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The impact of prudential regulations on the UK housing market and economy: Insights from an agent-based model

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Marco Bardoscia[1], Adrian Carro[2,3], Marc Hinterschweiger[1], Mauro Napoletano[5,6,7], Lilit Popoyan[4,5], Andrea Roventini[5,7], and Arzu Uluc[1]

[1]Bank of England
[2]Banco de España
[3]Institute for New Economic Thinking at the Oxford Martin School, University of Oxford
[4]Queen Mary, University of London
[5]Scuola Superiore Sant'Anna
[6]Universit. Côte D'Azur, CNRS, GREDEG

Abstract

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1 Introduction

The global financial crisis (GFC) has shown how the housing market can have a relevant role in boom-and-bust cycles in financial markets with destabilising repercussions for the real economy. In the aftermath of the GFC, the looming recession made evident the limitations of microprudential policies and conventional monetary policies in stabilising the adverse effects of credit and asset price boom, and maintaining financial and macroeconomic stability (Hanson et al., 2011; Claessens and Kodres, 2014; Kahou and Lehar, 2017; Claessens et al., 2021). This induced policymakers to shift their attention to the macroprudential framework to mitigate systemic risk (Akinci and Olmstead-Rumsey, 2018).

Macroprudential policies have now been deployed in over one hundred countries using various instruments (see Bank of England, 2011; Hanson et al., 2011; De Nicolo et al., 2014; Claessens et al., 2013; Cerutti et al., 2017; Alam et al., 2024; Meuleman and Vander Vennet, 2020, among others). The prominence of their use has also grown over the years, with more recent actions as part of the policy response to the COVID-19 pandemic focusing on supporting the flow of credit to the real economy (Benediktsdóttir et al., 2020; Buch et al., 2021). Despite the wide adoption of macroprudential regulatory policies (Claessens, 2015; Boar et al., 2017; Akinci and Olmstead-Rumsey, 2018), understanding of the impact of these policies and their efficacy remains an open question. While a number of studies have already looked at the use and effectiveness of prudential policies (Cerutti et al., 2017; Altunbas et al., 2018) and the factors affecting the enforcement of different regulations (Gaganis et al., 2020; Apergis et al., 2021), very few contributions have explicitly analysed how borrower-based instruments interact with capital- or lender-based policies, and how this interaction affects financial and macroeconomic stability, from a quantitative modelling perspective.

To answer those questions, we develop a macroeconomic model to study the joint impact of borrower- and lender-based prudential policies on the housing and credit markets, and the economy more widely. To deal with the complex interactions within the economy, we have adopted an agent-based computational framework. While mainstream macro models make simplifying assumptions (i.e., representative agents, rational expectations) that limit the degree of heterogeneity and non-linearity that they can cope with, agent-based models (ABMs) are able to sidestep some of these limitations by simulating actors' behaviour with simple rules. This is a key advantage for areas such as housing, where prudential regulations often involve threshold effects and where heterogeneity in income/wealth plays a key role in tenure decisions and market dynamics.

Macro ABMs have been develop to understand the impact of, for example, fiscal and monetary policies, and financial regulation. Among these, macro ABMs with a fiscal application point to the positive effect of fiscal expansions (Russo et al., 2007; Haber, 2008; Dosi et al., 2010), their redistributive capacities, and the impact of budgetary policy on cyclical dynamics (see Dosi et al., 2013, 2015; Teglio et al., 2019). Monetary policy issues and the optimal design of regulatory schemes for banks and the financial market have also gained increasing attention from the ABM community. In particular, those models either rely on a comparison of Taylor rule variations on macro and micro dynamics (Dosi et al., 2013; Gatti and Desiderio, 2015; Ashraf et al., 2016; Salle and Seppecher, 2018) or examine how a Taylor rule including indicators of economic and financial stability (e.g., leaning against the wind) can improve economic performance and stability (see Popoyan et al., 2017; Chiarella and Di Guilmi, 2017; Krug, 2018). Another essential stream in applying macro ABMs in monetary policy is the heterogeneous expectation formation processes and learning dynamics, and their impact on the policy transmission mechanisms (Salle, 2015; Dosi et al., 2020). Yet another branch of macro ABM models focuses on post-crisis financial regulatory policy applications (see Krug and Wohltmann, 2016; Popoyan et al., 2020; Catullo et al., 2021). A large part of these models focus on capital requirements, including countercyclical components, converging to the same conclusion—tightening capital requirements in good times and relaxing them in bad times contributes to macroeconomic and financial stability (Raberto et al., 2017; Van Der Hoog and Dawid, 2019; Alexandre and Lima, 2020; Riccetti et al., 2021). Some of those models enlarge the regulatory spectrum by adding reserve requirements (see Hoog, 2018), or leverage and liquidity requirements (Popoyan et al., 2020; Liu et al., 2020). Our model lies in the last stream of the macro ABM models, focusing on financial regulatory policies. The aim is to analyse the impact of borrower- and lender-based instruments, and also their interaction, on the housing market and the broader economy.

Our work is related to an expanding body of literature that employs ABMs to capture the heterogeneity and complexity of local and national housing markets. This research stream has its origins in the seminal works of Geanakoplos et al. (2012) and Axtell et al. (2014), who developed an ABM to represent the housing market in Washington DC and explore the origins of its house price cycle. After expanding this original model with life-cycle dynamics, an autonomous rental market and a dynamic buy-to-let (BTL) sector, Baptista et al. (2016) and Carro et al. (2022) turn their attention to assessing the impact of borrower-based macroprudential instruments on the UK housing market. In addition to confirming the effectiveness of these measures in reducing house prices fluctuations, the authors also analyse their heterogeneous impact on different types of households. Furthermore, they uncover that these policies lead to a shift in lending from owner-occupiers to BTL investors. These pioneering works have inspired a series of related contributions by Cokayne (2019), Laliotis et al. (2020), Catapano et al. (2021), Tarne et al. (2022), Mérő et al. (2023), Carro (2023), and Catapano (2023).[1] While focusing on different variables —from the amplitude of the house price cycle to household inequality— as well as on different countries —from Hungary and Denmark to Italy and Spain— these contributions share a common interest in assessing the impact of borrower-based macroprudential instruments. With respect to this body of literature, this paper contributes *(i)* a macroeconomic extension of the housing model, incorporating a fully dynamic corporate sector and, thereby, endogenising household income and consumption; *(ii)* a more detailed banking sector, with (ex-post) heterogeneous banks; *(iii)* an analysis of lender-based prudential measures, such as capital requirements, which are compared to and interacted with borrower-based instruments.

Our model builds on two previously developed ABMs, the macro ABM in Popoyan et al. (2017) and the ABM of the housing market in Carro et al. (2022). The stock-flow consistent model is populated by heterogeneous households, firms and banks, which interact via a goods market, a labour market, a financial market, and a housing market, as well as a Central Bank and a Government. Households can be either entrepreneurs (i.e., owning a firm and employing other workers or owning a bank), employees, or being unemployed. At the same time, they can either own or rent the property they live in. Households that own the property they live in can also own additional properties, which they can rent out to tenants. Households' housing tenure —i.e., owner-occupiers, tenants and BTL investors—, can endogenously change over time, depending on households' decisions. Those decisions are based on behavioural rules and involve consuming goods, starting or closing a firm, changing jobs, and buying or selling properties. Banks hold household deposits and provide both credit to entrepreneurs to finance production and mortgages to households to finance the purchase of properties. Firms and households can fail to repay their loans, exposing banks to losses and potentially to failure.

The Central Bank sets both monetary policy and prudential policies. Monetary policy follows a dual-mandate (inflation-targeting) Taylor rule. Prudential policies

[1] For contributions with a focus on the spatial features of housing markets rather than macroprudential regulation, see Ge (2013, 2017), Pangallo et al. (2019) and Evans et al. (2023). For an assessment of the role of trend-following behaviour in housing markets, see Glavatskiy et al. (2021).

can act both on lenders (banks) in the form of requirements on capital ratios and on borrowers (households) in the form of caps on loan-to-value (LTV) and loan-to-income (LTI) ratios for new mortgages. The Government levies a sales tax whose proceeds are used to pay interest on its debt, targeting a constant debt-to-GDP ratio.

We tailor the model to the UK economy partly by calibrating some parameters and partly by estimating residual parameters through the method of simulated moments. We validate the model empirically and are able to replicate a range of stylised facts such as cross-correlations between macro variables, and housing market characteristics.

We perform three experiments: (i) an increase of *total* capital requirements from 18% to 25%; (ii) the introduction of a cap on owner-occupier mortgages whose LTI ratio is above 3; and (iii) the joint introduction of both instruments at the same time. We also perform a robustness analysis by exploring the impact of different levels/thresholds of capital requirements and LTI limits.

We find that tightening capital requirements lead to a sharp decline in commercial loans and mortgage approvals to owner-occupiers and BTL investors. While the number of housing transactions decreases significantly, the house price-to-income ratio stays at similar levels compared to the benchmark case. However, when the LTI cap is in place, house prices decrease sharply relative to income without significantly changing mortgage approvals to owner-occupiers, while significantly increasing mortgage approvals to BTL investors. This spillover effect also impacts the rental market, as the LTI cap leads to a sharp decrease in the proportion of owner-occupiers, with a corresponding increase of renters and BTL investors. When both experiments are combined, we find that housing transactions and prices drop. Regarding the distributional effects of the policies, we find that while the LTI cap leads to a lower share of high LTI and LTV lending, an increase in capital requirements does not have any distributional effects on LTV, LTI, and house-price-to-income ratios.

At the macroeconomic level, both policies positively affect real output and unemployment dynamics. This result is a consequence of the intertwined mechanisms between the financial accelerator (Bernanke, 2007; Gertler et al., 2007; Gatti et al., 2010) and a substitution effect between housing, production and consumption which is frequently observed in empirical studies (see Li et al., 2016; Been et al., 2020; Khorunzhina, 2021, among others). The results indicate a shift of resources from the housing sector to the goods-producing sector, which leads to an increase in output and a decrease in unemployment. Additionally, our results do not find a material effect on inflation and the real interest rate, consistent with the literature (see Suh, 2012; Spencer, 2014). Finally, we find that the impact of policies is not additive: the sum of the impact of standalone levers is considerably larger from their combined impact.

The rest of the paper is organised as follows. Section 2 describes the model. Section 3 sets out the validation of the model and Section 4 reports the results of our policy experiments. Section 5 concludes.

2 The model

The model is based on previous work by Ashraf et al. (2017), Popoyan et al. (2017) and Carro et al. (2022) and illustrates a self-organising network of firms (i.e., shops), banks, and households coordinating production and trading activities through mechanisms of exchange.

The model has five types of agents: (i) households, (ii) shops, (iii) banks, (iv) a Central Bank, and (v) a Government. Since both shops and banks are owned by households, we will use shop/shop-owner and bank/bank-owner interchangeably when it is not ambiguous in the remainder of the paper. Households provide labour, consume two types of non-perishable goods, and consume/invest in housing. Each household is characterised by the pair (i, j), where i denotes that the household can supply one unit of labour of type i per week to produce good i, and j denotes that the household can consume two types of goods j and $j + 1$ (primary and secondary consumption goods). Moreover, $i \neq j$ and $i \neq j + 1$, which implies that each household cannot consume the good it produces. We assume that there is one household per each combination of labour type and good, and therefore, the number of households is $N = n(n - 2)$.

Consumption goods are produced and sold by *shops*. Each shop is owned by a household, the shop owner, and it produces the good corresponding to the shop owner's labour type, say i, using as input labour of the same type. The good produced is then sold in the market to households whose primary or secondary consumption good is i. This gives rise to evolving endogenous trading and employment patterns. Moreover, in our simulated economy, goods and labour markets feature a costly search, which we consider a critical part of the coordination process.

Regarding housing tenure, households can be categorised into three groups: renters, owner-occupiers, and buy-to-let (BTL) investors. Households' housing decisions depend on their income and wealth, and, for BTL investors, also on the expected return of their investment in properties, which is a function of the expected capital gain and rental yield. Houses are heterogeneous and characterised by a discrete parameter, their quality, making some of them more desirable than others.[2] Households participate in two housing markets: the sales market, in which they can buy or sell houses, and the rental market, in which they rent properties let by BTL investors. House purchases can be financed with mortgages, supplied by banks. Mortgages are regulated by the Central Bank, which can set limits on borrowing based on loan-to-value (LTV) or loan-to-income (LTI) ratios.

There is a fixed number M of banks each owned by a household.[3] At the beginning of the simulation, banks have similar balance sheets.[4] The banking sector provides credit (i.e., commercial loans) to open new shops or finance the ongoing production if the shop owner's wealth is insufficient. Loans are made with full recourse and are collateralised by inventories. Banks also provide mortgages to households. Both the supply of commercial loans and mortgages are subject to prudential regulation constraints. When banks' capital ratios fall below a self-imposed target, they start to constrain credit. Banks must comply with minimum capital requirements and they are resolved if they breach them. We assume that resolution is orderly, in the sense that banks' ownership is simply transferred to another household, without imposing any costs on its customers or on the Government via bail-outs.

Macroeconomic policy is conducted by the Central Bank and the Government. In particular, the Central Bank is in charge for monetary policy and it sets the nominal interest rate using a dual-mandate Taylor rule. Additionally, the Central Bank supervises the banking system and implements prudential regulation by setting capital requirements and borrower-based measures. The Government levies a sales tax and services the stock of debt. As the fiscal authority, it adjusts tax rates in response to changes in the ratio of Government debt to GDP and it serves the interest rate on bonds using taxes.

In the following subsections, we first provide a description of the timeline of events (see Section 2.1). We then present a general description of how agents make their decisions and interact in the goods, labour, and credit markets (see Sections 2.2 – 2.11). Throughout these subsections, we use Latin letters for identifying specific model variables and Greek letters for parameters. The specific values of the parame-

[2]In our model, this quality can be interpreted as a score that summarises the individual characteristics of a property, such as its type (e.g., flat, terraced or detached), location (e.g., proximity to schools), size (e.g., number of bedrooms, existence of a garden or garage), and overall condition. The quality of each house is a fixed parameter whose value is randomly assigned at the beginning of the simulation.

[3]Consumption goods are grouped also in M sectors (i.e., one sector for each bank, and the same number of goods for each sector). Shops can bank with the one corresponding to the sector that their good belongs to.

[4]Banks' balance sheets are not identical due to differences in the number and composition of customers.

ters can be found in Table 8 in Appendix A. More details on the modelling decisions, as well as the description of the estimation and calibration procedures and further information on parameters, can be found in Popoyan et al. (2017) and Carro et al. (2022).

2.1 Timeline of events

At the beginning of each simulation, the desired number of households is created, with their characteristics drawn from suitable distributions estimated from data.[5] Each household is assigned a primary and secondary consumption goods, as well as a production good. Production plans for shops are initialised relying on the distribution of household characteristics and the types of goods in the economy. Furthermore, houses are created and initially distributed among households according to the distribution of houses per household as observed in the data.[6] After this initialisation, agents interact over a finite time horizon, divided in $t = 1, \ldots, T$ periods (or time steps). Each period t corresponds to a week unless stated otherwise.[7] In every period, the following sequence of events takes place:

1. New shops decide whether to enter the market;
2. Search and matching occur in the goods and labour markets;
3. Banks check the creditworthiness of prospective borrowers; assess their own compliance with prudential regulation; take remedial actions if needed (such as restrictions on the extension of credit); and update the interest rate on commercial loans. If banks breach minimum capital requirements they are put into resolution;
4. Households decide on their consumption and savings, and pay their current housing expenses (i.e., mortgage instalments or rent);
5. Housing decisions are made, which will take effect next month (monthly);
6. Housing markets (sales and rental) are cleared (monthly);

[5] We refer the reader to Carro et al. (2022). In the case of parameters for which no convenient data is available for estimation, parameter values were chosen with the method of simulated moments, by trying to make the median outcomes across simulations match certain properties of the real data.

[6] Note that this is different from the model by Carro et al. (2022), where houses are initially distributed among households purely at random and thereby not in line with the observed distribution of houses per household.

[7] It is worth noting that some actions in the model take place on a monthly (e.g., housing decisions) or yearly basis (e.g., adjustment of the tax rate or the Central Bank's policy rate). In particular, we consider that there are 48 weeks per year and 4 weeks per month.

7. Banks pay interest on liquidity borrowed from the Central Bank and receive interest from Government bonds; the Central Bank provides liquidity to banks, if needed;
8. Labour, goods and fire-sale market trading take place;
9. Monetary and fiscal policies are set;
10. Bankrupt shops and banks exit;
11. Prices for consumption goods and wages are updated.

2.2 Entry of the shops

Each shop is owned by a household. Households can become entrepreneurs at the start of a period if they do not own a shop or bank. This happens with probability θ, which represents the propensity to become an entrepreneur. A potential entrepreneur would enter the market only if she has sufficient fixed capital and can afford immediately to pay S units of either of her consumption goods into the shop's fixed capital as a set-up cost. This fixed capital can be obtained from the prospective entrepreneur's legacy capital (if any), fire-sale markets (available to the entrepreneur at a publicly known fire-sale price $P_{f,t}$), or stores with which she has a trading relationship. The fire-sale price is set at the value

$$P_{f,t} = \frac{W_t(1+\pi^*)}{2}, \tag{1}$$

where W_t is the average wage rate and π^* is the Central Bank's weekly inflation target.

The overall liquidity of this prospective entrepreneur consists of money, deposit holdings, and possibly a credit line provided by her bank, which is capped at $P_{h,t}(S+I_{i,t})$, where I is the potential entrepreneur's stock of inventories and P_h is the haircut price discussed later in Section 2.4, Eq. (13).

If the potential entrepreneur has the financial resources to enter, she develops a *business plan*. First, she performs a profitability test. She randomly chooses the mark-up ($\mu_{i,t}$) and the sales target ($s_{i,t}^{trg}$),[8] and computes the price at which she would sell her good. Based on those, the entrepreneur calculates her expected profits from

[8] More specifically, the mark-up $\mu_{i,t}$ is drawn from a uniform distribution over the support $[0; 2\overline{\mu}]$, where $\overline{\mu}$ measures the average percentage mark-up over variable cost ($w_{i,t}$). $s_{i,t}^{trg}$, instead, is extracted from a uniform distribution over $[1; n]$, where n is the quantity of goods in economy. The latter facilitates a straightforward measurement of the potential output of the economy.

entry, $\Pi_{i,t}$, as

$$\Pi_{i,t} = w_{i,t}(\mu_{i,t}\, s_{i,t}^{trg} - (F-1)) - w_{i,t}\, i_t^D(s_{i,t}^{trg} + F - 1) \tag{2}$$

where F and $w_{i,t}$ stand for the weekly fixed cost and the economy-wide average wage, respectively. The first term is the shop owner's operative margin. The second one reflects the opportunity cost of instead investing in a deposit account with interest rate i_t^D, which is set equal to the weekly policy rate (i_w).[9]

If the profitability test is successful (i.e., if the expected profits are positive $\Pi_{i,t} > 0$), then the entrepreneur moves to the next step and engages in a market search to find a prospective customer and a prospective worker who would like to form an employment relationship with the new shop. In particular, she sends messages to two randomly chosen households, one of which is an unemployed worker with the same production good and the other one is a consumer whose consumption good (either primary or secondary) is the one the shop produces.

The message to the possible worker communicates the wage rate the shop owner intends to set in case she opens the shop. The wage rate $w_{i,t}$ reads

$$w_{i,t} = W_t(1+\pi^*)^{\frac{\Delta+1}{2}}\,, \tag{3}$$

where W_t is the employment-weighted average wage rate across all shops, computed and publicly communicated by the Government, Δ is the fixed contract period, and π^* is the Central Bank's target inflation rate. The prospective worker will accept the job offer by the new shop if the offered wage is more than her effective wage [defined in Section 2.8, Eq. (24)], i.e., $w_t^{eff} < w_{i,t}/(1+\pi^*)$. Operating the shop entails a fixed overhead cost of F units of type i labour per week and a variable cost of one unit of type i labour per unit of good i produced.

The search for the potential consumer takes place in a similar way. In the message sent, the shop owner communicates the price of the goods the consumer would find in the store. The potential consumer will accept to become a customer of the new shop if the offered price $p_{i,t}^{nor}$ is below her effective price, p_t^{eff}, i.e., if $p_t^{eff} > p_{i,t}^{nor}/(1+\pi^*)$, where the price $p_{i,t}^{nor}$ is defined as

$$p_{i,t}^{nor} = \frac{(1+\mu_{i,t})}{(1-\tau_t)} w_{i,t}\,, \tag{4}$$

where τ is the sales tax rate (see Eq. (27)) and μ is the mark-up.

[9] Note that the -1 present in both terms is related to the fact that the shop-owner does not need to pay a wage for her own work.

All in all, the entrepreneur decides to enter the market if: *(i)* she can afford a necessary amount of fixed capital to cover the set-up cost; *(ii)* the financial viability and profitability tests are passed; and *(iii)* the prospective customer and worker respond affirmatively to her invitations to form relationships with her shop. If any of the three conditions is not satisfied, the entrepreneur decides not to open the shop. If all of the three conditions are met, the entrepreneur opens the shop with a posted wage $w_{i,t}$, a posted price $p_{i,t}$, a markup $\mu_{i,t}$, a sales target $s_{i,t}^{trg}$ drawn from a uniform distribution with support $[1, n]$, an inventory level $I_{i,t}$ equal to the entrepreneur's legacy inventory, and an input target equal to

$$x_{i,t}^{trg} = s_{i,t}^{trg} + F + \lambda_I (s_{i,t}^{trg} - I_{i,t}) \,, \tag{5}$$

where λ_I is the weekly inventory adjustment speed and F is the weekly fixed cost the shop owner faces.[10]

2.3 Search and matching in labour and goods markets

In each period, every household has an opportunity to create trading relationships through both job search and shop search. In particular, each household (except for shop owners) engages in a job search with certain probability σ (with $0 \leq \sigma \leq 1$), asking the effective wage of a randomly chosen household with the same production good i. If the searcher's effective wage is below the communicated one, the searcher would ask the responding household's employer for a job. If the matched household is a shop owner herself, the searcher would ask for a job directly and would accept if the shop's wage is above her effective wage. The labour contract is signed and the potential worker is hired if: *(i)* the labour employed in the last period by the shop owner is not sufficient to meet her current input target; and *(ii)* the wage offered to the searcher is higher than her effective one.

In contrast to job search, every household, directly or indirectly, engages in a shop search (for either the primary or secondary consumption good). In a direct search, the household asks a randomly chosen shop if it trades either of its consumption goods and, if so, what the posted prices are. In the indirect mode, a household would ask another randomly chosen household with the same primary or secondary consumption good for its effective retail prices. In both cases, the household decides to switch to a new shop if and only if the shop's effective price for that good is less than the searcher's. Once search and matching activities are completed, house-

[10]It is worth noting that in contrast to legacy fixed capital, legacy inventories cannot be part of the setup cost (S) since they are in units of a person's production good, while S must be incurred in units of consumption goods.

Table 1: Banks' balance sheet.

Assets	**Liabilities**
Central Bank reserves ($R_{m,t}$)	Deposits ($D_{m,t}$)
Government bonds ($B_{m,t}$)	Borrowing from the Central Bank ($L^{CB}_{m,t}$)
Seized collateral ($SC_{m,t}$)	
Commercial loans ($L_{m,t}$)	
Mortgages ($MG_{m,t}$)	Equity ($E_{m,t}$)

holds adjust their balance sheets and set their expenditures plan as discussed in Section 2.5.

2.4 Banks and credit markets

The banking sector consists of M banks ($m = 1, \ldots, M$), each serving a specific shop sector. This means that shops are grouped into M sectors, depending on the good they produce, each sector containing the same number of goods. In period t, the balance sheet of bank m on the asset side consists of credit lines ($L_{m,t}$) defined as commercial loans extended to shop owners, measured as the value of principal and interest payable that period/week; mortgages ($MG_{m,t}$) extended to households; seized collateral ($SC_{m,t}$), consisting of inventories and fixed capital seized by the bank from defaulting shops and valued at the fire-sale price $P_{f,t}$; Government bonds ($B_{m,t}$) and Central Bank reserves ($R_{m,t}$). The liabilities of bank m consist of household deposits ($D_{m,t}$) and loans from the Central Bank ($L^{CB}_{m,t}$). Equity is simply assets minus liabilities. Accordingly, each bank's balance sheet looks as in Table 1.

The key quantity for banks' operations and regulatory compliance is their capital ratio, i.e., the ratio between their equity ($E_{m,t}$) and their risk-weighted assets $\text{RWA}_{m,t}$

$$\frac{E_{m,t}}{\text{RWA}_{m,t}} = \frac{E_{m,t}}{\alpha_R R_{m,t} + \alpha_B B_{m,t} + \alpha_L L_{m,t} + \alpha_{SC} SC_{m,t} + \alpha_{MG} MG_{m,t}}, \tag{6}$$

where α_x is the risk weight for the asset x. For the remainder of the paper we use a simple set of risk weights for different exposures: *(i)* Central Bank reserves (α_R) and Government bonds (α_B) have a risk weighting of 0%; *(ii)* commercial loans (α_L) and seized collateral (α_{SC}) have a risk weighting of 100%; and *(iii)* residential mortgages (α_{MG}) have a risk weighting of 50%.[11]

First, banks face a minimum capital requirement. This means that, if the capital

[11] These risk weights are in line with the Basel I capital standard, which allows us to keep our analysis simple.

ratio of bank m falls below the minimum requirement $\chi_{\min}$,

$$\frac{E_{m,t}}{\mathrm{RWA}_{m,t}} < \chi_{\min} \,, \tag{7}$$

then bank m is resolved. The resolution process consists of a transfer of ownership from the previous owner to the bank's largest depositor. This leads to an increase in the bank's equity, as the new owner's deposits are fully converted into equity. It is important to stress that, in our model, such a resolution process is practically costless, in the sense that the bank can continue to operate seamlessly under a new owner.

Second, banks target a *desired* capital ratio. If the capital ratio of bank m is above its desired level, χ_{des}

$$\frac{E_{m,t}}{\mathrm{RWA}_{m,t}} \geq \chi_{\mathrm{des}} \,, \tag{8}$$

then bank m will meet all the demand for credit it receives —both commercial loans to shops and mortgages to households— provided that the prospective borrowers are deemed to be sufficiently creditworthy (see below).[12] In the intermediate regime, in which the capital ratio is higher than the minimum requirement but lower than the bank's self-imposed desired level

$$\chi_{\min} \leq \frac{E_{m,t}}{\mathrm{RWA}_{m,t}} < \chi_{\mathrm{des}} \,, \tag{9}$$

bank m gradually reduces the supply of credit. More specifically, the demand for credit of each borrower deemed to be sufficiently creditworthy is met in full with the following probability

$$\frac{\frac{E_{m,t}}{\mathrm{RWA}_{m,t}} - \chi_{\min}}{\chi_{\mathrm{des}} - \chi_{\min}} \,. \tag{10}$$

We refer to the distance between the desired capital ratio χ_{des} and the minimum requirement $\chi_{\min}$ as *capital buffer*.[13]

In each period, the bank owner receives a fraction f_{Π} of the bank's profits. Banks' profits are their net interest income, computed as the difference between interest earned on commercial loans, mortgages, and Government bonds minus interest paid on deposits and loans from the Central Bank. However, if the capital ratio of bank m is smaller than the distribution threshold χ_R, the fraction of profits transferred to

[12] Banks extend credit by endogenously creating money (McLeay et al., 2014). This means that banks simultaneously create an asset on their balance sheet (either a commercial loan or a mortgage) and a matching liability (a deposit).

[13] Appendix B gives further information on capital buffers by providing a comparison between the capital stack implemented in the UK and the simplified version of it used in our model.

its bank owner is further apportioned by a factor f_R, meaning that the bank owner receives only a fraction $f_\Pi f_R$ of its bank's profits. Mimicking the schedule in BIS (2019), f_R is determined as

$$f_R = \begin{cases} 1 & \text{if } \frac{E_{m,t}}{\text{RWA}_{m,t}} \geq \chi_R \\ 0.6 & \text{if } 0.75\chi_R \leq \frac{E_{m,t}}{\text{RWA}_{m,t}} < \chi_R \\ 0.4 & \text{if } 0.5\chi_R \leq \frac{E_{m,t}}{\text{RWA}_{m,t}} < 0.75\chi_R \\ 0.2 & \text{if } 0.25\chi_R \leq \frac{E_{m,t}}{\text{RWA}_{m,t}} < 0.5\chi_R \\ 0 & \text{if } \frac{E_{m,t}}{\text{RWA}_{m,t}} < 0.25\chi_R \end{cases} . \tag{11}$$

As mentioned above, banks extend credit to prospective borrowers after checking their creditworthiness, which happens only once, at loan origination. For shops, banks monitor the quick ratio (QR) and the return on assets (ROA), and require these to be larger than fixed thresholds:

$$QR_{i,t} = \frac{\text{Current Assets} - \text{Inventories}}{\text{Current Liabilities}} = \frac{D^s_{i,t} + H^s_{i,t} - I_{i,t}}{L^s_{i,t}} \geq \kappa \,, \tag{12a}$$

$$ROA_{i,t} = \frac{\text{Net income (after tax)}}{\text{Total assets}} = \frac{\Pi^s_{i,t}}{D^s_{i,t} + H^s_{i,t} + I_{i,t}} \geq \psi \,. \tag{12b}$$

D^s_i and H^s_i are, respectively, shop i's deposits and cash (i.e., their internal liquid resources), $I_{i,}$ is the value of its inventories, and $\Pi^s_{i,}$ are its profits. The parameters κ and ψ are between zero and one.

Commercial loans are made with full recourse, but are also collateralised by inventory and fixed capital. Each bank applies a haircut to collateral —each week, it specifies a "haircut" price $P_{h,t}$, and will lend $P_{h,t}$ for each unit of inventory or fixed capital it accepts. Banks set the haircut price by applying a pro-cyclical loan-to-value ratio h to the estimated marginal cost of production $W_t(1+\pi^*)$

$$P_{h,t} = hW_t(1+\pi^*), \tag{13}$$

where W_t is the average wage rate and π^* is the Central Bank's weekly inflation target.[14] Accordingly, the total size of the commercial loan granted to shop i is

$$L^s_{i,t} = P_{h,t}(I_{i,t} + S) = hW_t(1+\pi^*)(I_{i,t} + S) \,. \tag{14}$$

[14] The pro-cyclical loan-to-value ratio is calculated as the sum of the average loan-to-value ratio $\bar{h}$ and an increasing function of real GDP with an adjustment speed of λ_h. Please see Ashraf et al. (2017), Section 8.2, for details.

One can interpret h as the level of risk tolerance of banks when providing credit to shops.

Banks offer two different mortgage products to owner-occupiers and buy-to-let (BTL) investors, in line with the general features of the UK mortgage market. In our model, owner-occupiers are offered fixed-rate repayment mortgages with a maturity ν of 25 years,[15] while BTL investors are offered instead interest-only mortgages with the same fixed rate and maturity.[16]

In order to assess the creditworthiness of households applying for a mortgage, we assume that banks apply four different criteria.[17] The first one is a loan-to-value (LTV) limit. Banks set a maximum LTV ratio Γ, which caps the ratio between the amount the bank is willing to lend and the purchase price of the house. The ratio Γ_b depends on whether the mortgage is offered to owner-occupiers or BTL investors, with the subscript b differentiating the two. The maximum possible down-payment that household z can afford at time t is equal to its bank deposits $D_{z,t}$. Therefore, the amount $q_{z,t}$ the bank is willing to lend to household z at time t is capped by:

$$q_{z,t} \leq \frac{\Gamma_b}{1-\Gamma_b} D_{z,t} \,. \tag{15}$$

The second criteria is a loan-to-income (LTI) limit. Banks set a maximum LTI value Φ for mortgages to owner-occupiers based on the ratio of the maximum amount $q_{z,t}$ they are willing to lend over the gross annual employment income of household z measured at time t. The gross annual employment income is estimated simply as the gross weekly employment income times the number of weeks in a year, i.e., 48. Thus, $q_{z,t}$ must satisfy

$$q_{z,t} \leq 48 Y^e_{z,t}\, \Phi \,. \tag{16}$$

The third criteria is a debt-service-to-income (DSTI) limit and represents an affordability test. Banks set a maximum DSTI value Ψ for mortgages to owner-occupiers based on the ratio of the monthly mortgage payment over the household's gross

[15] While mortgages with a fixed rate for the whole term are typical for the US and many other countries, mortgage products beyond an initial 10-year fixed rate are not common in the UK. However, since we do not consider the re-mortgaging behaviour of households, we expect variable rate mortgages to have only a marginally small impact on our results.

[16] A significant portion of BTL mortgages in the UK are interest-only, with the repayment of the principal due only at the end of the term. In our model, BTL investors do not have a specific savings goal for the final repayment of the principal. In order to avoid an excessive level of bankruptcies when BTL mortgages come to the end of their term, we impose that, during the two-year period leading up to maturity, investors try to sell their property if their financial wealth is insufficient to repay the full principal amount.

[17] See Table 8 in Appendix A for details on the calibration of the parameters entering these criteria.

monthly employment income. The gross monthly employment income is estimated simply as the gross weekly employment income times the number of weeks in a month, i.e., 4. Writing the monthly mortgage payment as a function of the monthly mortgage rate $i_t^m/12$ and the mortgage term expressed in months $12 \cdot \nu$, $q_{z,t}$ must satisfy

$$q_{z,t} \leq 4Y_{z,t}^e \, \Psi \, \frac{1 - \left(1 + i_t^m/12\right)^{-12\nu}}{i_t^m} \,. \tag{17}$$

The fourth criterion is an interest-coverage-ratio (ICR) limit for BTL mortgages. Banks set a minimum ICR ratio Ω between the expected annual rental income of the prospective BTL property and the annual interest expense to service the corresponding mortgage. This serves as a buffer for other expected expenses (e.g., taxes) and against unforeseen shocks (e.g., periods of vacancy). The higher Ω the more conservative the banks' lending standards. The maximum amount $q_{z,t}$ that banks are willing to lend must thus satisfy

$$q_{z,t} \leq \frac{D_{z,t}}{\Omega \, \frac{i_t^m}{\bar{s}} - 1} \,, \tag{18}$$

where the bank deposits $D_{z,t}$ corresponds to the maximum possible down-payment that household z can afford at time t, i_t^m is the monthly mortgage rate, and $\bar{s}$ is the current exponential moving average rental yield over all house qualities.

In addition to these internal underwriting standards, all banks must ensure that their mortgages comply with lending regulations imposed by the Central Bank, which may set limits on the LTV, LTI, DSTI and ICR ratios. These limits can be hard, meaning that lending beyond the cap is not allowed. Alternatively, they can be soft, which permits a certain percentage of new mortgages to exceed the corresponding caps, calculated over a 12-month rolling window (see Carro et al., 2022, for more details).

In Section 4, we provide a comparison between a benchmark case with no regulatory limits on mortgage lending and policy experiments with a soft LTI limit imposed by the Central Bank.

All in all, credit provisioning (commercial and mortgage) is potentially limited by lenders' self-imposed underwriting standards and risk appetite.

Banks set the weekly interest rate they pay on deposits at the nominal policy rate i_w (see Section 2.9). The weekly interest rate demanded on new commercial loans is set to i_w plus a fixed spread $s_c/48$, where s_c is the annual spread. Similarly, the annual interest rate on new mortgages is equal to the annualised nominal policy rate $(1 + i_w)^{48}$ plus an annual fixed spread s_m. The fixed spread is based on our simplifying assumption that banks do not compete on price with each other, hence they all offer the same interest rate. As a consequence, banks do not adjust prices when their capital ratios change. Instead, they adjust quantities by rationing lending when their capital ratios fall below their self-imposed target (χ_{des}).

After the housing sales market clears (see Section 2.7), banks with reserves in excess of a reserve target use the buffer above the target to repay their debt with the Central Bank and invest the remainder of the buffer in Government bonds. Banks with a liquidity shortfall (i.e., with negative reserves) borrow the corresponding amount from the Central Bank.

2.5 Budget planning

As part of the budget planning, all households first adjust their permanent income from the previous period according to the following rule

$$\Delta Y^p_{z,t} = \lambda_p (Y_{z,t} - Y^p_{z,t-1}) , \tag{19}$$

where Y_z is the actual weekly income, Y^p_z is the permanent income of household z, and λ_p is the adjustment speed parameter. Actual weekly income is composed of gross weekly employment income $Y^e_{z,t}$ and weekly housing income minus housing expenses. Gross weekly employment income is meant here in a broader sense and consists of wages for shop employees, shop profits for shop owners, and a fraction of bank profits for bank owners. Weekly housing income consists of the rent collected monthly on BTL properties divided by the number of weeks in a month, i.e., 4. Weekly housing expenses comprise of monthly mortgage payments and rents divided by the number of weeks in a month: every month, property owners with an outstanding balance make mortgage payments to their respective bank, while renters make rental payments to their landlord.

After updating its permanent income according to Eq. (19), each household sets its weekly planned consumption expenditure PCE as a fixed fraction υ of its total wealth,[18]

$$PCE_{z,t} = \upsilon (A_{z,t} + Y^p_{z,t}) , \tag{20}$$

where $A_{z,t}$ is household z's financial wealth, which consists of bank deposits and money holdings minus outstanding commercial loans, and $Y^p_{z,t}$ is the capitalised value of the permanent income of the household. After planned consumption ex-

[18] Following Ashraf et al. (2017), υ is computed based on the weekly rate of time preference ρ_w of an intertemporal logarithmic utility function. We derive ρ_w from the annual rate of time preference ρ using the following transformation $(1 + \rho) = (1 + \rho_w)^{48}$.

penditure is set and housing expenses are paid, households decide how to reallocate the remaining wealth between deposits and cash, taking into account that their consumption expenditure is paid in cash.[19]

2.6 Housing decisions

Housing decisions follow closely Carro et al. (2022)[20] apart from life-cycle dynamics. In Carro et al. (2022), every period, some households are born, some die, and the rest of them age. This life-cycle dynamic ensures that some renters become first-time homeowners. However, in our model, households live infinitely and can switch tenure between being a renter and a homeowner.[21] Additionally, every owner-occupier household can become a buy-to-let investor, whereas this was only possible for a subset of owner-occupiers in Carro et al. (2022).

Households make decisions on whether to rent/let or buy/sell properties, depending on their current tenure,[22] and make their bids and offers accordingly. For instance, a household after selling its house or a tenant at the end of its rental contract, decides whether to buy a new house or rent. In order to make this decision, households compare the cost of buying a house, reflecting factors such as mortgage payments and expected house price appreciation, with the cost of renting an equivalent home, allowing for an adjustment that represents the empirical preference of households to own their homes rather than to rent them.

If household z decides to buy a house at time t, then it sets its desired purchase price p^d to be a multiple α of its gross annual employment income $48 \cdot Y^e_{z,t}$,

$$p^d_{z,t} = \min\left(48 Y^e_{z,t} \, \alpha \, e^{\varepsilon}, \, p_{\max}\right) \, , \tag{21}$$

where ε is a Gaussian noise with mean ε_μ and variance ε_σ. The desired purchase price is capped by the price the household could afford given the maximum mortgage amount that it can secure from a bank, $p_{\max}$.[23] In contrast to Carro et al. (2022), this equation is linear in income. We found this specification to be more parsimonious in our model, where nominal house prices have a secular upward trend over time,

[19] We refer the reader to Popoyan et al. (2017), Section 2.5, for further details.

[20] This section is a brief summary of housing decisions, and the reader is referred to Carro et al. (2022) for a full exposition. Differences with respect to Carro et al. (2022) are set out in the main text.

[21] Therefore, there are no first-time buyers in our model.

[22] There are mainly three types of housing tenure: *(i)* owner-occupiers; *(ii)* renters; and *(iii)* BTL investors. In addition to these, there is a temporary and cost-free accommodation, called *social housing*, in which households might end up while trying to find a house to rent or buy.

[23] The desired purchase price is further limited by the average sale price of houses in the highest quality band to prevent households from aspiring to unreasonable prices.

as opposed to their model, where house prices are real and move around a long-run average.

Furthermore, the household must decide whether to pay in cash or apply for a mortgage and, if so, also on the size of the corresponding down-payment. In particular, the household pays in cash if its financial wealth is higher than the price of the house. If the household requires a mortgage, its desired down-payment is assumed to correspond to the same percentile, within an estimated distribution of down-payments, as its income, estimated from data.[24] This result is adjusted by the current house price index to account for inflation and market conditions. Finally, it should be noted that actual down-payments are bounded by the banks' mortgage underwriting standards, i.e., the household being allowed to make larger but not smaller down-payments.

If household z decides to rent at time t, then it sets its desired rental price $r^d_{z,t}$ to be proportional to its gross monthly employment income $4 \cdot Y^e_{z,t}$

$$r^d_{z,t} = \iota \; 4Y^e_{z,t} \,, \tag{22}$$

where ι is the fraction of gross monthly employment income allocated to rent. As opposed to Eq. (21) for the desired purchase price, this equation does not include any noise term. This is to reflect the empirical observation that rents are much less volatile than house prices. Similar to the case of desired house prices described above, this equation is linear in income, in contrast with Carro et al. (2022). This makes it simpler to account for secular increases in nominal rents.

The probability of a household selling its owner-occupied house is exogenous, reflecting factors outside the model, e.g., changes to family circumstances. Once household z decides to sell its home at time t, the offer is sent to the sales market at a price $p^s_{z,t}$ given by

$$\ln p^s_{z,t} = \ln(\overline{p_Q}) + \eta \,, \tag{23}$$

where $\overline{p_Q}$ is the exponential moving average sale price of houses of the same quality and η is a random mark-up drawn from a distribution estimated from data. Sellers reduce the offer price every month in which the property remains unsold with a given probability. If a price reduction would result in the seller having negative equity, then the offer is withdrawn.

Homeowners decide each month whether they want to buy an investment property and whether they want to sell any vacant investment properties they may

[24] This mechanism is equivalent to the one in Carro et al. (2022), with the only difference being that we do not consider any specific behaviour for first-time buyers here, as these are not included in our model.

already have. These decisions are based on the expected rental yield and expected capital appreciation, as well as on the specific preference for one or the other characterising the household.[25] Investors with vacant properties try to rent them out, reducing the offer price each month until they find a tenant. For further details about the precise mechanisms for investors' buying, selling and letting decisions, we refer the reader to Carro et al. (2022).

2.7 Housing markets

The sales and the rental market are interconnected in the sense that BTL investors purchase properties in the sales market and rent them out via the rental market. Also, conditions in the sales market influence whether renters can successfully become homeowners. After collecting bids and offers in each market, clearing occurs based on the double auction process described in Carro et al. (2022). In short, first, owner-occupying bids are matched to the highest quality offer they can afford and BTL bids to the offer with the highest expected gross rental yield they can afford. In both cases, cheaper houses are preferred in case of equal characteristics. Then, while offers with a single bidder directly lead to a transaction, for offers with multiple bidders one of them is randomly chosen for the transaction, after potentially increasing the price by a small amount. Any unfulfilled offers at the end of the round are maintained for the next round, but can be updated. All unsuccessful bids are dropped, so households have to bid again in the next round.

2.8 Trading in fire-sale, labour, and goods markets

After the housing markets clear, households interact in the fire-sale, labour and goods markets.

The fire-sale market matches the demand and supply for inventories. Inventories are offered by banks that seek to liquidate assets they have acquired during foreclosures and by shop owners whose current inventory exceeds their inventory target or who have exited the market (see Section 2.10). The demand side comprises shops whose actual inventories are below their inventory target or prospective shop owners purchasing fixed capital. Both on the demand and supply sides, queues are formed based on the type of production good i. The shop owner in need of inventories is matched to the first seller (if any) in the i-*th* queue. The first supplier sells whatever quantity she can, and if she cannot fulfil the entire order, the queue

[25] In particular, as Carro et al. (2022), we consider three types of investors depending on the intensity of their interest in capital gains as opposed to rental yield: capital-gains-driven, rental-income-driven and mixed.

goes to the next supplier. The trading continues until the order is fulfilled or the queue runs out of suppliers. When the fire-sale market closes, labour and goods market trading starts.

The labour market matches the demand and supply of the workforce. The demand side of the labour market consists of shop owners, while the supply side comprises households with different employment statuses (i.e., self-employed, employed or unemployed). The search and match mechanism in the labour market is based on matching production goods, meaning that each shop owner searches for a worker with precisely the same production good, while each household searches for a shop owner who produces the same product as its production good.

A household is identified as self-employed (e.g., shop owner) if it uses its unit endowment as input. If the household has no employer, then it trades in the labour market. If the household has an employer with positive money holdings ($H_{i,t}$), it offers to trade its endowment in exchange for the "effective wage" (w_t^{eff}) according to the rule

$$w_t^{eff} = \min(w_{i,t},\ H_{i,t})\,. \tag{24}$$

The shop accepts the request of the worker unless its labour input is above its target and the ratio of the inventory-to-sales target (IS) exceeds the critical threshold value $IS > 1$ (see Table 8 in Appendix A). If the matching between the worker and the employer is successful, a wage is paid in exchange for the provided inputs for production according to the posted wage rate [see Eq. (3) in Section 2.2 as well as an explanation of how wages are updated in Section 2.11].

The goods market matches the demand and supply for consumption goods. Let $j(z)$ and $j(z)+1$ be the two consumption goods of household z, $c^1_{z,t}$ and $c^2_{z,t}$ the quantities that household z demands of good $j(z)$ and $j(z)+1$ at time t, and $p^1_{z,t}$ and $p^2_{z,t}$ the prices posted by the shops from which household z buys its goods at time t.[26] Household z chooses the quantities of its desired consumption goods $c^1_{z,t}$ and $c^2_{z,t}$ to maximise the utility function

$$u(c^1_{z,t}, c^2_{z,t}) = \left(c^1_{z,t}\right)^{\Upsilon/(\Upsilon+1)} + \left(c^2_{z,t}\right)^{\Upsilon/(\Upsilon+1)}\,, \tag{25}$$

with the demand parameter $\Upsilon > 0$, and subject to the budget constraint $p^1_{z,t} \cdot c^1_{z,t} + p^2_{z,t} \cdot c^2_{z,t} = PCE_{z,t}$, where $PCE_{z,t}$ is the planned consumption expenditure determined in the previous stage (see Section 2.5). If household z has an established

[26] If one of the shops has no inventories or the household does not have a shop for that good, then the household's effective price is set to infinity, and the search for a shop is happening in $t+1$. Household z places orders for amounts, $c^1_{z,t}$ and $c^2_{z,t}$, subject to the cash-in-advance constraint $p^1_{z,t} \cdot c^1_{z,t} + p^2_{z,t} \cdot c^2_{z,t} \leqslant H_{z,t}$.

relationship with only one shop, say the shop that sells good $j(z)$ with posted price $p^1_{z,t}$, then the household orders the amount $PCE_{z,t}/p^1_{z,t}$ from that shop. Finally, the shop that sells good $j(z)$ agrees to sell amounts $c^{\text{eff},1}_{z,t} = \min(c^1_{z,t}, I^1_{z,t})$, where $I^1_{z,t}$ is its inventory at time t, in exchange for the amount $p^1_{z,t}c^{\text{eff},1}_{z,t}$ of money, and analogously for the shop that sells good $j(z) + 1$.

The trading relationships established in this section may be interrupted randomly with a probability δ of quitting the labour or goods markets. This will result in the unconditional breakdown of the active trading relationships of the household with employers or stores.

2.9 Macro policies

In our model, the Central Bank sets the monetary policy, lends to banks and regulates the banking sector. The Government levies a sales tax to service the interest on its debt, issued as bonds.

Monetary policy is set by using a dual-mandate Taylor rule and revising it every month (4 weeks). Accordingly, the nominal interest rate is computed as

$$\log(1+i) = \max\{\log(1+i^*) + \phi_\pi[\log(1+\pi) - \log(1+\pi^*)] + \phi_y(y - y^*), 0\}, \quad (26)$$

where ϕ_π and ϕ_y are fixed coefficients, π is the inflation over the past 12 months, π^* is the inflation target, y is the current 3-months moving average for the weekly average log GDP and y^* is the Central Bank's evolving estimate of weekly log potential output (see Ashraf et al. (2011)). Relying on the above Taylor rule, the weekly interest rate is determined according to $1 + i_w = (1 + i)^{1/48}$.

Fiscal policy sets the retail sales tax rate (τ) once per year (i.e., in the last week of the year) equal to a value τ^*, which would leave the debt-to-GDP ratio unchanged (see Ashraf et al. (2011)) plus an adjustment factor that is proportional to the difference between the actual and the target debt-to-GDP ratio:

$$\tau_t = \tau^* + \lambda_\tau \left(\frac{B_t}{P_t(1+i_w)48e^{y^*}} - b^* \right), \quad (27)$$

where λ_τ is the adjustment coefficient, B_t is the total stock of Government bonds, P_t is the current price level, i_w is the weekly nominal interest rate set by the Central Bank, y^* is the potential output, and b^* is the target debt-to-GDP ratio. The Government uses taxes to fund the interest payments on the stock of public debt issued as Government bonds.

2.10 Exit of shops

The population of shops evolves endogenously due to entry and exit dynamics. Shops can exit the market *(i)* if the shop owner is bankrupt; *(ii)* for exogenous reasons with probability δ; and *(iii)* voluntarily if the shop cannot afford to pay for the coming week's fixed costs and is unprofitable.

A shop is declared bankrupt if the value of its financial wealth is lower than the value of its outstanding loans,

$$A^s_{i,t} = H^s_{i,t} + D^s_{i,t} + P_{h,t} * I_{i,t} - L^s_{i,t} < 0\,. \tag{28}$$

When the shop exits, regardless of the reason for the exit, all trading relationships (with both employees and customers) are dissolved and the shop is obliged to repay its bank loan to the extent possible. If the sum of money holdings and deposits of the shop exceeds the bank loan, it repays the whole loan to the bank. Otherwise, the bank seizes inventories, consisting of fixed capital, valued at a fire-sale price in the balance sheet, and joins the queue for the fire-sale market in each of those goods.

2.11 Wage and price setting

Shops update their posted wage when contracts with their employees expire, i.e., every Δ periods. Shops first update their sales target $s^{trg}_{i,t}$, setting it equal to the period's actual sales. Then they proceed to update wages according to the following rule:

$$w_{i,t} = \overline{w_{i,t}} \left[\left(1 + \beta \left(\overline{x^{trg}_{i,t}} / \overline{x^{pot}_{i,t}} - 1 \right) \right) (1 + \pi^*) \right]^{\Delta/48}, \tag{29}$$

where $\overline{w}$ is the current wage, $\overline{x^{trg}}$ is the average input target, $\overline{x^{pot}}$ is the potential input, and the parameter β stands for the degree of wage and price flexibility.

Next, every period, shops review their retail price. Shops keep the "normal" price reported in Section 2.2, Eq. (4), unless their inventories are sufficiently far from their target sales. In particular, the price change follows the rule:

$$p_{i,t} = \begin{cases} p^{nor}_{i,t} \cdot \delta_p, & \text{if } I < s^{trg}_{i,t} \cdot IS^{-1} \\ p^{nor}_{i,t} \cdot \delta_p^{-1} & \text{if } I > s^{trg}_{i,t} \cdot IS \\ p^{nor}_{i,t}, & \text{otherwise} \end{cases}, \tag{30}$$

where $p^{nor}_{i,t}$ is the normal price of shop i at time t, defined in Eq. (4), δ_p and IS are, respectively, the size of the price cut and the critical inventory-to-sales ratio (see Table 8 in Appendix A), and $s^{trg}_{i,t}$ is the sales target of shop i at time t.

3 Validation

As is typically the case for agent-based models (ABMs), our model does not allow for analytical and closed-form solutions (see Fagiolo and Roventini, 2017, for a discussion). Accordingly, we perform Monte Carlo simulations to study the stochastic processes driving the co-evolution of micro and macro variables in the model. We consider 100 independent runs of the model, each of them comprising 85 years of simulation. As is customary for ABMs, we treat the initial period (in our case, 25 years) of each simulation as a transient. Therefore, all results are based on model outputs for 60 years (i.e., from year 26 onward). Note that, for consistency, we focus hereafter on real variables, i.e., adjusted for inflation.

In this section, we provide an empirical validation of the model (see Fagiolo et al., 2019, for further information on the validation of ABMs) before assessing the impact of different borrower- and lender-based prudential policy experiments on the housing and credit markets as well as on the real economy (see Section 4).

We consider the performance of the model with respect to macroeconomic variables and housing market statistics. In term of the macroeconomic performance, Table 2 shows that the model can broadly reproduce the average inflation, unemployment, and real interest rate in the UK.

The model can also reproduce a list of stylised facts pointing to the model's capacity to capture the long-run and short-run behaviour of the economy (see Haldane and Turrell, 2019, for a summary of the literature). We investigate to which extent our calibrated model can qualitatively replicate the co-movement of different macroeconomic indicators with output over the business cycle. Following the methodology described in Stock and Watson (1999) and Napoletano et al. (2006), in Table 3 we compute the cross-correlation structure between the output and the main macroeconomic variables, including leads and lags of up to 4 years.[27] In line with empirical evidence (see Stock and Watson, 1999; Napoletano et al., 2006), the cross-correlation analysis reveals the pro-cyclical nature of consumption, interest rate, credit, inflation and money stock (i.e., the sum of cash and deposits), and the counter-cyclical behaviour of unemployment. Table 3 also indicates a pro-cyclical co-movement between house prices and the output level, in accordance with numerous empirical studies which uncover a strong synchronisation between housing and macroeconomic cycles (see Claessens et al., 2012; Hirata et al., 2013; Leamer, 2015,

[27] Following the methodology described in Stock and Watson (1999), Table 3 is constructed based on the correlation between x_t and y_{t+k}, where x_t is the HP filtered (transformed) series listed in the first column and y_{t+k} is the k lead/lag of the filtered real output. A large positive correlation at $k = 0$ indicates pro-cyclical behaviour of the series; a large negative correlation at $k = 0$ indicates counter-cyclical behaviour.

Table 2: Macroeconomic indicators.

	Simulation		1989 – 2008		
	Mean	**Std**	**Mean**	**Min**	**Max**
(a) Inflation (%)	1.9	0.02	2.7	0.8	7.5
(b) Unemployment (%)	10.0	0.44	6.8	4.8	10.4
(c) Real interest rate (%)	5.0	0.10	3.3	-3.8	6.4

Source: (a) 'CPI Annual Rate 00: All Items' from the Office for National Statistics (ONS). (b) 'Unemployment rate (aged 16 and over, seasonally adjusted)' from ONS. (c) 'UK Real Interest Rate (%) not seasonally adjusted' from World Bank via Datastream. Note that 1989 is the earliest for which CPI is available, and data after 2008 is subject to various shocks absent from our model.

Table 3: Cross-correlation between output and other macro variables. Values correspond to means across 100 simulations. Simulated series have been detrended with an HP filter and lags/leads are expressed in years.

	$t-4$	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Output	−0.0511	−0.1227	−0.2985	−0.1366	1.0000	−0.1366	−0.2985	−0.1227	−0.0511
Unemployment	0.0525	0.1212	0.2779	0.1011	−0.9818	0.1930	0.3034	0.1041	0.0388
Consumption	−0.0475	−0.1249	−0.3098	−0.1033	0.9897	−0.1617	−0.2896	−0.1140	−0.0539
Interest rate	−0.0313	−0.0685	−0.1402	−0.1745	0.4978	0.1409	−0.1339	−0.2454	−0.0001
Comm. credit	−0.0247	−0.0296	−0.0497	−0.0498	0.2695	−0.0617	−0.0748	−0.0342	−0.0206
Inflation	−0.0053	−0.0149	−0.0223	−0.0299	0.0610	0.1697	−0.1667	−0.0633	0.0608
Money stock	−0.0168	−0.0260	−0.0393	0.2500	0.1026	−0.2365	−0.1037	0.0402	−0.0014
House prices	0.0004	−0.0076	−0.0482	−0.0350	0.1260	0.0313	−0.0245	−0.0795	−0.0204

among others).

We also show that our simulation results match with a wide range of housing and mortgage market indicators observed in the data. Table 4 demonstrates that the number of housing transactions and mortgage approvals are within the range of the minimum and maximum values observed in the data between 2005 and 2014, while average monthly house prices are slightly higher. Table 5 shows that the model does a very good job in matching the first moments of the loan-to-value (LTV), loan-to-income (LTI), and house-price-to-income ratios of owner-occupier mortgages.[28]

Although the approach frequently taken by the macro ABM literature is to validate models on the first and second moments, we go beyond and focus on some distributions (also see Carro et al., 2022, for a discussion). Figure 1 (a-c) shows that the model is able to replicate the distributions of the LTV, LTI, and house-price-to-income ratios of owner-occupier mortgage borrowers observed in the real data. Figure 1 (d) shows the proportion of households by each housing tenure category

[28]Simulation results generate an average (real) annual employment income of around £38 500, which is comparable to the average gross employment income (£44 400) from the Wealth and Asset Survey Wave 3 (ONS, 2022).

Table 4: Housing and mortgage market indicators.

	Simulation		2011	2005 – 2014	
	Mean	**Std**	**Mean**	**Min**	**Max**
(a) average house prices (£1,000)	207.9	7.7	167.9	153.9	193.2
(b) housing transactions (1,000)	60.6	3.3	73.7	51.6	149.4
(c) mortgage approvals (1,000)	40.5	2.5	49.3	26.6	129.1

Source: (a) UK average house prices are obtained from the Office for National Statistics (ONS). (b) Housing transactions are the number of residential property transactions in the United Kingdom with a value of £40 000 or above per month (HM Revenue and Customs). (c) Seasonally adjusted mortgage approvals for sterling loans secured on dwellings, net of cancellations (Bank of England). For (b) and (c) see underlying data of Bank of England June 2014 Financial Stability Report Chart 2.8.

Table 5: Owner-occupier mortgage characteristics.

	Simulation Mean	PSD Mean
Mean LTV ratio (%)	69.6	68.3
Mean LTI ratio	3.0	3.0
Mean House Price-to-Income ratio	4.6	4.7

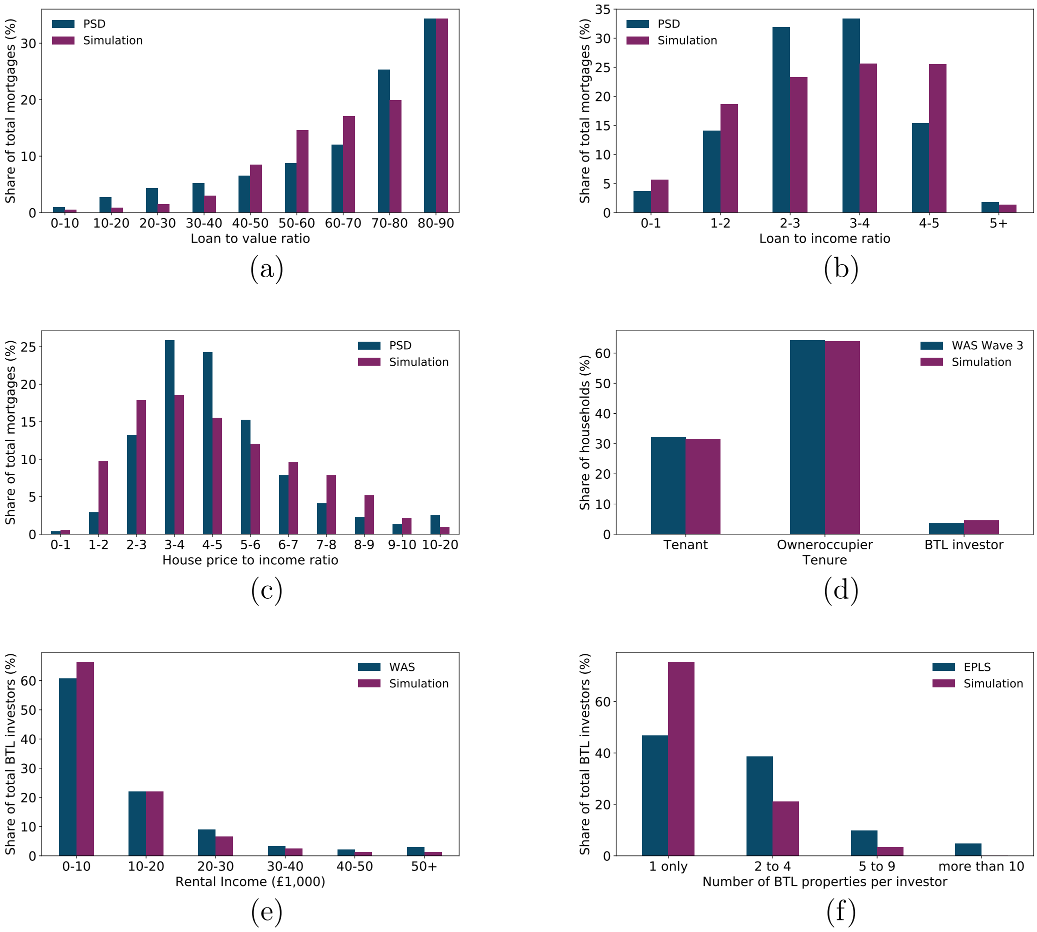
Source: The above statistics are calculated for 2011 based on Financial Conduct Authority's (FCA) loan-level Product Sales Data (PSD), which include regulated mortgage contracts only.

and provides support for the ability of the model to replicate the empirical UK housing tenure structure. Figure 1 (e-f) shows that the distribution of rental income earned by buy-to-let (BTL) investors and the number of BTL properties held per BTL investor are comparable to the real data.

4 Policy experiments

After having empirically validated the model, we investigate different hypothetical prudential policies, with a particular focus on the interaction mechanism between borrower-based and lender-based regulatory rules. We perform three experiments: *(i)* an increase in capital requirements affecting all lending; *(ii)* an introduction of a soft loan-to-income (LTI) limit on owner-occupier mortgages; and *(iii)* the simultaneous introduction of these two experiments.

In the first experiment, we increase capital *buffers* from 8% to 15%. Since we keep the minimum capital requirement fixed at 10%, this corresponds to raising the total capital requirement from 18% to 25%. In our model, banks start to reduce their



Source: (a)-(c) The Financial Conduct Authority's (FCA) loan-level Product Sales Data (PSD, 2011), which include regulated mortgage contracts only; (d)-(e) Wealth and Asset Survey (WAS) Wave 3 (2010-2012) (ONS, 2022); (f) English Private Landlord Survey (EPLS, 2018) (collected by MHCLG, 2019).

Figure 1: Comparison of key quantities of the housing market produced by the model with real data. Model results are averaged over 100 simulations.

lending as soon as they dip into their capital buffers.[29] When they breach minimum capital requirements they are resolved efficiently, without frictions or bankruptcy costs.[30] As a consequence, in our model, the size of capital buffers should have a larger effect on banks' lending than the level of minimum capital requirements. For the second experiment, we introduce a cap on owner-occupier mortgages whose

[29] In practice, banks can adjust their risk-weighted capital ratio in several ways such as by increasing retained earnings, increasing the lending spread to boost profits, issuing new equity, reducing their loan portfolio or selling assets, replacing higher risk-weighted loans with lower risk ones or with government securities, and finally reducing lending growth. In our model, we focus on the last channel.

[30] The benefits of a better capitalised banking system include reducing the probability and cost of financial crises, holding all else equal. However, we do not focus on financial crises in our analysis as we assume an effective banking resolution system.

LTI ratio is above 3.0. This is a soft limit in the sense that each bank can have 10% of the mortgages it grants above this threshold. In the third experiment, we apply both policies at the same time, thereby investigating their interactions. The size of these experiments is set at highly binding levels for expositional purposes. We also provide a robustness analysis by conducting experiments with varying levels/thresholds of capital requirements and LTI limits. The key results hold even with smaller interventions. Note that our quantitative results should only be seen as indicative.

We analyse the impact of these prudential policy experiments by employing boxplots (see Figures 2 and 6), which report the minimum, maximum, median, first, and third quartiles of variables of interest. We further check if the results of the experiments are statistically different with respect to the baseline outcome of the model (see Tables 6 and 7). It is worth noting that we are not investigating the short-term/immediate effects of the policies. Our analysis is a comparative statics exercise which provides comparisons of long-term effects between different policy experiments against the benchmark case.

4.1 Impact on mortgage and housing markets

Figure 2 and Table 6 show that tightening capital requirements leads to a sharp decrease in mortgage approvals to both owner-occupiers and buy-to-let (BTL) investors (respectively, a 27% and a 31% decline on average). The number of transactions in the housing market also decreases significantly, though the house price-to-income ratio stays at similar levels compared to the benchmark case. On the other hand, when the LTI cap is in place, house prices decrease sharply relative to income (from a multiple of 4.6 to 4.0 on average). Interestingly, the LTI cap leads to a small increase in mortgage approvals to owner-occupiers and to a larger increase in mortgage approvals to BTL investors (a 41% increase). This result suggests a spillover effect in the sense that a policy targeting the owner-occupier mortgage market benefits BTL investors. While this spillover effect is intuitive, the impact of the LTI cap on mortgage approvals to owner-occupiers (a small increase) may seem counter-intuitive at first, but can be explained as follows. When the LTI cap is in place, average house prices are 10% lower compared to the benchmark case. This translates into owner-occupiers requiring smaller mortgages (in particular, the size of the average mortgage is 20% smaller with the LTI cap), and thus indicating an adjustment at the intensive rather than the extensive margin. Importantly, activity in the housing market is maintained, as the average number of housing transactions does not significantly change. This is due to both lower house prices and an increase in the share

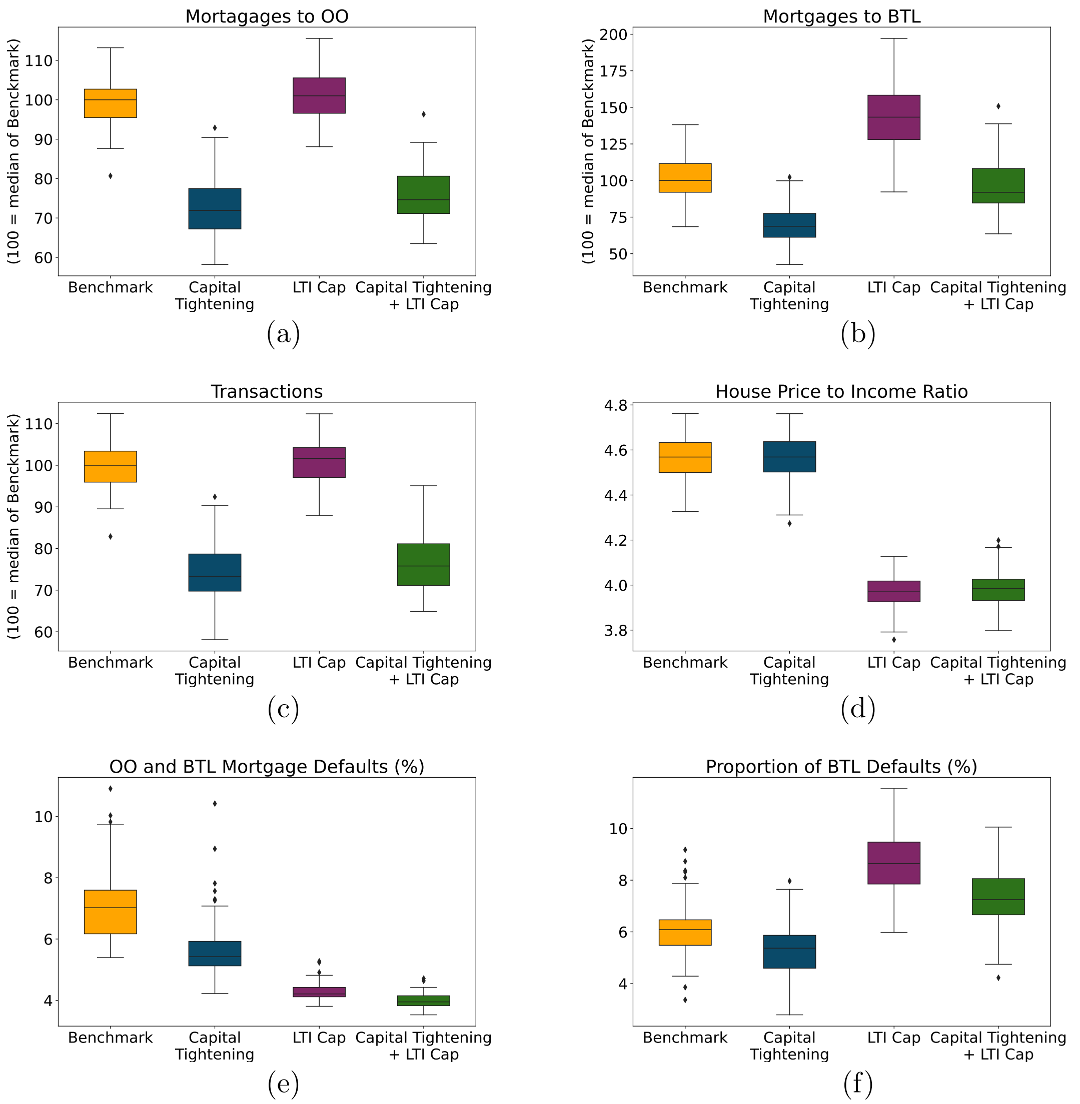


Figure 2: Comparison between different policy experiments and the benchmark case. Box plots show the corresponding distributions across 100 simulations, each averaged across the length of the simulation. Boxes span the interquartile range and the middle line is the median.

of housing transactions by BTL investors compared to owner-occupiers (Figure 3), consistent with an increase in mortgage approvals to BTL investors (Figure 2 (b)).

These results indicate that while capital regulation has an extensive margin effect, the LTI cap works via the intensive margin. The mechanism at play is as follows:

- The tightening of capital requirements leads banks to restrict their lending. This credit rationing works via limiting the number of loans issued, but not via issuing smaller loans (i.e., the demand for credit of each borrower deemed to be sufficiently creditworthy is met in full with a lower probability when capital

Table 6: Comparison of mean values of housing and mortgage market indicators in the benchmark case and the policy experiments. Significance refers to t-tests with different variances.

	ΔCapital	**ΔLTI**	**ΔCapital+LTI**
Mortgages HM (%)	-26.97^{***}	1.68^{**}	-23.62^{***}
Mortgages BTL (%)	-31.49^{***}	41.08^{***}	-6.10^{***}
Transactions (%)	-25.55^{***}	0.83	-23.53^{***}
Debt/Income OO (pp)	-13.42^{***}	-11.37^{***}	-20.82^{***}
Rental Yield (pp)	-0.29^{***}	0.49^{***}	0.14^{***}
House Price/Income	0	-0.60^{***}	-0.58^{***}
Sale Price (%)	-0.29	-9.61^{***}	-10.65^{***}
Household Defaults (pp)	-1.46^{***}	-2.79^{***}	-3.08^{***}
Proportion of BTL Defaults (pp)	-0.74^{***}	2.70^{***}	1.23^{***}

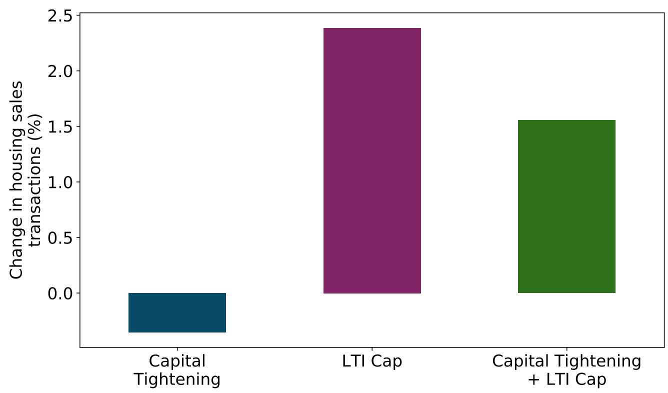


Figure 3: Change in housing transactions by BTL investors.

requirements are tightened). Hence, while this mechanism affects the number of loans issued and hence housing transactions, it does not significantly affect house prices.

- The LTI cap, on the other hand, reduces the maximum mortgage households can obtain. Households who decide to buy a property determine their desired purchase price by taking into account the maximum mortgage they can get, which is limited by the LTI cap. Lower desired purchase prices (and hence lower bid prices) lead to lower average house prices and the need for smaller mortgages, but not necessarily significantly affect the number of mortgage approvals and/or housing transactions.

We should also emphasise that the tightening of capital requirements decreases mortgages to both owner-occupiers and BTL investors. On the other hand, the LTI cap increases BTL mortgages as they are not in the scope of the policy. This spillover

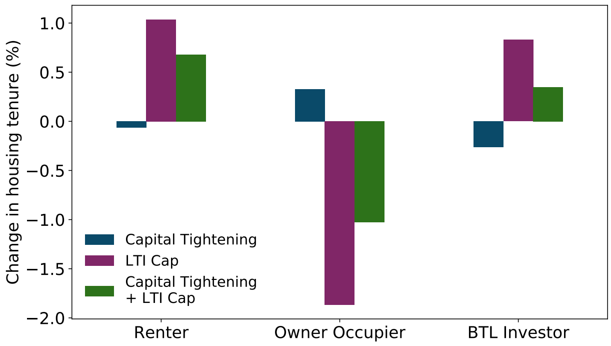


Figure 4: Change in housing tenure.

to the BTL sector leads to an increase in housing demand/transactions by BTL investors and has a mitigating effect on house price drops driven by owner-occupiers (i.e., house prices could have been lower without the increased demand by BTL investors). This spillover to the BTL sector also affects both the supply of and demand for rental properties. Figure 4 shows that the LTI cap leads to a sharp decrease in owner-occupiers, which corresponds to an almost equal increase of renters and BTL investors. On the other hand, the impact of an increase in capital requirements on tenure and the rental market is less pronounced as it affects all mortgages more or less equally.

Figure 5 shows the distributions of LTV and LTI ratios of owner-occupier mortgages under different policy experiments. As discussed above, an increase in capital requirements has a significant impact on mortgage approvals, but it affects all borrowers similarly and does not have any distributional effects with respect to these two ratios.[31] On the other hand, the LTI cap leads to a decrease in high LTI and LTV lending. We observe a bunching effect — when the LTI cap is in place, the share of mortgages just under the LTI threshold doubles. We also observe that the LTI cap affects the LTV distribution as well, as the share of mortgages with high LTV (above 70%) decreases by 8 percentage point compared to the benchmark case. When both capital and LTI policies are in place, the impact of these policies on the LTV and the LTI distributions is very similar to the case in which only the LTI cap is in place. This is because only the LTI experiment has an effect on these distributions, and there are no unexpected interactions between these policies when both of them are introduced.

Figure 2 (e) and Table 6 also show that both capital tightening and the LTI cap lead to a decrease in total mortgage defaults. Though with a difference — as shown

[31] A possible explanation, as set out above, is that, in our model, banks' capital requirements and credit spreads are not risk-sensitive with respect to LTV or LTI ratios.

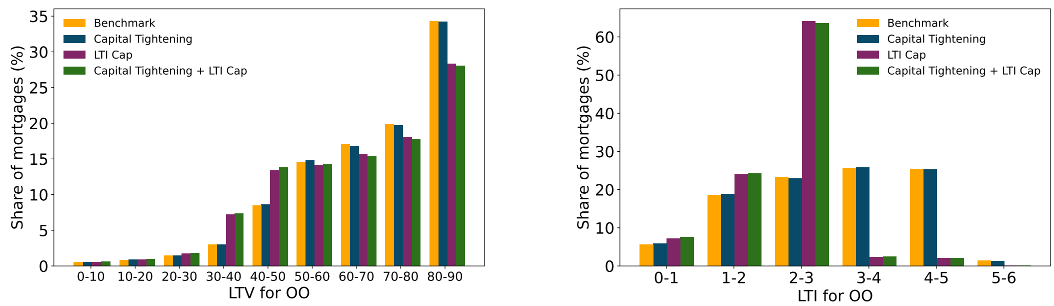


Figure 5: Comparison of distributions between different policy experiments and the benchmark case.

by Figure 2 (f), while the proportion of BTL mortgage defaults in total mortgage defaults are lower with capital tightening, they are higher when the LTI cap is in place due to the spillover effects mentioned above, i.e., a sharp increase in BTL mortgages. When the two policies are in place at the same time, capital tightening mitigates the spillover effects of the LTI cap and hence we see a limited increase in BTL mortgage defaults.

4.2 Impact on the real economy

In this section, we investigate the impacts of the two experiments and possible interactions between them on macroeconomic variables such as real output, loans, interest rates, unemployment and inflation, under a dual-mandate monetary policy (i.e., focusing on output and inflation). An essential emergent phenomenon generated by the model is a financial accelerator, which means that "endogenous developments in credit markets work to amplify and propagate shocks to the macroeconomy" (Bernanke, 2007; Gertler et al., 2007; Gatti et al., 2010). Considering that procyclical lending is one of the primary arguments for regulating the financial sector through macroprudential tools (Altunbas et al., 2018), this feature is of paramount importance for our model.

Simulation results show that both tighter capital requirements and the LTI cap lead to a decrease in mortgage lending (the former via the extensive margin and the latter via the intensive margin) while increasing the overall income level, reinforcing the demand for goods, raising the output level, and decreasing unemployment (see Figure 6 and Table 7).[32] This is because the downward pressure on housing consumption causes a substitution effect, where households redirect their spending from

[32]Tighter capital requirements lead to a decrease in commercial loans as shown in Figure 6. Although in practice this might affect firms' (shops') investment decisions, capital accumulation and hence GDP, this channel is not captured in our model following Ashraf et al. (2017).

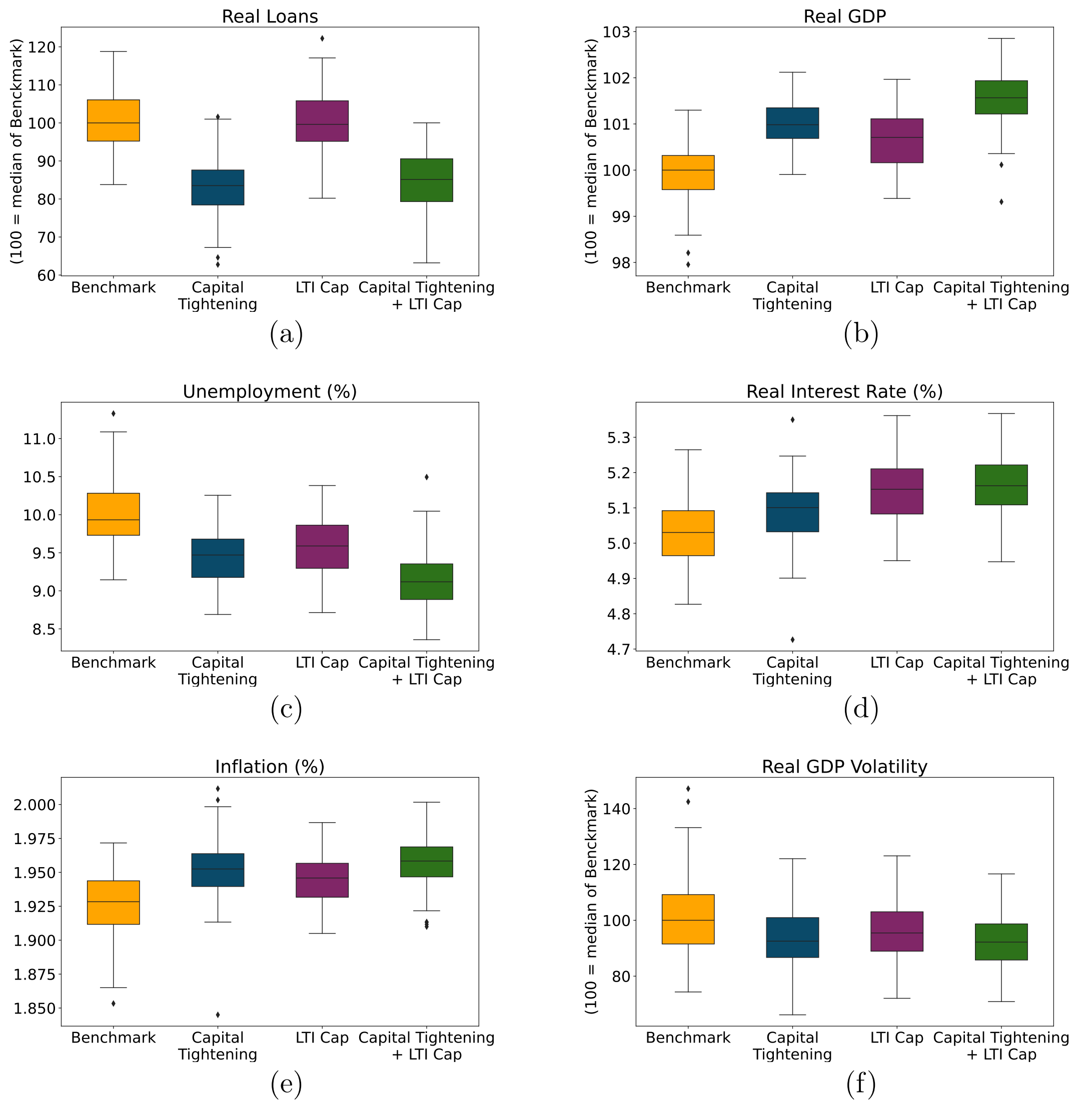


Figure 6: Comparison between different policy experiments and the benchmark case. Box plots show the distribution across 100 simulations, each averaged across the length of the simulation. Boxes span the interquartile range, and the middle line is the median.

housing towards consumption goods. This substitution effect between housing and goods consumption has been revealed both in theoretical and empirical studies (see Li et al., 2016; Been et al., 2020; Khorunzhina, 2021). To the extent that housing may be considered a non-productive investment, this shift toward the productive sector (i.e., shops) would tend to be beneficial for the economy (see Arku, 2006, for a nuanced discussion).[33] Additionally, both tighter capital requirements and the LTI

[33]One sector which does not contribute to GDP in our model is housing construction. The housing stock is assumed to be fixed, and all houses are created at the beginning of the simulation. As construction tends to be pro-cyclical empirically, our model economy would, therefore, tend to be less pro-cyclical than in reality. To the extent that this sector contributes to exuberant housing

Table 7: Comparison of mean values of macro variables in the benchmark case and in the policy experiments. Significance refers to t-tests with different variances.

	ΔCapital	**ΔLTI**	**ΔCapital+LTI**
Real GDP (%)	1.05***	0.71***	1.60***
Real Loans (%)	−17.18***	−0.13	−15.71***
Unemployment (pp)	−0.53***	−0.41***	−0.85***
Real Interest Rate (pp)	0.06***	0.12***	0.13***
Inflation (pp)	0.03***	0.02**	0.03***
Real GDP Volatility (%)	−8.01***	−4.89**	−8.12***

cap result in a decrease in output (i.e., real GDP) volatility (Table 7), indicating stabilising effects of these policies on the economy.

The real interest rate and inflation are marginally affected. This confirms the empirical observation that lender-based measures have limited effect on the real interest rate and inflation (see Suh, 2012; Spencer, 2014). Our results are also in line with Richter et al. (2018), who showed in a large cross-country panel of 56 countries that LTV ratio limits appear to have a negligible effect on inflation. As our paper does not assess the sensitivity of these results to alternative monetary policy rules, the stance on monetary policy constitutes a promising avenue for future research.

4.3 Policy interactions

Finally, an interesting pattern emerges when both the capital and the LTI experiments are in place. The average impact on most variables is smaller under the combined experiments than the sum of the capital and LTI-only experiments. For example, Table 7 shows that the unemployment rate falls by 0.53pp in the capital experiment and by 0.41pp in the LTI experiment. The combined impact of -0.85pp when both experiments are applied is lower (in absolute terms) than the sum of the individual experiments (-0.94pp). For most housing variables in Table 6 (except mortgage approvals for BTL investors and the sale price), the difference is about -3 to -37%. For the macro variables in Table 7, the difference is between -9 and -37%. These observations are consistent with Popoyan et al. (2017) and Popoyan et al. (2020).

This finding suggests that experiments in our model are subject to diminishing marginal returns, i.e., the impact of a new experiment is smaller when another experiment is already in effect. The implication for policy is that the accurate

markets, and crashes, the lack of construction would result in a positive effect on financial stability in our model.

calibration of instruments may be influenced by the portfolio of tools being implemented and/or already in place. Relying on the assessment of the potential impact of a given instrument in isolation may lead to a calibration that is too conservative when interactions with other policies are possible. Therefore, a holistic evaluation of the expected impacts of concurrent policies and their interactions is advisable.

4.4 Sensitivity analysis

This section considers two sets of sensitivity checks to verify how our artificial economy reacts, regarding macroeconomic (see Figure 7) and housing dynamics (see Figure 8), to a gradual change in lender-based capital requirements and in the borrower-based LTI cap. The left-hand side figures show the sensitivity of a gradual increase in capital buffers from 8% to 10%, 12%, 15%, 18%, and finally to 21%, keeping the minimum capital requirement fixed at 10%, which will result in raising the total capital requirements from 18% up to 31%. The right-hand side figures show the sensitivity of a tightening of the LTI cap from 5.6 to 2.5 (the x-axis is mirrored, so a tightening corresponds to a move from left to right as in the case of increasing capital buffers). The figures show the percentage change in the variable of interest between the respective experiment and the benchmark case (without any policy).

The figures reveal that the impact of tightening capital requirements is rather smooth and broadly proportional to the degree of tightening. For the LTI policy, some variables (unemployment, real sale price, rental yield) show a noticeable kink around 4.5. The reason is that, given our calibration, the LTI cap is not very binding at high levels. That is, other constraints, such as the bank-imposed LTV limits and affordability checks are likely to be more relevant than the LTI cap at these levels. Only when the LTI cap gets tighter does it become the binding constraint on borrowers.

5 Conclusion

In this paper, we have developed a large-scale agent-based macro model combining the goods and labour markets in Popoyan et al. (2017) with the housing market in Carro et al. (2022). In the model, the credit activity of banks is essential for supporting firms and home buyers. Banks are subject to prudential regulation, including housing policies. We used the model to assess the standalone and joint impact of different borrower- and lender-based prudential policies on the housing and mortgage markets and the broader economy, revealing potential spillovers. After testing the

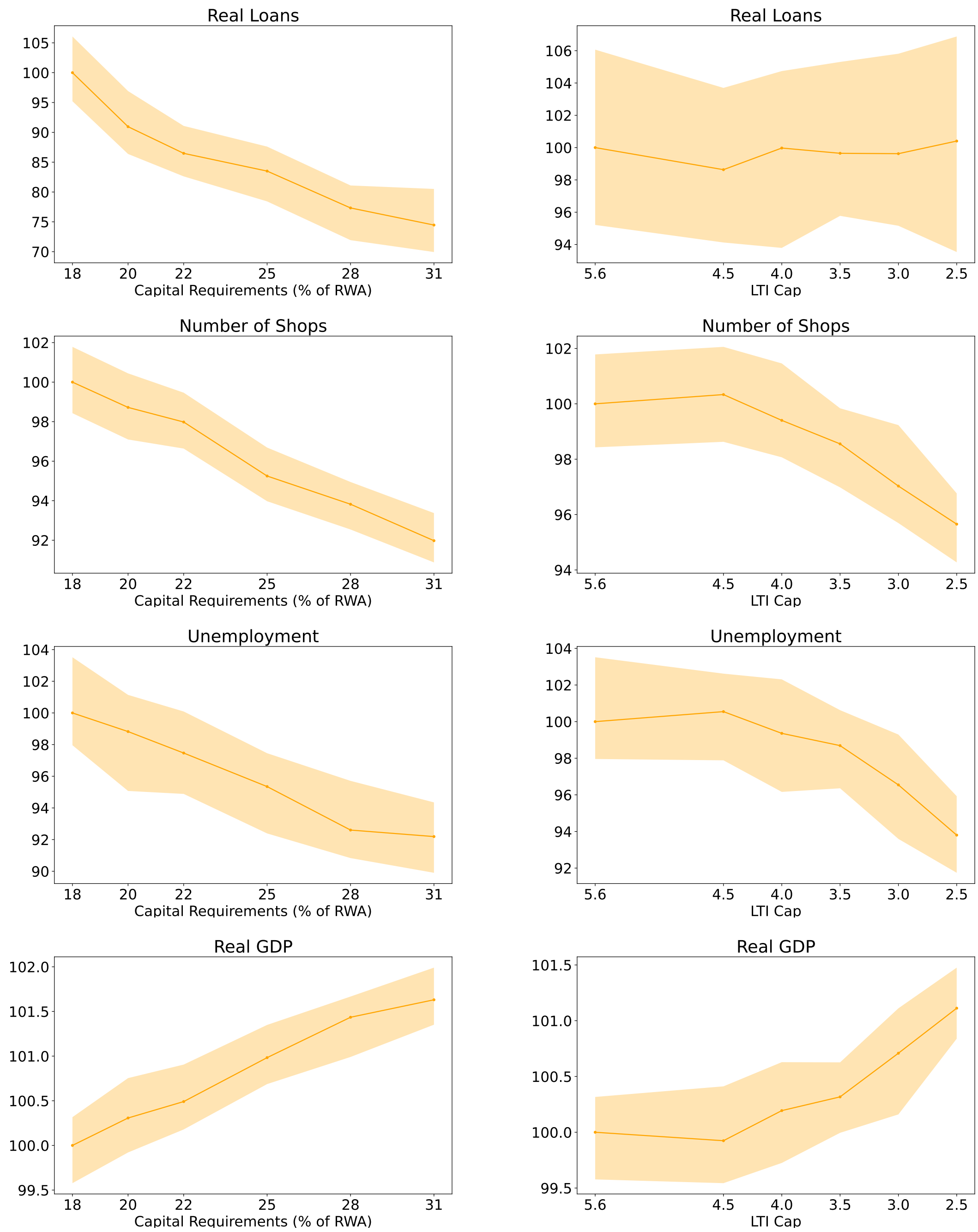


Figure 7: Comparison between different policy experiments and the benchmark case. Solid lines correspond to the median of the distribution across 100 simulations, each averaged across the length of the simulation. Semi-transparent regions span the interquartile range of the same distribution. All quantities are indexed to the median of the benchmark case

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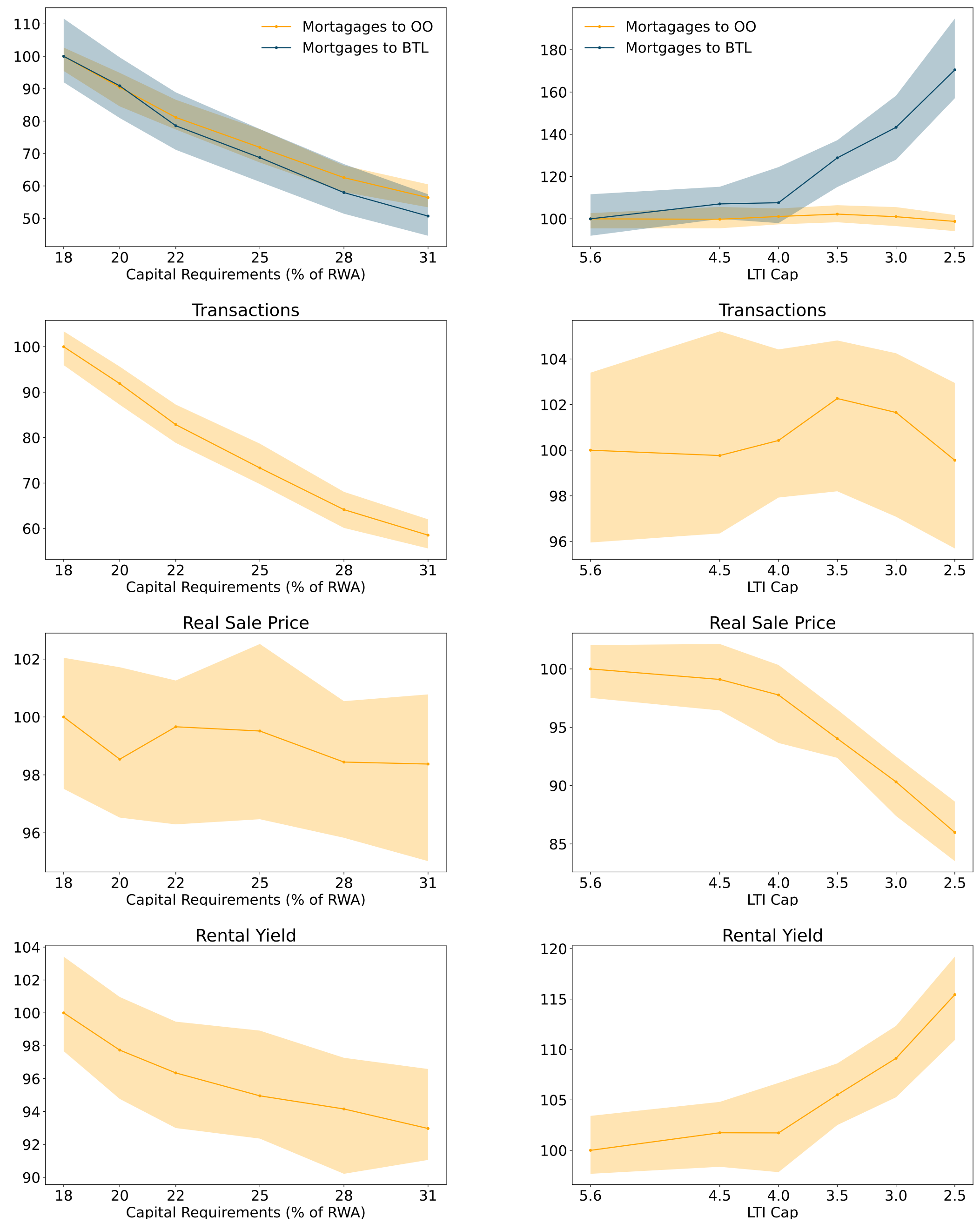

Figure 8: Comparison between different policy experiments and the benchmark case. Solid lines correspond to the median of the distribution across 100 simulations, each averaged across the length of the simulation. Semi-transparent regions span the interquartile range of the same distribution. All quantities are indexed to the median of the benchmark case

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ability of the model to reproduce an ensemble of macroeconomic and housing market dynamics, we performed policy experiments by: *(i)* increasing capital requirements (lender-based); *(ii)* imposing a soft loan-to-income (LTI) limit on owner-occupier mortgages (borrower-based); and *(iii)* jointly introducing both experiments.

We find that tightening capital requirements leads to a sharp decline in commercial loans and mortgage approvals to owner-occupiers and buy-to-let (BTL) investors. While the number of housing transactions decreases significantly, the house price-to-income ratio stays at similar levels compared to the benchmark case. However, when the LTI cap is in place, house prices decrease sharply relative to income, with a small increase in mortgage approvals to owner-occupiers and a significant increase in mortgage approvals to BTL investors. The impact of an increase in capital requirements (an introduction of the LTI cap) on the housing tenure and the rental market is less (more) pronounced as it affects all mortgages more or less equally (is designed to only bind on mortgages to owner-occupiers, with BTL investors being able to increase their market share and rent out more properties). Both policies lead to a decrease in total mortgage defaults as a result of limited household leverage/indebtedness.

From a macroeconomics perspective, both borrower- and lender-based prudential policies positively affect real output and unemployment dynamics. This is driven by a shift of resources from the housing sector to the goods-producing sector, increasing the output level and lowering unemployment. Our results do not find any tangible effect on inflation and the real interest rate, as confirmed by the literature (see Suh, 2012; Spencer, 2014). Additionally, both policies decrease output volatility. Finally, we find that the impact of policies is not additive: the sum of standalone levers are considerably different from the combined impact, suggesting a relevant role for non-linear interactions within the model.

We should note that our results do not present a fully fledged cost and benefit analysis as the model does not capture all the relevant mechanisms that banks may utilise as a response to policy interventions. Furthermore, our experiments should not be seen as describing short-term dynamics, but as a comparative statics exercise allowing us to compare the long-term effects of different experiments against the benchmark case. As such, our quantitative results are indicative only.

Our work can be extended in several ways. First, alternative monetary policy rules (e.g., leaning-against-the-wind) could be introduced to study the possible conflicts, complementarities and substitutabilities with borrower- and lender-based prudential policies. This could also allow to detect which channels are responsible for the neutrality of prudential tools on inflation and interest rates. Second, we could consider other borrower- and lender-based instruments in order to have a complete regulatory toolkit and explore their impact on macro and micro dynamics, as well as their capacity to mitigate financial instability. Finally, our model could be extended to consider pro-cyclical and counter-cyclical adjustments of borrower- and lender-based instruments to explore their capacity to address risks, thus contributing to the resilience of the financial system.

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Appendices

Appendix A Parameters of the model

Table 8: Parameters of the model.

Parameter	Description	Equation	Value	Source
	Household Parameters			
N	Number of households		4760	(a)
λ_p	Permanent income adjustment speed	(19)	0.4	Ashraf et al. (2017)
ρ	Rate of time preference (annual)	(20)	0.04	Ashraf et al. (2017)
Υ	Demand parameter	(25)	7.0	Ashraf et al. (2017)
θ	Propensity to become entrepreneur		0.021	(b)
σ	Job search probability		0.5	Ashraf et al. (2017)
	Housing Parameters			
	Number of houses		4073	(c)
α	Desired purchase price multiple	(21)	4.5	(d)
ε_μ	Desired purchase price, mean of Gaussian noise	(21)	−0.0177	Carro et al. (2022)
ε_σ	Desired purchase price, std. dev. of Gaussian noise	(21)	0.4104	Carro et al. (2022)
ι	Desired rent as share of income	(22)	0.3	(e)
η	Initial rent price mark-up	(23)	est. distribution	Carro et al. (2022)
	Shop Parameters			
n	Number of goods		70	Modeller's choice
$\bar{\mu}$	Average markup over wage	(2)	1.138	Ashraf et al. (2017)
F	Fixed cost	(2),(5)	3.5	Ashraf et al. (2017)
Δ	Length of the contract period	(3),(29)	72	(f)
λ_I	Inventory adjustment speed	(5)	0.16	Ashraf et al. (2017)
S	Setup cost	(14)	15	Ashraf et al. (2017)
β	Wage adjustment parameter	(29)	0.3	Ashraf et al. (2017)
IS	Critical inventory-to-sales ratio	(30)	3.0	Ashraf et al. (2017)
δ_p	Size of price cut	(30)	1.017	Ashraf et al. (2017)
δ	Exit probability for shops		0.00075	Ashraf et al. (2017)

(a) The number of households N is determined by the number n of non-perishable goods, which are produced with n types of labour. Assuming that there is one person of each type, the economy's population is calculated as $N = n(n-2)$.
(b) The parameter is computed as the ratio between the supply of entrepreneurship (100 per period) and the economy's population (N). The parameter value was searched manually to (loosely) match the median outcomes across simulations to certain properties of the UK data.
(c) Chosen to match the empirical ratio of (privately owned or rented) houses to households in the UK, 0.8557. To compute this ratio, in turn, the empirical number of houses in the UK is estimated from ONS Table 101 (discontinued) for 2011 as the sum of the number of owner-occupied and privately rented dwellings.
(d) Assuming household would like to spend the same share of income of 30% on renting (see (e) below) and mortgage payments, a 4.5 multiple is consistent with a typical mortgage with a 25-year term, a 10% down-payment, and an interest rate of about 5.5%.
(e) We assume that households' desired rental expenses as a share of their income is the maximum affordable share as defined by the ONS, see www.ons.gov.uk/peoplepopulationandcommunity/housing/bulletins/privaterentalaffordabilityengland/2012to2020.
(f) This is derived from Harrison and Oomen (2010). They find a Calvo readjustment probability for the resetting of wages of about 0.16, which implies an average wage contract length of $1/0.16 = 6.25$ quarters, which is roughly 1.5 years. This translates into 72 weeks in our model.

Table 8: Parameters of the model.

Parameter	Description	Equation	Value	Source
	Bank Parameters			
M	Number of banks		5	Modeller's choice
f_Π	Fraction of profits distributed to bank owner		0.25	(g)
κ	Quick ratio	(12a)	0.05	Popoyan et al. (2017)
ψ	Return on assets	(12b)	0.1	Popoyan et al. (2017)
$\bar{h}$	Average loan-to-value ratio for shops	(13),(14)	0.5	Ashraf et al. (2017)
λ_h	Loan-to-value adjustment speed for shops		2.5	Modeller's choice
Γ	Loan-to-value ratio for home-mover (BTL) mortgages	(15)	0.9 (0.75)	Carro et al. (2022)
Φ	Loan-to-income ratio for home-mover mortgages	(16)	5.6	Carro et al. (2022)
Ψ	Debt-service-to-income ratio for home-mover mortgages	(17)	0.4	Carro et al. (2022)
ν	Mortgage term	(17)	25 years	Carro et al. (2022)
Ω	Interest-coverage ratio for BTL mortgages	(18)	1.25	Carro et al. (2022)
s_c	Commercial loan spread		0.0211	(h)
s_m	Mortgage spread		0.0299	Carro et al. (2022)
	Prudential Regulation Parameters			
χ_{min}	Minimum capital requirement	(7),(9),(10)	0.10	Modeller's choice
χ_{des}	Desired capital level	(8),(9),(10)	0.18	Modeller's choice
χ_R	Distribution threshold	(11)	0.15	Modeller's choice
	Fiscal and Monetary Policy Parameters			
π^*	Target inflation rate	(1),(3),(13),(14),(26),(29)	0.02	(i)
ϕ_π	Inflation coefficient in Taylor rule	(26)	1.497	(j)
ϕ_y	Output gap coefficient in Taylor rule	(26)	0.1512	(j)
b^*	Target debt-to-GDP ratio	(27)	0.6	(k)
λ_τ	Fiscal adjustment speed	(27)	0.054	Ashraf et al. (2017)

(g) Manual calibration to target the stability of macroeconomic quantities and banks' balance sheets.
(h) Commercial loan spread is calculated as the difference between the monthly average of UK MFIs' (excluding central bank) effective interest rates for loans to private non-financial corporations and the Bank of England base rate between 2003 – 2014. Source: Bank of England, Bankstats tables, TabG1.4, sheet PNFC stock rates, column HSDC, see `https://www.bankofengland.co.uk/statistics/tables`.
(i) The inflation target of the Bank of England is 2%, see `www.bankofengland.co.uk`.
(j) Parameter values (posterior mean) taken from Bank of England's COMPASS model, see `www.bankofengland.co.uk/-/media/boe/files/working-paper/2013/the-boes-forecasting-platform-compass-maps-ease-and-the-suite-of-models.pdf`, Table 3.
(k) A ratio of 60 % is considered to be a sustainable level of government debt, and is consistent, for example, with the EU's framework for fiscal policies, see `www.europarl.europa.eu/factsheets/en/sheet/89/the-eu-framework-for-fiscal-policies`.

Appendix B Capital stack

In Figure 9, the left panel presents the capital stack implemented in the UK,[34] while the right panel displays the simplified version of this capital stack used in the model. In reality, banks can be resolved when they breach minimum capital requirements (Pillar 1 + Pillar 2A of Basel III), and restrictions on the distribution of dividends kick-in when banks breach a combined capital buffer consisting of several components (countercyclical capital buffer, capital conservation buffer, and systemic buffers). Similarly, in our model, banks are resolved when their capital ratio falls below χ_{min}, while the transfer of profits to the bank owner is increasingly reduced when the capital ratio is below χ_{R}. Additionally, in our model, banks start to ration credit when their capital requirements fall below χ_{des}, which is generally larger than χ_{R}. The distance between χ_{des} and χ_{R} can be interpreted as a further buffer, such as the PRA buffer, which in reality is bank-specific.

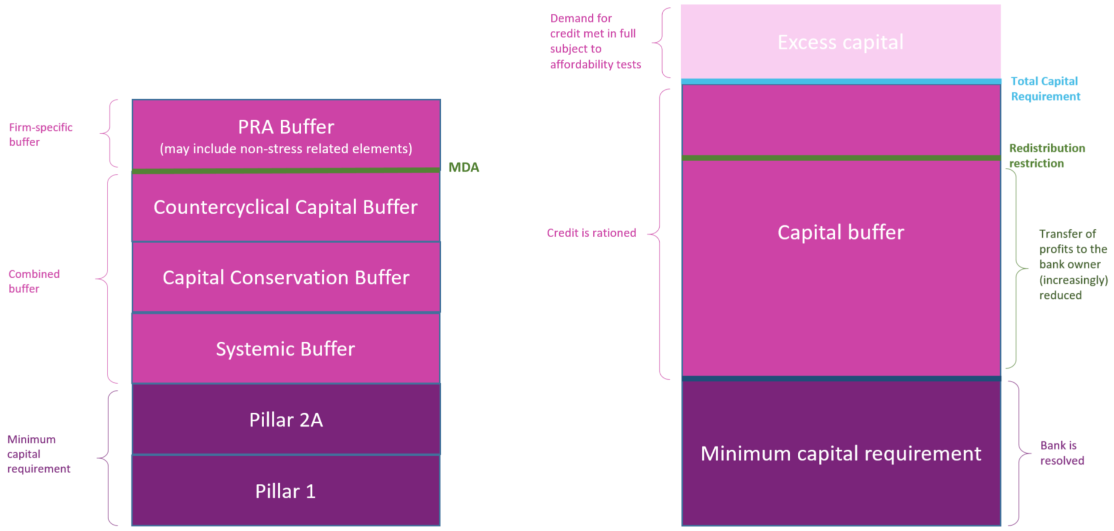

Figure 9: Left panel is a representation of the capital stack in the UK (slightly amended based on Bank of England, 2019, p.6). The right panel is a representation of the capital stack in the model.

[34] For further information, see Bank of England (2019).