Estimate Bunching Mass

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Abstract

This paper provides an estimate of bunching mass across different groups with different characteristics in response to a well-known regulatory policy in mortgage market —the conforming loan limit, which is the maximum loan size eligible for purchase by Fannie Mae and Freddie Mac. Counterfactual distributions and bunching masses are estimated using polynomial regressions across different groups. We further conduct an analysis of whether groups with certain characteristics are having a more salient bunching effect.

Four group characteristics, including gender, ethnicity, race, and loan purposes are focused in this paper, whose effect on bunching are shown as a conclusion to this paper. The effect of first three group characteristics are shown to be statistically significant while the last one is left undecided since our lack of data to generate precise estimations on bunching mass. Although it is true that this paper adopt a simple baseline model with homogeneity and frictionless assumptions, it further inspire us to propose bunching as a proxy to measure individuals' ability of reacting to large stake regulatory policy like the CLL, even though much of the analysis here ignore the fact of frictions and heterogeneity that may prevent people from bunching or introducing noises to our analysis to uncover the structural parameters.

1 Introduction

Recent years, there has been a wide variety of applications of bunching approaches in Economics. Bunching was originally developed to estimate behavioral responses to tax systems, but is now applied to other settings. In this paper, we will discuss the application of bunching approach in household finance—more specifically, estimating bunching mass and the effect of various group characteristics, which includes gender, ethnicity, race, and loan purposes, on bunching in the U.S. mortgage market.

Generally, in the U.S., homes and mortgage debts are two single largest items on most households' assets and liabilities. The Federal Housing Finance Agency (FHFA) sets a conforming loan limit (CLL) under which the loan is eligible for purchase by Freddie Max and Fannie Mae. Such regulatory requirement directly influences mortgage rates through the purchase activity of the government-sponsored enterprises (GSEs). More generally, if a household is purchasing a house valued near the CLL, there is very strong and salient incentive to only borrow just below it. The reason is that if you borrow more than the CLL, you pay a higher average interest rate on the entire mortgage balance. This regulatory policy creates a notch in one's budget constraint when taking a mortgage (More is explained in Section 2 & 3), and a bunching effect, meaning people will generally avoid taking out loans above the CLL but instead bunch to the limit at least theoretically (DeFusco & Paciorek, 2014). Under this setting, it will be meaningful to estimate the bunching mass, and explore whether there are correlations between bunching estimates across groups of different gender, ethnicity, and race. We also try to analyze if groups with different loan purposes will bunch differently. Using regressions of our bunching estimates on groups characteristics mentioned above, this paper concludes that groups of different gender, ethnicity, and races indeed bunch differently, and that difference is statistically significant.

2 Literature Review on Bunching Theory

Traditional Bunching theory was initially developed by Burtless & Hausman (1978) to study the individuals' earning response on non-linear budget set. They started from the observation that income tax and transfer system create a piece-wise linear budget set with kink points. However, bunching theory has not been widely adopted until recent years because of the increasing release of administrative data. As a general application, bunching theory is used for researchers who realize features of discontinuities around specific points in the data, where they try to explore individuals' behavioral responses and estimate the structural parameters (Kleven, 2016).

To explain more specifically about the recent popularity of the bunching theory, we need to answer two questions: (1) what are the discontinuities around specific points and (2) why can we only use administrative data for bunching research.

Generally speaking, discontinuous points are direct results of regulatory policies implemented by government sectors. There are two kinds of such points which appear in different settings and are followed by different designs of bunching. One is called a kink point, which by definition, is a discrete change in the slope of individuals' choice sets (Saez, 2010). The most well-known example is the U.S. income tax system where the U.S. government changes the marginal tax rate on certain specific income levels. Another discontinuity is called a notch point which, by definition, is a discrete change on the level of individuals' choice sets, developed initially by Kleven & Waseem (2013). Although notch model is originally developed in the background of the Pakistan income tax schedule settings, the concept of a notch point is widely used in many non-tax system settings, such as the mortgage interest rate schedule which this paper is focusing on.

To answer the second question, as explained by Kleven (2016), we should realize one important nature of bunching: in local interval, households change their decisions and move to specific points nearby. This nature of bunching requires data with large sample size and each entry to be very precise. These requirements are exactly fulfilled by administrative data. As a result, the recent increasing availability of such data promotes the development of bunching theory.

Our paper uses the settings of mortgage market which we could easily obtain administrative data like HMDA and CoreLogic (we will introduce these two data sets in detail in Section 4). Unlike the dominant trend of using the kink model to deal with bunching, notch model is more suitable for estimating bunching in the U.S. mortgage market. The reason is that the government policy states that once the mortgage amount exceeds the CLL, the borrower pays a higher average interest on the entire balance, which creates a notch instead of a kink.

As the key idea of the notch model (which a formal and technical discussion is included in Section 3), a notch point causes a discontinuity on the level of one specific value, such as income tax rate and mortgage interest rate. After this discontinuity appears, household's budget constraint line changes and therefore creates an impact on household's decision of utility maximization. Households within a range of interval will strictly prefer the notch point (or the cutoff) so those who originally locate above the cutoff will then move to a point exactly at or just below the cutoff. This condition will show a clear gap on the right-hand side of the cutoff in the density distribution diagram and households who are previously in the gap will eventually bunch to the notch point.

3 Methodology

In our research, we adopt the methodology from Defusco and Paciorek, who modified the baseline notch model into the mortgage market. Defusco and Paciorek posited that households live for two periods, assuming that each household purchase one unit of house in the first period at an exogenous price p. Households can finance their purchase with a mortgage m, which should not exceed the value of the house p. The interest rate is given by r and does not depend on the mortgage amount in the baseline model. In the second period, Housing is liquidated, mortgage is paid off, and households consume all of their remaining wealth. The households' problem now become the maximization of their lifetime utility by choosing non-housing consumption in each period, denoted by c_1 and c_2. Defusco and Paciorek also defined the income in the first period as y, and a discount factor $\delta \in (0, 1)$. In general, the household solves the following maximization problem:

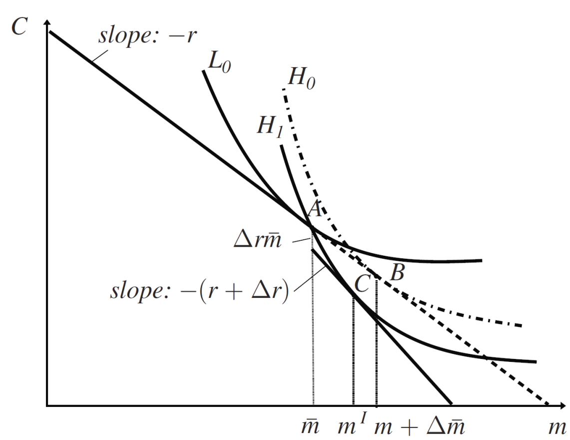
$$max_{c_1,c_2}\{U(c_1, c_2) = u(c_1) + \delta u(c_2)\} \tag{1}$$

$$\begin{aligned} \text{s.t.} \qquad c_1 + p &= y + m \\ c_2 &= p - (1 + r)m \\ 0 \leq m &\leq p \end{aligned} \tag{2}$$

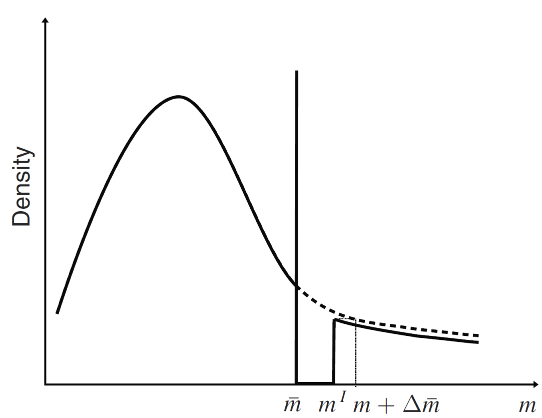
They then introduce a notch to the baseline interest rate. The new interest rate function becomes $r(m) = r + \Delta r \times I(m \geq \bar{m})$. Now, equation 2 is combined to yield the lifetime budget constraint, where:

$$c_1 + c_2 = y - m \times [r + \Delta r \times I(m > \bar{m})] \tag{3}$$

Figure 1. Budget Constraint Diagram and Mortgage Size Density



(a) Figure A



(b) Figure B

The budget constraint and indifference curves of two representative households are plotted in Figure 1 Panel A, where household L is the household that borrows exactly at the CLL $\bar{m}$ (household L has the largest possible δ, so he wants to borrow less in his ability), and household H is the marginal bunching individual with the lowest possible δ in this particular setting. More specifically, all individuals that had earnings in the interval $(\bar{m}, \bar{m} + \Delta\bar{m})$ will now adjust their optimization and bunch to the threshold $\bar{m}$ due to the introduction of the notch. Individuals that originally located exactly at $(\bar{m}, \bar{m} + \Delta\bar{m})$ are the marginal bunching individuals—that is, they are exactly indifferent between the notch point $\bar{m}$ and the best interior point m^I after the introduction of the notch. Those who originally located above $(\bar{m}, \bar{m} + \Delta\bar{m})$ will now stay in the interior of the upper bracket, namely $[m^I, +\infty)$. It should be noticed here that the notch model creates a strictly dominated region $(\bar{m}, \bar{m} + \Delta m^D)$ in the sense that the choice set of people originally located within that region will be strictly dominated by the new optimization point $\bar{m}$, because individuals can increase leisure by reducing their earnings and increase their after-tax income at the same time regardless of their utility. Note here people originally located in the interval $(\bar{m} + \Delta m^D, \bar{m} + \Delta\bar{m})$ will also bunch to the threshold $\bar{m}$, but will be subject to the shape of individuals' indifference curves. In the most extreme case, individual with Leontief preference will not bunch to threshold if they were originally located in the interval $(\bar{m} + \Delta m^D, \bar{m} + \Delta\bar{m})$. However, regardless of the shape of individuals' indifference curves, individuals inside the strictly dominated region will always bunch to the threshold.

So far, we have reviewed the setup of the baseline notch model, but the question remains to be how to actually estimate $\Delta\bar{m}$. Denoting total bunching by B, we can link earnings response to the bunching mass with the following equation:

$$B = \int_{\bar{m}}^{\bar{m}+\Delta\bar{m}} h_0(m)\, dm \;\cong h_0(\bar{m})\Delta\bar{m} \tag{4}$$

where the approximation assumes the counterfactual density $h_0(m)$ is constant on the bunching segment $(\bar{m}, \bar{m} + \Delta\bar{m})$. Figure 1, Panel B shows the density graph of the notch model, and the bunching mass B. Since the bunching mass, or the total bunching, B, can be estimated simply by plotting the data and simulating the counterfactual distribution $h_0(m)$, we can then estimate the bunching interval, $\Delta\bar{m}$, using equation 4.

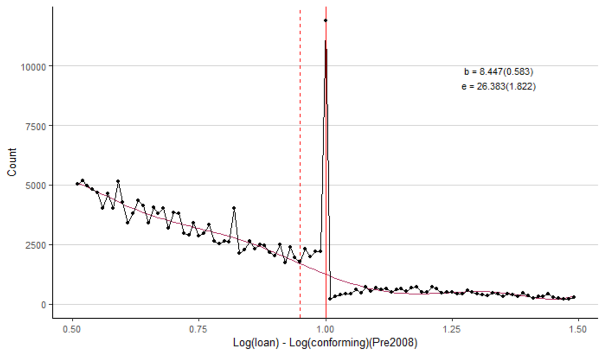
3 Data

To conduct our empirical analysis, we use data from two main sources. The first is a loan-level dataset from CoreLogic, a private vendor that provides information on consumer credit, capital markets, and real estate across the United States. These data serve as our primary source of information on loan and property. The second data source consists of mortgage information collected by the Home Mortgage Disclosure Act (HMDA) platform. HDMA is a regulatory technology application for financial institutions to submit mortgage information on loan and, more importantly, borrowers' characteristics, where correlations between bunching estimates could be found across groups of different gender and ethnicity. Note here the bunching mass will be estimated across groups—that is, each group of people will have a unique estimate of bunching mass. On individual level, however, many people do not bunch because the houses they purchase are either too cheap and they do not need to borrow up to CLL, or too expensive and if they bunch to CLL they will not be able to afford it. In other words, estimated bunching mass cannot capture the bunching behavior of a single individual in a group. We cannot predict how a specific individual will behave supposedly without such CLL policy, and our estimation only suggests that on average how much will an individual bunch if he has certain characteristics.

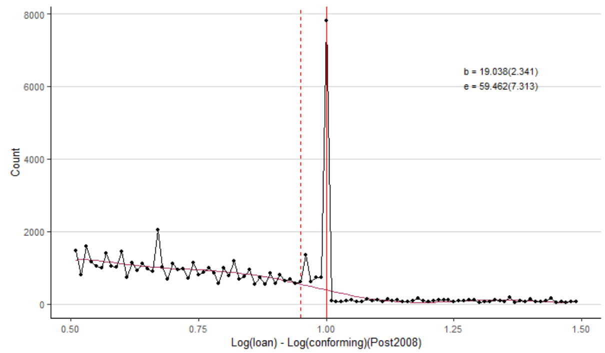
3.1 CoreLogic Data

The CoreLogic data consists of two separate datasets, and the first one, LLMA, includes mortgage transactions in the United States from 1999 to 2021. A single conforming loan limit was set across the United States prior to 2008, but after 2008 was reset each year. Therefore, we also take the other data set into consideration, which consists of the conforming loan limit from each year. These two data sets will be merged into one and then separated into two periods, as the mortgage market was largely changed by the financial crisis in 2008. As shown in Figure 2, a brief glimpse at data shows that the normalized bunching mass(8.447 before 2008, and 19.038 after 2008 as shown in the top right corner) differs significantly before and after 2008.

Figure 2. Bunching Behavior Pre&Post 2008



(a) Figure A



(b) Figure B

Each record in our final data set represents a single transaction and contains information on loan amount, date of transaction, CLL of that year, origination & maturity date, sale price, and other characteristics of the household.

After dropping the transactions whose loan to value ratio is a clear outlier, we then plot the loan size of each individual from the data across the United States, which then generate a loan size density. From there we will estimate the counterfactual distribution and the bunching mass using polynomial regression across different time (more details will be explained in Section 4). We will first conduct a baseline estimation for households in each year, which later will be used to compare with estimations of different groups. Note here we conduct estimation across different time because regulatory policies may change across year and therefore households' preference and bunching behavior may change. In other words, households are more likely to be consistent within the same year—we want to minimize the heterogeneity in this aspect to decrease the amount of noise that need to be dealt with. Also, conducting estimations across time will allow us to see whether households sharing certain characteristics bunch differently over time. We will discuss more about this in Section 4 with our specific strategy and Section 5 with our empirical results.

3.2 HDMA Data

Each record of the HDMA data set consists of the state in which the transaction took place, basic information of the loan, and characteristics about the borrower. After estimating the counterfactual distribution along with the bunching mass, we will correlate the bunching mass estimates with characteristics of borrowers provided, including ethnicity, gender and race. Then we will conduct a regression of bunching mass estimates on these characteristic variables and check for statistical significance. HDMA data also shows the loan purpose of each household—we will also estimate bunching mass on groups that have a loan purpose of refinancing and regular home purchasing.

In conclusion, bunching mass estimation are conducted across four group characteristics—gender, ethnicity, race, and loan purpose. Bunching mass of these groups will be shown as our empirical results in Section 5, and we will also provide analysis about regressions of bunching mass on these group characteristics to show whether their effect on bunching is statistically significant. Lastly, we will provide a brief analysis to show whether households are learning by experience.

4 Empirical Strategy

4.1 Basic Data Cleaning & Manipulation

Before introducing the actual empirical strategies, we need to discuss briefly about the data cleaning and manipulation, since the nature of bunching analysis requires precise estimations, and one single outlier may result in significantly large standard errors of bunching estimation. As we introduced before, there is a reason for the recent popularity of bunching analysis, and that is the increasing availability of the administrative data. So one thing worth mentioning is that in order to provide precise estimations on bunching mass, we need to have enough entries in our data sets regardless of which group characteristic we choose to focus on. In order to run regressions and provide information on significance level on estimated coefficients, we separated our data sets into different states after selecting a specific group characteristic. 50 states are recorded in our data set, excluding areas that do not have enough data to generate estimations with small standard errors. For example, suppose we are focusing on estimating bunching effect of different gender. The first thing we do is to zoom into each of the 50 states and estimate the normalized bunching mass (so they can be compared across different states with different population) of both male and female. Then, we will run regressions of these estimated bunching mass on the dummy variable, gender, treating pairs of estimations from different states as independent observations.

4.2 Estimating the Counterfactual Distribution

In this section, we will introduce the specific empirical methodology we use to estimate the counterfactual distribution. We first take the logarithms of the loan amounts and center them at CLL+1 so that differences are shown in percentage terms (we do not center them exactly at the CLL so we can avoid package complications of binning data and estimating the counterfactual distribution at the origin). Then we group those normalized loan amounts into bins centered at the values m_j, where $j = -J, \ldots, L, \ldots, 0, \ldots, U, \ldots, J$, and count the number of loans in each bin, n_j. Note here $[m_L, m_U]$ is the excluded region around the conforming loan limit. After defining the excluded region, the following regression is fitted:

$$n_j = \sum_{i=0}^{p} \beta_i (m_j)^i + \sum_{k=L}^{U} \gamma_k \times I(m_k = m_j) + \varepsilon_j \tag{5}$$

And the estimated counterfactual number of loans in each bin is calculated along with bunching and missing mass as:

$$\hat{n_j} = \sum_{i=0}^{p} \hat{\beta}_i (m_j)^i \tag{6}$$

$$\hat{B} = \sum_{j=L}^{0} (n_j - \hat{n_j}) = \sum_{j=L}^{0} \hat{\gamma_j} \tag{7}$$

$$\hat{M} = \sum_{j>0}^{U} (n_j - \hat{n_j}) + \sum_{j>0}^{U} \hat{\gamma_j} \tag{8}$$

As we introduced before, in order to have an estimation of the bunching interval, $\Delta\hat{\bar{m}}$, we need to have an estimation on bunching and the counterfactual distribution. Bunching is estimated using equation 7, and the counterfactual distribution is estimated by $\hat{g}_0(\bar{m}) = \sum_{j=L}^{0} \frac{\hat{n_j}}{|(m_0 - m_L)/L|}$.

In short, we first normalize our data around the CLL and recenter them to 1. After that, we bin our data and perform the estimation methodology introduced above to estimate the counterfactual distribution and the bunching mass. The regressions of bunching mass on various group characteristics we run later are simply ordinary least squares regressions, and we will not introduce that anymore here.

5 Empirical Results

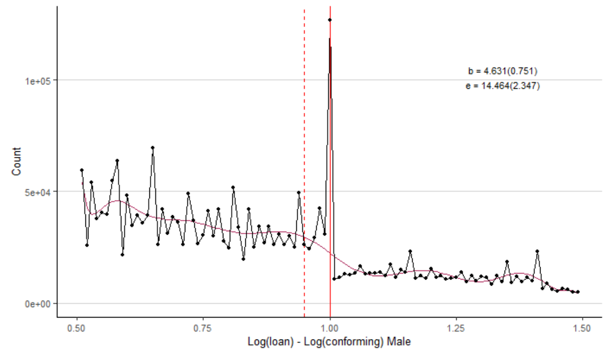
5.1 Gender Effect on Bunching

Although more than seventy percent of the mortgages are marked to be borrowed by male, there are still two million observations in our data set marked to be borrowed by female, so our bunching estimation for female has a decent standard error. Figure 3 shows the estimated counterfactual distribution and normalized bunching mass of both male and female. The normalized bunching mass for male is 4.631 with a standard error of 0.751, and the normalized bunching mass for female is 3.973 with a standard error of 0.755. A simple OLS regression further shows that keeping other variables same, an average male tends to bunch 0.622 more units than female at a significance level of 0.001, with an extremely small p-value.

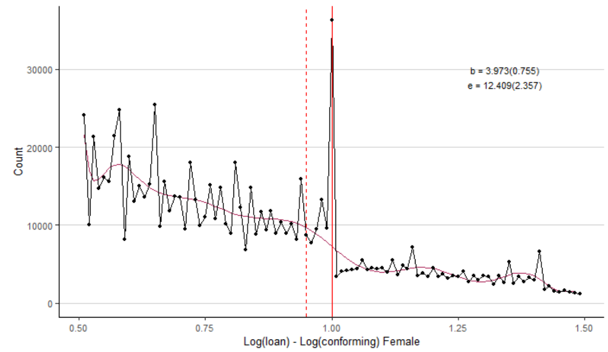
5.2 Bunching Estimates of Different Ethnicity

More than ninety percent of the mortgages are marked to be borrowed by individuals with ethnicity other than Hispanic, and only about seven percent of our data can stand for Hispanics. With that in mind, Figure 4 shows the estimated counterfactual distribution and normalized bunching mass of both Hispanics and other ethnicity. The normalized bunching

Figure 3. Bunching Behavior of Male&Female



(a) Figure A



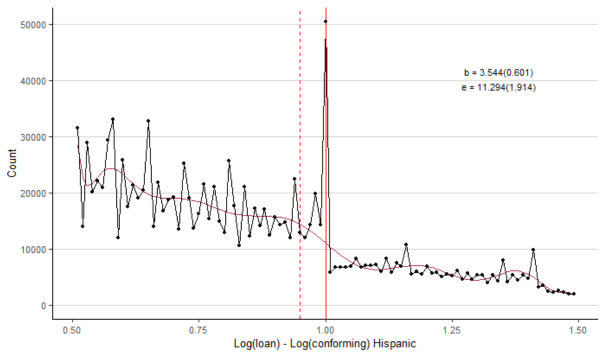
(b) Figure B

mass for Hispanics is 3.544 with a standard error of 0.601, and the normalized bunching mass for other ethnicity is 4.715 with a standard error of 0.799. A simple OLS regression further shows that keeping other variables same, an average Hispanic tends to bunch 0.806 less units than other ethnicity at a significance level of 0.05, with a p-value of 0.0639.

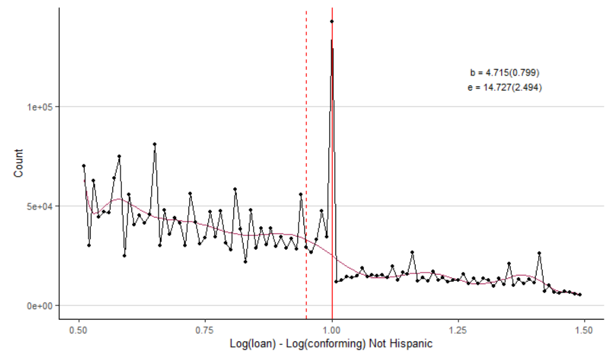
5.3 Bunching Estimates of Different Race

More than sixty percent of the mortgages are marked to be borrowed by White Americans, and about ten percent of our data can stand for African Americans. With that in mind, Figure 5 shows the estimated counterfactual distribution and normalized bunching mass of both African Americans and White Americans. The normalized bunching mass for African Americans is 2.391 with a standard error of 0.463, and the normalized bunching mass for White Americans is 4.78 with a standard error of 0.834. Just for comparison, we also estimate the normalized bunching mass for Asian Americans, which is about 4.44 with a standard error of 0.685. The numbers here show a significant difference in terms of bunching and we further check if the difference here is statistically significant. A simple OLS regression shows that keeping other variables same, an average African American tends to bunch 3.0175 less units than White American at a significance level of 0.001, with a p-value approaching zero. The difference here is salient and huge, so we believe that

Figure 4. Bunching Behavior of Hispanic&Nonhispanic



(a) Figure A



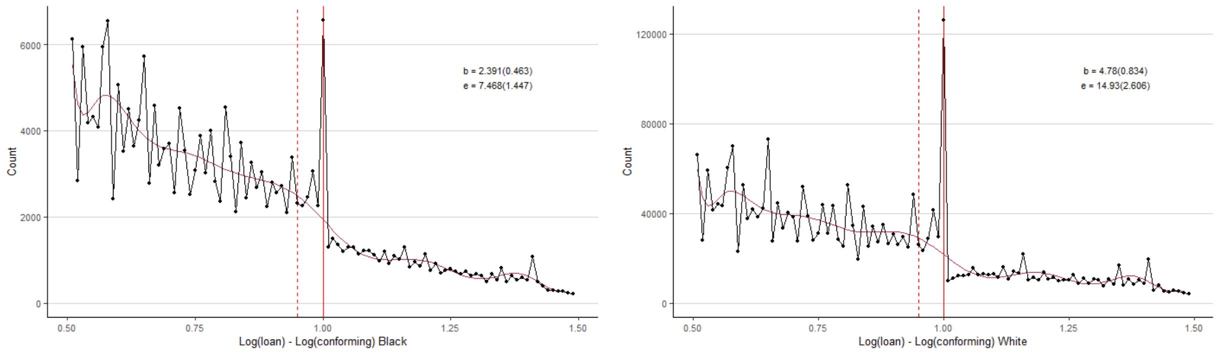
(b) Figure B

further studies exploring the reasons of African Americans not bunching as much will be interesting. This is important because the very point of our paper is to provide evidences on differences in bunching mass so that future studies can explore to explain such differences and even propose bunching as a proxy to measure individuals' ability on making other large stake decisions.

5.4 Bunching Estimates of Individuals With Different Loan Purpose

The HMDA dataset also provides us information on the occupancy status of each property. From that information we identify individuals' loan purposes to be principal dwelling and investment. More than ninety-eight percent of the mortgages are marked to be borrowed by individuals with a loan purpose of principal dwelling after 2008, and only about two percent of our data can stand for investors. With that in mind, Figure 6 shows the estimated counterfactual distribution and normalized bunching mass of both individuals with a loan purpose of principal dwelling and investment. The normalized bunching mass for investors is 5.129 with a standard error of 1.069, and the normalized bunching mass for individuals with a loan purpose of principal dwelling is 4.306 with a standard error of 0.709. We do not perform any regression here in this case since we do not have enough data of investors to have precise estimates on their bunching behavior across

Figure 5. Bunching Behavior of African Americans&White Americans



(a) Figure A

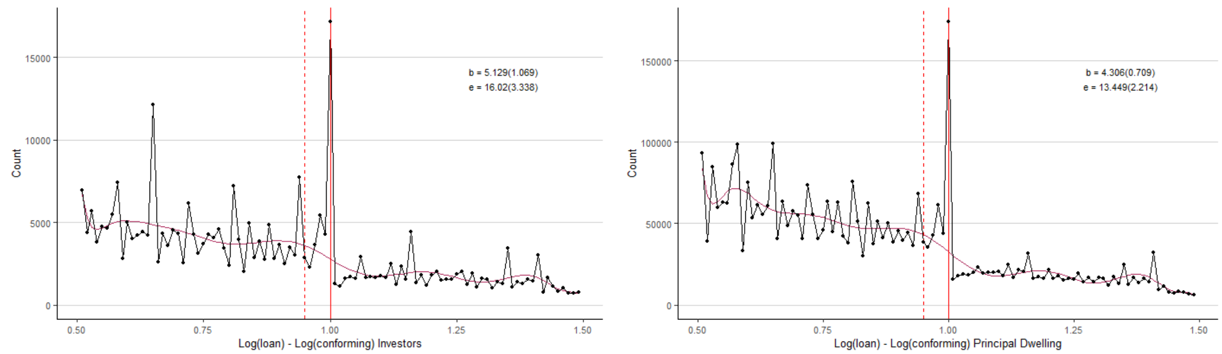
(b) Figure B

different states—certain states do not have enough investors to generate such estimation.

6 Conclusion

In this paper, we focus on estimating the counterfactual distribution and the bunching mass of groups with different characteristics, including gender, ethnicity, race, and loan purposes. There are potentially other characteristics that other data sets might have and one can use a similar methodology introduced in this paper to conduct estimations and interpretations. In short, bunching mass, as a group level estimation, provide us a quantitative measure of people's behavioral response to a regulatory policy that creates a discontinuity in one's budget constraint. In other words, keeping other characteristics same, how will an average individual with certain characteristic react to such policy, compared to individuals categorized otherwise in the same characteristics. Although this paper only shows differences of bunching mass in terms of four group characteristics, where only three of them are statistically significant, it points out that for many groups, people are reacting very differently to such a regulatory policy and they are making significantly different decisions even though the potential stake here is very large. This inspires us to further propose bunching as a proxy of people's ability to make important decisions like this in financial markets. Note here, the bunching mass we

Figure 6. Bunching Behavior of Investor&Non-Investors



(a) Figure A (b) Figure B

measured here is actually a revealed preference measure of such ability since we were analyzing their actual behavioral reactions to a specific regulatory policy.

Indeed, there are still many caveats we did not clean out. It should be noticed here that in real-world scenario, a single individual fails to bunch because of various reasons. Frictions like information cost should be ruled out if we want to recover the structural estimation of people's ability to make large stake decisions. Also, people may have different preferences, especially for people living in different states. Certain historical policies and major events (like the subprime mortgage crisis in 2008) may also change people's preference. However, although such heterogeneity should also be considered in the model we introduced previously, ruling them out may be complicated, since our bunching estimation depends on large data set and categorizing people into different groups with similar preference will very likely jeopardize the precision of our bunching estimates. Fortunately, with recent increasing availability of administrative data, we might find potential solutions to these limitations in future research.

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