The interaction of borrower-targeted macroprudential tools in the Irish mortgage market: a baseline multi-agent approach

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Abstract

Lax credit conditions and speculative behaviours can combine to bring about leveraged real estate bubbles that pose a threat to financial stability. This risk can be pushed away by the adoption of proper macroprudential polices. Borrower-based macroprudential tools, namely loan-to-value and debt-to-income ratios, are designed to dampen the procyclicality of credit and to enhance the resilience of financial institutions. By putting a ceiling to borrowing the financial sustainability of mortgages can be improved for borrowers and lenders. This paper studies the interaction of the two instruments by means of an agent-based model calibrated on the Irish mortgage market. I construct several policy scenarios grounded on residential loans data to run counterfactual experiments and explore alternative settings of macroprudential policy. This approach provides granular artificial data about the distribution of loan-to-value and debt-to-income ratios at origination, credit, and house prices. [FINDINGS HERE].

JEL classification: C63, E58, G21, R30.
Keywords: Agent-based model, financial stability, LTV, LTI, macroprudential policy, mortgage market.

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1. Non-technical summary

2. Introduction

According to *Clement [2010]*, the first appearance of the term “macroprudential" in a public document could be dated back at 1986 in a report of the Bank for International Settlements about innovations in international banking. However, the literature on macroprudential policy (MaP henceforth) has had the major diffusion in the aftermath of the Great Financial Crisis (GFC) of 2007/8, when policymakers and economists recognised the importance of a system-wide approach to prudential regulation culminating in the Basel III measures. As stated by *Borio [2011]* paraphrasing the famous phrase of Milton Friedman, "*We are all macroprudentialists now*". The paradigm shift from micro to macro prudential approaches was primarily driven by the belated admission by the vast majority of the scientific community and by policymakers that the instruments in place before the Great Financial Crisis of 2008 were defective to prevent it. Prior to the GFC, the focus of the regulation was to guarantee the soundness of individual financial institutions relying in particular on capital requirements, following the Basel II capital accord. Despite the goal of Basel II was financial stability, the stress was put on the solidity of single institutions: financial stability could be pursued if everyone was complying with the regulatory capital ratios. The failure of this approach was clear in the aftermath of the GFC, as it was realized that it missed the systemic dimension of the risk. Lehman Brothers itself was compliant with capital requirements until few days before its default, nevertheless it could not avoid the financial sector to be compromised. Many contagion channels were ignored or unknown and it was not so clear how the burst of a real estate bubble could yield a cascade effect in the wide financial sector with serious negative feedbacks on the real economy.

MaP is designed to mitigate systemic risk. It should do so by carefully looking at the interconnections in the financial system and to the real-financial interlinkages, which could act as a channel of contagion and amplification of the original distress and turn it into a systemic event. In this view, the procyclicality in the financial system and the fragility of the banking sector has had a remarkable importance for the Irish economy. The past events suggest that the sustained growth of the Celtic Tiger from 1990 to 2007 brought to uncontrolled lending and to a bubble that eventually caused a disastrous collapse of the real estate sector and a deep recession. In light of this, it appears essential to put a limit to the potential growth of credit in Ireland and strengthen the resilience of banks. Borrower-targeted instruments are a subset of macroprudential tools whose scope is to mitigate the excessive build-up of risk in mortgage lending. Their relevance is explained by the boom-and-bust dynamics that is often observed in the real estate sector and is associated with larger financial crises in some cases *[Lo Duca et al., 2017]*. After the catastrophic collapse of property prices in 2008 the Central Bank of Ireland (CBI) has introduced a new set of measures to regulate the Irish mortgage market in 2013 under *Section 48* of the *Central Bank (Supervision and Enforcement) Act*. The regulations have been in force since February 2015 and is reviewed annually. Central Bank aims to safeguard financial stability by reducing pro-cyclicality and enhancing financial resilience *[Cassidy and Hallissey, 2016]*. To do so, MaP targets several classes of borrowers (first-time-buyers, second-time-buyers, buy-to-let investors) and fix a ceiling on the maximum amount of mortgage lending on the base of two regulatory ratios: Loan-To-Value (LTV) and Loan-To-Income (LTI). Both restrict the maximum amount of mortgage credit that can be borrowed respectively in proportion to the house value (LTV) and to the gross annual income of the borrower (LTI).

The aim of this paper is to explore the interplay between alternative settings of borrower-targeted macroprudential measures. The work is intended to provide support to the ex-post valuation of borrower-based measures, which is conducted annually *[of Ireland, 2018]*. The motivation lies with the impossibility to experiment different policy regimes in a short lapse of time. Nonetheless the outcome would be valuable for the regulator as it allows to form an idea about the effects that policy changes could produce. Otherwise, a model can account for what cannot be observed in the real world. I build a model able to replicate selected peculiarities of the Irish mortgage market, next I conduct some counter-factual experiments by changing the setting of macroprudential tools. In particular I focus on a handful of variables that are only a subset of those employed by CBI to review the mortgage measures: LTV and LTI ratios, house prices, credit, access to lending, and mortgage arrears.

The adopted methodology is agent-based-computational economics. Agent-based modelling is an emerging methodology shared by economics and finance. It has been proposed as an alternative to conventional methodologies *[Farmer and Foley, 2009]* because it permits to depart from limiting assumptions in the mainstream paradigm. As described in *Napoletano et al. [2012]*, agent-based models (ABM) go beyond the limits of the representative agent, perfect rationality, and general market equilibrium. As such, ABM are able to provide a finer description of the economy than other approaches, reproduce a set of stylized facts, and mimic observed distributions. All in all, their characteristics make them good for policy analysis. This flexibility brings some disadvantages: high computational costs, greater complexity, and difficult analytical solution. However, these limitations are been gradually reduced by technological progress in computing, methodological advances, standardization of the approaches, and the increasing number of available references *[see for instance Gatti et al., 2018]*. In ABM the interaction of a multitude of agents at the micro-level produces aggregate outcomes that feed back into the behaviour of the agents themselves. Furthermore, ABM can generate a vast set of longitudinal data that can be exploited to reproduce empirical distributions. In conclusion, the agent-based methodology appears suitable for the purpose of the paper because: (i) it can reproduce granular data that match the distributions of loan-to-value and loan-to-income ratios; (ii) being based on a model, the parameters of the simulation (or the behavioral equations) can be modified to run counterfactual policy analysis.

[Anticipate the findings here]

The agent-based model is explained in section 3. Results are described in section 4. Conclusions are in section 5.

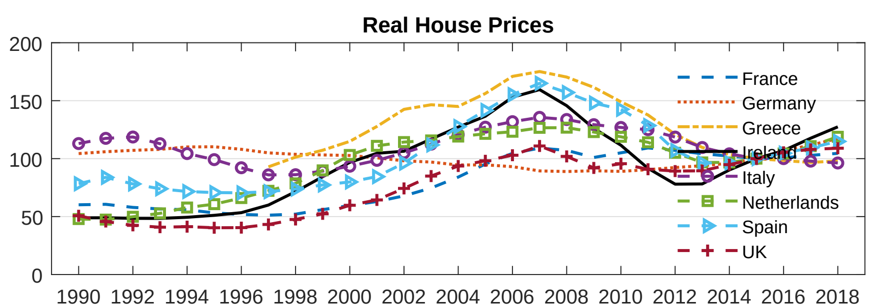

Figure 1: *Real residential property price indexes for selected European countries , 2015 normalized to 100. Source: OECD (2019), Housing prices (indicator).*

2.1. Literature review

A general discussion about the nexus between real estate markets and macroprudential policy can be found in *Hartmann [2015]*. He observes that boom-and-bust cycles in real estate markets characterized many financial crises. However, prudential regulation had been inadequate in Europe before 2007 despite property prices were clearly overvalued. The approach of policy-makers has radically changed after the great financial crisis, as the use of instruments addressed to real estate markets is being more and more backed by the theoretical and empirical literature. In particular, borrower-targeted tools as the LTV and DTI ratios have shown their effectiveness in dampening the price cycle and reducing credit growth. The question has shifted from “what" to “how", *i.e.* how macroprudential policy should be implemented. For instance, how to empower the competent authorities, how to define the role of macroprudential policy respect to monetary policy, and how to account for regional differences in real estate cycles.

To date, many theoretical and empirical contributions aims to assess the effectiveness and the impact of macroprudential policy. *Angelini et al. [2011]* study the interaction of monetary and macroprudential policy in a DSGE model with financial frictions and banks but without systemic risk. Moreover, a monetary and a macroprudential authority can choose to cooperate or to attain individually their objectives. The former is represented by a central bank that sets the policy rate, while the latter is a macroprudential authority that manages countercyclical capital requirements and the LTV ratio. When the economy is hit by a financial shock *Angelini et al. [2011]* show that the contribution of macroprudential policy is highly beneficial, especially when there is cooperation between the two authorities. In other words, the economy is stabilized thank to the reduction of the volatility of output and credit-to-GDP ratio. Another DSGE model that combines rational and moving-average expectations is developed by *Gelain et al. [2013]*. It results that a debt-to-income ratio is the best policy response to reduce the volatility of house prices and household debt compared to increasing reference interest rate or decreasing the LTV ratio. *Allen and Carletti [2013]* study the effect of macroprudential policies in a theoretical pricing model that generates real estate price bubbles. They find that a decrease in interest rate can trigger a bubble for high values of LTV, a transfer tax on purchases helps to prevent a bubble, and a limit on LTV can contain the increase in house prices during a boom.

On the empirical side, a rapidly growing body of empirical literature is in agreement about the ability of borrower-targeted tools to dampen credit growth and to stabilize real estate prices. Several cross-country studies *[inter alia Lim et al., 2011, Dell'Ariccia et al., 2012]*, find that macroprudential policies succeed in mitigating leverage and the procyclicality of credit, although their efficacy is weaker during busts *[Cerutti et al., 2017]*. The empirical evidence in *Claessens et al. [2013]* suggests that two simple tools, *i.e.* LTV and DTI, are effective in reducing the growth of bank leverage and house prices. The experiences of Hong Kong and Korea are two famous case studies for assessing the effectiveness of borrower-targeted measures. *Igan and Kang [2011]* studies the residential housing and mortgage market in Korea after the introduction of LTV and DTI regulations in early 2000s. They exploit both aggregate time-series and micro survey data. They find a delayed reduction in the number of transactions and in the growth of prices after a tightening of regulatory ratios. The introduction of borrower-targeted tools is shown to affect the expectations of households through the stabilization of prices: this deters speculation and favor first-time buyers. Similar results on the effectiveness of LTV and DTI are found by *Ahuja and Nabar [2011]*, that rely on cross country and VAR analyses for Hong Kong SAR and other countries with pegged exchange rates and currency boards. *Kelly et al. [2018]* bridge the literature on credit and house prices to that about the effects of macroprudential policy for Ireland. They use granular loan-level data of the Irish mortgage market between 2003 and 2010 to investigate how macroprudential policy would have affected house prices through mortgage credit. They show that the majority of borrowers were constrained by LTI limits imposed at the bank level; macroprudential measures are crucial to curb credit growth and house prices; the effectiveness of macroprudential measures is larger when the price cycle is close to the peak than in the initial ascending phase.

Hybrid methodologies are adopted by *[Gross and Población, 2017]* and *Allen et al. [2017]*. *Gross and Población [2017]* propose a data-driven model of households' balance sheets based on survey data for 15 European countries. The model integrates a macro component, modelled with a GVAR, and a micro one, that is based on a logistic model of the employment status of household members. The aim is to understand the impact of lending standards associated to macroprudential measures on the economy and the risk parameters of borrowers. They find that both LTV and DSTI caps are effective to reduce borrowers' probability of default and loss-given-default at the cost of slowing down the pace of the economy in the short-run. *Allen et al. [2017]* develop a microsimulation model to study the impact of changes in macroprudential policy for first-time-buyers in Canada. They consider the effects on household borrowing and mortgage credit. The model is calibrated with loan-level and household survey data. The main finding from the simulation is that an LTV constraint has the largest impact on first-time buyers compared to debt-service policies: it reduces the number of buyers in the market and the amount of debt they hold, and makes households less vulnerable to interest rate shocks.

ABM have been applied to study the housing and mortgage markets. *Gilbert et al. [2009]* develop an ABM of the English housing market with the aim of reproducing key features of the real world in a simple framework. Their model incorporates a spatial grid controlled by realtors that act as price intermediaries. *Ge [2017]* proposes a spatial ABM to explain what factors determine an endogenous housing price bubble without external shocks. Agents follow simple adaptive behavioural rules partly modelled on the basis of interviews with real-estate agents. Her findings suggests that the two main factor driving instabilities in the housing market are leniency in banks' lending practices (*i.e.* high LTV ratio) and speculative behaviours. Hence, policies that affect speculation, such as land or property taxes, can stabilize the market. *Erlingsson et al. [2014]* find a trade-off between economic growth and access to credit in a macroeconomic ABM that encompasses housing and mortgage markets. Results from the simulations reveal that ease to access to mortgage loans leads to economic instability through the creation of a house price bubble. *Kouwenberg and Zwinkels [2015]* study the formation of an endogenous bubble in the housing market. They relax the assumption of perfect rationality and market efficiency. Instead agents are boundedly rational with a swinging heuristics mechanism, that is they can deviate from the expectation that price always reverts to its fundamental value due to market efficiency. They develop and estimate a simple ABM for the U.S. housing market. It results that boom-and-bust cycles can arise from the interaction between agents. The out-of-sample forecast of the econometric model derived from the ABM *[Kouwenberg and Zwinkels, 2014]* is show to be better than standard models. Other works where expectations interact with the housing price cycle are *Bolt et al. [2019]* and *Dieci and Westerhoff [2012]*.

The contributions of *Baptista et al. [2016]* and *Laliotis et al. [2019]* are the most related to this work. *Baptista et al. [2016]* build on a workstream that investigates the housing market bubble in Washington D.C. between 1997 and 2009 *[Axtell et al., 2014, Geanakoplos et al., 2012, Goldstein, 2017]*. The paper studies the impact of macroprudential policies on the UK housing market. The ABM includes households (home-owners, renters, investors), one bank and the central bank and is calibrated on UK micro-data following the approach of *Axtell et al. [2014]*. It is employed to analyse the impact of the buy-to-let market and macroprudential policies (LTI) on boosts and busts in house prices. They find that policies aimed at reducing the buy-to-let sector or the introduction of a ceiling on the LTI ratio can stabilize the housing market. *Laliotis et al. [2019]* resort to a one-period model without renters and investors based on *Baptista et al. [2016]* to investigate the impact of a cap on the LTV ratio. The model is calibrated with probability distributions from European survey data, and multivariate distributions are estimated by means of copulas. They find that an increase in LTV shifts the distribution of buyers leftwards as the middle-low price segment is more affected by the change. Moreover, based on a cross country comparison, *Laliotis et al. [2019]* classify countries in 5 groups depending on their reactions to LTV caps and the impact on different price segments. *Cokayne [2019]* is strictly related to the paper of *Baptista et al. [2016]*, but rental properties are owned by large investors that only rent them out. Moreover, the rental market is divided in controlled rental accommodations and non-controlled accommodations.

This paper shares the modelling approach in *Baptista et al. [2016], Axtell et al. [2014], Geanakoplos et al. [2012], Goldstein [2017].* Nonetheless, it differs in several aspects. Above all, the model complexity is reduced to a lower degree. More in detail: the microcalibration of behavioral equations is less data intensive; the matching mechanism is simpler without quality bands; the choice of the downpayment relies on the joint distribution of price-to-income and downpayment-to-income ratios; savings are affected by a downpayment target; calibration is on Irish data.

3. Methodology

3.1. Overview

The economy is populated by a discrete number households and one bank. Moreover, there is a constant number of dwellings. The objective of households is to buy one or more properties. I assume that the cost of owning is always lower than the cost of renting, as can be understood looking to data for Ireland. Therefore, households in the model aim to be home-owners rather than renters. Households are of two kinds: those that access for the first time to the housing market to buy their primary residence are defined fist-time-buyers (FTB). A limited fraction of home-owners can buy other dwellings beyond their primary residence. Those agents are defined buy-to-let investors (BTL). They invest in the residential property market by buying houses and renting them out in order to attain a positive yield from rents and the capital gains. I assume that some home-owners leave the model and are replaced by new households under certain conditions. These are met if a FTB becomes home-owner, its primary dwelling is sold, and the mortgage is paid-off. Otherwise those that enter again in the housing market should be considered second-time buyers and should be subject to different macroprudential rules.

The role of bank is to collect deposits from households and supply mortgages. It operates so as to maintain its profitability and comply with prudential regulation. The last consists in minimum capital requirements and borrower-targeted MaP.

Interactions take place in three markets: household participate in the housing and rental markets, whereas they turn to banks in the mortgage market. The time in the artificial economy is marked by discrete units corresponding to months. Each time-unit (period) is composed by a sequence of events in which agents make their choices and interact. Each period is described by the following sequence of events.

1. Households receive an exogenous income that is consumed and saved.

2. Perspective buyers and sellers form their desired prices.

3. Perspective buyers apply for a mortgage approval. Banks determine the maximum size of mortgage depending on borrowers' characteristics.

4. Buyers and sellers interact in the housing market.

5. Those who do not own a house rent from the landlords. If they cannot find a free rental accomodation they are assigned to social housing.

6. Homeowners repay the mortgage; renters pay the monthly rent.

3.2. The Agent-Based Model

3.2.1 Income and unemployment

The annual gross permanent income across households follows a lognormal distribution whose parameters match the Irish data (see section 3.3.1 for an overview of the data used in the calibration).

$$y_i^p \sim Lognorm\left(\mu_y, \sigma_y\right)$$

At each period households receive an income y computed as the monthly fraction of permanent income times a transitory component.

$$y_{i,t} = \frac{1}{12} y_i^p \psi_{i,t} \quad \psi \sim Lognorm(0,\ 0.1) \tag{1}$$

Another factor affecting households' income besides the transitory component is unemployment. It results in a prolonged income shock which impairs the ability to service the debt. The rate of unemployment in the economy is assumed fixed and equal to a constant u. A random sample is drawn from the population and assigned to unemployment so that a fraction u of households is unemployed in each period. I assume that the duration of unemployment is extracted from a binomial distribution $\mathbb{B}(u^n, u^p)$, where parameters are calibrated so as to mimic the duration of unemployment from 1 to 24 months reported by Eurostat (Ireland, years 2015-2018, male and female). Unemployment periods lasting more than two years are not included as I arbitrarily assume that they are associated to households with low credit scores that cannot access to credit. I random draw the length of unemployment using weights that are inversely proportional to the relative income of households, so that the length is conditioned on income.

3.2.2 Consumption

The behavioural rule for consumption is determined according to the buffer-stock theory of saving *[Carroll et al., 1992, Carroll, 1997]*. Carroll shows how the buffer-stock saving behaviour can emerge from a standard dynamic optimization problem. Under income uncertainty consumers are both impatient and prudent. As a result, consumption behaviour changes over a target wealth stock, which is taken as a reference to smooth consumption. Below the target households save, above they dissave. In contrast to the standard implementation of the Carroll's rule in agent-based models *[see Dawid and Delli Gatti, 2018]*, I assume that households target cash-on-hand in terms of downpayment-to-income ratio. This is in line with the findings of *Engelhardt [1996]* by which households save more when young in order to cumulate funds for mortgage borrowing. Once the liquidity constraint is relaxed, consumption increases.

Households set a consumption budget c as in (2). Absent an explicit representation of the goods market, I assume that the consumption budget is always spent in full.

$$c_{i,t} = \begin{cases} y_{i,t}^d + \kappa(m_{i,t} - (1+\vartheta)d_i) & if\ H_i = 0 \\ y_{i,t}^d + \kappa(m_{i,t} - \vartheta d_i) & if\ H_i = 1 \end{cases} \tag{2}$$

The monthly disposable income y^d is defined as the sum of gross labour income (y), rent, and net of the total mortgage repayments. $y_{i,t}^d \equiv y_{i,t} + rent_{i,t} - \sum_{k+1}^{K} rep_{ik,t}$. Money holdings ($m$) are kept in form of bank deposits. The desired downpayment is d. The value of d is determined once for FTB (see how in section 3.2.3) and it is updated for BTL each time they decide to buy a property. k and ϑ are parameters. $H \in 0, 1$ states whether i is an owner $H = 1$) or not ($H = 0$). I assume that $H = 0$ for all BTL investors, so that they do not reduce their saving propensity after home-purchases.

3.2.3 Downpayment

The choice of the downpayment is crucial to match the empirical LTV and LTI distributions. I assume that households have a target downpayment-to-income ratio, which is a function of desired price-to-income. This setting produces values of d that are consistent with data and are robust to the endogenous development of housing prices in the model: for example, if the prices raise, downpayment-to-income adjusts accordingly. Price-to-income is associated to downpayment-to-income ratio by looking at the bivariate distribution (fig.2) obtained from Irish data before macroprudential regulation was put in place (before 2015). This data subset should reflect the "natural" preferences for downpayments, that is the multiple of annual income that household wish to spend to finance house purchase absent external constraint. The realized values of downpayments are then corrected upwards when borrowers-targeted rules are binding.

The downpayment choice is executed as follows: the joint distribution of price and downpayment to-income ratios is obtained from Irish Loan-Level data. Observations of price-to-income are divided into 10 bins of the same size. Throughout the simulations households are associated to a bin based on their realized desired purchase price-to -income ratio. Each household receives a value of downpayment-to-income randomly picked from the bivariate distribution and corresponding to the bin assigned. The range of values is restricted so that the downpayment cannot exceed the desired purchase price.

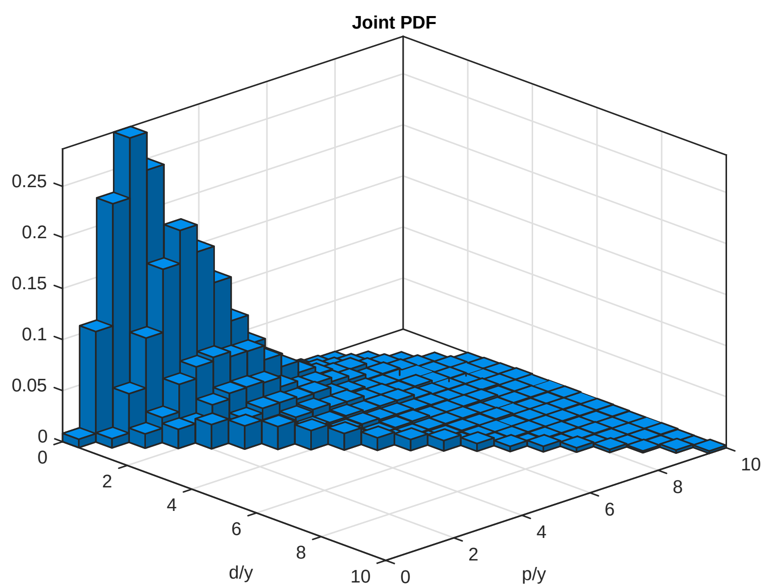

Figure 2: *Joint pdf of downpayment-to-income (d/y) and price to income (p/y).*

3.2.4 Housing demand and supply

Perspective buyers determine the desired purchase price based on average annual income $\bar{y}_t$ and expected house price growth g.

$$p^d_{i,t} = \frac{\varepsilon^d_{i,t}\bar{y}_{i,t}}{1-\beta g_t} \tag{3}$$

The term $\varepsilon^d \sim Lognormal\left(\mu_d,\ \sigma_d^2\right)$ captures the heterogeneity in data. In other words, it explains the differences in desired price by households with the same income, so accounting for unobserved idiosyncratic factors.[1]

The supply of houses is exogenous and randomly determined. A value for the length of home-ownership extracted from a $\mathcal{N}(\mu_l,\ \sigma_l^2)$ is assigned to each house when it is bought. At the end of the period the house is put on sale. Irrespective of this rule, BTL households sell their rental properties only if they decide to opt out of the investment (see eq.??).

When an house is put on the market the listing price is the product of three variables. A random variable $\varepsilon^s \sim Lognormal\left(\mu_s,\ \sigma_s^2\right)$ accounts for heterogeneity in prices across houses with similar characteristics. The reference price for house j is equal to its initial sell price ($p^s_{j,0}$ corrected for the value of HPI at the end of the previous period.

$$p^s_{j,t} = \varepsilon^s_{j,t} p^s_{j,0} HPI_t \tag{4}$$

The listing price is then reviewed downwards by 1% each month if the house is unsold.

3.2.5 Random matching mechanism

Housing market The housing market is designed as a double auction mechanism where buyers and sellers are matched. Potential buyers that reached their desired downpayment target and obtained a positive approval from the bank enter the market. Sellers are house-owners that put their property for sale or BTL that opt out of the investment. Both buyers and sellers have a desired bid or ask price determined in (3) and (4).

I assume that sale prices and houses' values correspond, so that the most expensive house is the most preferred by each buyer. In other words, price changes of the same unit reflect the improvements or deterioration to which it has been subject since the last time it was on the market.

The matching mechanism works as follows:

i. Each buyer form a list of the houses that cost p^d or less and sort it in decreasing order of price.[2]

ii. Houses are auctioned from the most to the least expensive.

iii. Each house is matched with the vector of buyers that can afford it. If there is more than one potential buyer, the winner is chosen randomly.

iv. The matching algorithm is repeated until there are no buyers left, or all houses have been sold, or a maximum nuumber of iterations is reached.

The matching mechanism does not include any bargaining game on price because it would not add much to the model's dynamics. As the aim of the paper is not to explain in detail the working of the housing market, the preferred solution is to keep things as simple as possible. Variations in the house price index are mainly generated by demand and supply through the effect of ε^d and ε^s on desired and listing prices. When demand is high, many buyers access to the market. They will buy the most expensive house they can afford. This makes more likely that houses for which the realization of $\ln(\varepsilon^s) > 0$ is positive are sold. The new sale price is greater than the reference price, therefore house-price-index (HPI) increases. In turn, listing prices are increased by HPI

[1] Eq. 3 is the same in *Baptista et al. [2016]*, $p^d_{i,t} = \frac{\alpha^d + \exp\left(\epsilon^d_{i,t}\right)}{1-\beta g_t}\tilde{y}_{i,t}$, but it is written in compact form by rescaling ϵ^d by α^d.

[2] An house can be purchased if the downpayment plus the bank's approval is greater or equal than the listing price. A household can be a cash buyer if its deposits are at least two times the listing price.

in (4) in the subsequent periods. The upward movement in house prices come to an end when the most expensive houses cannot be sold. If desired prices do not adjust to the supply or available credit is not enough, listed units whose realization of $\ln(\varepsilon^s)$ is negative are more likely to be sold. This results in a decrease in HPI. Naturally, the price dynamics is amplified by speculation of BTL agents.

Rental market In line with the objectives of the paper, which is focused on the mortgage market and macroprudential policy, the representation of the rental market is just sketched. A future revision can include a more detailed description and relate it to the developments on the housing market, as in the real estate literature *[see for instance Di Pasquale and Wheaton, 1992]*.

The rental market is simply described as follows. Those households that are not home-owners seek a rental accommodation. On the supply side, BTL rent out their properties. Renters are ranked in descending order of gross income. The first renter of the list is matched to the most expensive house (in terms of the last sale price), and so on (second renter with second house, etc.). If there are more renters than houses, the difference is assigned to social housing. The rent is fixed at one third of households' gross income.

3.2.6 Supply of credit

The banking sector supplies mortgage credit to households. Moreover, banks hold the money of households in deposit accounts. If deposits are not enough to cover new lending, by assumption the banking sector can access to unlimited liquidity at the same cost of deposits. The credit supply of bank h is limited to a fraction of its equity (nw^b) by minimum capital requirements defined as the ratio of Common Equity Tier 1 (CET1) capital to Risk Weighted Assets (RWA). CET1/RWA should be greater or equal than $\lambda = 8\%$, that is the sum of basic requirement (4.5%), capital conservation buffer (2.5%), and countercyclical capital buffer (1%). The risk weight on outstanding mortgages (q) is set equal to $\underline{\omega} = 29\%$ for performing loans (indexed by s) and $\overline{\omega} = 93\%$ for non-performing (indexed by z).[3]

$$L^s_{h,t} \leq \frac{1}{\underline{\omega}\lambda} nw^b_{h,t} - \left(\sum_{s=1}^{S} q_{h,t,s} + \frac{\overline{\omega}}{\underline{\omega}} \sum_{z=1}^{Z} q_{h,t,z} \right) \tag{5}$$

Potential buyers visit the bank to apply for a mortgage approval before entering the housing market. The maximum amount of credit (7) is restricted by macroprudential tools (loan-to-value and loan-to-income ratios) and by a solvency condition (6). This links the maximum amount of the approval to the payment obligations of households. In other words, borrowers' income should be enough to afford a minimum consumption (a) and to pay-back the future instalments (R), including those underlying the new mortgage. The bank accepts to lend at most $q_{iK,t+1}$ to i with the K^{th} mortgage.

$$solv_{hi,t} \equiv q_{i,t+1,K} \leq \frac{1-(1+r/\tau)^{-n}}{r/\tau} \left(\frac{\bar{y}_{i,t}}{\tau} - a \right) - \sum_{k=1}^{K-1} q^0_{i,t,k} \tag{6}$$

In (6) the annual nominal mortgage rate is r, n is the mortgage duration, $\tau = 12$ is the number of months in one year, k indexes the mortgages of household i, and q^0 is the value of the mortgage at

[3]Risk weights are the averages of 2018 values of the main Irish banks. See the report of the Department of Finance of the Irish Government: `https://www.gov.ie/en/publication/ff6c0a-risk-weighted-assets-in-ireland-the-link-to-mortgage-interest-rates/`

the origination. The maximum mortage approval to i is:

$$\tilde{q}_{hi,t} \leq \min\left(\frac{LTV}{1-LTV}\ d_{i,t},\ LTI\ \bar{y}_{i,t},\ solv_{hi,t}\right). \tag{7}$$

Only fixed rate mortgages are introduced in the model in order to avoid unnecessary complexity.[4] Future versions of the paper could account for adjustable rate, interest only and tracker mortgages. The duration is set to 35 and 25 years for FTB and BTL respectively, accordingly to the categories' modes observed in loan level data. The interest rate r is a constant equal across all households.

Exemptions Based on the mortgage measures established by the CBI, some borrowers can be excepted from the regulatory ratios. The exemptions included in the model are reported in table 1. In detail, 5% of lending to FTB can exceed the LTV ratio of 0.9, and 10% of mortgages to BTL can have a LTV greater than 0.7. Moreover, 20% of the mortgages to FTB can be above the LTI cap of 3.5. These allowances are based on the total lending in the calendar year and de facto are granted on a *"first come, first served basis"* to households. The mechanism is implemented as follows: the bank estimates its credit demand by computing the value of total lending in the previous year. Next, it determines the maximum annual amount for each type of allowances. Lending starts on the first month of the calendar year while supplies last. Allowances are then updated at the end of the last month for the subsequent year.

	LTV	**LTI**
FTB	Up to 5% of mortgages can be above 0.9.	Up to 20% of mortgages can be above 3.5.
BTL	Up to 10% of mortgages can be above 0.7.	No limits.

Table 1: *Summary of the exemptions present in the model.*

3.2.7 Buy-to-let sector

As remarked by *[Geanakoplos, 2010]*, investors can be seen as natural buyers that desire assets more than the public. As they buy a substantial share of total assets by leveraging the investment, they have a major role in driving asset prices. Losses or limited access to credit for natural buyers might cause sharp declines in the market. In view of this, BTL agents are included in the model. A certain fraction of high-income households has a "buy-to-let gene" that allow them to buy other properties in addition to their primary residence. These BTL are a minority of total agents, nevertheless can affect the market much more. BTL follow the same behavior of FTB whith respect to the purchase of their primary dwelling, but can choose to invest in the housing market.

BTL compare the net yield per euro invested to the yield of a leveraged alternative investment, taking into account the expected growth of housing prices g^e, and the yearly maintenance cost of

[4]Under the fixed rate regime the repayments of interests and principal adjust so as to keep constant the monthly instalment R for the entire life of the loan.

$$R \equiv q\frac{r/\tau}{1-(1+r/\tau)^{-n}}$$

Interest repayments are computed on the residual balance of the loan: $int_t = q_{t-1}(r/\tau)$. Capital repayments are the difference between the instalment and interests: $cap_t = R - int_t$.

the dwelling ϕ. The entry probability is determined by the logistic function (8).

$$btl_{i,t}^{entry} = \frac{1}{1+\exp(-\nu(\chi_t - \overline{\chi}))} \tag{8}$$

Where $\chi_t \equiv \frac{yield_t^r + g_t^e - \phi)}{r^{free}}$. The opting-out or exit probability is $btl_{i,t}^{exit} = 1 - btl_{i,t}^{entry}$.

3.2.8 House price index, net worth, arrears, and mortgage pay-off

The house price index (HPI) is computed as a Laspeyres index:

$$HPI_t = \sum_{i=0}^{n} \left(\frac{p_{kt}}{p_{k0}}\right) s_{k0} = \sum_{k=0}^{n} \frac{p_{kt}q_{kt}}{p_{k0}q_{k0}}. \tag{9}$$

With $s_{k0} = \frac{v_{k0}}{\sum_i v_{k0}}$ and $v_{k0} = p_{k0}q_{k0}$.

The net worth of households is the difference between assets and liabilities (10). The first include deposits m and the nominal value of the house(s) (hs^{val}); the latter are the mortgage balance b.

$$nw_{it}^h = m_{it} + \sum_k hs_{ik,t}^{val} - \sum_k b_{ik,t} \tag{10}$$

The house value hs is computed as:

$$hs_{ht} = p_{h0}\frac{HPI_t}{HPI_0}$$

Where p_0 is the purchase price and HPI_0 is the house-price index at the purchase date. House equity is the difference between the market value of the house and the mortgage balance:

$$hs_{kt}^{eq} = hs_{kt}^{val} - b_{kt}.$$

Some borrowers might run short on deposits and not repay the instalments due to unexpected income shocks. This happens if disposable income is less than a minimum consumption threshold. In that case households suspend the loan repayments. If households have not enough funds, first they skip the repayment of interests and then capital. With the purpose to keep the model as simple as possible in mind, I do not consider strategical defaults on underwater mortgages or repossessions from the bank. Rather, the bank does not receive the interest repayment and writes off the missed capital repayments from its stock of mortgages.

Finally, the model allows to pay-off the residual balance of the mortgage. If deposits exceed the balance, mortgagors always pay-off the balance.

3.3. Calibration

3.3.1 Data

The calibration employs Irish data on residential loans from the two interlinked sources described in *Kinghan et al. [2016]*. Details about the mortgages that had been originated before the regulation has been in force can be traced-back in the loan-level dataset (LLD). LLD contains information submitted every six months by the five major financial institutions active in the Irish mortgage market. A more recent dataset known as Monitoring Templates Data (MTD) *[see Kinghan, 2018]* is available since 2015. It contains granular information about new residential mortgage lending transmitted to the CBI as a monitoring tool for lenders' compliance with MaP. MTD are updated twice-yearly with loan-by-loan data reported by financial institutions that grant at least €50 million of new residential mortgage lending in a six months period.

Overall, the data range from 2000 to 2018, contain about 850,000 observations, and report several information among which mortgage balance, loan size, loan term, value of collateral, origination date, purpose of the loan, interest rate type, age and income of borrowers, type of borrower (FTB, SSB, BTL), region, LTI, LTV, exemptions. For the purpose of calibration I account for fixed interest rate loans originated between 2000 and 2018 towards FTB or BTL for purchasing new properties in the Republic of Ireland. I further restrict the selection to households with an annual gross income above €15 thousand on average per person.

3.3.2 Initialization

The model is initialized with N^{hh} households, N^{hs} houses, and N^{bb} banks. All houses are put on the market by construction firms at the beginning of the simulation. When all houses are sold, construction firms become inactive. The price of new houses is extracted from a lognormal distribution with parameters μ_p and σ_p fitting the Irish loan-level data between 2015 and 2018. Each household is endowed with an amount of deposits equal to its yearly gross income. This ensures the convergence of the HPI around its initial level after a short transient. Gross income is lognormally distributed with different parameters for FTB and BTL ($\mu_y^{ftb},\ \sigma_y^{ftb},\ \mu_y^{btl},\ \sigma_y^{btl}$).[5] The balance sheet of banks is initialized with liquidity on the asset side and household deposits as a liability. Liquidity is determined so that the net-worth is equal to the initial value of total deposits.

3.3.3 Calibration strategy

The calibration of the bid and ask prices determines the dynamics of HPI and the ability of the model to reproduce real distributions. Therefore, I focus on the calibration of ε^d and ε^s. Setting the right parameters in (3) allows households to receive a downpayment which is consistent with the actual purchase price in the housing market (see section 3.2.3). By the same token, calibrating 4 makes the distribution of bid prices compatible with ask prices thus improving the efficiency of the random matching mechanism and market clearing.

To calibrate ε^d I match the desired price to income ratio (p^d/y^p) to data. First, a lognormal distribution is fitted to the sample data of price-to-income via maximum likelihood. Then I introduce a random variable π that is lognormally distributed with the estimated parameters. Next, I set the value of ε^d under the hypothesis that $\frac{p^d}{y^p} = \pi$.

From (3):

$$\frac{p^d}{y^p} = \pi = \frac{\alpha \exp(\varepsilon^d)}{1 - \beta g} = c \exp(\varepsilon^d)$$

with $c \equiv \frac{\alpha}{1-\beta}$ assuming that $g = 1$.

Rescaling $\exp(\varepsilon^d)$ by the factor c results in a new random variable $\hat{\varepsilon}^d \equiv c \exp(\varepsilon^d)$ which has a lognormal distribution with parameters $(\ln(c) + \mu_d,\ \sigma_d^2)$.

$$\hat{\varepsilon}^d \sim Lognormal\,(\ln(c) + \mu_d,\ \sigma_d)$$

Finally, I set the parameters of $\hat{\varepsilon}^d$ so to match those of the fitted distribution $(\mu_\pi,\ \sigma_\pi)$.

[5] Many of the calibration parameters are obtained by fitting probability distributions to loan-level data. In almost all cases I resort to a lognormal distribution. Despite some data could be fitted more precisely by other distribution (e.g. the Burr XII distribution for income), lognormality is a convenient choice because: (i) it can replicate the actual distribution of data well, namely its log likelihood is close or lower than the best alternative distribution; (ii) its functional form is analytically tractable and its properties allow to combine it with other lognormal distributions.

The calibration of ε^s is conducted computationally by exploring the parameter space defined by $(\mu_s,\ \sigma_s)$ so that: (i) the HPI reverts to its initial values; (ii) the empirical distribution of LTV, LTI are matched by the model.

[PUT FIGURE HERE]

3.3.4 Parameters

Parameter	Value	Description
T	1000	Length of the simulation.
N^{hh}	1000	Number of households.
N^{hs}	900	Number of houses.
N^{bb}	1	Number of banks.
μ_y^{ftb}	11.0567	Gross income of FTB. Location parameter for $\ln(y_p^{ftb})$ in (1).
σ_y^{ftb}	0.4172	Gross income of FTB. Scale parameter for $\ln(y_p^{ftb})$ in (1).
μ_y^{btl}	11.477	Gross income of BTL. Location parameter for $\ln(y_p^{btl})$ in (1).
σ_y^{btl}	0.644203	Gross income of BTL. Scale parameter for $\ln(y_p^{btl})$ in (1).
μ_d	4.5	Bidding price. Location parameter for $\ln(\varepsilon^d)$ in (3).
σ_d	0.5	Bidding price. Scale parameter for $\ln(\varepsilon^d)$ in (3).
μ_s	0.04	Asking price. Location parameter for $\ln(\varepsilon^s)$ in (4).
σ_s	0.2	Asking price. Scale parameter for $\ln(\varepsilon^s)$ in (4).
μ_π		Price to income. Location parameter for $\ln(\pi)$.
σ_π		Price to income. Scale parameter for $\ln(\pi^s)$.
ζ	0.05	Targeted value of unemployment rate.
u^n	89	Length of unemployment. Parameter of the binomial distribution (number of trials).
u^p	0.1	Length of unemployment. Parameter of the binomial distribution (success probability).
κ	0.1	Velocity of adjustment of deposits to consumption in (2).
ϑ	1.2	Multiplier of desired downpayment in (2).
$\underline{\omega}$	0.29	Risk weight on performing loans in (5).
$\overline{\omega}$	0.93	Risk weight on non-performing loans in (5).
λ	0.08	Regulatory threshold on minimum capital in (5).
r	0.03	Nominal mortgage fixed interest rate in (6).
LTV	$\{0.9,\ 0.7\}$	Maximum loan-to-value ratio for FTB and BTL in (7).
LTI	3.5	Maximum loan-to-income ratio for FTB in (7).
ν	0.25	Steepness of the logistic curve in (8).
$\overline{\chi}$	10	x-value of the logistic's midpoint in (8).
r^{free}	0.01	Rate of return on a risk-free asset in (8).
ϕ	0.02	Yearly maintenance cost of residential properties in (8).

Table 2: *Parameters of the model.*

4. Results

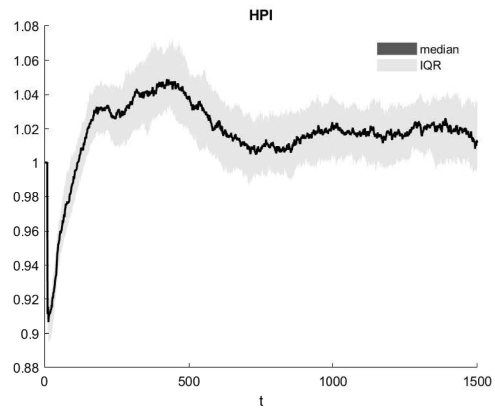

Figure 3: *Median and interquantile range (IQR) of HPI.*

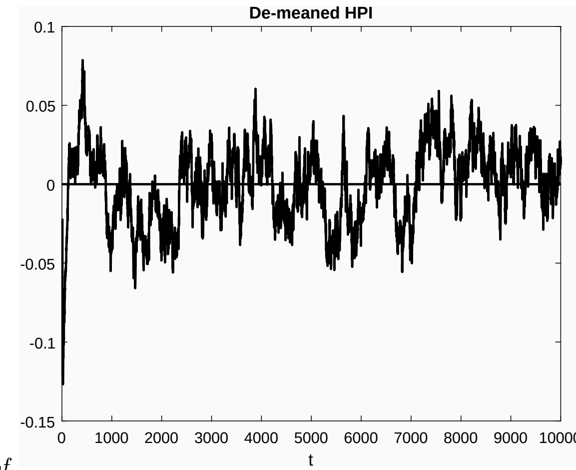

Figure 4: *De-meaned series of HPI (sample size of* 10^4 *periods). Statistical tests for unit-root (ADF, Phillips-Perron, KPSS) exclude non-stationarity at a confidence level of* 99%.

5. Conclusion

Mortgage market measures aim to enhance the resilience of both borrowers and banks and to dampen the pro-cyclicality of mortgage credit and house prices. The ex-post evaluation of mortgage market measures is conducted yearly by CBI after an extensive evaluation process on the basis of which it is established whether to revise them or not. Borrower-based tools are assessed against several factors, among which the developments in the housing and mortgage markets, the risk characteristics of new mortgage lending, and the wider macroprudential framework.

This paper contributes to inform the ex-post evaluation by focusing on the risk characteristics of new mortgage lending, and partly on the potential developments of the housing and mortgage markets. I conduct several counterfactual experiments in which I vary the setting of borrower-targeted measures. This produces different distributions of LTV and LTI ratios at the origination, house prices and mortgage lending. Simulations are based on an ABM calibrated and validated against observed data. Therefore, the counterfactual analysis can provide model-based results about the possible outcomes of future policy changes given the specific characteristics of the Irish economy.

[FINDINGS HERE]

This work can be extended in several directions. Some improvements could be made at the household level: better characterizing the rental market; define defaults on mortgages and repossessions. The model could include more than one bank and the behaviour of the banking sector could be further developed. Expectations could be introduced for both households and bank. Finally, adding a macroeconomic dynamics would allow to account for the evolution of income, unemployment and business cycles.

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