Taxes and Borrower Behavior: Evidence from the Mortgage Interest Deductibility Limit

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Abstract:
This paper examines the effect of mortgage interest tax deductibility on mortgage borrowing. I estimate bunching in the loan distribution at the deductibility limit where a discrete change in the marginal interest rate occurs. Using data on 2004-2016 mortgage originations, I estimate a counterfactual distribution that accounts for bunching at salient loan amounts. Findings suggest an excess of about 53,000 loans at the deductibility limit, or 4.4% of the sample. The level of bunching implies an average reduction in borrowing around the limit of 9.4 percent, and mortgage demand elasticities between -0.132 to -0.115 for home purchase loans.

JEL: G21; H24; G18; R22

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I. Introduction

Housing markets in the United States are subsidized by preferential treatment in the tax code. At the federal level, the tax preferred status of housing is predicted to result in $3.28 trillion in forgone revenue over the next decade.[1] There are many ways housing is preferred in the federal tax code, including the exclusion of imputed rent and the deductibility of property taxes, but arguably the most visible to consumers is the mortgage interest deduction (MID),[2] which alone is estimated to cost $896 billion over the next decade. Expenditure on the MID is likely to be smaller than forecast due to the recently passed Tax Cuts and Jobs Act (TCJA) (P.L. 115-97), as this law lowers deductibility limits on new mortgages (from $1million to $750,000), increases the standard deduction, and eliminates home equity loan interest deductibility. Although the TCJA surely downsizes the MID in terms of foregone revenue, the MID is likely to continue to affect housing markets through the dramatic changes brought about by the TCJA, the legislated expiration of those changes in 2025, and the role of U.S. state-level policies.

Understanding the MID may be particularly important in housing markets because it lowers the price of purchasing additional housing using debt financing, which may result in increased consumer borrowing. High debt to equity levels and negative equity are associated with foreclosures (Bhutta et al. 2010), monthly mortgage payment reductions are causally linked

[1] Forgone revenue figures are from the 2017 Analytical Perspectives of the U.S. Budget, Tax Expenditures section produced by the Office of Management and Budget. The housing expenditures included in this calculation are: the exclusion of imputed rental income, the mortgage interest deduction, the exclusion of capital gains on the sale of housing, the property tax deduction, and the low-income housing tax credit. These estimates do not include changes from the Tax Cuts and Jobs Act that limit mortgage interest deductibility to a $750,000 loan, increase the standard deduction, limit the property tax deduction, and eliminate home equity loan deductibility.

[2] The MID allows for interest paid on a mortgage used for home purchase to be deducted from income for tax purposes. Taxpayers can deduct interest paid on a mortgage from a primary and one secondary residence from gross income. Only taxpayers that itemize deductions can claim the MID. Only the cumulative debt below the MID limit is permissible for a tax deduction.

to reductions in mortgage default (Fuster and Willen 2017), and household mortgage debt is linked to slowed growth in the overall economy (Mian, Sufi, and Verner 2017).

Most of the previous work on the MID examines how it effects homeownership (Glaeser and Shapiro 2003; Hilber and Turner 2014), home prices (Martin and Hanson 2016), the size of home purchased (Hanson 2012a), and government revenues (Poterba and Sinai 2011). More recently, Sommer and Sullivan (2018) simulate how eliminating the MID would impact housing markets using a calibrated equilibrium model. Despite the likely link between the MID and borrower behavior, empirical work to date has not produced a causal estimate of the relationship between the policy and U.S. consumer borrowing.[3]

This paper identifies the effect of the MID on borrower behavior using the budget constraint kink created by limits on the tax deductibility of interest. Prior to recent tax law changes, mortgage interest deductibility was limited to home purchase loans of $1 million.[4] Tax deductibility limit changes the net-of-tax interest rate for borrowers on marginal borrowing over the limit, creating a kink in the budget constraint for borrowers. Recent work by DeFusco and Paciorek (2017) examines bunching in the mortgage distribution around conforming limits,[5] but this is the first paper to investigate how the budget kink created by tax deductibility limits affects

[3]Hendershott and Pryce (2006) use deductibility limits in the U.K. housing market to estimate the relationship between tax deductibility and mortgage demand. The Hendershott and Pryce (2006) estimates rely on creating a two-stage model that uses a predicted probability a home-buyer decides to purchase a home above the deductibility limit. Follain and Dunsky (1997) and Dunsky and Follain (2000) examine the sensitivity of mortgage borrowing using data from the Survey of Consumer Finances on mortgage size and variation in estimated individual marginal tax rates that occurs because of the Tax Reform Act of 1986.

[4] The $1 million home purchase cap applies to married filing jointly and single tax filers, a $500,000 cap applies to married filing separately tax filers. HELOC loans are subject to a $100,000 cap for married filing jointly and single tax filers, a $50,000 cap applies to married filing separately tax filers. Internal Revenue Service individual summary statistics show that in 2014, the last year of data available at the time of this writing, 56 percent of itemizing tax filers file a return under married filing jointly status, 32.5 percent as singles, and 2.5 percent as married filing separately.

[5] The conforming loan limit is the largest loan eligible to be purchased by Fannie Mae and Freddie Mac. Conforming loan limits have a national minimum and maximum but are generally based on local market home prices. DeFusco and Paciorek use a sample of loans from California in their analysis.

borrower behavior. The current work also extends the general literature on bunching by considering that the policy-induced kink points may coincide with salient loan amounts that also cause bunching.

The elasticity estimates in DeFusco and Paciorek (2017) focus on a part of the mortgage distribution that includes smaller sized mortgages,[6] is geographically limited to California, and covers the time period 1997-2007. Observable borrower characteristics across the mortgage size distribution are dramatically different– for example average income for a borrower with a new mortgage between \$300,000 and \$400,000 is \$134,000, while for a borrower with a new mortgage between \$900,000 and \$1,000,000 average income is \$365,000.[7] Income differences as well as borrower wealth, geographic location, and changes to the mortgage market across time could all contribute to a changing mortgage demand elasticity, highlighting the need to consider alternative estimates. In addition, there is an emerging literature that suggests consumers may respond differently to tax-induced price differences than they do to price differences induced by other factors, making it important to understand the direct effects of the MID (as opposed to market interest rates) on borrowing.

I use data on a national sample of 2004-2016 mortgages from the Federal Financial Institutions Examination Council (FFIEC) to estimate bunching at the MID kink point using a counterfactual distribution that accounts for bunching at salient loan amounts. I use the bunching estimate to determine the magnitude of the borrower's behavioral response as measured by the reduction in borrowing that occurs for loans around the limit. Using marginal tax rates to create a

[6] The national conforming loan limit for a mortgage between 1997 and 2007 ranged from \$214,600 to \$417,000.

[7] Reported averages are for first lien mortgages on owner occupied 1-4 family homes from 2016 Home Mortgage Disclosure Act Data.

price change at the limit, I also estimate elasticities of mortgage borrowing with respect to after-tax interest rates.

I find evidence of substantial bunching at the MID home purchase lending limit. Findings that account for salient loan bunching at other $1 million increments and $100,000 increments in the distribution suggest an excess of 53,373 loans bunched at the MID limit. The number of bunched home purchase loans represents approximately 4.4 percent of the sample of loans. The level of bunching, and estimated counterfactual number of loans, implies an average reduction in the amount borrowed between 9 and 10 percent and mortgage demand elasticities for home purchase loans between -0.132 and -0.115 for home purchases.

The estimated elasticities I find are about double the size estimated by DeFusco and Paciorek (2017), suggesting that borrowing at the MID limit is more sensitive to interest rate changes than borrowing near conforming loan limits. Using the estimated elasticity of mortgage borrowing, I simulate how the recent reduction in MID limit from $1 million to $750,000 is likely to impact borrowing across U.S. states. Simulation results suggest an aggregate annual reduction in mortgage borrowing on the order of $350 million among borrowers that lose marginal tax deductibility from the TCJA. Applying the estimated elasticities to the larger mortgage market, I estimate that from 2004-2016 the MID induced about $30 billion in deadweight loss, with two-thirds of the welfare loss coming in the 2004-2007 period.

The remainder of the paper begins with a short background on the mortgage interest deduction and a simple model of how the deductibility limit induces behavioral change. Section III presents the empirical estimation strategy. Section IV introduces the data used in estimation. Section V presents results for the primary estimation strategy and several alternatives. Section VI implements a validity check on the estimation strategy that explores the possibility for lender behavioral change. Section VII presents applications of the estimated elasticity of mortgage demand: a deadweight loss calculation and a simulation analysis of the TCJA change to the MID cap. The final section of the paper concludes.

II. Policy Background and Theoretical Framework

Interest paid on a mortgage loan has been deductible since the inception of the federal income tax in 1913. In the original design of the federal income tax, filers could deduct all interest payments from income, mortgage interest was not unique (Ventry, 2010). With the passage of the Tax Reform Act of 1986, interest paid on personal loans like credit cards, was no longer deductible; however, the MID became an explicitly allowed itemized deduction. The Omnibus Budget Reconciliation Act of 1987 (OBRA87) clarified the rules for the MID, limiting interest payments to two residences per tax filing unit (a primary and secondary), and capping the amount of total debt for home purchase at $1 million per tax filing unit (Ventry, 2010).[8] The limits from OBRA87 were in place until the end of 2017, when the TCJA lowered the cap on a qualifying mortgage to $750,000. Notably, the $1 million cap applies to all loans made before December 14th, 2017. In addition to the federal MID, many states that tax income explicitly

[8] The data used in this paper are limited to the amount of debt used to purchase a primary residence at the time of mortgage origination. Because the MID is available for both a first and second mortgage, individual borrowers could find the total deductibility limit binding at lower mortgage amounts in the home purchase distribution than the $1 million limit. Total indebtedness being spread between a primary and secondary mortgage will not affect bunching around the $1million limit in this paper unless there are a substantial number of these loans very close to the $1million limit (for example, many $950,000 loans on a primary residence accompanied by secondary loans where the total exceeds the MID limit). I may, however, be underestimating the total amount of mortgage bunching throughout the distribution by not observing borrowers that bunch on cumulative (first plus second) debt of $1 million.

allow for mortgage interest deductibility or do so passively by adopting federal definitions of itemized deductions.[9]

The change in deductibility that occurs at the MID limit, coupled with high marginal tax rates on borrowers with mortgages of $1 million, creates a large discontinuous increase in the marginal net (after deduction) mortgage interest rate. Figure 1 demonstrates the change in the net marginal interest rate that occurs at the MID limit for tax filers in the top two federal tax brackets and across states with different top marginal tax rates. The figure demonstrates that the change in the net marginal interest rate is large, and discontinuous at the MID limit. For a market interest rate of 5 percent, net marginal interest rates more than double in California (moving from 2.405% to 5%), while they rise by 38 percent (from 3.6% to 5%) for tax filers in non-MID states in the 28 percent federal bracket.

The discontinuity in the net marginal interest rate that occurs at the MID limit creates a non-linearity in a consumers budget constraint when choosing between mortgage size and consumption of other goods. DeFusco and Paciorek (2017) lay out the basic theoretical model of consumer response to a non-linearity in the mortgage interest rate schedule. The DeFusco and Paciorek context examines a "notch"[10] around the federal conforming loan limit, and the resulting bunching by consumers immediately below that notch. DeFusco and Paciorek present a two-period model of mortgage choice based on Bruckner (1994) that shows how consumers

[9] As of the last year of data in this paper (2016) the following states allow an MID: AL, AR, AZ, CA, CO, DC, DE, GA, HI, IA, ID, KS, KY, LA, MD, ME, MN, MO, MS, MT, NC, ND, NE, NM, NY, OK, OR, SC, UT, VA, and VT. WI allows a state credit to be claimed that is a percentage of federal itemized deductions. Only RI and LA have changed state policy in the years of data used in this paper, RI eliminated the state MID in 2011 and LA adopted a state MID in 2007.

[10] A notch occurs when incremental changes in behavior cause discrete changes in net tax liability (Slemrod 2013). This happens when the full value of a transaction is taxed upon crossing a threshold value, rather than just the marginal value over the threshold. See Kopczuk and Munroe (2015) for an analysis of a notch in the New York/New Jersey real estate market generated by a 1 percent transactions tax on property sold for $1 million or more. Also see Slemrod, Weber, and Shan (2017) for an examination of how a transaction tax notch in the District of Columbia housing market affects sales price manipulation and ultimately welfare.

trade-off between lifetime consumption and size of mortgage, and use the model to show how non-linearities in the mortgage schedule result in bunching behavior by consumers.

The intuition for the MID case is similar to the conforming loan limit case presented in DeFusco and Paciorek, but instead of a notch in the mortgage schedule, the cap on the MID creates a “kink” or change in slope. A kink occurs because all mortgage interest is deductible below the limit; however, marginal dollars borrowed over the limit are not deductible. Figure 2 shows the budget constraint change resulting from the MID cap (m_{cap}) for borrowers that only have access to the federal MID and pay marginal tax rate τ_f,(panels A and B), and for borrowers living in states that have a MID and pay the additional, τ_s, marginal income tax (panels C and D).

Below the cap, the slope of the budget constraint is $-r(1-\tau_f)$ in Panels A and B, but is $-r(1-\tau_f-\tau_s)$ in Panels C and D. The net interest rate increases by $r(\tau_f)$ for marginal borrowing over the MID cap in places without a state MID, while the net interest rate increases by $r(\tau_f+\tau_s)$ in places with a state MID. Allowing deductibility at rate τ_s flattens the pre-cap budget constraint (Panels C and D) relative to the federal only model (Panels A and B), but does not change the slope of the budget constraint beyond the MID cap (it is always -r).

Indifference curves in Panel A of Figure 2 show preferences for a representative individual with the largest pre-kink mortgage amount ($m_{cap}+\Delta m_{1}$) that moves to a mortgage of size m_{cap} under the kinked budget constraint with federal deductibility. Panel B shows that individuals with stronger preferences for mortgages will reduce their mortgage size as a result of the cap but may not end up locating at the kink. It is also possible that individuals with different preferences may have located at m_{cap} even without the kink in the budget constraint, something that is accounted for empirically in estimating the counterfactual distribution.

Comparing Panel A with Panel C of Figure 2 shows what happens as a result of the cap when the discount applied to pre-cap mortgages becomes larger. The flatter sloped budget line means that the marginal bunching borrower will come from further out on the mortgage distribution, or that there will be a larger behavioral change from the marginal borrower in places that have additional state MIDs. Panel D shows the case of a non-bunching borrower in a place with a state MID. Panel D shows that the MID cap will reduce borrowing in places with an additional state MID more than in places with the federal MID only, or that $m_{cap}^{**} > m_{cap}^{*}$, but that some borrowers may still not locate at the kink.

Unlike the notch case in DeFusco and Paciorek (2017), where there is a range of mortgage values where no individuals will locate, other preference-types will still locate on the interval between m_{cap} and $m_{cap}+\Delta m$ in the kink case, but the density of the mortgage distribution will change around the kink point. The intuitive behavioral predictions from the model are that the kink in the budget constraint will cause an increase in the density of mortgages exactly at $m_{cap,}$ and a decrease in density of mortgages between the cap and $m_{cap}+\Delta m$. The model also predicts that $m_2 > m_1$, or that the marginal bunching individual will reduce their mortgage size more when exposed to a greater price increase (as a result of lost tax deductibility on marginal borrowing over m_{cap}).

III. Empirical Estimation

I follow empirical work in Saez (2010) and Chetty et al. (2011) to create an empirical estimate of the amount of bunching that occurs as a result of the budget kink at the MID cap.[11] The primary bunching estimates rely on the net interest rate variation that occurs at the federal $1

[11] The procedure using a notch, rather than a kink, described in Kleven and Waseem (2013) and DeFusco and Paciorek (2017) is the same for the initial bunching estimate, but notches also allow for estimating the missing mass in the distribution resulting from a set of choices that are inferior to locating at the limit.

million limit. I also use variation across states with differing MID policy and marginal tax rates to explore how bunching at the MID limit changes.

Using the bunching estimate as a base, I create an estimate of Δm, or the largest loan amount affected by the cap (as a percentage of the MID limit) and use this to describe the behavioral response to the kink in the budget constraint. Combining the empirical estimates for Δm with the change in net interest rate, I create estimates for the elasticity of mortgage borrowing with respect to interest rates net of the MID subsidy.

An estimate of *excess* bunching in the mortgage distribution resulting from the MID limit relies on creating a counterfactual distribution to compare with the actual distribution of mortgages. To create the counterfactual distribution, I start with the following regression:

$$n_j = \sum_{i=0}^{d} \beta_i s_j^i + \sum_{k=l}^{u} \delta_k \mathbf{1}\left(b_k = b_j\right) + \gamma \mathbf{1}\left[s_j = r\right] + \varepsilon_j \quad (1)$$

Where n_j is a count of the number of loans in size bin *j*, there are *N* bins created in one percent bins relative to the MID limit of loan size s_j, with the distribution of loan size centered on the MID limit at *j*=0.[12] The term under the first summation is a degree *d* polynomial in loan size. I estimate (1) using a range of values for *d*, and consider an optimal choice of *d* based on the polynomial the minimizes the sum of absolute value difference between predicted and actual counts. The term under the second summation is a set of indicator variables (where **1** represents the indicator function) to represent the region around the MID limit that is excluded from creating the counterfactual distribution. The MID limit of $1 million is in the excluded region in

[12] The size of the bin width is a choice in other bunching estimator applications, for the data used in this paper, loan amounts are rounded to the nearest thousand dollars, making it the smallest possible bin width.

all specifications, and I explore sensitivity to a range of values for the excluded region around the limit.

Estimating using equation (1) differs from the standard regression used in the bunching literature by including the term $\gamma\mathbf{1}[s_j = r]$. This term represents a series of indicator variables for salient loan amounts, where borrowers may bunch even without policy changes. [13] The standard identifying assumption in estimation without adding a term for salient indicators is that the loan size distribution would be smooth if not for the discontinuous change in net marginal interest rates caused by the MID limit. Figure 3 shows the mortgage distribution centered around the MID limit demonstrating the lumpiness at other parts of the distribution besides the MID limit, suggesting that a smooth counterfactual will not give an accurate prediction. I use various values of r to represent salient-number loans in increments of $1,000,000, $100,000, $50,000, and combinations of these values. The indicators for $1,000,000 amounts rely on loans that exceed the MID cap by at least $1 million, and I use data on loans up to $5,000,000 to produce these estimates.[14] The primary assumption behind identifying bunching using the salient indicators is that bunching at the $1,000,000 limit would have been similar to bunching at other salient loan amounts if not for the change in tax treatment.[15]

[13] This may happen, for example, if borrowers exhibit left-digit bias in deciding on a loan size. The idea behind left-digit bias is that more attention is given to the left-most digit of a number than other digits (Poltrock and Schwartz 1984; Hinrichs, Berie, and Mosell 1982). See Busse et al. (2013) for an example of left-digit bias showing that retail price and sales volume are higher for automobiles with mileage less than 10,000 mile increments compared with price and volume of automobiles with slightly more than a 10,000 mile increment. Lacetera, Pope, and Sydnor (2012) is an example of left-digit bias in the wholesale automobile market.

[14] Because the number of loans bunched at round 100k and 50k intervals is increasingly small for loans in excess of $2 million dollars, I use round loan indicators that account for $100,000 increments between $600,000 and $1,900,000, inclusive. For the same reason, I use $50,000 indicators for loans between $650,000 and $1,950,000. Adding indicators at $100,000 and/or $50,000 increments larger than these intervals creates larger bunching estimates, as the estimated spike at these intervals falls.

[15] The conforming loan limit for certain high-priced areas in the U.S. is also a point where bunching occurs. Including indicator variables for these limits will not improve the prediction of a counterfactual at the MID limit as it never coincides with the conforming loan limit.

After estimating (1), the counterfactual loan count distribution is then created using the predicted values of loan counts, as in:

(2) $$\widehat{n_j} = \sum_{i=0}^{d} \widehat{\beta_i} s_j^i$$

Excess bunching is the difference between the counterfactual distribution and the actual distribution, over the excluded region, up to the limit, or:

(3) $$\hat{B} = \sum_{j=l}^{0} (n_j - \widehat{n_j})$$

Chetty et al. (2011) point out that (3) will over-estimate excess bunching because it does not impose the constraint that the area under the counterfactual and actual distributions be equal. They propose adjusting the counterfactual distribution to the right of the limit upwards until this integration constraint is met. The amount of upward shift is determined by the initial excess bunching estimate being distributed over the distribution of loans to the right of the limit. This is done by estimating the following regression, accounting for the integration constraint:

(4) $$n_j \left(1 + \mathbf{1}[\mathrm{j} > 0] * \frac{\hat{B}}{\sum_{j=1}^{N} n_j}\right) = \sum_{i=0}^{d} \beta_i^I s_j^i \; + \; \sum_{k=l}^{u} \delta_k^I \mathbf{1}\left(b_k = b_j\right) + \gamma \mathbf{1}\left[s_j = r\right] + \varepsilon_j$$

Using the $\widehat{\beta^I}$ estimates from (4) to create a counterfactual loan count distribution, $\widehat{n_j^I}$ adjusted for the integration constraint, the alternative bunching estimate is:

(5) $\hat{B}^I = \sum_{j=l}^{0}(n_j - \widehat{n_j^I})$

The excess bunching estimates, $\hat{B}$ and $\hat{B}^I$ are expressed in the number of excess loans occurring at the MID limit. Standard errors for $\hat{B}$ and $\hat{B}^I$ are calculated using the same procedure in Chetty et al. (2011) and DeFusco and Paciorek (2017). This parametric bootstrap procedure draws from the error distribution in (1) or (4) with replacement to generate a new set of counterfactual loan counts and then recalculates $\hat{B}$ and $\hat{B}^I$. This procedure is repeated (1,000 times) and the standard errors of are $\hat{B}$ and $\hat{B}^I$are defined as the standard deviation of the distribution of replicated $\hat{B}$ and $\hat{B}^I$ estimates.

DeFusco and Paciorek (2017) demonstrate that the number of bunched loans (B) at a discontinuity in the budget constraint can be approximated using the counterfactual density (f_0) along the interval between m_{cap} and m_{cap}+Δm as, $B \approx f_0(m_{cap})\Delta m$. With estimates of bunching (B) and the counterfactual density of the mortgage distribution ($f_0(m_{cap})$), I can solve for the behavioral response Δm, or the point in the distribution where the marginal bunching borrower is estimated to have come from. I use the counterfactual density one bin to the right of m_{cap}, or m_{cap+1}, to approximate the counterfactual distribution beyond the MID limit because the counterfactual density at the MID limit is meant to capture salient bunching and is not representative of the distribution to the right of the limit. Empirically, I estimate Δm as a percentage of m_{cap}, or the percentage reduction in loan size that happens as a result of the net of tax interest rate change.

IV. Data

I use data from the Federal Financial Institutions Examination Council (FFIEC) on mortgages originated between 2004 and 2016 for the empirical work in this paper. This data is commonly referred to as the HMDA data, because it is available as a result of the Home Mortgage Disclosure Act. The HMDA requires lending institutions to collect and publicly report data on all mortgage applications (loans used to purchase, refinance, or for home improvement), and I use the subset of mortgages that are originated for a first lien, on an owner occupied 1-4 family home for the purposes of this paper. HMDA requires nearly all for-profit lenders with assets above an annually determined threshold,[16] and many not-for-profit lenders (subject to different asset criteria), to report on mortgage application and origination activity annually. The HMDA data cover an estimated 80 percent of nationwide lending, and are representative of the general lending market (Avery, Brevoort, and Canner 2006).

The HMDA requires lending institutions to report the loan amount to the nearest $1,000, characteristics of the borrower, and in some cases the terms of the loan, for each loan origination. Borrower characteristics include race, whether the loan was co-signed, and borrower location at the census tract level (among other items). I match each loan to state-year data on the presence of a state MID and the top marginal income tax rate in the state, provided by the NBER TAXSIM model. I use the top marginal rate, rather than the series of state rates, as the HMDA data on income is insufficient to determine a borrower's actual marginal tax rate. In addition, most state top rates set in at income levels below where a $1 million mortgage would be feasible for a borrower.

The HMDA data is ideal for investigating bunching as it contains a large amount of loan data, and specific information about the size of the mortgage. For the purposes of estimation in

[16] The asset threshold for HMDA reporting in 2017 is $44 million and has remined unchanged since 2013 when it was $43 million according to the Consumer Financial Protection Bureau.

this paper, I use only loans between $600,000 and $5 million to create the counterfactual distribution of loans at the MID limit of $1 million. Table 1 shows summary statistics for the sample of loans used in estimation, and the full sample of HMDA loans. The estimating sample for home purchase loans includes just over 1.2 million loans, slightly more than 3 percent of the full sample. Not surprisingly, borrowers in the higher valued loan sample have higher income and are more likely to have a co-signer on the loan. Somewhat surprisingly, the percent of non-white borrowers is over 10 percentage points higher in the high value loan sample.[17]

Table 1 also shows the percentage of loans in the full and estimating sample that is exactly at the MID limit, and the percentage of loans that are for an amount over the limit. The percentage of home purchase loans made for exactly $1 million is 0.16% of the sample, which is about 5 times the average density (0.033%) at a given loan amount. For the purchase sample used in estimation, loans made for exactly $1 million represent 5.2% of the sample, which is 280 times the average (0.018%) density at a given loan amount in the range between $600,000 and $5 million.

Figure 3 shows a histogram of home purchase loans in the sample between $600,000 and $1.4 million, or 40 percent of the MID limit.[18] The density of loans over this part of the distribution is generally declining as loan size increases, with a few major exceptions. Most notably, the distribution shows a dramatic increase in density at exactly the $1million MID limit.

[17] The difference between whites and non-whites in the full and estimating sample is largely a function of many of the loans in the estimating sample originating in California, Florida and Texas- all places with relatively high non-white populations. Over 50 percent of loans in the estimating sample originate in these states. It may also be a function of lower wealth levels among non-white families. Emmons and Noeth (2015) report the average ratio of wealth to income is 2.67 for African American families, 2.9 for Hispanic families, and 5.64 for white families. Minority borrowers purchasing a high-priced home may have high incomes, but lower levels of wealth, and may thus purchase a house using more debt.

[18] Anderson, Clemens, and Hanson (2007) produce a similar figure showing bunching at the $1million MID limit using 2004 HMDA data. Their analysis focuses on the user cost of housing changes that would result from lowering the MID limit and does not attempt to quantify bunching or use it to estimate demand elasticities.

Figure 3 also shows substantially smaller upticks in density at other loan amounts, these are generally other salient values which I account for in estimating the counterfactual distribution.

In all cases, I take the natural log of the loan amount and difference it with the natural log of the MID limit, making a value of zero equal to the MID limit. In all cases, loan data is presented and estimated in one percent bins from the MID limit.

V. Results

This section presents results of the bunching estimates described in the previous section. I present results for a range of specifications that combinations of indicator variables to account for salient number bunching as in equation (8). I follow the primary estimates with robustness checks that vary the degree of polynomial and range of excluded region. I also present results that examine heterogeneity in the primary estimates across the sample period and results that use state variation in MID policy to test for differential bunching. Along with an estimate of the amount of bunching, I present estimates for the behavioral change parameter and finally for the elasticity of mortgage demand.

Bunching Estimates and Behavioral Change

Figures 4 and 5 show the mortgage distribution by size of loan (logged and normalized to the MID limit) and separate counterfactual predictions. Figure 4 depicts the counterfactual distribution estimated without salient loan amount indicators, while Figure 5 uses the procedure with indicators for salient dollar amounts. The indicators pick up much of the variation in the distribution leading up to the MID limit as well as beyond the limit, as evidenced by the overlap between the actual and counterfactual distributions in Figure 5. The counterfactual distribution in

Figure 4 demonstrates that the standard prediction misses some features of the mortgage distribution that are relevant for estimating an accurate counterfactual at the MID limit.

Table 2 shows estimates of $\hat{B}$ and $\hat{B}^I$ using a specification with only a polynomial control, and various combinations of indicator variables accounting for salient number effects. All estimates in Table 2 use an "optimal" polynomial calculation. This calculation uses the polynomial that minimizes the sum of the absolute value of the difference between the actual count of loans and the predicted count across the distribution from among the options considered. I find the optimal degree polynomial in this application is an order 13. All results in Table 2 reflect a range of zero, or only the bunching that exists exactly at the $1 million MID limit.

The results in Table 2 all suggest a substantial amount of bunching in the mortgage distribution at the MID limit. Specifications using the salient number indicators and the standard measure of bunching suggest that there are between 50,512 and 59,886 mortgages or between 4.16 and 4.94 percent of the loan sample, bunched at the MID limit. For comparison, column (1) of Table 2 presents an estimate that does not use salient indicators which suggests bunching of 63,000 loans or 5.19 percent of the sample. The bunching estimates are not sensitive to estimating using the integration constraint as these results are only slightly smaller than the standard results. Bunching estimates using the salient number indicators all have small standard errors relative to the point estimate and are statistically significant in all cases.

Table 2 also presents estimates of the behavioral change parameter, Δm presented in percentage change terms. These estimates reflect the reduction in loan size for a marginal bunching borrower. The salient number specifications in Table 2 show that borrowers reduce their borrowing by between 9.3 and 10 percent, depending on the indicators used to construct the counterfactual distribution. The differences across the combinations of salient number specifications reflect the fact that the estimated amount of bunched loans changes *and* the counterfactual density at the limit changes. The preferred specification uses indicators for both other $1million dollar loan amounts and indicators for $100,000 loan amounts shown in column (5) and suggests that removing the MID results in borrowers reducing their loan size by 9.4 percent with 53,373 loans bunched at the MID limit. All of the Δm estimates have small standard errors relative to the point estimate.

Basic Robustness: Polynomial and Excluded Region

Table 3 shows estimates of $\hat{B}$ and Δm that examine sensitivity to the excluded region around the limit and the degree of polynomial used to create the counterfactual distribution. A range of zero for the excluded region means that only bunching at actual MID limit is accounted for with an indicator variable when creating the counterfactual distribution. Moving to a range of 1% means that 1 bin on each side of the limit is accounted for with indicator variables in addition to the limit itself, as loans are aggregated into 1% bins. Moving to a range of 3% includes indicator variables for 7 total bins in the estimation, the MID limit and the three bins to the left and right.

Table 3 shows that estimates are generally not sensitive to moving the excluded region up to 3% on either side of the limit. Estimates that expand the excluded region show larger amounts of bunching than the zero-limit case, but not substantially so. These estimates show that between 54,904 and 61,443 loans are bunched at the MID limit, or between 4.53 and 5.06 percent of the sample. Bunching results are sensitive to further expansion of the excluded region- as the excluded region goes to 5 bins and beyond, the standard errors begin to get increasingly large relative to the bunching estimate. Estimates of Δm are also not sensitive to expanding the excluded region and remain in the 9-10 percent range.

Table 3 also shows that estimates of $\hat{B}$ and Δm are not sensitive to the choice of polynomial used to construct the counterfactual distribution. Bunching estimates using degree 6, 8, and 10 polynomials all produce magnitudes within a small range of the preferred estimate and all with small standard errors. Behavioral change estimates are all slightly larger for the differing degree polynomials than they are in the preferred specification, but not appreciably so. Using lower degree polynomials than shown in the table produces results that are appreciably larger than the results in Table 3.

Heterogeneity in Sample Years

The mortgage market has undergone substantial changes throughout the sample period covered by the data used to produce bunching and behavioral change estimates in Table 2. The cycle of boom, bust, and recovery during this period coupled with changes in the mortgage regulation landscape suggest that the primary estimates may also change over the period. To investigate this further, I break the data into three time periods, pre2008, 2008-2012, and post2012, roughly corresponding to the boom, bust, recovery in housing and mortgage markets.[19]

Table 4 shows estimates of $\hat{B}$ and Δm across the three identified periods in the data. Bunching at the MID limit exists in all three periods but is substantially smaller in the bust and recovery period than it is in the boom (even represented as a percent of the sample). Bunching estimates in the bust and recovery period are less than half of the size of the equivalent specification for the boom period. The behavioral change parameter is substantially larger in the

[19] The data only has indicators for year when a mortgage is originated, so I cannot be more precise with identifying these time periods.

boom period than the equivalent full sample results, suggesting that the MID cap results in as much as an 18.7 percent reduction loan sizes. Again, the bust and recovery periods display smaller estimated behavioral changes than in the boom, with the bust period being closer to the full sample results.[20]

State MID Policy Variation

The state-level variation in MID policy creates differences in the net marginal interest rate that occur at the MID limit, as shown in Figure 1. Figure 2 demonstrates that when borrowers face a relatively larger net interest rate increase at the MID limit (caused by additional state MID policy or higher marginal tax rates), it will induce a larger behavioral change among borrowers. While the state changes all occur at the $1million limit, they represent different net interest rate increases, and I use this variation to explore how the estimated bunching parameters may change as a result.[21] Two states, Rhode Island (eliminated, 2011) and Louisiana (introduced, 2007) changed their MID policy during the sample years, I also examine differential bunching in these states on either side of the policy change to see if it follows the expected pattern.

Table 5 shows results that separate the HMDA data sample into loans made in states with an additional MID, and loans made in states with only federal deductibility. The results show that states with only a federal MID have a slightly smaller share of loans bunched at the MID limit than places with an added state MID, but the behavioral response estimates are larger in places with a state MID. Depending on the specification, the behavioral response estimate is

[20] As a robustness check on the primary results in Table 2, I removed the worst bust years, 2008-2010 and re-estimated results. Both the amount of bunching (4.6% of sample) and behavioral change (9.2%) are not substantially affected by this restriction.

[21] Kopczuk and Munroe (2015) examine a state level real estate transactions tax in the New York and New Jersey housing market that occurs at $1 million in *sales* price. As a robustness check on the primary results in Table 2, I removed all loans made in New York and New Jersey and re-estimated results. Both the amount of bunching (4.5%) and the behavioral change (9.3%) are not substantially affected by removing loans made in these areas.

about 5.5 percent larger in MID states than it is in states where only a federal MID applies. The pattern of a larger behavioral response for borrowers in places with an additional state MID fits with the prediction in Figure 2.

Table 6 shows bunching and behavioral response estimates for two states that changed MID policy during the years of the data. These results rely on extremely small sample sizes, and suffer from large standard errors, but offer the only possibility to look at a within state policy change in MID generosity. The pattern of bunching and the behavioral response both follow what is expected when the MID is removed (Rhode Island in 2011) or implemented (Louisiana in 2007). Before Louisiana implemented a state MID 2.3 percent of loans bunched at the MID kink and the behavioral response was 4.3%; after implementing a state MID 3.5 percent of loans bunched at the kink and the behavioral response increased to 6.1%. Before Rhode Island eliminated a state MID, bunching was 4.9% of the sample, and behavioral change was 12.2%; after eliminating the state MID, bunching fell to 2.2% of the sample and behavioral change fell to 4.9%.

Mortgage Demand Elasticity

The primary bunching results and extensions using state policy variation all point to a substantial degree of bunching and show a significant borrower behavioral response to the change in net marginal interest rates. Using the behavioral response as the change in quantity, I can estimate the elasticity of mortgage demand for a change in net of tax treatment interest rates that happens at the MID limit.

I calculate the average percentage change in price, or net interest rate, that occurs at the limit as a weighted average of borrowers in the sample based on the state and year of residence to account for differences in state MID policy using the following equation:

$$(6) \qquad \%\Delta p = \frac{-\sum_{t=2004}^{2016}\sum_{i=1}^{51} w_{i,t} * TopMTR_{i,t}}{(1-\sum_{t=2004}^{2016}\sum_{i=1}^{51} w_{i,t} * TopMTR_{i,t})}$$

Where $w_{i,t}$ is the sample weight for loans from a state-year in the sample (number of loans in state *i* for year *t*, divided by all loans), and $TopMTR$ is the average combined top federal and state (including the District of Columbia) marginal tax rate for the years of the sample (2004-2016).

Table 7 shows the calculated average percent increase in net marginal interest rate ($\%\Delta p$) that occurs at the MID limit. This calculation is the same for the baseline and "no salient indicator" estimated samples, but changes based on the composition of states for the MID state sample. In the baseline sample, $\%\Delta p$, or the price increase at the limit is 71.2%. Price changes are larger in MID states, with an 80.4% average increase at the MID limit.

Combining $\%\Delta p$ with the appropriate sample $\%\Delta m$ estimates, Table 7 reports elasticity of mortgage demand calculations with respect to net of tax-treatment interest rate. The elasticities for specifications using the salient indicators range between -0.132 to -0.115, indicating that for a 10 percent increase in net of tax-treatment price, the amount borrowed falls by 1.32 to 1.15 percent. For comparison, the first column of Table 7 shows an elasticity estimate that does not account for salient number bunching. The estimated elasticity using a standard bunching estimate is -0.145, suggesting that borrowers are slightly more responsive to net of tax interest rate changes.

The most comparable study, DeFusco and Paciorek (2017), finds that when interest rates rise by 1 percentage point (100 basis points), mortgage demand falls by between 2 and 3 percent. Translating the baseline elasticities estimated here into a comparable semi-elasticity, the primary results suggest that a 1 percentage point (100 basis point) increase in the interest rate reduces mortgage demand for home purchases by about 6.7 percent. There are several reasons why the estimates presented here could be larger than the DeFusco and Paciorek estimates. The elasticities presented here identify mortgage demand elasticity from a different set of borrowers that may be more price sensitive– the DeFusco and Paciorek estimates use conforming loan limits, which are well below $500,000 in most markets, to identify the mortgage demand elasticity. Borrowers near the conforming loan limit not only have smaller mortgages, but have different characteristics (lower income, different geographic location) than borrowers near the MID limit- these differences may contribute to estimated elasticity differences. The difference in elasticity estimates could also be driven by borrowers being more sensitive to interest rate changes caused by tax treatment than they are to interest rate changes caused by other factors, or that tax treatment changes are more salient. A growing literature suggests consumer demand may be more sensitive to tax-induced price changes than price changes caused by other factors.[22]

VI. Validity Check: Lender Behavioral Changes

A potential confounding factor in using bunching methodology to estimate mortgage demand elasticities is the possibility that lenders are also reacting to the change in tax treatment that occurs at the MID limit by adjusting the gross interest rate. I test for the possibility of a

[22] See Chetty, Looney, and Kroft (2009) for a theoretical model of tax induced price salience. See Chetty, Looney, and Kroft (2009), Hanson and Sullivan (2014), and Rivers and Schaufele (2015) for empirical evidence suggesting that consumers react differently to tax induced price changes than to price changes caused by other factors in a variety of settings.

supply side response by examining the gross interest rate on mortgage loans as a function of the MID limit. If lenders respond to the removal of the marginal subsidy by adjusting gross interest rates for loans over the limit, this will dampen the bunching effect by reducing the marginal interest rate increase that would otherwise occur. [23]

I examine this possibility using a Regression Kink Design (RKD) following Card et al. (2015). The regression kink design tests for a change in slope that happens on either side of a value, in this case the MID limit. I estimate the following Regression Kink Design model:

$$R_{i,s,t} = \alpha + \delta(Loan\ Amt - Limit)_i + \beta(Loan\ Amt)_i * \mathbf{1}(Loan\ Amt > Limit)_i + X_i\gamma + \rho_s + \pi_t + \varepsilon_i \tag{7}$$

Where $R_{i,s,t}$ is the interest rate on a loan in the HMDA data for individual *i*, in state *s*, made during year *t*. I estimate (7) using data on individual loans made for amounts between \$600,000 and \$1.5 million for the purpose of a home purchase during the 2004-2016 period. A caveat to estimating (7) with the HMDA data is that interest rate information is only available for loans where the interest rate exceeds a threshold value. The value of the interest rate threshold varies by year and loan type but is tied to the rate on a U.S. Treasury Bond of similar term to the individual loan. Therefore, I also estimate an alternative for (7) using a discrete measure of whether the interest rate is reported for the originated loan.

I estimate (7) controlling for a variety of individual loan characteristics, X_i, including co-applicant status (an indicator for co-signed loans), race of the primary borrower (an indicator for

[23] Hanson (2012b) examines the gross interest rate change at the \$1million MID limit using 2004 HMDA data and finds that the gross marginal interest rate declines by 3.3–4.4 percent above the MID limit. This result is based on a small sample of 2004 HMDA data, so I revisit the question here for the full 2004-2016 sample.

non-white borrowers), and reported income, in addition to state fixed effects (ρ_s) and year of loan effects (π_t).

Figures 6 and 7 plot the relationship between the loan amount (natural log and normalized around the MID limit) and the continuous (Figure 6) or discrete (Figure 7) measures of the mortgage interest rate. Both Figure 6 and 7 suggest no appreciable change in the interest rate as a result of the MID limit. If anything, interest rates are potentially less likely to be reported (meaning a lower rate, as they do not exceed the reporting threshold) on loans at exactly the MID limit than they are for loans either above or below the limit.

Table 8 shows the results of estimating (7) for the continuous and discrete measures of interest rates. While the interest rate sample is substantially smaller than the full sample of loans because of the limited data available on the interest rate in the HMDA data, it strongly suggests that gross interest rates do not adjust to changing MID policy at the $1 million loan limit. The magnitude of the β coefficient in all specifications is essentially zero (although statistically significant). The coefficients suggest that for every $1,000 borrowed above the deductibility limit, gross interest rates rise by only 0.021% of a standard deviation. At this level, even for a loan $100,000 above the limit, gross interest rates do not adjust more than 2.1% of a standard deviation and move in the opposite direction that one would expect if lenders are trying to smooth the discontinuity that happens because of the tax treatment change. The discrete measure of interest rate availability suggests a similar story, with a slightly larger magnitude, but again the opposite sign of what would be expected from a supply side effect.

The presence of bunching at the value of the assignment variable where a policy change happens generally invalidates the usefulness of the regression kink (or discontinuity) design. This is because the presence of bunching suggests that the assignment variable is being manipulated. In the case of mortgage borrowing, exact manipulation of mortgage size for borrowers would be quite easy as it depends only on the availability of equity to the home purchaser to allow them to substitute away from debt for a given home purchase amount. The RKD results presented here are meant to be a probe into the possibility of a supply side response in the mortgage market, not as definitive evidence that no supply side effect exists.[24]

VII. Applications of Mortgage Demand Elasticity

Welfare Analysis

Following Poterba (1992) and Hanson and Martin (2014) the behavioral change parameter estimated by bunching can be used to give an idea about the welfare consequences of subsidizing mortgage purchase through the tax code. To get an idea of the welfare consequences of the mortgage interest deduction in the mortgage market, I start with Poterba (1992) in applying a simple Harberger triangle formula for deadweight loss (DWL):

$$DWL = 0.5\varepsilon RH(dR)^2 \tag{8}$$

Poterba (1992) examines welfare consequences for the larger housing market, and thus sets R as the user cost of housing, and H as the quantity of housing, where dR is the user cost change resulting from the tax treatment of housing. I limit my setting to only the mortgage market and thus replace RH with the amount of mortgage borrowing and dR with the net of subsidy interest rate change caused by the MID. I weight the amount of mortgage borrowing by

[24] I also investigated the behavior of loan denials around the MID limit. RKD tests suggest no change in loan denial behavior around the MID limit; however, a graphical analysis clearly shows a lower denial rate for applicants at exactly the MID limit (lower than the denial rate for mortgages on either side of the limit). While this could be interpreted as a supply side effect, it is consistent with more financially sophisticated (or less risky) borrowers bunching at exactly the MID limit.

the national share of tax filers claiming the MID, ranging from 21.9 to 28.5 in the years of my data), to limit the scope of welfare consequences to borrowers who are affected by the MID. I calculate (8) separately for each state-year, applying the appropriate net of subsidy interest rate change in the data and then aggregate to a national measure of deadweight loss.[25]

Table 9 shows deadweight loss estimates from the mortgage interest deduction on the mortgage market for home purchase loans broken out by the boom, bust, recovery periods that roughly correspond to years in the data. Over the full sample, the amount of deadweight loss is $49.52 billion dollars, or 2.5 percent of MID covered borrowing. Nearly two-thirds of the welfare cost occurs during the boom years of 2004-2007, the welfare loss during the bust ($9.07 billion) and recovery ($8.81 billion) is much smaller.

Predicting Borrowing Changes from TCJA Policy

The recently passed Tax Cuts and Jobs Act (TCJA) (P.L. 115-97) created substantial changes to the tax treatment of mortgage borrowing. Notably, this law lowers deductibility limits on new mortgages from $1million to $750,000, increases the standard deduction, and eliminates home equity loan interest deductibility. The elasticities produced in this paper are ideal for examining the likely effects of lowering the MID limit on borrower behavior as they are an elasticity with respect to the net of tax treatment that occurs at the MID limit, and among a sample of relatively high-dollar loan amounts that include the range of the new MID limit.

To get an idea of how the lower MID cap is likely to affect the U.S. mortgage market, I simulate the affect at the state level for all 50 states using the price change that occurs because of

[25] A caveat to my calculation of (8) is that it calls for the income compensated elasticity of demand and elasticities I produce here are uncompensated elasticities. Poterba (1992) suggests that the compensated elasticity for housing is roughly 80% of the uncompensated elasticity. To get closer to the income compensated elasticity of mortgage demand I deflate my uncompensated elasticities by twenty percent.

the tax deductibility removal on the distribution of mortgages that would have been newly exposed to the $750k cap had it been implemented in 2016. There are several caveats to this analysis. First, this simple analysis does not consider any supply side effects in the lending industry and it assumes that the distribution of 2018 borrowing would have been the same as the distribution in 2016. Second, it does not consider the full scope of the TCJA law changes, which include increasing the standard deduction and changing both tax brackets and marginal rates. Lastly, it does not account for any macroeconomic affects of the TCJA on the lending industry.

The simulation I present here merely applies the estimated elasticity of mortgage borrowing (I use the baseline estimate of -0.093) to the mortgage distribution as it exists in the most recent version of the HMDA data (2016) across states that experience different net-of-tax price changes.[26] Table 10 shows both a summary of the mortgage distribution across states in 2016 and the simple simulation results.

The HMDA data shows that in 2016, there were 43,110 home purchase mortgages made for an amount between the new $750,000 cap and the existing $1 million cap, and that these loans include about $5 billion dollars of borrowing that would be exposed to the lower cap.[27] There is substantial variation across U.S. states in both the number of borrowers in this range and the amount of total borrowing. California has by far the largest number of borrowers (16,404) and the most exposed borrowing ($1.9 billion) in this range of mortgage amounts. The price change for each state is calculated as the increase from a fully deductible loan at the state and federal level to marginal dollars that are no longer deductible.

[26] I apply a federal marginal tax rate of 35 percent in the simulations here. The top rate in 2016 was in fact 39.6. The top rate under the TCJA is 37 percent, and a 35 percent rate applies to married tax filers with incomes between $400,000 and $600,000 and for single tax filers with incomes between $200,000 and $500,000.

[27] The total amount of borrowing for loans in this range of mortgage amount is $37.3 billion, but only incremental borrowing between the new $750,000 and old $1 million cap loses tax preference.

The elasticity-based simulation shows that borrowing is likely to be reduced in the newly exposed portion of the mortgage distribution by about $348 million dollars, or $8,071 per borrower. The simulation predicts substantial variation across states, with the largest total reduction ($164 million) and per borrower reduction ($10,056) in California.

VIII. Conclusion

This paper presents evidence that borrowers respond to the discontinuous change in the tax treatment of home purchase mortgages by bunching at the $1 million interest deductibility limit. My estimates suggest substantial bunching MID limit. The amount of estimated bunching and corresponding reduction in borrowing that occurs implies mortgage demand elasticities between -0.132 to -0.115 for home purchases, accounting for salient number bunching in the mortgage distribution. These results are consistent across a variety of specification changes, sample changes, and hold up to several robustness checks. The most comparable study, DeFusco and Paciorek (2017), finds that when interest rates rise by 1 percentage point, mortgage demand falls by between 2 and 3 percent. Translating the baseline elasticities estimated here into a comparable semi-elasticity suggests that a 1 percentage point (100 basis point) increase in the interest rate reduces mortgage demand for home purchases by about 6.7 percent. The estimates presented here are substantially smaller than previous estimates in the literature, based largely on descriptive analysis, that place the tax-price elasticity of mortgage demand near -1.

The deductibility limits used to identify bunching in this paper show that removing tax-preferred treatment of borrowing reduces the size of mortgage that borrowers purchase. This result implies that the *existence* of tax-preferred borrowing below the limits induces *additional* borrowing. To the extent that the tax-preferred status of mortgage borrowing induces additional borrowing it may also be linked to problems associated with higher levels of household debt such as increased propensity for foreclosure. The estimates in this paper are useful in determining how behavior will change from reductions in the MID cap at the upper end of the mortgage distribution, as in the recently passed TCJA. Simulation results suggest that the TCJA changes are likely to reduce borrowing in the exposed range of mortgages by about $348 million in the aggregate, with differential effects across U.S. states.

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Figure 1: Marginal Net Mortgage Interest Rate Near MID Limit

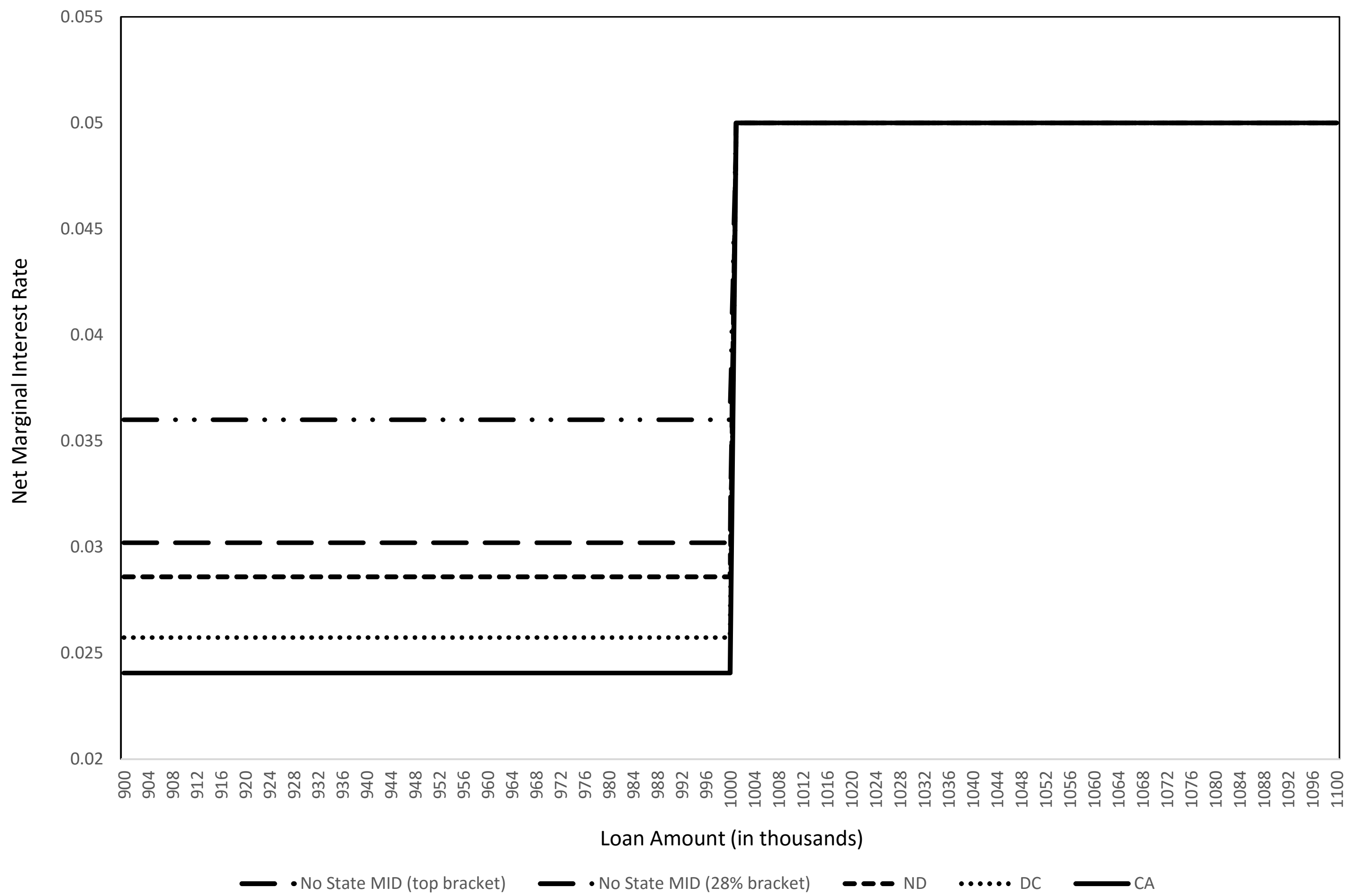


Figure 2: Bunching and Non-Bunching at MID limit, Federal and State MID

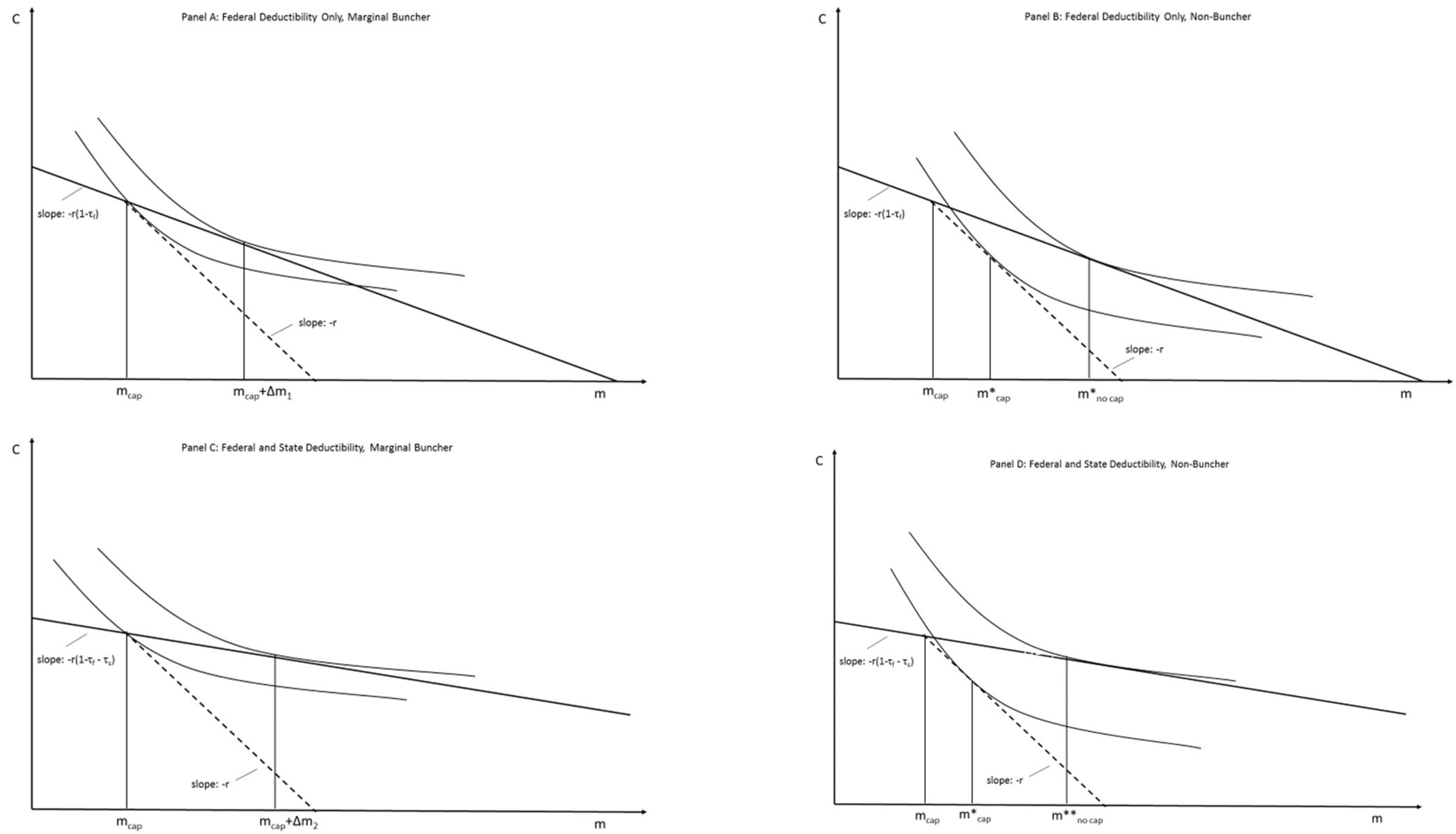
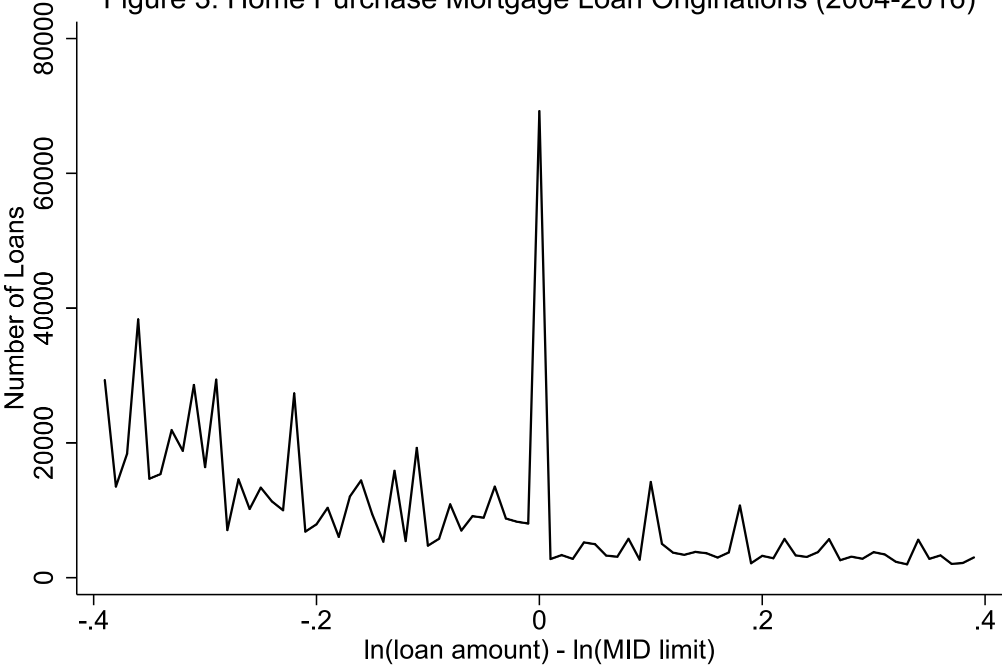
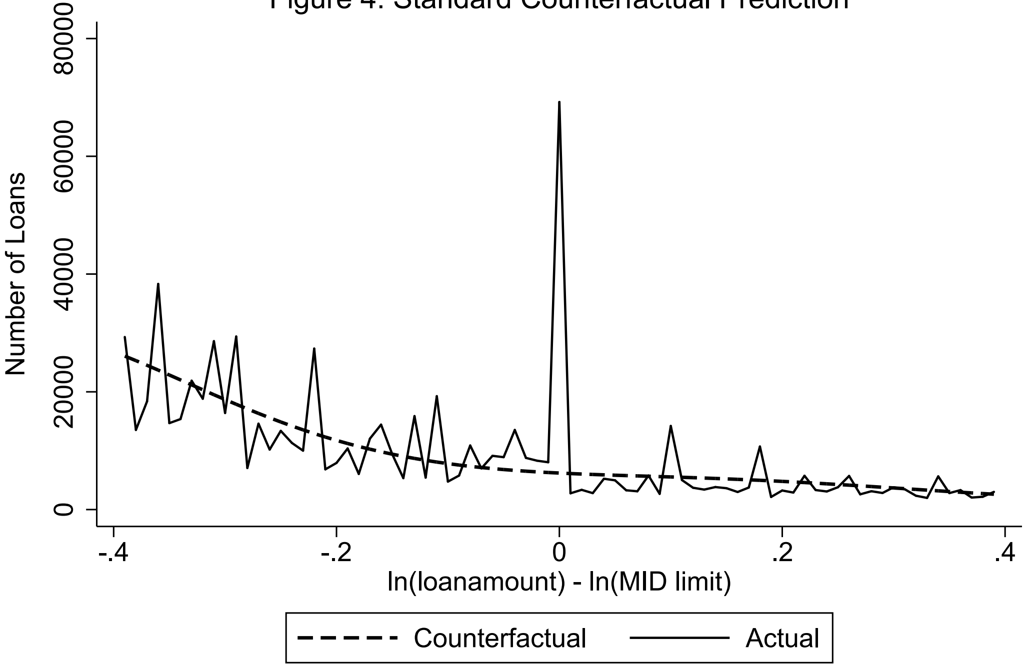


Figure 3: Home Purchase Mortgage Loan Originations (2004-2016)



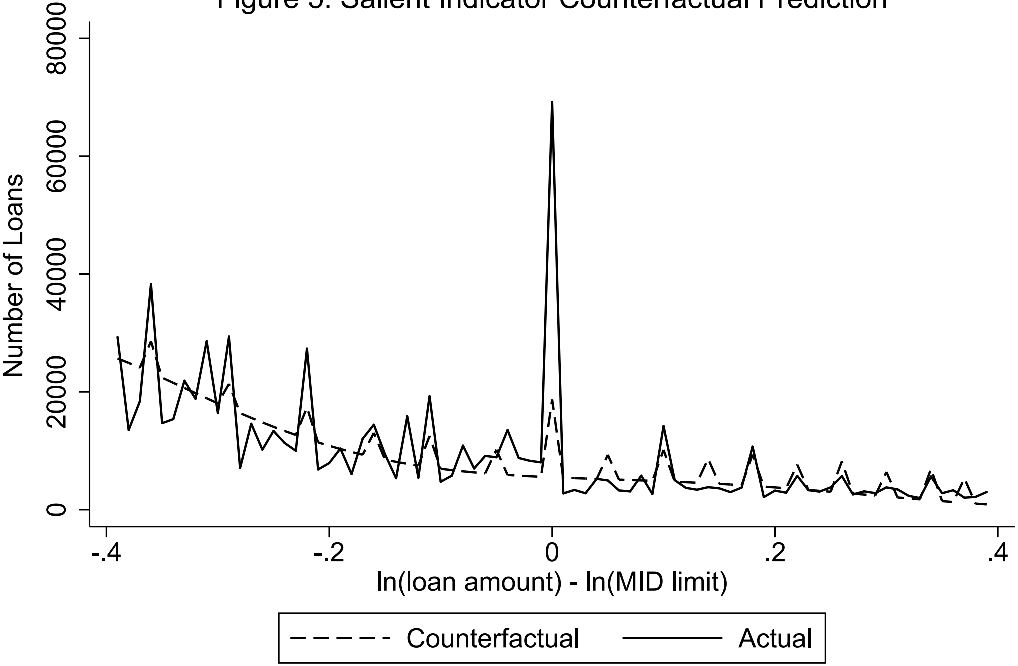
Notes: Figure shows home purchase mortgage originations for all single family, first lien, home purchase mortgages.

Figure 4: Standard Counterfactual Prediction



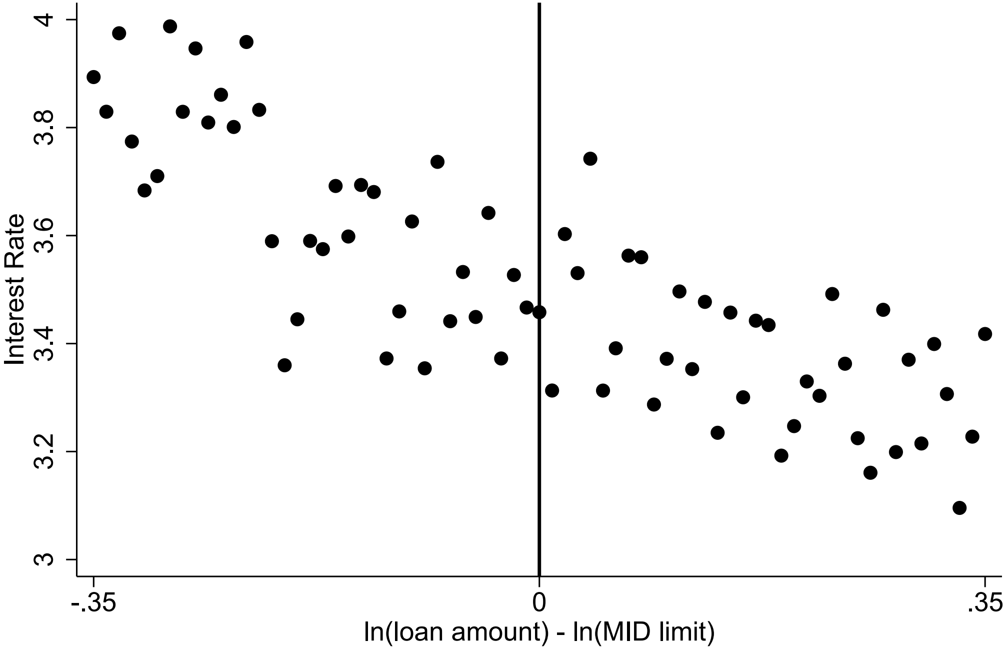
Notes: Figure shows home purchse mortgage originiations for all single family, first lien, home purchase mortgages.

Figure 5: Salient Indicator Counterfactual Prediction



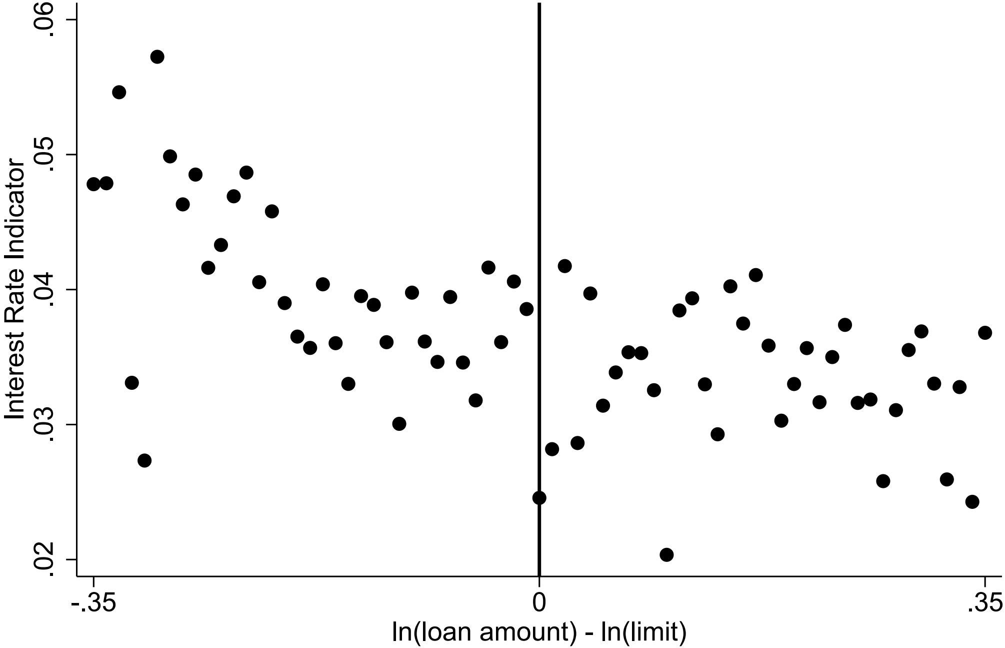
Notes: Figure shows home purchase mortgage originations for all single family, first lien, home purchase mortgages.

Figure 6: Interest Rate and MID Limit



Note: Interest rate is measured as a ratespread, or the difference between loan interest rate and a similarly termed U.S. Treasury bond.

Figure 7: Interest Rate Indicator and MID Limit



Note: Interest Rate Indicator is the percentage of loans reporting a ratespread for a given loan amount bin.

Table 1: Summary Statistics for 2004-2016 HMDA Data

	N	Ave. Loan Size	Reported Income	Percent Co-Sign	Percent Non-white	% at Cap	% Over Cap
Full HMDA (Home Purchase)	38,720,106	214	96	45.26%	21.62%	0.16%	0.65%
$600k to $5mil Sample	1,213,253	912	380	62.65%	31.94%	5.23%	20.79%

Notes: Loan size amounts and income in thousands of dollars. Income is amount of annual income reported to the lender. Summary statistics based on 2004-2016 HMDA data for home purchase mortgage originations on first lien owner-occupied 1-4 family homes. % at cap reflects loans made for exactly the MID limit amount. % over cap reflects loans made in excess of the MID.

Table 2: Bunching and Behavioral Change Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bunched Loans	63,023	59,459	58,627	59,886	54,904	56,248	54,345	50,512
	(985)	(3058)	(1808)	(1775)	(3465)	(3346)	(2271)	(3677)
Percent of Sample	5.19%	4.90%	4.83%	4.94%	4.53%	4.64%	4.48%	4.16%
Bunched Loans (with integration constraint)	62,543	58,372	57,638	59,438	53,373	55,225	53,366	49,041
	(1000)	(3092)	(1833)	(1843)	(3478)	(3386)	(2274)	(3566)
Fraction of Sample	5.15%	4.81%	4.75%	4.90%	4.40%	4.55%	4.40%	4.04%
Behavioral Change Parameter (%Δm)	0.103	0.097	0.101	0.103	0.094	0.096	0.101	0.093
	(0.023)	(0.021)	(0.021)	(0.019)	(0.020)	(0.022)	(0.023)	(0.021)
$1,000,000 indicator	N	Y	N	N	Y	Y	N	Y
$100,000 indicator	N	N	Y	N	Y	N	Y	Y
$50,000 indicator	N	N	N	Y	N	Y	Y	Y

Notes: Estimates use loans originated for the purchase of an owner-occupied 1-4 family home between 2004 and 2016. Loans between $600,000 and $5 million are included in estimation. Estimates use a 13 degree polynomial, and include a dummy variable for loan amounts that occur every $1,000,000, $100,000, $50,000, or a combination of these. Only indicator variables at $1million increments above the MID cap can be used to construct the counterfactual. All estimates use only the excess mass that exists at the MID limit (a range of zero). Standard errors are calculated using the procedure in Chetty et al. (2011) with a bootstrap of 1,000 replications with replacement.

Table 3: Bunching and Behavioral Change Estimates, Basic Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Degree of Polynomial				Range of Excluded Region		
	Optimal	6	8	10	0%	1%	2%	3%
Bunched Loans	54,904	55,720	55,300	55,498	54,904	56,857	58,983	61,443
	(3465)	(3479)	(3483)	(3497)	(3465)	(3791)	(4685)	(5627)
Percent of Sample	4.53%	4.59%	4.56%	4.57%	4.53%	4.69%	4.86%	5.06%
Behavioral Change Parameter (%Δm)	0.094	0.095	0.100	0.094	0.094	0.096	0.100	0.104
	(0.020)	(0.016)	(0.021)	(0.020)	(0.020)	(0.022)	(0.028)	(0.030)

Notes: Estimates use loans originated for the purchase of an owner-occupied 1-4 family home between 2004 and 2016. Loans between $600,000 and $5 million are included in estimation in 1 percent bins. Estimates use a 13 degree polynomial, and include a dummy variable for loan amounts that occur every $1,000,000, $100,000. Only indicator variables at $1million increments above the MID cap can be used to construct the counterfactual. All estimates use only the excess mass that exists at the MID limit, unless otherwise indicated. Standard errors are calculated using the procedure in Chetty et al. (2011) with a bootstrap of 1,000 replications with replacement.

Table 4: Heterogeneity in Bunching and Behavioral Change Estimates Across Housing Cycle

	(1)	(2)	(3)	(4)	(5)	(6)
	Pre 2008		2008-2012		Post 2012	
Bunched Loans	34,119	31,069	9,821	9,239	10,963	9,911
	(1510)	(1457)	(987)	(1110)	(1610)	(1736)
Percent of Sample	7.50%	6.83%	3.46%	3.25%	2.31%	2.09%
Behavioral Change Parameter (%Δm)	0.174	0.187	0.085	0.085	0.040	0.038
	(0.051)	(0.059)	(0.037)	(0.037)	(0.010)	(0.012)
Salient Indicators	1mil, 100k	1mil, 100k, 50k	1mil, 100k	1mil, 100k, 50k	1mil, 100k	1mil, 100k, 50k

Notes: Estimates use loans originated for the purchase of an owner-occupied 1-4 family home between 2004 and 2016. Only loans between $600,000 and $5 million are included in estimation. Columns (1) and (2) show estimates for loans in states that allow a state-level MID in addition to the federal policy, columns (3) and (4) show estimates for loans in states that only allow the federal MID. Columns (5) and (6) show estimates for loans in states that allow a state-level MID and have a marginal tax rate above the median state-year, 6 percent in the years of the data. All estimates use a 13 degree polynomial to create the counterfactual prediction. All estimates use only the excess mass that exists at the MID limit (a range of zero). Standard errors are calculated using the procedure in Chetty et al. (2011) with a bootstrap of 1,000 replications with replacement.

Table 5: Bunching and Behavioral Change Estimates, State Tax Differences

	(1)	(2)	(3)	(4)
	Additional State MID		Federal MID Only	
Bunched Loans	37,923	35,197	16,926	15,273
	(2601)	(2932)	(831)	(873)
Percent of Sample	4.40%	4.09%	4.85%	4.38%
Behavioral Change Parameter (%Δm)	0.093	0.092	0.088	0.087
	(0.023)	(0.023)	(0.016)	(0.018)
Salient Indicators	1mil, 100k	1mil, 100k, 50k	1mil, 100k	1mil, 100k, 50k

Notes: Estimates use loans originated for the purchase of an owner-occupied 1-4 family home between 2004 and 2016. Only loans between $600,000 and $5 million are included in estimation. Columns (1) and (2) show estimates for loans in states that allow a state-level MID in addition to the federal policy, columns (3) and (4) show estimates for loans in states that only allow the federal MID. All estimates use a 13 degree polynomial to create the counterfactual prediction. All estimates use only the excess mass that exists at the MID limit (a range of zero). Standard errors are calculated using the procedure in Chetty et al. (2011) with a bootstrap of 1,000 replications with replacement.

Table 6: Bunching and Behavioral Change Estimates, State MID Policy Changes

	(1)	(2)	(3)	(4)
	Louisiana		Rhode Island	
	With MID	Without MID	With MID	Without MID
Bunched Loans	81	13	41	14
	(11.09)	(7.66)	(6.49)	(8.89)
Percent of Sample	3.48%	2.31%	4.89%	2.18%
Behavioral Change Parameter (%Δm)	0.061	0.043	0.122	0.049
	(0.016)	(0.625)	(0.416)	(0.209)
Salient Indicators	1mil, 100k	1mil, 100k	1mil, 100k	1mil, 100k

Notes: Estimates use loans originated for the purchase of an owner-occupied 1-4 family home only in states indicated by columns. Louisiana implemented a mortgage interest deduction in 2007, while Rhode Island eliminated a mortgage interest deduction in 2011. Only loans between $600,000 and $5 million are included in estimation. All estimates use a 13 degree polynomial to create the counterfactual prediction. All estimates use only the excess mass that exists at the MID limit (a range of zero). Standard errors are calculated using the procedure in Chetty et al. (2011) with a bootstrap of 1,000 replications with replacement.

Table 7: Elasticity of Mortgage Demand Estimates

	No Salient Indicators	Baseline	MID States
%Δp	0.712	0.712	0.804
%Δm	0.103	0.094	0.093
Elasticity	-0.145	-0.132	-0.115

Notes: Percentage change in price is the net marginal interest rate change at the MID limit. Percent change in price is calculated as a weighted average of the combined federal and state-level tax treatment of mortgage interest. Weights are based on the percentage of loans made in each state over the time period and relevant sample. Salient indicator MID state, and High MTR quantity change estimates are from the specification using $1,000,000 and $100,000 indicators and the optimal polynomial.

Table 8: Regression Kink Estimates for Loan Outcome Changes at MID Limits

	(1)	(2)	(3)	(4)
	Rate Spread (continuous)		Rate Spread (discrete)	
Loan Amount (δ)	-0.0006	-0.0007	-0.0001	-0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Loan Amount*Above Limit (β)	0.0003	0.0003	0.0001	0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Percent of Standard Deviation	0.021%	0.021%	0.047%	0.046%
Loan Characteristics	N	Y	N	Y
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	94,838	90,160	1,941,671	1,894,653

Notes: Regression results from 2004-2016 HMDA data on home purchase mortgages between $600,000 and $1.5 million. Loan characteristics include co-signer status (an indicator if a cosigned loan), borrower race (an indicator if borrower is non-white), and the income reported to the lender. The average interest rate for home purchase loans in the sample, measured as a "ratespread" between the contract interest rate and a similarly termed U.S. Treasury, is 3.83 with a standard deviation of 1.41.

Table 9: Deadweight Loss Estimates from Mortgage Interest Deduction

	Sample Weighted Price Change	Behavioral Change Parameter	Deadweight Loss ($ billions)	Percent of Covered Borrowing
2004-2007	0.553	0.174	$31.64	3.86%
2008-2012	0.660	0.085	$9.07	1.92%
2013-2016	0.811	0.040	$8.81	1.36%

Sample weighted price change is the percentage change in interest rates that occurs when tax treatment of mortgage interest changes, weights reflect the amount of borrowing in a state-year relative to all other states that year. The behavioral change parameter is separately estimated for each time period using the same method as results in Table 5 where indicators of both $1million and $100,000 are used to reflect salient number effects. Deadweight loss is measured as the loss from additional borrowing during the time period, and does not reflect the full stock of outstanding debt at the time. Deadweight loss estimates are calculated at the state-year level and aggregated to the national time period level. Deadweight loss estimates weight the size of the annual mortgage market by the percentage of tax filers claiming the MID.

Table 10: Analysis of TJCA Legislation on Home Purchase Mortgage Market

State	Exposed Loans	Exposed Dollars (millions)	Price Change	Borrowing Change (millions)	Per Borrower Change
AL	129	$11.91	53.85%	$0.60	$4,661
AK	17	$1.43	66.67%	$0.09	$5,266
AZ	592	$68.48	72.12%	$4.63	$7,823
AR	50	$4.49	65.40%	$0.28	$5,508
CA	16,404	$1,959.87	89.75%	$164.95	$10,056
CO	1,068	$118.15	65.65%	$7.27	$6,810
CT	654	$82.25	72.41%	$5.59	$8,541
DE	30	$3.08	78.41%	$0.23	$7,537
DC	541	$58.51	71.23%	$3.91	$7,224
FL	1,806	$219.67	53.85%	$11.09	$6,142
GA	808	$92.13	69.49%	$6.00	$7,430
HI	635	$64.59	76.37%	$4.63	$7,285
ID	60	$6.26	78.51%	$0.46	$7,675
IL	1,395	$165.08	73.61%	$11.40	$8,169
IN	153	$16.72	53.85%	$0.84	$5,517
IA	36	$4.28	53.85%	$0.22	$5,998
KS	124	$13.45	65.56%	$0.83	$6,667
KY	77	$9.14	69.49%	$0.60	$7,732
LA	153	$15.30	69.49%	$1.00	$6,515
ME	39	$4.74	53.85%	$0.24	$6,141
MD	964	$107.47	68.78%	$6.93	$7,190
MA	1,951	$228.10	72.86%	$15.58	$7,988
MI	379	$41.71	53.85%	$2.11	$5,557
MN	356	$37.97	81.32%	$2.90	$8,134
MS	34	$3.36	69.49%	$0.22	$6,446
MO	221	$21.66	66.67%	$1.35	$6,129
MT	36	$3.91	72.12%	$0.26	$7,345
NE	22	$1.92	68.92%	$0.12	$5,637
NV	199	$22.51	61.03%	$1.29	$6,475
NH	52	$6.01	71.94%	$0.41	$7,793
NJ	1,654	$190.96	53.85%	$9.64	$5,830
NM	49	$5.27	53.85%	$0.27	$5,431
NY	3,289	$394.04	66.39%	$24.53	$7,459
NC	662	$73.83	53.85%	$3.73	$5,632
ND	13	$1.33	78.00%	$0.10	$7,489
OH	289	$33.00	53.85%	$1.67	$5,766
OK	76	$8.78	66.67%	$0.55	$7,220
OR	438	$45.83	81.49%	$3.50	$7,996
PA	538	$57.47	53.85%	$2.90	$5,394
RI	35	$3.47	53.85%	$0.18	$5,006
SC	345	$37.48	72.41%	$2.55	$7,377
SD	16	$1.95	53.85%	$0.10	$6,151
TN	380	$40.81	53.85%	$2.06	$5,423
TX	2,213	$251.80	53.85%	$12.71	$5,745
UT	237	$26.39	66.67%	$1.65	$6,961
VT	10	$1.40	68.78%	$0.09	$9,055
VA	1,635	$176.20	78.41%	$12.96	$7,924
WA	2,057	$230.24	53.85%	$11.63	$5,652
WV	19	$2.66	70.94%	$0.18	$9,306
WI	155	$17.57	53.85%	$0.89	$5,725
WY	15	$1.62	53.85%	$0.08	$5,440
U.S. Total	**43,110**	**$4,996.24**	**-**	**$347.96**	**$8,071.41**

Notes: Calculations are based on 2016 home purchase mortgage distribution for loans made between $750,000 and $1million. The reduced MID cap in the TCJA applies to home purchase mortgages made after December 14th, 2017, older mortgages are still granted deductibility up to the $1 million limit. Calculations in the table are based on a federal marginal tax rate of 35% and top state rates in 2016 and use the mortgage borrowing elasticity of -0.054.