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An agent-based model for the assessment of LTV caps

DIMITRIOS LALIOTIS†, ALEJANDRO BUESA †‡, MIHA LEBER§ and JAVIER POBLACIÓN *†

†DG Macroprudential Policy and Financial Stability, European Central Bank, Sonnemannstrasse 22, Frankfurt a.M., Germany
‡Universidad Complutense de Madrid, Campus de Somosaguas, Pozuelo de Alarcón, Spain
§DG Microprudential Supervision II, European Central Bank, Kaiserstrasse 29, Frankfurt a.M., Germany

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We assess the effects of regulatory caps in the loan-to-value (LTV) ratio for housing mortgages using an agent-based model. Sellers, buyers and banks interact within a computational framework that enables the application of LTV caps to a one-step housing market. We first conduct a simulation exercise; later, we calibrate the probability distributions based on actual European data from the Household Finance and Consumption Survey. In both cases, the application of an LTV cap results in a modified distribution of buyers in terms of property values, bidding prices and properties sold, depending on the probability distributions of the LTV ratio, wealth and debt-to-income ratios considered. The results are of similar magnitude to other studies in the literature embodying other analytical approaches, and they suggest that our methodology can potentially be used to gauge the impact of common macroprudential measures.

Keywords: Agent-based models; Macroprudential policy and house prices; Household survey

JEL codes: D14, D31, E50, R21

1. Introduction

Housing markets are among the most important sectors of modern economies, real estate probably being the largest asset class in the world, owing to their relationship with macroeconomic dynamics. Following the literature (see, for example, Reinhart and Rogoff 2013), real estate bubbles and bursts characterize almost all financial crises, with the recent episode of the Great Recession being no exception.

However, because housing price characteristics such as illiquidity, locality, leverage or heterogeneity often render modelling demanding and difficult, researchers sometimes choose convenient shortcuts that in most environments represent a good approximation.

In this paper, we use an agent-based model (ABM) to assess loan-to-value (LTV) cap measures and to determine the evolution of portfolio credit parameters, the impact on the provision of credit by banks and the evolution of housing prices after the application of such caps.

The literature on housing markets is extensive. On the one hand, much conceptual work has started to appear related to macroprudential policy; some examples are Kuttner and Shim (2012), Nier *et al.* (2012), Kannan *et al.* (2012), and Christsensen (2011). Mendicino (2012) shows that countercyclical LTV ratios in response to credit growth can smooth the credit cycle, whereas Unsal (2011) examines the relation between monetary policy and macroprudential regulation in an open economy dynamic stochastic general equilibrium model with nominal and real frictions. The last author finds that macroprudential measures can usefully complement monetary policy. A recent study summarizing the experiences with *ex ante* impact assessments of macroprudential instruments can be found in CGFS (2016).

On the other hand, research—though still scarce—is evolving on the empirical modelling side. Crowe *et al.* (2011) use state-level US data to find a positive relation between LTV at origination and subsequent property appreciation. Lim *et al.* (2011) evaluate the effectiveness of macroprudential instruments such as LTV caps in reducing systemic risk over time and across markets using data from 49 countries.

*Corresponding author. Email: javier.poblacion@bde.es
The affiliations of some of the authors at the time of publication have changed: Dimitrios Laliotis (International Monetary Fund), Alejandro Buesa (Banco de España and Universidad Complutense de Madrid), Javier Poblacián (Banco de España).

Price (2014), as well as Bloor and McDonald (2013), use a Bayesian vector autoregression to conduct ex ante counterfactual analyses prior to the introduction of borrower-based policies in New Zealand. Building on the same approach, Cussen *et al.* (2015) conduct a micro simulation exercise based on loan-level data to quantify the impact of various caps on loan volumes in Ireland†. Almeida *et al.* (2006) provide evidence that in countries with higher LTV ratios, house prices and demands from new borrowers are more sensitive to income shocks. Lamont and Stein (1999) find that in cities where a greater fraction of households have high LTV ratios, house prices respond more sensitively to economic shocks‡. For Korea, Igan and Kang (2011) find that LTV and debt-to-income ratio caps help to contain house price growth. Finally, Lambertini *et al.* (2011) highlight the importance of an expectations channel by developing a model of the housing market that incorporates expectations-driven cycles, then showing that countercyclical LTV rules responding to credit growth can reduce the volatility of loans and the loan-to-GDP ratio.

The contribution of our paper, seen against this strand of the literature, is to simulate a handful of simple models with agent-based techniques and to assess their efficiency in capturing the underlying dynamics. The intention is not to provide a fully-fledged analytical framework, but rather a proof of concept on the suitability and efficiency of such behaviour-capturing models to contribute to the impact assessment of macroprudential measures of this type.

ABMs are not novel in the literature; some examples are Farmer (2014), Dawid *et al.* (2011), Colander *et al.* (2008), Gilbert *et al.* (2009) or LeBaron and Tesfatsion (2008). Our approach is based on Axtell *et al.* (2012, 2014), who proposed a new and comprehensive model of the housing market in Washington, DC. This particular modelling approach is innovative in the literature in the sense that micro-level data is used to calibrate behavioural equations instead of postulating theoretical top-down rules. The main focus of their work was on demonstrating the causal relationship between leverage and the formation of a housing bubble.

Following the same overall approach in the use of multiple sources of micro data to elicit behaviours, Baptista *et al.* (2016) develop an ABM of the UK housing market to study the impact of macroprudential policies on key housing market indicators. This view enables them to tackle the heterogeneity in this market by modelling the individual responses and interactions of first-time buyers, home owners, buy-to-let investors and renters from the bottom up, as well as to observe the resulting aggregate dynamics in property and credit markets.

In line with these works, in our paper the housing market is viewed as a universe of interacting heterogeneous agents comprising sellers, buyers and banks. Following autonomous decision rules, these agents interact directly with one another and with the economic environment, producing an overall economic outcome that emerges from complex interactions that cannot be easily derived from the agents' objectives and behavioural rules.

In this respect, table 1 compares our framework with the two aforementioned closest references. Our approach is the simplest one because we do not predict housing prices, but rather we assess the impact of the application of borrower-based macroprudential measures. That is the reason why we do not consider either investors or renters in our model.

Since they largely influence the choice of simplifications in our approach, there are two specific characteristics of the task of measuring the impact of macroprudential measures that should be noted. First, the results are relative in the sense that answers are sought on metrics (credit provision, housing prices) with or without the application of caps. Second, for the time being, one-time-step models are more critical to design, since our focus is on the impact related to the application of the macroprudential measure and not on the convergence of a more complex multi-stage ABM that focuses on forecasting the housing cycle.

As a result, we initially present simulated results based on stylized, yet pragmatic assumptions. Subsequently, we calibrate the probability distributions from empirical data. We use the second wave of the European Central Bank's *Household Finance and Consumption Survey*, and a copula-based approach for the estimation of multivariate distributions of initial liquid wealth, debt-service-to-income ratios, LTV ratios and loan-to-income (LTI) ratios. Based on the probability distributions of this real data, we present the distributions of properties that are actually traded in the auctions pre- and post- the application of an absolute LTV ratio cap, as well as under the assumption of a proportionate cap. Banks are allowed to exceed the imposed cap for a certain proportion of their newly originated exposures, i.e. some borrowers are indeed allowed to be granted loans in excess of the cap level, based on the bank's credit assessment. Finally, we divide the sample by country in order to present the results at the country level.

We compute the variation in house prices and mortgage credit under all the LTV cap specifications considered. Country estimates for real estate prices range from 5% increases to -12% contractions, whereas credit is shown to decrease within the 6%–12% interval. These results are are similar in magnitude to other studies in the literature which adopt a variety of quantitative methods, showing that the approach is a useful and possibly complementary alternative to the existing analytical frameworks for assessing the impact of borrower-based macroprudential measures.

The remainder of our paper is organized as follows: In Section 2, we sketch an outline of the model and its components. In Section 3, we present the results, first from a series of simulations and subsequently based on a model calibration through real survey data to illustrate the impact of applying an LTV cap on mortgage lending. Section 4 concludes.

2. The agent-based model

Agent-based models (ABMs) are computational tools in which heterogeneous agents interact directly with one another

† Further related work for Ireland can be found in Hallissey *et al.* (2014), Lydon and McCarthy (2013) and Kelly (2011).
‡ A list of related studies includes, with no intent of being exhaustive, Gerlach and Peng (2005), Ahuja and Nabar (2011), Wong *et al.* (2011), Funke and Paetz (2012), and Wong *et al.* (2014).

Table 1. Comparison between this paper and its closest peers in the literature.

	Baptista *et al.* (2016)	Axtell *et al.* (2014)	This paper
	Macroprudential policy in an agent-based model of the UK housing market	An agent-based model of the housing market bubble in metropolitan Washington, DC	An Agent-based model for the assessment of LTV Caps
Policy questions to address	(1) Booms and bust dynamics conditional on . . . . . . size of rental/Buy-to-let sector . . . different types of Buy-to-let investors (2) Qualitatively assess the effect of macro-prudential policies, such as a Loan-to-income limit	Housing price dynamics (booms and busts)	Impact of borrower-based macroprudential measures (LTV, LTI caps)
Agent types	Households, banks, central bank	Households, banks	Households, banks and regulators (could be a central bank or a government)
Household types	First-time buyers, buy-to-let investors, renters, owner-occupier	Home buyers and sellers, investors	Home buyers and sellers
Role of bank agents	Supply of mortgage loans	Supply of mortgage loans	Supply of mortgage loans
Role of central bank agents	Set LTV and LTI	–	Set LTV caps
Role of government	–	–	Set LTV caps
Role of non-financial firms	–	–	–
Markets in the model	Housing and rental market	Housing and rental market	Housing market, mortgage loan market
Demographic features for households	Age (related: birth, death and inheritance)	–	–
Empirical calibration	Micro calibration: Household survey, housing market data; macroeconomic indicators	Micro calibration: Household survey, real estate transactions data, mortgage loans series	Any micro-data source that covers the required inputs (possibly HFCS database for European countries)

Note: Table 1 compares our framework with the two aforementioned closest references (Axtell *et al.* 2014, Baptista *et al.* 2016).

and with their economic environment, following autonomous decision rules.

Our approach is based on a straightforward ABM where we model the interactions of sellers, buyers and banks within a computational framework that maps the economic environment, in the form of credit provision by banks and the applied LTV caps, into the emergence of a one-step housing market settlement state, where specific properties are sold at specific prices during the one-step time interval. Therefore, the ABM can be viewed as a set of parallel-run property auctions, one for each seller, on the properties offered by the universe of sellers, where the buyers' behavioural trends and the banks' imposed financing constraints define the demand side. Since the problem is that of assessing the impact of imposing LTV caps, the whole computational model has to be set up as a relative/differential model in the sense that the results should be compared in the pre- and post- LTV cap cases.

In that context, we restrict ourselves to a single time step - how the housing market *clears* for one period with or without the cap - and we ignore any multiple period aspects - how housing prices *evolve* over time and how this is linked to the formation of price imbalances. This consideration is relatively scarce in the ABM literature, where more often the target is to predict the long-term equilibrium for an entire housing cycle, that is, the multiple-stage evolution of house prices and the respective imbalances.

2.1. *The seller agents*

The model assumes that there are N sellers at the beginning of the period, each of them offering a single property in the market; for each seller, there is a parallel auction with all the buyers interested in buying the house. This implies that from a computational perspective, N parallel auctions would be needed in order to identify a final market clearing ratio, defined as the percentage of N that is finally sold in the market, and the 'equilibrium' prices for those properties. The latter also entails the emergence of a settlement price for all properties: A transaction price for those sold and an average bid-ask price for those not sold.

The model is agnostic regarding the actual distribution of seller-asked prices. It only assumes that sellers uniformly cover the entire spectrum of the market, with no concentration on specific segments of buyers. More precisely, sellers can be ordered based on the asking price S_i, an ordering that is linked to the quality of the property, i.e. a higher price corresponds to a higher-quality property, with the term quality encompassing several features of the property such as location, size, age, and proximity:

$$S = S_1, S_2, \ldots, S_N, S_1 \leq S_2 \leq \cdots \leq S_N$$

Calibration includes the setting of initial asking prices at levels that would ensure uniformity across the distribution of buyers, although alternative and more complex distributions of starting asking prices for the seller agents can be incorporated relatively easily.

For the sellers, the model also assumes a passive behaviour in the sense that they start the auction with an asking price. If they are not 'lifted', that is, if the transaction does not originate by a corresponding buyer willing to pay the asking price, they will lower their asking price with probability p_d^S, trying to match a buyer agent in the auction until a limit of a fixed factor r percentage points from the initial asking price S_i is reached. In other words, there is a probability p_d^S that a seller, if not matched by a buyer at the initiation of the auction process, will gradually mark down its asking price from S_i to $S_i \times (1-r)$ in an attempt to match a buyer: This is what we call an aggressive seller. Obviously p_d^S becomes important for calibration purposes, since it defines the supply side and the behavioural tendency of seller agents to mark down property prices.

2.2. *The buyer agents*

Buyer agents represent households seeking to buy a property. A liquid wealth distribution is assumed for each buyer, a percentage of which may be used for the down payment of a mortgage loan. Each buyer is assigned an original LTV ratio which, combined with the maximum preferred down payment, results in the highest value of property up to which the agent can bid. Therefore, we assume a set of bids B from M buyer agents:

$$B = B_1, B_2, \ldots, B_M, B_1 \leq B_2 \leq \cdots \leq B_M.$$

where

$$B_k = \begin{cases} \min\left\{\dfrac{D_k}{1-LTV_k}, a \times \omega_k\right\} & LTV_k < 1. \\ a\omega_k, & LTV_k \geq 1. \end{cases}$$

LTV_k represents the loan-to-value ratio associated with buyer agent k drawn from a probability distribution. Essentially, agents with an LTV ratio above 1 will bid as much as a multiple a of their liquid wealth ω_k. As for those having less than unity LTVs, they will choose between the latter amount and a multiple $1/(1-LTV)$ of the down payment D_k, which is randomly drawn as a fraction of liquid wealth in the range (a_1, a_2) or calibrated on the basis of an empirical distribution.

In principle, the model assumes that each buyer agent will always go for the highest quality property and bid in auctions for properties of higher value given the practical limitations imposed by its buying value price B_i. However, with probability p_d^B, buyer k will also decide to participate in auctions where the starting asking price of the seller is smaller (up to a fixed factor g) than its original buying price B_k. This gives buyers the opportunity to react to excessive demand and competition by participating in the auctions of lower quality properties, always within the limits of a given distance g from the maximum quality they can attain with their buying price. Therefore, as in the case of p_d^S for seller agents, p_d^B for buyers represents their tendency to also go for lower quality due to overcrowding conditions. A high value of p_d^B reflects a higher density of buyer agents due to excessive demand.

The behaviour of a buying agent during the initial phase, when no LTV limits/caps are considered, can be summarized by the decision tree in figure 1.

For the case of the buyer's behaviour following the application of LTV caps, an additional option is modelled: The choice, with fixed probability q_d^B, to raise the down payment for the mortgage so that the buyer ends up competing for properties that were within his quality reach before the implementation of the LTV cap (increased own participation). In other words, when the cap constrains the buyer agents to participate in auctions with properties below the range they had been allowed prior to the cap, they may raise their down payment by increasing the part of household initial liquid wealth they consume in the purchase of the property. If such an increase does not allow them to participate in auctions for properties they would have participated in the no cap case, buyers remain inactive in the auctioning process.

Calibrating the value of q_d^B is a sensitive matter given that it is an artefact of our model through which buyers can liquefy their wealth. We assume that increasing the down payment is linked to a stable or improving financial situation; the European data used in the empirical exercise in Section 3.2 allows for some tentative calibration; more details can be found in Appendix 1. With this addition, the buyer's behaviour under a cap in LTVs is summarized in figure 2.

2.3. *The auction process*

The N prices $S = S_1, S_2, \ldots, S_N, S_1 \leq S_2 \leq \cdots \leq S_N$ from the sellers are set in a way such that they are distributed across the entire spectrum of the buyer agents' bidding prices $B = B_1, B_2, \ldots, B_M$. The easiest way to achieve this computationally is to divide the M buyers into N buckets, using M/N buyers for each bucket. By letting $B_i^*, i = 1, 2, \ldots, N$ denote the maximum buying price within each bucket, the asking price of seller i is set as $S_i = B_i^* + \varepsilon$ where ε denotes a small positive constant.

Although such an assignment of asking prices is quite agnostic regarding the supply-side distributional characteristics, it corresponds to the relative strong assumption of a homogeneous market where sellers are distributed uniformly across the different quality segments. Based on the above description, figure 3 schematically depicts the auctioning mechanism of N parallel auctions with the different types of sellers (aggressor and non-aggressor) and buyers (opting for lower-quality and non-opting ones).

The market clearing process can then be treated as a set of parallel auctions—one for each property—with the buyers' behavioural patterns fully defining the auctions' demand side. Computationally, this set of parallel auctions can be fully resolved by starting with the auction at the higher valued property and serially resolving lower-quality properties. This serialization enables the gradual clearance of both sellers and buyers, since buyers that have been successful in bidding a higher valued property can be removed from lower quality auctions.

From the standpoint of the market mechanism, the cap case is treated exactly the same in the sense that buyers still

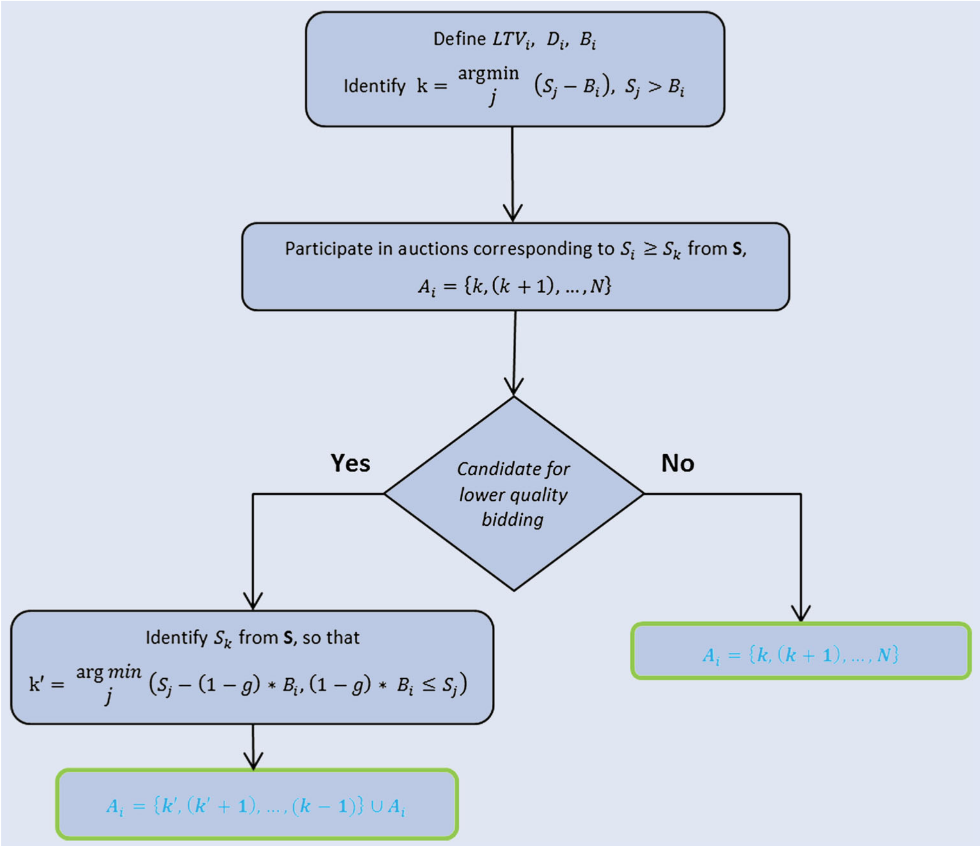


Figure 1. Buyer's decision tree for the no-cap case. This figure shows the behaviour of a buyer during the initial phase if no LTV limits are considered.

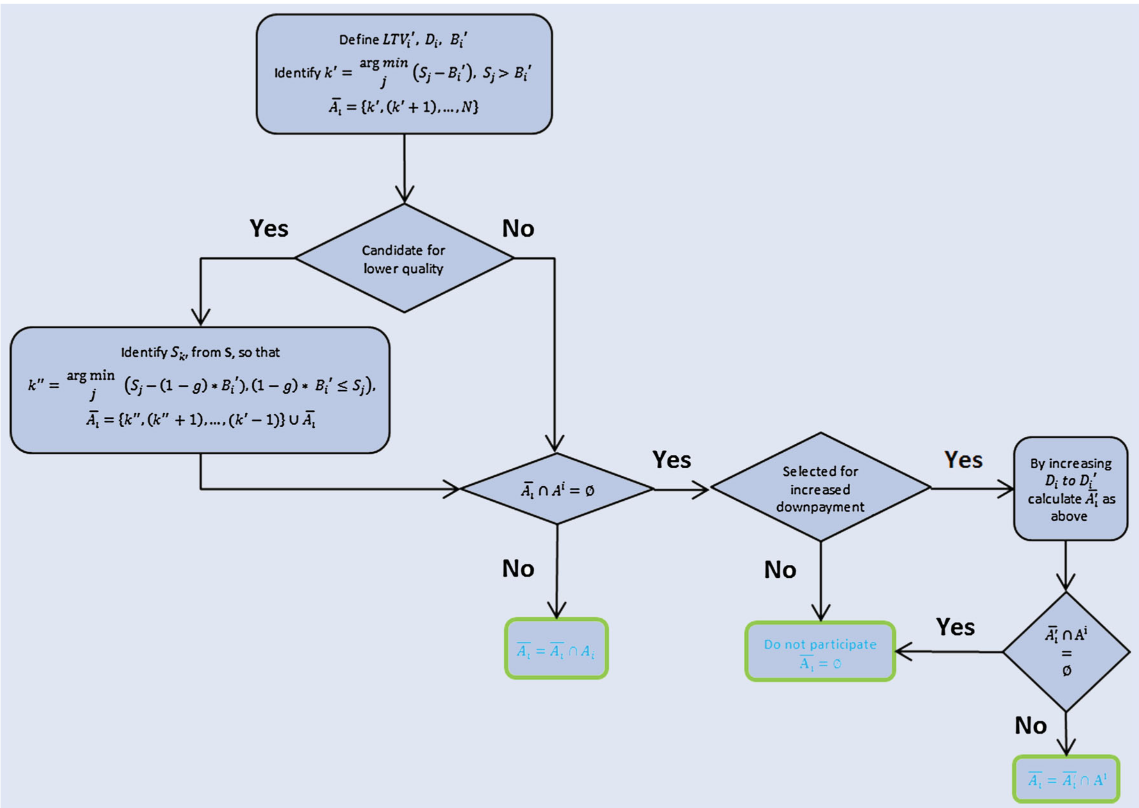


Figure 2. Buyer's decision tree if an LTV cap is in place.

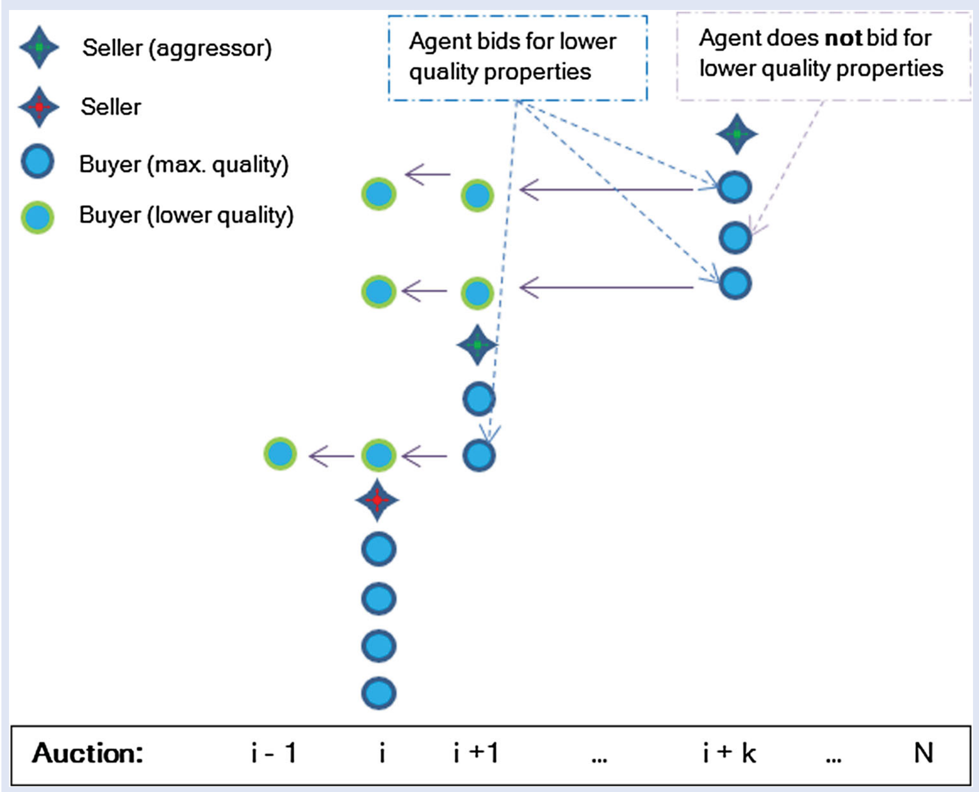


Figure 3. Schematic representation of the parallel auctioning process. Auctioning mechanism of N parallel auctions with different types of sellers (aggressor/non-aggressor) and buyers (opting/non-opting for lower quality). At auction $i + k$, there are three bidders, two of which are unsuccessful, therefore reduce their bidding price, and subsequently participate in a cheaper property auction.

have the option of increasing their down payment, bidding for cheaper properties or be subject to a seller that marks down the price.

The market clearing process is shown to converge for both cases, whether under a cap or not. Importantly, by controlling the number of buyers relative to that of sellers, the probability that sellers are willing to hit the bid of the best buyer if not lifted at the auction initiation, as well as the probability that a buyer mutates to the auctions of lower quality, can be used to calibrate the simulation process. They must be set to levels so that the desired clearing ratio (percentage of properties sold before the LTV cap) and demand uplift indicator (percentage of properties sold at a price higher than the one asked by the seller) are achieved.

It is relatively straightforward to calibrate control parameters so that the desirable clearing ratio and uplift ratio are attained in the no LTV cap case, and it is considered economically reasonable to restrain the initialization parameters to the two mentioned above. By way of the construction mechanism, the no LTV cap auction process results in an initial LTV distribution nearly identical to the desired one.

In this paper, we impose two different kinds of LTV caps: A simple absolute LTV cap and a more sophisticated one, the proportionate cap, in which banks are allowed to deviate from applying the cap only to a percentage of borrower exposures†. This second case requires the definition of a certain pecking order, based on which the deviation from the cap is applied to potential borrowers.

We have assumed three different types of pecking order‡. The first proportional cap benefits those with higher total wealth, which are the more likely to be granted a loan with an LTV exceeding what is allowed by the cap. To be more realistic, we added stochasticity to this selection process, allowing for some degree of randomness: A buyer is allowed to exceed the LTV cap with a probability that is analogous to his/her total wealth level; after selecting those that may be allowed to exceed the imposed cap, they are ranked based on their respective total wealth, and starting from the top ones, a serial selection process identifies the prospective buyers with the most total wealth until the exposure limit of the proportionate LTV cap is reached.

In the second type of proportionate cap, buyers closer to the median in total wealth will have a higher probability of receiving a loan with an LTV ratio beyond the limit. In this case, the probability will be inversely proportional to $\frac{|Wealth_{Total} - Wealth_{Median}|}{Wealth_{Median}}$, where $|\cdot|$ represents the absolute value. In both types of proportionate cap, this process may also involve some trial-and-error simulations in order to identify the number of borrowers that would be needed in order to reach the exposure percentage above the cap.

Finally, we propose a third, more realistic version where the probability of exceeding the LTV limit is decreasing in the loan-to-income (LTI) ratio. The intuition is that agents for

† Proportionate caps are common in OECD countries. See, for example, ESRB (2016) and Central Bank of Ireland (2015).

‡ As a robustness check, we create a fourth implementation where households above the cap can beat it with random probability; the results are not shown in the paper but are available upon request.

which the mortgage is a significant share (or even multiple) of total income are less solvent from the standpoint of the lending institution.

3. Results

In this section, we elaborate on the results from our model. These results are important as a whole because they demonstrate that even simple ABMs that allow for the disaggregation of agents' basic behavioural characteristics may be used to assess significant issues that arise when demand and supply are treated in an average or aggregated manner.

A first exercise uses a collection of simulated probability distributions to study the main features of the responses and the sensitivities to selected parameters. In a second pass, we calibrate the distributions based on empirical European data extracted from the second wave of the Eurosystem's *Household Finance and Consumption Survey*, combined with a copula methodology which allows us to produce multivariate distributions of initial liquid wealth, total wealth, LTV ratio and property value at origination.

3.1. Simulated data

We carried out our study assuming that loan-to-value ratios and wealth follow three different types of probability distributions. The property value distribution function is derived from the LTV density.

Our starting points are Gaussian distributions with mean and standard deviation (0.75,0.5) and (50,15) for the loan-to-value ratio and liquid wealth (in absolute units), respectively. Based on the Gaussians, we find densities from the log-normal and Rayleigh† families which cover roughly the same range for both variables but exhibit different skewness and kurtosis. The chosen distributions are shown in figure 4.

The multiplicity of starting densities considered acts as a robustness exercise for our results; more importantly, it may be used to model groups of agents with different behaviour in empirical exercises where data is scarce. For instance, one can think of a sample of home buyers obtained from a country where wealth is more uniformly distributed around the median and agents do not contract mortgage loans with high LTVs, even in the absence of a cap, owing to cultural aversion for over-indebtedness.

The absolute LTV cap is set at 80%, a reasonable level for most jurisdictions; however, useful insights into relative market impact can be extracted by comparing the results for different LTV caps, as discussed later in this section.

The left hand side of figure 5 summarizes the impact of the LTV cap on the distribution of 10,000 buyers for the Gaussian case, which are allocated in buckets corresponding to the value of the property they are bidding for‡. The application of an LTV cap shifts the distribution of buyers' bids towards the lower end of the price range, since the cap becomes binding for a significant proportion of buyers if we also assume that there is no change in their household's liquid assets and their ability to come up with the required down payment. The inverse is true for higher-priced homes, where demand is relatively weak due to the cap application.

One interesting effect arises when combining differently shaped distributions; on the right hand side of figure 5 we exhibit the particular case of a Rayleigh density for LTV ratios and a Gaussian distribution for liquid wealth. As a consequence of the cap, a sizeable mass of buyers from the upper and lower end of the property range clusters more intensely around average-valued homes, in a behaviour mimicking that of a proportional cap penalizing buyers whose wealth is further from a centrality measure such as the median, as we will analyse later in this section.

From a statistical point of view, it is reasonable to reckon that the correlation between LTV and wealth distributions plays a major role in the shape of the results. Despite having agnostically assumed zero correlation in the previous exercise, most estimates for European countries from the HFCS yield values of -0.3 on average; we therefore decide to compare the distribution of buyers across property buckets for five different correlations, which we show in figure 6. Using the zero case as a benchmark, a greater positive correlation naturally shifts the distribution of buyers towards lower price ranges, since the cap constraint becomes binding for a significant proportion of households under the assumption that there is no change in their household's liquid assets and their ability to come up with the required down payment. In the most extreme case (right corner) the distribution becomes bimodal, as if the market were more uniform, still slightly polarized around two types of representative property: One high-quality for the wealthy households who sign mortgages with high LTVs, and one low-quality for poor households who become prudent and borrow as little as possible. For the negative correlation cases, the effect seems to be much more marked: The average traded price decreases abruptly while low-tier buyers with high-LTV loans flood the auctions for the cheapest properties.

Figure 7 sketches the ordered buyers (by bids) and the bidding prices before and after the introduction of the cap. It also displays the non-uniform effect on prices that is also observed by comparing the distributions of figure 5. This suggests that different segments of the housing price curve would be affected differently. The magnitude of such effects would also depend on the households' initial liquid wealth distributions and the assumptions on their ability and willingness to increase down payments. Apart from the stylized approach used in the results presented here, where it is assumed that this behaviour does not change post-application of LTV caps, the use of more granular data to model possibly evolving behavioural patterns of buyers may result in significant changes in the way the demand side is comprised after the application of the cap.

One last consideration for the benchmark exercise of an absolute cap relates to how the distribution of agents pre- and post-cap may vary if liquid wealth increases by the same amount for all buyers. Our ABM is not particularly sensitive

† The probability density function of a Rayleigh distribution with parameter ρ is $f(x \mid \rho) = \frac{x\exp(\frac{-x^2}{2\rho^2})}{\rho^2}$.

‡ Throughout this section and unless stated otherwise, we use the following calibration: $N = 7500, p_d^S = 0.1, p_d^B = 0.15, q_d^B = 0.3, r = 0.2, g = 0.1, a = 5, a_1 = 0.25, a_2 = 0.95$.

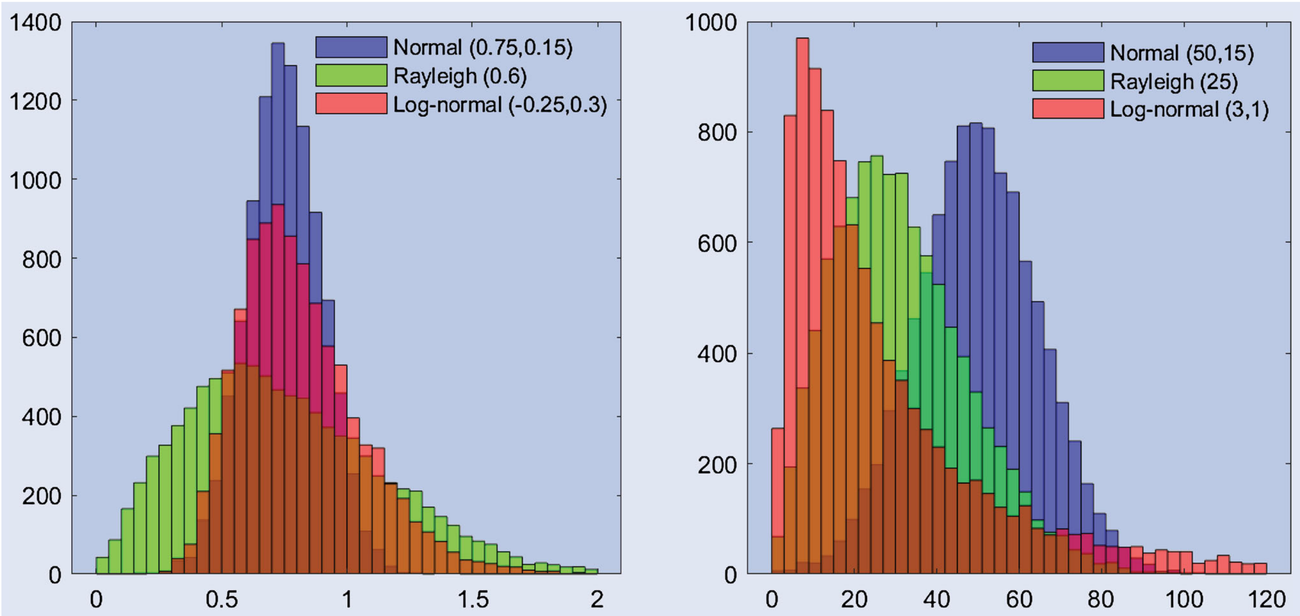


Figure 4. Probability distributions of LTV ratios (left) and liquid wealth (right). Liquid wealth is measured in absolute units. The brown area represents overlaps between the three distributions.

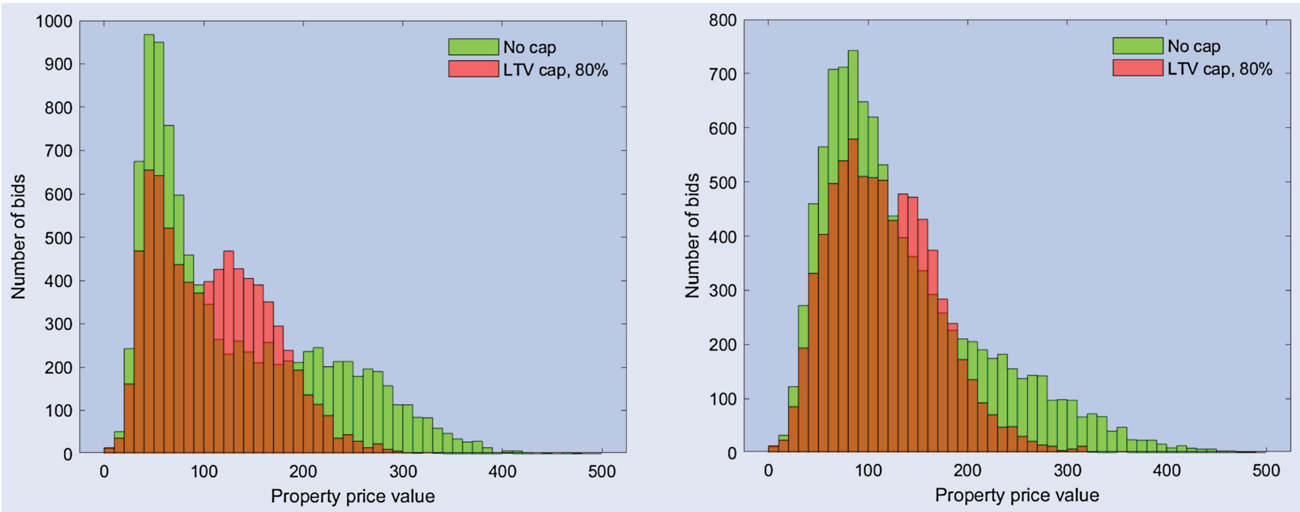


Figure 5. Pre- and post-cap distributions of buyer agents with simulated data. Case 1 (left): Gaussian density for LTV and liquid wealth. Case 2 (right): Rayleigh density for LTV ratios and Gaussian for liquid wealth. Property prices are expressed in absolute (wealth) units. The brown area represents overlaps between both distributions.

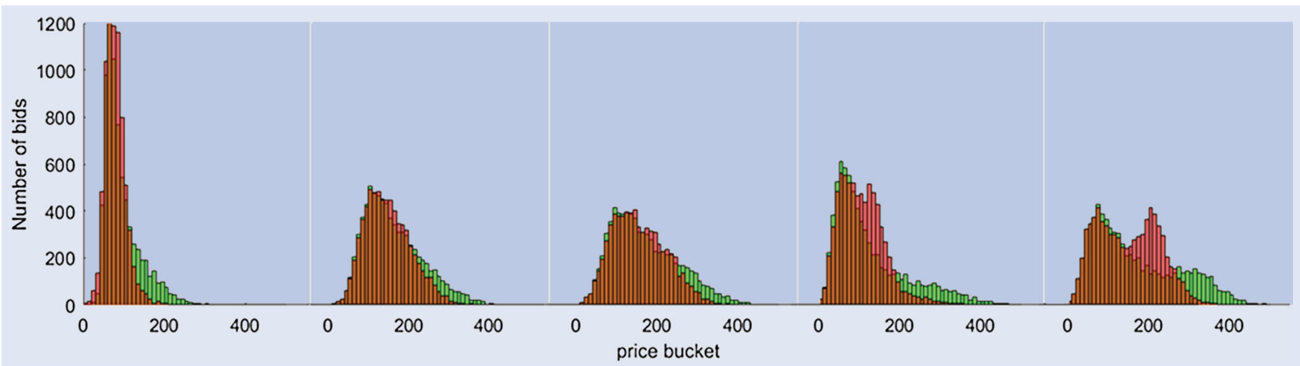


Figure 6. Distribution of buyers for different correlations between LTV and liquid wealth. Histograms correspond, to correlation values of $-0.75, -0.3, 0.0, 0.3, 0.75$. No LTV cap case (green), 80% LTV cap (red). Property prices are expressed in absolute (wealth) units. The brown area represents the overlap of both distributions.

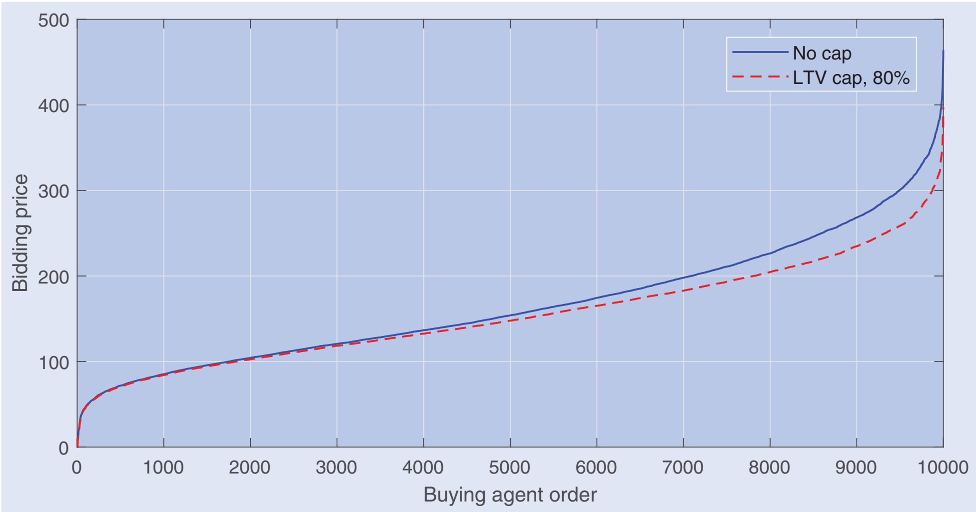


Figure 7. Ordered buyer bidding prices pre- and post-LTV cap.

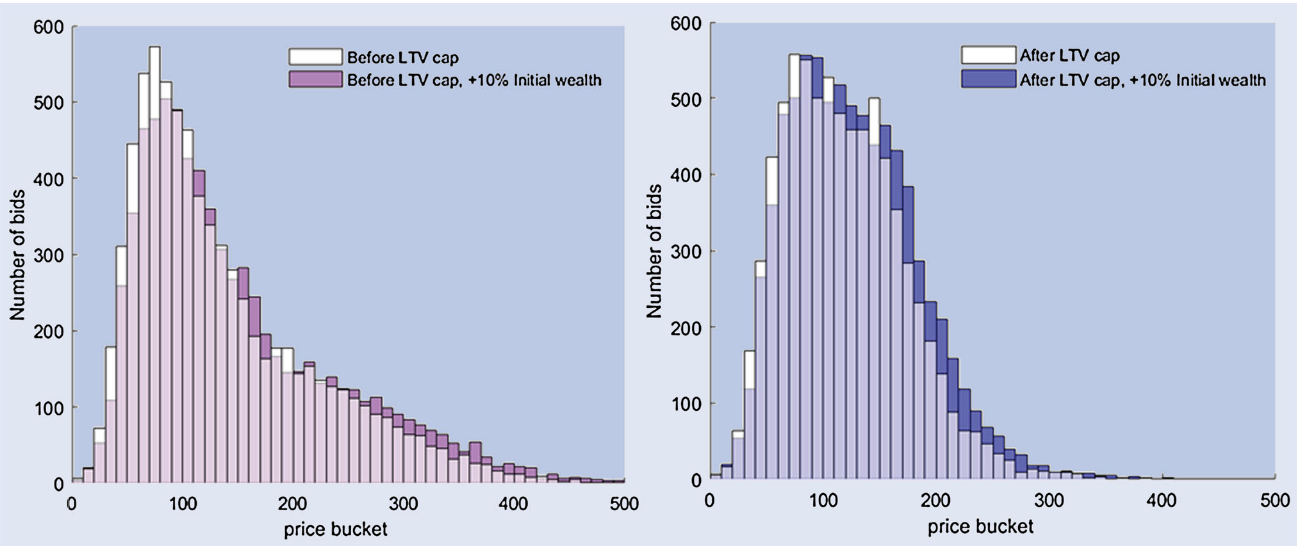


Figure 8. Effect of a global 10% increase in initial wealth on the distribution of buyers. This Figure shows the distributions of buyers for an overall 10% increase in wealth before and after the imposition of an LTV cap. Property prices are expressed in absolute (wealth) units. Light-coloured areas represent overlaps between both distributions.

with the benchmark calibration but is in line with intuition: As shown in figure 8, if wealth uniformly increases by one tenth of the initial value, the same buyers will be placed in auctions for mildly more expensive properties. Graphically, this entails a shift from the left to the right edges of the distribution.

In addition to what has been presented above, a wider set of metrics and indicators can be collected and compared for the two cases in question. Table 2 summarizes the findings for simulated runs for different LTV cap values and market density parameters (N/M, p_d^S, p_d^B). Simulation results are presented for several runs that represent different levels of LTV caps (90%, 85% and 80%). The results in different clearance ratios in the first column of the table segments can be used to determine the combination of parameters that would be closer to the real conditions of the housing market. In other words, for each city or country, it is possible to obtain yearly data on sold properties and the stock of unsold properties to infer the clearance ratio and market density (N/M). With real data from table 2, one can infer p_d^S, p_d^B, and other model initialization parameters.

The two segments of the table that refer to the cap and no cap cases also present statistics on the average traded price, the percentage of transactions that were secured by aggressive buyers, the percentage increase on the transaction price due to the aggressiveness of the buying agents and the split of the transaction price between credit provided by the bank and buyers' down payments.

Deriving metrics on the impact on housing prices is challenging due to the indexation process that might be required and the heterogeneity of the impact on different segments of the curve due to the 'crude' way the LTV cap impacts the demand side of higher quality properties. On the other side, based on the assumptions made, estimating the variation of banks' credit provision levels and increased own participation levels is a straightforward process due to the detailed available data associated with the individual agents of the simulated model.

Table 2. Simulation results for different calibrations of the model.

LTV Cap	N/M	Pd_s	Pd_b	WITHOUT CAP: Clearing ratio (%)	WITHOUT CAP: Avg traded price	WITHOUT CAP: Aggressors (%)	WITHOUT CAP: Avg credit by bank	WITHOUT CAP: Avg down payment	WITH CAP: Clearing ratio (%)	WITH CAP: Avg traded price	WITH CAP: Aggressors (%)	WITH CAP: Avg credit by bank	WITH CAP: Avg down payment	Credit/price metrics: Buyers that increased down payment (%)	Credit/price metrics: Credit diff (%)	Credit/price metrics: Price diff in common cleared properties (%)
			0.1	29.7	140.1	11.9	114.1	26.5	29.9	140.6	11.2	111.4	28.7	100.0	-1.75	-0.01
		0.2	0.2	39.0	139.7	23.7	113.5	26.1	39.4	140.4	22.2	111.0	28.3	100.0	-1.10	-0.01
			0.3	49.1	139.1	36.2	112.3	27.0	49.5	139.7	33.7	110.1	29.0	100.0	-1.24	-0.01
			0.1	37.1	138.9	10.6	112.7	26.4	37.3	139.2	10.1	109.9	28.6	100.0	-2.17	0.00
	0.75	0.3	0.2	44.8	139.4	21.6	113.0	26.0	45.1	139.7	20.0	110.4	28.2	100.0	-1.69	-0.01
			0.3	55.1	139.9	35.0	113.4	26.4	55.4	140.3	32.3	110.9	28.6	100.0	-1.56	-0.01
			0.1	46.3	139.9	9.8	113.2	26.5	46.4	140.1	9.2	110.5	28.5	100.0	-2.27	-0.01
		0.4	0.2	51.8	138.5	20.1	112.2	26.4	52.0	138.8	18.7	109.6	28.5	100.0	-1.89	0.00
90%			0.3	59.5	138.1	31.8	112.0	26.2	59.8	138.5	29.3	109.5	28.3	100.0	-1.79	-0.01
			0.1	32.3	139.8	15.5	113.1	26.0	32.6	140.3	14.6	110.8	28.4	100.0	-1.17	0.00
		0.2	0.2	44.2	137.5	30.3	111.0	26.4	44.5	137.9	28.6	108.5	28.5	100.0	-1.49	-0.01
			0.3	57.2	139.6	47.6	113.2	26.4	57.8	140.6	44.5	111.2	28.5	100.0	-0.66	-0.02
			0.1	39.1	139.9	13.3	113.3	26.6	39.2	140.2	12.4	110.7	28.7	100.0	-1.95	0.00
	0.6	0.3	0.2	50.7	136.7	28.9	110.1	26.2	50.9	136.9	27.4	107.8	28.5	100.0	-1.76	0.00
			0.3	61.9	139.2	45.2	113.2	26.2	62.4	139.6	42.2	110.6	28.5	100.0	-1.49	-0.01
			0.1	48.2	137.6	12.8	111.4	26.4	48.4	137.9	12.1	108.7	28.6	100.0	-2.07	-0.01
		0.4	0.2	55.4	138.8	26.4	112.5	26.1	55.7	139.2	24.5	109.9	28.4	100.0	-1.84	-0.01
			0.3	66.2	137.4	44.2	111.4	26.1	66.5	137.8	40.8	108.8	28.2	100.0	-1.80	-0.01
			0.1	29.4	137.2	11.8	111.3	26.5	29.9	138.3	9.6	106.2	30.2	100.0	-3.05	-0.02
		0.2	0.2	38.0	137.3	23.3	110.6	26.3	38.9	139.0	19.5	106.5	29.9	100.0	-1.60	-0.03
			0.3	49.0	138.3	36.0	112.0	26.2	50.2	139.5	28.1	107.3	29.7	100.0	-1.92	-0.04
			0.1	37.4	139.4	10.2	113.0	26.2	37.6	139.5	8.3	106.9	30.0	100.0	-4.82	-0.03
	0.75	0.3	0.2	45.4	139.1	21.7	112.2	26.4	45.9	139.4	17.9	106.9	30.1	100.0	-3.62	-0.03
			0.3	54.1	138.8	34.6	112.4	26.7	55.0	139.5	27.1	107.2	30.1	100.0	-2.98	-0.05
			0.1	46.6	139.8	9.8	112.9	26.8	47.0	140.2	7.8	107.5	30.2	100.0	-4.00	-0.03
		0.4	0.2	52.8	139.4	20.3	113.4	26.1	53.4	140.0	16.5	107.7	29.7	100.0	-4.04	-0.03
85%			0.3	58.5	138.0	31.1	111.5	26.6	59.2	138.4	23.5	106.1	30.0	100.0	-3.78	-0.04
			0.1	32.6	137.8	15.5	111.4	26.7	33.0	138.8	13.1	106.5	30.2	100.0	-3.09	-0.02
		0.2	0.2	44.7	138.1	30.2	111.3	26.8	45.6	139.2	24.9	106.8	30.1	100.0	-2.01	-0.04
			0.3	57.7	138.9	47.4	112.2	26.2	59.0	139.7	37.8	107.0	30.0	100.0	-2.52	-0.03
			0.1	40.4	138.0	13.9	111.8	26.3	40.7	138.3	11.8	105.9	30.1	100.0	-4.40	-0.02
	0.6	0.3	0.2	50.5	141.8	29.6	115.5	26.3	51.4	142.7	23.9	110.0	30.1	100.0	-3.05	-0.03
			0.3	61.7	137.5	45.6	111.3	26.0	62.9	138.2	36.2	106.1	29.6	100.0	-2.90	-0.03
			0.1	48.1	134.7	13.3	108.1	26.6	48.4	135.1	11.5	103.1	30.0	100.0	-3.89	-0.02
		0.4	0.2	56.8	139.6	27.5	113.1	26.4	57.7	140.4	22.1	107.9	29.9	100.0	-3.07	-0.03
			0.3	65.7	140.1	42.0	113.6	26.4	66.7	140.6	33.0	108.2	30.1	100.0	-3.26	-0.04
			0.1	30.4	143.1	11.6	116.7	27.1	30.9	142.9	7.1	105.7	31.4	70.5	-8.10	-0.19
		0.2	0.2	37.8	139.0	22.4	112.5	26.5	38.7	137.2	14.1	101.2	31.3	69.9	-7.85	-1.22
			0.3	49.1	138.4	36.0	112.3	26.0	50.0	132.8	20.4	97.3	30.6	71.0	-11.68	-2.50
			0.1	36.5	138.9	10.4	112.4	26.0	36.9	137.3	6.5	101.3	30.9	69.6	-8.90	-1.46
	0.75	0.3	0.2	45.8	140.3	22.8	113.8	26.5	46.4	136.3	13.3	100.3	31.3	72.2	-10.66	-2.25
			0.3	53.6	139.9	33.6	113.8	26.6	54.4	131.4	17.6	96.1	31.0	69.5	-14.25	-3.46
			0.1	45.0	137.7	9.4	111.5	26.2	45.2	135.7	5.5	100.1	31.0	69.4	-9.90	-1.64
		0.4	0.2	52.1	138.9	20.0	112.5	26.4	52.6	133.1	11.1	97.5	30.9	70.5	-12.54	-3.07
80%			0.3	59.3	138.4	32.7	112.2	26.4	59.9	130.5	16.4	95.4	30.8	70.7	-14.17	-4.32
			0.1	32.2	139.1	14.8	112.7	26.7	33.0	139.0	9.5	102.4	30.9	57.3	-6.66	-0.26
		0.2	0.2	45.1	139.2	31.2	112.9	25.7	45.8	135.9	18.8	99.9	30.1	56.5	-10.13	-0.64
			0.3	57.8	138.9	47.0	112.3	26.3	58.8	133.1	25.8	97.6	30.9	57.8	-11.62	-3.72
			0.1	40.4	137.9	14.3	111.5	26.4	41.0	136.6	8.9	100.7	31.1	56.4	-8.42	-0.41
	0.6	0.3	0.2	51.0	139.7	28.8	113.6	26.4	51.9	135.3	16.9	99.5	30.6	57.9	-10.88	-1.14
			0.3	62.4	141.1	45.4	115.1	26.3	63.3	132.1	24.6	96.8	30.6	58.3	-14.70	-3.79
			0.1	48.0	140.0	12.5	113.7	26.6	48.4	136.5	7.4	100.5	31.0	58.2	-10.84	-0.95
		0.4	0.2	56.7	138.1	27.4	112.0	26.6	57.2	132.9	15.7	97.6	31.0	58.3	-12.05	-2.27
			0.3	66.0	140.8	43.8	114.5	26.8	66.7	131.5	22.0	96.2	31.2	56.4	-15.08	-4.35

In this Table we present the findings for simulated runs for different LTV cap values and market density parameters.

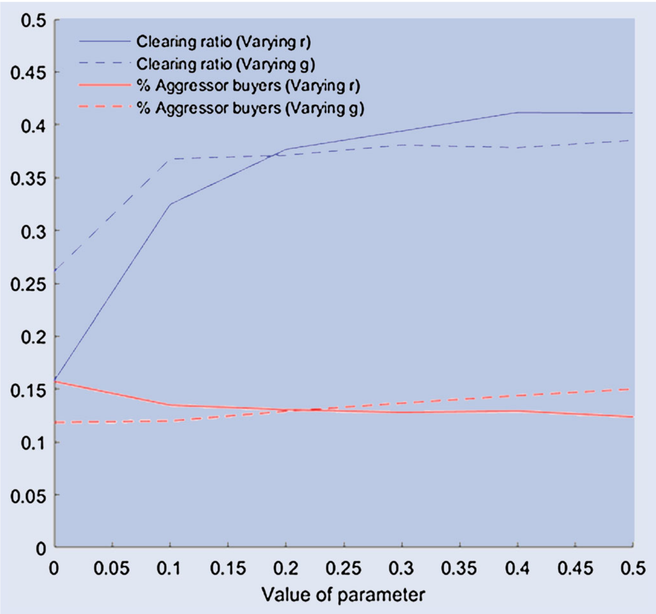


Figure 9. Sensitivity of key auction variables to changes in r and g.

Nevertheless, in table 2 we present two of those metrics: The difference in credit provided by banks (capturing the credit supply impact) and the difference in property prices that were cleared in both cases through the auctioning process†. These two estimates may be used as a proxy to compare the impact of different LTV cap levels on both credit supply and housing prices. It is worth noting that in table 2 differences in credit are much higher than differences in prices. This is because the difference in prices is estimated based on common sold properties (pre- and post-cap application), whereas difference in credit is taken from the whole sample.

The first thing to note in table 2 is that if we increase p_d^S and/or p_d^B, the clearance ratio increases because more houses are sold. It is interesting to note as well that, as expected, the higher the cap, the higher the percentage of buyers increasing down payments in order to buy a property. Conversely, if we increase p_d^B, the percentage of aggressors increases, but with a different intensity depending on the clearance ratio.

Differences in credit and price increases are more negative when there is a lower cap. This is unsurprising, since the lower the cap, the less credit is directed to buyers and, consequently, the less houses are sold. As explained above, the reduction in credit is much higher than the reduction in prices.

Note that although the actual cap level appears to be the dominant factor in determining the impact on the demand, density parameters do have some importance in some cases. Therefore, we tend to believe that calibrating the model using real data would reflect prevailing market dynamics—especially concerning LTV distributions and the dominance of buyers or sellers—which may significantly contribute to the accuracy of the results.

The effect of an increase in r and g before the introduction of the cap is negligible; however, following the cap, the effect on the clearing ratio and the number of aggressor buyers is more visible for low values of the parameters, then remains stable, suggesting that our auction mechanism is robust to both changes, as figure 9 illustrates; r is the markdown on prices the seller is willing to accept with probability p_d^s while g is the maximum distance that, with probability p_d^b, one buyer will deviate below the auction for the most expensive property he can afford. Both parameters are flexibility metrics; it is unsurprising that if they increase, the clearing ratio grows as there is more room for matching of buyers and sellers. The percentage of aggressor buyers, on the other hand, is only a function of the probabilities p_d.

A similar logic applies when looking deeper into the mechanisms behind p_d^s and p_d^b in figure 10: The more likely buyers or sellers are to haggle around the transaction price, the more properties will be sold thus increasing the clearing ratio. Besides, if p_d^s increases a buyer will be more likely to find himself bidding for a property which in principle he could not afford, so the percentage of aggressors should fall because their desired effect is somehow coming from the supply side of the market. Finally, a larger p_d^b implies by definition more aggressor buyers, as seen in the first part of the red series on the left hand side; however, a non-linear effect arises after a threshold is reached, from where the number of aggressors falls, likely when the market is too saturated because of the rest of calibrated values. In any case, the results in table 2 suggest that the auction mechanism is not largely affected by the calibration of these two probabilities if done within reasonable ranges.

3.2. *Survey data for European countries*

In this subsection, we discuss the results based on the estimation of a multivariate distribution of initial liquid wealth, total wealth, LTV ratio and the loan-to-income ratio using a real data set. To this end, we resort to the *Household Finance and Consumption Survey* (HFCS), a compilation of household surveys from European countries unified and collected by the European Central Bank.

Participating institutions, which are national central banks or national statistical institutes, conduct their own wealth surveys‡. The HFCS provides the Eurosystem with harmonized micro-level data on euro area households' finances and consumption. The survey is conducted every two or three years, the most recent one being 2016 (second wave) and our choice for this exercise.

† We have to be careful when assessing the housing price decline figures, since what is presented here is the difference in prices for properties that were sold in both cases, ignoring the other effects of properties that could not be sold due to the LTV cap. Deriving meaningful house price metrics for assessing the impact on house prices of the application of the macroprudential measure may not be a trivial task; however, since all the activity is captured at the agent level, several measures may be assessed.

‡ See https://www.ecb.europa.eu/pub/economic-research/research-networks/html/researcher_hfcn.en.html. A number of studies use survey data for the primary purpose of measuring household vulnerability. See, for example, Gross and Población (2017), May *et al.* (2004), Johansson and Persson (2006), Vatne (2006), Herrala and Kauko (2007), Hollo and Papp (2007), Fuenzalida and Ruiz-Tagle (2009), Sugawara and Zalduendo (2011), Costa and Farinha (2012), Djoudad (2012), IMF (2012), Albacete and Lindner (2013), Albacete *et al.* (2014), Ampudia *et al.* (2016) and ECB (2014).

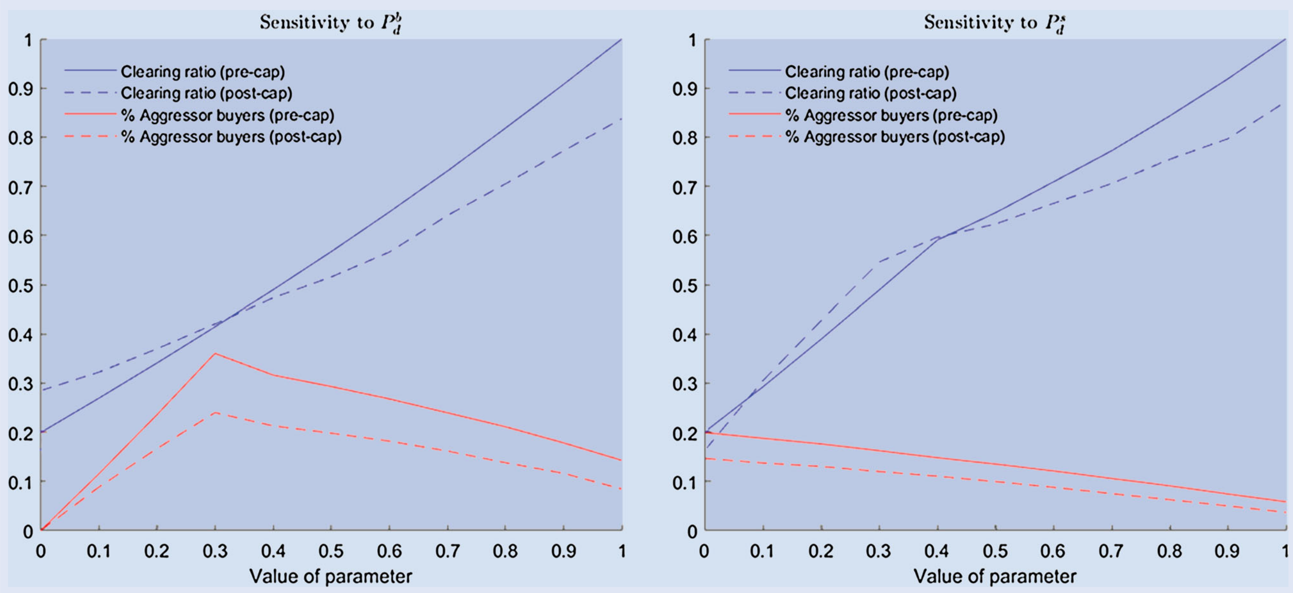


Figure 10. Sensitivity of key auction variables to probabilities p_d^s and p_d^b.

The HFCS is composed of questions that refer to the household as a whole or to each of its members. Basic demographic information is requested in a personal questionnaire for all participating household members above sixteen years old. The survey part, covering household-level questions, encompasses real assets and their financing, liabilities and credit constraints, private businesses and financial assets, intergenerational transfers and gifts and consumption/savings. Questions to individuals cover employment, future pension entitlements and labour-related income†.

However, even though data in the HFCS is harmonized, since macroprudential policies are implemented differently in each country, the empirical distributions might already be constrained by LTV, LTI and DSTI limits that each country has imposed‡. This is a first limitation of our study because the framework would differ when imposing a tighter or looser LTV constraint in a country with existing caps. This issue cannot be solved because we cannot reconstruct the database assuming that there were no measures in place; fortunately, however, the active measures at the time of the survey were very few. We give more details in the country analysis section.

The second limitation of our empirical study comes from the fact that the HFCS is a survey on outstanding rather than new loans. Hence, there may be a bias to cover longer-maturity (and therefore larger) mortgages. The impact of an LTV limit would instead be on new loans and thus would not affect the entire distribution.

We use the well-known non-parametric, copula-based approach for the estimation of multivariate distributions of initial liquid wealth, debt-service-to-income ratios, LTV ratios and loan-to-income (LTI) ratios§. Figure 11 shows the bivariate densities for the LTV ratio combined with wealth and the LTI ratio, respectively.

Our implementation of the non-parametric approach is via an accept-reject algorithm that can be sketched as follows: We start by estimating a four-variate kernel distribution function (using an Epanechnikov kernel) for each combination of variables. The joint probability density function will be bounded by four pairs of minima and maxima. Uniform random numbers are strewn into these bounds, which delineate a four-dimensional polyhedron: Whenever a quartet of uniform random numbers falls under the joint probability density function, the quartet is accepted; otherwise, it is rejected. The resulting random numbers from the accepted draws will replicate the shape of the initial four-variate distribution¶. Note that no distributional assumptions are imposed, neither on the marginal distributions nor on the copula that together constitute the joint distribution of the risk factors we examine.

Based on this multivariate probability distribution function, figure 12 illustrates the distributions of properties actually traded in the auctions before and after the introduction of an LTV cap. We consider an absolute 85% limit.

There are two housing segments that will be most impacted under an absolute LTV limit: In the next-to-cheapest properties, where less wealthy households with greater credit risk can have mortgages with high LTVs, the cap trims what can be regarded as sub-prime credit, although this idea will be discussed in greater detail in the following subsection. In parallel, wealthier agents with high LTVs will have to borrow less than they than intended, yet they have the capacity to shift to cheaper property buckets and purchase a house. In terms of

† Other income sources are covered at the household level.
‡ See ESRB (2016) for some examples.
§ We use *current* income as a proxy for calculating the LTI, as detailed in Appendix 1.

¶ For details about this general technique, which is an alternative to inverse CDF transform-based methods; see, for instance, Harry (2014). The alternative to the so-called smooth bootstrap version we describe here is what one could call 'plain' bootstrap, which would not involve a univariate or multivariate Kernel estimator in the first step but would resample directly from historical data. The reason for considering a smooth bootstrap is to avoid replicating possibly fine though spurious details in the data, which is a concern in short samples in particular.

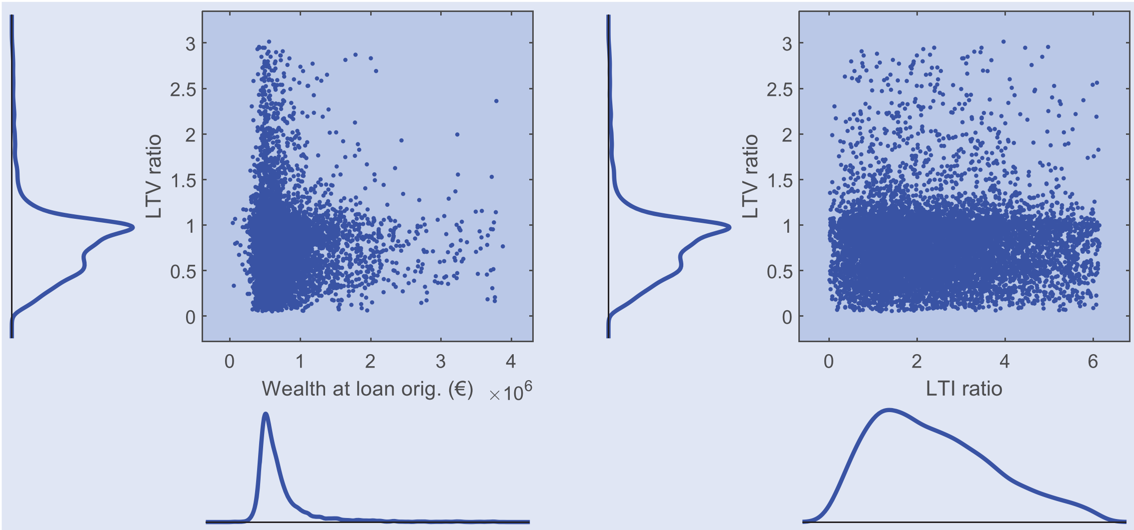
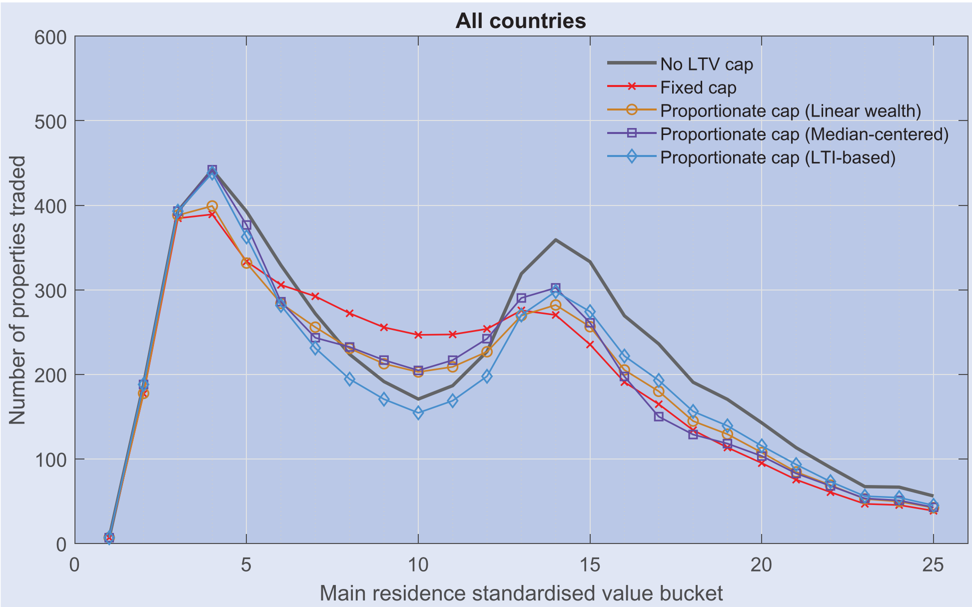


Figure 11. Bivariate probability distributions for aggregate HFCS data.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Fixed	0	-11	-9	-53	-59	-23	20	49	64	76	61	27	-43	-89	-98	-78	-71	-57	-57	-48	-38	-29	-20	-21	-18
Prop-linear	0	-11	-5	-43	-61	-45	-16	7	21	32	22	0	-49	-77	-77	-64	-56	-46	-41	-35	-29	-21	-15	-17	-14
Prop-median	0	0	0	0	-16	-43	-29	9	25	34	30	15	-29	-57	-72	-72	-86	-62	-52	-39	-30	-22	-14	-16	-13
Prop-LTI	0	0	0	-4	-30	-48	-41	-29	-21	-16	-18	-29	-49	-61	-59	-48	-43	-34	-31	-27	-20	-17	-11	-12	-11

Figure 12. Distribution of prices for sold properties pre- and post-LTV cap - HFCS data. This figure illustrates the distributions of properties actually traded in the auctions before and after the application of each of the four LTV caps considered. The table reflects the absolute change in traded properties with respect to the no-cap case.

our results, the latter entails a displacement of the transaction mass to the left of the distribution, which is observed in figure 12. Both of these phenomena will be easier to observe when we discuss the results at a country level, where national heterogeneity on indebtedness habits plays a larger role in amplifying or damping the effects of the cap.

The application of a rigid LTV cap, therefore, may have different impacts across segments of the housing market, which can lead to undesirable consequences. That is why it is reasonable to consider the possibility of a proportionate cap instead, an alternative that allows for more precise implementation of the policy. As stated the previous section, this type of cap requires the definition of a certain pecking order based on which it is applied to borrowers.

In our first alternative, we have assumed that lending institutions show a preference for wealthier buyers. By doing so, banks comply with a simplification of the intuitive creditworthiness principle, that is; potential borrowers with higher total wealth are more likely to be granted a loan with an LTV that exceeds the cap threshold as their probability of default is lower. This assumption relies on a short descriptive analysis using auxiliary variables in the HFCS sample† ; it could,

† In particular, we use variables HC0400(‘*did not apply for credit in the last three years due to perceived credit constraints*’) and HC1310(‘*was denied credit in the last three years*’) and explore their relationship with net wealth (DN3001). For credit-constrained households, the distribution of wealth has considerably lower average.

Table 3. Descriptive statistics of country clusters in the HFCS.

Country	Valid HHs	HH gross income (€)	House value at origination (€)	Mortgage value (€)	LTV (%)	LTI (%)
Austria	372	62971	236329	120519	59	221
Belgium	508	75567	175239	120826	78	198
Cyprus	362	54841	242969	150019	81	326
Germany	827	104051	250628	138327	65	168
Estonia	307	39471	73260	55223	92	176
Spain	1016	57386	172679	129965	91	315
Finland	*0*	*64294*	–	–	–	–
France	2260	72599	225142	150228	77	241
Greece	198	30180	113288	75270	77	323
Hungary	*41*	*10343*	*23130*	*13216*	*72*	*138*
Ireland	1566	87121	257831	193923	87	276
Italy	546	51029	160900	110210	81	284
Luxembourg	507	139390	428148	296021	74	268
Latvia	*33*	*40166*	*108228*	*65846*	*88*	*198*
Malta	*114*	*38014*	*116766*	*87578*	*85*	*263*
Netherlands	589	66032	183362	145363	92	244
Poland	262	22372	67969	42875	76	221
Portugal	1756	34414	127865	98008	83	360
Slovenia	*139*	*36432*	*127901*	*71054*	*63*	*250*
Slovakia	192	20216	56591	36557	83	210
All countries	11595	55344	165696	110580	79	246

HH = Households. Rows in italics represent discarded countries due to an insufficient number of observations.

however, be challenged or sharpened using other empirical evidence.

In the second variant, buyers closer to the median in wealth will have a higher probability of receiving the loan with a higher LTV than the one allowed by the cap. This illustrates a more expansive policy for banks that are trying to distribute the excessive leverage to a larger number of potential borrowers of lower average wealth. Finally, in the third variant we rank borrowers subject to the cap according to their LTI ratio: Those for which the loan is a smaller share of their total income will be more likely to obtain above-cap mortgages.

From figure 11 we observe that in aggregate terms high wealth is related to moderate LTV values (seldom above 100%) whereas mid- and low-level wealth are linked with higher LTVs. From the standpoint of our exercise, buyers with their LTV ratio in the medium range are the most likely to exceed the cap in the wealth-related proportionate case; such effect is likely to be present under a median-centred cap, too, but now buyers to the left of the median (not very wealthy, still with moderately high LTV) might also be allowed to beat the cap.

3.2.1. Country analysis. The aggregate HFCS results can be misleading in the sense that they abstract from country heterogeneity, which has proven to be notable and enriching within our agent-based framework. This subsection aims to shed light on the mechanisms through which the different LTV caps affect countries which have differing mortgage market attributes.

The HFCS comprises twenty countries. However, we do not have the same number of households with all the required information for each country; moreover, in some of them the number of data-sufficient households is too small to carry out a proper analysis so they were excluded†. Table 3 shows descriptive statistics for the main variables.

For the remaining countries, we compared the period of data collection in national surveys with applications of LTV caps by the relevant authorities. Cyprus, Latvia and Poland introduced limits as the survey was taking place; only the Netherlands, for which data was gathered in January and February 2014, had a loan-to-value cap of 100% since 2012‡.

Before showing what our agent-based model has to say on the application of caps across countries, a closer look at the initial loan-to-value ratio distributions for each geography, shown in figure 13, reveals notable differences in a number of dimensions; in terms of the third moments, densities are clearly left-skewed for Austria, Cyprus, Germany, and right-skewed for Spain, Ireland and Portugal; regarding kurtosis there are some cases of platykurtic distributions, most noticeably Poland and Slovakia, in contrast with Spain and Portugal which are more leptokurtic. These features, along with those of wealth distributions§, will shape and cluster the results considerably.

We now discuss our results focusing on the two most relevant variables with policy implications, property price growth and credit growth; we define the latter as the variation in the number of properties sold, given that our model implicitly

† In the case of Finland, no households at all with all the required information are available.

‡ More precisely, the Netherlands introduced a cap of 106% in 2012 which progressively lowered 100% in 2018. Among the 589 valid households in the survey, only 4% contracted loans between 2012 and 2014.

§ The differing supports and the similarity of shapes of wealth distributions render it difficult to extract information from plotting them in a way akin to figure 13. The bivariate country distributions of wealth with LTV and LTI ratios are included in Appendix A2.3.

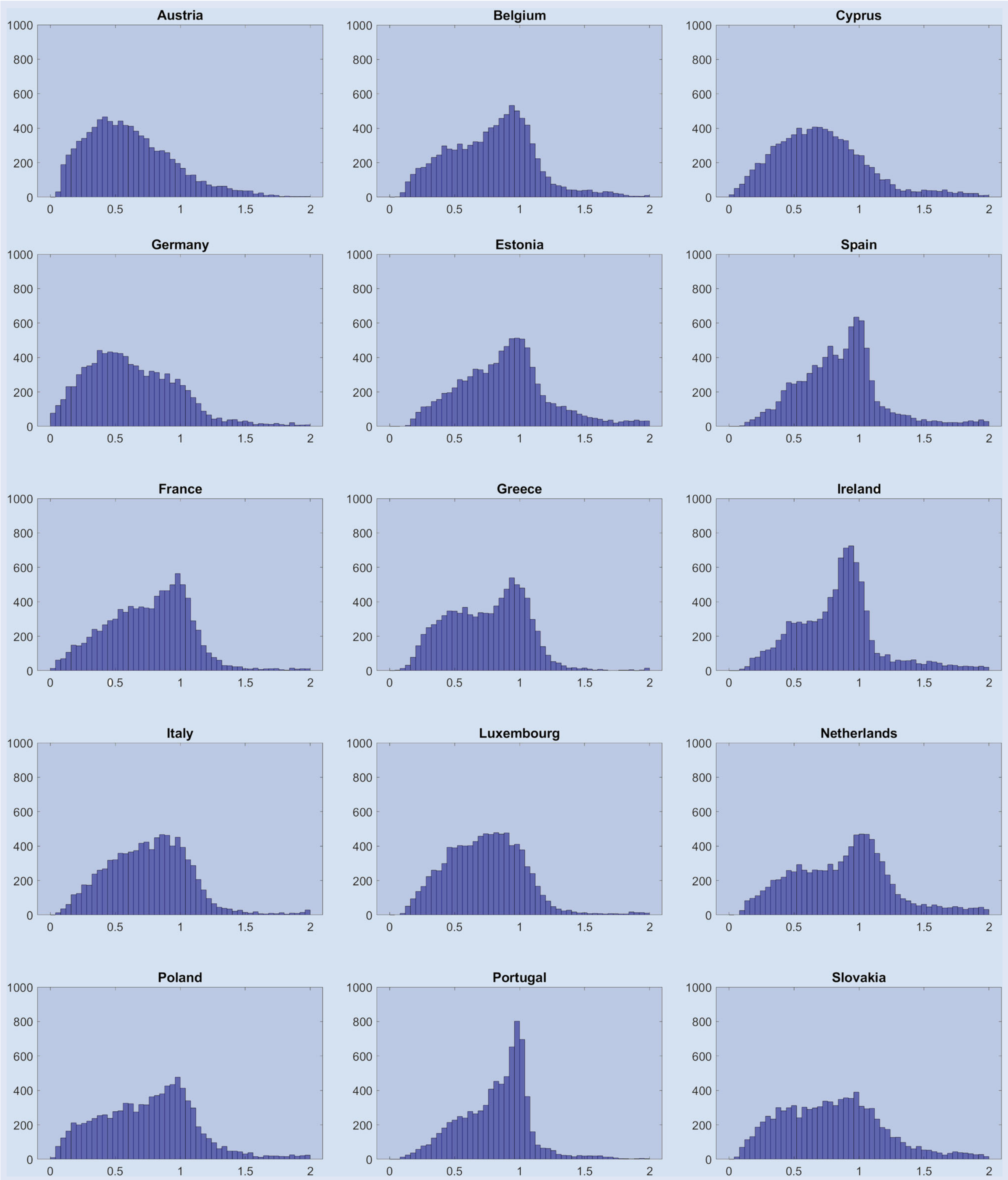


Figure 13. Generated loan-to-value ratio distributions by country.

assumes that every agent who buys a property has contracted a mortgage loan.

Starting with the behaviour of house prices, table 4 shows the variation by country produced by our exercise with HFCS data. Under the fixed cap, prices decrease across all countries; given that this type of LTV limit affects all households beyond the threshold, regardless of their wealth or perceived creditworthiness proxied by any variable other than the LTV ratio, the mortgage market shrinks across all property price buckets and the supply effect prevails. For the proportionate caps, prices might behave differently owing to the differences in initial LTV distributions. Both the wealth- and LTI-based implementations target less wealthy buyers: Once they are ruled out of the market, the effect on prices will be less negative than in the fixed cap case, with the possibility of a positive reaction, as is seen for Austria and Germany. For these countries, the bivariate distributions of LTV with wealth and LTI ratios would show considerably less low-income households

Table 4. Estimates of property price growth (%) with HFCS data.

Country	Fixed cap	Proportionate cap		
		Wealth	Median	LTI
Austria	– 5.74	0.30	2.31	4.09
Belgium	– 8.92	0.25	– 1.04	2.57
Cyprus	– 9.76	– 3.28	– 0.08	0.60
Germany	– 5.37	1.14	1.91	4.45
Estonia	– 12.23	– 3.70	– 1.79	0.19
Spain	– 9.11	– 5.15	– 2.86	0.73
France	– 10.13	– 5.24	– 1.32	– 0.51
Greece	– 10.23	– 1.41	– 1.58	1.02
Ireland	– 10.64	– 3.75	– 2.36	– 0.03
Italy	– 9.94	– 3.06	– 1.01	– 0.28
Luxembourg	– 9.31	– 3.86	– 0.99	– 0.06
Netherlands	– 11.17	– 1.05	– 1.62	1.71
Poland	– 10.96	– 2.93	– 0.82	1.03
Portugal	– 9.81	– 7.20	– 3.79	0.62
Slovakia	– 11.16	– 2.65	– 0.29	0.56
All countries	– 9.33	– 3.00	– 1.04	2.02

Table 5. Estimates of mortgage credit growth (%) with HFCS data.

Country	Fixed cap	Proportionate cap		
		Wealth	Median	LTI
Austria	– 10.55	– 11.61	– 8.43	– 10.15
Belgium	– 8.69	– 12.14	– 9.64	– 11.63
Cyprus	– 12.12	– 14.48	– 11.43	– 13.86
Germany	– 8.14	– 9.28	– 7.54	– 9.30
Estonia	– 10.22	– 13.54	– 12.79	– 14.75
Spain	– 7.79	– 11.00	– 11.19	– 13.23
France	– 11.29	– 12.88	– 11.08	– 14.17
Greece	– 10.44	– 14.58	– 10.82	– 13.89
Ireland	– 10.51	– 13.58	– 11.14	– 14.14
Italy	– 11.31	– 14.06	– 12.28	– 14.89
Luxembourg	– 12.22	– 14.37	– 12.18	– 14.40
Netherlands	– 3.83	– 14.80	– 10.26	– 13.12
Poland	– 10.56	– 13.81	– 11.34	– 13.34
Portugal	– 5.84	– 11.35	– 9.88	– 12.54
Slovakia	– 10.83	– 14.31	– 11.98	– 14.46
All countries	– 9.67	– 11.75	– 9.91	– 12.14

in relation to wealthy ones above the cap; Appendix A2.3 includes the relevant two-way density plots.

One noticeable feature of the LTI-linked version of the cap is that it induces property price increases in the majority of countries. This phenomenon is linked to the effects on overall credit growth, which are subsequently analyzed; anticipating the discussion, the LTI-based cap decreases the number of cheap properties traded (buckets 1–5) comparatively more than expensive properties (buckets 15 +). Moreover, while the median-centred cap can increase the total number of properties sold in some middle-tier buckets, the LTI-based cap decreases the number of traded properties in all cases. Less houses sold at the aggregate level combined with particularly less houses in the cheapest segments of the market will entail an increase in property prices†. More generally, the cap not only reduces credit but also induces buyers to move across value buckets; normally they will go for a cheaper property, leading to a decrease in average house prices, but it does not always have to be the case.

Turning to the effects on mortgage credit, which are presented in table 5, our estimates show that, as a ballpark estimate, our model with the current calibration generates decreases in the vicinity of -10% for the majority of countries in all versions of the cap; the precise magnitude will depend on the distribution of households for the LTV ratio, wealth and the LTI.

One remark is in order: Recall that, with the mechanism underlying our agent-based model, an LTV cap does *not* imply that households above it will be granted zero credit: Such an assumption would generate unreal, dramatically large contractions in mortgage credit; instead, these households are constrained to borrow only up to the point allowed by the cap.

This rationale justifies that the strength the effect of a fixed cap, which would be the largest if all credit above it were to be discarded, varies upon the country considered. From the standpoint of the lending institution, proportionate caps entail *a priori* that a residual share of households, the size of which depends on the type of cap, participate in the auction with an LTV above the limit; it is the auction itself and not the regulatory measure what ultimately determines the *a posteriori* effect on credit.

The previous two tables capture the considerable cross-country heterogeneity of the effects of all four types of caps, yet they do not display how the aggregate impacts are distributed across property buckets in each country. This dimension, however, is fundamental to draw a stylized picture of the mortgage credit markets in European countries, consistently with the phenomena observed in the probability distributions of households for wealth or LTVs.

One possibility to gain insights about the within-country transmission of an LTV limit is to look at the absolute variation for all property buckets in each country under the different LTV caps, as is done in figure 14. Among the 15 countries in the sample, we restrict our attention to three of them (Ireland, Spain and Austria) for the patterns they exhibit are very illustrative. Other countries behave similarly to the latter but it can be adventurous (and probably inaccurate) to create clusters of countries based only on visual information, lacking a detailed exploration of the socio-economic similarities that may justify the groupings. The full results, nonetheless, can be found in Appendix A2.1.

Ireland is our first showcase. In our estimates, the absolute cap seems to reduce credit more sharply for wealthy households than for low-income ones; the rationale behind it is the following: While there are households with very high LTVs (say above 125%) in the low-price segment there are also many wealthy buyers, comparatively more, who contract mortgages with LTVs above the cap. It is unsurprising that, in a country where macroprudential policy is well-established, wealthy individuals dare to borrow at high LTVs because their repayment culture, along with the regulatory pressure, makes them confident that they will be able to fulfil their obligations. Another noticeable feature related to the former is the more uniform effect of the LTI-based proportionate cap; given that the LTI distribution across wealth and LTV levels is relatively

† This rationale is easily seen in figure 14 by comparing the behaviour of the purple line (median-centred wealth cap) and the light blue line (LTI-based cap).

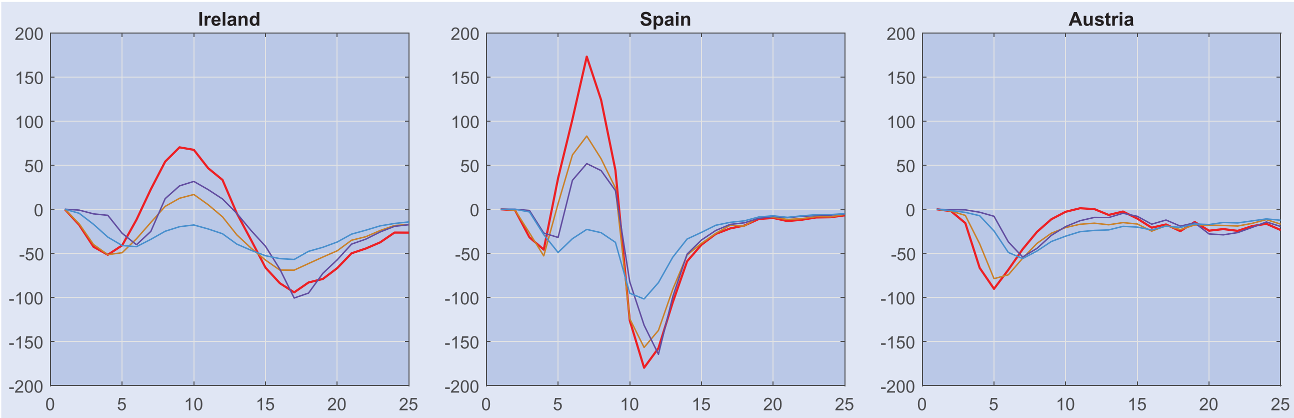


Figure 14. Absolute variation in properties traded by bucket for selected HFCS countries. Fixed cap (red), Wealth-linear proportionate (brown), Median-centred proportionate (purple), LTI-based proportionate (light blue). Results are presented in differences with respect to the no cap case.

uniform, the likelihood of beating the cap will be also more uniformly distributed, an effect visible also in the price bucket dimension.

We now turn to the effects of LTV caps in Spain. This case is similar to Ireland's in that low-income households suffer comparatively less from the measure than those above the median; however, the latter are located in cheaper property buckets and the cap seems to be almost neutral for those above the 15th segment. We name this the *wannabe effect*: Very rich households bidding for a property will do so with a low LTV, almost surely below the cap; instead, a large share of medium-high wealth households will try to purchase the property they want at the highest LTV possible, *as if* they were much wealthier. Such a behaviour was extensively observed in the years preceding the 2008 financial crisis, where banks were more prone to grant high-LTV loans to customers with relatively high yet volatile, intermittent income.

Our last object of discussion is Austria, a somehow paradoxical case. By looking at figure 14, it seems that the LTV cap in any of its forms is effective in tackling high-LTV credit granted to low-income households; in a country with low creditworthiness standards, this would be the optimal response to the policy, as the least favoured households are patronized by macroprudential regulation not to engage into transactions with high odds of becoming sub-prime credit† while the rest of agents remain largely unaffected by the measure. In contrast, Austria's retail banking sector has been traditionally very stable owing to the financial discipline of households; non-performing loan rates and defaulted credit risk exposures of assets secured on real estate are very low. Hence, like in the Irish case, low-income households will borrow as much as they need fully aware of the commitment to repay: The link between creditworthiness and wealth is more diffuse. Besides, in some countries like Austria the LTV ratio is usually computed with respect to the 'mortgage lending value' of the property, which represents its long-term value and is therefore less sensitive to house price fluctuations; this might mitigate the larger effects seen in other countries.

† Here again, recall that for simplification we assume that wealth explains a large share of how credit scores are allocated.

3.3. Empirical validation

The results we have presented so far concern quantitative artefacts of our agent-based model. Well aware of the variety of approaches that coexist within the literature of macroprudential measures, the following discussion aims to compare our estimates in the previous section with those found in those studies similar to ours.

As we went through the available literature to look for other estimates to benchmark our model against, we chose to mention only the studies that treat at least one of the countries in our sample, whether in an individual or aggregate fashion. Within this subset, the prevailing methodology uses panel data regression models over a set of countries.

The seminal work by Jacome and Mitra (2015) runs pooled regressions on six economies (among which Poland) to find that a 10% cut in the LTV limit has a maximum cumulative impact on mortgage credit of -0.7%. Later, Cerutti *et al.* (2017) widen the scope of their exercise to 119 countries (31 advanced, 64 emerging, 24 developing) over the time span 2000–2013; following the introduction of an LTV limit, the aggregate impact on credit growth is -14pp and real estate prices fall by -1.5pp. Finally, Nymoen *et al.* (2018) use a sample of 10 advanced open economies, among which Ireland and the Netherlands; they find that the introduction of an LTV limit impacts credit growth in -0.5 ± 3.2 percentage points and house prices in -1 ± 3.2 pp.

There are, however, other quantitative approaches in the literature. For instance, Crowe *et al.* (2011) use DSGE modelling to estimate that a 10% tightening in the LTV ratio increases nominal house prices by 13 percent; a permanent reduction in the LTV also decreases credit by -0.3pp on impact. For the Portuguese economy, Basto *et al.* (2019) build a DSGE model where a permanent instantaneous shock to the LTV ratio decreases loans by -10% on impact and prices fall by roughly 4%; they also conduct an exercise for the euro area as a whole where credit contracts by -6% and prices by -3%. Similarly, De Jong and De Veirman (2019) study the effect of a LTV cap in the Netherlands by looking at the cross-sectional LTV distributions in a VECM framework; their findings suggest that the average LTV ratio decreases by 2 percentage points, while the long-run effect on prices ranges from -5% to -8%. Finally, a recent study by Morgan *et al.* (2019) relies on panel data methods, but assembling a bank-level dataset for 46 countries, finding that the imposition of an LTV cap reduces credit by -5.9% after one year.

In general, most of the papers with an intent similar to ours yield effects on credit and property prices which are reasonably akin in magnitude to what our agent-based model produces, in spite of following completely different approaches.

4. Conclusions

In this paper, we propose a simple model relying upon agent-based techniques to assess the impact of a cap in the loan-to-value ratio. Results based on simulated data are presented first, assuming that initial liquid wealth, total wealth, LTV at origination and property value parameters follow three types of probability distributions in which initial liquid wealth and LTV at origination can be positively or negatively correlated. The application of an LTV cap naturally shifts the distribution of buyers towards lower price ranges, since the cap constraint becomes binding for a significant proportion of households under the assumption that there is no change in their household's liquid assets and their ability to come up with the required down payment. The inverse is true for higher-priced properties, where demand is relatively weak due to the cap.

After this simulation exercise, the relevant probability distributions are calibrated on actual European data. In that context, the second wave of the *Household Finance and Consumption Survey* (HFCS) is used. We also deploy a copula-based approach for the estimation of multivariate distributions of initial liquid wealth, debt-service-to-income ratios, LTV and LTI ratios.

When LTV cap impacts are calculated country by country, considerable heterogeneity arises owing to the peculiarities of the distributions for wealth and LTV ratios. The effects of the fixed and proportionate variants of the cap affect different property price segments in different magnitudes and shapes; nevertheless, we obtain estimates for property price growth and credit growth which are in line with other studies in the literature.

As stated above, based on our results we think that the approach is a useful and complementary alternative to the existing analytical framework for assessing the impact of macroprudential borrower-based measures such as LTV caps. The major benefits are the very few assumptions our method must make on the functional/distributional forms of observed credit lending parameters and its ability to incorporate, even in a probably unsophisticated fashion, features related to the behavioural response of borrowers to such measures. Moreover, due to the simplicity of the model, many simple extensions can be added. For example, sharper sequential mechanisms for property auctions or more than one time step. The vast amount of empirical data available could also allow for more precise country-level calibration.

Besides clear macroprudential implications arising, our findings stress the need for careful implementation of policies, regardless of their simplicity, the effects of which can vary considerably across agents as a function of their endowments (say wealth), appetite for credit (say LTV) or flexibility of preferences (say willingness to accept purchasing lower-quality housing).

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ORCID

Alejandro Buesa http://orcid.org/0000-0002-2975-1858
Javier Población http://orcid.org/0000-0001-6620-5533

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Appendices

A. Appendix 1. Details on the HFCS data

A.1. Data cleaning and preparation

In a first step (say 'quality assurance'), we remove from the sample every observation for which any of the following is true:

- DL2100i (Has mortgage payments) is not 1.
- DA1110i (Has main residence) is not 1.
- fHB0800 (Flag for property value at acquisition) is 'not imputed', 'originally not collected' or 'originally no answer'.
- fHB1401 (Flag for initial amount borrowed) is 'not imputed', 'originally not collected' or 'originally no answer'.
- DN3001 (Net wealth) is blank.
- HB0800 (Property value at acquisition) is blank.
- DL2110 (Mortgage payments for main residence, flow) is blank.
- DA1110 (Value of main residence) is blank.

Once the data is free from blanks and missing values, we define the initial LTV ratio as the quotient between variables HB1401 (Main residence mortgage: Initial amount borrowed) and HB0800 (Property value at the time of acquisition); The LTI ratio is proxied using current income as the quotient between HB1401 and DI2000 (Total household gross income). Finally, the debt-service-to-income ratio is defined as DL2110 (flow of mortgage payments for main residence) divided by one twelfth of DI2000 (because the latter is annual and the former is monthly). As a next step, we filter the observations that:

- Have an LTV ratio over 300%.
- Have a debt service-to-income ratio above 50% or below 0%.

After the data cleaning process, we are left with 11,595 valid observations out of 84,500.

A.2. Calibration of q_d^B

We have tentatively calibrated this parameter using aggregate information from the HFCS. q_d^B represents the probability of a buyer increasing his down payment; we deem reasonable to assume that this will only happen if its financial situation is sufficiently stable or, moreover, likely to improve. For this purpose, we use four indicator variables:

- HNB1700 ('Household makes extra mortgage payments over contractual amount').
- HNK0400 ('Household expects the overall economic situation to improve).
- HNI0700 ('Household expects to have more savings next year').
- (**1**-PNE2800x) ('Household expects the work situation *not* to worsen in the near future').

We calculate the probabilities of positive responses conditional on data availability for all 4 variables, then set q_d^B equal to their average. We obtain a value of 0.3024, which is what we use in the paper.

Appendix 2. Detailed country results

A.3. Absolute variation in properties traded

The following tables show the absolute change in traded properties for all three cap cases by standardized residence value bucket. Within each table, the red-white-green gradient represents negative-to-positive effects.

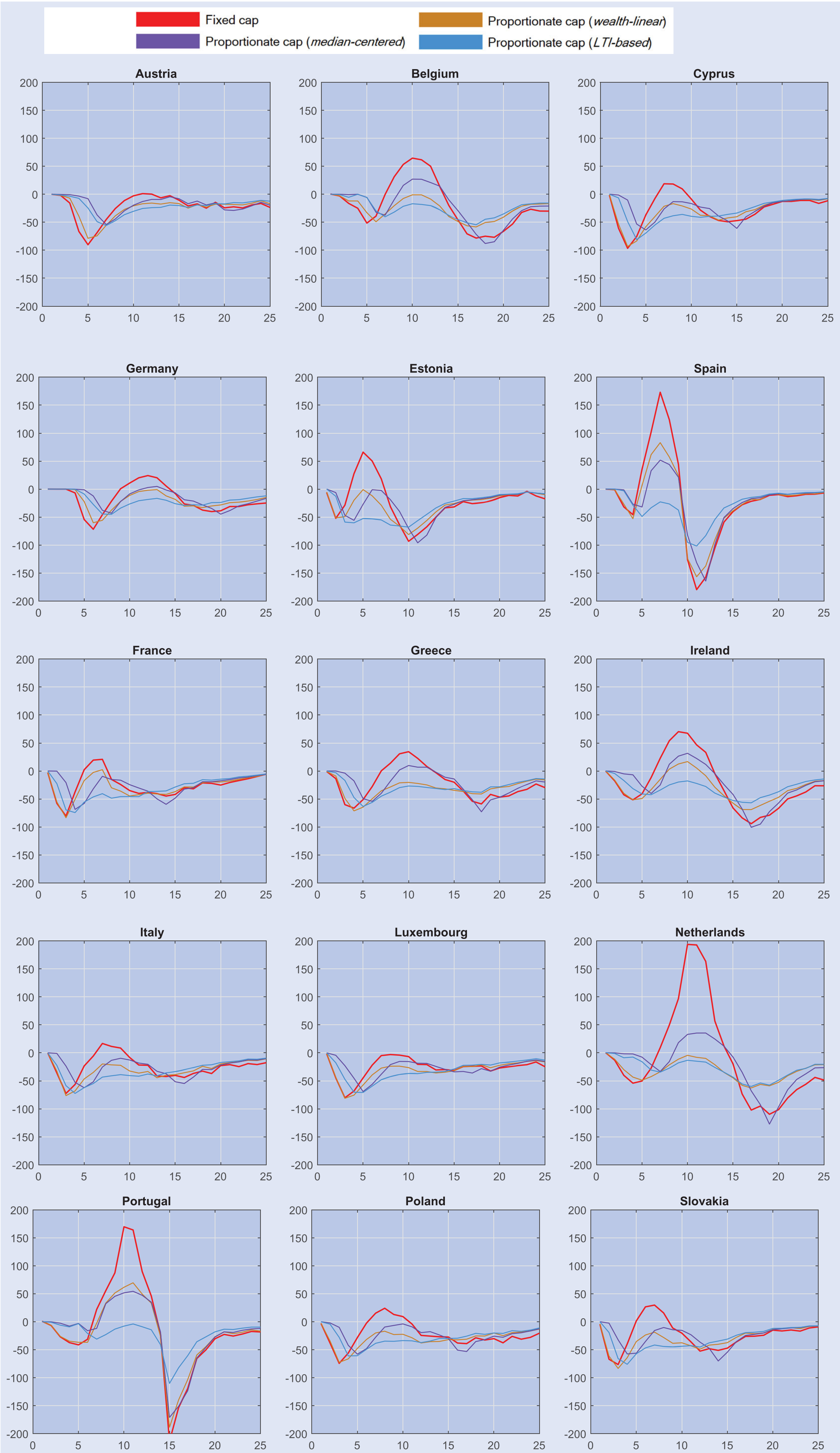
Absolute	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Austria	0	-2	-16	-66	-90	-69	-45	-26	-11	-3	1	0	-6	-3	-11	-21	-17	-25	-14	-24	-22	-24	-19	-16	-24
Belgium	0	-3	-16	-25	-52	-39	0	31	53	65	62	50	14	-20	-46	-71	-78	-75	-77	-66	-53	-32	-27	-30	-30
Cyprus	-2	-61	-97	-75	-37	-8	19	18	10	-9	-28	-40	-47	-49	-47	-45	-36	-23	-18	-13	-13	-11	-11	-16	-12
Germany	0	0	0	-7	-54	-72	-46	-22	1	11	20	24	20	6	-8	-27	-29	-38	-40	-39	-31	-31	-28	-26	-25
Estonia	-6	-52	-29	28	66	50	18	-31	-64	-93	-81	-67	-50	-33	-32	-22	-26	-24	-21	-15	-11	-12	-4	-12	-17
Spain	0	-1	-32	-46	35	102	173	124	44	-126	-180	-157	-106	-59	-40	-28	-22	-18	-11	-10	-13	-12	-9	-9	-7
France	-3	-58	-81	-37	2	19	21	-15	-24	-35	-40	-38	-40	-45	-42	-30	-32	-21	-22	-25	-21	-17	-14	-10	-6
Greece	-1	-14	-60	-66	-51	-28	0	14	31	34	23	8	-3	-15	-20	-36	-54	-59	-42	-47	-45	-37	-33	-23	-30
Ireland	0	-18	-42	-52	-41	-12	23	54	70	67	47	33	-5	-35	-66	-84	-94	-83	-79	-67	-50	-44	-37	-26	-26
Italy	0	-36	-73	-56	-23	-6	17	12	9	-8	-22	-22	-41	-42	-40	-44	-37	-33	-37	-23	-21	-25	-19	-21	-18
Luxembourg	-2	-45	-80	-68	-45	-22	-5	-3	-4	-7	-21	-21	-31	-30	-32	-25	-24	-23	-33	-27	-25	-23	-21	-16	-25
Netherlands	0	-13	-40	-54	-50	-27	9	50	97	194	193	163	57	12	-20	-74	-102	-95	-110	-102	-81	-66	-56	-44	-49
Poland	-3	-38	-74	-56	-28	-2	15	24	13	9	-4	-24	-26	-27	-27	-38	-39	-29	-33	-30	-38	-26	-31	-28	-20
Portugal	1	-7	-27	-37	-41	-31	22	56	87	170	164	90	46	-21	-214	-154	-119	-66	-50	-30	-23	-26	-22	-17	-18
Slovakia	-4	-67	-76	-40	2	27	30	16	-11	-20	-36	-53	-48	-51	-47	-36	-26	-26	-24	-15	-16	-15	-17	-11	-9

Proportional, linear on wealth	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Austria	0	-2	-7	-39	-79	-74	-55	-39	-27	-21	-17	-16	-18	-15	-17	-25	-19	-23	-18	-18	-18	-19	-16	-12	-17
Belgium	0	-3	-12	-12	-33	-49	-35	-20	-8	-1	-1	-9	-21	-40	-49	-56	-58	-51	-49	-41	-30	-21	-18	-17	-17
Cyprus	-1	-53	-93	-83	-58	-40	-22	-17	-21	-26	-38	-38	-46	-42	-40	-31	-27	-19	-15	-13	-11	-9	-9	-11	-8
Germany	0	0	0	-1	-22	-60	-56	-38	-22	-11	-4	-2	-1	-12	-18	-31	-30	-33	-30	-28	-24	-23	-21	-19	-15
Estonia	-5	-51	-49	-20	-1	-12	-29	-54	-66	-81	-70	-56	-41	-29	-26	-21	-20	-19	-16	-12	-10	-10	-5	-7	-10
Spain	0	-1	-27	-53	6	62	83	57	24	-124	-157	-137	-91	-52	-39	-27	-18	-19	-9	-9	-12	-11	-8	-8	-6
France	-3	-55	-84	-51	-17	-3	2	-30	-36	-45	-42	-40	-41	-42	-37	-28	-29	-21	-19	-20	-18	-15	-12	-10	-6
Greece	-1	-9	-49	-71	-65	-50	-35	-29	-21	-20	-22	-25	-30	-32	-35	-37	-41	-41	-32	-29	-28	-23	-18	-15	-16
Ireland	0	-16	-40	-51	-49	-33	-15	3	13	17	5	-9	-29	-44	-58	-69	-69	-62	-54	-47	-35	-31	-24	-18	-17
Italy	0	-33	-76	-68	-47	-35	-20	-21	-22	-32	-36	-33	-45	-40	-39	-36	-32	-24	-28	-20	-18	-16	-13	-14	-11
Luxembourg	-1	-44	-81	-76	-57	-39	-27	-24	-24	-26	-33	-33	-36	-35	-32	-24	-25	-21	-27	-22	-20	-18	-15	-14	-16
Netherlands	0	-11	-30	-43	-49	-43	-34	-21	-11	-4	-8	-10	-21	-35	-45	-58	-63	-56	-59	-53	-41	-33	-27	-21	-21
Poland	-3	-35	-73	-66	-48	-32	-20	-17	-23	-22	-29	-38	-36	-35	-32	-32	-31	-25	-26	-20	-25	-19	-18	-16	-13
Portugal	1	-7	-26	-35	-37	-37	-3	33	51	62	70	49	33	-25	-188	-140	-103	-59	-44	-27	-18	-21	-19	-15	-17
Slovakia	-4	-61	-83	-64	-35	-24	-19	-28	-39	-38	-43	-49	-42	-40	-37	-28	-20	-21	-20	-14	-12	-11	-12	-8	-8

Proportional, median-centered	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Austria	0	0	-1	-3	-8	-37	-54	-44	-30	-20	-13	-9	-9	-4	-8	-17	-12	-19	-15	-28	-29	-26	-21	-14	-19
Belgium	0	0	-1	0	-6	-32	-37	-10	16	27	27	21	15	-10	-29	-50	-72	-88	-85	-64	-44	-29	-22	-21	-21
Cyprus	0	-1	-10	-53	-64	-50	-26	-13	-13	-17	-23	-26	-39	-48	-61	-40	-31	-21	-15	-13	-11	-9	-9	-10	-8
Germany	0	0	0	0	-1	-12	-38	-43	-22	-9	-1	3	5	-2	-7	-19	-21	-28	-35	-45	-38	-30	-26	-21	-17
Estonia	0	-6	-47	-56	-27	-1	-2	-19	-40	-70	-96	-82	-51	-33	-27	-21	-19	-17	-15	-11	-9	-9	-5	-7	-9
Spain	0	0	-1	-27	-32	33	52	44	21	-82	-131	-164	-99	-51	-35	-24	-17	-15	-10	-8	-10	-8	-7	-7	-5
France	0	0	-21	-69	-58	-32	-9	-15	-16	-24	-30	-36	-50	-60	-48	-32	-30	-19	-19	-17	-15	-12	-11	-8	-6
Greece	0	0	-4	-18	-49	-54	-40	-18	2	10	7	7	-2	-11	-14	-32	-51	-73	-52	-47	-39	-31	-24	-18	-20
Ireland	0	-1	-5	-7	-27	-40	-25	12	27	32	22	12	-5	-24	-42	-68	-101	-95	-73	-57	-40	-34	-26	-19	-17
Italy	0	-1	-24	-53	-62	-52	-25	-13	-10	-13	-18	-20	-33	-37	-52	-55	-43	-30	-30	-22	-18	-16	-12	-13	-10
Luxembourg	0	-4	-23	-45	-69	-56	-38	-21	-15	-16	-19	-19	-24	-30	-34	-33	-36	-28	-33	-25	-22	-19	-15	-13	-15
Netherlands	0	0	-2	-2	-8	-21	-33	-16	18	33	35	35	25	12	-8	-35	-68	-93	-127	-97	-66	-47	-37	-27	-26
Poland	0	-2	-10	-42	-58	-48	-28	-9	-7	-4	-9	-19	-18	-24	-30	-51	-53	-35	-32	-26	-28	-21	-20	-16	-13
Portugal	0	0	-3	-8	-3	-16	-12	32	45	52	54	47	35	-18	-171	-151	-123	-65	-46	-27	-18	-19	-15	-13	-12
Slovakia	0	-2	-32	-58	-56	-35	-16	-10	-14	-15	-23	-36	-47	-70	-54	-35	-24	-22	-20	-14	-13	-11	-11	-8	-8

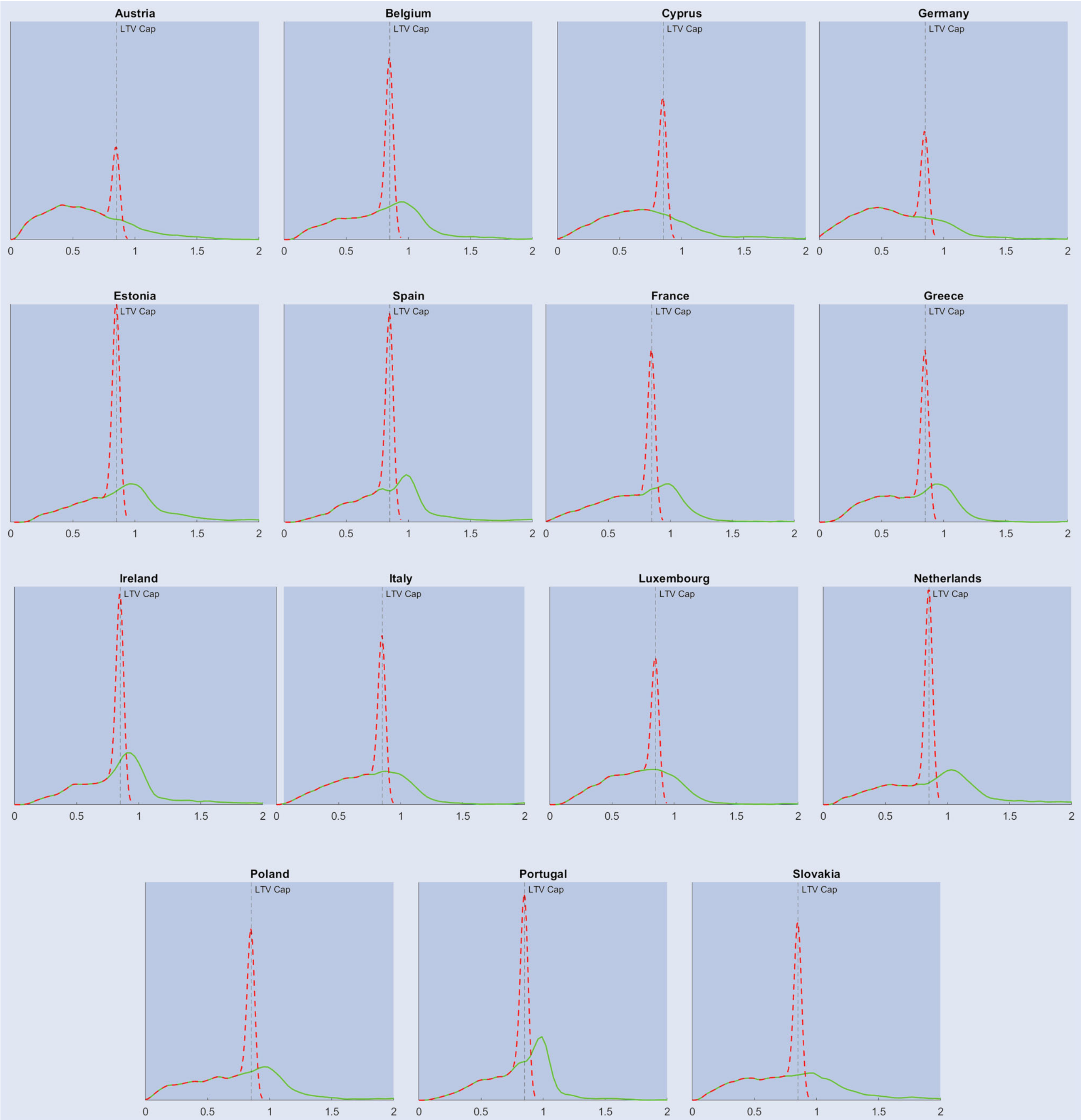
Proportional,LTI	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Austria	0	-1	-4	-7	-25	-49	-56	-47	-37	-30	-25	-24	-23	-19	-20	-23	-19	-20	-17	-17	-15	-15	-13	-11	-12
Belgium	0	-1	-5	0	-6	-30	-40	-32	-22	-17	-18	-20	-28	-38	-45	-51	-55	-45	-42	-35	-27	-19	-17	-16	-16
Cyprus	0	-6	-49	-81	-69	-55	-43	-38	-36	-39	-41	-40	-39	-36	-34	-28	-22	-16	-14	-11	-10	-8	-8	-9	-7
Germany	0	0	0	0	-9	-27	-44	-45	-34	-27	-21	-18	-17	-20	-26	-29	-28	-29	-24	-24	-20	-19	-16	-14	-12
Estonia	0	-13	-59	-60	-53	-53	-55	-64	-66	-68	-56	-45	-34	-26	-21	-17	-17	-15	-13	-10	-9	-8	-5	-7	-8
Spain	0	0	-3	-29	-49	-33	-23	-27	-37	-95	-102	-83	-54	-34	-26	-18	-15	-13	-9	-7	-9	-7	-6	-6	-5
France	0	-23	-70	-74	-56	-46	-41	-49	-46	-46	-46	-37	-36	-36	-29	-23	-22	-16	-16	-15	-14	-11	-9	-7	-5
Greece	0	-3	-17	-47	-63	-56	-45	-38	-30	-27	-28	-29	-31	-33	-32	-35	-37	-38	-28	-28	-24	-20	-17	-14	-14
Ireland	0	-4	-17	-32	-41	-42	-34	-25	-20	-18	-22	-28	-39	-47	-53	-56	-57	-48	-43	-37	-28	-24	-19	-16	-14
Italy	0	-22	-59	-73	-62	-55	-43	-41	-39	-41	-42	-38	-41	-36	-34	-30	-26	-22	-21	-17	-16	-14	-11	-11	-9
Luxembourg	0	-18	-47	-70	-71	-59	-48	-43	-39	-37	-37	-35	-34	-33	-29	-22	-22	-21	-22	-18	-17	-15	-13	-10	-13
Netherlands	0	-1	-9	-8	-16	-31	-34	-27	-18	-13	-15	-17	-26	-34	-43	-56	-60	-54	-58	-49	-40	-31	-28	-20	-20
Poland	0	-4	-28	-61	-61	-49	-39	-35	-35	-34	-34	-37	-34	-30	-30	-29	-26	-21	-23	-20	-21	-16	-17	-15	-11
Portugal	0	-1	-6	-9	-3	-21	-31	-23	-13	-8	-4	-9	-14	-41	-110	-82	-61	-36	-27	-18	-13	-14	-11	-10	-10
Slovakia	0	-19	-66	-76	-57	-47	-42	-44	-45	-44	-43	-45	-38	-35	-31	-24	-19	-19	-17	-12	-12	-10	-10	-7	-7

We also present the information in the table above by country, as in figure 14.

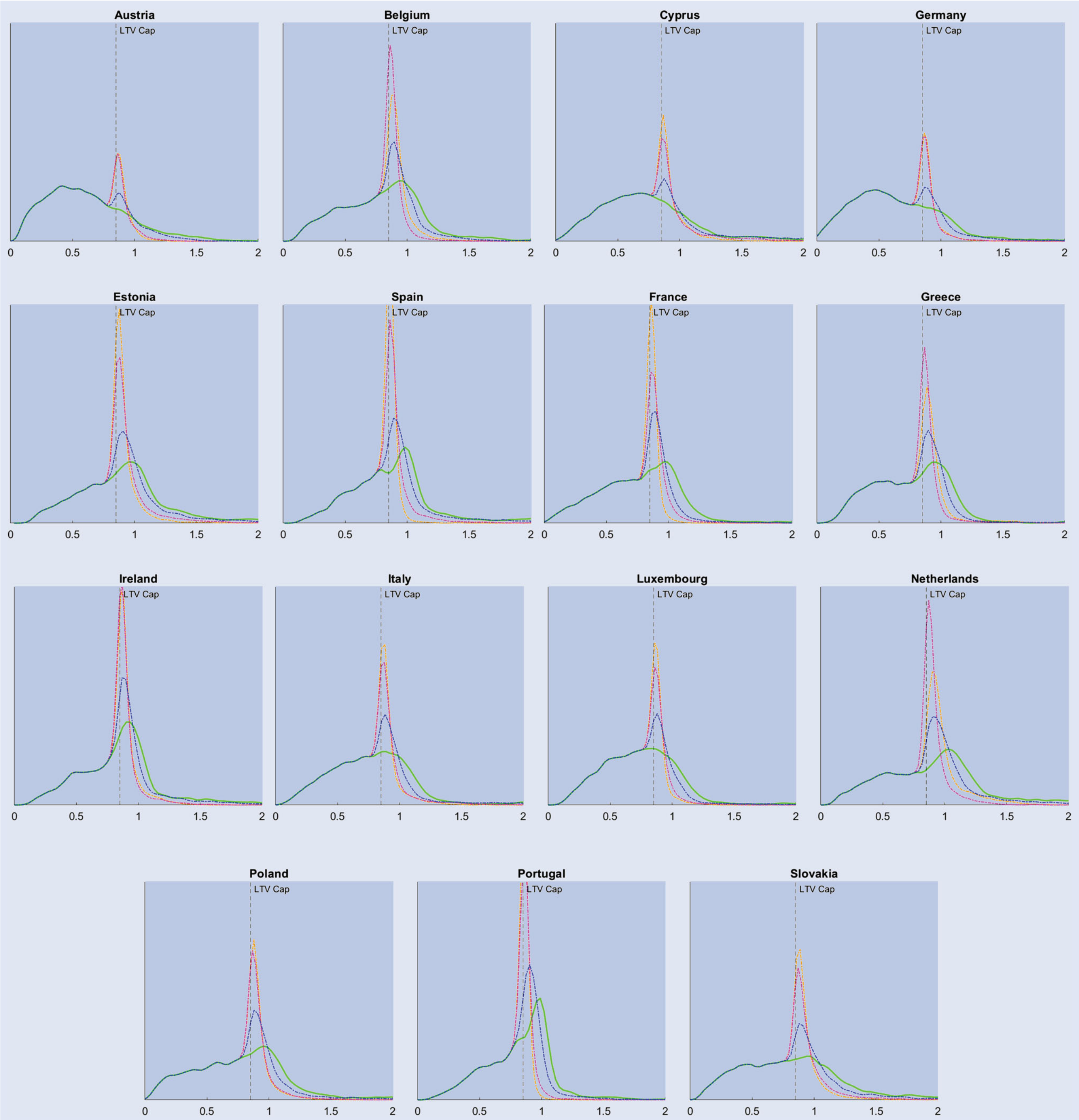


A.4. Effects on the LTV distributions

The following graphs show the effect of the fixed and proportionate caps on the *a priori* LTV distributions.



In this figure we show the effect of the fixed cap (dashed red) on the initial LTV ratio distributions (green).

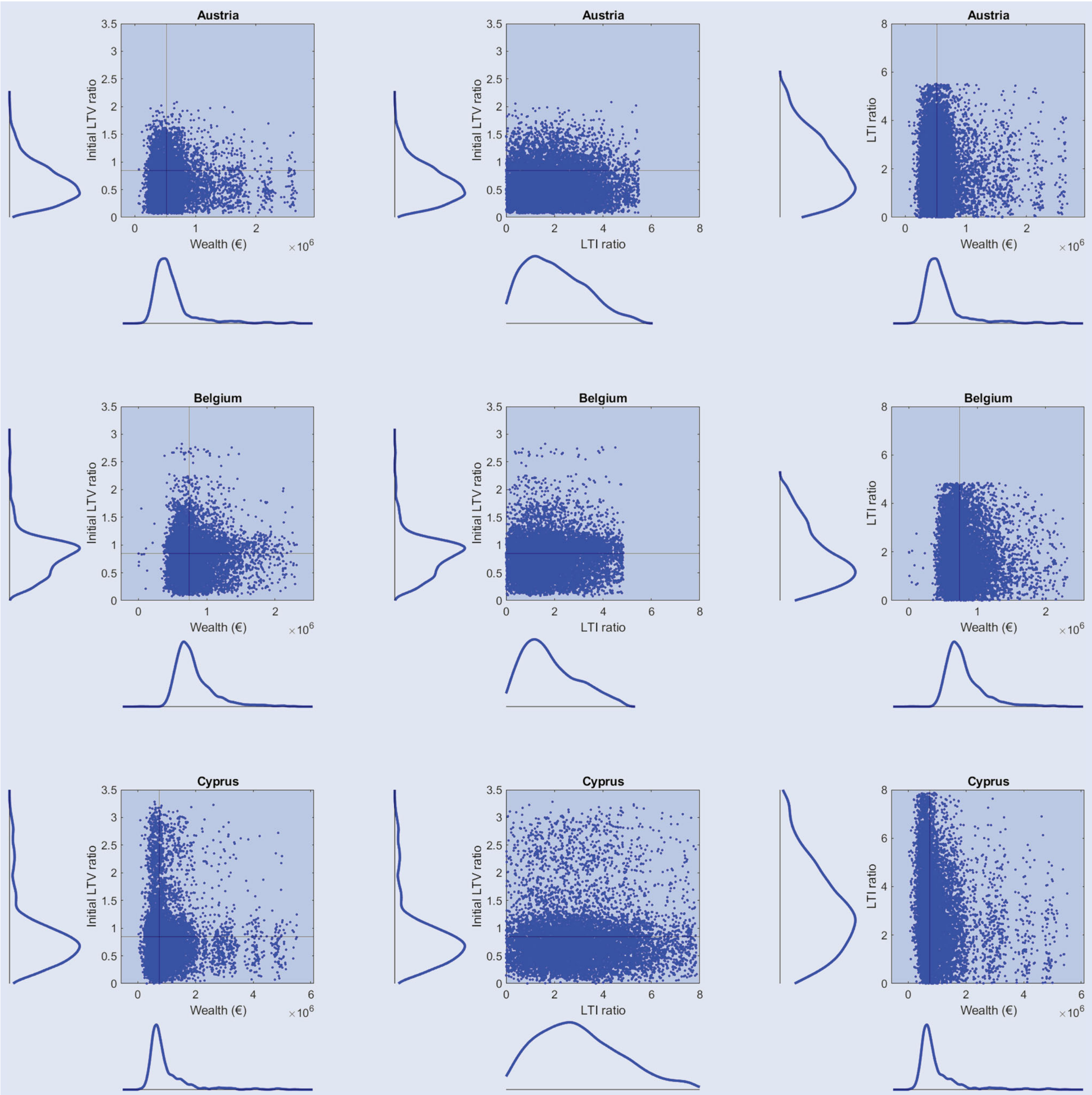


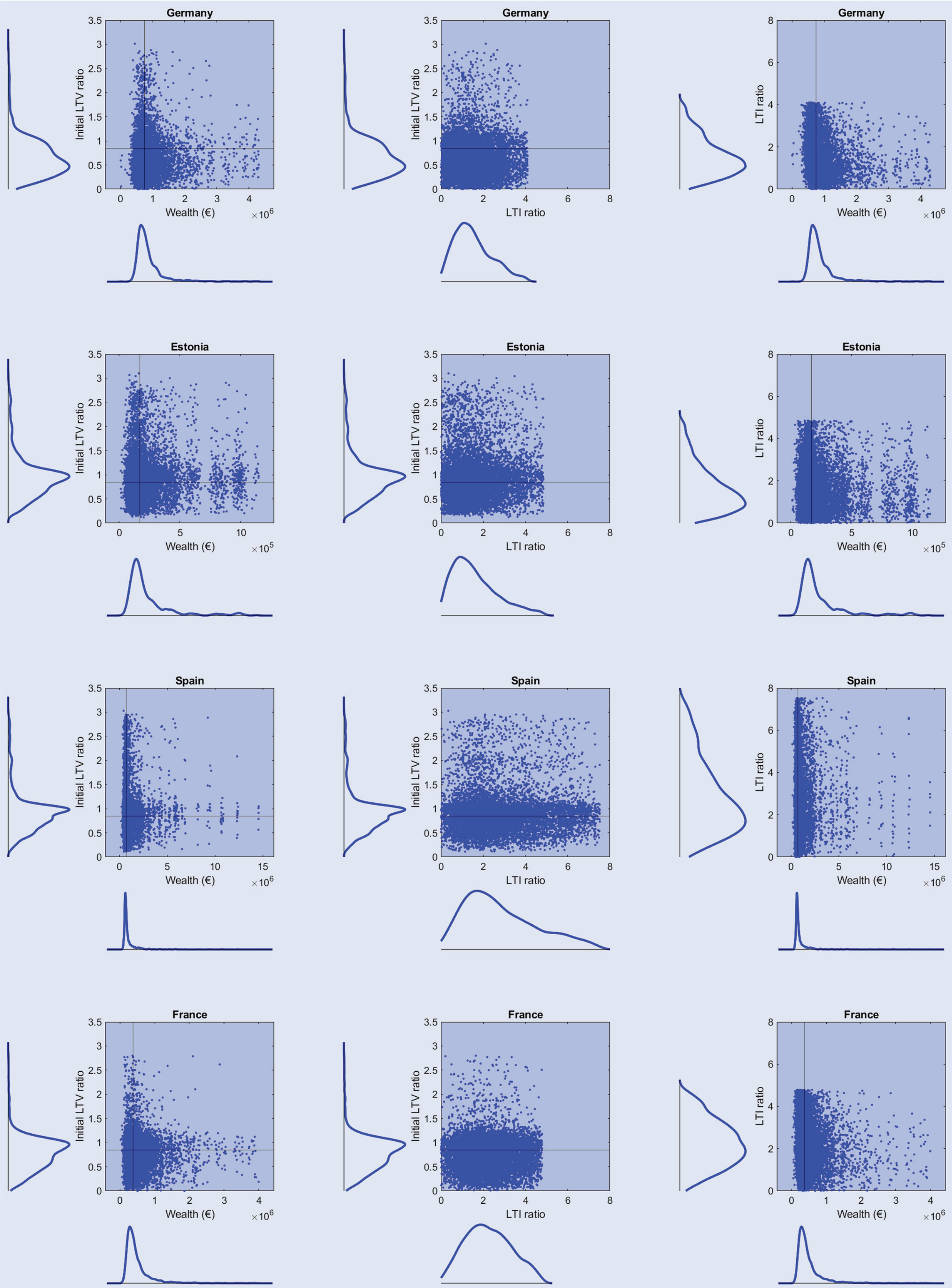
Initial LTV distribution (green), wealth-linear cap (orange), median-centred (magenta) and LTI-based (blue).

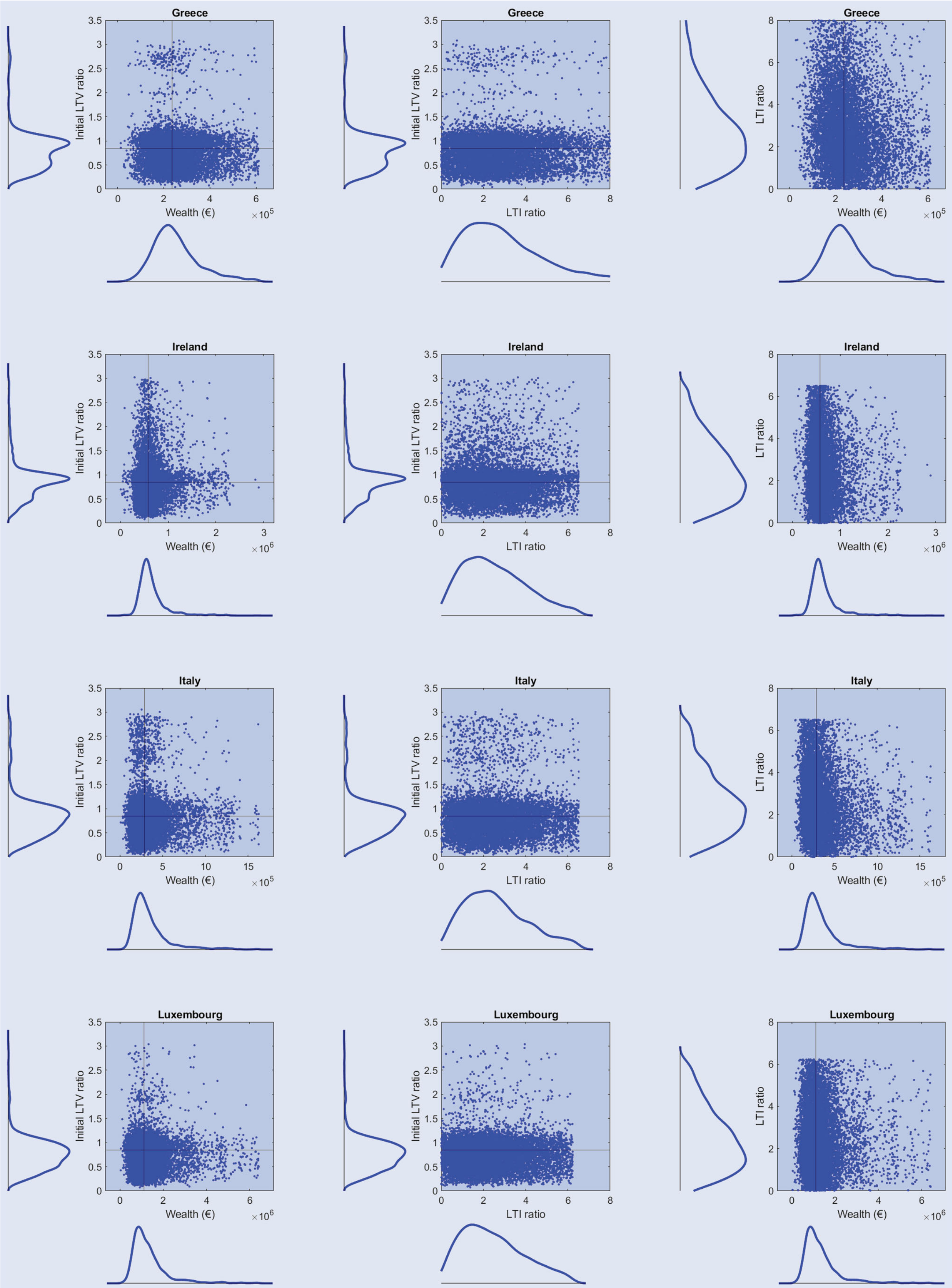
A.5. *Bivariate probability distributions by country*

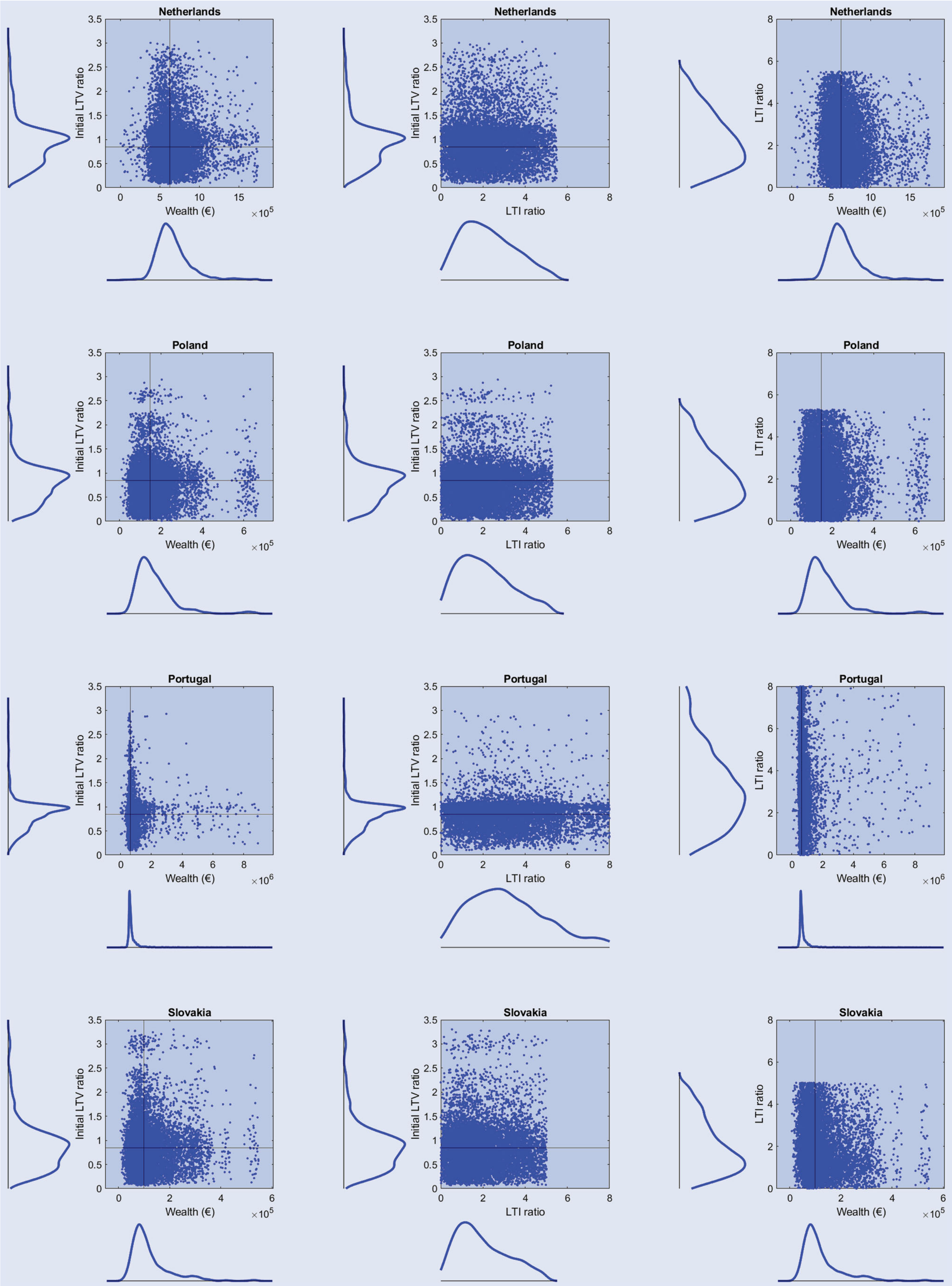
Finally, in order to better understand the extent to which the densities of wealth, LTV and LTI ratios alter the effects of each type of cap by country, the following matrix of graphs depicts three bivariate probability distributions: Wealth vs. LTV, LTI vs. LTV and Wealth vs. LTI.

Vertical lines indicate the median of the wealth distribution; horizontal lines show the 85% cap in our exercise.




Germany
Estonia
Spain
France
Initial LTV ratio
LTI ratio
Wealth (€)
×10^6
×10^5


Greece
Initial LTV ratio
Wealth (€)
×10^5
Greece
Initial LTV ratio
LTI ratio
Greece
LTI ratio
Wealth (€)
×10^5
Ireland
Initial LTV ratio
Wealth (€)
×10^6
Ireland
Initial LTV ratio
LTI ratio
Ireland
LTI ratio
Wealth (€)
×10^6
Italy
Initial LTV ratio
Wealth (€)
×10^5
Italy
Initial LTV ratio
LTI ratio
Italy
LTI ratio
Wealth (€)
×10^5
Luxembourg
Initial LTV ratio
Wealth (€)
×10^6
Luxembourg
Initial LTV ratio
LTI ratio
Luxembourg
LTI ratio
Wealth (€)
×10^6


Netherlands
Initial LTV ratio
Wealth (€)
$\times 10^5$
LTI ratio
Poland
Portugal
$\times 10^6$
Slovakia