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MACROPRUDENTIAL POLICY ANALYSIS VIA AN AGENT BASED MODEL OF THE REAL ESTATE SECTOR

by Gennaro Catapano*, Francesco Franceschi†, Michele Loberto† and Valentina Michelangeli†

Abstract

In this paper, we extend and calibrate with Italian data the Agent-based model of the real estate sector described in Baptista et al., 2016. We design a novel calibration methodology that is built on a multivariate moment-based measure and a set of three search algorithms: a low discrepancy series, a machine learning surrogate and a genetic algorithm. The calibrated and validated model is then used to evaluate the effects of three hypothetical borrower-based macroprudential policies: an 80 per cent loan-to-value cap, a 30 per cent cap on the loan-service-to-income ratio and a combination of both policies. We find that, within our framework, these policy interventions tend to slow down the credit cycle and reduce the probability of defaults on mortgages. However, with respect to the Italian housing market, we only find very small effects over a five-year horizon on both property prices and mortgage defaults. This latter result is consistent with the view that the Italian household sector is financially sound. Finally, we find that restrictive policies lead to a shift in demand toward lower quality dwellings.

JEL Classification: D1, D31, E58, R2, R21, R31.
Keywords: agent based model, housing market, macroprudential policy.
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Contents

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1 Introduction*

Housing markets play a crucial role in most economies: the value of the global real estate stock is the highest of any other asset class.[1] For the Italian economy in particular, this sector is of remarkable significance: real estate property is the biggest share of wealth for households[2] and it is a primary source of collateral; mortgages represent a sizeable share of the assets for banks,[3] and liabilities for households; the construction and real estate sectors represent a bit less than a fifth of the GDP[4]. For these reasons, the real estate sector is one of the main drivers of the business and of the financial cycles. Furthermore, as the Great financial crisis of 2007-2009 has shown so dramatically, housing and mortgage markets are critical elements in assessing the risks to financial stability (Kamin and DeMarco, 2010).

Housing markets possess a plethora of distinctive attributes that should be considered in the assessment of cyclical conditions and of risks to financial stability. Some characteristics, such as housing finance being often highly leveraged and playing a crucial role in credit and housing cycles (Brunnermeier, 2009), are largely acknowledged by researchers and policy makers. Other features are instead often overlooked. For instance, the housing market is more heterogeneous than most models allow for: housing is an heterogeneous good and agents interacting on these markets are also heterogeneous in income, wealth, preferences and therefore behaviour. Models that ignore this heterogeneity might draw incorrect conclusions (Fagiolo and Roventini, 2017). Moreover, housing markets have often a local nature and are slow to react to changing conditions (Riddell, 2004). This could imply that imbalances in housing markets might persist longer than some models indicate, and the effects of policy interventions may not be described accurately. Agent-based models (ABM) can contribute to shed light on these matters.

Baptista et al., 2016 have proposed an ABM of the UK real estate and mortgage sectors that they use to evaluate borrower-based macroprudential policies. It is a demand-driven model that explicitly takes into account housing and agents heterogeneity along

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[1] Sources: Savills world research; HSBC.

[2] Bank of Italy: Survey on Household Income and Wealth, 2016.

[3] Bank of Italy: Financial Accounts, June 5, 2020.

[4] European Commission: European construction sector observatory.

several dimensions. Their model has been adapted and used in the study of the Danish housing market (Cokayne, 2019).

Based on these contributions, we develop and calibrate an ABM of the Italian real estate sector. In our model there are four classes of agents: (i) households; (ii) a construction sector; (iii) a bank; (iv) a Central bank which mainly acts as a macroprudential authority[5]. Households are heterogeneous along several dimensions, such as: age; income; bank balance; investing strategy. Households may buy, sell, lease or rent residential properties. They may take up a mortgage in order to buy a house. Agents are boundedly rational and the aggregate dynamics emerge from their micro-interactions without the imposition of an equilibrium condition. The credit sector is overseen by the Central bank which sets the macroprudential policies.

We use this framework to analyze the effects of specific borrower-based macroprudential instruments, an 80% LTV cap and of a 30% LSTI cap, on the real estate cycle and on the risks to financial stability stemming from household debt in terms of mortgage defaults. We chose these borrower-based measures as they are among the most commonly adopted in Europe (ESRB, 2020), and because they tackle both the probability of borrower default and the expected loss (for banks) given default. Moreover, the levels of the caps were chosen in line with both the international experience and according to the definition of financial vulnerability that is prevalent in the literature (according to which, financially vulnerable households have an LSTI ratio exceeding 30%).

In general, macroprudential policies may either target financial intermediaries (e.g. banks by imposing capital requirements) or borrowers (e.g. households by imposing loan-to-value (LTV) or loan-service-to-income (LSTI) caps). Their aim is to reduce systemic risks by addressing the entire banking sector, whereas other instruments, such as microprudential supervision, target individual institutions. LTV and LSTI caps, in particular, are meant to decrease the flow of credit to households thereby diminishing indebtedness and the incidence of defaults. Empirical and theoretical papers provide insights on the effectiveness of these instruments in smoothing the real estate cycle (Greenwald, 2018) and in reducing household debt and increase resilience (Cassidy and Hallissey, 2016). Moreover, Grodecka, 2019 studies the interactions between LTV and LSTI limits, showing that multiple binding constraints can augment the effectiveness of LTV in tackling the rise in indebtedness.

[5] In this model we assume that the Central bank and the macroprudential authority coincide.

Evidence on the effectiveness of borrower-based measures on house prices and household debt is mixed. In some jurisdictions, such as Korea and Hong Kong, LTV and DTI caps induced a moderation of house prices and of the number of transactions. An early analysis based on a larger panel of countries (Kuttner and Shim, 2016) suggests that these effects are often weak. However, a more recent assessment on EU countries suggests that LTV and LSTI limits are indeed effective in hampering house prices growth and household debt growth (Poghosyan, 2019). Heterogeneity also emerge on the relative effectiveness of LTV and LSTI caps, with the latter having more often significant effects. Arena et al., 2020 provide a thorough analysis of the implementation of macroprudential policies in Europe and their effects on house prices. They show that before the Covid-19 pandemics, 19 European countries had an LTV limit in place, while 15 of them had some form of LSTI or DTI limits. Overall, they find evidence suggesting that borrower-based measures contribute to make economies more resilient, by cooling-off real estate cycles and reducing the share of riskier mortgages.

Our results show that within our framework both an 80% LTV and a 30% LSTI cap tend to moderate the credit cycle and to reduce the risk of default on mortgages. A joint implementation of both macroprudential measures has stronger effects than either policy in isolation, and the size of such a joint effect on the real estate cycle is significantly larger than the sum of each component.

However, with respect to the Italian housing market, we find only very small effects. After 5 years the average sale price and the number of transactions are reduced by about 2%, afterwards the market recovers toward the long-run levels. Mortgage defaults are also only marginally reduced by these macroprudential measures. These results suggest that the considered borrower-based measures, calibrated at the levels proposed in this paper, which are in line with the experience of other European countries, would have only marginally increased the resilience of the Italian financial system. This result is largely related to the already well documented financial resilience of the Italian households (Attinà, Franceschi, and Michelangeli, 2020), and to the current low average levels of LTV and LSTI in Italy. Moreover, the results should also be interpreted having in mind that our calibration, despite adopting an cutting-edge methodology, is for some variables limited to their first moment due to the lack of more granular data.

Finally, we also run some "reverse" experiments, trying to pin-down the least restrictive caps that would imply a significant response in terms of real-estate cycle and of defaults. We find that, given the characteristics of the Italian economy, only extremely tight caps would do the job (LTV at 40% or LSTI at 15%).

Finally, while the aggregate impact of the 80% LTV and 30% LSTI caps is small, some interesting insights emerge when studying their distributional effects. In fact, due to household heterogeneity, policies with comparable aggregate effects may differently impact distinct market segments. In our simulations, all restrictive policies induce a shift in housing demand toward lower housing quality levels. We find that this effect is stronger for market segments with a comparatively higher concentration of constrained households.

We also make several contributions to the existing literature from a methodological perspective. The present study is the first to use a formal, multivariate calibration procedure for models derived from Baptista et al., 2016 and in general for large-scale economics ABM. Moreover, we propose a novel parameter search strategy that combines low discrepancy series, genetic algorithms and machine learning surrogates.

This article is organized as follows: Section 2 concisely presents the most relevant literature on the housing markets, with regard to both equation-based and agent-based models; Section 3 provides a description of the original model and our adaptations and extensions; Section 4 discusses the model calibration; Section 5 is concerned with the simulation details; Section 6 describes the results of the policy experiments; Section 7 concludes. Finally, in the appendix there are some details of the methodology and results omitted in other sections.

2 Relevant literature

The literature on housing and macroeconomics has flourished in recent years. Early contributions, during the 2000s, were concerned about the implications of house price shocks on the business cycle (Iacoviello, 2008; Iacoviello and Neri, 2010). These contributions are based on dynamic stochastic general equilibrium (DSGE) models. However, DSGE models fail to explain some basic stylized facts regarding the volatility of house prices and the relation between residential investments and house prices (Piazzesi and Schneider, 2016). In addition, the literature following the Global financial crisis highlighted three fundamental aspects to be considered when modeling the housing market, which DSGEs cannot take into account. First, the distributional effects and segmentation of the housing market (Landvoigt, Piazzesi, and Schneider, 2015). Second, the importance of housing market illiquidity due to frictions in the search and matching process (Han and Strange, 2015; Hedlund, 2016b; Hedlund, 2016a). Third, the inconsistency of households' real estate investment decisions with the rational expectations paradigm (Glaeser and Nathanson, 2017).

"The trouble with macroeconomics" (Romer, 2016 referring mainly to DSGEs) has not been confined to models of the housing market. The inability of this framework to forecast and explain the Great financial crisis has sparked a debate about its general adequacy and core assumptions.[6] Some researchers argue for a non-disruptive evolution of the existing framework that extends it in several directions (Vines et al., 2018): inclusion of financial frictions; relaxation of rational expectations; introduction of consumers and firms heterogeneity; design of better microfoundations. Others contend that ABMs, as a different modeling paradigm, might be either a valid complement to the existing frameworks (Haldane and Turrell, 2018) or an outright superior alternative (Fagiolo and Roventini, 2017, Farmer, Foley, and Windrum, 2009).

According to a definition by a prominent ABM researcher, economics ABMs are concerned with: "the computational modeling of economic processes (including whole economies) as open-ended dynamic systems of interacting agents"[7]. Economics ABMs are often - but it is not an intrinsic limitation[8] - designed using significantly different hypothesis when compared to neo-classical models (Fagiolo and Roventini, 2017): bounded rationality is often used in lieu of a perfectly optimizing behaviour; extrapolative expectations preferred to rational expectations; the Walrasian equilibrium is seldom employed to determine prices and quantities exchanged[9]. More broadly, compared to equation-based models, ABMs are not constrained by the requirement of the analytical form. This fundamental difference originates two defining characteristics of this modeling approach: the virtually unbounded modeling freedom (that allows for, as an example, heterogeneous agents instead of a representative one) that is counterbalanced by the need for numerical solutions, high computational costs and the absence of well-established calibration protocols (Gobbi and Grazzini, 2019).

[6] For an excellent review of the debate on the future and issues of macroeconomic modeling please refer to the volume Vines et al., 2018.
[7] Quote from Tesfatsion, 2006.
[8] An interesting discussion on the structural characteristics of ABMs is in Tesfatsion, 2017.
[9] For an analysis of the main ingredients in economics ABMs, please refer to Fagiolo, Moneta, and Windrum, 2007.

In recent years, the development of economics ABMs has sped up favoured by some important factors: the cited concerns about the performance and assumptions underlying DSGE models; the growing interest for policies' and shocks' distributional effects coupled with the increasing availability of granular data; a burgeoning literature on novel ABM validation and calibration procedures[10]; the dramatic fall in computational costs. ABMs are indeed structurally well-suited to exploit granular data and to tackle heterogeneity and distributional effects (Fagiolo and Roventini, 2017, Farmer, Foley, and Windrum, 2009).

3 An ABM for the Italian housing market

Our analysis is based on the agent-based model of the housing market described in Baptista et al., 2016. In order to adapt the model to the Italian context we introduced some changes which are described in Section 3.3. It is a discrete-time model with four classes of agents: (i) households; (ii) a construction sector; (iii) a bank; (iv) a central bank. There are three asset classes: (i) currency; (ii) checking accounts; (iii) houses. Finally, houses can be rented and their property is exchanged on two double-auction markets. Figure 1 shows a scheme of the components of the model and their interactions.

[10] Notable works include: the Bayesian approach proposed by Grazzini, Richiardi, and Tsionas, 2017; the information theoretic approach proposed by Barde, 2017; the L-divergence-based approach proposed by Lamperti, 2015 and the less recent, but widely adopted, method of simulated moments detailed, for example, by Franke, 2009.

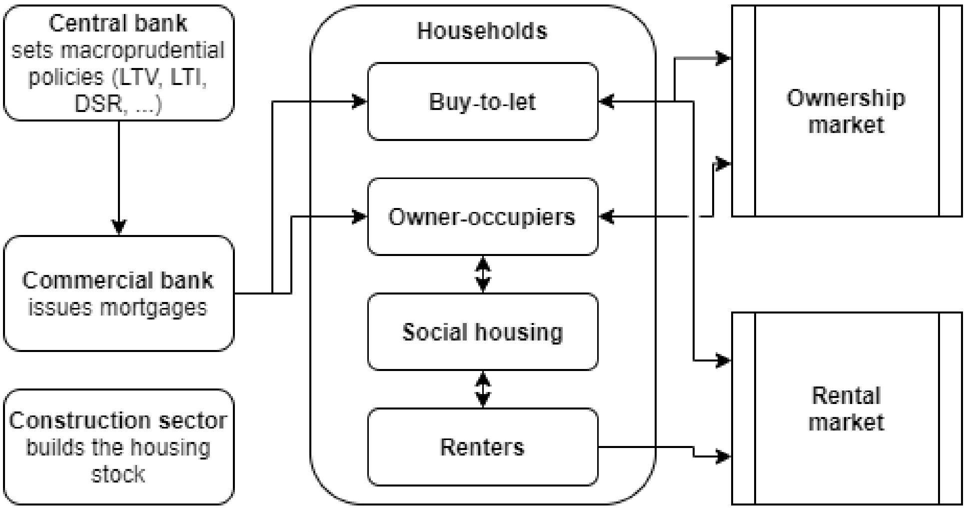

Fig. 1. Model components and their interactions.

Households receive an income, spend on both non-housing consumption and housing related expenses, may buy or sell residential properties and in doing so may take up a mortgage from the bank. The following section explores in more detail the main steps involved in the simulation of the model and the main behavioural rules the agents adopt. A complete description of the model is reported in Baptista et al., 2016.

3.1 Model overview

The model has a discrete time structure. As it is analytically intractable, it is numerically simulated. Each simulation time step is one-month long, and the following is an account of its structure:

1. **Demographics**: Households have a finite lifespan. Each period some households are born and assigned to an income quantile, all age, and some die. These dynamics reflect an appropriate age-income distribution.
2. **Construction**: Each house has a quality value taken from a discrete distribution. At the start of the simulation, the construction sector progressively adds new properties until the appropriate[11] equilibrium ratio of houses to households is reached.

[11] Calibrated using data for the Italian economy by Istat.

3. **Households**:
   (a) Households receive a stochastic exogenous income that is a function of their age and income quantiles.
   (b) Households spend part of their income on non-housing consumption. Their level of spending is chosen as to match an income-liquid wealth relationship[12].
   (c) Households may be randomly endowed with a "buy-to-let preference" (BTL) that allows them to buy and sell additional properties to be let out to renters.
   (d) Renters pay a rent and owners with a mortgage pay their mortgage payment.
   (e) Households who are unable to pay their mortgage or rent become bankrupt.[13]
   (f) Households are initially placed in social housing where they sustain no housing costs.[14] Households take their housing decisions according to their status:
      i. If in social housing, they decide whether to buy or rent a property.
      ii. If renting, they continue to pay the rent until the contract expires.
      iii. If owning a house, they decide whether to sell the property and get back to social housing[15].
      iv. If endowed with the BTL preference and owning-occupying a house, they decide whether to buy a new property and for each owned property decide whether to sell or rent it.
   (g) Households that have decided to buy or sell a property place their offers on the ownership market. Those that have decided to rent or rent out a property place their offers on the rental market.
4. **Markets**: Both the ownership and the rental markets have a double-auction structure.[16] The former is cleared first, the second afterwards. Both markets work as follows:
   (a) Bids and offers are collected as the households send them to the market.
   (b) Once all households ended their 'turn', bids and offers are matched in multiple rounds. Unmatched bids are removed from the market. Selling offers matched with multiple bids allow the seller to increase the asking price.

[12] Please refer to section 3.2 for the exact specification of this relationship. In particular, equation 1 determines the non-housing consumption level and equation 2 establishes the exact relationship between liquid wealth and income.

[13] Households who default on their payment agreements are not allowed to have a negative cash balance.

[14] Social housing is an option that is always available to households when they have no other option available. It is a proxy for being homeless or staying at the parents' house. Households strictly prefer to rent or buy a property rather than staying in social housing.

[15] Where they can decide whether to buy or rent a new property.

[16] In the ABM literature, a double-auction is the simplest and most used mechanism to endogenize market prices. Double auctions can be seen as an approximation to Walrasian auctions.

5. **The bank:** There exists only one bank that has a fixed credit supply target[17]. The bank offers mortgages to households following those rules:
   (a) The mortgage interest rate is a positive linear function of the difference between the actual volume loaned and the supply target.
   (b) The mortgage agreement must comply with the macroprudential policies set by the Central bank.
6. **Central bank**: The Central bank sets the macroprudential policy. It may put caps on the loan-to-value (LTV), loan service to income (LSTI) ratios. While in this paper we used simple, one-off policy interventions (eg: a permanent LTV cap), the model can be employed for the study of more general policy rules[18].

3.2 Main heuristics

This section provides details about some of the more important heuristics that determine households' behaviour[19]. All equations will use the same lower-case Greek letters (α, β, γ...) for parameters but each equation's parameters are different from the others.

1. **Non-housing consumption**: As the model does not include a production sector[20] the only significant function non-housing consumption performs is to reproduce the appropriate liquid-wealth distribution which in turn affects downpayments. Non-housing consumption C is set according to the formula:

$$C = max(\alpha(c - d), 0), \tag{1}$$

   where c is the current stock of financial wealth an household owns and d is its desired level at the end of the time-step and it is set as follows:

$$ln(d) = \delta\, ln(y) + \epsilon, \tag{2}$$

   where y is the household's income and ϵ is a white Gaussian noise term.

[17] That can be calibrated.
[18] As an example: the introduction of a restrictive policy whose timing and size is based on the credit growth observed in the previous years.
[19] The interested reader will find a complete description in Baptista et al., 2016 as this model largely follows theirs and all differences are elucidated in detail in the following section.
[20] Hence unemployment or growth dynamics are not modeled.

2. **House purchase budget**: Households needing a new home are represented as being in social housing. In order to choose whether to buy or rent a house, households must first decide on a desired house purchase budget $p_{desired}$:

$$p_{desired} = \frac{\alpha\, y\, exp(\epsilon)}{1 - \beta\, g}, \tag{3}$$

where y and ϵ are as in (2), and g is the expected monthly house price growth rate, defined as follows:

$$g_t = \alpha \left(\frac{h_{t-1} + h_{t-2} + h_{t-3}}{h_{t-13} + h_{t-14} + h_{t-15}} - 1 \right), \tag{4}$$

where h_t is the house price index for the month t.

3. **Buying vs renting**: The choice between buying and renting is a function of the cost of the two options. It is taken according to the following procedure:
   (a) The household decides on its home purchase budget $p_{desired}$ as in equation 3.
   (b) The household asks the bank for the highest mortgage principal it can borrow to purchase a house, p_{lent}. p_{lent} may be constrained by the macroprudential policy set by the central bank.
   (c) The actual house purchase budget p is the minimum between $p_{desired}$ and p_{lent}.
   (d) The household finds out the house quality q they can afford at the price p given the current market conditions.
   (e) The household finds out the annual cost $r(q)$ of renting an house of quality q for one year.
   (f) Finally, the decision between buying and renting is taken. The probability to buy is modeled as a logistic function:

$$P(buy) \;=\; \frac{1}{1 \,+\, e^{-\alpha x(q)}}, \tag{5}$$

   where $x(q)$ is the difference between the two costs:

$$\begin{aligned} x(q) &= Renting\, cost - Buying\, cost \\ &= r(q)(1 \,+\, \tau) \;-\; 12(m \;-\; pg), \end{aligned} \tag{6}$$

   where τ is the psychological cost of renting, m is the monthly mortgage payment. It is assumed that the household will buy a house at price p.

4. **Downpayment**: Once the decision to buy is made, households make their purchases either outright or by obtaining a mortgage. If the liquid financial wealth of the household is higher than a multiple k of the purchase price, the household won't request a mortgage. Otherwise, the household will determine a downpayment d by the following rule:

$$d = p\,max\{\,0, \alpha + \beta\epsilon\,\}, \tag{7}$$

where p is the purchase price, ϵ is a Gaussian noise. Parameters α and β are differentiated according to the specific household status: buy-to-let investor; first time buyer; home owner.

5. **Initial sale price**: If an household decides to sell an house, il will offer it on the market at a price p_s given by:

$$p_s = \alpha + ln(\overline{p}_{sold}) - \beta\, ln(1 + \overline{f}) + \epsilon, \tag{8}$$

where $\overline{p}_{sold}$ is the average price at which properties have been sold on the market, $\overline{f}$ is the average time required to sell a house.

6. **Sale price reduction**: If a house remains on the market from the previous time-step, its asking price might be reduced, with probability $p_{reduction}$, according to the following formula:

$$p_t = p_{t-1}(1 - exp(\epsilon)), \tag{9}$$

where ϵ is drawn from a Gaussian ditribution with the appropriate moments.

7. **Mortgage interest rate**: Each month the bank sets the mortgage interest rate according to the following rule:

$$i_t = max\,\{\,i,\; i_{t-1} \,+\, \alpha(M_{t-1} \,-\, T)\,\}, \tag{10}$$

where i is an exogenous floor to the interest rates, M_{t-1} is the total supply of mortgages in the previous month and T is an exogenous supply target. This equation defines a simplified interest-setting behaviour, the introduction of a more realistic agent-based banking sector will be the focus of future extensions to the model.

8. **Minimum bank balance for buy-to-let investors**: Buy-to-let investors won't consider buying a property if:

$$l \leq y, \tag{11}$$

where l are their liquid financial assets and y their annual income.

3.3 Changes to the original model

This section provides a detailed account of all the differences between our model and the one in Baptista et al., 2016.

1. **Cost comparison in buy vs rent choice**: Equation 6 did not take into account the downpayment in the cost comparison. Our model substitutes it with the following equation:

$$\begin{aligned} x(q) &= Renting\,cost - Buying\,cost \\ &= r(q)(1 + \tau)l - (12m\,l + d - p), \end{aligned} \tag{12}$$

   where l is the mortgage duration in years, d is the downpayment and all other symbols have the same meaning as in equation 6.
2. **Mortgage interest rate**: In equation 10, α determines the magnitude of the interest rate adjustment due to a discrepancy between the target and actual credit supply. It had been set at a value of 0.5 and was not included among the free parameters. Using the Italian data with the original value we found that the interest rate would take thousands of time steps to settle into its steady-state value. Hence we increased its value to 20.0. There were no differences in the steady-state average value for all variables of interest. The model reached its steady-state much earlier. Please refer to section 8.2 for a comparison of the model dynamics under the two parameter values.
3. **Households' income idiosyncratic shocks**: We added an idiosyncratic shock to the households' income process. Each period an household might experience an income shock with probability p_1 and, with equal probability, its income jumps to the highest or lowest income decile for l months. The income process is determined by the following equation:

$$y(q, p) = \tilde{x}y(q) + (1 - \tilde{x})[\tilde{z}y(q_{high}) + (1 - \tilde{z})y(q_{low})], \tag{13}$$

   where:

$$\tilde{x} \sim Ber(p_1), \tilde{z} \sim Ber(p_2), \tag{14}$$

p_1 is a free parameter, p_2 has been set at 0.5 and $y(q)$ is the income for quantile q. This process is a generalization of the one in Baptista et al., 2016 as it can be clearly seen by setting $p_1 = 0$.

In the model, the main driver of the mortgage defaults are households' income fluctuations. The introduction of a parametric jump in the income process allows for a finer calibration of this defaults rate.

4. **Reduction of the parameter space**:

   (a) The parameter β in equation 8 determines the amplitude of the initial price reduction due to the average waiting time a seller has to wait, keeping $\overline{p}_{sold}$ constant. Given that equation 9 already establishes a price reduction mechanism for unsold houses, β has been set to zero. This slightly simplifies the calibration procedure.

   (b) There are functionally identical equations for the initial price setting and subsequent price reductions for the rental market. For these equations there has been the same simplification described above.

   (c) Equation 7 has been simplified. The vector (α, β) is now independent of the household status. This is due to a lack of more granular data on the relationship between average income and specific classes of households.

4 Model calibration and validation

Not being limited by the constraints of the analytical tractability, ABMs might represent very complex[21] and realistic economies. This plasticity implies that the main limiting factor in the usefulness of a well-specified[22] ABM is its correct estimation.[23] Despite a growing body of literature on new ABM calibration methodologies, ABMs still lack a well-established approach to calibration (Gobbi and Grazzini, 2019). Moreover this

[21] Of course other limits arise as the complexity of the model increases. The amount of computational power available and the feasibility of the analysis of more and more complex relationships might become binding constraints.

[22] That is: assuming that the model is correctly specified in regards to the phenomenon of interest.

[23] In fact, it has been argued by Fagiolo, Guerini, et al., 2017 that recent advancements in the calibration of ABMs might bring them to the same level of development as DSGEs.

stream of literature is plagued by a lack of applications to large-scale ABMs and by a paucity of comparisons of different methodologies, as reported by Platt, 2019[24].

To calibrate (both directly and indirectly, as detailed below) the model we used empirical data that spans the 13 years from 2005 to 2013 for the Italian economy. In what follows we detail the adopted strategy.

4.1 Direct calibration

Some parameters reflect quantities that are observable[25], given the available empirical data. For those parameters, sophisticated calibration techniques are not required and the parameter values can be simply set to the value assumed by their empirical counterparts. In what follows, we outline the main data categories that we used to directly calibrate some of the parameters. For sake of clarity we defer the detailed exposition of the parameters to the appendix.

1. Housing data. The model uses data on the ratio of houses per household, distributional features of the cross-section of house prices and rental yield.
2. Households data. Joint distribution age/income, life expectancy, prevalence of BTL households, ratio of housing and non-housing-related consumption, income-wealth relationship.
3. Financial data. Returns on liquid wealth, various features of outstanding mortgages[26] and macroprudential measures.

4.2 Indirect calibration

As the complexity of this model places it beyond analytical tractability, simulation-based methodologies are employed to calibrate remaining, unobservable parameters. Any calibration method consists of two main components: (i) a function that measures the distance between empirical and simulated time-series; (ii) a search procedure that samples the parameter space. More formally:

[24] In Platt, 2019 there is the only comparison of calibration methodologies available, there is also one application to a large-scale ABM.
[25] Or for which straightforward estimation procedures exist.
[26] Namely: the average duration in years; the minimum interest rate the bank can charge; the average credit flow.

$$\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta} \in \boldsymbol{\Theta}} f(\boldsymbol{\theta}), \tag{15}$$

where $\boldsymbol{\theta}$ is a vector of parameters, $\boldsymbol{\Theta}$ is the parameter space and $f : \boldsymbol{\Theta} \to \mathbf{R}$ is a function that measures the distance between the simulated and empirical time-series[27].

In the following subsections we give an account of our choice for the measure function and for the design of the sampling strategy. Before doing so, we highlight that the methodological literature on large-scale economics ABMs offers very little guidance on the choice or comparison of different calibration approaches, with the only exception being Platt, 2019.

The measure

We adopted a moment-based measure as the first component of our calibration methodology. More specifically, we used the objective function of the method of simulated moments (MSM). This measure is widely used in the context of the economics ABM literature that employs a formal indirect calibration. Here we only outline the measure and the rationale for its choice. An excellent and detailed description of the methodology can be found in Franke, 2009 or in Chen and Lux, 2018. This approach specifies the measure function $f(\boldsymbol{\theta})$ as the following quadratic form:

$$f(\boldsymbol{\theta}) = \boldsymbol{g(\theta)}^{\top} \boldsymbol{W} \boldsymbol{g(\theta)}, \tag{16}$$

where $\boldsymbol{g(\theta)}$ is the vector of differences between empirical and simulated moments and $\boldsymbol{W}$ is a moment-weighting matrix that should reflect the precision in the estimation of the different moments.

To choose this particular measure function, we took into account the peculiarities of our particular optimisation problem:

1. High dimensional, continuous parameter space[28];
2. Short empirical time series[29];

[27] As an example, in Grazzini, Richiardi, and Tsionas, 2017 the distance is measured via the Likelihood function (numerically estimated with Kernel density smoothing) and the search is performed by a Monte Carlo Markov Chain algorithm (MCMC) (either Metropolis-Hastings or Metropolis-in-Gibbs).

[28] As will be detailed in the Appendix, we perform the 'indirect calibration' on 22 parameters.

[29] Our empirical time-series contain about 150 observations.

3. High computational cost of the simulations[30].

We considered two main families of measure functions: likelihood-based and moment-based[31]. The three characteristics above, all pointed towards the choice of a moment-based measure: as highlighted in Rosenthal and Roberts, 2009, likelihood-based measures are very sensitive to hyperparameters in high-dimensional search spaces[32]; short empirical time-series couldn't allow for a reliable estimation of the likelihood function[33]; moment-based measures are generally faster to compute than likelihood-based ones.

Finally, we highlight that to the best of our knowledge our work is the first exploiting a multivariate calibration procedure for this class of models.

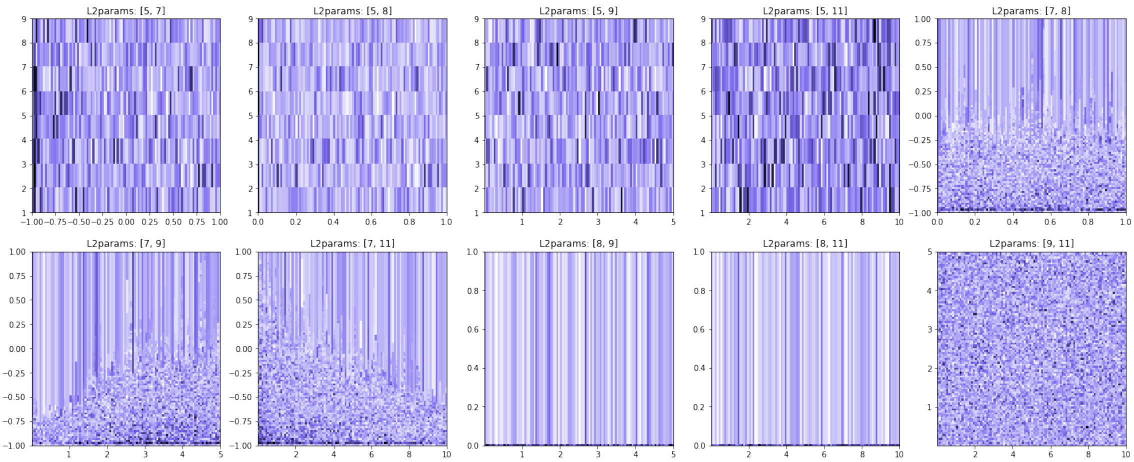

Fig. 2. Bi-dimensional projections of the calibration hyper-surface. A selection of couples of parameters.

[30] Each simulation takes between 30 and 60 seconds to run. The variability in the execution time depends on the parameter vector chosen. This long execution time is mainly due to the long transient phase, documented in Baptista et al., 2016 as well.

[31] Of course this is not an exhaustive categorization, but the first category could proxy all measures that use an entire distribution and not just some moments.

[32] Especially when coupled with an MCMC search algorithm.

[33] This is especially true for the tails of the distribution.

The search strategy

We designed a novel search strategy, that we describe in detail. As mentioned before, the model is computationally heavy and a meaningful, formal calibration procedure requires significant time and computational resources[34]. Moreover it is very hard to predict how many samples (from the parameter space) will be needed to achieve the desired statistical proximity between the simulated and empirical time-series. Hence, at the outset of the calibration, we chose a temporal limit by which the procedure had to end[35].

The search strategy uses a sequence of three sampling methodologies:

1. **The Halton low-discrepancy series.** The Halton sequence is a low-discrepancy series that has good space-filling properties.[36] A desirable property of this sequence is that it allows to iteratively sample new points while preserving the homogeneous density of the sampled points in the searched hypercube.
2. **A random-forest classifier.** Since ABMs can be computationally expensive, it has been suggested that the use of a machine-learning surrogate might reduce the calibration costs. We trained a random-forest classifier on the data that is generated as the calibration procedure progresses. A large pool of points from the parameter space is drawn randomly. Those points are then evaluated by the trained surrogate. The best fitting points, according to the surrogate, are then evaluated using the model. This methodology is akin, although it uses a different machine learning algorithm, to the one used in Lamperti, Roventini, and Sani, 2018.
3. **A simple genetic algorithm.** At each generation, the best fitting candidates (parameter vectors) get randomly selected for reproduction. They have a positive chance to incur in at least one mutation in their genome (parameter values). Once the reproductive stage has been completed, the worst fitting individuals (in this case parameter vectors) are no longer considered for the next reproductive stage.

The search procedure is performed in a sequence of successive iterations. Each iteration is subdivided in three steps:

[34] For example, discretizing the 22-dimensional hypercube (the search space) such that each dimension has k points it would take k^{22} simulations to completely explore it. With a mere $k = 2$ it would take $2^{22} = 4,194,304$ simulations (assuming an unrealistic ensemble of size 1) that would take about 6 years to complete (on a single-core machine).

[35] We picked a two-months time window on a 32 cores XEON i7-6700HQ machine.

[36] Niederreiter, 1992 describes the algorithm and its properties. For an analysis of its behaviour in high dimensional spaces, please refer to Sloan and Wanga, 2008.

1. **Sampling the parameter space.** In a sequence, each of the three sampling algorithms described above is used to sample a set of parameter vectors. The only difference in the operation of these three methods is the use of the information gathered at the step 4 of the previous iterations:

   (a) The Halton sequence does not use any information gathered at previous iterations;

   (b) The random forest algorithm uses the entire set of previously explored parameter vectors (along with their measured distance from the empirical time series) to try and reconstruct the optimization hyper-surface.

   (c) The genetic algorithm only uses the set of the best points (measure-wise) previously explored as a base for a further evolution.

2. **Simulating the sampled vectors.** For each of the parameter vector sampled at the previous step, the procedure runs a Monte Carlo ensemble of simulations.

3. **Measuring and storing the data.** For each of the simulated time-series the simulated moments are computed. These are then use to compute the distance from the empirical time-series as in equation 16.

4. **Measured distance is stored.** Each explored parameter vector, along with its measured distance is stored in a persistent database.

Algorithm 1 describes the high-level structure of our search strategy.

while *Temporal limit has not been reached* **do**
  Sample the parameter space using the Halton sequence;
  Sample the parameter space using a machine learning surrogate;
  Sample the parameter space using a genetic algorithm;
  Simulate and measure newly sampled points[a];
  if *Global minimum has been reached*[b] **then**
    End search;
  else
    Keep searching;
  end
end

Algorithm 1: Search strategy

[a] Once a parameter vector has been sampled (i.e.: selected), it can be used to perform a batch of simulations. The resulting output time-series can then be used to measure the statistical distance between the simulated and empirical time-series.

[b] As it is impossible to know whether a global minimum has been reached, we chose, as breaking condition, a measured distance very close to zero.

These search algorithms work synergically. The Halton series samples the parameter space evenly, not making use of any prior or newly generated information (during the search procedure). Once a sufficient number of points sampled with the Halton series has been simulated and the resulting distance measured, this information set can be used by the machine learning surrogate. This algorithm then samples points randomly from the regions of the parameter space deemed most promising (i.e. those with the lowest expected distance). Finally, the entire information set is used by the genetic algorithm that is best suited to a local search (see eg: Elbeltagi, Hegazy, and Grierson, 2005).

4.3 Model validation

We computed a vector of moments of endogenous variables and compared those to their empirical counterparts. Using a similar vector of statistical features to the one used for calibration for validation is a standard approach (as noted by Platt, 2019). Table 1 shows this comparison:

As it appears from Table 1, there is a generally good fit of endogenous variables to their empirical counterparts. It is striking the poor fit of the autocorrelation of house

Table 1. A comparison of empirical and simulated moments. All simulated moments pertain to endogenous variables of the model.

Variable	Observed values	Simulated values
House prices mean	186,469	188,851
House prices std dev	9,258	7,934
House prices AC 6mo	0.931	0.518
House prices AC 12mo	0.742	0.345
House prices AC 24mo	0.22	0.133
Mortgage interest rate	0.047	0.044
Rental yield	0.042	0.054
Borrowers DTI	3.500	3.677
Percentage new mortgages defaults	0.012	0.008
All annual tot income	31,400	31,646
Borrowers LTV	0.620	0.713
Owner occupier LSTI	0.320	0.277

prices. This might be due to either an intrinsic characteristic of the model or to an unsuccessful calibration (or a combination of the two). The vastness of the parameter space[37] coupled with its non-convex and highly non-linear shape[38], a sample of which is depicted in Figure 2, implies that there can't be any guarantee to reach the global minimum in equation (15). Moreover, as shown in Lee and Ingram, 1991, the consistency of the MSM estimator is only guaranteed at the global minimum. The dual problem of proving that the model is unable to express the empirical statistical features would also require a complete and unfeasible exploration of the parameter space.

5 Simulation

After discarding the initial observations, belonging to the transient phase, the last 500 observations were kept[39]. As in Baptista et al., 2016, 10,000 households and 48 house quality levels were simulated.

[37] Its cardinality is in the order of $\mathbf{R}^{23}$.

[38] Here we are referring to the hypersurface generated by the use of the measure in equation (15).

[39] As it is clear from figure 5 the model has a very long transient phase. This behaviour has been observed in other related models (Baptista et al., 2016, Cokayne, 2019). We discarded the first 5,500 observations to be sure that the model had settled into its stationary dynamics. The long transient phase has no economic relevance and can be seen as a mere technicality.

To reduce the influence of sampling variability (due to pseudo-random number generation) each parameter vector has been simulated multiple times with varying random seeds. For the calibration procedure the ensemble size[40] has been set to 20[41], while for policy experiments it has been set to 12,000.

6 Results

6.1 Baseline behaviour

The calibrated model offers a reasonable adaptation to the moments of the Italian housing market (Table 1). Figure 3 depicts a sample trajectory along with its Monte Carlo ensemble mean and standard deviation interval. The model has been calibrated as to reflect long-term stationary housing prices.[42] Hence, while the ensemble mean is stable (at the value it has been calibrated on), the individual trajectories display a cyclical dynamic around the mean. Prices and transactions depend on the interaction between buyers and sellers, with macroprudential policy having a role in steering the cycle.

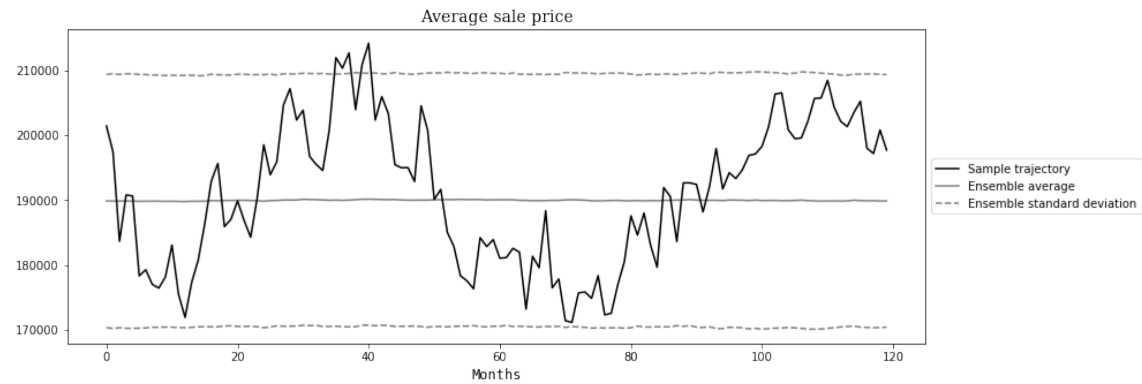

Fig. 3. A sample house prices trajectory generated by the calibrated model in the steady state. The plot also depicts the Monte Carlo ensemble average and a two standard deviation interval for 12000 trajectories.

40 The ensemble size is the number of different presudo-random seeds simulated for each parameter vector.

41 Although this might seem a low ensemble size, carrying out the calibration procedure requires an extraordinary amount of computational power. A bigger ensemble size was simply infeasible at the time of writing. This is a novel (and more formal) approach to calibration for this class of models.

42 This model, and the one it is based on (Baptista et al., 2016), has not been designed to analyse growth dynamics.

Adaptive price expectations are the main driver for the cyclical price behavior: when buyers expect prices to rise in the future, demand for houses increases, generating an actual price growth. Conversely, when buyers expect negative price growth, demand is reduced and prices fall. Consistent with the empirical evidence on the Italian housing market (Bologna, Cornacchia, and Galardo, 2020), the model also implies a mild positive relationship between credit growth and house price growth (Figure 4).

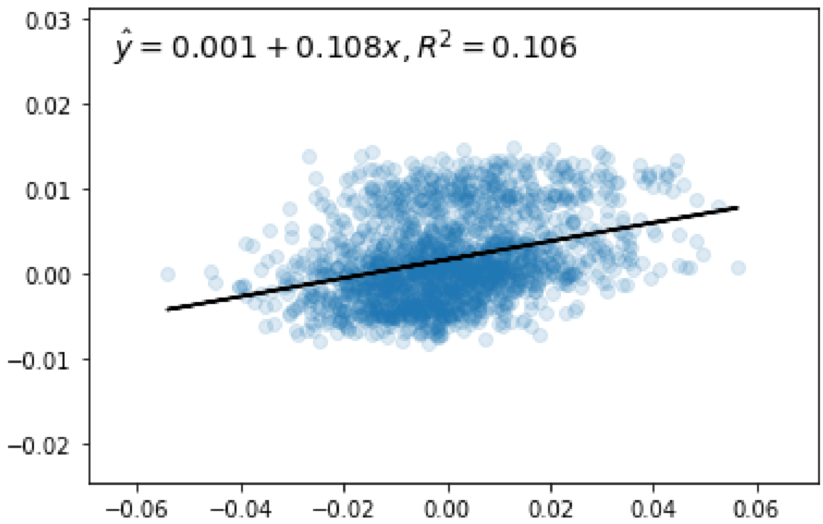

Fig. 4. Simple linear regression between the house prices yearly growth rate (y-axis) and the credit supply yearly growth rate (x-axis).

Figure 5 shows the long-run (steady state) mean behavior of the housing market once the model has been calibrated with the data on the Italian economy. The model exhibits a long transient phase after which all endogenous variables become stationary.[43]

6.2 Design of policy experiments

We used the calibrated model to assess the effects of two borrower-based macroprudential policy interventions: a loan-to-value (LTV) cap set at 80% and a loan service to income (LSTI) cap set at 30%. Then, we also analyze the effects of the joint application of both caps (BOTH).

[43] Please refer to the Appendix for a more complete representation of endogenous variables.

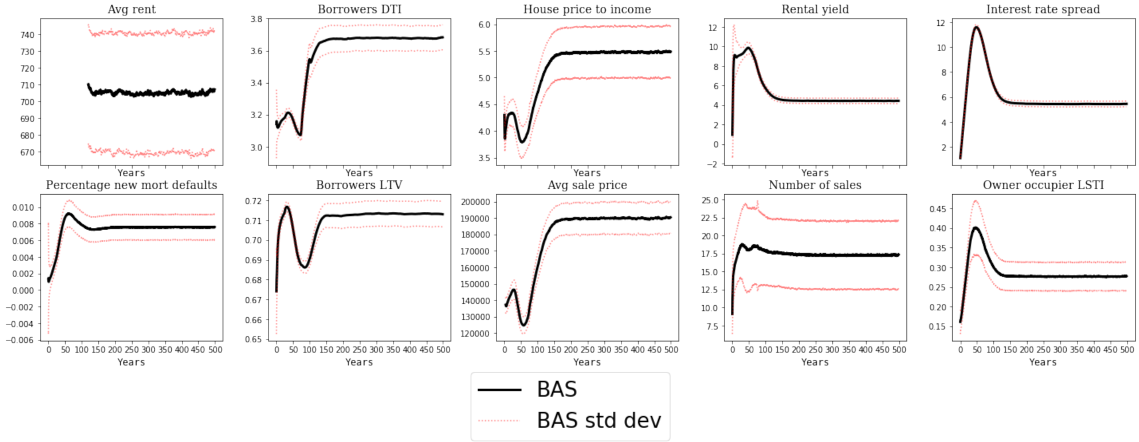

Fig. 5. After a transient phase, model's variables become stationary.

In terms of the implementation of the policy shocks in our model, we introduced them in the last 25 years of the simulation. Hence, for each element in the ensemble, four trajectories were generated: a baseline trajectory and the other three related to the policy interventions. Finally, to assess the average response, the cross-section of the trajectories (for each policy intervention) was averaged across all elements in the ensemble.[44]

6.3 Policy shocks

Before any detailed description of the results and of their economic relevance, it is important to observe that the effects of the macroprudential measures, generated by the model, go in the expected direction. The objective of macroprudential policies is to decrease the severity and frequency of financial crisis by reducing the excessive accumulation of risks and increasing the resilience of the financial system. Our results show that both the LTV and the LSTI caps increase household financial resilience, by reducing debt levels and mortgage defaults. As these policies only target newly approved mortgages, these positive effects build up over a longer time frame. Over the short-term both measures tend to curb the real estate market activity, by inducing a transient reduction in the average sale price and in the average number of transactions (Fig. 7 and Tab. 2).

Figure 6 shows the distribution of the debt-to income ratio (DTI) and of the LSTI ratio just before and 25 years after the adoption of the measures. The policy shocks have

[44] And cross-sectional standard deviations were also computed.

a direct impact on the cross-sectional distributions; the LSTI distribution gets squeezed below the 30% cap with a noticeable peak just below this threshold.

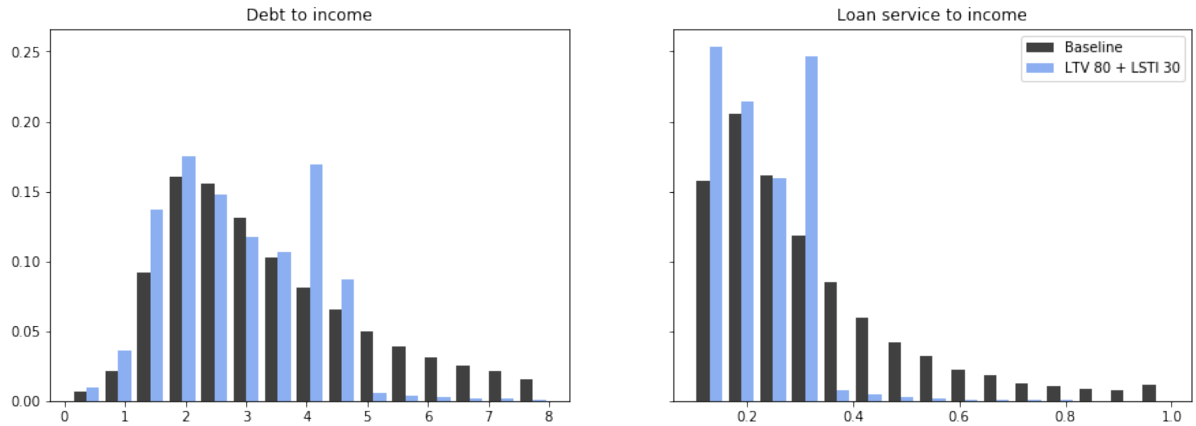

Fig. 6. Monte Carlo average simulated distributions of debt to income and loan service to income as impacted by the combined (loan to value and loan service to income ratio caps) macroprudential policy interventions. The histograms compare the baseline and the 25 years post-intervention distributions.

The mechanism behind the overall effects on the real estate cycle relies on the lower demand for housing (and lower credit), and such effects tend to be moderately amplified by a positive feedback induced by the adaptive expectations on house prices (Baptista et al., 2016, Cokayne, 2019). Over the medium-term, the restrictive effect of the macroprudential policy is mitigated by the endogenous reduction in the interest rate on mortgages, due to lower demand for credit and constant credit supply (equation 10).

Looking more closely at the impact of these measures on the Italian housing market, we conclude that it is overall quite modest in size. In fact, the introduction of an 80% LTV limit induces a reduction in the average sale price and in the number of transactions of just 2% after 5 years. Moreover, over a longer horizon, these effects tend to fade out. A 30% LSTI cap produces even smaller effects.

The impact of these measures on the level of the average household debt and on the number of defaults builds up over time, but even after several years it remains quite small. In particular, after the first 5 years the effect of the LTV limit on the share of new mortgage defaults over the total number of mortgages is extremely small (less than 1.5 basis points from a baseline of 80 basis points), as that on the average borrower debt-to-income ratio (just 0.05 percentage points from 3.677). After 25 years, when all mortgages granted before the policy intervention come to maturity, the effect is larger, but still of little economic significance (10 basis points reduction in the share of defaults; 0.12 percentage points in DTI). The impact of a 30 per cent LSTI limit are significantly smaller both on household debt and defaults.

The overall low magnitude of these effects reflects the well documented financial resilience of Italian households (Attinà, Franceschi, and Michelangeli, 2020), and their low debt compared to other European countries. The baseline number of defaults is already quite low, even before any policy intervention, and it reflects the long-run average flow of bad loans (mortgages) for Italian households.

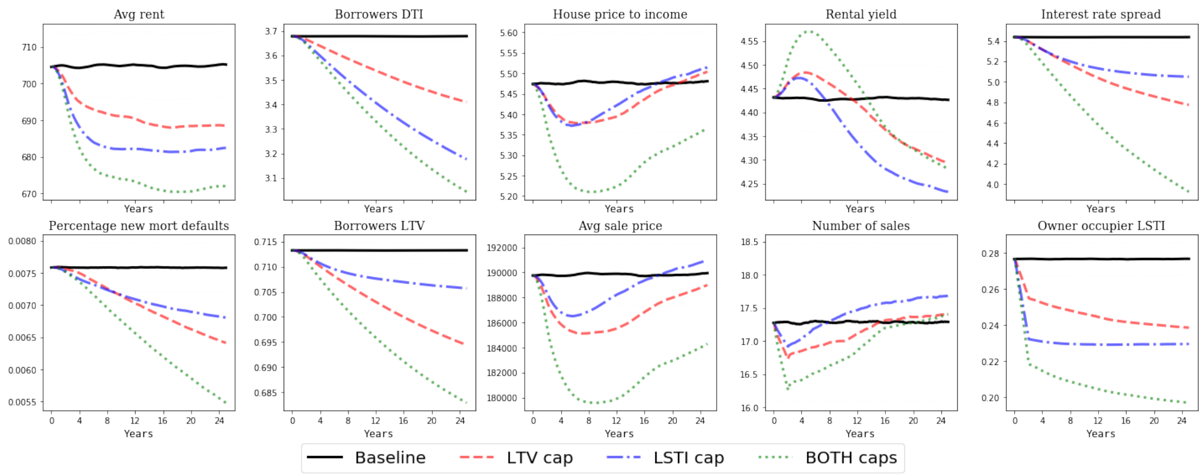

Fig. 7. Model dynamics as affected by policy shocks.

Table 2. Quantitative variations, due to policy interventions, to a selection of endogenous variables.

	LTV 80%			LSTI 30%			BOTH		
	+5yrs	+10yrs	+15yrs	+5yrs	+10yrs	+15yrs	+5yrs	+10yrs	+15yrs
Average rent	−1.52 %	−1.94 %	−2.26 %	−2.67 %	−3.22 %	−3.24 %	−3.60 %	−4.38 %	−4.73 %
Borrowers DTI	−0.05 pp	−0.12 pp	−0.17 pp	−0.11 pp	−0.23 pp	−0.33 pp	−0.13 pp	−0.29 pp	−0.43 pp
House price to income	−0.09 pp	−0.09 pp	−0.05 pp	−0.10 pp	−0.08 pp	−0.02 pp	−0.24 pp	−0.26 pp	−0.21 pp
Rental yield	0.05pp	0.01pp	−0.05 pp	0.04pp	−0.05 pp	−0.14 pp	0.14pp	0.07pp	−0.04 pp
Interest rate spread	−0.16 pp	−0.34 pp	−0.48 pp	−0.15 pp	−0.28 pp	−0.34 pp	−0.33 pp	−0.72 pp	−1.04 pp
Percentage new defaults	−1.41 bp	−4.37 bp	−7.19 bp	−2.23 bp	−4.24 bp	−5.87 bp	−3.12 bp	−8.28 bp	−13.0 bp
Borrowers LTV	−0.41 pp	−0.86 pp	−1.26 pp	−0.32 pp	−0.52 pp	−0.61 pp	−0.73 pp	−1.48 pp	−2.10 pp
Average sale price	−2.26 %	−2.43 %	−1.73 %	−1.67 %	−1.24 %	−0.34 %	−4.72 %	−5.39 %	−4.54 %
Number of sales	−2.24 %	−1.65 %	−0.13 %	−0.94 %	0.65%	1.51%	−4.68 %	−3.29 %	−0.97 %
Owner occupier LSTI	−2.55 pp	−6.38 pp	−7.02 pp	−4.62 pp	−4.74 pp	−4.76 pp	−6.38 pp	−7.02 pp	−7.47 pp

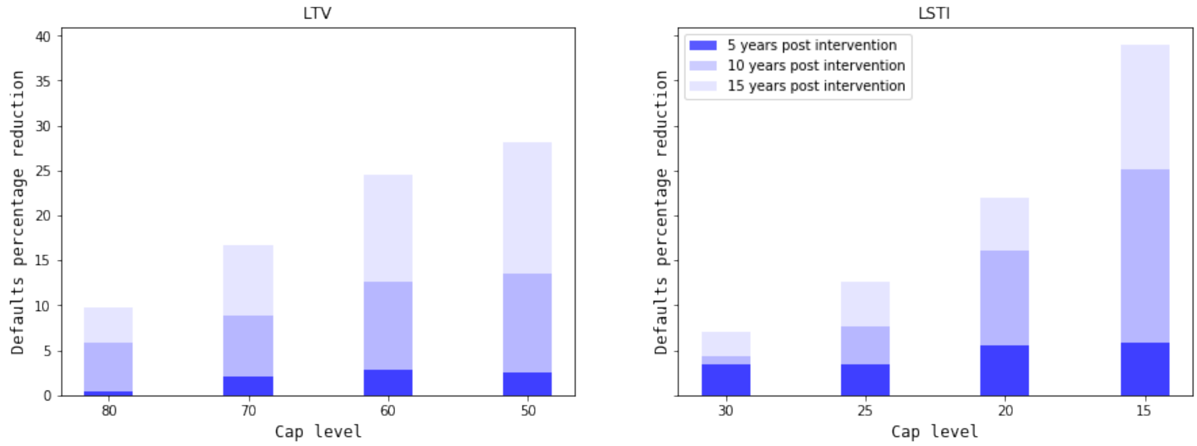

Fig. 8. The effects on default rates of progressively stricter macroprudential caps on LTV and LSTI ratios.

A joint adoption of both policies produces stronger effects than either of the policies in isolation in terms of debt to income ratio, of number of defaults, and of sale prices. The effects are however still rather modest after 5 years, which would likely represent a reasonable time-horizon for the view of a macroprudential authority. Only after more than 15 years the effects of this policy would have some economic relevance.

However, in more general terms, it is interesting to observe that the combined policy adoption, compared to either policy in isolation, seems to result in lower defaults at the cost of milder effects on some variables that may be correlated to households' welfare (such as the number of transactions or number of mortgage approvals). This kind of considerations suggests that the ABM framework may also contribute to the discussion on the optimal design of macroprudential policies and on their welfare implications.

Given the very limited size of the impact of these macroprudential policies, we sought to determine the least restrictive cap levels that would be necessary in order to reach a significant reduction in defaults in the short to medium term. We conducted a sequence of experiments with progressively stricter caps on LTV and LSTI ratios. We found that within a 5 years horizon it is almost impossible to achieve a reduction in defaults that is significantly larger than 5%, even with very restrictive policies (Figure 8). This is because these policies only affect newly issued mortgages and because of the baseline low level of mortgage defaults. Over the longer term (10 to 15 years), significant reductions in defaults (in the order of 35 to 40%) would only be possible with very restrictive policies, such as a 15% LSTI cap or a 40% LTV cap. However, these measures would be unprecedented:

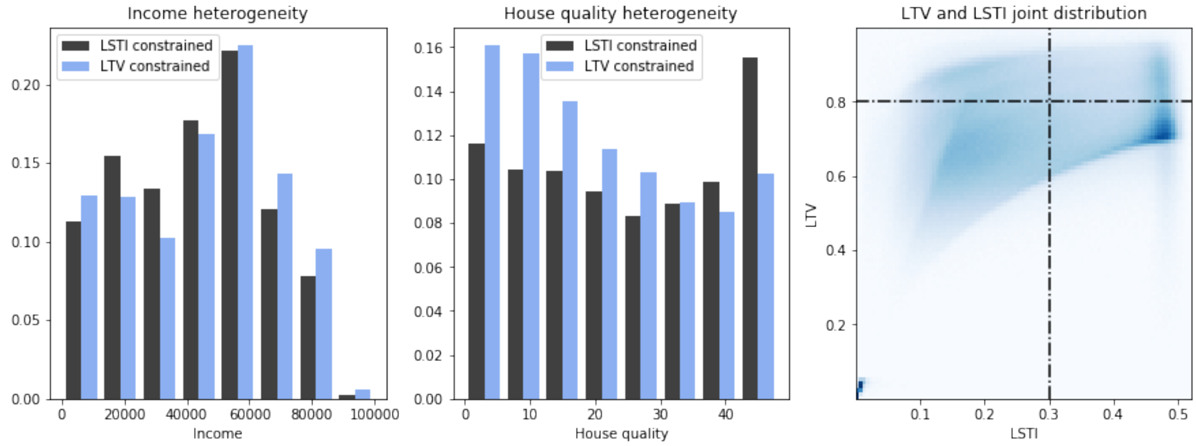

Fig. 9. The first two figures from the left highlight the income and current house quality preference for constrained individuals under the LTV and LSTI policy interventions. The rightmost figure shows the joint distribution of the Monte Carlo average of the LTV and LSTI ratios in the baseline steady state simulation.

to the best of our knowledge, no country in Europe has ever adopted borrower-based measures that are even close to these levels. Moreover, a 15% LSTI cap or of a 40% LTV cap would have extremely high costs (freeze of the real estate market, collapse of banks' profits, limited house affordability by households) and might, in turn, increase risks to financial stability.

In similar ABM frameworks, some researchers have argued that the difference in the magnitude of the effects of different borrower-based macroprudential policies is due to the number of agents constrained (Cokayne, 2019). We don't find support for this observation: as shown in figure 9, in our simulation the number of agents constrained by the LSTI cap is higher than those constrained by the LTV cap and yet the effects of the former are stronger. It seems that the intensive margin, meaning how much the macroprudential measures change the behaviour of constrained agents, matters as well. However, further research is required to elucidate the channels through which this result emerges. Moreover, it is important to highlight that for the present study, only the first moment of the LTV and LSTI distributions has been calibrated and some differences between empirical and simulated moments persist (please refer to the validation in table 1 and to the calibrated moments in table 4). An even more refined calibration, that would take into account the distributional characteristics of the Italian households (especially in terms of indebtedness), would help in shedding light on the different effects of these policy interventions and yield a more reliable parallel with the Italian economy.

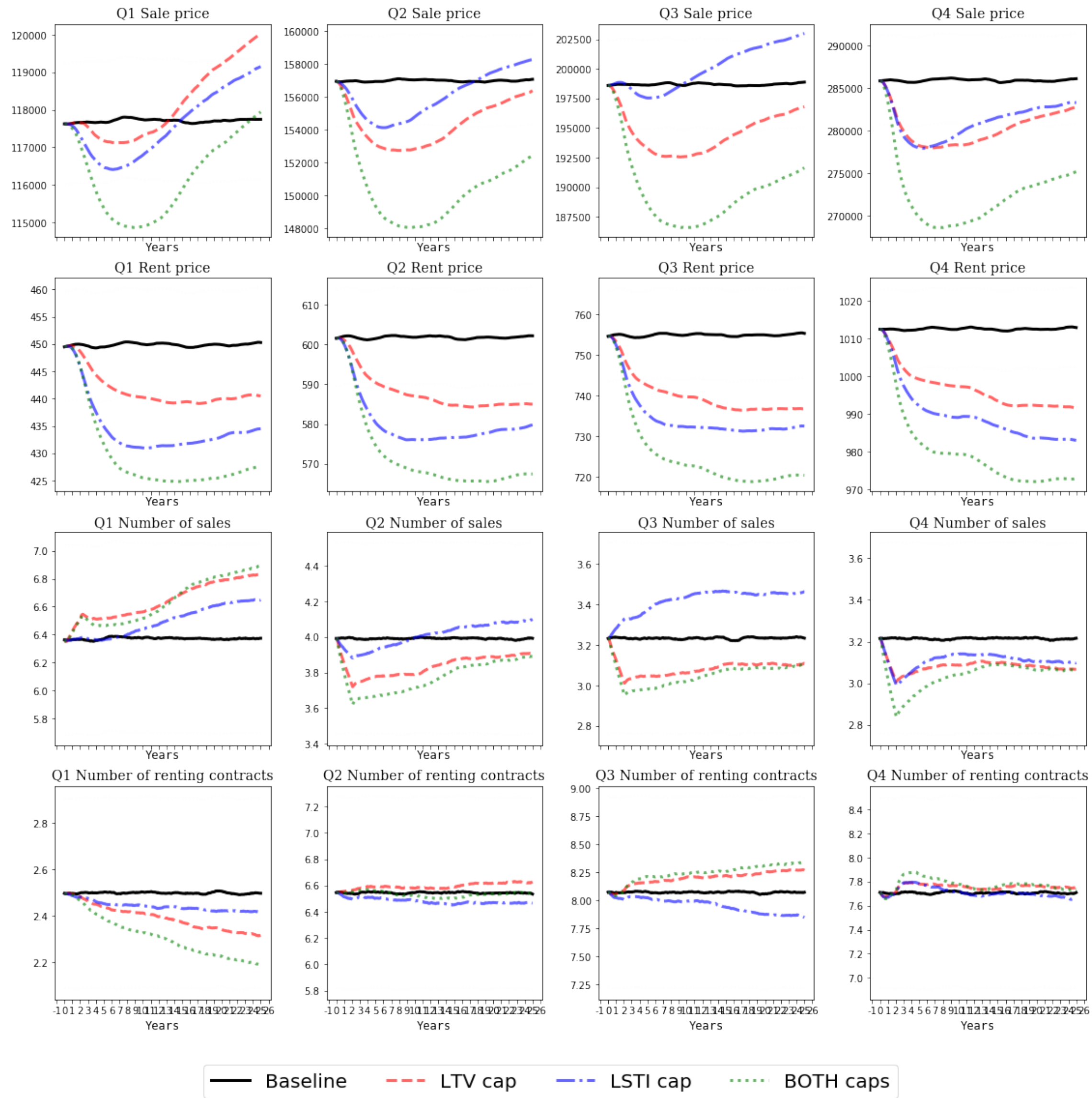

Fig. 10. Housing market segments as affected by policy shocks.

So far we have discussed the average effects of the two policies. However, our ABM approach also allows to get insights on the distributional consequences of these macroprudential measures. In fact, even if the effects of the LTV and LSTI caps are small, some interesting insights emerge when looking at the different market segments and household income quantiles. Figure 9 shows graphical evidence of the income and of the house quality heterogeneity among individuals constrained by the two policies in our simulations. The LTV cap, compared to the LSTI cap, constrains individuals more likely to own a lower quality dwelling. Figure 10 shows how each house-quality quartile is affected by the macroprudential policies. The restrictive policies induce a general re-allocative effect toward lower quality properties. These experience a less severe decline in prices and in the number of transactions. We observe that this effect is modulated by the household heterogeneity. As the individuals constrained by the LSTI cap are particularly concentrated in the highest housing-quality quartile, the policy induces an increase in prices in the third quartile. Considering the other policy intervention,[45] the lowest quality houses experience a more pronounced increase in prices over the medium term. Hence, housing quality levels with an higher concentration of constrained households, experience a more severe shift in demand. We conclude that, macroprudential policies that have similar aggregate effects may impact income quantiles and market segments differently. ABMs can contribute to shed light on the distributional effects of macroprudential policies.

6.4 An alternative parameter vector

As can be seen from table 1, the distance between some simulated policy-sensitive variables (especially the mean LTV and LSTI) and their empirical counterparts is not insignificant. As mentioned before, the research on the formal calibration[46] of an economic ABM, although very active, hasn't reached maturity yet[47]. Moreover, there are still no published examples of a successful formal calibration of a large-scale macroeconomic ABM or of an ABM belonging to the same family as the one presented in this paper.

[45] Where the LTV-constrained households are more concentrated in lower quality quartiles.

[46] Here "formal" is opposed to an "ad-hoc" or "by-hand" calibration that is often performed on macroeconomic ABMs.

[47] See for example Platt, 2019 or Grazzini, Richiardi, and Tsionas, 2017.

This is due to the fact that such a procedure is computationally very expensive[48] while the methodologies aren't as refined as those available for other modeling approaches.

Still, to address the concern that our results are significantly driven by the calibration of the most sensitive policy relevant variables, we study an alternative but suboptimal paramter vector[49]. It has a better fit of the mean LTV and LSTI at the expense of a lower accuracy for the house price autocorrelations[50] (table 3).

Table 3. A comparison of empirical and simulated moments for an alternative parameter vector. All simulated moments pertain to endogenous variables of the model.

Variable	Observed values	Simulated values
House prices mean	186,469	182,241
House prices std dev	9,258	6,748
House prices AC 6mo	0.931	0.21
House prices AC 12mo	0.742	0.109
House prices AC 24mo	0.22	0.122
Mortgage interest rate	0.047	0.044
Rental yield	0.042	0.036
Borrowers DTI	3.500	3.758
Percentage new mortgages defaults	0.012	0.008
All annual tot income	31,400	31,241
Borrowers LTV	0.620	0.655
Owner occupier LSTI	0.320	0.300

Using the alternative parameter vector, we run the policy experiments described in the previous sections (LTV, LSTI caps and their joint adoption). In particular, we compare the dynamics of the flow of new mortgage defaults, as this is the main outcome variable from the policy perspective (figure 11).

It can be clearly seen that, from a qualitative point of view, the overall dynamics are compatible. Moreover, from a quantitative point of view, the magnitude of the reduction of the new defaults is comparable. We notice that, when using the alternative parameter vector, the LSTI cap results in a more pronounced effect (and this is due to the higher average LSTI). Finally, the overall effect of the joint adoption of both policies is similar.

[48] Our calibration procedure took more than three months of continuous computation to complete on a 32-cores machine.

[49] One of those explored during the execution of the calibration procedure.

[50] Which are not crucial for the dynamics of the main policy outcome variable: the flow of new mortgage defaults.

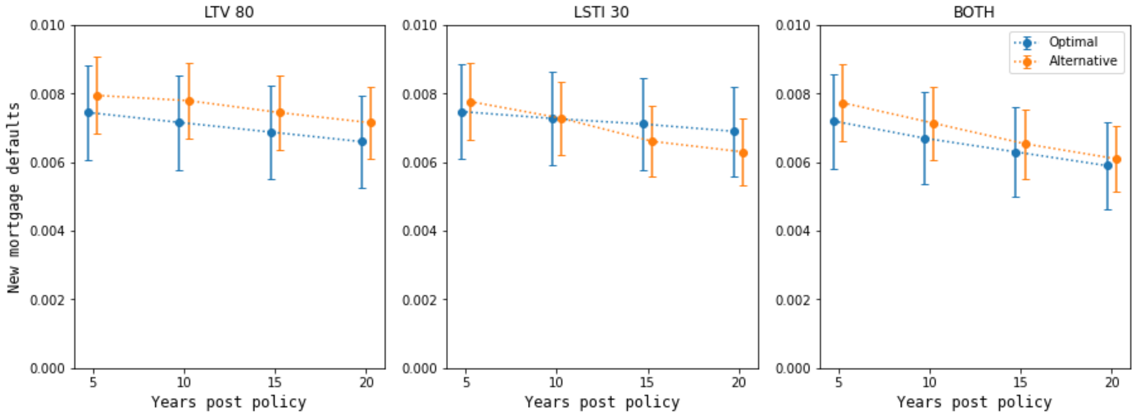

Fig. 11. Comparison of policy reactions. The vertical bars mark a one standard deviation interval around the MC mean.

We conclude that, while the model calibration can still be improved, the main policy conclusions drawn in the previous sections are robust to small variations in the calibrated values of the average LTV an LSTI.

7 Concluding remarks

We adapt, extend and calibrate an ABM for the Italian housing market that is based on Baptista et al., 2016. We use the calibrated model to evaluate the effects of two borrower-based macroprudential policies and of their joint adoption.

From the methodological perspective, our main contribution to the existing literature is twofold: we are the first to use a formal calibration approach to a large scale ABM of the housing and credit markets; we design and use a novel parameter search strategy. Our results prove that it is feasible to validate a large scale ABM as to fit empirical data.

From the policy-oriented standpoint, we contribute to the debate on borrower-based measures by analyzing the effects of an 80% LTV limit, of a 30% LSTI limit, and of their joint adoption. We find that all these policies induce the expected responses: a slow-down of the credit cycle, a reduction in households' debt and a decrease in mortgage defaults. Our results confirm, therefore, that borrower-based measures are an important component of the macroprudential toolikit and should be readily available to the macroprudential authority.

However, once the model is calibrated to fit the statistical properties of the Italian housing market, the effects of LTV and LSTI limits are very small, and no needs for their adoption in the near-term emerge. Overall, our results are consistent with the low indebtedness of Italian households and with the weak conditions of the Italian real estate market.

Moreover, we find that the restrictive macroprudential measures induce a general shift in demand toward lower quality properties. This re-allocative effect, due to household heterogeneity, is stronger for market segments with an higher concentration of constrained households.

Finally, in regards to the modeling approach, we support the view that agent-based models may enrich the policy maker toolkit by providing complementary insights, in particular by allowing analysis on the heterogeneous effects of macroprudential policies.

8 Appendix

8.1 Moments used for indirect calibration

As mentioned before, moment-base estimation methodologies can be criticized for the arbitrary choice of moment conditions. While many moment vectors could have been chosen, we settled for those in table 4. Our choice has been determined by notable works in the economic ABM literature, like Chen and Lux, 2018 and Franke, 2009, and by the data availability.

In regards to the sample empirical moments, we sought to use a sufficiently long time window as to wash out cyclical effects. Empirical moments are computed on monthly observations from 2006 to 2018[51].

Table 4. Vector of moments used in calibration. This vector is the basis on which the vector $\boldsymbol{g}(\boldsymbol{\theta})$ in (16) is built. While all moments refer to the relevant time-series, each observation refers to the cross-sectional mean.

Variable	Description	Moment
House prices	The average house price. It is computed as the average of the average transaction value for each quality level.	Mean
-	-	Standard deviation
-	-	Skewness
-	-	Kurtosis
-	-	1 month autocorrelation
-	-	6 months Autocorrelation
-	-	12 months Autocorrelation
-	-	18 months Autocorrelation
-	-	24 months Autocorrelation
Rental yield	Rental yield	Mean
Interest rate spread	The spread that the Bank applies on top of the basic Central Bank lending rate.	Mean
LTV	Cross-sectional mean of the loan-to-value.	Mean
LSTI	Cross-sectional mean of the loan-service-to-income ratio.	Mean
New defaults ratio	Ratio of the number of defaulted mortgages over the total number of mortgages.	Mean

[51] For house prices the time window spans 2005 to 2018.

8.2 Trajectory stability

Trajectories' coefficient of variation

Figure 12 shows how the time-series variability of the cross-sectional ensemble mean, at the steady state, decreases as the ensemble size increases (thus employing more trajectories generated using different random seeds). We measured the variability using the coefficient of variation. All endogenous variables show a similar behaviour: with a moderate ensemble size of 100 or more, the coefficient of variation drops below one percent.

Bank's reactivity parameter

Figure 13 shows that the steady state values of the model's endogenous variables are the same across two different Bank reaction parameter. In our experiments we used the 'Calibrated' version. The original version of the model would require more than a millennium to reach the steady state. The very long transient phase would more than double the time required to indirect-calibrate the model.

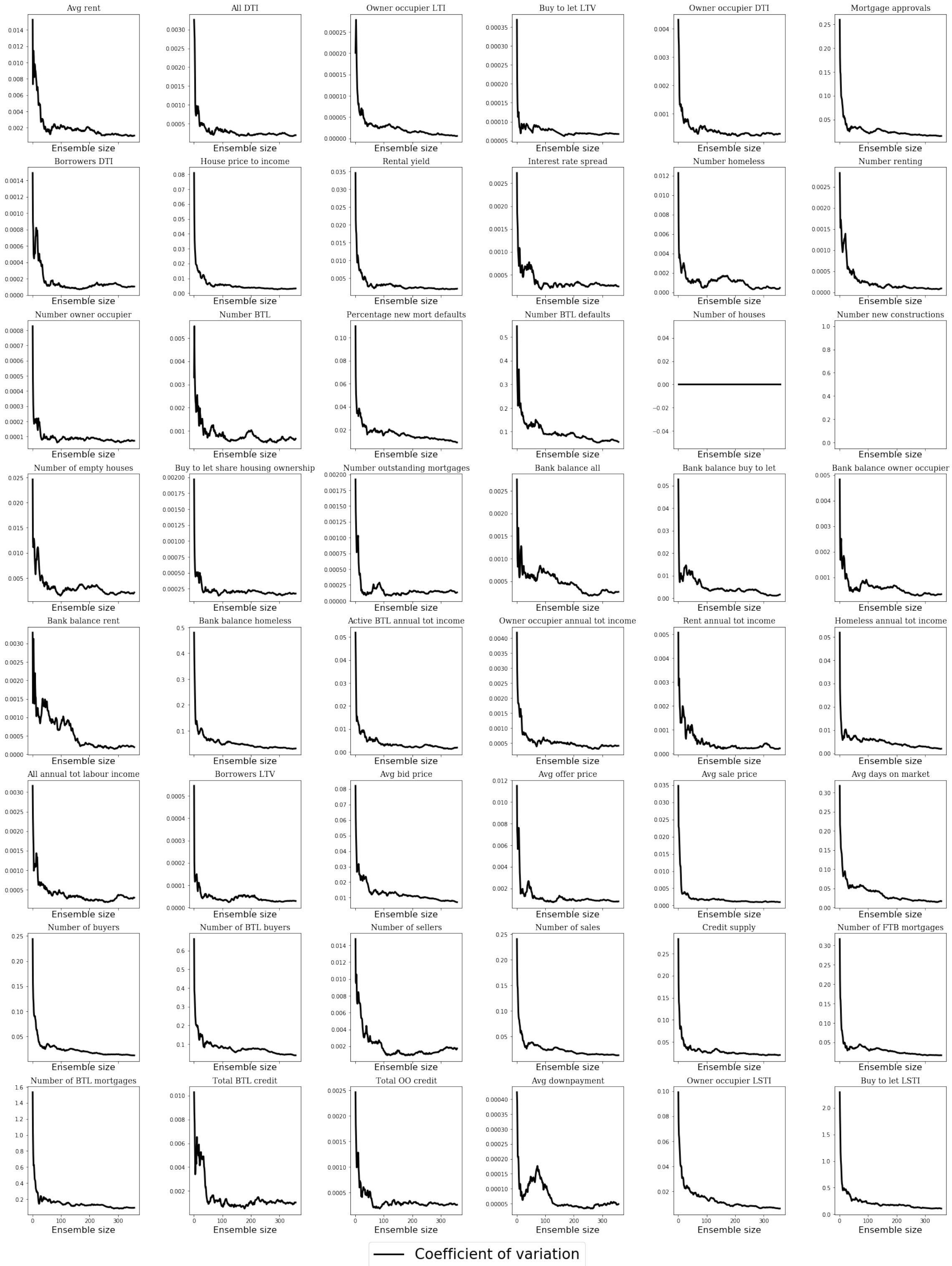

Fig. 12. Time-series variability at the steady state drops as the ensemble size increases.

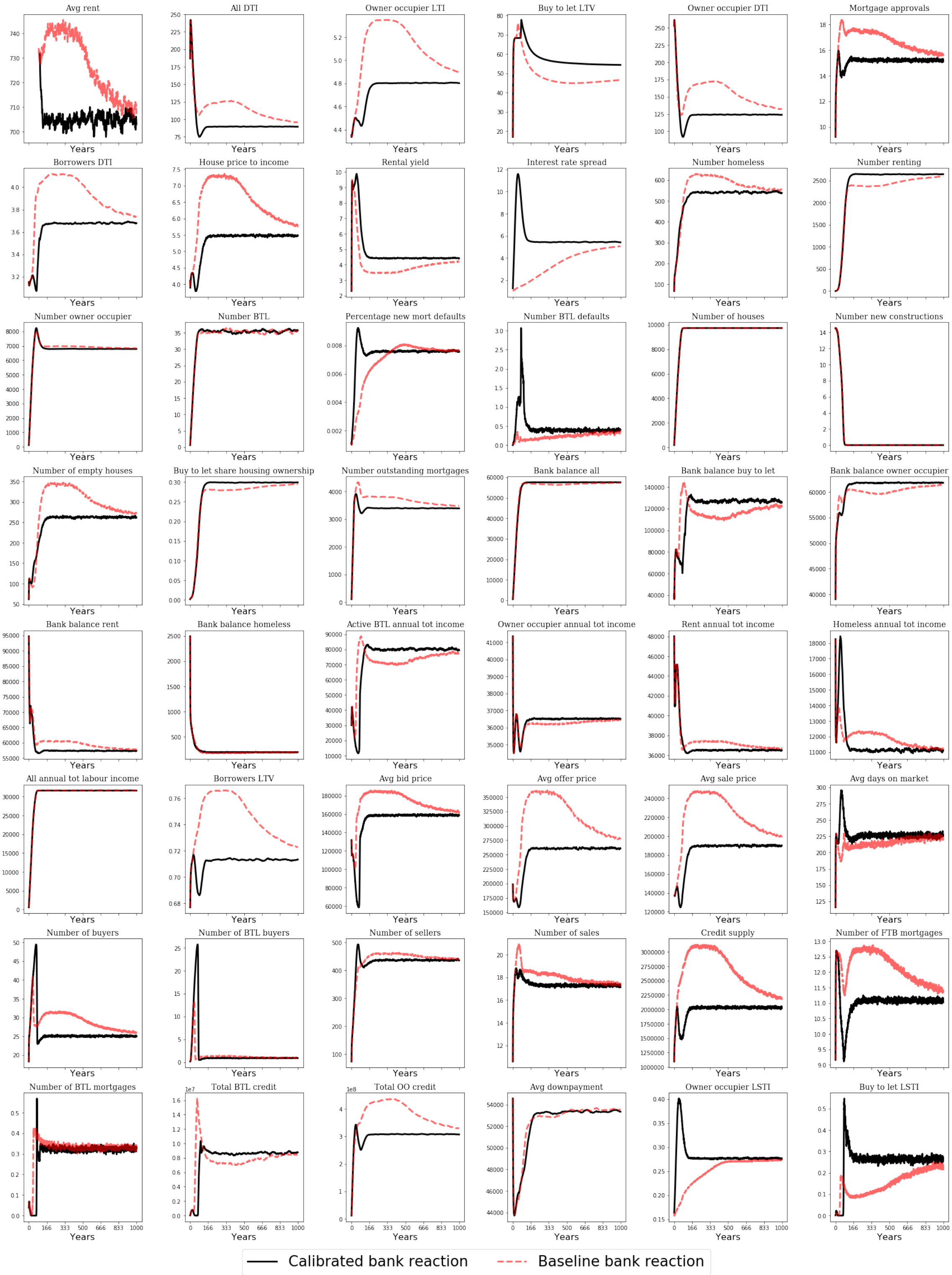

Fig. 13. Different dynamics as impacted by the Bank's reaction parameter.

8.3 Remarks on model validation

Axtell and Epstein, 1994 and Barde and Hoog, 2017 proposed a general classification scheme to evaluate the degree of empirical validity of an ABM:

Level 0: The model is a caricature of reality. Proven via simple graphical devices (eg: agents motion).

Level 1: The model is in qualitative agreement with empirical macro structures. Proven showing qualitative matching between simulated and empirical macro structures (eg: stylised facts matching).

Level 2: The model is in quantitative agreement with empirical macro structures. Proven via statistical procedures (refer eg to Platt, 2019 for a comparison of calibration procedures).

Level 3: The model is in quantitative agreement with empirical micro structures. Proven via cross-sectional and longitudinal analysis of the agent population.

Both Barde and Hoog, 2017 and Fagiolo, Guerini, et al., 2017 note that the most recent literature on economics ABM is in the process of transitioning from the 'Level 1' to the 'Level 2' empirical validation[52].

This model keeps the core mechanics of the model described in Baptista et al., 2016, as described in earlier paragraphs. Hence we assume that 'Level 0' and 'Level 1' validation is achieved, as it is the case for their model. We sought to assess the degree of empirical validation against the 'Level 2' definition. To this end we computed the validation table 1.

In the existing literature there are no examples of 'Level 2' validated large-scale economics ABMs. We improved upon the existing literature on models derived from Baptista et al., 2016 and our results show a progress towards a 'Level 2' empirical validation.

[52] They further note that the objective is to transition to 'Level 3' validation. They observe that one of the main reasons for the difficulty in reaching this objective is the lack of sufficient granular data.

8.4 Parameter vector and data sources

Table 5: The entire set of parameters of the model.

Parameter	Description	Calibration
	Housing market parameters	
BIDUP	Smallest proportional increase in price that can cause a gazump.	Set to zero as it has been noted that in Italy this phenomenon is not significant.
MARKET AVERAGE PRICE DECAY	Decay constant for the exponential moving average of sale prices	Indirectly calibrated.
INITIAL HPI	Initial housing price index (HPI).	Left at 1.0.
HPI MEDIAN	Median house price.	Calibrated using the Italian data value 185899 Eur.
HPI SHAPE	Shape parameter for the log-normal distribution of housing prices.	Calibrated using the Italian data value 0.468.
RENT GROSS YIELD	Rental yield for buy-to-let investors.	Calibrated using the Italian data value 0.042.
	Demographic parameters	
TARGET POPULATION	Target number of households.	Set to 10000 as in Baptista et al., 2016.
FUTURE BIRTH RATE	Births per year per capita.	Set to 0.018 as in Baptista et al., 2016.
DATA DEATH PROB GIVEN AGE	Distribution of death probability given age.	Calibrated using the Italian data.
	Household parameters	
RETURN ON FINANCIAL WEALTH	Monthly return on financial wealth. Compounds the current account balance.	Since it is wealth that can be liquidated without loss it must be a liquid investment. Hence we set it to short term govt bonds: 0.00167.
TENANCY LENGTH AVERAGE	Average number of months a tenant will stay in a rented house.	Calibrated it with the Italian data value: 144 months.
TENANCY LENGTH EPSILON	Standard deviation of the noise in determining the tenancy length. This is the cross-sectional variation in tenancy length.	We used the standard deviation of the Italian time series of the cross-sectional mean: 24 months.
	Household behaviour parameters	

Continuation of Table 5

Parameter	Description	Calibration
P INVESTOR	Probability of being endowed with the buy-to-let gene.	Calibrated it with the Italian data value: 0.02.
MIN INVESTOR PERCENTILE	Minimum income percentile for a household to be a buy-to-let investor.	Calibrated it with the Italian data value: 0.85.
FUNDAMENTALIST CAP GAIN COEFF	Buy-to-let households weight on capital gain in their choices if fundamentalists.	Indirectly calibrated.
TREND CAP GAIN COEFF	Buy-to-let households weight on capital gain in their choices if trend-follower.	Indirectly calibrated.
P FUNDAMENTALIST	Probability that a BTL investor is a fundamentalist versus a trend-follower.	Indirectly calibrated.
	Renting parameters	
PSYCHOLOGICAL COST OF RENTING	'Utility funct cost' of renting compared to buying a house.	Indirectly calibrated.
SENSITIVITY RENT OR PURCHASE	Sensitivity parameter in the choice of renting compared to buying a house.	Indirectly calibrated.
	General parameters	
BANK BALANCE FOR CASH DOWNPAYMENT	If the ratio between the buyer's bank balance and the house price is above this, the property will be bought without a mortgage.	Indirectly calibrated.
HPA EXPECTATION FACTOR	A multiplicative factor in agent's extrapolative expectations for house price growth.	Indirectly calibrated.
HPA YEARS TO CHECK	The number of years households consider to compute the expected future house price appreciation.	Indirectly calibrated.
HOLD PERIOD	Average period, in years, for which owner-occupiers hold their houses.	Calibrated it with the Italian data value: 25 years.
	Sale price reduction parameters	
P SALE PRICE REDUCE	Monthly probability of reducing the price of a house on the market if left unsold.	Calibrated it with the Italian data value: 0.089. Source: estimated from immobiliare.it data.
REDUCTION MU	Mean percentage reduction for prices of houses on the market.	Calibrated it with the Italian data value: 0.049. Source: estimated from immobiliare.it data.
REDUCTION SIGMA	Standard deviation of percentage reductions for prices of houses on the market.	Calibrated it with the Italian data value: 0.069. Source: estimated from immobiliare.it data.
	Consumption parameters	

Continuation of Table 5

Parameter	Description	Calibration
CONSUMPTION FRACTION	Fraction of the monthly budget allocated for consumption, being the monthly budget equal to the bank balance minus the minimum desired bank balance.	Indirectly calibrated.
Initial sale price parameters		
SALE MARKUP	Initial markup over average price of same quality houses.	Calibrated it with the Italian data value: 0.133. Source: estimated from immobiliare.it data.
SALE EPSILON	Dispersion (noise) of the initial price offering.	Set to 0.05 as in Baptista et al., 2016.
Buyer's desired expenditure parameters		
BUY SCALE	Multiple of yearly salary an household is willing to spend to buy a house.	Indirectly calibrated.
BUY WEIGHT HPA	Weight given to house price appreciation when deciding how much to spend for buying a house.	Indirectly calibrated.
BUY EPSILON	Standard deviation of the noise.	Indirectly calibrated.
Demanded rent parameters		
RENT MARKUP	Markup over average rent demanded for houses of the same quality.	Calibrated it with the Italian data value: 0.054. Source: estimated from immobiliare.it data.
RENT EPSILON	Standard deviation of the noise.	Indirectly calibrated.
RENT MAX AMORTIZATION PERIOD	Effectively define the minimum expected rental yield buy-to-let investors are willing to accept to buy a property.	Calibrated it with the Italian data on rental yield: 24.9 years.
RENT REDUCTION	Percentage reduction of demanded rent for every month the property is in the market, not rented.	Calibrated it with the Italian data value: 0.042. Source: estimated from immobiliare.it data.
Downpayment parameters		
DOWNPAYMENT MEAN	Average downpayment, as percentage of house price.	Calibrated it with the Italian data value: 0.332.
DOWNPAYMENT EPSILON	Standard deviation of the noise.	Calibrated it with the Italian data value: 0.100.
Desired bank balance parameters		
DESIRED BANK BALANCE BETA	Multiplicative coefficient of the yearly income to establish the desired bank balance	Indirectly calibrated.
Selling decision parameters		

Continuation of Table 5

Parameter	Description	Calibration
DECISION TO SELL HPC	Enters the function that determines the probability to sell a property. Determines the strength of countercyclical effect of the number of houses on the market.	Indirectly calibrated.
DECISION TO SELL INTEREST	Enters the function that determines the probability to sell a property. Determines the strength of countercyclical effect of the prevailing interest rate on mortgages.	Indirectly calibrated.
	Bank parameters	
MORTGAGE DURATION YEARS	Mortgage duration in years.	Set at the approximate Italian duration: 25 years.
BANK INITIAL BASE RATE	The minimum annual interest rate bank may charge on mortgages.	Set at the average ECB's marginal lending facility average rate on the period considered: 0.01.
BANK CREDIT SUPPLY TARGET	Bank's target supply of credit per household per month.	Calibrated it with the Italian data value: 120 Eur per capita.
BANK MAX FTB LTV	Maximum LTV ratio that the private bank would allow for first-time-buyers.	Left at 1.0 in the baseline scenario.
BANK MAX OO LTV	Maximum LTV ratio that the private bank would allow for owner-occupiers.	Left at 1.0 in the baseline scenario.
BANK MAX BTL LTV	Maximum LTV ratio that the private bank would allow for BTL investors.	Left at 1.0 in the baseline scenario.
BANK MAX FTB LTI	Maximum LTI ratio that the private bank would allow for first-time-buyers.	Set to 6.0 as in Baptista et al., 2016.
BANK MAX OO LTI	Maximum LTI ratio that the private bank would allow for owner-occupiers.	Set to 6.0 as in Baptista et al., 2016.
	Central bank parameters	
CENTRAL BANK MAX FTB LTI	Maximum LTI ratio that the central bank would allow for first-time-buyers.	Set to 6.0 as in Baptista et al., 2016.
CENTRAL BANK MAX OO LTI	Maximum LTI ratio that the central bank would allow for owner-occupiers.	Set to 6.0 as in Baptista et al., 2016.
CENTRAL BANK MAX LTV	Maximum LTV ratio that the central bank would allow.	Set at various values to evaluate policies.
CENTAL BANK MAX LSTI	Maximum LSTI ratio that the central bank would allow.	Set at various values to evaluate policies.
	Construction sector parameters	
CONSTRUCTION HOUSES PER HOUSEHOLD	Target ratio of houses per household.	Calibrated it with the Italian data value: 1.02 houses per household.

Continuation of Table 5

Parameter	Description	Calibration
	Lifecycle income parameters	
DATA INCOME GIVEN AGE	Bivariate distribution of income and age.	Calibrated it with the Italian data.

References

Arena, M., T. Chen, S. Choi, N. Geng, C. Anta Gueye, T. Lybek, E. Papageorgiou, and Y. Zhang (2020). "Macroprudential Policies and House Prices in Europe." In: *IMF Working Paper, WP/20/03, International Monetary Fund, Washington, DC.*

Attinà, C., F. Franceschi, and V. Michelangeli (2020). "Modeling households' financial vulnerability with consumer credit and mortgage renegotiations." In: *International Journal of Microsimulation 2020; 13(1); 67–91.*

Axtell, R. L. and J. M. Epstein (1994). "Agent-based modeling: Understanding our creations." In: *he Bulletin of the Santa Fe Institute, 9(2):28–32.*

Baptista, R., J. D. Farmer, M. Hinterschweiger, K. Low, D. Tang, and A. Uluc (2016). "Macroprudential policy in an agent-based model of the UK housing market." In: *Bank of England Staff Working Paper, 619.*

Barde, S. (2017). "A Practical, Accurate, Information Criterion for Nth Order Markov Processes." In: *Computational Economics 50, 281–324.*

Barde, S. and S. van der Hoog (2017). "An empirical validation protocol for large-scale agent-based models." In: *Studies in Economics 1712, School of Economics, University of Kent, July 2017.*

Bologna, P., W. Cornacchia and M. Galardo (2020). "Prudential policies, credit supply and house prices: evidence from Italy". In: *Bank of Italy working papers; N. 1294; September 2020.*

Brunnermeier, M. K. (2009). "Deciphering the Liquidity and Credit Crunch 2007–2008." In: *Journal of Economic Perspectives, Volume 23, Number, Pages 77–100.*

Cassidy, M. and N. Hallissey (2016). "The Introduction of Macroprudential Measures for the Irish Mortgage Market." In: *The economic and social review, policy Section Articles. Vol. 47 No. 2, Summer (2016).*

Chen, Z. and T. Lux (2018). "Estimation of Sentiment Effects in Financial Markets: A Simulated Method of Moments Approach." In: *Computational economics 52, 711–744.*

Cokayne, G. (2019). "The Effects of Macroprudential Policies on House Price Cycles in an Agent-based Model of the Danish Housing Market." In: *Danmarks Nationalbank working paper, No. 138.*

Elbeltagi, E., T. Hegazy and D. Grierson (2005). "Comparison among five evolutionary-based optimization algorithms". In: *Advanced Engineering Informatics, 19, 43–53.*

ESRB, European Systemic Risk Board (2020). *A Review of Macroprudential Policy in the EU in 2019*. Reports of the ESRB. European Systemic Risk Board.

Fagiolo, G., M. Guerini, F. Lamperti, A. Moneta and A. Roventini (2017). “Validation of agent-based models in economics and finance.” In: *LEM Working Paper Series, 23*.

Fagiolo, G., A. Moneta and P. Windrum (2007). “A Critical Guide to Empirical Validation of Agent-Based Models in Economics: Methodologies, Procedures, and Open Problems.” In: *Computational economics, 30, 195-226*.

Fagiolo, G. and A. Roventini (2017). “Macroeconomic policy in dsge and agent-based models redux: New devel- opments and challenges ahead.” In: *Journal of Artificial Societies and Social Simulation, 20*.

Farmer, J. D., D. Foley and P. Windrum (2009). “The economy needs agent-based modelling.” In: *Nature, 460, 685-686*.

Franke, R. (2009). “Applying the method of simulated moments to estimate a small agent-based asset pricing model.” In: *Journal of Empirical Finance, volume 16 issue 5, 804–815*.

Glaeser, E. and C. Nathanson (2017). “An extrapolative model of house price dynamics.” In: *Journal of Financial Economics, 126, 147–170*.

Gobbi, A. and J. Grazzini (2019). “A basic New Keynesian DSGE model with dispersed information: An agent-based approach.” In: *Journal of Economic Behavior & Organization* ***157****, 101–116*.

Grazzini, J., M. G. Richiardi and M. Tsionas (2017). “Bayesian estimation of agent-based models.” In: *Journal of Economic Dynamics & Control.* ***77****, 26–47*.

Greenwald, D. (2018). “The Mortgage Credit Channel of Macroeconomic Transmission.” In: *MIT Sloan Research Paper No. 5184-16*.

Grodecka, A. (2019). “On the Effectiveness of Loan-to-Value Regulation in a Multiconstraint Framework.” In: *Journal of money, credit and banking, Volume 52, Issue 5, 1231-1270*.

Haldane, A. G. and A. E. Turrell (2018). “An interdisciplinary model for macroeconomics.” In: *Oxford Review of Economic Policy, Volume 34, Issue 1-2, Spring-Summer 2018, Pages 219–251*.

Han, L. and W. Strange (2015). “The microstructure of housing markets: Search, bargaining, and brokerage.” In: *Handbook of regional and urban economics, 5, 813–886*.

Hedlund, A. (2016a). “Illiquidity and its discontents: Trading delays and foreclosures in the housing market.” In: *Journal of Monetary Economics, 83, 1–13.*

— (2016b). “The cyclical dynamics of illiquid housing, debt, and foreclosures.” In: *Quantitative Economics, 7, 289–328.*

Iacoviello, M. (2008). “House prices, borrowing constraints, and monetary policy in the business cycle.” In: *American Economic Review, 95, 739–764.*

Iacoviello, M. and M. Neri (2010). “Housing market spillovers: evidence from an estimated DSGE model.” In: *American Economic Journal Macroeconomics, 2, 125–64.*

Kamin, S. B. and L. P. DeMarco (2010). “How Did a Domestic Housing Slump Turn into a Global Financial Crisis?” In: *Federal Reserve, International Finance Discussion Papers, Number 994.*

Kuttner, K. and I. Shim (2016). “Can Non-Interest Rate Policies Stabilize Housing Markets? Evidence from a Panel of 57 Economies.” In: *Journal of Financial Stability, Volume 216(C).*

Lamperti, F. (2015). “An information theoretic criterion for empirical validation of time series models.” In: *LEM Working Paper Series, 2.*

Lamperti, F., A. Roventini and A. Sani (2018). “Agent-Based Model Calibration using Machine Learning Surrogates.” In: *Journal of Economic Dynamics & Control, 90.*

Landvoigt, T., M. Piazzesi and M. Schneider (2015). “The housing market(s) of San Diego.” In: *American Economic Review, 105, 1371–1407.*

Lee, B. S. and B. F. Ingram (1991). “Simulation estimation of time-series models.” In: *Journal of Econometrics, 47 (2 - 3), 197 – 205.*

Niederreiter, H. (1992). *Random number generation and quasi-Monte Carlo methods.* CBMS-NSF Regional Conference Series in Applied Mathematics. SIAM. ISBN: 9781611970081.

Piazzesi, M. and M. Schneider (2016). “Housing and macroeconomics.” In: *Handbook of macroeconomics, 2, 1547–1640.*

Platt, D. (2019). “A Comparison of Economic Agent-Based Model Calibration Methods.” In: *Arxiv, https://arxiv.org/abs/1902.059380.*

Poghosyan, T. (2019). “How Effective is Macroprudential Policy? Evidence from Lending Restriction Measures in EU Countries.” In: *IMF Working Paper, WP/19/45, International Monetary Fund, Washington, DC.*

Riddell, M. (2004). “Housing-market disequilibrium: An examination of housing-market price and stock dynamics.” In: *Journal of Housing Economics, 13(2):120-135.*

Romer, P. (2016). "The Trouble With Macroeconomics." In: *Stern School of Business - New York University working paper*.

Rosenthal, J. S. and G. O. Roberts (2009). "Examples of Adaptive MCMC." In: *Journal of Computational and Graphical Statistics volume 18, issue 2 349–367*.

Sloan, I. H. and X. Wanga (2008). "Low discrepancy sequences in high dimensions: How well are their projections distributed?" In: *Journal of Computational and Applied Mathematics, 213, 366–386*.

Tesfatsion, L. (2006). "Agent-based computational economics: a constructive approach to economic theory." In: *Handbook of Computational Economics, Volume 2, chapter 16*.

— (2017). "Modeling Economic Systems as Locally-Constructive Sequential Games." In: *Iowa State University Economics Working Papers, number 17022*.

Vines, D., S. Wills, O. Blanchard, S. Wren-Lewis, J. E. Stiglitz, R. Wright, R. Reis, P. Krugman, W. Carlin, D. Soskice, F. Ghironi, A. G. Haldane and A. E. Turrell (2018). *Rebuilding macroeconomic theory.* Oxford Review of Economic Policy, volume 34, numbers 1-2. Oxford university press.

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ARNAUDO D., G. MICUCCI, M. RIGON and P. ROSSI, *Should I stay or should I go? Firms' mobility across banks in the aftermath of the financial crisis,* Italian Economic Journal / Rivista italiana degli economisti, v. 5, 1, pp. 17-37, **WP 1086 (October 2016).**

BASSO G., F. D'AMURI and G. PERI, *Immigrants, labor market dynamics and adjustment to shocks in the euro area,* IMF Economic Review, v. 67, 3, pp. 528-572, **WP 1195 (November 2018).**

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BURLON L., A. NOTARPIETRO and M. PISANI, *Macroeconomic effects of an open-ended asset purchase programme,* Journal of Policy Modeling, v. 41, 6, pp. 1144-1159, **WP 1185 (July 2018).**

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CIANI E., F. DAVID and G. DE BLASIO, *Local responses to labor demand shocks: a re-assessment of the case of Italy,* Regional Science and Urban Economics, v. 75, pp. 1-21, **WP 1112 (April 2017).**

CIANI E. and P. FISHER, *Dif-in-dif estimators of multiplicative treatment effects,* Journal of Econometric Methods, v. 8. 1, pp. 1-10, **WP 985 (November 2014).**

CIAPANNA E. and M. TABOGA, *Bayesian analysis of coefficient instability in dynamic regressions,* Econometrics, MDPI, Open Access Journal, v. 7, 3, pp.1-32, **WP 836 (November 2011).**

COLETTA M., R. DE BONIS and S. PIERMATTEI, *Household debt in OECD countries: the role of supply-side and demand-side factors,* Social Indicators Research, v. 143, 3, pp. 1185–1217, **WP 989 (November 2014).**

COVA P., P. PAGANO and M. PISANI, *Domestic and international effects of the Eurosystem Expanded Asset Purchase Programme,* IMF Economic Review, v. 67, 2, pp. 315-348, **WP 1036 (October 2015).**

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FOA G., L. GAMBACORTA, L. GUISO and P. E. MISTRULLI, *The supply side of household finance,* Review of Financial Studies, v.32, 10, pp. 3762-3798, **WP 1044 (November 2015).**

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PANCRAZI R. and M. PIETRUNTI, *Natural expectations and home equity extraction,* Journal of Housing Economics, v. 46, 4, **WP 984 (November 2014).**

PEREDA FERNANDEZ S., *Teachers and cheaters. Just an anagram?*, Journal of Human Capital, v. 13, 4, pp. 635-669, **WP 1047 (January 2016).**

RIGGI M., *Capital destruction, jobless recoveries, and the discipline device role of unemployment,* Macroeconomic Dynamics, v. 23, 2, pp. 590-624, **WP 871 (July 2012).**

2020

ALESSANDRI P. and M. BOTTERO, *Bank lending in uncertain times,* R European Economic Review, V. 128, **WP 1109 (April 2017).**

ANTUNES A. and V. ERCOLANI, *Public debt expansions and the dynamics of the household borrowing constraint,* Review of Economic Dynamics, v. 37, pp. 1-32, **WP 1268 (March 2020).**

ARDUINI T., E. PATACCHINI and E. RAINONE, *Treatment effects with heterogeneous externalities,* Journal of Business & Economic Statistics, , v. 38, 4, pp. 826-838, **WP 974 (October 2014).**

BOLOGNA P., A. MIGLIETTA and A. SEGURA, *Contagion in the CoCos market? A case study of two stress events,* International Journal of Central Banking, v. 16, 6, pp. 137-184, **WP 1201 (November 2018).**

BOTTERO M., F. MEZZANOTTI and S. LENZU, *Sovereign debt exposure and the Bank Lending Channel: impact on credit supply and the real economy,* Journal of International Economics, v. 126, article 103328, **WP 1032 (October 2015).**

BRIPI F., D. LOSCHIAVO and D. REVELLI, *Services trade and credit frictions: evidence with matched bank – firm data,* The World Economy, v. 43, 5, pp. 1216-1252, **WP 1110 (April 2017).**

BRONZINI R., G. CARAMELLINO and S. MAGRI, *Venture capitalists at work: a Diff-in-Diff approach at late-stages of the screening process,* Journal of Business Venturing, v. 35, 3, **WP 1131 (September 2017).**

BRONZINI R., S. MOCETTI and M. MONGARDINI, *The economic effects of big events: evidence from the Great Jubilee 2000 in Rome,* Journal of Regional Science, v. 60, 4, pp. 801-822, **WP 1208 (February 2019).**

COIBION O., Y. GORODNICHENKO and T. ROPELE, *Inflation expectations and firms' decisions: new causal evidence,* Quarterly Journal of Economics, v. 135, 1, pp. 165-219, **WP 1219 (April 2019).**

CORSELLO F. and V. NISPI LANDI, *Labor market and financial shocks: a time-varying analysis,* Journal of Money, Credit and Banking, v. 52, 4, pp. 777-801, **WP 1179 (June 2018).**

COVA P. and F. NATOLI, *The risk-taking channel of international financial flows,* Journal of International Money and Finance, v. 102, **WP 1152 (December 2017).**

D'ALESSIO G., *Measurement errors in survey data and the estimation of poverty and inequality indices,* Statistica Applicata - Italian Journal of Applied Statistics, v. 32, 3, **WP 1116 (June 2017).**

DEL PRETE S. and S. FEDERICO, *Do links between banks matter for bilateral trade? Evidence from financial crises,* Review of World Economic, v. 156, 4, pp. 859 - 885, **WP 1217 (April 2019).**

D'IGNAZIO A. and C. MENON, *The causal effect of credit Guarantees for SMEs: evidence from Italy,* The Scandinavian Journal of Economics, v. 122, 1, pp. 191-218, **WP 900 (February 2013).**

ERCOLANI V. and F. NATOLI, *Forecasting US recessions: the role of economic uncertainty,* Economics Letters, v. 193, **WP 1299 (October 2020).**

MAKINEN T., L. SARNO and G. ZINNA, *Risky bank guarantees,* Journal of Financial Economics, v. 136, 2, pp. 490-522, **WP 1232 (July 2019).**

MODENA F., E. RETTORE and G. M. TANZI, *The effect of grants on university dropout rates: evidence from the Italian case,* Journal of Human Capital, v. 14, 3, pp. 343-370, **WP 1193 (September 2018).**

NISPI LANDI V., *Capital controls spillovers,* Journal of International Money and Finance, v. 109, **WP 1184 (July 2018).**

PERICOLI M., *On risk factors of the stock–bond correlation,* International Finance, v. 23, 3, pp. 392-416, **WP 1198 (November 2018).**

RAINONE E., *The network nature of OTC interest rates,* Journal of Financial Markets, v.47, article 100525, **WP 1022 (July 2015).**

RAINONE E. and F. VACIRCA, *Estimating the money market microstructure with negative and zero interest rates,* Quantitative Finance, v. 20, 2, pp. 207-234, **WP 1059 (March 2016).**

RIZZICA L., *Raising aspirations and higher education. Evidence from the UK's widening participation policy,* Journal of Labor Economics, v. 38, 1, pp. 183-214, **WP 1188 (September 2018).**

SANTIONI, R., F. SCHIANTARELLI and P. STRAHAN, *Internal capital markets in times of crisis: the benefit of group affiliation*, Review of Finance, v. 24, 4, pp. 773-811, **WP 1146 (October 2017).**

SCHIANTARELLI F., M. STACCHINI and P. STRAHAN, *Bank Quality, judicial efficiency and loan repayment delays in Italy,* Journal of Finance , v. 75, 4, pp. 2139-2178, **WP 1072 (July 2016).**

2021

ALBANESE G., E. CIANI and G. DE BLASIO, *Anything new in town? The local effects of urban regeneration policies in Italy,* Regional Science and Urban Economics, v. 86, **WP 1214 (April 2019).**

FIDORA M., C. GIORDANO and M. SCHMITZ, *Real exchange rate misalignments in the Euro Area,* Open Economies Review, v. 32, 1, pp. 71-107, **WP 1162 (January 2018).**

LI F., A. MERCATANTI, T. MAKINEN and A. SILVESTRINI, *A regression discontinuity design for ordinal running variables: evaluating central bank purchases of corporate bonds,* The Annals of Applied Statistics, v. 15, 1, pp. 304-322, **WP 1213 (March 2019).**

LOSCHIAVO D., *Household debt and income inequality: evidence from Italian survey data,* Review of Income and Wealth. v. 67, 1, pp. 61-103, **WP 1095 (January 2017).**

NISPI LANDI V. and A. SCHIAVONE, *The effectiveness of capital controls,* Open Economies Review, v. 32, 1, pp. 183-211, **WP 1200 (November 2018).**

PEREDA FERNANDEZ S., *Copula-based random effects models for clustered data,* Journal of Business & Economic Statistics, v. 39, 2, pp. 575-588, **WP 1092 (January 2017).**

FORTHCOMING

ACCETTURO A., A. LAMORGESE, S. MOCETTI and D. PELLEGRINO, *Housing Price elasticity and growth: evidence from Italian cities,* Journal of Economic Geography, **WP 1267 (March 2020).**

ALBANESE G., G. DE BLASIO and A. LOCATELLI, *Does EU regional policy promote local TFP growth? Evidence from the Italian Mezzogiorno,* Papers in Regional Science, **WP 1253 (December 2019).**

ANZUINI A. and L. ROSSI, *Fiscal policy in the US: a new measure of uncertainty and its effects on the American economy*, Empirical Economics, **WP 1197 (November 2018).**

APRIGLIANO V. and D. LIBERATI, *Using credit variables to date business cycle and to estimate the probabilities of recession in real time*, The Manchester School, **WP 1229 (July 2019).**

BALTRUNAITE A., C. GIORGIANTONIO, S. MOCETTI and T. ORLANDO, Discretion and supplier selection in public procurement, Journal of Law, Economics, and Organization, **WP 1178 (June 2018)**

COVA P., P. PAGANO, A. NOTARPIETRO and M. PISANI, *Secular stagnation, R&D, public investment and monetary policy: a global-model perspective,* Macroeconomic Dynamics, **WP 1156 (December 2017).**

DE PHILIPPIS M., *Multitask agents and incentives: the case of teaching and research for university professors,* Economic Journal, **WP 1042 (December 2015).**

DEL PRETE S. and M. L. STEFANI, *Women as "Gold Dust": gender diversity in top boards and the performance of Italian banks,* Economic Notes, Monte dei Paschi di Siena, **WP 1014 (June 2015).**

HERTWECK M., V. LEWIS and S. VILLA, *Going the extra mile: effort by workers and job-seekers,* Journal of Money, Credit and Banking, **WP 1277 (June 2020).**

METELLI L. and F. NATOLI, *The international transmission of US tax shocks: a proxy-SVAR approach,* IMF Economic Review, **WP 1223 (June 2019).**

MOCETTI S., G. ROMA and E. RUBOLINO, *Knocking on parents' doors: regulation and intergenerational mobility,* Journal of Human Resources, **WP 1182 (July 2018).**

PERICOLI M. and M. TABOGA, *Nearly exact Bayesian estimation of non-linear no-arbitrage term-structure models,* Journal of Financial Econometrics, **WP 1189 (September 2018).**