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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Abstract

This paper investigates the direct effect on household debt of macroprudential borrower-based measures, namely Loan to Income (LTI) and Loan to Value (LTV) limits. The analysis focuses on the Netherlands, in a period characterized by growing vulnerabilities from the housing market and changes in the macroprudential policy. Results show that a LTI limit targeting debt repayment capacity is only binding at the left tail of the income distribution. Instead, a progressive tightening of the LTV limit that did not impose any downpayment constraint doubled the share of LTV-constrained borrowers. Results also show the role of increasing house prices as additional binding constraints for household borrowing choices.

Keywords: Borrower based measures, macroprudential policy, LTV, LTI, DSTI.
JELcodes: D14, G21

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1 Introduction

Understanding the causes of the Great Recession has been one of the main challenges for economists and policy makers in the last decade. A major cause has been attributed to financial conditions such as loosening lending standards and financial innovation: changes in models of banking origination first led to a strong increase in lending to households, causing mortgage debt to double between 2000 and 2007 (Brown et al. 2010) along the whole income distribution (Adelino et al. 2016) and particularly among subprime borrowers (Mian and Sufi, 2009). The increase in lending boosted housing demand and house prices, which in turn had feedback effects on household debt through home equity based borrowing (Mian and Sufi, 2011) or expectations of higher house prices (Kaplan, Mittman and Violante, 2020). The initial increase in house prices rapidly transformed into a bubble that burst shortly after, leading to undesired outcomes such as foreclosures (Mian, Sufi and Trebbi, 2015), defaults (Mayer, Pence and Sherlund, 2009) and consumption cuts (Mian, Rao and Sufi, 2013). As a consequence, a lesson from the Great Recession was that to prevent future financial and economic crises it is important to look at lending growth and household debt, and in particular to the housing finance component (Schularick and Taylor, 2014). Policy makers around the world took a stronger regulatory approach in the residential real estate sector, and have been increasingly relying on macroprudential policies to prevent excessive risk-taking, among both lenders and borrowers.

This paper investigates the effect of macroprudential policies on the level of household debt. The goal of the paper is to estimate the causal effect of borrower-based measures, i.e. macroprudential policies targeting borrowers via debt limits such as Loan-to-income (LTI) and Loan-to-Value (LTV) limits. The analysis focuses on the Netherlands, a country characterized by high vulnerabilities stemming from the housing markets, such as the second highest level of mortgage debt worldwide[1] and one of the strongest house price growth in the recent years[2]. In fact, despite the introduction and tightening of macroprudential policies in the form of both capital- and borrower- based measures, the Netherlands received further recommendations[3] to activate and tighten macroprudential measures to reduce such vulnerabilities stemming from the housing market.

Estimating the effect of borrower-based measures on household debt is challenging for different reasons. First, macroprudential limits often consist of common caps and thresholds. These hamper the identification of any causal effect, and typically produce local effects by impacting

[1]See Oecd National account statistics, available at http://www.oecd.org/sdd/na/

[2]See the IMF Global Housing watch, available at https://www.imf.org/external/research/housing/

[3]See ESRB 2016/4 and ESRB 2019/3

high-risk groups only. This paper exploits exogenous, unanticipated and granular changes in LTI limits to identify their causal effect on household debt, and uses a bunching approach[4] (Chetty et al. (2011), Kleven and Waseem (2013), Kleven (2016)) to estimate the number of borrowers constrained by the regulation, i.e. the local effect on the LTI and LTV ratio distributions. Second, overheating housing markets force liquidity constrained borrowers to borrow larger amounts, closer to or at the macroprudential limit. Even without a change in the limit, this becomes more binding, but ultimately because of the increase in house prices. I address this by using local house price indexes at the level of each municipality, to account for the confounding effect of increasing house prices. Third, controlling for house price dynamics may not be enough, as the interplay between household debt, debt limits and house prices can even run in the opposite direction. For instance, a relaxation of lending standards allows borrowing larger debt amounts, which in turn fuels housing demand and house prices[5]. To deal with this potential reverse causality issue, I rely on an instrumental variable approach close to Mian and Sufi (2011) in which prices are instrumented using a proxy of the total housing supply, represented by the share of developable land and the share of unoccupied dwellings.

Regarding LTI limits, results show that they are binding on average, but their effect decreases steeply along the income distribution: LTI limits are particularly binding for low income households, who often borrow at the LTI limit or qualify into one of the exceptions established by the regulation to be able to borrow above the limit. For this group, results indicate that changes in macroprudential limits translate into equivalent changes in household debt, as borrowers use all their borrowing capacity. On the contrary, changes in household debt are independent from changes in macroprudential policy at high incomes. Regarding LTV limits, results show that even a very generous LTV limit that does not impose any formal downpayment obligation can have strong binding effects on borrowers: the progressive 6% reduction in the LTV limit during the 2012-2018 period impacted up to 45% of highly leveraged borrowers. Eventually, results provide evidence of the role of house prices as additional binding factor for household borrowing choices. The remainder of the paper is organized as follows: Section II contain a review of the literature on BBMs. Section III provides institutional details about BBMs in the Netherlands, Section IV and V present the data and the empirical analysis. Section VI concludes.

[4]The literature on bunching has recently grown in terms of applications to the mortgage market literature (De Fusco and Paciorek (2017), De Fusco, Johnson and Mondragon (2019), Best et al. (2020)). This approach exploits the presence of non linearities in agents' budget sets to retrieve an estimate of the response at that specific point of the budget set. See Kleven (2016) for a review.

[5]The litarature shows that house prices and household debt are likely to be jointly determined, for example by an omitted variable such as shock to expected income growth, as shown in Attanasio and Weber (1994), Muellbauer and Murphy (1997), Mian and Sufi (2011).

2 Literature Review

According to Claessens (2017), by definition, macroprudential policies distort individual behavior. Howerver, the literature has mostly took a maroeconomic approach and has focused on the macroeconomic effects of BBMs. For example, Poghosyan (2019) show that LTV and DSTI limits are effective in curbing house price and credit growth. Similarly, Lim et al (2011) show that LTV and DSTI limits reduce the procyclicality of credit growth. Cerutti et al (2017) obtain similar findings for credit growth, and conclude that there is little complementarities between LTV and DSTI/LTI limits. Igan and Heedon (2011) show that housing market transactions drop after the introduction of LTV and LTI limits. Acharya et al (2020) show that the introduction of a LTV limit in Ireland led to a substantial reallocation of credit from low to high income households, while Georgescu and Martin (2021) show that DSTI and LTV limits contain the build-up of systemic risk at the cost of increasing inequality. De Araujo et al (2020) and Tzur-Ilan (2020) investigate the effect of LTV limits on housing choices using a difference in difference approach, and show that borrowers acquire less expensive properties after the introduction of the limit. Richter et al (2019) investigate the side effects of LTV limits, and show that they have contractionary effects on GDP and no effect on inflation, while Sanchez and Rohn (2016) show that the use of BBMs is associated to less tail risks for GDP growth. This paper contributes to the literature on BBMs by taking a micro approach to show the impact on household borrowing. The contribution of the paper is to estimate the causal effect of BBMs by dealing with the endogeneity between BBMs, house prices and household debt.

3 Institutional framework

The macroprudential regulation is a policy framework aimed at limiting risk intake in the financial system and ensuring the stability of the financial system as a whole. Among the various tools, borrower-based measures (BBM hereafter) target borrowers' behavior, and include instruments such as LTV and LTI limits. In the Netherlands, BBMs are under the control of the Dutch government.

The LTV limit establishes the maximum debt that can be lent to a borrower, relative to the collateral value of its house. The rule was introduced in 2012 and established that mortgage amounts cannot exceed 106% of the value of the house used as collateral. The limit has been gradually reduced by 1% every year until 2018, when the LTV limit reached 100%. The LTV limit in the Netherlands is one of the most generous worldwide and, despite its reduction, it still does not impose any downpayment constraint. Also, the LTV ratio displays no cross-sectional variation, as it applies indistinctly to all borrowers.

The LTI limits are set by the Dutch government at the recommendation of the National Institute for Family Finance Innovation (NIBUD) as debt-service-to-income limits (DSTI). A DSTI limit establishes the maximum debt service amount that a household affords to pay as a percentage of income, and are obtained via budgeting computations that account for the cost of living and incorporate factors such as changes in prices and taxation. The DSTI limits can be converted into equivalent LTI limits that establish the maximum loan amount that can be lent to a borrower, as a multiple of its gross annual income. In the remainder of the paper I will only refer to the resulting LTI limits, as these are the ones that banks apply at origination. Since the resulting LTI limits reflect the affordability of debt repayments, they depend on household income and on the interest rate paid on the mortgage, which is part of the debt service.

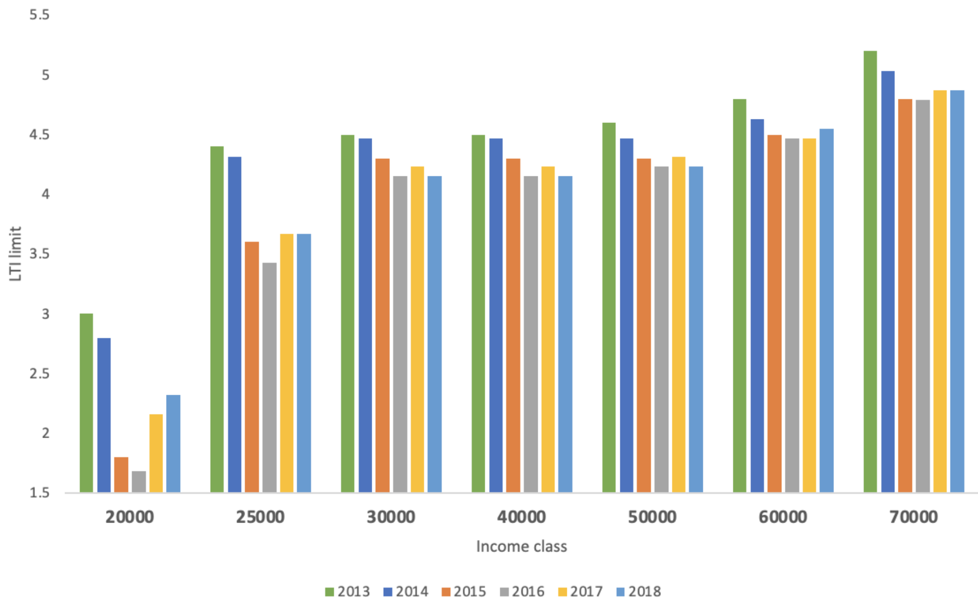
Figure 1: Regulatory Loan-to-Income limits (Heatmap).

Gross	**Interest rate**				
annual income	3.75%	4.25%	4.75%	5.25%	5.75%
19500	3.0	2.9	2.8	2.7	2.6
20000	3.1	3.0	3.0	2.9	2.8
20500	3.3	3.2	3.1	3.0	2.9
21000	3.5	3.4	3.3	3.2	3.1
21500	3.6	3.5	3.4	3.2	3.1
22000	3.8	3.6	3.5	3.4	3.3
22500	3.9	3.8	3.8	3.7	3.6
23000	4.0	4.0	3.9	3.8	3.8
23500	4.1	4.1	4.0	3.9	3.9
24000	4.2	4.2	4.1	4.0	3.9
25000	4.4	4.3	4.2	4.2	4.1
26000	4.5	4.4	4.3	4.2	4.1
28000	4.6	4.5	4.4	4.3	4.2
55000	4.7	4.6	4.5	4.4	4.3
58000	4.8	4.7	4.6	4.5	4.4
61000	4.9	4.7	4.6	4.5	4.4
63000	4.9	4.8	4.7	4.6	4.5
65000	5.0	4.9	4.8	4.7	4.6
68000	5.1	5.0	4.9	4.8	4.6
70000	5.2	5.1	5.0	4.8	4.7
75000	5.3	5.2	5.0	4.9	4.8
77000	5.3	5.3	5.2	5.1	5.1
79000	5.4	5.3	5.3	5.2	5.1
85000	5.5	5.4	5.4	5.3	5.2
96000	5.6	5.5	5.4	5.4	5.3
110000	5.7	5.6	5.5	5.4	5.4

Note: The figure shows the table containing the Loan-to-Income (LTI) limits in force in 2014. LTI limits depend on the gross annual household income (vertical axis) and on the interest rate charged on the mortgage loan (horizontal axis). Stricter limits are depicted in green, while larger limits are depicted in red.

Figure 1 reports an example of the table containing the LTI limits in force in 2014, and shows the considerable cross-sectional variation that characterizes these limits. LTI limits range from 2.6 to 5.7 depending on income and the interest rate. A LTI limit of 4 indicates that the loan amount cannot exceed four times the gross annual income of the debtor. Clearly, stricter limits apply to lower-income households and to higher interest rate mortgages. These LTI limits also display considerable time variation, as the recommendations are revised annually.

Figure 2: Changes in LTI limits



Note: The figure shows the LTI limits in force between 2013 and 2018, for different income categories. The interest rate class is the same for all years and income categories, and equals 4.75%. The choice made for the interest rate class simply ensures that the same interest rate class exist for all years of the analysis.

Figure 2 shows the changes in the LTI limits over the sample period, for different income classes[6]. Between 2014 and 2016, LTI limits in these income categories by an average of 0.5. Since the LTI limits give maximum debt amounts as multiple of income, the corresponding decrease in the maximum mortgage amount that equals EUR 20.000 for a borrower with a gross annual income of EUR 40.000, and EUR 35.000 for a borrower with a gross annual income of EUR 70.000. Last, a key feature of the LTI regulation in the Netherlands is that it is a *comply or explain* rule, i.e. there are exceptions that allow banks to grant mortgages above the LTI limit. In particular, banks can exceed the limit in case of (*i*) mortgage refinancing (*ii*) energy saving investments and (*iii*) bridge loans. In additions to these cases, lenders are allowed to exceed the LTI limit if the decision is substantially motivated and documented. A notable example is the case of an expected increase of capital or labor incomes[7]. For the LTV limit, banks are never allowed to originate a mortgage exceeding the original 106% limit.

[6]In these example, the interest rate is the same over time and across all income categories, in order to show time changes only attributable to changes in the regulation

[7]For further details regarding the regulation, see Van't Hof (2017).

4 Data and descriptive statistics

The data used in the empirical analysis is the Loan Level Data (LLD) collected by De Nederlandsche Bank (DNB). As of 2012, financial institutions must comply with the transparency policy of the ECB in order to securitize their loans. Under this policy, banks should report various information on the loans in their residential mortgage portfolio of banks (Mastrogiacomo and Van der Molen, 2015). This information consists of borrower, property and loan characteristics for about 85% of the population of bank residential mortgages. The Dutch mortgage market is a very concentrated market in which three banks account for more than 80% of the market shares. The activity of these three banks is well reported in the LLD, together with that of other 6 less systemic institutions. The LLD is then linked to three other data sources. The first consist of house price indexes based on individual real estate transaction data from the Dutch Association of Real Estate Brokers (NVM). The frequency of the indexes is quarterly and the level of granularity is the two digits postal code (Van Dijk, 2019) that, in the Netherlands, approximately represents the level of the municipality (at least for the largest cities, that have a unique two-digit postal code). Eventually, the last two data sources are municipality level data from Statistics Netherlands and the NIBUD tables containing all the LTI limits in force during the analysis period. Table 1 reports descriptive statistics on the most important property, borrower and loan characteristics in the LLD. The reported information only refers to first-time buyers (*starters*)[8]. The table shows several interesting trends. One is the sustained increase in household debt over the sample period, coupled with the simultaneous increase in property valuations. A second important trend is the progressive decrease in interest rates that has characterized the analysis period. While this represents a sign of loosening financial conditions per se, it also contributed in fueling housing demand, as the interest rate is one of the factor that determines household borrowing capacity via the LTI limits. A third trend is the decrease LTV limit that, despite it restricted household debt capacity by 6% of the property value, it did not impose any downpayment constraint. The table also reports the average of the LTI limits in force in each year (showed in Figure 1) and shows that income based measures have been both tightened and eased during the sample period.

[8] I focus on FTB because macro prudential limits tend to be more binding for this group, as they typically lack home equity to finance their house purchase. Since the FTB indicator is missing in the data, I identify starters thanks to a change in regulation that establishes that as of 2013, the only mortgage types eligible for mortgage interest deduction ('*hypotheekrenteaftrek*') are annuity and linear mortgages. Due to the generous tax deduction, other mortgage types such as interest-only and deferred amortization products became very expensive and almost disappeared from the market. Therefore, I identify starters as borrowers whose mortgage has been originated and firstly reported after 2013, and whose mortgage type is either linear or annuity.

Table 1: Descriptive statistics (LLD)

		2014	2015	2016	2017	2018
Mortgage Debt						
	Mean	177.312,7	189.895,6	206.336.2	231.812,1	254.126.6
	Med	161.200,0	171.700,0	182.500,0	199.475,0	224.000,0
	N	52.251	56.575	62.530	67.807	57.426
Property Valuation						
	Mean	218.305,8	234.425,3	255.414,7	291.610,9	293.955,3
	Med	185.000,0	198.000,0	215.000,0	235.000,0	250.000,0
	N	52.005	55.760	62.095	67.665	57.426
Interest Rate						
	Mean	0,035	0,028	0,024	0,022	0,023
	Med	0,036	0,028	0,023	0,022	0,022
	N	52.005	55.760	62.095	67.665	57.426
Maturity						
	Mean	29,3	29,3	29,4	29,3	29,3
	Med	30	30	30	30	30
	N	52.251	56.575	62.530	67.807	57.426
Household Income						
	Mean	53.779,6	56.771.2	61.884.5	64.428.3	60.000,2
	Med	44.443,3	46.617,6	50.423,0	52.876,8	52.976,2
	N	52.251	56.575	62.530	67.807	57.426
Loan to Income						
	Limit(avg)	4.81	4.70	4.69	4.81	4.76
	Mean	3.63	3.67	3.65	3.87	3.84
	Med	3.8	3.9	3.9	4.1	4.3
	N	52.132	56.739	62.509	67.406	57.426
Loan to Value						
	Limit	104.0	103.0	102.0	101.0	100
	Mean	85.9	86.7	86.2	84.2	84.3
	Med	98.2	98.7	97.5	95.8	98.9
	N	51.808	55.509	61.799	67.406	57.426

Note: Descriptive statistics at loan and borrower level in the Loan Level Data (LLD). The top panel reports mean and median loan characteristics at origination. The bottom panel reports mean and median borrower characteristics.

The increase in debt over the sample period is partly the result of the strong increase in house prices evident from Table 2, showing that in the period 2013-2018 house prices grew by more than 17% countrywide, and by nearly 50% in Amsterdam. The following analysis aims at explaining the reasons behind the increase in household debt, with a particular focus on the role of the macroprudential regulation and increasing house prices.

Table 2: Descriptive statistics (NVM)

	2014	2015	2016	2017	2018		2014	2015	2016	2017	2018
National	100.9	103.7	109.0	117.2	125.6	Amsterdam	109.8	120.5	136.8	156.0	170.5
Drenthe	99.4	100.9	103.0	108.5	115.7	North Brabant	102.5	104.5	108.7	114.0	116.3
Flevoland	103.5	104.9	109.9	119.1	130.4	North Holland	103.3	108.7	117.7	130.2	139.5
Friesland	96.2	98.1	101.9	108.0	115.0	Overijssel	98.1	100.3	104.2	110.5	119.4
Gelderland	98.0	99.8	103.5	110.3	116.6	South Holland	102.5	105.5	110.9	120.2	119.3
Groningen	99.9	102.6	107.4	113.5	119.8	Utrecht	101.6	105.5	112.2	122.4	129.6
Limburg	102.4	104.4	108.6	113.9	120.5	Zeeland	105.9	106.4	109.0	112.0	118.6

Note: Descriptive statistics in the NVM data. The table reports the house price indexes at the provincial level for the period 2014-2017. The table also reports in the top of the table the national house price index and the local house price index in the municipality of Amsterdam. The base year is the value of the national house price index in the last pre-sample year (2013).

5 Empirical analysis

5.1 Macroprudential limits, house prices and household debt

This section investigates the joint effect of BBMs and house prices on household debt. In overheating housing markets house prices act as an additional constraint, as they induce liquidity-constrained households to borrow more in order to purchase more expensive properties for sale. At the same time, increasing prices lead to higher collateral valuations which allow banks to grant larger debt amounts. Therefore, increasing house prices lead borrowers to take on debt amounts closer to or at the limit. Conversely, tightening BBMs also lead households to borrow close or at the limit, but for reasons attributable to changes in the macroprudential policy. As such, changes in BBMs and house prices have competing effects on household debt. This section quantifies and disentangles the effect on household debt attributable to changes in BBMs and to changes in house prices, and aims at obtaining the causal effect of changes in BBMs. To do so, I exploit the cross-sectional and time variation of the LTI limits showed in Figure 1 and 2. Changes in LTIs are arguably exogenous and unanticipated for different reasons. First, the LTI recommendations are made by an independent institute on the basis of budgeting computations based on the debt repayment capacity. Second, the interest rate and income classes defined have changed over time[9]. This change in classification not only makes it difficult to anticipate changes in LTI limits, but induces (exogenous) variation in LTI limits solely due to changes in the classification itself. Third, the recommended LTI limits become public in November and effective in January. Given the time needed to take a mortgage and buy a property, this excludes possible anticipation effects and arbitrage opportunities. The effect of LTI limits and house prices on household debt is estimated via the following equation:

$$log(Mortgage\,amount)_{i,m,t} = \beta_1\, log(LTI\ limit)_{i,t} + \beta_2 P_{m,t} + \delta' \mathbf{X}_{i,m,t} + \epsilon_{i,m,t} \tag{1}$$

where the dependent variable is the logarithm of the mortgage amount taken out by borrower i in municipality m in year t, and the main coefficient of interest is β_1, capturing the effect of LTI limits on household debt. $\mathbf{X}_{i,m,t}$ consists of borrower, property and loan characteristics and $P_{m,t}$ is the house price index in municipality m in year t, and represents the key conditioning variable to account for the competing effect of house prices on household debt. Lastly, the specification includes bank, time, and region fixed effects and estimated on a pool of repeated cross-sections[10].

Eq. (1) is estimated using an instrumental variables (IV) approach that deals with the potential endogeneity issue between household debt and house prices. In fact, house prices and household debt may be simultaneously determined. For example, higher house prices induce liquidity-constrained households to borrow more in order to purchase more expensive properties. Similarly, a shift in credit supply induces households to take on more debt, fueling housing demand and house prices. The local house price index is instrumented using a proxy of the total housing supply elasticity, as proxied by the share of developed land[11] and the share of unoccupied dwellings in each municipality. The share of developed land (see Saiz (2010), Hilber and Vermeulen (2016), Mian and Sufi (2009)) captures potential supply expansions coming from urban developments: for a given shock to housing demand, house prices are likely to increase more in municipalities characterized by limited possibilities for urban development. Instead, the share of unoccupied dwellings captures the potential supply coming from the existing stock of houses: for a given shock to housing demand, house prices are likely to increase less in municipalities characterized by excess supply and many unoccupied dwellings.

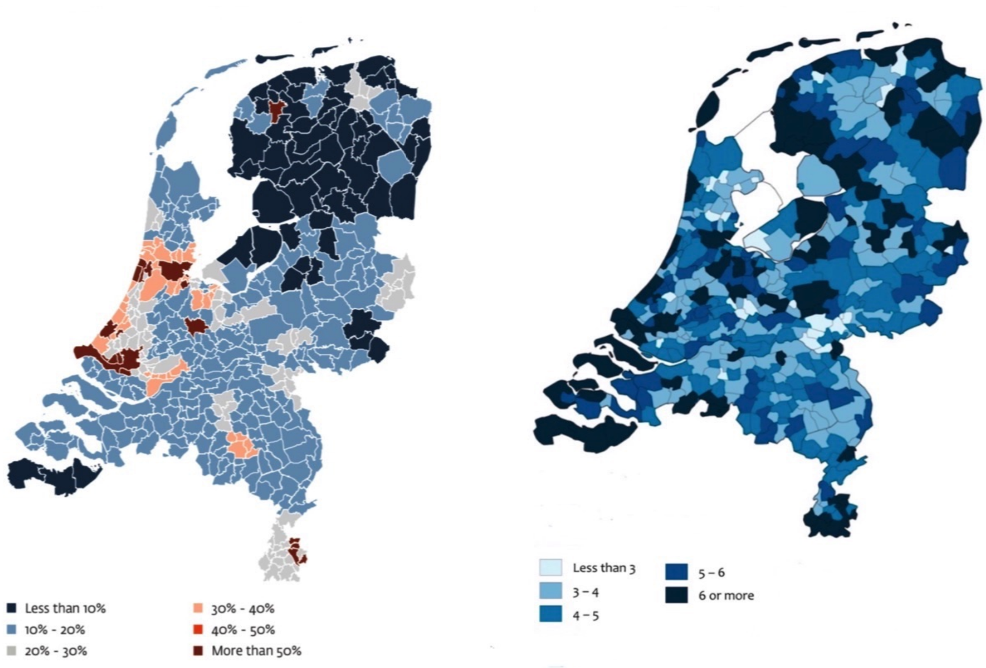
[9] The 2014 table defined a total of 130 combinations of income and interest rate classes, while the 2018 table contains a total of 1140 combinations.

[10] Since we look at borrowers at mortgage origination, we observe each borrower once.

[11] The share of developed land is taken from the land use classification provided in the Land Cover Map. It is defined as the size of the developed land over the total developable land. Water, despite being developable in the long run, is excluded from the total developable land which includes mostly fields, grass and woods.

Figure 3 shows the geographical variation of the two instrumental variables: in the Randstad area, where the four largest cities are located, the share of developed land is above 50% and possibilities of urban expansions are limited. Here, the share of unoccupied dwellings is lower than outside the Randstad area, and the housing market is generally more tight.

Figure 3: Instrumental Variables



Note: The Figure shows the geographical variation in the share of developed land (left) and in the share of unoccupied dwellings (right) at the end of 2013, right before the sample period of the analysis.

Given the presence of two instruments and one over-identifying restriction, specification 1 is estimated via two-step GMM, which is more efficient than 2SLS in the over-identified case. Results are reported in Table 3 and include also the OLS estimates. Four main conclusions can be draw from the results in Table 3. First, LTI limits are binding BBMs as a one percent change in the LTI limit is associated, on average, to a one percent change in household debt. Second, the effect is highly heterogenous along the income distribution. Figure 4 reports the marginal effect of a LTI limit change: at low-incomes, changes in the LTI limits are associated to changes in household debt of the same magnitude, at high-incomes, changes in debt are totally decoupled from changes of the limit. This means that BBMs are binding only for low-income households, as for them changes in lending standard result into a one-to-one change in household debt. Mid-incomes also respond to changes in lending standards but only to some extent, as changes in the LTI limit cause a less than proportional change in debt. Third, LTV constrained borrowers are more likely to be also LTI constrained, as they borrow larger loan amounts at any income level. Fourth, increasing house prices act as an additional binding factor for household borrowing choices: the IV specifications suggest that a one percent increase in house prices is associated to a 0.6 percent increase in household debt. The overidentificaction test for the GMM specifications does not reject the null hypothesis of validity of the instruments.

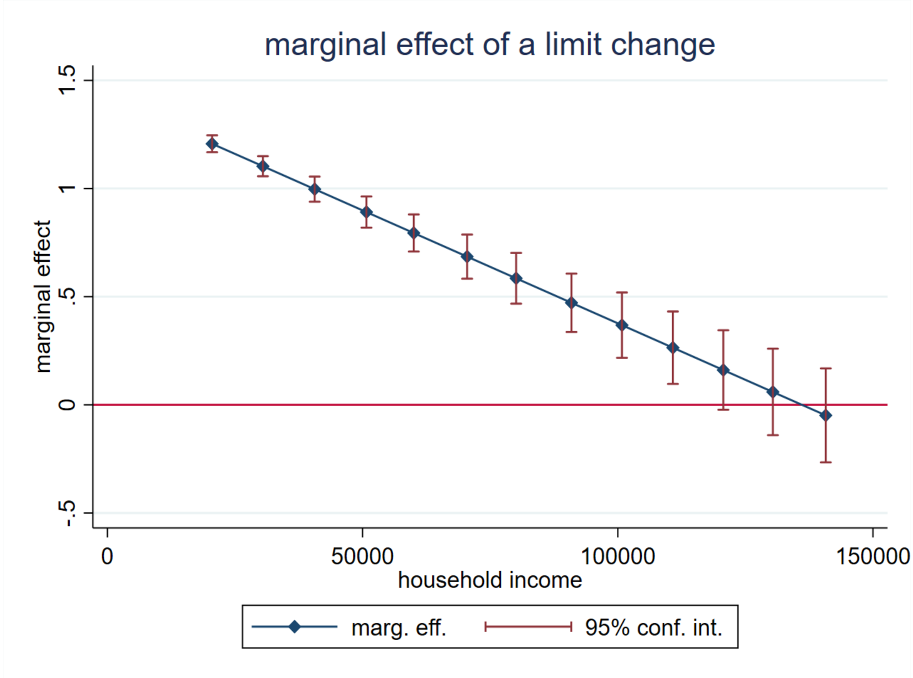
Table 3: The Effect of LTI Limits and House Prices on Household Debt

	Dependent variable: loan amount					
	(1)	(1)	(2)	(2)	(3)	(3)
	OLS	IV-GMM	OLS	IV-GMM	OLS	IV-GMM
LTI limit	1.318***	1.009***	1.413***	1.269***	1.347***	1.176***
	(0.0184)	(0.0459)	(0.0225)	(0.0307)	(0.0220)	(0.0321)
LTI limit × income			-0.006***	-0.014***	-0.006***	-0.015***
			(0.0008)	(0.0015)	(0.0008)	(0.0015)
LTI limit × income × LTV constr.					0.001**	0.002***
					(0.0015)	(0.0020)
Local house price index	0.300***	0.673***	0.301***	0.672***	0.293***	0.624***
	(0.0126)	(0.0825)	(0.0126)	(0.0823)	(0.0125)	(0.0810)
Hansen's J (overid test)	-	0.0021 (0.96)	-	0.0022 (0.96)	-	0.0007 (0.98)
N observations (Nt)	263.585	259.524	263.585	259.524	263.585	259.524

Note: The dependent variable is the log of the borrowed loan amount. The estimates of columns (1), (3) and (5) are Pooled OLS, while the estimates in columns (2), (4) and (6) are two-step GMM estimates (IV). Clustered standard errors at the level of the municipality in parenthesis. The main explanatory variables (LTI limits and local house prices) are expressed in logarithm. The control variables include loan characteristics (NHG, interest rate, maturity), borrower characteristics (income and age), a set of employment status dummies and a set of house type dummies and an indicator for urban areas. All specifications include bank, time and region fixed effects. The number of observations and the value of Hansen's J statistics are reported in the bottom panel, with p-value in parentheses. The symbols *, **, and *** denote conventional statistical significance levels.

Interestingly, Table 3 shows that shifting from the OLS to the GMM specification yields an effect of house prices that is double in magnitude, while the effect of LTI limit reduces. My interpretation is that this shows the confounding effect of house prices: once the endogeneity between changes in house prices, debt and debt limits is dealt with, results show a larger role of house prices as a binding factor for household borrowing choices. This reflect the fact that in overheating housing markets, house price developments force liquidity constrained borrowers to take debt amounts closer to or at the limit, but ultimately due to house prices themselves. Eventually, the last specification show that LTI and LTV limits tend to bind jointly, as borrowers that are LTV constrained (and thus liquidity constrained, as borrowing at the LTV limit requires no downpayment) tend to use more of their LTI space as compared to non-constrained borrowers, at any level of income.

Figure 4: Marginal effect of LTI limit changes



Note: The figure shows the marginal effect of a LTI limit change, as a function of the annual household income. The marginal effect is obtained from specification (2) is averaged over the sample.

5.2 Bunching at the LTI and LTV limit

The previous section investigate how changes in borrower based measures affect household debt levels. A different question is to what extent households are actually constrained by the LTI and LTV limit. Since these policies put a cap on household debt levels, they should produce local effects on high risk borrowers only. This is well described by a stylized model of borrowing, available in Appendix 1. The model shows that looking at wether a household borrows at the limit is not a sufficient condition to qualify them as a constrained borrower. This is due to the presence of the so called marginal borrowers, i.e. households *choosing* to borrow at the limit, but ultimately unconstrained by the policy. Instead, the model shows that the number of constrained borrowers can be identified by the number of borrowers *bunching* at the limit, i.e. the excess density at the limit in the LTI and LTV ratio distributions. The model also shows that the bunching statistic has informative value for the calibration of macroprudential policies, as the change in aggregate household debt levels (due to changes in BBM) depend on the number of constrained borrowers. This section proposes a bunching approach similar to Chetty et al. (2011), Saez (2010), Kleven (2016), De Fusco et al (2019) to estimate the number of LTI and LTV constrained borrowers.

5.2.1 LTI limit

The extent to which LTI limits are binding is assessed by estimating the size of the spike in the LTI distribution based on a counterfactual distribution, i.e. the distribution that would be observed in absence of any LTI limit. This counterfactual distribution is estimated under the assumption that the LTI limit only affects the LTI distribution is locally (at the LTI limit). In other words, the LTI limit is assumed to affect only high risk borrowers that would take high LTI mortgages in absence of the policy. This assumption implies that the counterfactual distribution matches the observed distribution away from the LTI limit. Instead, the two distributions differ at the limit, where the counterfactual density is obtained via a smooth interpolation between the observed densities at the right and the left of the LTI limit.

Importantly, the LTI policy is a so called *comply or explain* regulation. This means that some borrowers qualify in one of the exceptions and take mortgage amounts above the limit[12]. This in turn ensures that the observed LTI ratio distribution displays positive density also at the right of the limit, and that a linear interpolation can be obtained to estimate the counterfactual distribution, in line with the approach first introduced by Chetty et al. (2012) and Saez (2011). In particular, the following specification is estimated:

$$n_j = \sum_{i=1}^{p} \beta_i (z_j)^i + \sum_{s=-k}^{+k} \delta_s \mathbf{1}\left[z_j = z_{c+s}\right] + \epsilon_j \tag{2}$$

Where n_j is a count variable for the number of loans in each bin j. The running variable z_j is the bin count obtained by discretizing the LTI ratios distribution is J equally-spaced bins. In formulas: $z_j = [1, ..., z_c, ..., J]$ where z_c is the LTI limit bin. The first part of eq. 2 is a p-degree polynomial fit of the distribution of LTI ratios. The second term of the equation contains a set of dummies taking value one in all bins in a window of size $2k$ around the LTI limit bin z_c. This term captures the local spike of the LTI distribution due to the presence of LTI-constrained borrowers. Assuming smoothness of the true counterfactual distribution[13], the estimated counterfactual distribution is obtained as the predicted value of eq. 2 omitting the contribution of the dummies, that is: $\widehat{n_j} = \sum_{i=1}^{p} \beta_i (z_j)^i$. This provides a fit of the counterfactual distribution based on the whole shape of the observed distribution, besides the region around

[12]This shows the role of the flexibility option given by a comply or explain rule. In fact, the higher the mass at the right of the limit and the lower the spike at the limit, as more and more borrowers will turn unconstrained by qualifying in one of the exceptions.

[13]The assumption implies that without the LTI regulation, the LTI distribution would be smooth, i.e. with no spikes or discontinuities. Equivalently, the assumption implies that the the effect of the LTI limit is local, and that the spike at the LTI limit in the observed distribution is solely attributable to the LTI regulation.

the LTI limit. Let B be the excess number of loans at the LTI limit, then:

$$\begin{aligned}\widehat{B} &= n_j - \widehat{n_j} \\ &= \sum_{s=-k}^{+k} \delta_s \mathbf{1}\left[z_j = z_{c+s}\right]\end{aligned} \tag{3}$$

The estimates $\widehat{B}$ is an absolute measure of bunching, and is measured in number of loans. I also obtain the relative measure of bunching $\widehat{b}$ by scaling the previous statistic by the average density in the LTI constraint area:

$$\widehat{b} = \frac{\widehat{B}}{\sum_{s=-k}^{k} \widehat{n}_{c+s}/(2k+1)} \tag{4}$$

The statistics $\widehat{B}$ and $\widehat{b}$ represent reduced-form non-parametric estimates of the number and the share of constrained borrowers, respectively.

Due to the presence of multiple LTI limits, all borrowers sharing the same LTI constraint are grouped together and separate bunching estimates are run at all LTI limits between 4.4 and 5.3[14]. Also, the parameters J, p and k of eq. (3) are chosen in such a way that the resulting estimates are as conservative as possible[15].

The bunching estimates for the LTI distributions are reported in Table 4, with bootstrap standard errors in parentheses. Results shows significant bunching estimates for all borrowers subject to LTI limits below 4.8, with those subject to a 4.6 LTI limit being the most constrained. Borrowers in the [4.6-4.8] categories represent more than 40% of all borrowers, and consist of households with incomes below 60.000€, as also evident from Figure 1.

Figure A2 in the Appendix provides a graphical representation of the results in Table 4. The area within the two dashed red lines represents the analysis area, while the area within the two green lines represents the LTI limit area. The thick black line is the estimated counterfactual distribution. Results show that at high LTI limits the bunching mass is nonsignificant as the two distributions overlap at the LTI limit. Instead, at low LTI limits the estimated distribution

[14]Since this approach requires large data, this interval is chosen in such a way that all estimates have at least 10.000 observations. This selection excludes borrowers in the tails of the income distribution, but includes approximately 90% of all borrowers in our data

[15]The main choice for the calibration is given by the choice of j, i.e. the number and size of the bins the distribution is divided into. This poses a trade-off between estimation accuracy and result interpretation: the higher the number of bins, the more accurate the counterfactual distribution, but the less economically meaningful each bin is. For this reason I make this choice based on the regulation and the data at hand since and, since LTI limits vary by 0.1 in the Nibud tables, I discretize the distribution bins of width 0.05 ($j = 0.05$) to be conservative in terms of estimation accuracy. The choice of all other parameters is consequential to this: for the bunching area (k) we take a window of 1 bin around the LTI limit. Also this is a conservative choice, not to include too many bins around the one set by the macroprudential rules. Eventually, in line with the literature, the estimate of the counterfactual distribution is based on a 7th-degree polynomial (p).

is below the actual distribution and the bunching mass is high and statistically significant. This implies that low income households are more affected by the policy, as they tend to use all of their LTI space. Also, the share of explainers (density above the LTI limit) is high as compared to high income borrowers. This suggests that the participation of low income borrowers in the mortgage market is often conditional on qualifying in one of the exceptions[16].

Table 4: Bunching at the LTI limit

Limit = 4.4	est.	95% conf. int.	**Limit = 4.9**	est.	95% conf. int.
$\widehat{B}$	245.6***	[+149.2 ; +367.5]	$\widehat{B}$	1.7	[-56.0 ; +52.6]
$\hat{b}$	0.703***	[+0.416 ; +1.101]	$\hat{b}$	0.026	[-0.779 ; +0.819]
N	10.705		N	15.887	
Limit = 4.5	est.	95% conf. int.	**Limit = 5.0**	est.	95% conf. int.
$\widehat{B}$	1484.9***	[+1297.5 ; +1699.5]	$\widehat{B}$	18.3	[-33.1 ; +52.5]
$\hat{b}$	1.166***	[+1.007 ; +1.340]	$\hat{b}$	0.470	[-0.733 ; 1.485]
N	39.552		N	12.364	
Limit = 4.6	est.	95% conf. int.	**Limit = 5.1**	est.	95% conf. int.
$\widehat{B}$	2727.5***	[+2489.4 ; +3005.9]	$\widehat{B}$	16.9	[-44.2 ; +69.6]
$\hat{b}$	1.634***	[+1.477 ; +1.829]	$\hat{b}$	0.269	[-0.618 ; +1.198]
N	55.984		N	10.131	
Limit= 4.7	est.	95% conf. int.	**Limit = 5.2**	est.	95% conf. int.
$\widehat{B}$	1036.5***	[+787.1 ; +1272.4]	$\widehat{B}$	10.2	[-45.6 ; +58.9]
$\hat{b}$	0.726***	[+0.540 ; +0.906]	$\hat{b}$	0.136	[-0.547 ; +0.827]
N	60.117		N	17.620	
Limit = 4.8	est.	95% conf. int.	**Limit = 5.3**	est.	95% conf. int.
$\widehat{B}$	-177.2	[-260.8 ; -78.1]	$\widehat{B}$	56.8	[-13.3 ; +119.6]
$\hat{b}$	-0.846	[-0.906; -0.540]	$\hat{b}$	0.680	[-0.147 ; +1.529]
N	15.887		N	15.794	

Note: The table reports pooled bunching estimates for all LTI limit categories, in all sample years. The Table of the absolute ($\widehat{B}$) and relative ($\hat{b}$) bunching mass in correspondence of each LTI limit bin, as well as the corresponding 95% bootstrapped confidence intervals. Also, the Table reports the total number of borrowers (N) subject to the same LTI limit, as well as their corresponding income range of all borrowers . The symbol *** denote statistical significance at the 95% level.

[16]Lacking data on loan applications, I cannot investigate extensive margin responses to changes in BBM.

5.2.2 LTV limit

Differently from the LTI limit, the level of the LTV limit does not explain neither the cross-sectional nor the time variation of mortgage debt amounts[17]. Still, changes in the LTV limit can have distributional effects, in line with those induced by the LTI limits. This section investigates the effect on the LTV ratio distribution of further tightenings of the limit, and quantifies the number of borrowers constrained by the LTV rule.

The bunching approach applied in the previous section is not well suited to investigate the effect of the LTV limit. This is because the LTV regulation is stricter than the LTI regulation, as banks cannot grant mortgages exceeding the original 106% limit. This means that the LTV ratio distribution does not display sufficient density at the right of the LTV limit, making it difficult to obtain a good estimate of the counterfactual distribution. I overcome this issue by using the observed LTV distribution prior to the policy change, instead of an estimated counterfactual distribution. In particular, I use the LTV ratio distribution of 2012, right before the implementation of the policy[18].

My approach is similar to the one developed by De Fusco et al (2019) who compare the change in the distributions of mortgages originated in two different segments of the U.S. mortgage market, one of which is exempt to the regulation (a rule in the Dodd-Franck Act). They identify the effect of the regulation using cross-sectional variation in the distributions. Instead, I exploit time variation in the LTV distribution to estimate how changes in borrowers' budget sets (due to stricter LTV limits) affect the LTV distribution and the share of constrained borrowers. In fact according to Kleven (2016), it is possible to use both cross-sectional and time variations in the size or location of the kink to identify behavioral responses as difference in bunching.

I estimate the effect of LTV limit tightenings in two steps. First, to make the distributions directly comparable, the total number of loans in each bin are normalized by dividing them by the total number of loans in the analysis area. That is:

$$\overline{n}_j^t = \frac{n_j^t}{\sum_{j=1}^{J} n_j^t} \qquad t = 0, .., T \tag{5}$$

Where $\overline{n}_j^t$ denotes the density in bin j of the LTV distribution at time t. Again, $j = 0, .., J$ de-

[17]First, it does not explain the cross-section of household debt because the LTV limit, unlike the LTI limit, is the same for all borrowers. In other words, including the LTV limit as a regressor in eq. (1) would induce collinearity with the time effects. Second, the LTV limit does not explain the time variation of household debt, as maximum debt amounts are relatively to the value of the property used as collateral. For instance, the LTV limit was been reduced by 1% every year between 2013 and 2018, but house prices increased on average by 4% a year during the same period. As a result, borrowers in 2018 could borrow larger amounts than in 2013.

[18]The reduction of the LTV limit was announced in November 2012 and implemented starting from 2013.

notes the bins included in the analysis area[19]. We consider bins of size 0.5 in the range [85-110] of the LTV distribution. Also, this normalization rules out any extensive margin response, and makes sure that differences in the distributions only reflect responses on the intensive margin, i.e. on the actual Loan-to-Values. Second, I deal with the fact that changes in the distributions over time may be due to reasons unrelated to the change in the LTV regulation. For example, higher house prices typically induce borrowers to use more of their LTV space. To deal with this issue, two statistics are estimated:

$$\widehat{B_t} = \sum_{j=-k}^{k} \left(\overline{n}^t_{c+j} - \overline{n}^0_{c+j} \right) \qquad \widehat{M_t} = \sum_{j=k+1}^{J-c} \left(\overline{n}^t_{c+j} - \overline{n}^0_{c+j} \right) \tag{6}$$

Where $\overline{n}^0_{c+j}$ denotes the density in bin $c + j$ in the LTV distribution at time $t = 0$, i.e. the latest LTV distribution observed before the introduction of the new LTV rule. The density at the LTV limit is the density in a $\pm k$ window around $\overline{n}^t_c$.

The first statistic $(\widehat{B_t})$ denotes the Bunching estimate. This is analogous to the one computed in the previous section, but it's now obtained using the observed LTV distribution in 2012 instead of an estimated a counterfactual distribution. The second statistic $(\widehat{M_t})$ denotes the Missing Mass to the right of the LTV limit at time t , that I use to account for confounding factors such as increasing house prices. The intuition is the following: as the LTV limit decreases, more borrowers get constrained and the bunching mass increases. Equivalently, as house prices increase, more borrowers end up borrowing at higher LTVs, causing the bunching mass to increase as well. However, confounding factors such as house price increases can shape the LTV distribution only at the left of the LTV limit, given that under the new rule the limit is binding. On the contrary, changes in the LTV distribution at densities to the right of the LTV limit can only be attributed to the LTV limit tightenings. I estimate the Missing Mass to the right exactly to disentangle changes in the bunching mass that are directly attributable to the LTV regulation from those attributable to other factors, such as changes in house prices. This statistic identifies the excess number of borrowers that (i) borrow at the LTV limit and (ii) would have borrowed at higher LTV loans in absence of the regulation. Results are reported in Table 5, and a graphical represention is reported in Figure A3 in the Appendix. Results show that in 2013, a few months after the new regulation was announced, the LTV distribution looked very similar to that of one year before. The Bunching, i.e. the excess mass at the new 105% LTV limit was just 2.4% higher than the year before when the LTV limit was 106%. At

[19] As before, I set j based on the data and regulation at hand, and since LTV limit changes equal 1%, I set $j = 0.5\%$ to be conservative in terms of estimation accuracy. As before, I also set a window of 1 bin around the LTV limit ($k = 1$).

the right of the limit, the two distributions are almost overlapping, as captured by the estimated Missing Mass being close to zero and statistically insignificant. When the LTV limit was progressively reduced the following years, more and more borrowers got LTV constrained. The Bunching estimate increases from 2.4% in 2013, to 27,5% in 2015 and up to 35.9% in 2018. Correspondingly the Missing Mass, i.e. the part attributable to the policy change, progressively jumps from +1.5% in 2013 to -45.4% in 2017. This result indicates that progressive reductions of the LTV limit by 5% (from 106% to 101%) contributed to make this constraint binding for up to about 45% of borrowers taking out loans with LTVs in the range between 85 and 110.

Table 5: Bunching at the LTV limit

Limit = 105%	est.	95% conf. int.	**Limit = 104%**	est.	95% conf. int.
$\widehat{B}$	0.024***	[0.021 ; 0.030]	$\widehat{B}$	0.212***	[0.208 ; 0.217]
$\widehat{M}$	+0.015***	[0.018;0.012]	$\widehat{M}$	-0.148***	[-0.143 ; -0.152]
N	25.224		N	52.171	
Year	2013		Year	2014	
Limit = 103%	est.	95% conf. int.	**Limit = 102%**	est.	95% conf. int.
$\widehat{B}$	0.275***	[0.270; 0.279]	$\widehat{B}$	0.307***	[0.303 ; 0.311]
$\widehat{M}$	-0.231***	[-0.223 ; -0.236]	$\widehat{M}$	-0.321***	[-0.314 ; -0.326]
N	56.755		N	62.537	
Year	2015		Year	2016	
Limit = 101%	est.	95% conf. int.	**Limit = 100%**	est.	95% conf. int.
$\widehat{B}$	0.330***	[0.328 ; 0.334]	$\widehat{B}$	0.359***	[0.356 ; 0.363]
$\widehat{M}$	-0.401***	[-0.395 ; -0.407]	$\widehat{M}$	-0.454***	[-0.447 ; -0.460]
N	67.795		N	56.557	
Year	2017		Year	2018	

Note: The Table reports LTV bunching estimates in all LTV limits. The Table shows the bunching mass ($\widehat{B}$), the missing mass to the right of the LTV limit ($\widehat{M}$). Also, the Table reports the corresponding 95% bootstrapped confidence intervals. On the bottom of each panel the Table reports the year and total number of starters (N). The symbol *, ** and *** denote conventional statistical significance levels.

6 Concluding remarks

This paper investigates the impact on household debt of macroprudential policies in the form of borrower-based measures (LTI and LTV limits). Thanks to the use of exogenous, unanticipated and granular changes in LTI limits, and after dealing with the endogeneity between debt, debt limits and house prices, the paper estimates the causal effect of BBMs on household debt. Three main conclusions can be drawn from the analysis. First, I show that a LTV limit which does not impose any downpayment constraint can be more binding than a LTI limit targeted to the affordability of debt repayments. This result can be explained by the role of increasing house prices as additional binding constraints for household borrowing choices: in overheating housing market, price-to-income ratios increase and force liquidity constrained borrowers to borrow at higher LTV limits, as savings cannot keep up with the increase in house prices. As a result, macroprudential limits become more and more binding, but ultimately because of increasing house prices. Second, I show that the effect of the macroprudential policy is highly heterogenous along the income distribution: lower income households tend to be more constrained by income-based BBMs (LTI or DSTI limits). Relatively to higher income households, these borrowers tend to qualify more frequently in one of the exceptions established by the regulation. This shows that granular limits can overcome the "one size fit all" drawback that is typical of macroprudential policies, and shows the role of a comply-or-explain regulation as a flexible tool to minimize extensive margin responses related to BBM tightenings or house price increases. Third, the paper shows that the number of borrowers that are effectively constrained by BBMs can be identified by the bunching at the limit, that naturally deals with the presence of marginal borrowers. Eventually, it is shown that the change in household debt caused by a change in BBMs explicitly depends on the bunching at the limit, which therefore has an informative value for the calibration of macroprudential policies.

References

[1] Acharya, V., Bergant, K., Crosignani, M., Eisert, T., McCann, F. (2020). The Anatomy of the Transmission of Macroprudential Policy: Evidence from Ireland. *NBER Working Paper* n. 27292.

[2] Adelino, M., Schoar, A., Severino, F. (2016). Loan origination and default in the Mortgage Crisis. *The Review of Financial Studies*, vol. 29 no. 7.

[3] Attanasio, O., Weber, G. (1994). The UK Consumption Boom of the Late 1980's: Aggregate Implications of Microeconomic Evidence. *Economic Journal*, vol. 104, issue 427, pp. 1269-1302.

[4] Best, M., Cloyne, J., Ilzetzki, E., Kleven, A. H. (2020). Estimating the Elasticity of Intertemporal Substitution Using Mortgage Notches. *Review of Economic Studies*, 87 (2), pp. 656-690.

[5] Brown, M., Haughwout, A., Lee, D., Van der Klaauw, D. (2010). The Financial Crisis at the Kitchen Table: Trends in Household Debt and Credit. *Federal Reserve Bank of New York Staff Report.*

[6] Brueckner, J. K. (1994). The Demand for Mortgage Debt: Some Basic Results. *Journal of Housing Economics*, no. 3, pp. 251-262.

[7] Cerrutti, E., Claessens, S., Laeven, L. (2017). The Use and Effectiveness of Macroprudential Policies: New Evidence. *Journal of Financial Stability*, vol. 28, pp. 203-224.

[8] Chen et al. (2020). Aggregate and Distributional Impacts of LTV Policy: Evidence from China's Micro Data. *NBER Working Paper*, n. 28092.

[9] Chetty, R., Friedman, J. N., Olsen, T., Pistaferri, L. (2011). Adjustment Costs, Firm Responses, and Micro vs. Macro Labor Supply Elasticities: Evidence from Danish Tax Records. *The Quarterly Journal of Economics*, vol. 126(2), pp. 749-804

[10] De Araujo, D. K. G. Blanco Barroso, J. B. R. and Gonzales, R. B. (2020). Loan-To-Value Policy and Housing Finance: Effects on constrained borrowers. *Journal of financial intermediation*, vol 42.

[11] De Fusco, A., Paciorek, A. (2017). The Interest Rate Elasticity of Mortgage Demand: Evidence from Bunching at the Conforming Loan Limit. *The American Economic Journal: Economic Policy*, vol. 9, no. 1, pp. 210-240.

[12] De Fusco, A., Johnson, S., Mondragon, J. (2019). Regulating Household Leverage. *The Review of Economic Studies*·, Vol. 87 (2), pp. 914?958.

[13] European Systemic Risk Board (2016/10). Warning on medium-term vulnerabilities in the residential real estate sector in the Netherlands.

[14] European Systemic Risk Board (2019/7). Recommendation on medium-term vulnerabilities in the residential real estate sector in the Netherlands.

[15] Hilber, C. A. L., Vermeulen, W. (2016). The Impact of Supply Constraints on House Prices in England. *Economic Journal*, vol. 126, pp. 358-405

[16] Igan, D. and Kang, H. (2011). Do loan-to-value and debt-to-income limits work? Evidence from Korea *IMF Working Papers* n. 11/297, pp. 1?34

[17] Kaplan, G., Mitman, K., Violante, G.L. (2020). The Housing Boom and Bust: Model meets Evidence. *Journal of Political Economy*, vol. 128(9).

[18] Kleven, H. J. (2016). Bunching. *Annual Review of Economics*, Vol. 8, pp. 435-464.

[19] Kleven, H. J., Waseem, M. (2013). Using Notches to Uncover Optimization Frictions and Structural Elasticities: Theory and Evidence from Pakistan. *The Quarterly Journal of Economics*, vol. 128(2), pp. 669-723.

[20] Lim, C. H., Costa, A., Columba, F., Kongsamut, P., Otani, A., Saiyid, M., Wezel, T. and Wu, X. (2011). Macroprudential policy: what instruments and how to use them? Lessons from country experiences. *IMF working paper* n. 11/238.

[21] Mastrogiacomo, M., Van der Molen, R. (2015) . Dutch Mortgages in the Loan Level Data *DNB Occasional Studies*, vol 13 (4).

[22] Mayer, C., Pence, K., Sherlund, S. M. (2009). The Rise in Mortgage Deafults. *Journal of Economic Perspective*, vol. 23, no. 1, pp. 27-50.

[23] Muellbauer, J., Murphy, A. (1997). Boom and Busts in the UK Housing Market. *Economic Journal*, vol. 107, issue 445, pp. 1701-27

[24] Mian, A., Sufi, A (2009). The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis. *The Quarterly Journal of Economics*, Volume 124, Issue 4, pp. 1449-1496.

[25] Mian, A., Sufi, A (2011). House Prices, Home Equity-Based Borrowing, and the US Household Leverage Crisis. *American Economic Review*, vol. 101, no. 5, pp. 2132-56.

[26] Mian, A., Rao, K., Sufi, A. (2013). Household Balance Sheet, Consumption and Economic Slump. *The Quarterly Journal of Economics*, Volume 128, Issue 4, Pp. 1687?1726.

[27] Mian, A., Sufi, A., Trebbi, F. (2015). Foreclosures, House Prices, and the Real Economy. *The Journal of Finance*, 70, pp. 2587-2634.

[28] Piazzesi, M., Schneider, M. (2016). Housing and Macroeconomics. *NBER Working paper*, No. w22354.

[29] Poghosyan, T. (2020) . How Effective is Macroprudential Policy? Evidence from Lending Restriction Measures in EU Countries. *Journal of Housing Economics*, vol. (49).

[30] Richter, B., Schularick, M. and Shim, I. (2019). The costs of Macroprudential Policy. *Journal of International Economics*, 118, 263-282

[31] Saez, E. (2010). Do Taxpayers Bunch at Kink Points? *American Economic Journal: Economic Policy*, Vol. 2, No. 3, pp. 180-212

[32] Sanchez, A.C. and Röhn, O. (2016). How do policies influence GDP tail risks? *OECD Economics Department Working Papers* 1339.

[33] Schularick, M., Taylor, A. M. (2012). Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008. *The American Economic Review*, vol. 102, no. 2, pp. 1029-61.

[34] Tzur-Ilan, Nitzan (2020). The real consequences of LTV limits on housing choices. *Working paper.*

[35] Van't Hof, A. (2017). Designing Macroprudential Regulation and Supervision Outside the Scope of the Banking Union: Lessons from the Netherlands and Ireland. *Journal of Banking Regulation*, vol. 18, pp. 201-212.

[36] Van Dijk (2019). Commercial and Residential Real Estate market liquidity. PhD thesis, Universiteit van Amsterdam.

Appendix 1: Theoretical framework

We consider a stylized model of borrowing similar to Brueckner (1994), Defusco and Paciorek (2017) and generalized by Piazzesi and Schneider (2016). In the economy there are N households indexed by i. Household i has liquid assets a_i distributed over the support $[\underline{a}, \overline{a}]$, according to a cumulative density function $F(a)$. In this simplified model housing choice is exogenous and all borrowers need to finance a house of size h worth ph. Each borrower maximizes:

$$max\ U_{c_1,c_2} = u(c_1) + \beta u(c_2) \tag{7}$$

$$s.t. \quad c_1 + ph = w_i + m$$

$$c_2 = ph - Rm$$

Where $w_i = y + a_i$ is the endowment of each borrower, given by income and liquid assets. The former is assumed to be constant across borrowers, while the latter is heterogenous and distributed according to $F(a)$. In the model, the mortgage m is a consumption smoothing device that allows borrowers to finance their house purchase. The mortgage choice affects the future level of consumption via home equity, i.e. the difference between the asset value ph and the outstanding mortgage debt Rm. The interest rate $R = 1 + r$ is assumed to be fixed and agreed upon the contract. Assuming logarithmic utility, the unconstrained demand is equal to:

$$m_i^u = \frac{ph(1 + \beta R) - \beta R(y + a_i)}{R(1 + \beta)} \tag{8}$$

The optimal level of debt increases with the property valuation and decreases with the amount of available assets.

Next, I introduce two BBMs: the first is a loan-to-income (LTI) limit that allows to borrow up to a given multiple of borrower's income, the second is a loan-to-value (LTV) limit that allows to borrow up to a fraction of the collateral value. Borrowers decisions are thus subject also to the following constraints:

$$m \leq \theta y \qquad\qquad m \leq ph(1 - \delta) \tag{9}$$

Since the income and property value is the same among all borrowers, they are also subject to the same BBMs. Let $\lambda[m - \theta y] = 0$ and $\eta[m - ph(1 - \delta)] = 0$ be the Kuhn Tucker conditions for the LTI and LTV constrains, respectively. The constrained mortgage choice equals:

$$m^c = min\big\{\theta y\,; ph(1 - \delta)\big\} \tag{10}$$

In words, the constrained mortgage amount equals the limit that binds first. In this model, whether BBMs are binding or not ultimately depends on each individual's endowment a_i, which is the only element of heterogeneity in the population: households with less liquid assets take higher debt positions to increase current consumption vis-a-vis future consumption. The break-point level of a can be obtained by equating the unconstrained to the constrained mortgage functions, in formulas: $a^* : m_i^u = m^c$. Suppose the LTI binds first, then:

$$\frac{ph(1+\beta R) - \beta R(y + a_i)}{R(1+\beta)} = \theta y_t \tag{11}$$

Leading to:

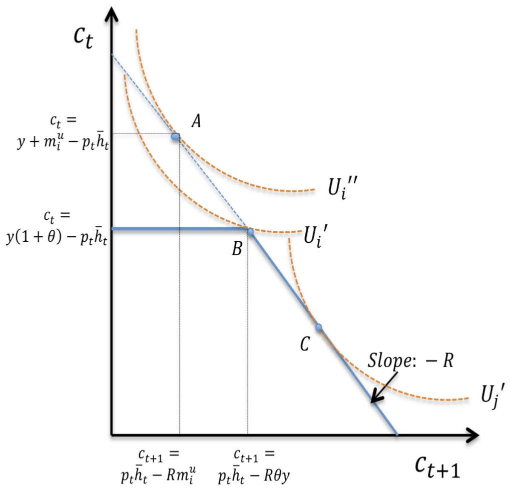
$$a^* = \frac{ph(1+\beta R) - \beta Ry - \theta yR(1+\beta)}{\beta R} \tag{12}$$

The value of β^* identifies marginal borrowers, i.e. households whose unconstrained and constrained mortgage choice coincide. Importantly, marginal borrowers are unaffected by the policy as they are able to borrow their desired loan amount. Figure 5 provides a graphical representation of the result in the simple two periods case under the terminal condition $w_{t+1} = c_{t+1}$: with no BBM, household i locates in $A = (c_1^*, c_2^*)$ that is the unconstrained optimal choice. If BBM are introduced, the inter-temporal budget set features a discontinuity and the borrower locates at point B, which is a second-best corner solution as $U'_i < U''_i$. The same would not be true for household j that, having more liquid assets than i (i.e. $a_j > a_i$), chooses a mortgage amount lower than the limit that still allows to reach the unconstrained optimal allocation C. The implication is that, in absence of leverage constraints, the mortgage distribution in the population is the same as the distribution of liquid assets $f(m) = f(a)$ (dashed line), while in presence of leverage constraints the same distribution would feature a spike at the leverage limit. The size of the spike is proportional to the number of borrowers constrained by the regulation.

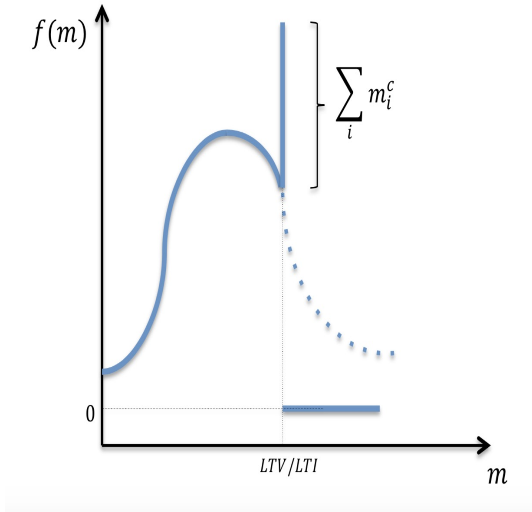
Aggregation

This section aggregates all household borrowing choices to determine the aggregate debt level in the population. According to the value of a^*, the population can be divided in two groups: the first group of unconstrained borrowers is made of wealthier households, these are all $i \ : \ a_i \in [a^*, \overline{a},]$. The second group contains all constrained borrowers with $a_i \in [\underline{a}, a^*)$. Again, the value of a is distributed according to a cumulative density function $F(a)$. In the first group, each individual debt level is different, as it depends on one's endowment. On the contrary, the demand of all borrowers in the second is the same and equal to the BBM that

Figure A1: Optimal mortgage choices and the mortgage distribution.



(a)



(b)

Note: The left figure shows the constrained (solid line) and the unconstrained (solid + dashed line) budget sets and the corresponding optimal solutions for current and future consumption. The right figure shows the constrained (solid line) and unconstrained (solid+dashed line) mortgage debt distributions.

binds first. Let M^1 and M^2 be the corresponding aggregate group debt levels. Then, it follows that the average debt level in the population is the weighted sum of the debt levels in each group:

$$\begin{aligned} M(\theta) &= \sum_i m_i \\ &= F(a^*)m^c(\theta) + \int_{a^*}^{\bar{a}} m_i^u f(a_i)\, da_i \end{aligned} \tag{13}$$

Where $F(a^*)$ is the share of constrained borrowers, which is increasing in the level of prices and decreasing in the level of available assets. From the last equation, the debt level in the population explicitly depends on the policy parameter θ: the macroprudential limit affects not only the debt amount of constrained borrowers, but also the share of constrained borrowers in the population via the relation with $a^* = a^*(\theta)$. In fact:

$$F(a^*) = Pr(a_i \leq a^*) = F\left(\frac{ph(1+\beta R) - \beta R y - \theta y R(1+\beta)}{\beta R}\right) \tag{14}$$

In particular, the stricter the leverage limit and the higher the share of constrained borrowers. As a result, we can derive the change in the average debt level due to a change in the leverage constraint as:

$$\frac{\partial M(\theta)}{\partial\, \theta} = f(a^*)\big[m^c(\theta) - 1\big]\frac{\partial\, a^*}{\partial\, \theta} + F(a^*)\frac{\partial\, m^c(\theta)}{\partial\, \theta} \tag{15}$$

Where $f(a) = F'(a)$ is the probability density function. The first term captures the change in the share of constrained borrowers caused by a change in the limit. The second term captures the change in the mortgage demand of constrained borrowers, given the change in the limit. In other words, changes in the policy parameter cause two effects: on the one hand they change the fraction of constrained and unconstrained borrowers in the population, on the other hand it changes the mortgage demand of constrained borrowers. Importantly, the change in the aggregate debt level caused by a change in the leverage limit is proportional to the bunching mass at the limit, captured by $F(a^*)$: the higher the share of constrained borrowers and the larger the response to a further change in the macroprudential limit. The following figures show empirical estimates of the bunching mass at the LTI and LTV limits.

Figure A2(a) Bunching at the LTI distribution

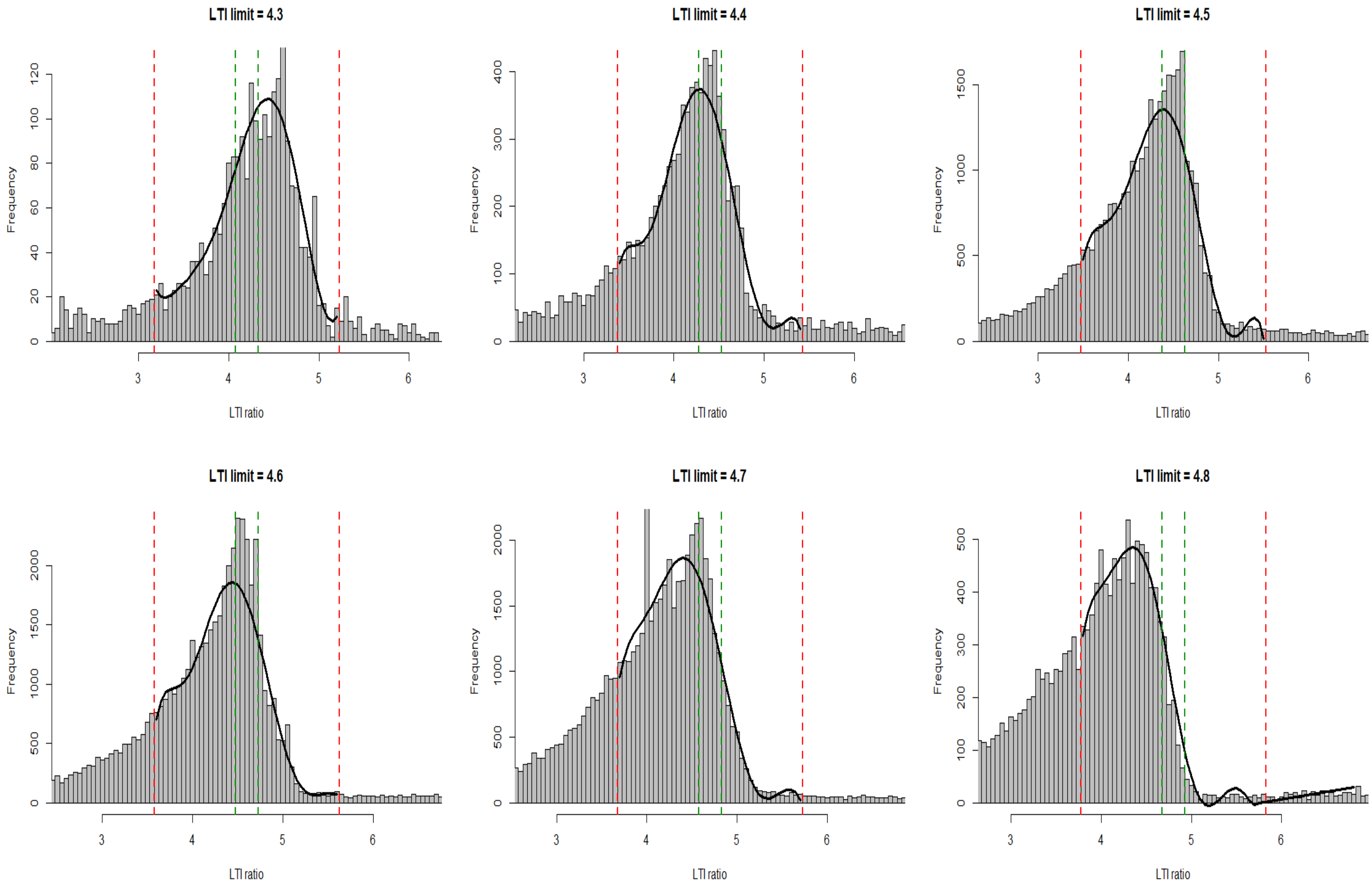
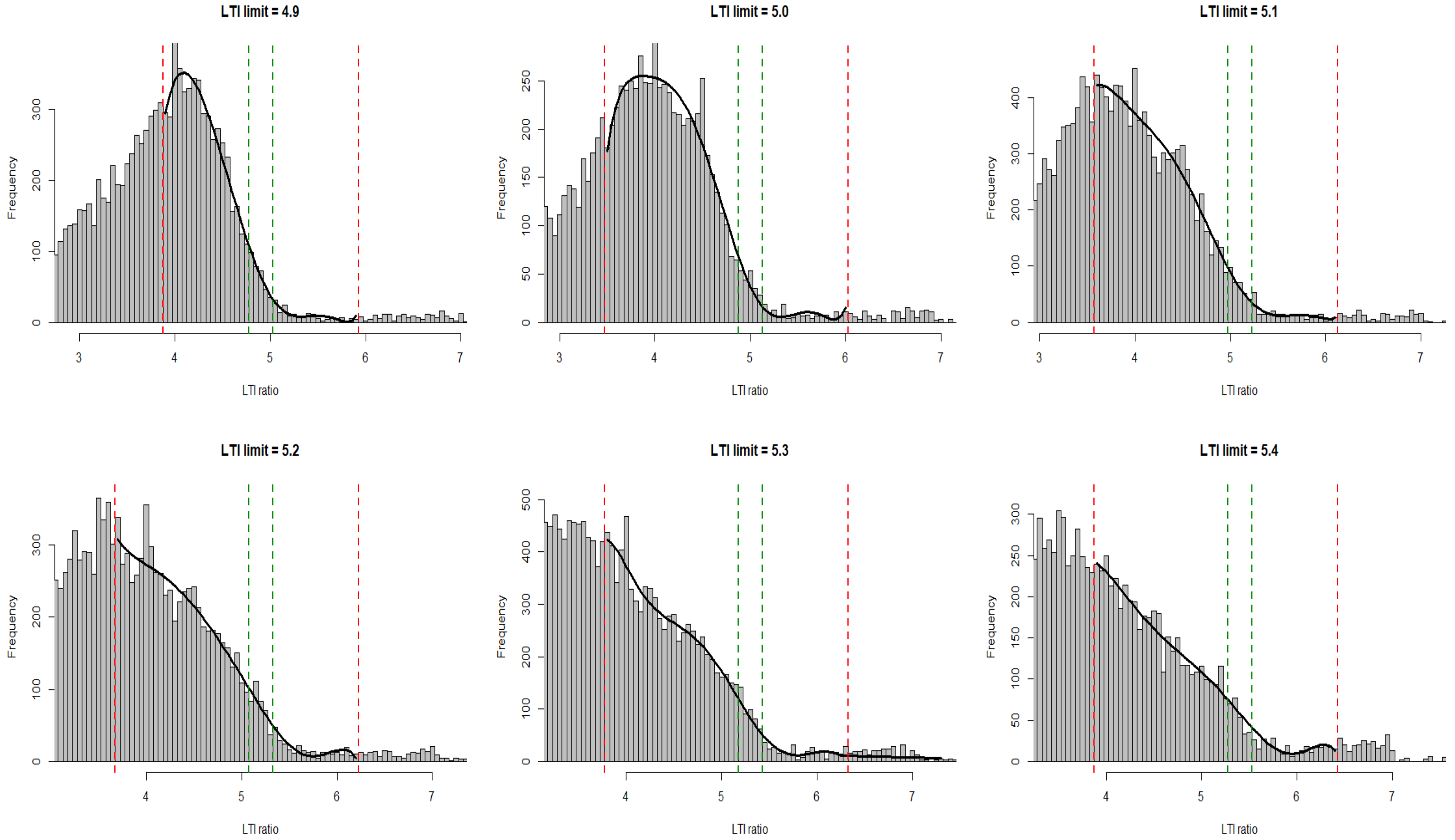
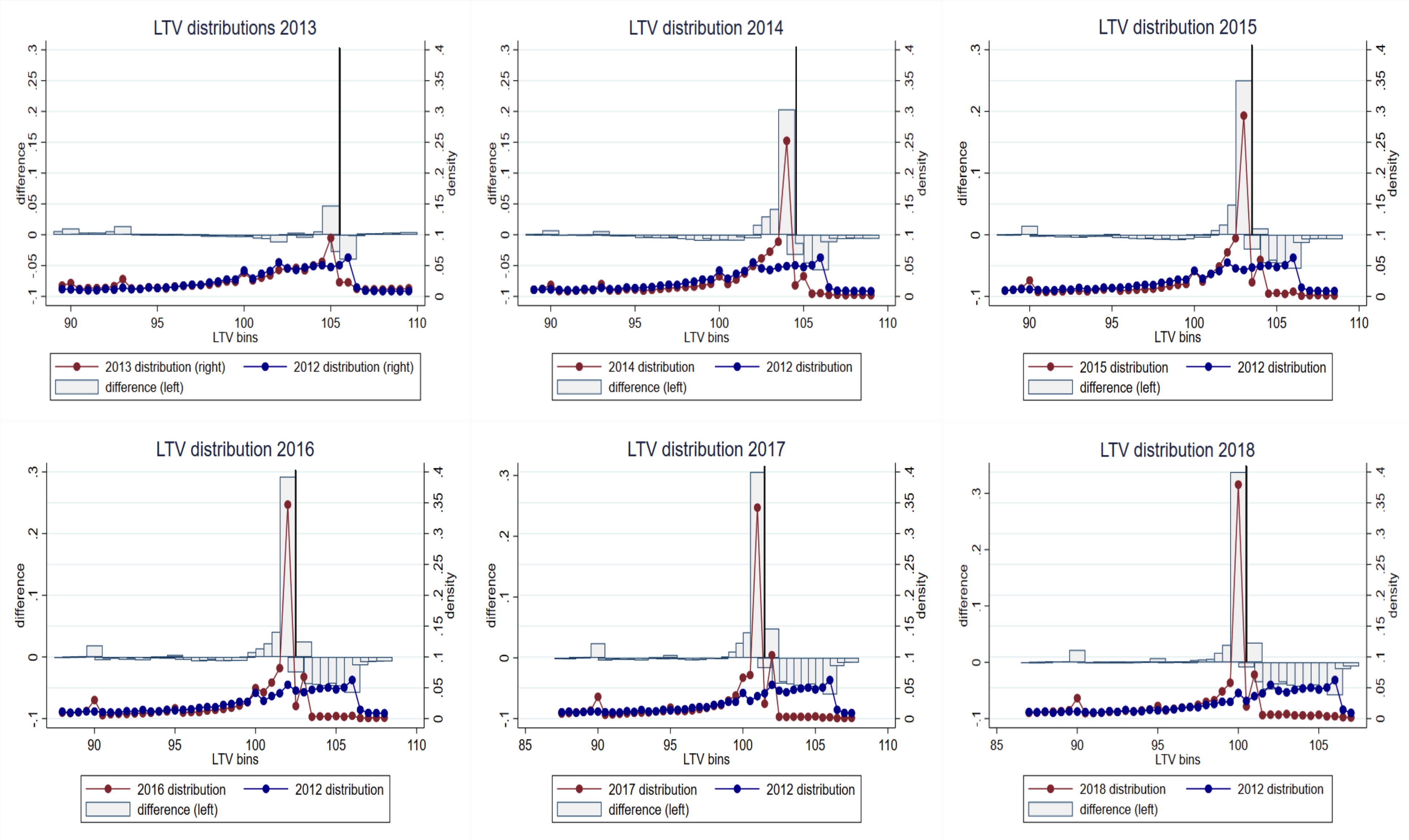


Figure A2(b) Bunching at the LTI distribution



Note: The figure shows the actual LTI distributions (grey bars) for borrowers subject to different LTI limits. Also the figure reports the estimated counterfactual distribution (black line) and LTI bins included in the LTI area (between the two dashed green lines) and in the analysis area (between the two dashed red lines). The extra density above the counterfactual distribution and within the LTI area is the estimated bunching mass ($\widehat{B}$).

Figure A3: Bunching at the LTV distribution



Note: The figure shows the LTV distributions of starters (red line) and renegotiators (blue line) in a window of observation bins around the LTV limit, and their difference (grey bars) in each LTV bin. The difference between the densities in correspondence to the LTV limit represents the estimated bunching difference. ($\widehat{B}$). The difference between the densities to the right of the LTV limit is the estimated missing mass ($\widehat{M}$).

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