Leverage Constraints, House Prices and Household Debt: Evidence from the Netherlands

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Abstract

This paper investigates the effect of leverage constraints and house prices on the level of household debt in the Netherlands. I focus on a period characterized by annual changes in leverage limits, namely Loan-to-Income (LTI) and Loan-to-Value (LTV) limits, and a strong and persistent house price growth. I use exogenous changes in leverage constraints to estimate, both parametrically and non-parametrically, the effect on household debt at origination, and I address potential reverse causality between house prices and household debt growth using as instrument a proxy of the total potential housing supply, as measured by the share of developing land and the number of unoccupied dwellings in each municipality. I find that variations in the LTI limits are binding only for low income households, while progressive LTV limit tightenings double the share of LTV-constrained borrowers. Eventually, I find that increasing house prices act as a strong additional binding factor in households' borrowing choices. The policy implication points in favor of the co-existence of LTI and LTV rules to properly limit over-indebtedness in overheating housing markets.

Keywords: Housing wealth effect, Expectations, maintenance, renovations, home improvements
JELcodes:

1 Introduction

Understanding the origins and the causes of the Great Recession has been the main challenge for economists and policy makers in the last decade. Among the different explanations, a predominant view attributes the main cause to the "credit-driven demand channel", which caused a small problem in the US mortgage market to trigger a worldwide financial meltdown. Changes in models of banking origination first led to a strong increase in lending to households: mortgage debt almost doubled between 2000 and 2007 (Brown et al. 2010), it increased across the whole income distribution (Adelino et al. 2016) and also among subprime borrowers (Mian and Sufi, 2009). The increase in lending then boosted household demand and led to an increase in house prices, which in turn had a feedback effect on household leverage through home equity based borrowing (Mian and Sufi, 2011) or expectations of higher house prices (Kaplan, Mittman and Violante, 2017). The initial increase in house prices rapidly transformed into a bubble, that lasted until the inevitable crash. This eventually led 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 valuable 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 thus took a stronger regulatory approach in this segment of the financial sector and, in particular, they have been increasingly relying on macro-prudential policies to prevent excessive risk-taking in the financial system.

In this paper I investigate the effects of macro-prudential policies and house prices on household mortgage debt in the Netherlands, in a period characterized by annual changes in leverage constraints and by a strong and persistent house price growth. In particular, using administrative data at the loan level merged to local house price indexes constructed from real estate individual transactions data, I study the effect of leverage constraints in the form of Loan-to-income (LTI) and Loan-to-Value (LTV) limits on the debt amounts of newly-originated residential mortgages. These macro-prudential rules establish the maximum amount that can be lent to a borrower conditional on income and on the collateral value of the house, respectively. Also, I study the competing effect of increasing house price that, by making properties more expensive, induce an increase in the level of household debt, especially among liquidity constrained borrowers.

Currently, the Netherlands is one of the most interesting countries in which to study the link between leverage constraints, house prices and households indebtedness: according to the

Oecd[1], the Netherlands is the country with the second highest level of mortgage debt in the world and according to the International Monetary Fund[2] it is also the country with the sixth fastest house price growth rate worldwide of the recent years. In fact, according to the Financial Stability Report[3] published by the Dutch Central Bank, the links between the housing and the mortgage markets are now considered the most important sources of financial stability risk in the Netherlands. For example, new increases in house prices could induce further increases in household debt and raise solvency concerns, while a sudden fall in house prices may lead a large fraction of borrowers (especially first-time buyers, who bought at the top of the market) to have underwater mortgages. The introduction of leverage constraints then was particularly needed in order to contain households over-indebtedness, which has been traditionally very high in the Netherlands[4].

According to Claessens (2017) macro-prudential policies, by definition, distort individual behaviors. However, few theoretical models exist and the design of these policies usually starts from generic concerns rather than from first principles. Also, the literature mostly focuses on the aggregate effects of these policies, such as the effects on financial vulnerability indicators (credit growth, house prices, bank leverage) and the real economy (output)[5].

In this paper I contribute to the literature on macro-prudential policy by taking the micro-perspective, i.e. by studying how macro-prudential policies affect households incentives and, thus, their borrowing decisions.

Estimating the effect of leverage constraints on borrowing is challenging for several reasons. The first reason is that, in overheating housing markets, the effect of leverage constraints can be confounded by the increase in house prices that, by making properties more expensive, force liquidity constrained borrowers to borrow more. If not properly controlled for, the effect of leverage constraints on household debt is likely to be overestimated, as households would then borrow closer to or at the limit for reasons unrelated to changes in the regulation. To deal with this, I use very granular house price indexes at the local level to account for the increase in house prices within municipality, as well as for the heterogeneity in house price growth rates across municipalities.

The second reason is that, even after controlling for changes in housing market conditions, house prices and household debt are likely to be jointly determined by an omitted variable

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

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

[3] Available at https://www.dnb.nl/en/news/news-and-archive/Persberichten2019/dnb384297.jsp

[4] In the pre-crisis period, it was pretty common to borrow mortgages with LTV ratios between 100% and 120%. In fact, most of the high household debt in the Netherlands is due to the mortgage debt component.

[5] See Galati and Moessner (2013), Claessens (2017) for extensive literature reviews.

such as shock to expected income growth (Mian and Sufi, 2011; Attanasio and Weber, 1994; Muellbauer and Murphy, 1997) and, on top of this, there may be reverse causality between the two, as higher house prices may induce households to borrow more to purchase more expensive properties, while increasing household borrowing may lead to higher house prices by boosting households demand. To obtain proper identification of the parameters of interest, I rely on an instrumental variable approach in which changes in house prices across Dutch municipalities are instrumented using a proxy of the total housing supply elasticity in each municipality. My approach is close to the one proposed by Mian and Sufi (2011), that I complement using as instrument a proxy of the total housing supply elasticity.

The third reason is that macro-prudential policies typically consist of common limits, caps and thresholds. Therefore, the identifying variation associated to changes in macro-prudential policies can be low, and the effect of such changes are often difficult to evaluate using quasi-experimental methods. In the Netherlands instead, Loan-to-Income are proposed by an independent institution on the basis of budgetary rules that consider both household characteristics (such as income) and changes in macro-economic factors (price and interesest rate changes). For these reasons, Loan-to-Income limits display cross-sectional variation (they are assigned on the basis of the income and interest rate class of the borrower) and time variation (the limits are also revised annually) that I exploit to evaluate the effect of this policy[6].

The contribution of this paper is therefore to estimate, both parametrically and non-parametrically, the causal effect that leverage constraints have on the level of household debt.

In the non-parametric specification, I contribute to the literature on bunching introduced by Chetty et al. (2011); Kleven and Waseem (2013) and 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. (2018)). This approach, similar to quasi-experimental approaches, exploits the presence of non linearities in agents' budget sets to retrieve an estimate of the behavioral response at that specific point of the budget set[7].

In particular, I first propose a stylized theoretical model of borrowing to show how the effect of changes in leverage constraints on household debt is proportional to the mass of agents bunching at the LTI or LTV limit. Then, I use a bunching approach to obtain a reduced-form estimate of the number of households effectively constrained by the regulation. Eventually, I

[6]Instead, the change in the Loan-to-Value regulation has been introduced with a more traditional phased-in period, that I will take care of in the non-parametric specification.

[7]The typical example is the labor supply response in quantiles of the income distribution where the marginal tax rate sharply increases (kink). The response (labor supply elasticity) was shown to be proportional to the bunching mass at the kink point. See Kleven (2016) for a review.

extend the baseline approach to account for the change in house prices that, as discussed before, can confound the estimated effect of the policy change.

Results show that that LTI and LTV limits, together with increasing house prices, are all contributing to bind households' borrowing choices.

I find that LTI limits are binding on average, but the estimated change in household debt caused by a change in leverage constraints decreases along the income distribution. In particular, LTI limits are particularly binding for low income households, who often bunch at the leverage limits or qualify for the exceptions established by the regulation. For this group, changes in leverage limits translate into changes in household debt of the same size.

On the LTV side instead, I find that despite the very generous levels as compared to international standard, LTV limits are the most binding constraint, and that a 4% decrease in the LTV limits have doubled the share of constrained borrowers from 5.5% to 11%.

Regarding the link between the housing and mortgage market, I find that the recent increase in house prices has acted as an additional binding factor in households borrowing choice: the estimated effect suggest that, on average, a one standard deviation increase in house prices is associated to a 12% increase in house prices. The estimated response is comparable in magnitude to the effect of an LTI limit change.

The main policy implication I draw from this paper is that, in order to properly contain household debt, a macro-prudential regulation cannot overlook a LTI limit based on household debt affordability. The combination of an LTI rule with a LTV limit that helps in balancing the value of assets and liabilities in household balance sheets is desirable. On the contrary, an LTV rule alone cannot properly contain household debt growth in periods of booms and busts in the housing market. While this is the case in the Netherlands, most countries in the world, especially among advanced economies (see Cerrutti, Claessen, Leven, 2017), rely either on LTI or, most commonly, on LTV limits as only macro-prudential tools.

The remainder of the paper is organized as follows: Section II provides institutional details about the macro-prudential regulation in the Netherlands, Section III introduces a stylized theoretical framework that motivates and guides the following empirical study. Sections IV and V present the data and the descriptive and empirical evidence. Section VI concludes.

2 Institutional framework

2.1 Macro-Prudential Policy

The macro-prudential regulation is a policy framework that aims to limit risk intake in the financial system. In the European Union the ECB is the main macro-prudential regulator, but some macro-prudential policies remain under the control of national governments or national supervisory authorities (typically, national central banks). Among the different policies, LTV and LTI limits are the most common macro-prudential tools aimed at limiting excessive indebtedness of households and firms. These instruments represent the core of macro-prudential regulation also in the Netherlands.

The LTV limit establishes the maximum debt that can be lent to a borrower, relative to the collateral value of its house. The rule is straightforward: as of 2012 originated mortgage loan amounts must be at most equal to 106% of the appraised house value. Then this limit has been reduced by 1% every year up to 2018, when the LTV ratio has been set permanently to 100%. Therefore, the LTV ratio displays time variation but no cross-sectional variation as it is the same for all borrowers.

The LTI limits are set by the Dutch government at the recommendation of the National Institute for Family Finance Innovation (NIBUD) as a debt-service-to-income constraint (DSTI). A DSTI constraint establishes the maximum debt service amount that a household affords to pay on a monthly basis, as a percentage of its income. The NIBUD recommendations account for all the necessary expenses that families incur in: they are based on budgeting computations that account for changes in consumer prices, energy prices and taxation. Eventually, the recommended DSTI limits are converted into equivalent LTI limits that establish the maximum loan amount that can be lent to a borrower, as a multiple of family income. In the empirical analysis that follows, I will refer only to the resulting LTI rules, as these are the ones that banks apply at origination.

Since the resulting LTI limits reflect the affordability of debt repayment, they depend on total household income and on the interest rate paid on the mortgage, which is part of the debt service. Figure 1 reports an example of the table containing the recommended LTI limits. The example refers to the rule in force in 2014. The Figure shows the considerable cross-sectional variation that the limits display: depending on income and on the interest rate, they ranged from 2.6 to 5.7. An LTI limit of 4 indicates that the maximum loan amount that a household affords to repay is four times its gross annual income. Stricter LTI limits are assigned to

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

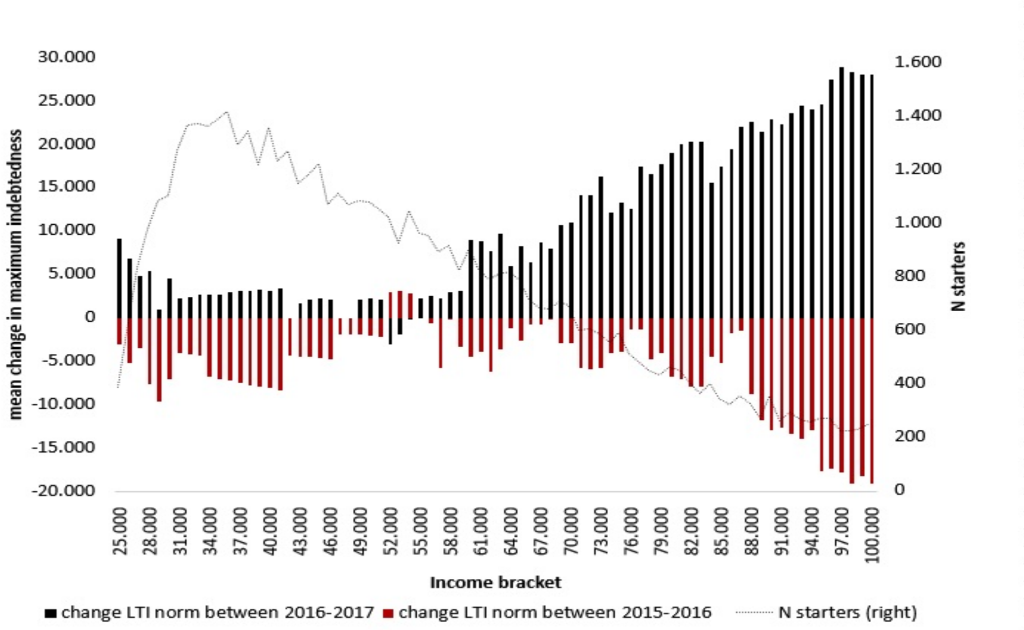
Bruto	Hypotheekrente				
jaarinkomen	3.75%	4.25%	4.75%	5.25%	5.75%
19500	3.0	2.9	2.8	2.7	2.6
20000	3.1	3.0	3.0	2.9	2.8
20500	3.3	3.2	3.1	3.0	2.9
21000	3.5	3.4	3.3	3.2	3.1
21500	3.6	3.5	3.4	3.2	3.1
22000	3.8	3.6	3.5	3.4	3.3
22500	3.9	3.8	3.8	3.7	3.6
23000	4.0	4.0	3.9	3.8	3.8
23500	4.1	4.1	4.0	3.9	3.9
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 heatmap of an example of the table containing the recommended Loan-to-Income (LTI) limits. 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. The example represents the 2014 LTI limits table. The LTI limits represent the maximum debt that can be lent to a borrower, as a multiple of its gross annual household income.

lower-income and riskier (high interest rate) households. These LTI limits also display considerable time variation other than cross-sectional variation, as the recommendations are revised annually. Figure 2 shows the changes in the maximum borrowing capacity between the years 2015-2016 and 2016-2017, for the different income brackets.

As an example, for a household with an annual income of 50.000 euro, a 0.2 LTI limit change reflects a 10.000 euro change in the maximum loan amount. The Figure shows that between 2015 and 2017 changes in the limits have been both positive and negative, and that the resulting changes in the borrowing capacity have been sizable, especially for high income households.

Figure 2: Changes in maximum allowed indebtedness



Note: The figure shows the average change in the maximum loan amounts in 2015-2016 (in red) and 2016-2017 (in black) respectively, for different household income categories. The change in each income category represents the average change among all interest rate categories in the same income category. Also the Figure shows the empirical income distribution among starters household in the sample considered.

Also, a key feature of the LTI rule in the Netherlands is that it is a *comply or explain* rule, i.e. there are established exceptions that allow for flexibility options for both lenders and borrowers. In particular, if borrowers can qualify into one of the established exceptions, banks are allowed to grant them a mortgage with an LTI higher than the established limit. Banks can exceed the LTI limit if one of the following cases apply: (*i*) mortgage refinancing (*ii*) energy saving investments and (*iii*) bridge loans (for borrowers who move into a new house, until the old house is sold). In additions to these specific cases, lenders are generally 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[8]. If the documentation doesn't meet the necessary requirement, banks willing to exceed the LTI limits are simply not allowed to do it, and must reduce the originated loan up to the limit. On the contrary, banks are never allowed to originate a mortgage exceeding the original 106% LTV cap and the LTV limit in place every year is a strict rule for first-time buyers (starters).

To summarize, LTI and LTV rules represent complementary leverage constraints aimed at limiting excessive household indebtedness. The former is a rule that takes into account the affordability of debt repayment, allows for flexibility options and depends on household char-

[8]For further legal details, see Van't Hof (2017).

acteristics. The latter is a strict rule for starters that applies in same way to everybody. The next section investigates the theoretical implications of the introduction of such rules.

2.2 Mortgage Market

The mortgage market in the Netherlands is dominated by the four largest banks that provide about the 80% of the total supply of mortgages. The remaining market share is controlled by small banks, pension funds and insurance companies that have recently entered the market (Kim and Mastrogiacomo, 2019 ; Thiel, 2020).

Traditionally, loan amounts granted by Dutch banks have always been very generous as compared to internal standards. In the period before the crisis, it was in fact fairly common for Dutch households to borrow mortgages having Loan-to-Value ratios up to 120%. Part of this phenomenon is certainly attributable to institutional features that explicitly incentivize high nominal debts in households' balance sheets, such as a mortgage interest deduction up to 51%, and a public housing guarantee (NHG, *Nationale Hypotheek Garantie*) that insure banks and borrowers to default risk, but whose premium is independent on loan riskiness[9]. For this reasons, a number of non-amortizing products (such as Interest-only mortgages) or products that allow for tax arbitrage (such as Savings, Insurance and Investment mortgages) gained popularity, and now represent the most common mortgage types (DNB Occasional Study 13-4). Eventually, despite the high debt levels of Dutch households, mortgage defaults have always been a minor issue as compared to the United States, mostly because of institutional differences. In fact, unlike in the U.S., in the Netherlands there is a full recourse system that allow lenders to lay claims on borrower's assets, other than those pledged as a protection.

2.3 Real Estate Market

The real estate market in the Netherlands is characterized by a huge supply shortage, due to zoning restrictions and the presence of one of the largest social rental housing sector in Europe that counts about 30% of the total stock of houses and is mostly owned by housing associations. While the existing stock of houses is scarce, there are also obstacles to increasing housing supply: municipalities depend on revenues from land development, but often lack incentives to grant new permits because they want to keep existing residents satisfied and because they are forced to lower land price to make the construction of non-rent regulated

[9] In particular, borrowers who bough NHG and default on the mortgage due to job loss, divorce or partner's death or disability, are insured against the possibility that the proceeds of the house sale are not enough to cover the outstanding nominal debt at default. The NHG premium consist of a one-off payment proportional to the debt amount at inception, but is independent on the value of collaterals.

housing profitable (DNB occasional study, 15-1). For these reasons, the price elasticity of housing supply in the Netherlands is among the lowest in Europe (OECD, 2011). In the recent period, the combination of a tight housing supply with a persistently increasing housing demand driven by immigration flows and an increasing investor activity have caused the housing market to overheat: house prices have rapidly increased in the 2013-2019 period at a very fast pace compared to international standards (and reached a new historical peak) and price to income ratios have been constantly rising too (DNB, 2019). This is clearly leading to increasing affordability issues.

3 Theoretical framework

This section introduces a stylized theoretical framework to investigate the effect of leverage constraints on household borrowing. The focus is thus on the households borrowing decisions at origination. The proposed model builds on Piazzesi and Schneider (2016) who provide a general framework that includes "*housing*" in a life-cycle model. In fact, the borrowing decision is simultaneous to the house purchase decision, so this has to be accounted for. Related analyses have been proposed in Brueckner (1994), Defusco and Paciorek (2017) and Stein (1995)[10].

This model has at least two key distinctive features: first, houses are assets that provide a non-tradable dividend, the housing service, which is a consumption good. Second, individuals derive utility from living in their house (the housing service) and the utility is increasing in house quality. Since the focus is on the debt origination used to finance the house purchase, I do not consider the existence of a rental market but I only look at starting homeowners. For the same reason I do not explicitly consider houses as technologies that depreciate if essential maintenance is not performed, and thus I exclude home improvement decisions from the analysis. Eventually, since the borrowing decision of a starting homeowner is by definition a one-time decision I do not explicitly treat time, as in Brueckner (1994), Defusco and Paciorek (2017) and Stein (1995). In particular, I consider households living T periods and borrowing at a given point in time $t < T$.

In the economy there are N households indexed by i. Household i has a discount factor β_i distributed over the support $[\underline{\beta}, \overline{\beta}]$, according to a cumulative density function $F(\beta)$. At time

[10]Brueckner (1994) studies the relation between the demand for mortgage and the interest rates on savings and mortgages. Defusco and Paciorek (2017) look at the interest rate elasticity of mortgage demand. Eventually, Stein (1995) investigates the role of down-payments in explaining fluctuations in the housing market when agents are second time buyers.

t each borrower i maximizes:

$$\tilde{U}_i = max_{c_t,h_t,m_t}\ U(g(c_t, s_t(h_t))) + \beta_i E_t[V(w_{t+1})] \tag{1}$$

$$s.t. \quad c_t + p_t h_t = w_t + m_t \quad ; \quad w_t = y_t$$

$$w_{t+1} = (w_t - c_t - p_t h_t)R + p_{t+1} h_t$$

Households choose consumption, the housing quality and the mortgage size that maximize life-cycle utility. Life-cycle utility corresponds to current utility, which is derived via consumption c_t and the housing service $s_t(h_t)$, and the expected future value of wealth $E_t[V(w_{t+1})]$ which represents the utility derived by optimally behaving in the remaining $T-t$ periods, conditional on w_{t+1} (Brueckner (1994)). Current utility takes the following functional form:

$$U(g(c, s(h))) = log\big(c^{\alpha}\ s(h)^{1-\alpha}\big) \tag{2}$$

While $V(w_{t+1}) = log(w_{t+1})$. From the first budget constraint the household uses its current endowment, represented by labor income y_t and the mortgage loan amount m_t, to finance the consumption expenses and the house purchase. A house of quality h_t is worth $p_t h_t$ and provides a housing service $s_t(h_t)$. Since the utility of living in a house is increasing in house quality, higher quality houses proportionally deliver higher housing services. Therefore, I follow Piazzesi and Schneider (2016) and set $s_t(h_t) = h_t$. From the second constraint, the housing and mortgage choice affect the level of future wealth w_{t+1} which is the difference between the future asset value of the house $p_{t+1}h_t$ and the outstanding mortgage debt Rm_t. I assume the interest rate $R = 1 + r$ to be certain and agreed upon the mortgage contract, while future house prices are uncertain. In particular, I assume that $p_{t+1} = p_t + \epsilon_t$ with $\epsilon_t \sim IID(0, \sigma^2)$.

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

$$m_t \leq \theta y_t \qquad\qquad m_t \leq p_t h_t(1-\delta) \tag{3}$$

Where θ and δ are the policy parameters that determine the level of the LTI and LTV limits, respectively. To solve the model, I follow Piazzesi and Schneider (2016) who propose a two stage solution approach to the problem. In the first stage households choose the house quality h_t that trades off housing expenditures and housing utility. In the second stage, conditional on the optimal house quality, households decide how much to consume and how much to borrow.

In other words, conditional on the house chosen, households use the mortgage as a consumption smoothing device. In the analysis that follows I focus on the second stage problem, taking the optimized house quality h_t as given to investigate the corresponding inter-temporal allocation decision represented by the financing choice[11]. This inter-temporal allocation depends on the time preference β_i that is heterogenous across households[12]. With no assumptions on the functional form of U, g and V and conditional on the optimal house quality h_t, the Euler equation of the unconstrained case, when neither the LTI nor the LTV constraint bind, is equal to:

$$U'[g(c_t, h_t)]g'(c_t, h_t) = \beta_i \, E_t[V'(w_{t+1})]R \tag{4}$$

It establishes the relation between current and future consumption in the optimal consumption path. Again, the household uses the mortgage loan not only to finance the house purchase, but also to reach the best possible resource allocation described by the Euler equation. Using the assumed functional forms of U, g and V, and using $E_t(p_{t+1}) = p_t$, from the Euler equation I solve for m_t to obtain the household i unconstrained mortgage function:

$$m_i^u = \frac{p_t h_t(\alpha + R\beta_i) - R\beta_i \, y_t}{R(\alpha + \beta_i)} \tag{5}$$

Where m_i^u denotes the mortgage size of borrower i in the unconstrained case[13]. The desired level of debt depends positively on property valuation and negatively on household income. Next, consider the constrained case with both constraints active and let $\lambda[m_t - \theta y] = 0$ and $\eta[m_t - p_t h_t(1-\delta)] = 0$ be the Kuhn Tucker conditions for the LTI and LTV constrains. Under these leverage limits the constrained mortgage amount is:

$$m_i^c = min\big\{\theta y_t \, ; p_t h_t(1-\delta)\big\} \tag{6}$$

In words, the constrained loan size is equal to the leverage constraint that binds first. Rearranging, the LTI limit binds first if:

$$\theta < \frac{p_t h_t}{y_t}(1-\delta) \tag{7}$$

Where $p_t h_t / y_t$ is the price-to-income ratio associated to borrowers' house purchases. In this model, whether leverage constraints are binding or not ultimately depends on each individual

[11] This approach, despite formally treated in Piazzesi and Schneider (2016), has been implicitly adopted also in Brueckner (1994). Instead, Stein (1995) takes the same approach in the opposite perspective and studies the house quality choice conditional on the available endowment.

[12] Please note that the discount factor is the only element of heterogeneity in the population, as households are assumed to share the same life-time utility function, as well as the same level of income. This assumption despite being strong in general, perfectly matches the aim of our empirical analysis that looks at the households' mortgage choices conditional on the observed household characteristics.

[13] The subscript t has been dropped to ease the notation.

unconstrained loan size m_i^u, and thus on each individual discount factor β_i which is the only element of heterogeneity in the population: more patient households require levels of future consumption that are higher than those of inpatient households who, given lifetime resources, take highly leveraged positions to increase current consumption vis-a-vis future consumption. I derive the breakpoint level of β by equating the unconstrained to the constrained mortgage functions, in formulas: $\beta^* : m_i^u = m_i^c$. Suppose the LTI binds first, then:

$$\frac{p_t h_t(\alpha + R\beta_i) - R\beta_i\, y_t}{R(\alpha + \beta_i)} = \theta y_t \tag{8}$$

Leading to:

$$\beta^* = \frac{\alpha(p_t h_t - \theta R\, y_t)}{R[y_t(1+\theta) - p_t h_t]} \tag{9}$$

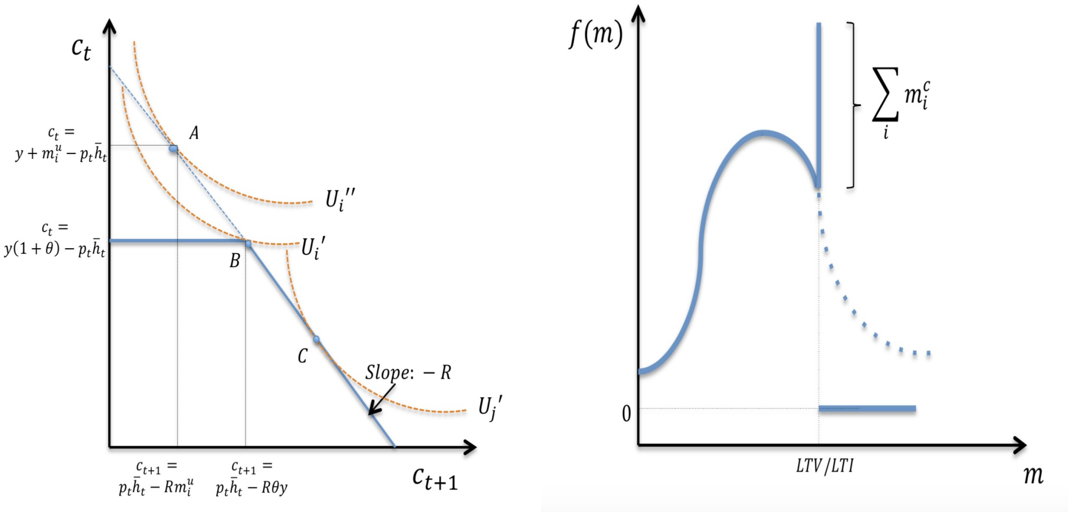
The value of β^* identifies marginal borrowers, i.e. the households whose unconstrained and constrained mortgage size coincide, for given levels of the leverage constraints. It is important to stress that marginal borrowers are completely unaffected by the policy since they are always able to borrow their desired loan size, which simply equals the first-binding constraint.

Figure 4 provides a graphical representation of the effect of leverage constraints on household debt in the simplest two periods case with the terminal condition $w_{t+1} = c_{t+1}$. In absence of credit constraints household i would locate in point $A = (c_t^*, c_{t+1}^*)$ that represents the optimal solution in the unconstrained case. If leverage constraints are introduced, the inter-temporal budget set features a discontinuity and the household gets constrained by the regulation and locates at point B. This allocation is a second-best corner solution as $U'_i < U''_i$. The same would not be true for household j that, being more patient that i (i.e. $\beta_j > \beta_i$) , chooses a mortgage size lower than the limit that still allows it to reach the unconstrained allocation in point C. The implication is that, in absence of leverage constraints, the mortgage distribution in the population is the same as the distribution of discount factors $f(m) = f(\beta)$ (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.

3.1 Aggregation

In this section, I aggregate all households borrowing choices to determine the aggregate debt level in the population and its relation with the level of leverage constraints. According to the

Figure 3: (Un)constrained optimal consumption and 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.

value of β^*, I can divide the population in two groups: the first group of unconstrained borrowers is made of patient households whose preferences imply taking low debt positions, these are all $i : \beta_i \in [\beta^*, \overline{\beta},]$. Conversely, the second group contains all constrained borrowers with discount factors $\beta_i \in [\underline{\beta}, \beta^*)$ that, being less patient, would tend to overindebt to maximize current utility in absence of leverage constraints. Again, the value of β is distributed according to a cumulative density function $F(\beta)$. In the former group, each individual debt level is different, as it depends on one's discount factor. On the contrary in the latter group everybody is constrained and takes the maximum allowed mortgage level. 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:

$$\begin{aligned} M(\theta) &= M^1 + M^2(\theta) \\ &= [F(\overline{\beta}) - F(\beta^*)]m_i^u + F(\beta^*)m_i^c(\theta) \end{aligned} \tag{10}$$

Where $F(\beta^*)$ is the share of constrained borrowers, which is increasing in the level of prices and decreasing in the level of income. From the last equation, the average debt level in the population explicitly depends on the policy parameter θ. The level of the leverage constraint affects not only the debt level of constrained households, but also the share of constrained borrowers in the population via the relation with $\beta^* = \beta^*(\theta)$. In fact:

$$F(\beta^*) = Pr(\beta_i \leq \beta^*) = F\left(\frac{\alpha(p_t h_t - \theta R\, y_t)}{R[y_t(1+\theta) - p_t h_t]}\right) \tag{11}$$

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

$$\frac{\partial M(\theta)}{\partial\, \theta} = f(\beta^*)[m_i^c(\theta) - m_i^u] + F(\beta^*)\frac{\partial\, m_i^c(\theta)}{\partial\, \theta} \tag{12}$$

Where $f(\beta) = F'(\beta)$ is the probability density function. In words, the change in the policy parameter has two effects: on one side it changes the fraction of constrained and unconstrained borrowers in the population, on the other side it changes the aggregate debt level 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 leverage limit, captured by $F(\beta^*)$: the higher it is, the higher the share of constrained borrowers and the larger the response to a leverage limit increase, as constrained borrowers' would use the policy change to increase their debt position. Note that eq. 2.12 holds for any possible density functions $F(\beta)$[14] and in the case the other constraint (LTV) binds first[15].

In a similar fashion, conditional on the same house bought[16], I can obtain the change in the aggregate debt level due to a change in house prices as:

$$\frac{\partial M(\theta)}{\partial\, p_t} = \begin{cases} \left[F(\overline{\beta}) - F(\beta^*)\right]\frac{\partial\, m_i^u}{\partial\, p_t} + f(\beta^*)\left[m_i^c - m_i^u\right] + F(\beta^*)\frac{\partial\, m_i^c}{\partial\, p_t} & if \quad \theta y_t > p_t h_t(1-\delta) \\ \\ \left[F(\overline{\beta}) - F(\beta^*)\right]\frac{\partial\, m_i^u}{\partial\, p_t} + f(\beta^*)\left[m_i^c - m_i^u\right] & if \quad \theta y_t \leq p_t h_t(1-\delta) \end{cases} \tag{13}$$

Interestingly, the effect of a house price change is different depending on which constraint binds first: since the borrowing capacity implied by the LTV limit $p_t h_t(1-\delta)$ is proportional to the level of house prices, an increase in prices induces a relaxation of the LTV-limit which in turn leads LTV constrained borrowers (captured by the term $F(\beta^*)\, \partial m^c/\partial p$) to increase the debt

[14] In case $\beta \sim U[\underline{\beta}, \overline{\beta}]$ and the LTI limit binds first, eq. 2.12 has a closed form solution equal to:

$$\frac{\partial M(\theta)}{\partial\, \theta} = \frac{1}{\overline{\beta} - \underline{\beta}}\left(\theta y_t - \frac{p_t h_t(\alpha + R\beta_i) - R\beta_i\, y_t}{R(\alpha + \beta_i)} + (\beta^* - \underline{\beta}\ )y_t\right)$$

[15] In this case, the level and the change in debt will be denoted with $M(\delta)$ and $\partial M(\delta)/\partial\, \delta$, respectively.

[16] Note that a change in house prices should also affect the corresponding first-stage optimal house choice h^*. However, house qualities are often discrete and households might not be able to slightly "downsize" their housing choice.

amount they require. In summary I obtain two main empirical implications from the model:

Empirical implication 1: Changes in house prices and changes in leverage limits jointly affect households' borrowing choice in terms of debt amount.

Following implication 1, an increase in house prices in a period of tightenings leverage constraints acts as an additional borrowing constraint. Conversely, in periods of constant borrowing constraints, an increase in prices pushes the level of debt towards the leverage limit, for reasons unrelated to the macro-prudential policy.

Empirical implication 2: If leverage limits are binding, the distribution of household debt features a spike at the limit which is proportional to the number of constrained borrowers.

Following implication 2, the aggregate effect on household debt of a policy aimed at changing the leverage limit will also be proportional to the bunching mass at the limit: in case of a limit increase, all borrowers take advantage of policy change to increase their debt position by an amount exactly equal to the increase in the limit.

4 Data and descriptive statistics

The main data source used in the empirical analysis is the Loan Level Data (LLD) collected by the Dutch National Bank. As of 2012Q4, financial institutions must comply with the 100% transparency policy of the ECB in order to be able to securitize their loans. Under this policy, banks must report all information required in the Residential Mortgage Backed Securities (RMBS) template of the ECB's European Data Warehouse. In the LLD, this information not only covers the pool of loans that banks plan to securitize, but refers to the entire mortgage portfolio of banks involved in securitization (see Mastrogiacomo and Van der Molen, 2015).
The information consists of borrower, property and loan characteristics for almost the 85% of the population of banks' issuing mortgage loans. The Dutch mortgage market is a very concentrated market in which the main three banks (ABN Amro, Rabobank and ING) control the largest share of the market. The activity of these three largest banks is well reported in the LLD.
I merge the LLD with three other data sources. The first and main data source comes from the

Dutch Association of Real Estate brokers (NVM). This data contains house price indexes at the local level. In particular, these house price indexes are constructed using individual transaction data in the housing market, they are at quarterly frequency and at the two-digits postcode level (Van Dijk, 2019). In the Netherlands, the two-digits postcode unit approximately represents the municipality: the four biggest cities have a unique two-digit postcode, while in countryside areas the same two-digits postcode can be shared by two or more towns of the same province. Thanks to the high granularity and the enough high frequency of these local house price indexes, I can easily account for the local differences in house price growth rate of the last years. Eventually, the last two data merged consist of municipality level information from Statistics Netherlands and the NIBUD Tables, a large file containing all the LTI limit recommendations set by the NIBUD Institute in the period 2012-2017.

Table 2.1 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*)[17]. The table shows that sustained increase in household debt over the sample years, in parallel with the increase in property valuations. While these trends may be due to a variety of factors (e.g. the decrease in the interest rate evident in Table 1, changes in the macro-prudential regulation etc.), the increase in property valuation may reflect the sustained increase in the house prices evident in the NVM data.

Table 2.2 shows that the increase in prices was generally sustained but varied substantially across regions: while the national house price index increased by almost 15% in a four year period, house prices have been increasing by 8% in the province of Drenthe 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 macro-prudential regulation and increasing house prices.

[17]We focus on First-time buyers because they are explicitly subject to the leverage constraints. Due to a reporting issue, we are not able to distinguish all renegotiating and starting borrowers in the data. To identify starters we exploit a recent 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 disappeared from the market. This rule applies to newly originated mortgages, while borrowers who took their loan before 2013 and holding other types of mortgages are still eligible for the mortgage interest deduction. Therefore, we identify starters as borrowers whose mortgage has been originated and firstly reported after 2013, and whose mortgage type is either linear or annuity. Correspondingly, we define as renegotiators all borrowers holding other types of mortgage (saving mortgages, investment mortgages etc.) and whose mortgage origination is (mis)reported after 2013. These borrowers are in fact renegotiating borrowers that, having switched to another bank during the renegotiation reset period, appear in the data with another identifier.

Table 1: Descriptive statistics (LLD)

		2014	2015	2016	2017
Mortgage Debt					
	Mean	177.312,7	189.895,6	206.336.2	231.812,1
	Med	161.200,0	171.700,0	182.500,0	199.475,0
	N	52.251	56.575	62.530	67.807
Property Valuation					
	Mean	218.305,8	234.425,3	255.414,7	291.610,9
	Med	185.000,0	198.000,0	215.000,0	235.000,0
	N	52.005	55.760	62.095	67.665
Interest Rate					
	Mean	0.035	0.028	0.024	0.022
	Med	0.036	0.028	0.023	0.022
	N	52.005	55.760	62.095	67.665
Maturity					
	Mean	29,3	29,3	29,4	29,3
	Med	30	30	30	30
	N	52.251	56.575	62.530	67.807
Household Income					
	Mean	53.779,6	56.771.2	61.884.5	64.428.3
	Med	44.443,3	46.617,6	50.423,0	52.876,8
	N	52.251	56.575	62.530	67.807
Loan to Income					
	Limit(avg)	4.81	4.70	4.69	4.81
	Mean	3.63	3.67	3.65	3.87
	Med	3.8	3.9	3.9	4.1
	N	52.132	56.739	62.509	67.406
Loan to Value					
	Limit	104.0	103.0	102.0	101.0
	Mean	85.9	86.7	86.2	84.2
	Med	98.2	98.7	97.5	95.8
	N	51.808	55.509	61.799	67.406

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 debt amount at origination, the collateral value (property valuation), the interest rate and the maturity. The bottom panel reports as borrower characteristics the mean and median LTI and LTV ratios, as well as the average LTI limit and LTV limit. The Table eventually reports the number of observations for each variable.

Table 2: Descriptive statistics (NVM)

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

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

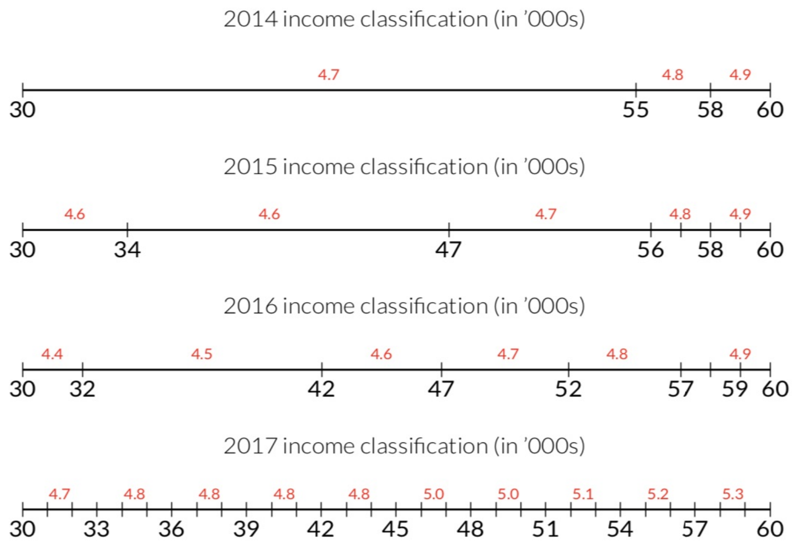
The empirical analysis is divided in three parts. The first subsection tests Empirical Implication 1 via a joint estimation of the effects of house prices and LTI and LTV constraints on the amount of household debt at mortgage origination. The second and third subsections test Empirical Implication 2 via a non-parametric estimation of the effects of LTI and LTV constraints on the corresponding distribution of the LTI and LTV ratios, respectively.

5.1 The effect of house prices, LTI and LTV limits

The first empirical implication drawn from the theoretical framework is that both leverage constraints and house prices affect household debt at mortgage origination. In particular, house price changes and changes in the leverage limits have a competing effect. Increasing house prices in a period of tightenings leverage constraints act as an additional borrowing constraint: when households' borrowing capacity decreases, higher house prices induce liquidity-constrained households to borrow more to purchase more expensive properties on sale. Conversely, in periods of constant debt limits, an increase in house prices pushes the level of debt towards the leverage limit, for reasons unrelated to the macro-prudential policy. This section tests this empirical implication, and aims at jointly estimating the effect of leverage limits and house prices on the level of household debt at origination.

To elicit the causal effect of the LTI regulation on household debt, I exploit the cross-sectional and time variation of the LTI limits as showed in Figures 2.1 and 2.2. Importantly, this variation is also exogenous, as the LTI recommendations are made by an independent institute on the basis of budgeting computations that account for changes in macroeconomic conditions such as changes in consumer prices, taxations and interest rates. Lastly, these variations can neither be anticipated nor foreseen: first, they cannot be anticipated as the LTI recommendations become effective in January, but become public only in November. Second, despite some of the changes in the macroeconomic conditions are easily predictable (e.g. the decrease in the interest rates due to the monetary policy stance), the resulting LTI limits are hard to predict because of the changing classification made by the NIBUD Institute during the sample period.

Figure 4: Exogenous changes in the income classification



Note: The Figure shows the change in the number and the size of the income brackets undertaken by the NIBUD Institute for the LTI limits classification. The dashes and the numbers in black denote the size of the different income brackets. The numbers in red denote the corresponding LTI limits, for the most frequent interest-rate category (3.0-3.5%).

Figure 2.4 clarifies this point: the NIBUD Institute decided to gradually switch from broad income classifications (a total of four income brackets in a 30.000 euro income interval in 2014) to a very granular classification in 2017 (having one income bracket every 1.000 euro). Evidently, part of the change in the LTI limits are due to this change in classification, which cannot be anticipated by borrowers. Given these premises, I estimate the following specification:

$$log(Mortgage\,amount)_{i,m,t} = \beta_1\, LTI^{max}_{i,t} + \beta_2 P_{m,t} + \mathbf{X}_{i,m,t}\delta + \epsilon_{i,m,t} \tag{14}$$

Where the dependent variable is the amount of mortgage debt taken out by borrower i in municipality m in year t, expressed in logs. The main coefficient of interest is β_1 that captures the effect of the LTI limit on the level of debt, while $\mathbf{X}_{i,m,t}$ is a $(n \times k)$ matrix of borrower, property and loan characteristics. $P_{m,t}$ is 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. These include the household gross annual income, the house type, the loan type, the mortgage interest rate and maturity, the employment status, an indicator for whether the borrower lives in a big city and an indicator for whether the borrower is covered by the National Housing Guarantee. Eventually, eq. 2.14 is augmented with bank, time, region and region-time fixed effects and estimated on a pool of repeated cross-sections[18].

To estimate eq. 2.14 I propose an identification strategy based on instrumental variables (IV) to deal with the potential simultaneity issue between household debt and house price growth. In fact, the causality may even run in the opposite direction than what eq. 2.14 shows: for instance, a positive shift in credit supply may induce households to take on more debt, and this would in turn boost housing demand and house prices in equilibrium.

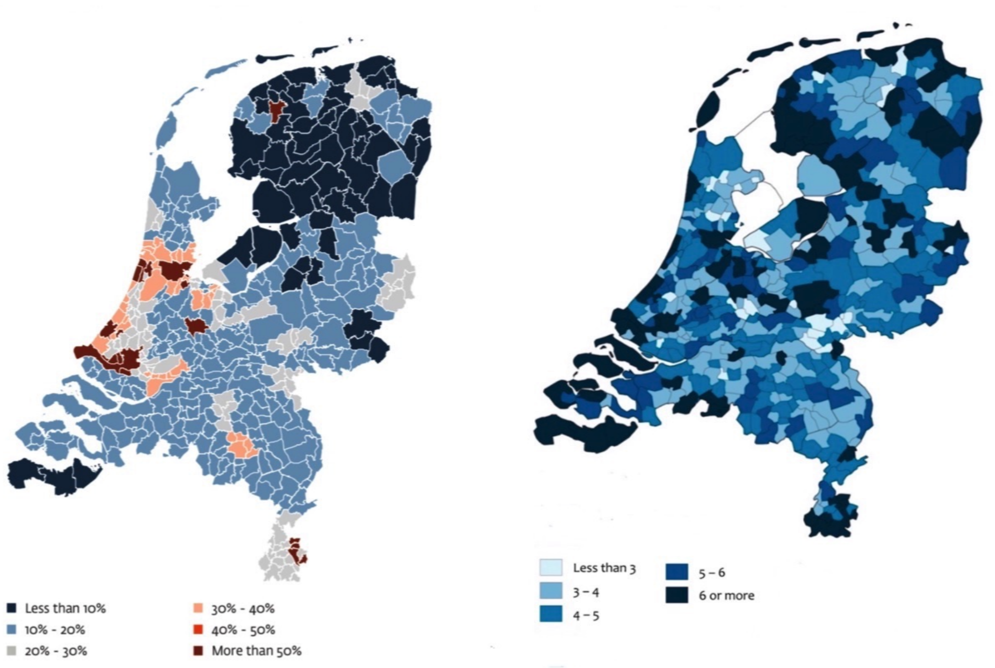
I instrument the local house price index using two proxies of the supply and supply elasticity in the local housing market in 2013. The first instrument is the share of developed land[19] introduced by Saiz (2010) studied in Hilber and Vermeulen (2016), and firstly used as instrument by Mian and Sufi (2009) for the United States. The intuition is the following: for a given shock to housing demand, the equilibrium price in the housing market should clear at higher levels in municipalities characterized by mostly urbanized and developed areas. In fact, the higher is the share of developed land and the lower are the possibilities for housing starts and urban expansions. The second instrument is the share of unoccupied dwellings. Contrarily to the share of developed land, which proxies for housing starts and thus the elasticity of housing supply, the share of unoccupied dwellings proxies housing supply via the existing stock of houses: for a given shock to housing demand, house prices should clear at lower levels in cities characterized by excess supply of existing dwellings.

Figure 2.5 shows the geographical variation of these two instruments: it shows that in the four big cities (where house prices are growing at the highest pace, see Table 2) the share of developed land is above 50% and new housing starts are therefore very limited. On the contrary, the share of unoccupied dwellings tend to be larger in the north and in the south-western part

[18]Since we look at the mortgage origination of starting homeowners we never observe the same borrower in different periods, as this borrowing and house purchase decision is by definition taken once in a life-time.

[19]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 5: Instrumental Variables



Note: The Figure shows the geographical variation in the share of developed land (left) and in the share of unoccupied dwellings (right).

of the Netherlands, which has more villages, smaller towns, and countryside places than the more-populated Randstad area. Given the presence of two instruments and one over-identifying restriction, I estimate specification 2.14 using Optimal GMM, which is more efficient than 2SLS in the over-identified case.

Results are reported in Table 2.3, that include also the OLS estimates of the same specification.

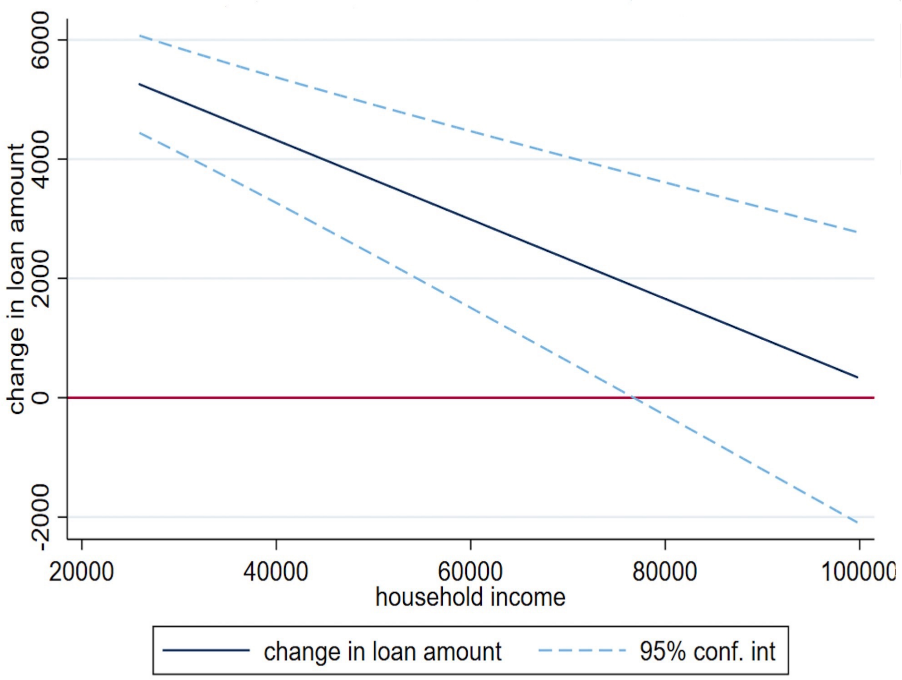
Table 3: The Effect of LTI Limits and House Prices on Household Debt

	Dependent variable: loan amount					
	OLS	IV-GMM	OLS	IV-GMM	OLS	IV-GMM
LTI limit	0.3779***	0.2733***	0.4656***	0.4028***	0.4403***	0.3670***
	(0.0046)	(0.0205)	(0.0053)	(0.0116)	(0.0052)	(0.0126)
LTI limit × income			-0.0043***	-0.0059***	-0.0041***	-0.0054***
			(0.0002)	(0.0003)	(0.0002)	(0.0003)
LTI limit × LTV constr.					0.0032**	0.0011
					(0.0015)	(0.0020)
LTI limit × income × LTV constr.					0.0004***	0.0005***
					(0.0000)	(0.0000)
Local house price index	0.0012***	0.0031***	0.0012***	0.0030***	0.0012***	0.0028***
	(0.0000)	(0.0004)	(0.0000)	(0.0004)	(0.0005)	(0.0004)
controls	✓	✓	✓	✓	✓	✓
bank FE	✓	✓	✓	✓	✓	✓
time FE	✓	✓	✓	✓	✓	✓
region FE	✓	✓	✓	✓	✓	✓
region × time FE	✓	✓	✓	✓	✓	✓
Hansen's J (overid test)	-	0.0021	-	0.0022	-	0.0007
N observations (Nt)	216.829	216.829	213.481	213.481	213.481	213.481

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 IV GMM estimates (Optimal GMM). Standard errors are clustered at the bank level. The set of covariates 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. The symbols *, **, and *** denote conventional statistical significance levels.

Regarding the LTI rule, results from Table 2.3 show that the level of LTI limits explains the amount of debt at origination and that, on average, LTI limits are binding. The coefficient is positive and statistically significant and the magnitude suggests that a 0.1 LTI limit change is associated to a 2.7%-3.7% increase in household debt. This effect is heterogeneous along the income distribution: Figure 2.6 reports the marginal effect of a 0.2 LTI limit change and shows that the LTI limit is particularly constraining for low-income households: for a EUR 30.000 income household, a 0.2 LTI limit increase is associated to an increase in the borrowing by about EUR 6.000, which corresponds to the increase in the borrowing capacity induced by the policy change. This result indicates a complete 'pass-through' of a change in borrowing capacity into a change in household debt for very low income households. On the contrary, changes in debt are totally decoupled from changes in the LTI limit at very high incomes, while for the mid income categories an increase in the LTI limit causes an increase in debt by a positive fraction.

Figure 6: Response to a 0.2 LTI limit change



Note: The figure shows the marginal effect of a 0.2 LTI limit change, as a function of the annual household income. The marginal effect is averaged over the sample.

Regarding house prices, results show that the strong increase in house prices acted as an additional binding factor in households' borrowing decisions. The coefficient of the IV specification suggests that a unitary increase in the house price index (corresponding to a increase in house prices by 0.7%-0.9%, depending on the municipality) is associated to an increase in household debt by 0,3%, and the standardized coefficient[20] indicates that a standard deviation increase in the local house price index causes a 13.4% increase in household debt at origination. The strength of this effect is comparable to the size of the effect of the LTI regulation.

The last two columns of Table 2.3 eventually indicate that borrowers that are LTV-constrained (i.e. their LTV at origination is equal to the LTV limit) are also more likely to be LTI-constrained, at any level of household income[21].

Interestingly, the overall results from Table 2.3 highlight the competing effect of changes in house prices and in leverage limits argued before: when shifting from the OLS to the IV specification the size of the effect of house prices increases in magnitude and, conversely, the size of the effect of LTI limits reduces in magnitude by almost one quarter.

[20]The standardized coefficients in the first IV specification are $\overline{\beta}_1 = 0.129$ and $\overline{\beta}_2 = 0.134$

[21]Please note since the LTV limit is the same for all borrowers, simply controlling for it (as done with the LTI limit) is not possible due to multicollinearity with the time fixed effects

5.2 Bunching at the LTI limit

The second implication drawn from the model is that, if LTI limits are binding we should observe a spike at the limit in the corresponding distribution of LTIs, and the size of this spike is informative on how binding LTI limits are.

Contrarily to the previous section, here I don't look at the effect of the LTI regulation on the amount of debt at origination, but I look at the effect on the LTI distribution. The aim is to understand how many borrowers are constrained by the LTI regulation, and to shed light on the role of the flexibility options that a *comply or explain* regulation allow to borrowers and banks.

With a strict LTI regulation that does not allow any flexibility, all constrained borrowers switch from the unconstrained choice to the constrained choice in which they borrow at the LTI limit. As depicted in Figure 3, this creates a spike in the mortgage distribution. With a comply or explain regulation, a third group of borrowers is likely to emerge: similarly to constrained borrowers, this group of borrowers demand a loan amount that exceeds the limit but, unlike them, they are granted it because they qualify into one of the exceptions established by the regulation. Therefore, borrowers in this group are *de facto* unconstrained.

I evaluate how binding LTI limits are by estimating the size of the spike in the LTI distribution[22]. The challenge in estimating this is that it is possible to observe the mortgage distribution either when LTI limits are in force or when they are not, but both distributions are never observed jointly. To overcome this, I rely on an estimate of the counterfactual distribution. This counterfactual distribution is estimated under the assumption that most of the effect of the LTI regulation on the LTI distribution is local, at the LTI limit. In particular, this counterfactual distribution matches the observed distribution away from the LTI limit area, but not at the limit, where the corresponding density is obtained as a smooth interpolation between the densities at the right and the left of the limit.

In such a way, I obtain an estimate of the distribution that I would observe in absence of the leverage limit, and that accounts for the presence of marginal borrowers. I do this by following the bunching approach first introduced by Chetty et al. (2012) and Saez (2011). Precisely, I follow the approach of Kleven (2016) and estimate the following specification:

$$n_j = \sum_{i=1}^{p} \beta_i (z_j)^i + \sum_{s=-k}^{+k} \delta_s \mathbf{1}\big[z_j = z_{c+s}\big] + \epsilon_j \tag{15}$$

[22]As clear from the theoretical model, to answer this question it is not enough to look at the share of households borrowing at the LTI limit. This is because marginal borrowers, who also borrow at the limit, are unconstrained by the regulation.

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 distribution is J equally-spaced bins. In formulas: $z_j = [1, ..., z_c, ..., J]$ where z_c is the LTI limit bin.

As a result, the first part of eq. 2.15 is a p-degree polynomial fit of the distribution of LTI. The second term of the equation contains a set of dummies that take value one for all bins in a window of size $2k$ around the LTI limit bin z_c. This term captures the local feature of the LTI distribution due to the presence of LTI-constrained borrowers. Assuming smoothness of the true counterfactual distribution[23], the estimated counterfactual distribution is obtained as the predicted value of eq. 2.15 omitting the contribution of the dummies, that is: $\widehat{n_j} = \sum_{i=1}^{p} \beta_i (z_j)^i$. This estimate provides a distributional fit based on the whole shape of the empirical distribution, but the local feature at the limit[24].

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

$$\begin{aligned} \widehat{B} &= n_j - \widehat{n_j} \\ &= \sum_{s=-k}^{+k} \delta_s \mathbf{1}\left[z_j = z_{c+s}\right] \end{aligned} \tag{16}$$

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:

$$\widehat{b} = \frac{\widehat{B}}{\sum_{s=-k}^{k} \widehat{n}_{c+s}/(2k+1)} \tag{17}$$

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

Due to the presence of multiple LTI limits, we group all borrowers sharing the same LTI constraint and we run separate bunching estimates at all LTI limits from 4.4 to 5.3[25]. Also, I choose the free parameters J, p and k of eq. 2.15 in such a way that the resulting estimate is as much conservative as possible[26].

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[23] In my case, the assumption is that without the LTI regulation, the LTI distribution would have been smooth, i.e. with no spikes or discontinuities. Equivalently, the assumption states that the spike at the LTI limit in the observed distribution is solely attributable to the LTI regulation.

[24] Please note that is thanks to the comply or explain nature of the LTI rule that we can obtain a smooth counterfactual density in the LTI limit area. In fact, it ensures the presence of enough mass at the left (comply) and the right (explain) of the LTI limit, so that the resulting interpolation is likely to be smooth.

[25] Since this approach requires large data, we choose this interval 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 almost 90% of all borrowers in our sample. For the same reason, I am not able to leverage on the time dimension of LTI changes, and I pool all borrowers subject to the same LTI limit over the whole sample period.

[26] The LTI distribution is discretized in bins of width 0.05 and the analysis area (J) includes a window of 60 bins. For the bunching area (k) we take a window of 1 bin around the LTI limit. Eventually, in line with the

I report the bunching estimates for the LTI distributions in Table 4. I compute the standard errors using a parametric bootstrap procedure in which I draw with replacement from the raw LTI distribution and we re-compute the parameters at each bootstrap replication. Table 4 shows significant bunching estimates in the mortgage distributions of all borrowers subject to LTI limits below 4.8. The class of borrowers mostly constrained by the regulation is the one subject to an LTI limit of 4.6, in which almost 2700 borrowers bunch at the limit and the estimated excess mass is almost 60% higher than the average counterfactual density. Also borrowers subject to nearby LTI limits seem to be strongly affected by the regulation: the bunching estimates are strongly significant for borrowers subject to LTI limits in the interval [4.5 , 4.7]. These three categories represent more than 40% of all borrowers in our sample and apply to below-average income borrowers earning less than 60.000€, as clear from Figure 1.

literature, the estimate of the counterfactual distribution is based on a 7th-degree polynomial (p).

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	10705		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 ** denotes statistical significance at the 95% level.

Figure A.1 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 instead the estimated counterfactual distribution.

For low LTI limits, we observe that the estimated distribution is way below the actual distribution in the limit region, and the corresponding bunching mass is very high. At high LTI limits instead, the estimated distribution perfectly fits the empirical distribution in the LTI limit region, and the corresponding bunching mass is thus almost invisible.

That means that richer households, who are subject to higher LTI limits, are relatively unaffected by the policy: they tend to borrow less than they could, and the share of explainers is very low. On the contrary, we see that the share of explainers is very high at low LTI limits. This indicates that low income households, who also lack assets to make large downpayments, afford to participate to the credit market only if they fall into one of the exceptions established by the law. This also suggests possible extensive margin responses to changes in LTI limits[27].

In summary, results presented in this section lead me to conclude that the number of constrained borrowers is high only among low-income households. However, the flexibility options offered by the regulation have an important role in relaxing the constraint, and allows many borrowers (that would be constrained otherwise) to exceed the LTI limit and being unconstrained.

5.3 Bunching at the LTV limit

Differently from the LTI limit, the LTV limit cannot explain neither the cross-sectional nor the time variation of household debt amounts[28]. However, changes in the LTV limit can still have distributional effects, similar to those induced by changes in the LTI limits. This section investigates the effect of further LTV limit tightenings and look at how many borrowers are LTV constrained.

The bunching approach applied in the previous section is not well suited to investigate the effect of the LTV limits for a simple reason: the LTV limit is not a comply of explain rule but is a strict rule for first-time buyers, meaning that the LTV distribution displays a sudden drop in the density at the right of the LTV limit, and this would not allow me to obtain a good

[27]Lacking data on loan applications, I cannot investigate this aspect.

[28]It cannot explain the cross-section of household debt amount because the LTV limit, unlike the LTI limit, is the same for all borrowers, and including the LTV limit as a regressor in equation 2.14 would cause collinearity problems with the time-specific effects. Instead, the reason why the LTV limit cannot explain the time variation of household debt is more subtle: since borrowers are allowed to borrow up to a fraction $(1-\delta)$ of the their property valuation $p_t h_t$, it follows that an increase in house prices mechanically translates to an increase in borrowing capacity. In our sample period, the LTV limit (δ) has been reduced by 1% every year, but the national house price index has increased by 4% a year. As a result, borrowers faced a LTV limit easing in terms of maximum borrowable amounts.

estimate of the counterfactual distribution[29].

I overcome this issue by exploiting the following feature of the LTV regulation: it is a strict rule for first-time buyers (*starters*), but refinancing borrowers (*renegotiatiors*) are allowed to take out loan amounts exceeding the LTV ratio[30]. Therefore, starters negotiate the terms and conditions of their contract at the same time renegotiators do, but this latter group is formally exempt from complying with the LTV regulation. Here, I use the observed LTV distribution instead of an estimate counterfactual distribution to evaluate the effect of the LTV regulation. My approach is similar to the one developed by De Fusco et al (2019) who compare the change in the distributions of originated mortgages in two segments of the U.S. credit market, one of which is exempt to the regulation they study (a rule part of the Dodd-Franck Act). Their aim is to analyze the intensive and extensive margin response to the rule in the market subject to the regulation. Instead, what I do is to compare local changes in the LTV distributions among starters and renegotiators to estimate how the change in the location of the kink (due to a LTV limit tightening) affects the mortgage distribution of constrained borrowers. In fact, according to Kleven (2016), in case of cross-sectional or time variation in the size or in the location of the kink it is possible to identify the behavioral response as the difference in bunching.

Implementing this empirical strategy requires overcoming a couple of issues. First, the volume of renegotiating mortgages is different from the volume of loans granted to first-time buyers, so the two distributions cannot be directly compared. I deal with this issue by normalizing the total number of loans in each bin by the total number of loans in the analysis area of each market segment. That is, we define:

$$\overline{n}_j^k = \frac{n_j^k}{\sum_{j=1}^{J} n_j^k} \tag{18}$$

Where $k = \{s\ ,\ r\}$ denote starters and renegotiators, respectively. The parameter J is set in such a way that the analysis area is common among the two groups[31].

The second and more important issue is that, over time, the LTV distribution will be affected

[29] Also, the levels of LTV is among the highest in the world, so it would still be difficult to imagine that banks are willing to grant many loans above the original 106% LTV limit.

[30] Renegotiators include second-time buyers, households borrowing out of their home equity and switchers, i.e. borrowers who already took out a mortgage loan and, at the end reset period, they renegotiate the terms and conditions of their mortgage (such as interest rate, maturity and loan amount) with another bank taking over the credit.

[31] In such a way, all loan counts sum up to 1 and each normalized loan count will be directly comparable as it equals the relative density in the analysis area. Also, this normalization rules out any extensive margin response, and makes sure that differences in the distributions reflect intensive margin responses.

by changes in the LTV limit as well as by changes in house prices. As evident from our theoretical model the actual LTV, obtained by dividing the unconstrained mortgage demand by the value of the house purchased, is an increasing function of house prices. Intuitively, given a positive shock to house prices, borrowers will have to increase their downpayment and/or their mortgage demand to compensate the increase in value of the house they want to buy. For example, credit constrained borrowers are likely to proportionally increase both to keep their LTV constant, while liquidity constrained borrowers are likely to rely on an increase in the amount granted by their bank, as they can't increase their offer using own means. Therefore, as in the first part of section IV, the house price increase can potentially confound the causal effect of the regulation. To deal with this issue I estimate the following two statistics:

$$\widehat{B} = \sum_{j=-k}^{k} \left(\overline{n}^{s}_{c+j} - \overline{n}^{r}_{c+j} \right) \qquad \widehat{M} = \sum_{j=k+1}^{J} \left(\overline{n}^{r}_{c+j} - \overline{n}^{s}_{c+j} \right) \tag{19}$$

The first statistics denotes the bunching estimate. This is analogous to the one computed in the previous section, but is now is obtained using the LTV distribution of renegotiating mortgages as counterfactual distribution. The second statistic denotes the missing mass to the right of the LTV limit in the distribution of starters and allows me to disentangle the causal effect of the regulation out of the confounding effect coming from the increase in house prices. The intuition is the following: as the LTV limit decreases, more people get constrained, and the bunching mass will increase. Equivalently, as house prices increase many households can't increase their down-payment and end up borrowing at higher LTVs, causing the bunching mass to increase too. In this latter case however, the increasing bunching mass is not attributable to changes in the LTV regulation. We estimate the missing mass to the right $\widehat{M}$ exactly to disentangle increases in the bunching mass that are attributable to the LTV regulation from those attributable to changes in prices. House price increases induce borrowers to ask for higher LTV mortgages, and this induce a shift to the right of the LTV distribution. LTV limit tightenings force constrained households to borrow lower LTV mortgages, causing a shift to the left of the LTV distribution. As a result, an increase in the missing mass to the right of the distribution $\widehat{M}$ in times of increasing house prices can only be attributed to LTV limit tightenings, that force starters (but not renegotiators) to reduce their credit demand to comply with the new LTV limit. We therefore identify the causal effect of tightenings of the LTV limit with the corresponding changes in the missing mass to the right of the distribution from one period to the other.

Results are reported in Table 5, and a graphical representation is reported in Figure A.2.

The Figure shows that the distributions of starters and renegotiators are very similar, and that in both groups the majority of households borrow at the LTV limit. However, since renegotiating borrowers are exempt from the regulation, the spike in their LTV distribution is higher, and most of the differences in the two distributions arise exactly at the LTV limit. The difference between the two spikes ($\widehat{B}$) ranges from 12% to 17% and increases over time. However, as explained, only part of this difference can be attributed to the causal effect of the LTV regulation: the estimated missing mass at the right of the LTV limit ($\widehat{M}$) increases from 5.5% to 11.1% over the sample period, when the corresponding LTV limit is reduced by 1% every year.

In summary, results from this section show that, in general, borrowers tend to be constrained more by the LTV limit rather than the LTI limit, as the bunching mass at the LTV limit is much higher than the bunching mass at (any level of) the LTI limit. Also, results show that the further reductions of the LTV limits (from 105% to 101%) established between 2014 and 2017 have contributed to double the share of LTV constrained.

Table 5: Bunching at the LTV limit

Limit = 104%	est.	95% conf. int.	**Limit = 102%**	est.	95% conf. int.
$\widehat{B}$	0.117***	[0.110 ; 0.122]	$\widehat{B}$	0.148***	[0.142 ; 0.154]
$\widehat{M}$	0.055***	[0.051 ; 0.058]	$\widehat{M}$	0.075***	[0.072 ; 0.080]
$\hat{b}$	0.117***	[0.110 ; 0.122]	$\hat{b}$	0.148***	[0.142 ; 0.154]
N	51.808		N	61.799	
Year	2014		Year	2016	
Limit = 103%	est.	95% conf. int.	**Limit = 101%**	est.	95% conf. int.
$\widehat{B}$	0.174***	[0.168 ; 0.179]	$\widehat{B}$	0.154***	[0.148 ; 0.159]
$\widehat{M}$	0.091***	[0.087 ; 0.095]	$\widehat{M}$	0.111***	[0.107 ; 0.115]
$\hat{b}$	0.117***	[0.110 ; 0.122]	$\hat{b}$	0.148***	[0.142 ; 0.154]
N	55.509		N	67.406	
Year	2015		Year	2017	

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 ($\widehat{M}$) and the relative bunching mass at the LTV limit ($\hat{b}$). Also, the Table reports the corresponding 95% bootstrapped confidence intervals. On the bottom of each panel the Table reports the total number of starters (N), the origination year and the national housing price index (2014 = 100). The symbol *, ** and *** denote conventional statistical significance levels.

6 Concluding remarks

6.1 Conclusions

In this paper I study the effect of leverage constraints on household borrowing decisions in a housing market boom. I show that increasing house prices, by making properties more expensive, act as an additional constraining factor in households borrowing decisions. Also, I show that increasing house prices induce a shift in the level of debt towards the macro-prudential limits for reasons unrelated to changes in the macro-prudential regulation, and if not properly dealt with, this can confound the estimate of the causal effect of the regulation.

Regarding house prices, I find that a one standard deviation increase in house prices translates into an increase in household debt by 13.4%. The size of this effect is comparable to the effect of changes in the LTI limit, for which a one standard deviation increase is associated to a 12.9% increase in household debt.

Regarding the LTI regulation, I find that LTI limits affect borrowing choices only among lower-income households. This is not surprising given that the limits are based on budgetary rules that reflect households' debt affordability. However, I find that the exceptions established by the regulation play a key role in relaxing the credit constraint and giving flexibility to borrowers and lenders, and Figure A.2.1 shows how widely this option is used among low-income borrowers. The share of explainers reaches about 70% in the lowest income brackets, due to the presence of borrowers that otherwise would not be able to participate in the credit market.

Regarding the LTV regulation, I find that the LTV rule is the most binding constraint, and that further LTV limit tightenings that reduced the overall level of these limits by 4% have doubled the share of LTV-constrained borrowers. These results are also perfectly consistent with a stylized life-cycle model with housing, heterogenous borrowers and leverage constraints.

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Figure A.2.1(a) Bunching at the LTI distribution

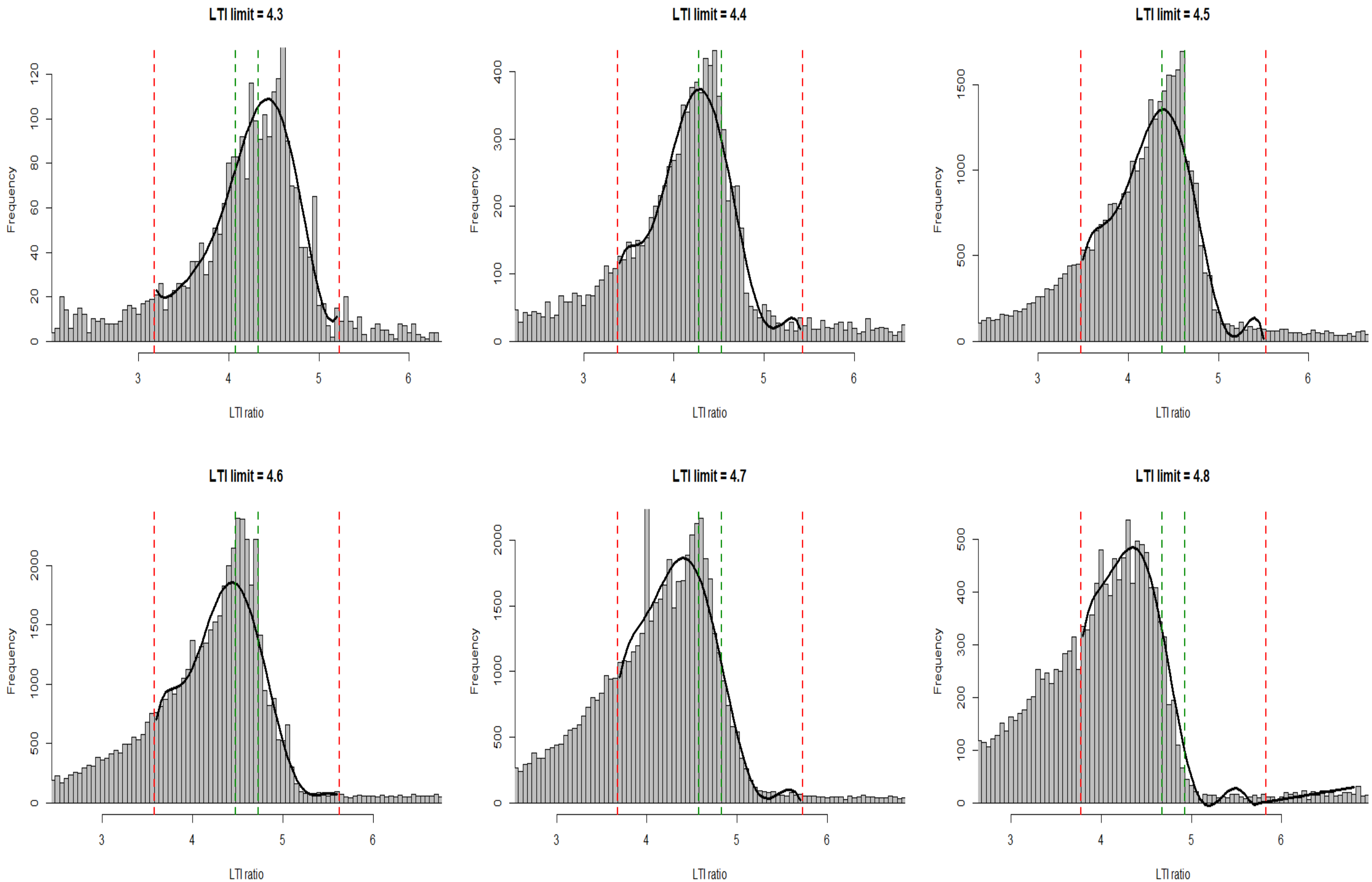
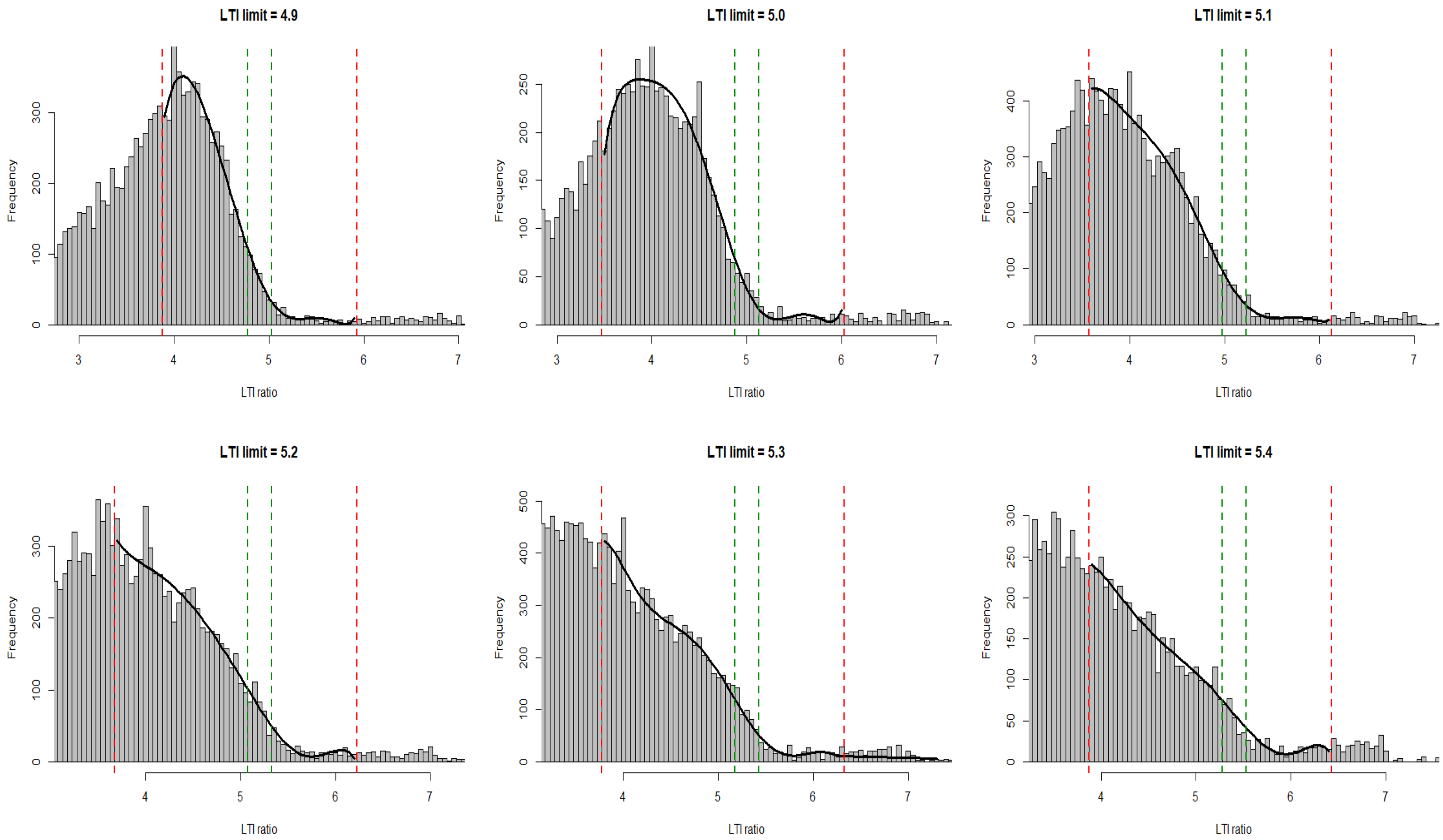
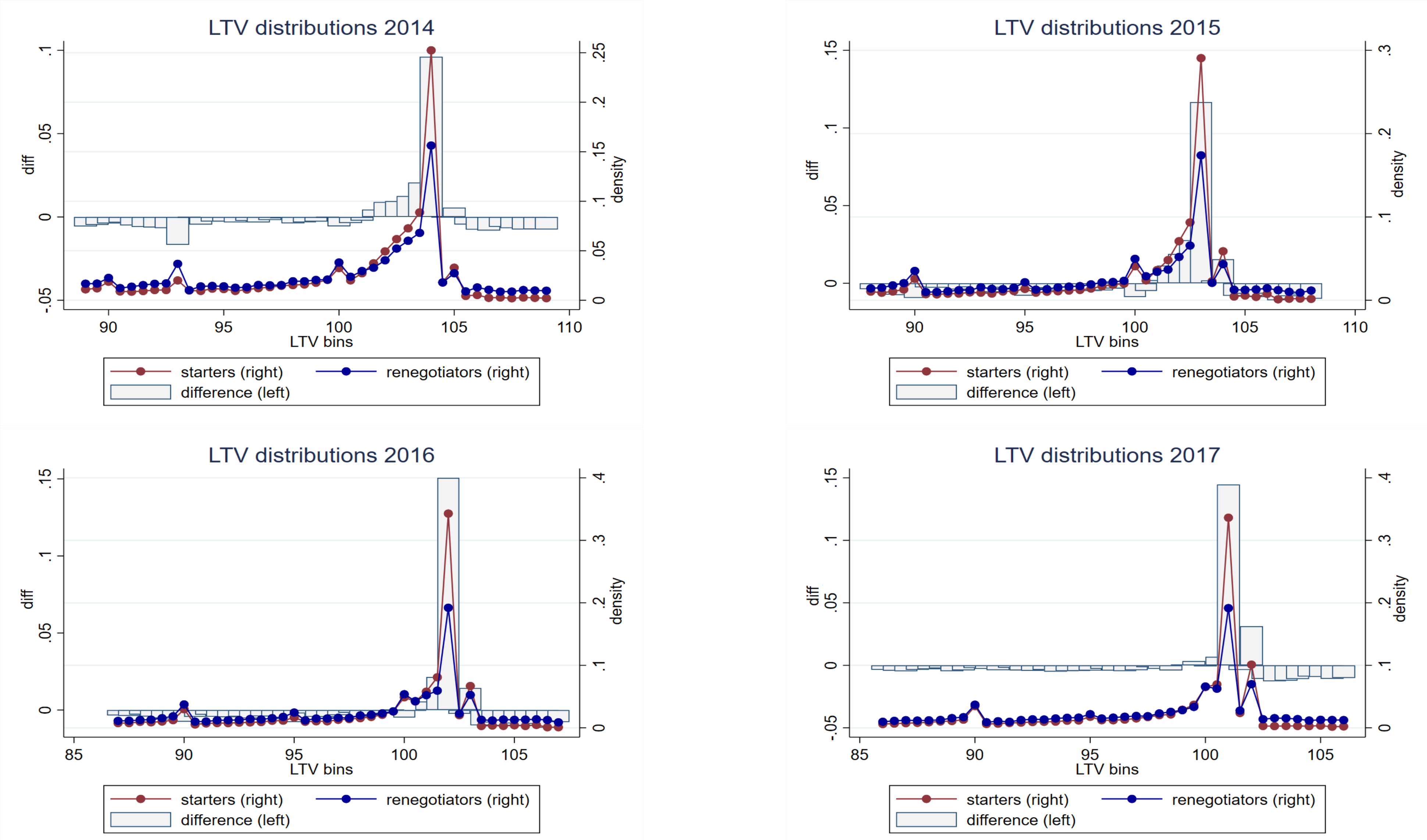


Figure A.2.1 (b) Bunching at the LTI distribution



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 A.2.2: 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 ($\widehat{M}$).