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

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Abstract

I study the effects of leverage constraints on household debt in the Netherlands in a period characterized by a strong and persistent house price growth. I focus on two types of leverage constraints: Loan-to-Income (LTI) and Loan-to-Value (LTV) limits. I find that variations in the LTI limits explain variations of household debt, but are binding only for low income households. On the contrary I find that variations in the LTV rule, despite being ineffective in limiting household debt at origination, still affect households' financing choices. The identification strategy proposed aims at disentangling the regulation-effect out of the price-effect in a overheating housing market, which acted as an additional binding factor in households' borrowing choices. The policy implication points in favor of the co-existence of LTI and LTV rules to limit over-indebtedness.

Keywords: Mortgage, Household Debt, Credit Constraints, Bunching

JEL codes:

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I - 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 market channel", which caused a relatively 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 especially 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 effect of macro-prudential policies on household mortgage debt in a period of strong and persistent house price growth. Using administrative data at the loan level and local house price indexes based on 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 origination of residential mortgages in the Netherlands. These rules establish the maximum amount that can be lent to a borrower conditional on income and on the collateral value of the house, respectively.

With this respect, the Netherlands is currently one of the most interesting countries in which to study the link between leverage constraints 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 highest house price growth rate worldwide, the first among advanced economies. The issue is therefore very relevant in the Netherlands, as new increases in house prices could induce an increase in household debt and raise solvency concerns, while a sudden fall in house prices may lead a large fraction of borrowers (especially first-time and recent buyers) 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.

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 most often 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). In this paper, I contribute to the literature on macro-prudential policies[3] by taking the household perspective to show how it affects individual incentives and, thus, financial decision making (borrowing).

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

The first contribution of the paper is to use a stylized theoretical framework to investigate households borrowing decisions when these are subject to Loan-to-Income and Loan-to-Value limits and, consistently with the findings, to empirically investigate the effect of leverage limits on household indebtedness. The analysis focuses on first-time buyers (starters) and on a period characterized by a strong and persistent house price increase: since households find more and more expensive houses for sale, the increase in house prices acts as an additional constraining factor. This is especially true for starters, who typically cannot count on existing assets to add on the loan amount to finance the house purchase. Studying the effect of leverage constraints on borrowing in a booming housing market is challenging for two reasons. First, if not properly controlled for, the effect of leverage limits would not only be confounded, but would also be over-estimated by the increase in house prices that may force households to borrow closer to or at the limit for reasons unrelated to changes in the regulation. To deal with this, I propose an identification strategy that aims at disentangling the regulation-effect out of the price-effect in an overheating housing market. I use exogenous variations in the leverage limits to estimate the effect on borrowing of the macro-prudential regulation, and 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 between municipalities. Second, even after controlling for changes the housing market conditions, house prices and household debt are likely to be jointly determined by an omitted variable such as shock to expected income growth (Mian and Sufi, 2011; Attanasio and Weber, 1994; Muellbauer and Murphy, 1997). Also, there may be reverse causality 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 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. Results show that changes in the limits cause a change in the level of household debt, especially for low income households who are the most constrained by the regulation. However, the most constraining factor seems to come from the developments in the housing market: the increase in house prices mostly translates into an increase in debt in households balance sheets.

The second contribution of the paper is to study the distributional implications on debt of the introduction of leverage limits. While the first part of the analysis aims at estimating the causal effect of leverage constraints on the average level of household debt, this looks at the corresponding effect on the distribution of debt. My approach is motivated by the recent literature on bunching introduced by Chetty et al. (2011), Kleven and Waseem (2013). This approach exploits the presence of non linearities in individuals' budget constraints to retrieve an estimate of the behavioral response at that specific point of the budget set[4]. In this paper, I contribute to the very recent literature on bunching in the household finance field (De Fusco and Paciorek (2017), De Fusco, Johnson and Mondragon (2017), Best et al. (2018)) by using this approach to show the behavioral response to the policy of interest and then to assess how many households are effectively constrained by the regulation. Results show that the LTI rule has strong distributional effects only among lower income households, and show that LTV limit tightenings are inducing more and more people to borrow at the limit.

My results have one main policy implication: in order to properly contain household debt, a macro-prudential regulation cannot overlook a LTI limit based on household debt affordability. A combination of this tool with an LTV limit can help in balancing the value of assets and liab-

[4]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.

ilities in household balance sheets, but an LTV alone cannot contain household debt 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.
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. Section IV presents the data and the empirical evidence. Section V concludes.

II - Institutional framework

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 underlying house worth. 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 recommendation are made in such a way to account for all the necessary expenses that families incur: 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. 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 lower-income and riskier (high interest rate) households. The LTI limits display also considerable time variation other than cross-sectional variation, as the recommendations are revised annually. Figure 2 shows the changes in the maximum loan amounts in the years 2015-2016 and 2016-2017, for the different income brackets. 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.

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 to allow for flexibility for both lenders and borrowers. 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[5]. 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 current limit is a strict rule for first-time buyers (starters).
To summarize, the 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 characteristics. 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.

III - 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)[6].
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 t each borrower i maximizes:

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

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

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

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

[6] 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.

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:

$$U(g(c, s(h))) = log\left(c^{\alpha}\, s(h)^{1-\alpha}\right)$$

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 $E(p_{t+1}) = p_t + \epsilon_t$ with $\epsilon_t \sim IID(0, \sigma^2)$.
Next, I introduce two leverage constraints: the first is a loan-to-income (LTI) constraint that allows to borrow up to a given fraction of borrower's income, the second is a loan-to-value (LTV) constraint that allows to borrow up to a given share of total house worth. Borrowers decisions are thus subject also to the following constraints:

$$m_t \leq \theta y_t \qquad\qquad m_t \leq p_t h_t(1-\delta)$$

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[7]. This inter-temporal allocation depends on the time preference β_i that is heterogenous across households[8].
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:

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

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

[7]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.

[8]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.

assumed functional forms of U, g and V, and using $E(p_{t+1}) = p_t$, from the Euler equation I solve for m_t to obtain the household i unconstrained mortgage function:

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

Where m_i^u denotes the mortgage size of borrower i in the unconstrained case[9]. The desired level of debt depends positively on property valuation and negatively on household income. Next, consider the constrained case with both constraints active. 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. If these are binding, the constrained mortgage size is:

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

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

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

Whether leverage constraints bind or not depends on each individual 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:

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

Leading to:

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

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 $T = t + 1$ and 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, 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 increasing in the number of borrowers constrained by the regulation.

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

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 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 weighted aggregate debt level in the population is the sum of the debt levels in the two groups:

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

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 aggregate debt level in the population explicitly depends on the policy parameter θ. In fact, the level of the leverage constraint affects the debt level of constrained group 2 households $M^2(\theta) = \sum_i m_i^c = N_c\, \theta y$ as well as the share of constrained households. In fact:

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

Which depends on the policy parameter through its relation with $\beta^* = \beta^*(\theta)$. In particular, the stricter is the leverage limit and the higher will be the share of constrained borrowers in the population. As a result, we can derive the change in the weighted aggregate debt level due to a change in the leverage constraint as:

$$\frac{\partial M(\theta)}{\partial\, \theta} = f(\beta^*)[m_i^c(\theta) - m_i^u] + F(\beta^*)\frac{\partial\, m_i^c(\theta)}{\partial\, \theta} \tag{2}$$

Where $f(\beta) = F'(\beta)$ is the probability density function. In words, the change in the policy parameter has two effects: on one side changes the fraction of constrained and unconstrained borrowers in the population, on the other side 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 is the share of constrained borrowers and the larger will be the response to a leverage limit increase, as constrained borrowers' would use the policy change to increase their debt position. Note that eq. (2) and the analysis carried out in this section holds for any possible density functions $F(\beta)$ and in the case the other constraint (LTV) binds first[10].

As an example, in the case in which $\beta_i \sim U[\underline{\beta}, \overline{\beta}]$ and the LTI limits bind first, eq. (2) has a closed form solution equal to:

$$\frac{\partial M(\theta)}{\partial\, \theta} = \frac{1}{\overline{\beta} - \underline{\beta}}\left(\theta y_t - \frac{p_t h_t(\alpha + R\beta_i) - R\beta_i\, y_t}{R(\alpha + \beta_i)} + \left(\beta^* - \underline{\beta}\ \right) y_t\right) \tag{3}$$

[10] In this case the level and the change in debt will be denoted with $M(\delta)$ and $\partial M(\delta)/\partial\, \delta$, respectively. The change in the constrained mortgage debt will be denoted instead with $\partial m_i^c(\delta)/\partial\, \delta$ according to the notation used in the previous section.

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

$$\frac{\partial M(\theta)}{\partial p} = \begin{cases} F(\overline{\beta})\frac{\partial m_i^u}{\partial p} + F(\beta^*)\big[\frac{\partial m_i^c}{\partial p} - \frac{\partial m_i^u}{\partial p}\big] + f(\beta^*)\big[m_i^c - m_i^u\big] & if\ \ \theta y_t > p_t h_t(1-\delta) \\ \big[F(\overline{\beta}) - F(\beta^*)\big]\frac{\partial m_i^u}{\partial p} + f(\beta^*)\big[m_i^c - m_i^u\big] & if\ \ \theta y_t \leq p_t h_t(1-\delta) \end{cases} \tag{4}$$

In words, conditional on the house choice, an increase in house prices increases debt as households need to finance more expensive houses. It increase the mortgage demand of all borrowers and, given the level of the leverage limit, changes the fraction of constrained and unconstrained borrowers in the population. Therefore, a sustained increase in house prices acts as an additional constraining factor.

Interestingly, the effect of house prices on household debt 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 house prices would cause a bigger change in household debt in the case the LTV binds first, as captured by the additional term $F(\beta^*)$ $(\partial m^c/\partial p)$. In other words, since for a given LTV limit the borrowing capacity changes as house prices change, also constrained borrowers are allowed to increase their debt position in case of an increase in house prices. On the contrary, when the LTI binds first the level of the limit is independent on house prices, and constrained borrowers are thus not allowed to take on extra debt.

In summary I obtain two main empirical implications from the model. First, in presence of binding leverage limits the aggregate debt level in the population explicitly depends on the level of leverage limits, and changes in the limits induce changes in household indebtedness. The strength of the relation also depends on the level of house prices, which represents an additional constraining factor. The second implication is that in presence of binding leverage limits the distribution of mortgages will feature a spike at the limit, and the spike is increasing in the number of constrained borrowers. These two implications, along with the result in eq. (2), together suggest that the increase in household debt caused by an increase in the leverage limit is proportional to the bunching mass at the leverage limit, as all borrowers that are still constrained will take advantage of the policy change to increase their debt position by an amount exactly equal to the increase in the limit, while all unconstrained borrowers would simply not respond to the policy change.

IV - Empirical analysis

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). Thus, 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 (namely ABN Amro, Rabobank and ING bank) 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. In the Netherlands, the two-digits postcode unit approximately represents the municipality: the main municipalities have a unique two-digit postcode, while in countryside areas the same two-digits code 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 1 reports descriptive statistics on the most important property, borrower and loan characteristics in the LLD. The reported information only refers to starting homeowners[11]. 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 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 house prices.

The effect of LTI limits and house prices on household debt

The first empirical implication drawn from the theoretical framework presented in Section III is that if leverage constraints are binding, the level and the changes in the leverage limits affect household debt. This section tests this empirical implication.
To elicit the causal effect of the LTI regulation on household debt, I exploit the high cross-sectional and time variation displayed by the LTI limits, as showed in Figures 1 and 2. Importantly, this variation is also exogenous from the household perspective, 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

[11]We focus on First-time buyers (starters) 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.

public only in November[12]. Second, despite some of the changes in the macroeconomic conditions are easily predictable (e.g. the decrease in the interest rates announced by the ECB), the resulting LTI limits are hard to predict because of the changing classification made by the NIBUD Institute during the sample period. Figure 4 clarifies this point: the NIBUD Institute decided to gradually switch from a broad income classification, with a total of four income brackets in a 30.000 euro income interval in 2014, to a very granular classification having one income bracket every 1.000 euro in 2017. Evidently, as a result of a changing classification, it is possible to observe a change in the LTI limit recommended to a specific income class even when all macroeconomic conditions remain constant.
Given these premises, I estimate the following specification:

$$y_{i,m,t} = \beta\theta_{i,t} + \phi P_{m,t} + \gamma' x_{i,m,t} + \iota'\Lambda + \epsilon_{i,m,t} \tag{5}$$

The dependent variable is the mortgage debt taken out by borrower i in municipality m in year t, expressed in logs. The main coefficient of interest is β that captures the effect of the LTI limit $\theta_{i,t}$ on the level of debt, while $x_{i,m,t}$ is a set of conditioning variables at the borrower, property, loan and municipality level. 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, the matrix $\Lambda \equiv [\eta_b, \delta_t, \lambda_r, \xi_{rt}]$ contains bank, time, region and region-time fixed effects, while ι is a vector of ones such that $\iota'\Lambda = \eta_b + \delta_t + \lambda_r + \xi_{rt}$. The specification is estimated on a pool of repeated cross-sections[13].
In eq. (5) the key conditioning variable is the local house price index at the municipality level $P_{m,t}$: by controlling for this, I make sure that the effect on household debt is solely due to variation in the LTI limit and is not confounded by the fact that higher house prices, by making properties more expensive, induce an increase in the level of borrowing towards the LTI limit. The parameters of interest are then ϕ and β that capture the effect of house prices and the LTI limit, respectively. Both parameters have an expected positive sign according to the model of Section 2: easing LTI limits should induce (constrained) borrowers to increase their debt position, and higher house price should induce more borrowing to finance more expensive houses.
To estimate eq. (5) I propose an identification strategy based on instrumental variables (IV). The aim is to deal with the simultaneity between household debt and house price growth. In fact, the causality may even run in the opposite direction than what eq. (5) shows: for instance, if a positive shift in credit supply induces households to take on more debt, this would boost housing demand and eventually increase house prices in equilibrium. I instrument the local house price index using two proxies of the supply elasticity in the local housing market. The geographical variation of the two instruments is displayed in Figure 5. The two instruments should affect the level of household debt only through their direct effect on house prices. The first instrument is the share of developed land[14] introduced by Saiz (2010) and studied in Hilber and Vermeulen (2016). 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

[12]Arbitrage opportunities are therefore excluded, as the time gap between the publication and introduction dates is less than two months. In fact, it is unlikely that in such a short period a borrower is able to search and pick a house, make a formal offer, deal the terms and conditions of the mortgage with the bank, obtain the appraisal value and the registration of the property and fix all the necessary notary practices.

[13]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.

[14]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.

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, the share of unoccupied dwellings proxies for the existing stock of houses: for a given shock to housing demand, housing market prices should clear at lower levels in cities characterized by excess supply of existing dwellings. Therefore, taken together the two instruments proxy for the total housing supply elasticity, defined as the sum of the existing stock of homes for sale and the housing starts[15]. The municipal variation in the total housing supply elasticity is used to instrument the local house price index. Results are reported in Table 3 and include the IV as well as the OLS estimates. The IV specification is estimated using Optimal GMM in the over-identified case (1 endogenous and 2 instrumental variables). Concerning the LTI rule, results in Table 3 show that, on average, LTI limits affect household borrowing at origination: in all specifications 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 across household types. Figure 6 reports the marginal effect of a 0.2 LTI limit change obtained from the specification in column (4) of Table 3 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 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. Eventually, the last two columns of Table 3 show that the 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. Concerning the effect coming from the housing market, Table 3 shows that the strong increase in house prices acted as an additional binding factor in households' borrowing decisions. In particular, the standardized coefficient[16] suggest that a standard deviation increase in the local house price index causes a 13.4% increase in household debt at origination, and the strength of this effect is comparable in size with the effect of the LTI regulation. Lastly, Table 3 highlights the confounding effect of house prices argued before: in the OLS specification the LTI limit seems to have most of the effect on debt, but when the change in house prices within municipality is instrumented with the proxy of the total housing supply elasticity in each municipality, the coefficient of the LTI limit reduces in magnitude by almost one quarter. Correspondingly, the coefficient capturing the house price-effect increases in magnitude and indicates that this is indeed the most binding factor for households borrowing choices: an increase by 1% in the house price index is associated to a 0.3% increase in household debt.

Bunching at the LTI limit

This section tests the second implication drawn from the theoretical framework. The implication is that the spike at the limit in the LTI distribution is informative on how constraining LTI limits are for the borrowers. Contrarily to the previous section, here I don't look at the effect of the LTI regulation on the average level of debt, but I look at the effect on the distribution of debt. Also, this section sheds more light on the "comply or explain" nature of the LTI rule that allows for a flexibility option to both borrowers and banks. With a strict

[15]Due to lack of data, I do not consider the transformation process (e.g. residential conversion of dismissed buildings and productive plants) in the total housing supply.

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

LTI regulation that does not allow any flexibility, the effect of LTI limits on the distribution of mortgage debt would be similar to what depicted in Figure 3: all constrained borrowers switch from their unconstrained choice (for example A) to the constrained corner solution B in which they borrow at the LTI limit, and this creates the spike in the mortgage distribution. Slightly different is the case of a "comply or explain" regulation: in this case, there will be a third group of borrowers that, just like constrained households, demand a loan amount higher than the LTI limit, but by qualifying into one of the exceptions established by the regulation they are able to exceed it. Therefore, borrowers in this group are *de facto* unconstrained as they are able to get the desired loan amount even if this exceeds the LTI limit. This means that the empirical implication drawn from the model doesn't change: the spike at the LTI distribution is still informative on how many borrowers are constrained by the regulations, i.e. those who "comply" and shift to the constrained solution. Eventually, it is important to stress that not all households borrowing at the LTI limit are constrained by the regulation: as clearly shown in the theoretical framework all marginal borrowers, i.e. those having a desired loan amount equal to the LTI limit amount, end up borrowing at the limit without being constrained by the regulation.
I assess the effect of LTI limits in the distribution of debt by estimating the size of the spike in the LTI distribution. 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 issue, I rely on an estimate of the counterfactual distribution that accounts for the features of the distribution away from the LTI area. 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 individuals. 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:

$$n_j = \sum_{i=1}^{p} \beta_i (z_j)^i + \sum_{s=-k}^{+k} \delta_s \mathbf{1}\left[z_j = z_{c+s}\right] + \epsilon_j \tag{6}$$

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. (6) 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[17], the estimated counterfactual distribution is obtained as the predicted value of eq. (6) 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 obtained by considering the whole shape of the raw distribution but the local feature at the limit. Also, the comply or explain nature of the rule ensures enough variability at the right of the LTI limit, that enables to obtain a counterfactual estimate that is smooth around the limit. Let B be the excess number of loans at the LTI limit, then:

$$\begin{aligned} \widehat{B} &= n_j - \widehat{n_j} \\ &= \sum_{s=-k}^{+k} \delta_s \mathbf{1}\left[z_j = z_{c+s}\right] \end{aligned} \tag{7}$$

[17]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.

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:

$$\widehat{b} = \frac{\widehat{B}}{\sum_{s=-k}^{k} \widehat{n}_{c+s}/(2k+1)} \tag{8}$$

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[18]. Also, I choose the free parameters J, p and k of eq. (6) in such a way that the resulting estimate is as much conservative as possible[19].
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 LTI 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€.
Figure 6 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. Within the bunching area, the density above the counterfactual corresponds to the estimated bunching mass $\widehat{B}$. For high LTI limits the actual distribution is smooth at the kink point and the counterfactual distribution provides a good local fit. Moreover, most of the density is in LTI bins below the limit bin. That is, richer households (subject to higher LTI limits) are unaffected by the policy as they tend to borrow less than what they are allowed to and thus have a low share of 'explainers'. On the other hand, at low LTI limits the bunching mass is big, as the counterfactual distribution is way below the actual density. Interestingly, at low LTI limits a great part of the unconstrained borrowers take out loans with LTIs exceeding the limit. In other words, most of the explainers are concentrated among low income classes. This is evident in the lowest LTI category (4.3) where the number of observations is low and the share of explainers is very high. This suggests that low income households, subject to low LTI limits, mostly participate to the credit market only if they fall into one of the exceptions established by the law. This also points to possible intensive margin responses (see De Fusco et al, 2017) going on[20].
In summary, results presented in this section lead me to conclude that the LTI regulation is binding only for mid and low income households, who show bunching behavior at the limit.

[18]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.

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

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

The flexibility options offered by the LTI regulation have an important role in relaxing the constraint, as the share of borrowers left unconstrained is considerable, especially at lowest income categories. On the contrary high income households are unaffected by the regulation as they tend to borrow loan amounts lower than the limits and no bunching is observed.

Bunching at the LTV limit

Differently from the LTI limit, the LTV limit cannot explain neither the cross-sectional nor the time variation in household debt. The reason why it cannot explain the cross-sectional variation of household debt is simple, and it is because the LTV limit, unlike the LTI limit, is the same for all borrowers[21]. 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. This was evident from the result of eq. (4) in the theoretical framework. Therefore, an increase in house prices acts in the same way as a leverage constraint easing. This issue is particularly relevant in our sample: while the LTV limit (δ) has been decreased by 1% every year, the national house price index has increase on average by 4% a year. Therefore, borrowers faced a LTV limit easing in real terms. Also, given the local differences in the house price trends, households were subject to different changes in borrowing capacity. Still, it can be the case that changes in the LTV rule had a distributional effect, and this is what this Section investigates. However, the bunching approach applied in the previous section is not well suited to investigate the effect of the LTV limits for at least two reasons: first, unlike the LTI case, the LTV limit is not a comply of explain rule but applies to all starters. Thus, the distribution has no variation at the right of the LTV limit and so I cannot obtain a good estimate of the counterfactual distribution. Second, even in the case of a comply or explain LTV rule, the estimated counterfactual distribution would violate the smoothness assumption because of the actual levels of the LTV limits. In fact, the original 106% LTV limit allows people to borrow a loan amount that is 6% higher than the corresponding collateral value of their house. Therefore, I cannot expect banks to be willing to originate loan amounts much larger than the LTV limit, and thus the resulting distribution would feature discontinuities at these LTV levels.

I overcome this issue by exploiting the following feature of the LTV regulation: it is a strict rule for starters, but refinancing borrowers are allowed to take out loan amounts exceeding the LTV ratio. Renegotiators are in fact borrowers who already had a mortgage loan and renegotiate the terms and conditions (such as interest rate, maturity and loan amount) with their bank. This group includes second-time buyers, households borrowing out of their housing wealth and simple renegotiators. Therefore, starters negotiate the terms and conditions of their contract at the same time renegotiators do, but this latter group is formally exempt from the LTV regulation.

Here, I use the subsample of renegotiators as a control group in order to build an estimate of the counterfactual distribution. My approach is similar to the one developed by De Fusco et al (2017) who compare the change in the distributions of originated mortgages in two segments of the credit market, one of which is exempt to the regulation they study. 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 the changes in the LTV distributions of starters and renegotiators to estimate how the change in the location of the kink (due to the decrease in the LTV limit) affects the mortgage distribution of constrained borrowers. In fact, according

[21] In other words, including the LTV limit in the estimating equation (5) would give a collinearity issue with the time fixed effect λ_t.

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.
However, implementing this empirical strategy is particularly challenging in our case for two reasons. First, the share of renegotiating mortgages is different in size from the distribution of starters, so the two distributions cannot be directly compared. To deal with this issue, I normalize 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:

$$\overline{n}_j^k = \frac{n_j^k}{\sum_{j=-J}^{J} n_j^k}$$

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. 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 changes in the allocation of credit among participants only.
The second and more important issue is that, over time, the LTV distribution will be affected by changes in the LTV limit as well as by the changes in house price. In fact, for a given shock to house prices, households need to anticipate more resources out of pocket in order to compensate the extra cost of houses: if they increase the down-payment proportionally to the increase in house price, the LTV limit would be the same. On the contrary if households cannot proportionally increase their down-payment, they will end up borrowing more to compensate the increase in price, and the resulting LTV limit will be higher. 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:

$$\widehat{B} = \sum_{j=-k}^{k} \left(\overline{n}_j^s - \overline{n}_j^r \right)$$

$$\widehat{M} = \sum_{j=k+1}^{J} \left(\overline{n}_j^r - \overline{n}_j^s \right)$$

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 decreases, more people get constrained, and the bunching mass will increase. However, due to the increase in house price, many households will not be able to increase their down-payment and will end up borrowing at higher LTVs towards the limit. As a result, the bunching mass at the LTV limit will also increase, but this increase cannot be attributed to the reduction in the LTV limit. Therefore, increases in bunching can be due to both LTV limit decreases and to house price increases. On the other hand, increase in the missing mass to the right of the distribution $\widehat{M}$ can only be attributed to LTV limit reductions that force starters (but not renegotiators) to reduce their credit demand to the new LTV limit from points at the right of it. Instead, the regulation ensures that increases in the bunching mass attributable to increases in house prices, can only come from points to the left of the LTV limit. As a result, I use the changes in the estimated $\widehat{M}$ to disentangle the effect of LTV limit reductions out of the confounding effect of house prices in the estimated bunching

mass $\widehat{B}$. Results are reported in Table 4, and a graphical representation of the result is reported in Figure 7. The Figure shows that most households heavily rely on debt and borrow at the LTV limit, as evident from the spike in both distributions. However, since renegotiating borrowers are exempt from the regulation, the spike in the distribution of starters is much higher and most of the difference in the two distributions arise exactly at the LTV limit. The difference between the two local spikes (bunching) ranges from 12% to 17% and increases over the sample period. However, as explained, only part of this difference can be attributed to the causal effect of the LTV regulation. The estimate of missing mass at the right of the LTV limit ($\widehat{M}$) ranges from 5.5% to 11.1% and, also, increases over time: by further reducing the LTV limit, more borrowers get credit constrained and end up bunching at the LTV limit. The remaining share of the bunching mass at the limit ($\widehat{B}$) is not due to the LTV limit change, and possibly reflects the increase in house prices.
In summary, results show that despite a generous LTV limit level, and despite a pro-cyclical borrowing capacity that increases as house prices increase, the LTV rule is still a binding rule for many borrowers who increasingly borrow at the regulatory limit. Part of the increase in the share of limit-borrowers can be attributed to a macro-prudential policy that is progressively tightening the leverage constraint: among starters, the share of borrowers constrained by the regulation is estimated to be increasing from 5% to 11% as the LTV limit is further tightened. Unsurprisingly, this share has dropped only in 2016, when LTI limits have been but along the whole income distribution. In fact, once the maximum borrowing capacity established by the LTV increases as house price increase, borrowers can effectively increase the amount of debt they take only to the extent that the LTI limits also increase.

V - Concluding remarks

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 and induce a shift in the level of debt towards the macro-prudential limits, and I show that this effect can confound the effect of the regulation if not properly dealt with. I find that the increase in house prices has been the most binding factor for Dutch households' borrowing decisions of the recent years. According to the estimates, a one standard deviation increase in house prices translates into an increase in debt in households balance sheets by 13.4%. Then, LTI and LTV limits play a second-level role: Loan-to-Income limits, being based on debt affordability, affect the level of debt only among lower income households, and the exceptions established by the regulation play a key role in relaxing the credit constraint and giving flexibility to borrowers and lenders. Estimates in Table 6 show that the *Explain* option is costly and Figure 7 shows how widely this option used among low-income borrowers: on average, explainers are charged 7 basis point (out of 50) more than compliers and while the share of explainers is negligible in above-median income brackets, it is about 70% among very low income borrowers, that otherwise would not be able to participate in the credit market. Loan-to-Value limit tightenings instead induce more and more borrowers to bunch at (lower) limits, but are ineffective in limiting the *level* of debt due to the pro-ciclicality of the borrowing capacity implied by the LTV, that mechanically increases when house prices increase. Results are perfectly consistent with a stylized life-cycle model with housing, heterogenous borrowers and credit constraints. The policy implication I draw is that to properly control the level of household debt in periods of boom and bust in the housing market, it is preferable to adopt a macro-prudential tool that is based on household debt affordability and is independent on the housing market conditions.

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Tables and Figures

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).

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) and (3) are Pooled OLS, while the estimates in columns (2) and (4) 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.

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.

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.

Table 6: The cost to Explain

	Dependent variable: mortgage interest rate				
	whole sample	2014	2015	2016	2017
Explain	7.729***	1.151	9.936***	1.400	12.56***
	(0.482)	(1.4804)	(0.756)	(1.093)	(0.838)
Controls	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓
N	228.299	50.136	53.714	57.708	65.741

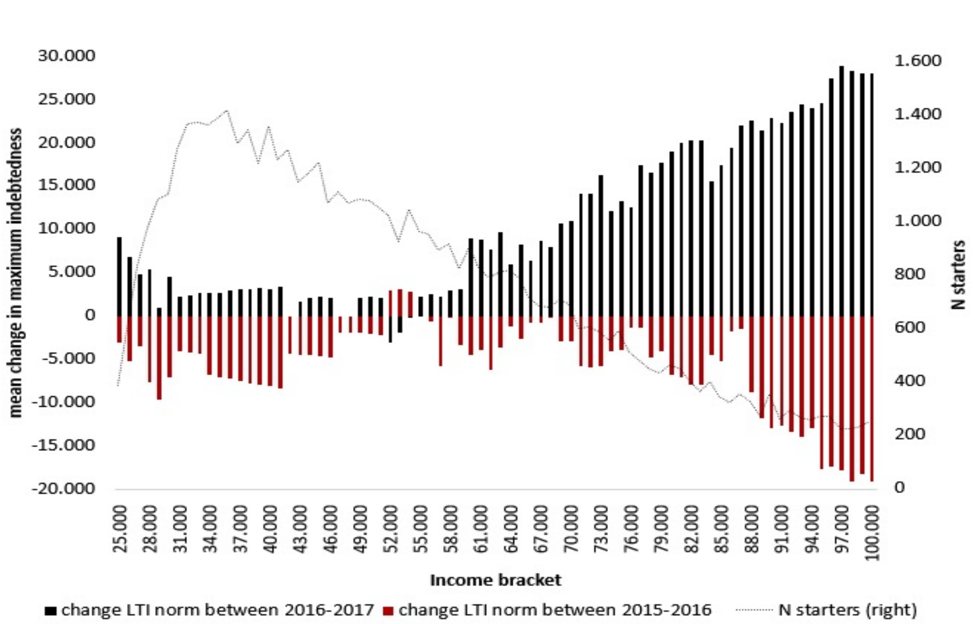
Note: The Table reports estimates of the cost associated to the option to exceed the LTI limit (Explain). The dependent variable is the interest rate, expressed in basis points (b.p.). The difference in the borrowing cost between compliers and explainers can be at most equal to the range of the interest rate categories, which is equal to 50 basis points. The set of controls includes the LTV at origination, the LTV limit, the LTI limit, the household income at origination, the property valuation, age, the NHG indicator, employment status dummies. The symbol *, ** and *** denote conventional statistical significance levels.

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

Bruto jaarinkomen	Hypotheekrente 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

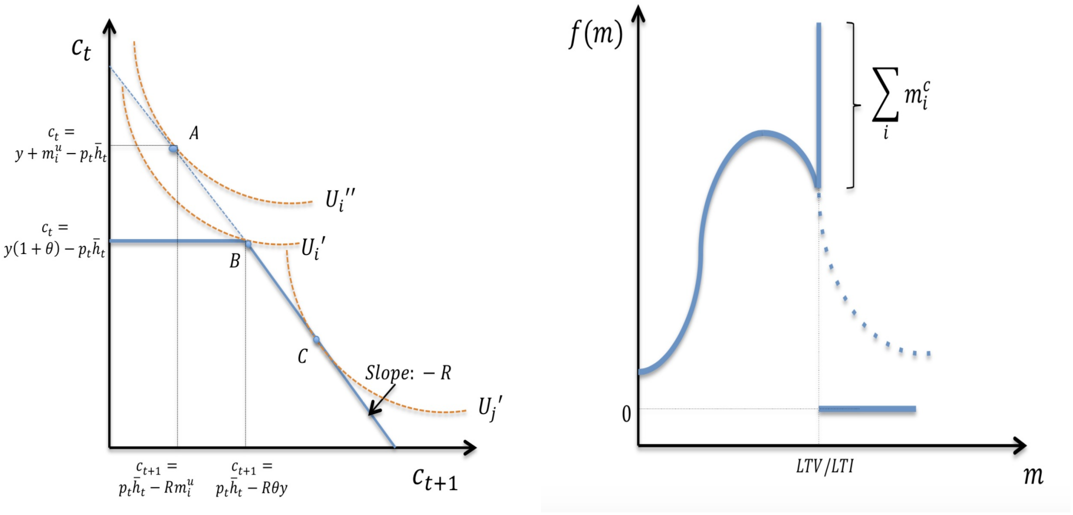
Note: The Figure shows the heatmap of an example of the table containing the recommended Loan-to-Income (LTI) limits. LTI limits depend on the gross annual household income (vertical axis) and on the interest rate charged on the mortgage loan (horizontal axis). Stricter limits are depicted in green, 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.

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.

Figure 3: (Un)constrained optimal consumption and mortgage distribution.



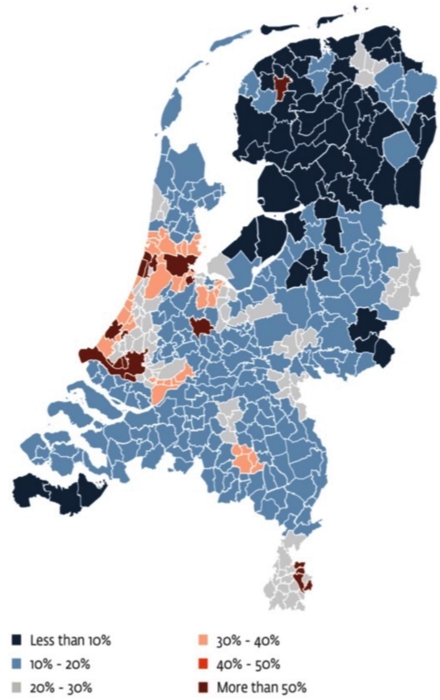
(a) (b)

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.

Figure 4: Exogenous changes in the income classification

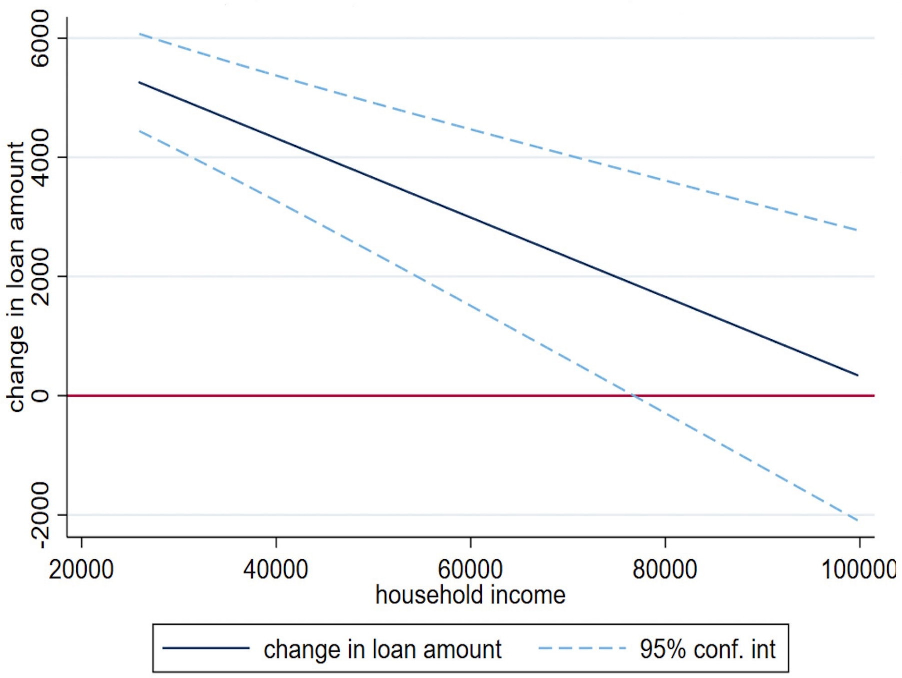
Note: The Figure shows the change in the number and the size of the income brackets undertaken by the NIBUD Institute for the LTI limits classification. The dashes and the numbers in black denote the size of the different income brackets. The numbers in red denote the corresponding LTI limits, for the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

Figure 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).

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.

Figure 7: (a) Bunching at the LTI distribution

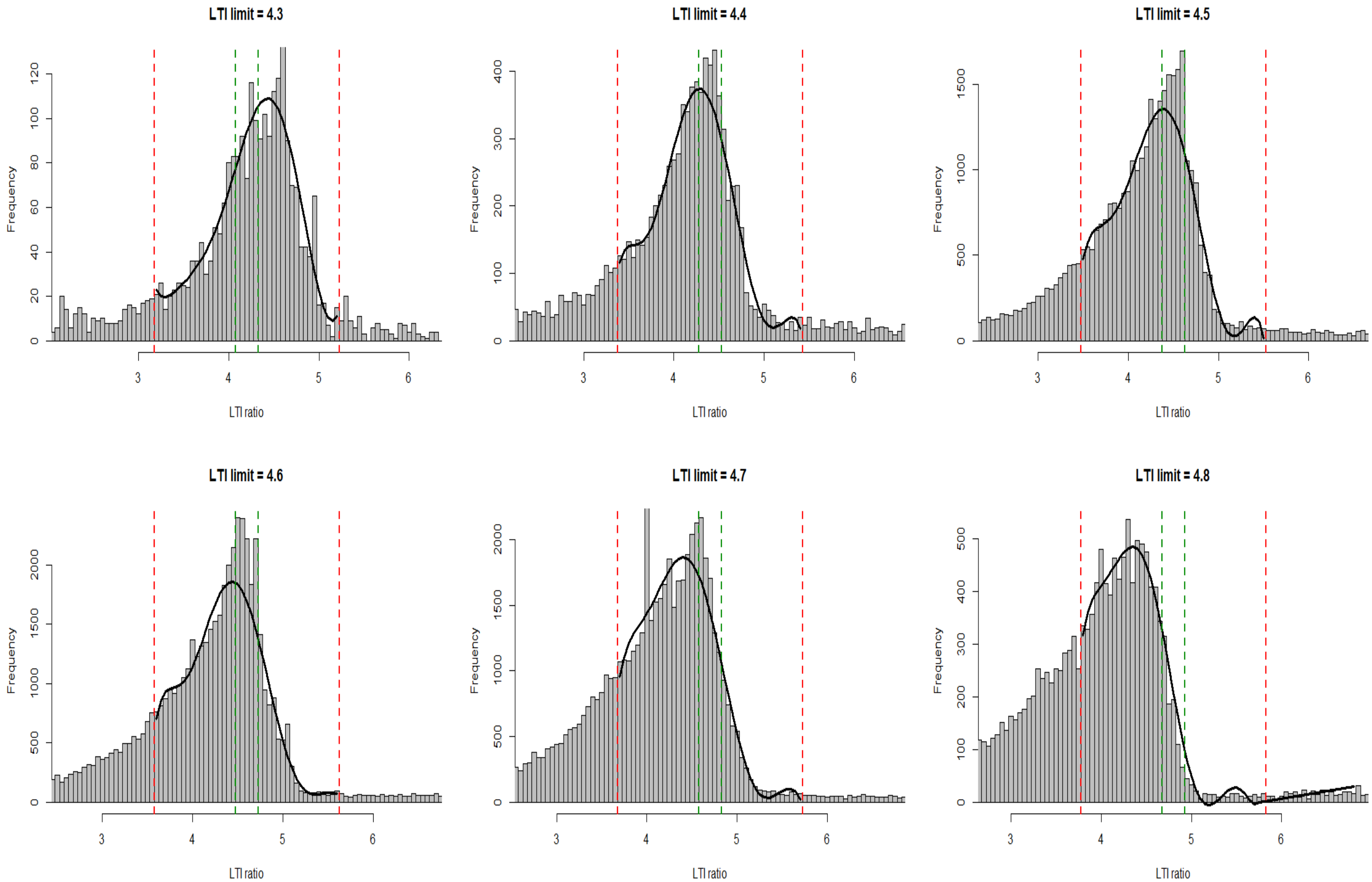
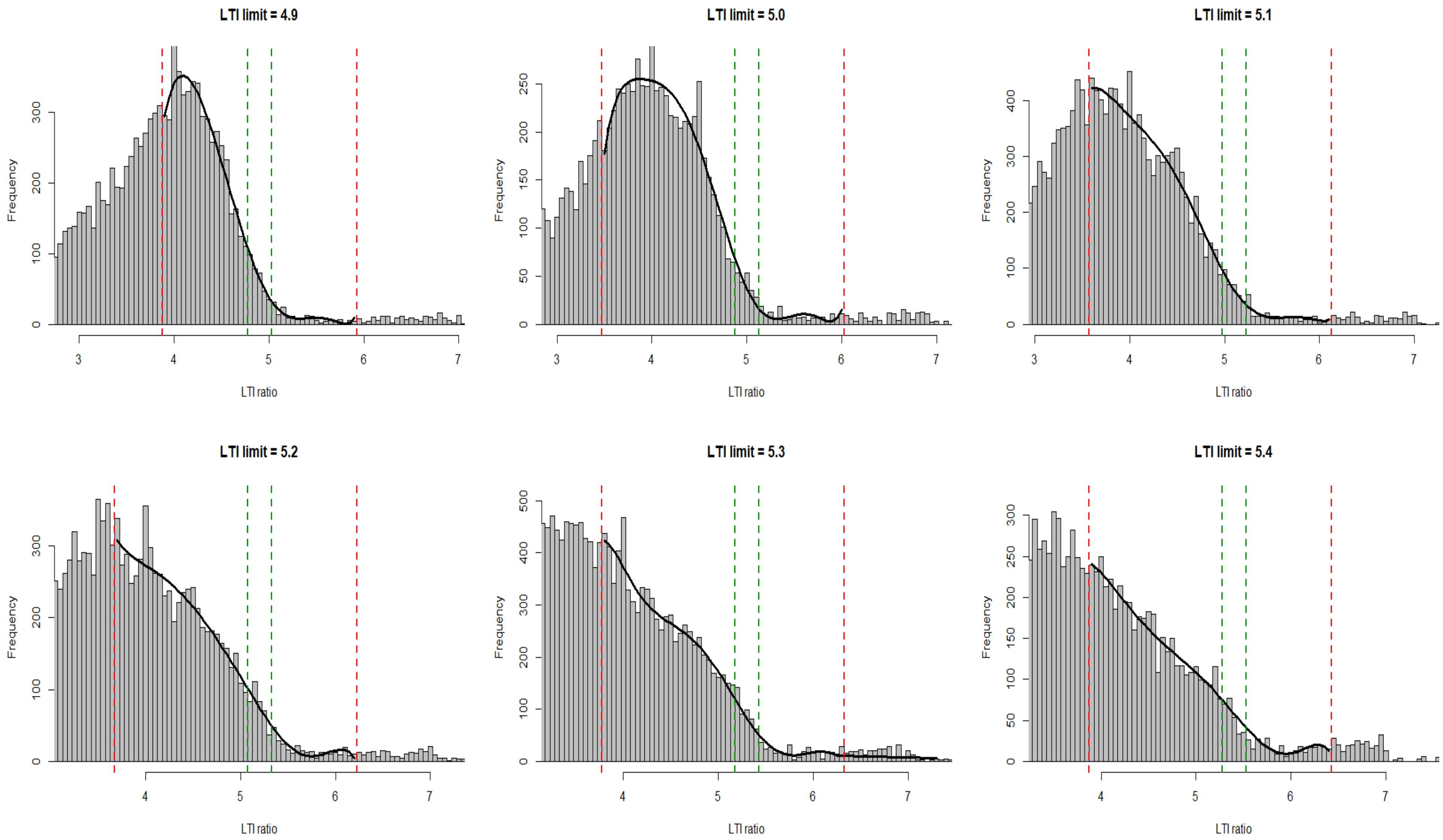
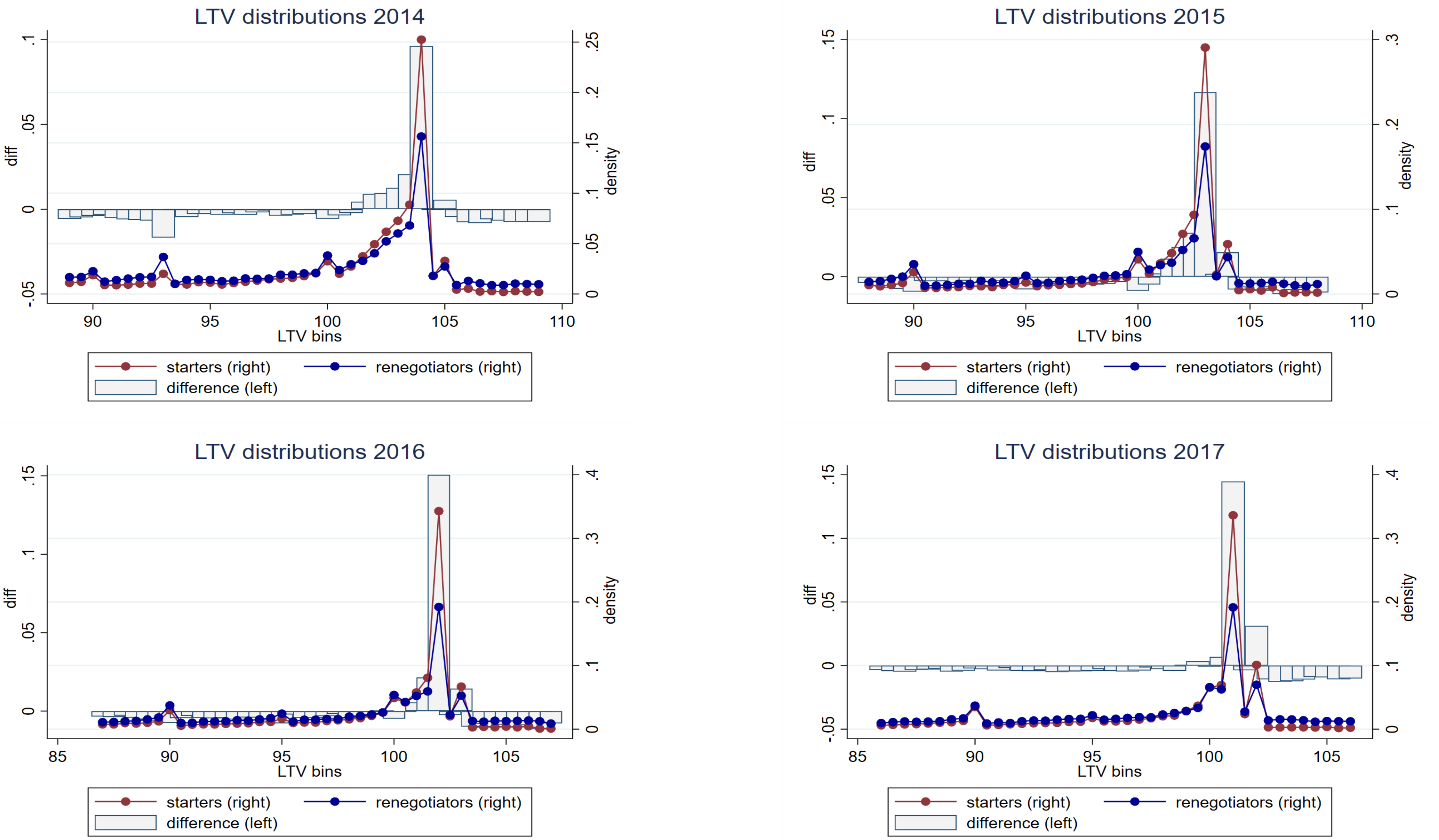


Figure 7: (b) Bunching at the LTI distribution



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 8: 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 ($\widehat{M}$).