. (2003) do not show a significantly negative effect on sales price for women relative to men, which contrasts with the findings of Goldsmith-Pinkham and Shue (2019).

Our results show that in another facet of the home purchase process single female borrowers are experiencing worse outcomes than single male borrowers. Specifically, female borrowers are not taking advantage of a significant pricing discontinuity at mortgage origination. This lower likelihood of loans originated to single female borrowers bunching at the high-cost loan limit relative to those originated to single males is also visible in refinance originations; thus amplifying gender differences in mortgage outcomes.

3 Data and Methodology

3.1 Home Mortgage Disclosure Act

We first use loan-level data from the Home Mortgage Disclosure Act (HMDA). The data include all loan transactions for HMDA-filing institutions. Filing is required by both depository and non-depository lenders that meet certain asset-size thresholds, location tests, and loan activity tests. Overall, the HMDA data is highly representative of US mortgage originations, especially in large metro areas.

For 2010-2017, the HMDA data include limited information on borrower and loan characteristics at origination. Importantly, it includes information on borrower gender and loan value, which are the primary dimensions of our analysis. Starting in 2018, the HMDA data includes detailed information on borrower and loan characteristics, including credit score, property value, and loan term. We restrict our analysis to the use of the 2010-2017 variables in order to provide consistent estimates over time. However, we use the 2018-2019 detailed attributes as a check on our analyses.

Apart from in 2018 and 2019 HMDA data, HMDA data does not contain information on borrower credit scores, property values, interest rate, or loan term.[2] We are also able to classify institutions by type (i.e., bank, credit union, or non-depository) using information from the HMDA Reporter Panel, which contains institution-level aggregates.

[2]HMDA data does contain an indicator of interest rates with a rate-spread above certain thresholds, though that is not used in our analysis.

3.2 National Mortgage Database

We also use loan-level data from the National Mortgage Database, which is a 1-in-20 sample of first-lien mortgage originations drawn from consumer credit records. This data provides detailed information on both borrower and loan characteristics at origination. We exploit key variables, such as borrower gender, credit score, loan value, property value, interest rate and loan term. The data does not include information on originating institution characteristics.

The NMDB data is comparable to the HMDA data for 2018-2019, but is available for the entire sample period. Thus we exploit the detailed borrower and loan characteristics in NMDB to generate robust estimates of the bunching estimates over the period of analysis. We then extend the analysis to HMDA in order to estimate the bunching effects in the larger sample (see Section 3.3).

3.3 Empirical Methodology

The objective of our analysis is to document differences in loan amount bunching just below the high-balance limit, or national conforming loan limit in high-cost areas. To do so we need a counterfactual of what the distribution of loan amounts might be absent such a limit. We therefore use NMDB and HMDA loan-level mortgage originations data for owner-occupied properties from 2010 to 2019 in high-cost counties to estimate the amount of excess bunching at the high-balance limit. We do this by splitting the data into \$1,000 bins based on loan amount then fitting a flexible polynomial to this dataset of loan amounts by bins. The bunching estimates are captured by the 10th degree polynomial:

$$S_b = \sum_{k=0}^{P} \beta_k \times (V_b)^k + \delta \times 1[V_j = L] + \epsilon_b \tag{1}$$

where S_b is the share of loans in value bin b, V_b is the bin loan value, L is the bin containing the high-balance limit, P is the degree of polynomial (10), and δ is the excess bunching at that occurs at the high-balance limit. Each bin contains loans within a \$1,000 range, with the high-balance limit bin containing loans between less than \$1,000 of the limit and up to the limit. To compare bunching across borrower gender groups, we estimate separate polynomials for each borrower group sample. In the analysis described above we limit the sample to originations with a loan amount within \$400,000 of the high-balance limit, which is \$417,000 from 2010 to 2016, then increases slightly on a yearly basis through 2019.[3] This loan amount restriction means that our sample covers 96 percent of loans during our sample period.

The methodology above allows us to accurately capture the empirical difference between the expected and actual number of loans at the high-balance limit in these high-cost counties. Yet, this approach cannot aid us in understanding what factors drive the differential bunching behavior across gender. To do so, we estimate loan-level ordinary least squares (OLS) linear probability models, where the outcome of interest is whether the loan amount is at the high-balance limit (i.e., in the bin containing the loan limit).[4] These models have the following form for loan i in county j at time t:

$$AtLimit_{ijt} = \alpha_i Male_i + \beta_i Joint_i + \gamma_i X_i + \mu_t + \iota_t + \lambda_j + \epsilon_{ijt} \tag{2}$$

where $AtLimit_{ijt}$ is an indicator of the loan amount being at the high-balance limit; $Male_i$ indicates the loan is taken out by a single-male borrower: $Joint_i$ indicates a loan taken out jointly by two borrowers, specifically by a male and a female borrower; X_i is a vector of other borrower and loan attributes, detailed in Table 1; μ_t and ι_t are month and year of

[3]See Appendix A for the historic evolution of the conforming loan limit and the number of counties that were designated as high-cost.

[4]Logit estimates are comparable and presented in the Appendix.

origination fixed effects; and λ_j are county fixed effects. The main variables of interest to gauge the differential bunching by gender are therefore $Male_i$ and $Joint_i$. With the excluded borrower gender category in the regression being single-female borrowers, α_i and β_i capture the percentage point difference in the likelihood of a loan being at the high-balance limit between single-female and single-male borrowers, and between single-female and joint borrowers, respectively.

While the model above could be run on the same sample of loans as for the flexible polynomial analysis highlighted at the start of this section, it does not make sense to model borrowers' decisions to get a loan amount just below the high-balance limit if their property values are such that this limit will never be achievable. We therefore restrict the sample in this section of the analysis to loans for properties with a minimum value equal to the high-balance limit divided by 0.97 (this corresponds to properties for which a 97 percent LTV ratio is at least equal to the high-balance limit). We further limit the analysis to properties with a valuation not greater than 1.25 times the high-balance limit (this corresponds to properties for which an 80 percent LTV ratio is not greater than the high-balance limit). We carry out some sensitivities in our results with respect to this second restriction, with bunching estimates tending to become larger as maximum property values in the sample increase. We therefore adopted this more conservative 1.25 times the high-balance limit versus other higher valuation restrictions. Throughout the period where the national conforming loan limit is constant (2010-2016), the property values in our main analysis sample are between \$429,897 and \$521,250. Starting in 2017, this dollar range is shifted slightly upward each year, in accordance with the evolution of the national conforming loan limit.

Ideally, we would apply this property value-based restriction to both HMDA and NMDB data. However, while NMDB includes property value at underwriting in all years, property value information is not available in HMDA data prior to 2018. As such, in order to include the full 2010-2019 HMDA data in our analysis, we modify the restriction to being based on the loan amount. Specifically, having applied the property value restriction to NMDB data, we capture the minimum and maximum loan amounts in a given county and year of origination cell. We then apply these county-by-year-specific minimum and maximum loan amounts to the HMDA data, so that the county-by-year loan amount range in HMDA and NMDB matches. In order to gauge the extent to which this may bias the bunching estimates we apply the same restriction to the NMDB sample and compare results for that dataset using the property value- and loan amount-based restrictions. Likewise, we apply the property value-based restriction to 2018-19 HMDA data, where property value is available. We then compare the results in this limited HMDA sample when applying the loan amount-based restriction.[5]

Table 1 presents summary statistics for the sample of all owner-occupied properties for the HMDA sample and Appendix B.1 summary statistics for the NMDB sample.[6] The first thing to note in these summary statistics tables is that the breakdown of loans by borrower gender group is similar for HMDA and NMDB loans from 2010-2019. Specifically, in both samples 20 percent of loans are originated to female borrowers, 26 percent to male borrowers and 50-51 percent to joint borrowers. Also notable is the fact that HMDA data is significantly larger in size, with the HMDA sample consisting of 10.2 million loans compared to 556 thousand loans in NMDB, thus likely to provide a better gauge of the "true" bunching differences in the mortgage market. Contrasting Table 1 to Appendix B.1 also reveals the differences in the borrower and loan attributes available in HMDA and NMDB.

Comparing across columns in Table 1 and Appendix B.1 reveals that single female borrowers have on average the lowest incomes, loan amounts, credit scores, and house values. By

[5]Appendix Table A2 presents summary statistics for the various samples using property value and loan amount restrictions.

[6]Summary statistics for the NMDB property value restricted sample and the HMDA loan amount restricted sample are presented in Appendix B.2.

contrast, joint borrowers have the highest values for all these attributes, which is consistent with joint borrowers generally having access to greater financial resources due to the pooling of income and assets from both individuals. Also of note in Table 1 and Appendix B.1 is the fact that joint borrowers are the ones most likely to refinance and single males the most likely to obtain purchase mortgages. Column 2 in Appendix B.1 reveals that single females have the greatest share of their refinances being cash-out refinances, while at the other end of the spectrum, joint borrowers have the smallest share of refinances being cash-out refinances. This corroborates the view that single female borrowers are likely to have the lowest level of financial resources and are more likely to require a cash-out refinance. It also suggests that single female borrowers may be less willing to make use of refinancing opportunities to lower their monthly mortgage payments through taking advantage of lower rates. This could come about due to lower levels of financial capacity to refinance, lower financial literacy, or lesser engagement with loan originators. This latter point is something we will return to when contrasting borrowers' bunching decisions by lender institution type. From Table 1, we can observe that single male borrowers are the most likely to have originated their loan through non-depository institutions and least likely to use banks or credit unions. The opposite is true for joint borrowers, who are most reliant on depository institutions for mortgage origination.

4 Results

4.1 Polynomial Bunching Estimates

Figure 2 presents the empirical distribution of loan amounts in NMDB. Loans are grouped into $1000 bins and reported relative to the high-balance loan limit, which falls in the zero bin. It is clear from the figure that bunching at the high-balance loan limit is occurring, seen in the spike at the value of zero. To more formally capture this bunching we turn to the flexible polynomial approach in order to contrast the number of loans in the high-balance limit bin to the number of loans we would expect to see in this bin given the overall distribution of loan amounts.

Figure 3 displays the empirical distribution of loan amounts by loan bin (in blue bars), the polynomial predicted distribution of loan amounts (in orange line), and the estimate of the share of loans at the high-balance limit bin (in orange circle) for HMDA 2010 to 2019 data.[7] Estimates are presented separately for the three borrower gender groups. It is clear that the height of the orange circle, indicating the share of loans at the high-balance limit, is smallest for single female borrowers, followed by single male borrowers and then joint borrowers. While the visual contrast is striking, it is hard to discern how greater a share of loans is in that high-balance limit bin than would be expected by the polynomial estimate. To do so, we turn to the estimates presented in Table 2, which reported the estimates of the bunching coefficient across borrower gender group samples for both HMDA and NMDB. Note that since this is a loan bin-based estimation, the number of observations is the same across all three borrower gender group samples. The sample size is 801, which corresponds to 400 bins on either side of the high-balance limit bin in addition to the high-balance limit bin itself.

Turning to the results displayed in Panel A of Table 2, using the HMDA data, we see that 1.83 percent of loans to female borrowers bunched at the high-balance limit, compared to 2.78 percent and 3.47 percent for male and joint borrowers, respectively. The male-female and joint-female differences are 0.95 and 1.64 percentage points, respectively, and reported in columns (4) and (5). Both differences in bunching are statistically significant. The results for the NMDB sample, visible in Table 2 Panel B, are not distinguishable from those detailed above for the HMDA sample. As indicated earlier, given the larger number of observations in the HMDA data, we believe it to more accurately represent the entire mortgage mar-

[7]Comparable charts obtained using NMDB 2010-2019 data are visible in Appendix C.

ket so we will tend to place more weight on results from the HMDA sample than NMDB. That being said, estimates from both samples are essentially the same, which is encouraging.

4.2 Bunching Decision Estimates - Property Value Restriction

Having established that there is a clear difference in the share of loans at the high-balance loan limit across borrower gender groups, this section of the analysis aims to more accurately assess this differential bunching behavior by modeling the decision of borrowers to bunch at the high-balance loan limit. As we indicated in Section 3, restricting the sample to loans originated for properties for which the high-balance limit lies between 80 percent and 97 percent of the property value creates a group of loans for which the decision to bunch at the high-balance limit is meaningful. In other words, if the property value is too low then the loan amount would never reach as high as the high-balance limit; conversely, if the property value is too high then the loan amount would only reach the high-balance limit in cases where the loan amount is significantly below the property value. If we were to keep loans for properties valued above 125 percent of the high-balance limit, *i.e.* with the high-balance limit being below 80 percent of the property's value, the bunching estimates would be larger.

To apply the property value restriction detailed above to the entire sample period we must use NMDB data, as property value information in HMDA is limited to 2018 and 2019 originations. Table 3 displays the estimates obtained from modeling the bunching decision of borrowers using the specification detailed in equation (2) using NMDB data for 2010-2019 with single females being the excluded category. As we move from columns (1) to (5) we add more control variables to the estimating equation. This allows us to observe exactly how our estimates of differential bunching by borrower groups changes. The difference between the probability of single female borrowers bunching and that of single male and joint borrowers is visible in the first two coefficient estimates displayed in the Table. These correspond to the estimates of α_i and β_i parameters in equation (2) and capture the percentage point difference in the likelihood of a loan being at the high-balance limit loan across borrower gender groups.

Turning to the results in column (1) we can see that without controlling for any borrower, loan, geographic, or time characteristics, single male and joint borrowers are 0.76 and 0.41 percentage points more likely to bunch than single female borrowers, respectively. These estimate are smaller in magnitude then the ones displayed in Table 2 Panel 2 and highlight how the simple polynomial estimate of the bunching behavior can be sensitive to differences in the distribution of loan amounts across borrower groups. In particular, the difference in the estimate of female-to-joint borrower differences in bunching is substantially reduced. This is indicative of the fact that joint borrowers tend to have larger loan amounts and are therefore more likely to be able to bunch at the high-balance loan limit.

As we add controls to the estimating equation, we observe that the difference between female and joint borrowers' likelihood of bunching at the high-balance limit is no longer statistically significant. In particular, adding borrower income and an indicator for whether any borrower on the loan is white non-Hispanic reduces the estimate to zero. This emphasizes how differences in borrower financial capacity, as captured by their income used at underwriting, drove the bulk of the differences in bunching between female and joint borrowers. This is not a surprising result given that two borrowers are able to pool financial resources in order to buy or refinance a home in a manner not available for single borrowers.

By contrast to the female-to-joint differences, the female-to-male differences in bunching do remain statistically significant even in our most robust specification, visible in Table 3 column (5). Once we control for the full set of covariates, male borrowers are still 0.35 percentage points more likely to bunch than their female counterparts. Given the average likelihood of bunching for single female borrowers is 1.9 percent, this percentage point difference equates to an 18.4 percent increase in the likelihood of bunching for male relative to female borrowers. Comparing the estimates in column (1) to column (5) we see that differences in borrower, loan, geographic, or time of origination characteristics account for over half of the difference in the likelihood of bunching between single female and single male borrowers. That being said, the 0.35 percentage point difference that remains in column (5) is economically meaningful. This difference may be driven by differences in lender choice, borrower-lender interaction, mortgage shopping behavior, financial literacy, or other unobserved characteristics across female and male borrowers. Differences in bunching that may be driven by lender choice is something we tackle later in the analysis.

Turning to the impact on bunching of some of the other control variables in the regression, it is noteworthy borrower income and loan type are strongly associated with bunching. Borrower income is likely correlated with a borrower's overall financial capacity, namely the amount of financial assets they may be able to draw upon in order to reduce the loan amount while still being able to carry out a mortgage origination. As such, finding that it is positively correlated with the likelihood of bunching is to be expected. The results on loan type are revealing, in that purchase mortgages are most likely to bunch, followed by rate/term refinances and cash-out refinances. This suggests that there is greater flexibility in the determination of the initial loan amount than when a refinance occurs. This might be because borrowers seeking to purchase a home likely only do so when they have amassed the requisite financial assets, which therefore allows them to toggle the loan amount at origination more easily then for refinance mortgages. It is certainly true that rate-term mortgages, *i.e.* mortgages where the new loan amount does not significantly change relative to the previous mortgage, are not expected to have much flexibility when it comes to the actual loan amount itself. Though borrowers could chose to pay down their previous loan in order to obtain a new loan at the high-balance limit, it appears they are less likely to do so than purchase mortgage borrowers. Lastly, borrowers obtaining cash-out refinance mortgages appear to have less flexibility in the loan amount compared to purchase mortgage borrowers. These borrowers may need funds for some other purpose that leads to reduced flexibility in loan amount.

4.3 Bunching Decision Estimates - Loan Amount Restriction

Next, we use the HMDA data to estimate equation 2 since HMDA likely provides a more complete picture of the mortgage market in high-cost counties. We employ a loan amount-based restriction to HMDA since property value is not available prior to 2018. To do this, we restrict the range of loan amounts in a given county and year of origination cell to be the same as that obtained from applying the property value-based restriction to the NMDB data. We call this the loan amount sample as compared to the property value sample.[8] Estimates of modeling the bunching using this HMDA sample are presented in Table 4.

Given the differences in how the samples are created, a direct comparison of estimated differences in bunching across Table 3 (NMDB, property value) and Table 4 (HMDA, loan amount) is not very informative. That being said, the patterns in the female-male and female-joint differences are similar moving across columns from left to right in Tables 3 and 4. The female-male difference remains significant as we add a greater number of controls. The female-joint difference does not remain significant with added controls. This is interesting since there are differences in the specific borrower and loan characteristics we can control for across the two data sets. One notable difference in the controls is that in HMDA we can control for the type of lending institution that originated the loan. From the results in Table 4 columns (3) and (4) we see that the lending institution used by borrowers has an

[8] We apply both the property value and loan amount restrictions to HMDA 2018-2019 data and contrast estimates in Appendix E. Results in this table show that female-male difference estimates are smaller under the loan amount based restriction, but the opposite is true for female-joint differences. Given we will focus on female-male differences using HDMA 2010-2019 data with loan amount restriction, these are likely to be under-estimates of the true difference.

important role to play in the bunching decision. This is a point we will investigate further in the next section. Having highlighted the potential limitations of comparing coefficients across Tables 3 and 4, it is encouraging to see that the most rigorous estimates of the differences in bunching across gender groups in both tables, seen in the rightmost columns of each table, are remarkably similar. In Table 4, our final estimate of the bunching difference between single female and single male borrowers is 0.31 percentage points. Given the average likelihood of bunching for single females in the HMDA sample is 2.2 percent, this represents a 14.1 percent increase in the likelihood of bunching for single male relative to single female borrowers.

4.4 Bunching By Lender Type

One driver of the differences in bunching by borrower gender group is the choice that borrowers make with regards to the type of institution they obtain their mortgage from. Figure 4 reports the polynomial bunching estimates by borrower gender group and institution type and makes this fact particularly salient. While raw differences in the likelihood of bunching at the high-balance loan limit are always evident across borrower gender groups, the differences in the overall level of bunching by institution type are particularly stark. Borrowers originating loans through mortgage brokers are markedly more likely to bunch than those using banks or credit unions. Borrowers using credit unions are the least likely to bunch.

While Figure 4 presents raw differences in bunching, the results in Table 4 confirmed that those raw differences still remain after controlling for borrower, loan, geographic and time of origination characteristics. From column (4) in Table 4 we can see that borrowers originating their loans through non-depositories and banks are 1.59 and 0.33 percentage points more likely to bunch than those originating their loans through credit unions, respectively. There are numerous potential reasons why this difference in the likelihood of bunching across institution types is occurring. One possible reason is that mortgage brokers in non-depository institutions have greater familiarity with the intricacies of mortgage pricing, such as the differential pricing for loans above and below the high-balance limit, than do individuals working in depository institutions. Another potential driver of this difference is if borrowers who end up originating their loans through a broker are more likely to have shopped around for their mortgage and hence may have been informed about the pricing advantage of being at the high-balance limit instead of above. It is also possible that non-depositories have an incentive to originate conforming loans, which are the easiest to securitize.[9]

Given that there is a clear difference in the likelihood of bunching based on the lender institution type and, as seen in Table 1, single male borrowers are the most likely to use mortgage brokers, this naturally contributes to the gap between single female and single male bunching. In Table 5 we assess whether differences in bunching across borrower groups are different across institution types. Our findings indicate that while the overall difference in bunching across borrower gender groups is indeed driven in part by the choice of institution type, female-male differences in bunching are not statistically different across institution types. By contrast, female-joint differences in bunching are 0.77 percentage points larger in non-depository originations and 0.18 percentage points larger in commercial bank originations. Together, these results suggest that increasing the share of female borrower originations occurring through non-depository institutions may lead to a shrinking of the gap in bunching likelihood between single female and single male borrowers.

[9]Although jumbo conforming, or "high-balance" loans, can be securitized through the GSEs, standard conforming loans may be easier to securitize compared to jumbo conforming in certain markets. Fisher et al. (2020) provide a discussion of differences in GSE-securitization between standard conforming and jumbo conforming loans.

4.5 Bunching By Year

Thus far we have documented the existence of differences in the likelihood of loan amounts bunching at the high-balance limit across borrower gender groups, throughout the entire 2010-2019 period. In this section we analyze whether these borrower gender group differences are changing over time. This exercise is informative since the national conforming loan limit, and hence the high-balance limit, starts increasing annually after 2016. Additionally, the number of counties designated as high-cost also varies on a yearly basis depending on the evolution of home prices. [10]

Figure 5 displays polynomial estimates of bunching by borrower gender group for each year. We see that within each borrower gender group the bunching estimates are stable form 2010 to 2016 and then drop through 2018, stabilizing in 2019. The fact that the share of loans bunching at high-balance limit drops in 2017, when the limit starts increasing on an annual basis, is consistent with fewer loans bunching as the limit becomes further to the right of the loan amount distribution. Recall that female-joint differences in bunching disappeared once we narrowed the sample by property value or loan amount but were larger than the female-male differences in the polynomial estimates using the entire sample. That pattern is consistent with the distribution of loan amounts for single borrowers being generally to the left (smaller amounts) than that of joint borrowers. This explains why joint borrowers bunch more. A similar phenomenon may be driving the lower likelihood of bunching evident since 2017.

The other factor that could drive the difference in bunching by origination year concerns the salience of the high-balance loan limit itself. When the limit remained unchanged for a number of years it is likely that borrower familiarity with that limit grew, yet once the limit started changing on an annual basis familiarity with the exact dollar limit may

[10] See Appendix A.

have fallen. This could lead to a smaller likelihood of bunching due to decreased familiarity with the limit. Both of these potential mechanisms, familiarity and loan size distribution relative to the limit, suggest that bunching would decrease starting in 2017, as the limit increases on an annual basis. To gauge this empirically, we turn to estimates of the bunching decision in which we compare bunching pre- and post-limit changes, presented in Table 6.

Results in Table 6 confirm that post limit changes the overall likelihood of loans bunching at the conforming limit decreases. This is evident in the negative coefficient estimate for the post-limit changes indicator in column (1) of Table 6. Furthermore, we observe that following the introduction of limit changes, the female-male and female-joint bunching differences become smaller as well. These results suggest that indeed both the familiarity and loan distribution-size distribution versus limit may be driving decreased bunching likelihood post limit changes.

5 Conclusion

This paper has analyzed the extent to which a pricing differential for mortgages in high-cost counties with a loan amount at or below the high-balance limit (or national conforming limit) induces the bunching of loan amounts at that limit. We find clear evidence that bunching indeed occurs across all borrower gender groups. Our results also show that female borrowers are less likely to bunch at the high-balance limit than their male counterparts. This lower likelihood of bunching leads to fewer female borrowers taking advantage of a mortgage pricing difference occurring for loans at versus above the limit, and may be contributing towards some of the disparities evident in the financial standing of female borrowers relative to male. Our most robust estimates suggest that single male borrowers are approximately 0.3 percentage points or between 14.1 percent and 18.6 percent more likely to bunch at the limit than their single female counterparts, depending on the estimation sample.

We further find that differences in borrower, loan, geographic, and time of origination characteristics account for 54 percent to 74 percent of the raw difference between female and male borrower bunching likelihoods. While this is encouraging, in that it suggest a large amount of the difference in bunching and hence savings may be reduced by narrowing the disparity in attributes across borrower gender groups, the 0.3 percentage point estimate of the difference remains after controlling for all these factors. Future research should focus on what drives this persistence difference. We posit that it can arrive through a few channels, namely differences in: borrower mortgage shopping behavior; borrower engagement with the lender; financial literacy; or financial capacity.

In order to address the concern that mortgage shopping behaviour or differential lender engagement by gender group drives some of the gender group differences in bunching we plan on supplementing the analysis herein with survey data from the National Survey of Mortgage Originations (NSMO). This survey of borrowers who recently originated a mortgage ask questions along these dimensions that will hopefully allow us to observe whether differential patterns across gender groups are evident.

6 References

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Figure 1: Interest Rate at Origination

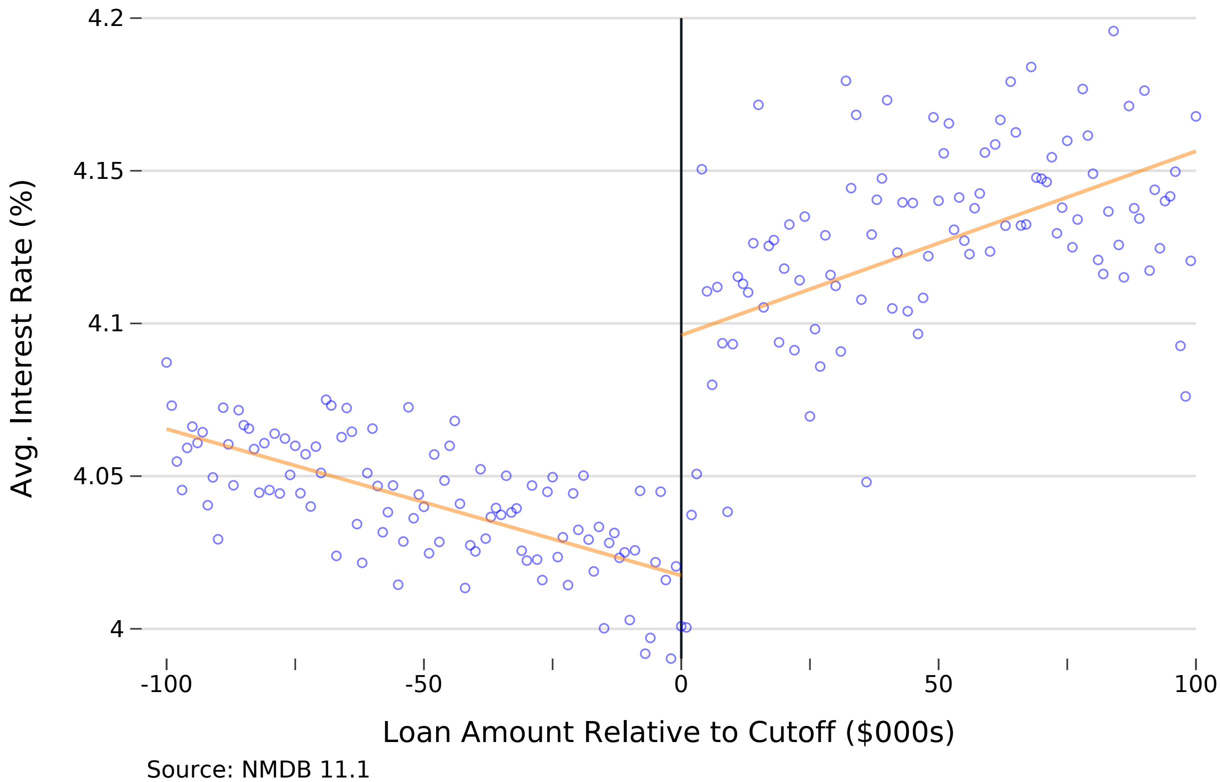


Figure 2: Distribution of Loan Amounts

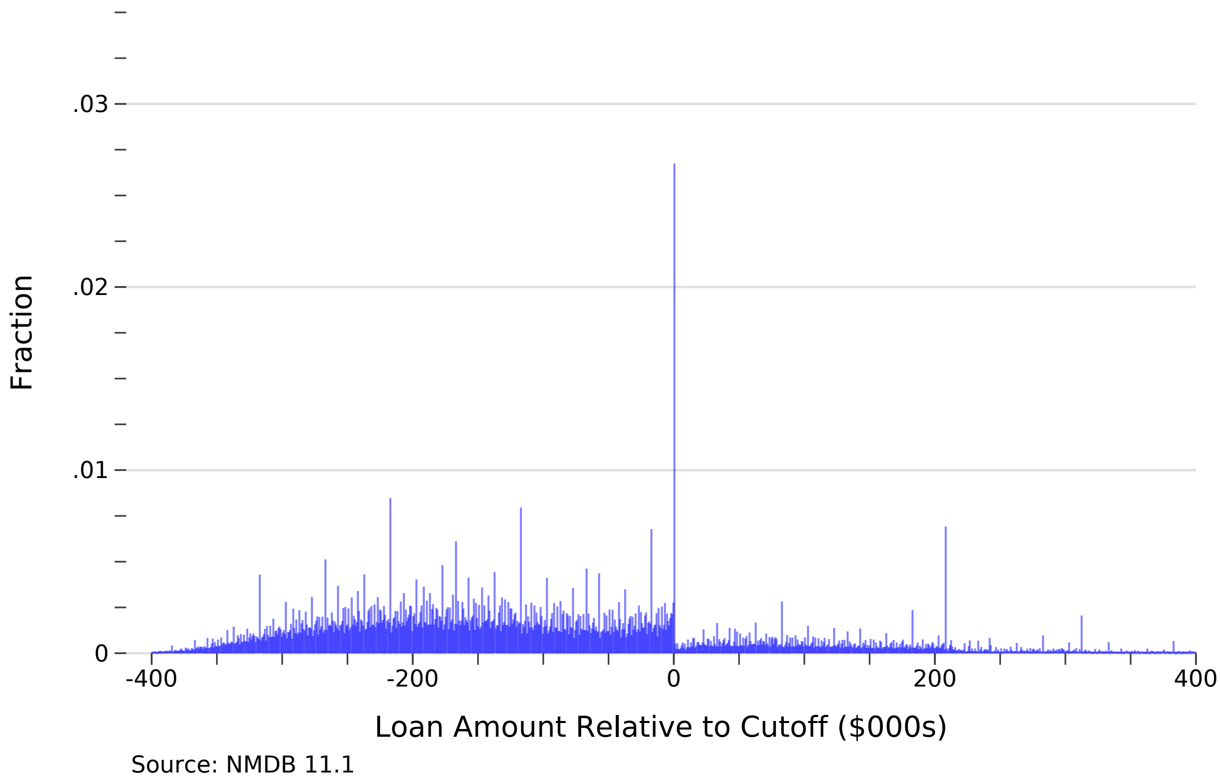
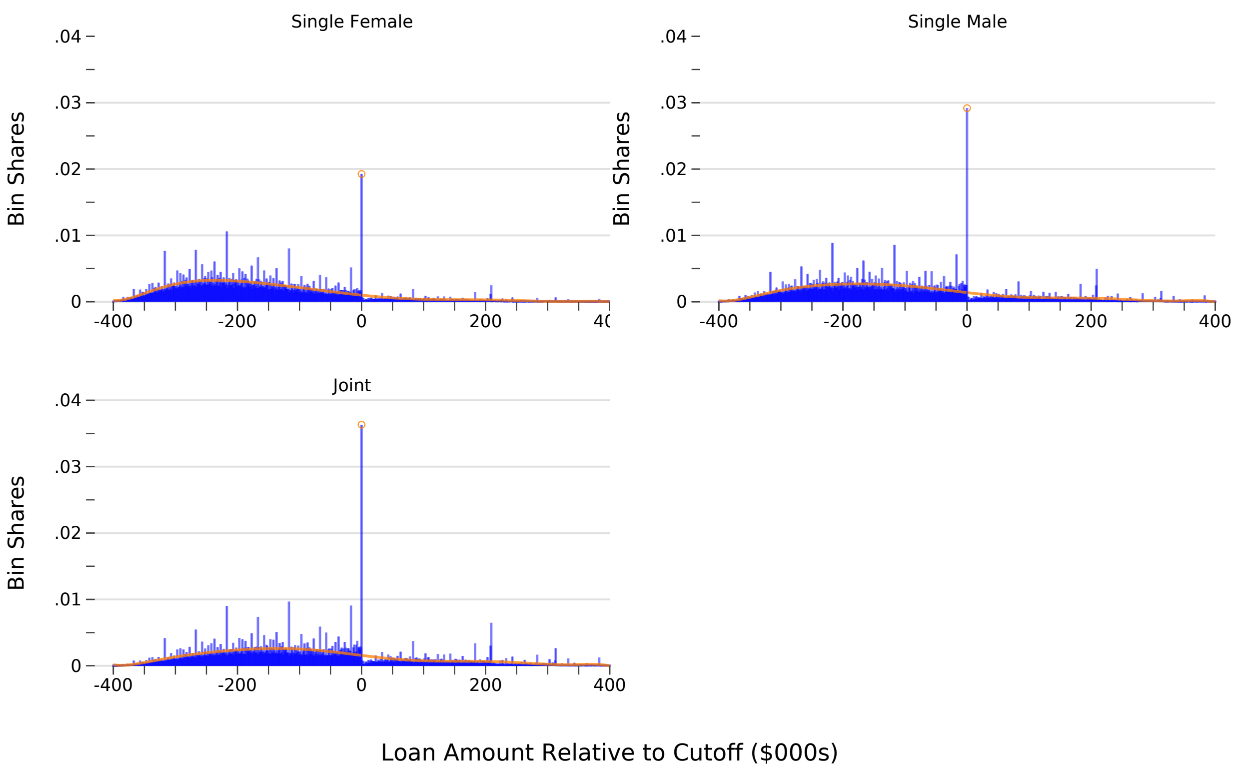


Figure 3: Polynomial Estimates by Gender



Source: HMDA

Figure 4: Polynomial Estimates by Gender and Institution Type

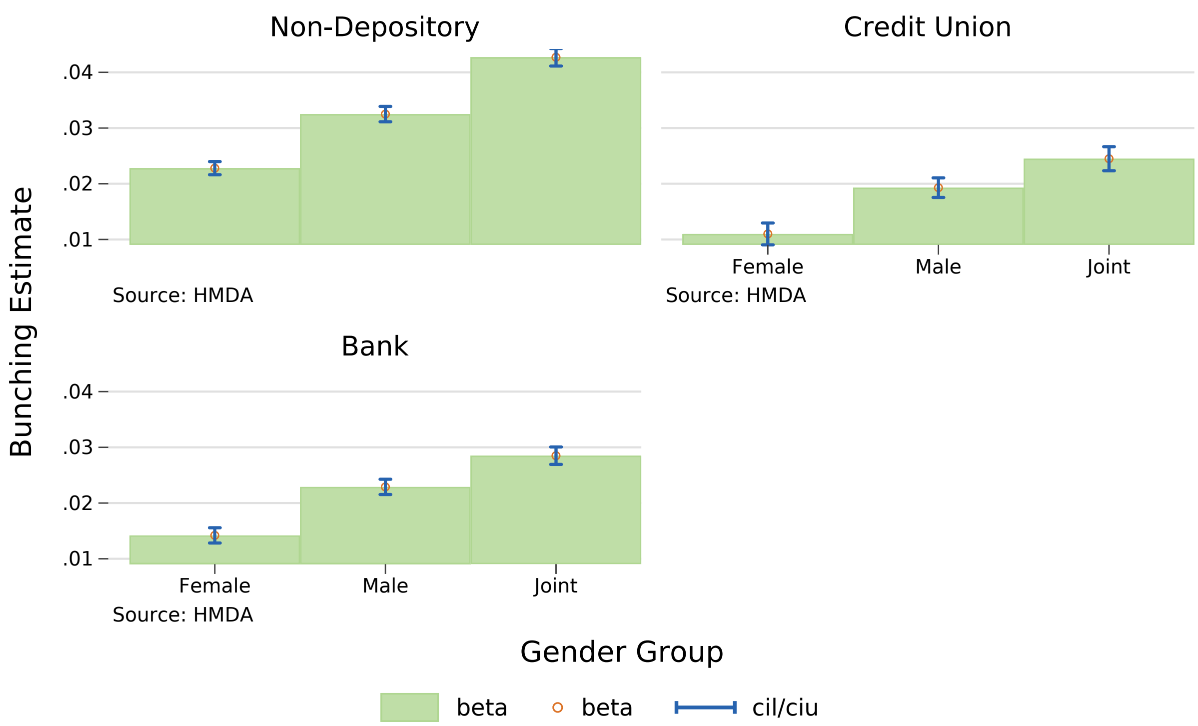


Figure 5: Polynomial Estimates by Gender and Year

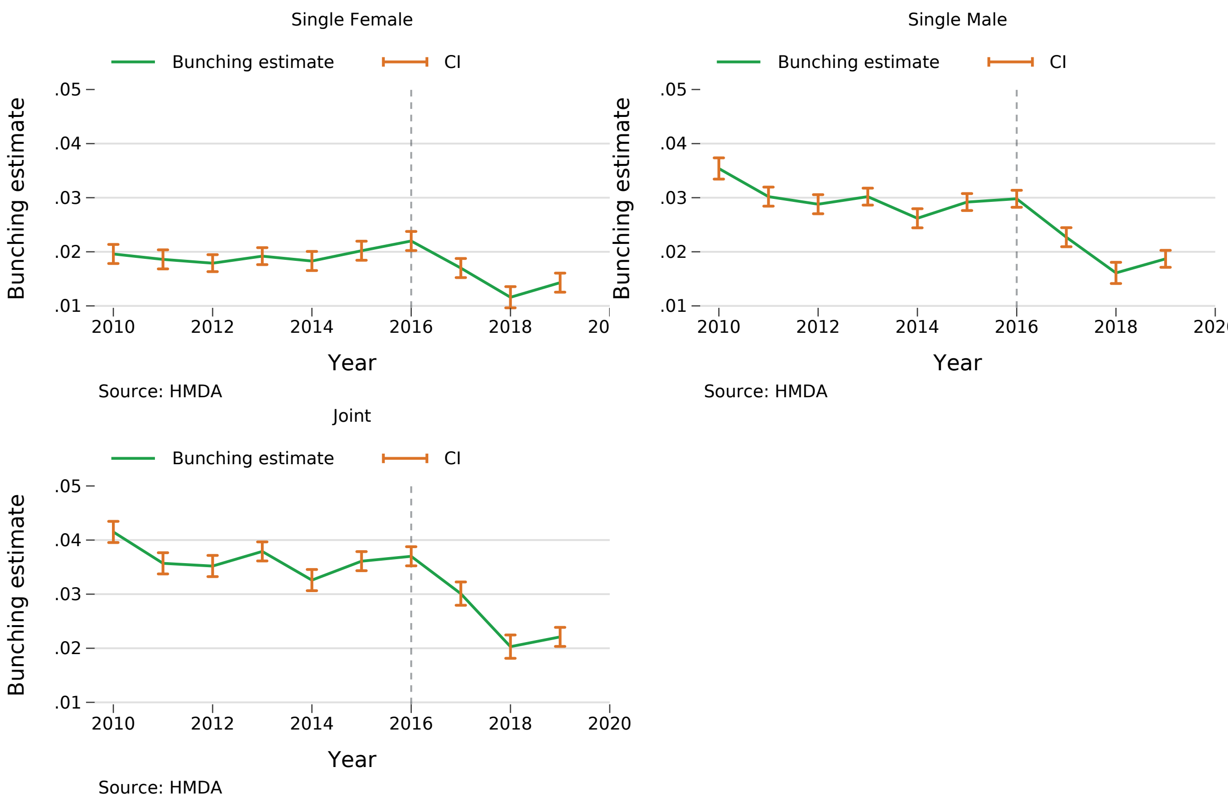


Table 1: Summary Statistics: HMDA, 2010 - 2019

	All	Female	Male	Joint
	(1)	(2)	(3)	(4)
Income at Origination ($000s)	131	92	119	152
Loan Amount ($000s)	322	271	322	342
Purchase	.32	.34	.37	.28
Refi	.68	.66	.63	.72
Conforming	.78	.88	.79	.74
High-Balance	.16	.10	.16	.19
Jumbo	.05	.02	.05	.07
Non-depository	.48	.49	.53	.46
Bank	.46	.45	.43	.48
Credit Union	.06	.06	.05	.07
Single Female	.21	1	0	0
Single Male	.27	0	1	0
Joint	.52	0	0	1
Observations	10,260,282	2,086,063	2,695,963	5,225,195

Note: Reported as shares unluss indicated otherwise.

Table 2: Polynomial Fit by Borrower Gender Group

Panel A: HMDA, 2010 - 2019					
	(1)	(2)	(3)	(4)	(5)
	Female	Male	Joint	Male - Female	Joint - Female
Bunching	0.0183***	0.0278***	0.0347***	0.0095***	0.0164***
	(0.0007)	(0.0007)	(0.0008)		
R-sqr	0.794	0.803	0.792		

Panel B: NMDB, 2010 - 2019					
	(1)	(2)	(3)	(4)	(5)
	Female	Male	Joint	Male - Female	Joint - Female
Bunching	0.0173***	0.0244***	0.0330***	0.0071***	0.0157***
	(0.0006)	(0.0006)	(0.0007)		
R-sqr	0.827	0.818	0.813		

Note: Number of observations is 801 for all regressions, which is equal to the number of bins.

Table 3: Effect on Probability of Bunching at Limit, NMDB Property Value Sample

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	1(At Limit)	1(At Limit)	1(At Limit)	1(At Limit)	1(At Limit)
Single Male	0.0076***	0.0055***	0.0037*	0.0036*	0.0035*
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Joint	0.0041***	-0.0006	0.0013	0.0008	0.0008
	(0.0012)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
White Non-Hispanic		0.0008	0.0014	0.0012	0.0010
		(0.0011)	(0.0011)	(0.0011)	(0.0011)
Ln(Borrower Income)		0.0150***	0.0109***	0.0116***	0.0131***
		(0.0010)	(0.0010)	(0.0010)	(0.0010)
Refi			-0.0276***	-0.0293***	-0.0250***
			(0.0018)	(0.0020)	(0.0020)
Cash-out Refi			-0.0336***	-0.0351***	-0.0333***
			(0.0013)	(0.0014)	(0.0014)
Month FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
County FE	NO	NO	NO	YES	YES
NMDB Controls	NO	NO	NO	NO	YES
R-sqr	0.0003	0.0027	0.0156	0.0191	0.0210

Note: Sample size for all regressions is 71,815 loans. NMDB-specific controls include borrower credit score at origination and loan term.

Table 4: Effect on Probability of Bunching at Limit, HMDA Loan Amount Sample

	(1)	(2)	(3)	(4)
Dependent Variable:	1(At Limit)	1(At Limit)	1(At Limit)	1(At Limit)
Single Male	0.0121***	0.0029***	0.0024***	0.0031***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Joint	0.0209***	-0.0008***	0.0001	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
White Non-Hispanic		-0.0046***	-0.0043***	0.0016***
		(0.0002)	(0.0002)	(0.0002)
Ln(Borrower Income)		0.0504***	0.0504***	0.0505***
		(0.0002)	(0.0002)	(0.0002)
Refi			-0.0058***	-0.0140***
			(0.0002)	(0.0002)
Non-Depository			0.0140***	0.0159***
			(0.0003)	(0.0003)
Bank			0.0045***	0.0033***
			(0.0003)	(0.0003)
Month FE	NO	NO	NO	YES
Year FE	NO	NO	NO	YES
County FE	NO	NO	NO	YES
R-sqr	0.0020	0.0213	0.0224	0.0332

Note: Sample size for all regressions is 7,012,310 loans.

Table 5: Difference-in-differences estimates by Gender and Institution Type, HMDA

	(1)
Dependent Variable:	1(At Limit)
Single Male	0.0025**
	(0.0009)
Joint	-0.0043***
	(0.0007)
Non-depository	0.0109***
	(0.0006)
Bank	0.0012
	(0.0007)
Single Male # Non-depository	0.0012
	(0.0009)
Single Male # Bank	-0.0003
	(0.0009)
Joint # Non-depository	0.0077***
	(0.0008)
Joint # Bank	0.0018*
	(0.0008)
Borrower Controls	YES
Loan Controls	YES
Month FE	YES
Year FE	YES
County FE	YES
# of Observations	7,520,007
R-sqr	0.0292

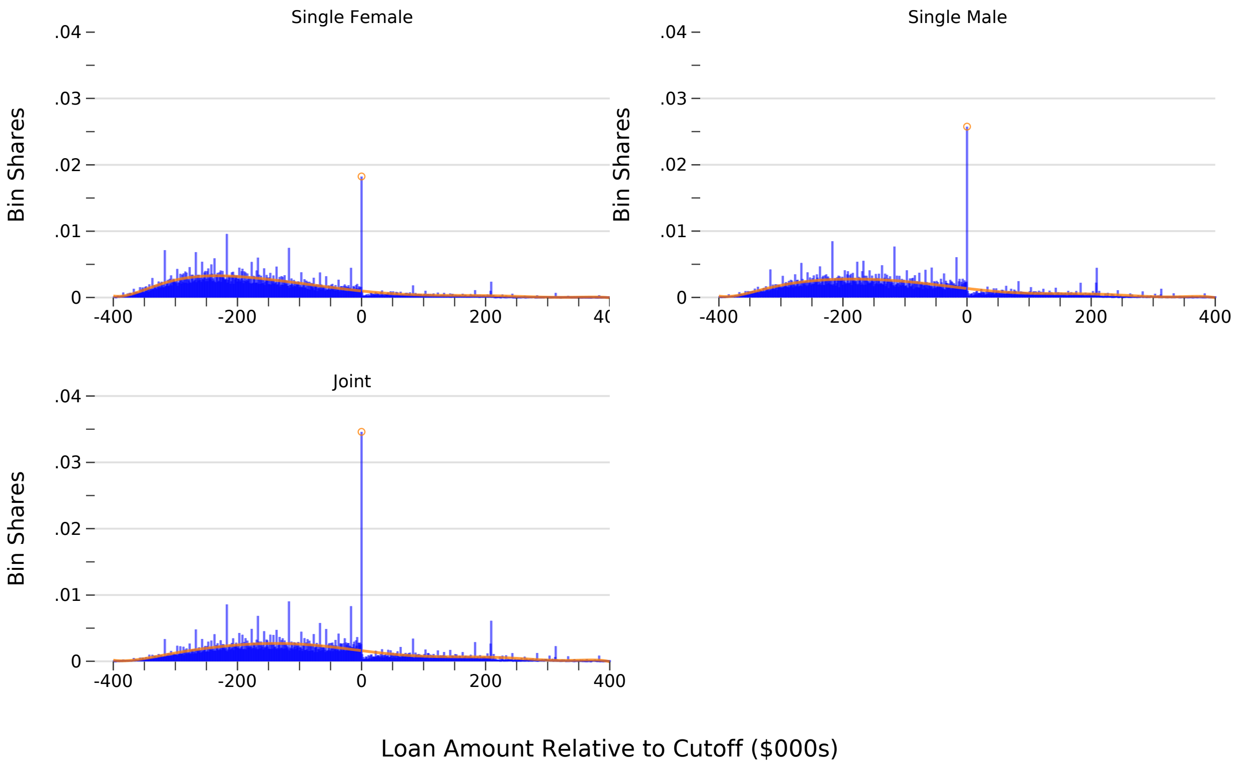
Note: Borrower controls include white non-Hispanic indicator, log income at origination. Loan controls include loan purpose group indicators.

Table 6: Difference-in-differences estimates by Gender and Time, HMDA

	(1)
Dependent Variable:	1(At Limit)
Male	0.0043***
	(0.0002)
Joint F-M	0.0028***
	(0.0002)
Post Limit Changes	-0.0232***
	(0.0004)
Male # Post Limit Changes	-0.0074***
	(0.0005)
Joint F-M # Post Limit Changes	-0.0131***
	(0.0005)
Borrower Controls	YES
Loan Controls	YES
Month FE	YES
Year FE	NO
County FE	YES
# of Observations	7,520,007
R-sqr	0.0286

Note: Borrower controls include white non-Hispanic indicator, log income at origination. Loan controls include loan purpose group indicators and depository institution type.

Appendix C. Polynomial Estimates by Gender in NMDB



Source: NMDB 11.1

Appendix A. Historic Conforming Limits and County of High-Cost Counties

Year	Standard Conforming Limit	Number of High Cost Counties
2010	417,000	326
2011	417,000	200
2012	417,000	200
2013	417,000	200
2014	417,000	209
2015	417,000	234
2016	417,000	234
2017	424,100	238
2018	453,100	220
2019	484,350	199

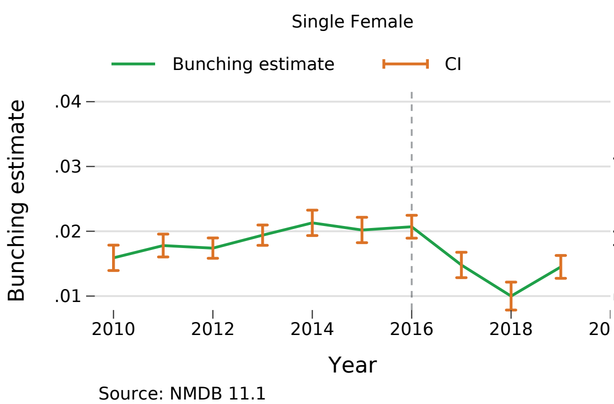
Note: Total number of US counties is 3,006.

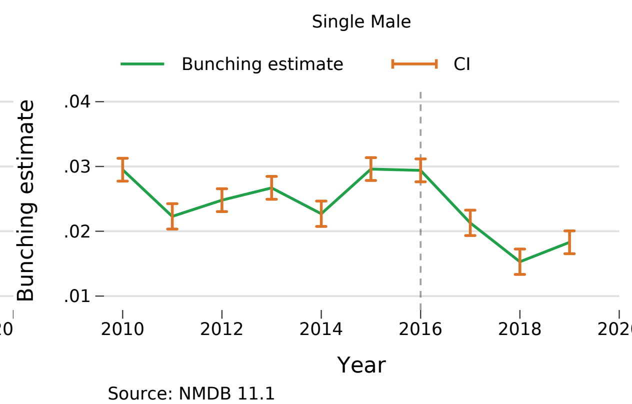
Appendix B.1. Summary Statistics: NMDB, 2010 - 2019

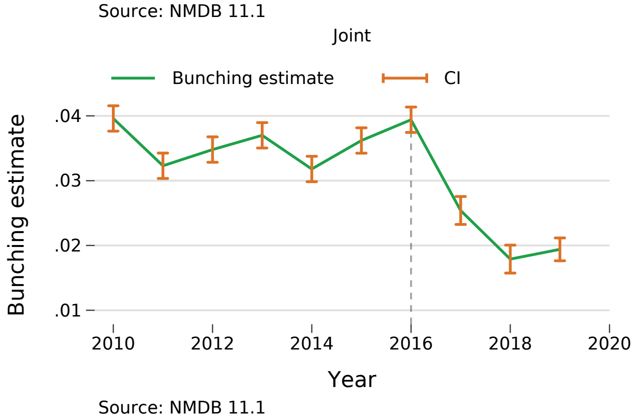
	All (1)	Female (2)	Male (3)	Joint (4)
Income at Origination ($000s)	127.5	92.7	114.1	146.6
Credit Score	762	751	750	773
Interest Rate at Origination (%)	4.1	4.2	4.1	4.1
Property Value in Underwriting ($000s)	515.3	435.3	478.0	562.1
Loan Amount ($000s)	325	276	320	345
Loan Term (Months)	322	329	328	317
At or below 80% LTV	.78	.77	.74	.81
Purchase	.35	.37	.42	.30
Refi	.10	.08	.09	.12
Cash-out Refi	.54	.55	.49	.58
Conforming	.81	.89	.82	.78
High-Balance	.15	.093	.15	.18
Jumbo	.04	.02	.03	.05
Single Female	.21	1	0	0
Single Male	.27	0	1	0
Joint	.52	0	0	1
Observations	556,245	112,495	143,365	276,060

Note: Reported as shares unluss indicated otherwise.

Appendix D. Polynomial Estimates by Gender and Year in NMDB







Appendix E. Effect on Probability of Bunching at Limit, HMDA 2018-2019

	(1)	(2)
Dependent Variable:	1(At Limit)	1(At Limit)
Male	0.0028***	0.0018***
	(0.0007)	(0.0003)
Joint F-M	0.0005	0.0012***
	(0.0006)	(0.0003)
White Non-Hispanic	-0.0009	0.0032***
	(0.0006)	(0.0003)
Ln(Borrower Income)	0.0036***	0.0211***
	(0.0004)	(0.0003)
Refi	-0.0173***	0.0033***
	(0.0005)	(0.0003)
Non-Depository	0.0046***	0.0078***
	(0.0009)	(0.0005)
Bank	-0.0009	-0.0001
	(0.0010)	(0.0005)
Borrower Controls	YES	YES
Loan Controls	YES	YES
Month FE	YES	YES
Year FE	YES	YES
County FE	YES	YES
Property Value Sample (PV)	X	
Loan Value Sample (LV)		X
N	227,245	1,070,123
R-sqr	0.0096	0.0133

Note: Additional borrower controls include borrower credit score at origination