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The effect of borrower-specific loan-to-value policies on household debt, wealth inequality and consumption volatility: An agent-based analysis

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\textbf{A B S T R A C T}

This paper analyses the effects of borrower-specific credit constraints on macroeconomic outcomes in an agent-based housing market model, calibrated using UK household survey data. We apply different Loan-to-Value (LTV) caps for different types of agents: first-time buyers, second and subsequent buyers, and buy-to-let investors. We then analyse the outcomes on household debt, wealth inequality and consumption volatility. The households' consumption function, in the model, incorporates a wealth term and income-dependent marginal propensities to consume. These characteristics cause the consumption-to-income ratios to move procyclically with the housing cycle. In line with the empirical literature, LTV caps in the model are overall effective while generating (distributional) side effects. Depending on the specification, we find that borrower-specific LTV caps affect household debt, wealth inequality and consumption volatility differently, mediated by changes in the housing market transaction patterns of the model. Restricting investors' access to credit leads to substantial reductions in debt, wealth inequality and consumption volatility. Limiting first-time and subsequent buyers produces only weak effects on household debt and consumption volatility, while limiting first-time buyers even increases wealth inequality. Hence, our findings emphasise the importance of applying borrower-specific macroprudential policies and, specifically, support a policy approach of primarily restraining buy-to-let investors' access to credit.

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\begin{itemize}
\item 1. Introduction
\end{itemize}

Many advanced economies experienced a massive rise in household mortgage debt in recent decades increasing the probability of financial crises and enhancing the severity of recessions (Bezemer and Zhang, 2019; IMF, 2012; Jappelli et al., 2008; Jordá et al., 2016; Sutherland et al., 2012). To limit rising household debt, central banks increasingly apply macroprudential policies, including Loan-to-Value caps (LTV) and Loan-to-Income caps (LTI) (Galati and Moessner, 2018).

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These measures directly intervene in wealth accumulation, economic growth (Richter et al., 2019) and the wealth distribution (Colciago et al., 2019). While some central banks have an explicit mandate to support financial stability, like the Bank of England, lowering wealth inequality is typically not a concern. However, central bankers are increasingly discussing the potential consequences their policies could have on distributional issues as these could entail negative side effects, including weak consumption and growth (Fontan et al., 2016; Furceri et al., 2018; Hansen et al., 2020).

Moreover, there is rising awareness among policymakers that the effectiveness of macroprudential policies may depend on the type of borrower and the state of the house price cycle and the credit cycle. Against this backdrop, a joint report by the International Monetary Fund, the Financial Stability Board and the Bank for International Settlements has called for the application of borrower-specific macroprudential rules (IMF-FSB-BIS, 2016). The effects of such rules on macroeconomic outcomes (intended and unintended) are largely unexplored as data is limited (Kelly et al., 2015). Both micro- and macroeconomic dynamics are relevant, with heterogeneity in terms of borrower types, assets and income positions.

To address these challenges, we analyse in an agent-based housing market model the effects of borrower-specific LTV caps on the reduction of household debt and consumption volatility. And we study the impact on wealth inequality, an unintended side effect. Changes in household debt, consumption volatility and wealth inequality result from interactions between households (of different borrower type) and a commercial bank over the housing cycle, which have been pronounced in the UK. Therefore, our model is a modification of Baptista et al. (2016), calibrated to the UK using micro data sources to match key housing market indicators. Compared to Baptista et al. (2016), we introduce wealth-dependent and income-dependent marginal propensities to consume into the model, leading to consumption cycles moving with the housing cycle. The model considers the different types of agents active in the UK housing market: first-time buyers (FTB), second and subsequent buyers (SSB), buy-to-let investors (BTL), tenants in the private market and tenants in social housing. This setup allows us to analyse the consequences of borrower-specific macroprudential requirements which distinguish between FTB, SSB and BTL borrowers.

We find that the effects of borrower-specific LTV caps on debt reduction, wealth inequality and consumption volatility differ strongly in their efficiency. Limiting BTL investors’ access to credit leads to the most substantial reductions in debt, wealth inequality and consumption volatility while limiting SSB and FTB agents has only limited effects. Restricting FTB agents increases wealth inequality. The effect of restrictions to BTL investors’ credit, as in Carpentier et al. (2018) for wealth inequality, is linked to their search for yield, a different motivation for house purchases than in the case of SSB and FTB buyers of owner-occupied homes (Haughwout et al., 2012). Our results support the idea of applying borrower-specific macroprudential policies, with a priority of limiting investors’ access to credit.

In the next section, we review the literature on effects of macroprudential policies on household debt, consumption volatility and wealth inequality. Section 3 presents the structure and calibration of the model. In Section 4, we report the baseline dynamics of the benchmark model. In Section 5 we present simulation results for different macroprudential policy regimes. We trace how these results arise from granular changes in the transaction patterns of the housing market. Section 6 is a policy application. Guided by the results from Section 5, we propose a modification of the borrower-specific LTV rules currently applied by the Central Bank of Ireland in its macroprudential framework. Section 7 discusses limitations of our modelling approach. In Section 8, we conclude.

2. Related literature

2.1. Macroprudential policy and target variables

Our paper contributes to the literature about the effectiveness of (borrower-specific) macroprudential policy addressing household debt and its potential side-effects on consumption volatility and wealth inequality (Alam et al., 2019; Cardaci, 2018; Richter et al., 2019). More generally we contribute to the literature on agent-based model policy simulations.

Macroprudential policy measures seek to prevent excessive household indebtedness. By far the largest part of credit to the household sector are mortgages. A significant rise in household debt increases the probability of financial crises and the subsequent real economic damage (Bezemer and Zhang, 2019; IMF, 2012; Jappelli et al., 2008; Jordá et al., 2016; Sutherland et al., 2012). Excessive household indebtedness undermines the debt repayment capacity, increasing households’ financial vulnerability (Bezemer et al., 2016) and restricting household consumption (Mian et al., 2013). These effects can be long-lasting (Drehmann et al., 2018).

Several studies estimate the effect of macroprudential policies on credit growth. Due to data limitations, only few analyses study borrower-specific Loan-to-Value caps. Most empirical studies add dummy variables to their model specifications to control for the effect of macroprudential policies. For instance, Cerutti et al. (2017) find for 119 countries from 2000-2013 that introducing LTV caps is associated with reductions of 1.5 percentage points in annual household credit growth and 1.2 percentage points in real house price growth. Krznar and Morsink (2014) find for Canada—between 1998 and 2013—that a reduction in LTV caps for new mortgages by one percentage point led to an average reduction of yearly mortgage credit

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1 Such rules have been applied by the central banks of Ireland, Israel, Finland and Singapore for some years now.
2 Our model lacks macroeconomic feedbacks which is why we focus on consumption volatility.
3 For a recent survey on the literature on the effectiveness of macroprudential policy, see Galati and Moessner (2018) and for a broader meta-analysis Araujo et al. (2020).
growth by 0.5 percentage points. Jácome and Mitra (2015) find for a sample of five countries that a ten percentage points decrease in the LTV cap results in a 0.7% decrease in the level of housing credit after about one year. Alam et al. (2019) find for a set of 63 countries different effects of smaller and larger reductions in LTV caps. Reductions in LTV ratios of less than 10 percentage points lead to a cumulative 0.65 percentage point reduction (per LTV percentage point) in one-year lagged household credit growth. LTV reductions between 10 and 25 percentage points lead to credit growth reductions of 0.36 percentage points. These magnitudes are comparable to the credit response in our model when limiting LTV caps for FTB and SSB buyers, while the effect of limiting the LTV caps for BTL investors is considerably stronger.

Side-effects of such macroprudential policies include increases in wealth inequality (Arrondel et al., 2019; Carroll et al., 2014) with knock-on effects on aggregate demand and thus economic growth. These effects are still under-researched (Colciago et al., 2019). They may run through effects on house prices, for given home ownership distributions (Domanski et al., 2016; Kuhn et al., 2020). Since equities are concentrated at the top while real estate is more equally distributed, in the run-up to the financial crisis, house prices which rose faster than equity prices, led to a decline in wealth inequality in the U.S. (Kuhn et al., 2020), in France (Garbinti et al., 2017) and in Spain (Martinez-Toledano, 2020). Conversely, equity prices rising faster than house prices increased wealth inequality since the Global Financial Crisis (Domanski et al., 2016). On the basis of European household survey data, Carpentier et al. (2018) estimate the effect of households’ LTV ratios (at origination) on the wealth distribution. Their results suggest that higher LTVs are associated with higher (future) wealth inequality, mainly driven by households with high LTVs ending up at the lower end of the wealth distribution. However, the reasons for this effect are not clear-cut, especially since the most obvious explanation—highly leveraged households experiencing wealth losses due to falling house prices—does not seem to drive the results (the effect of LTVs is persistent when average house price changes are accounted for).4

The effect of macroprudential policies on income growth is therefore not unambiguous. Sánchez and Röhn (2016) find for a panel of mostly OECD countries that macroprudential policies go together with lower average economic growth (due to lower household expenditures, in particular residential investment). Sánchez and Röhn (2016) also report smaller growth shocks, i.e. lower volatility due to macroprudential policies. Boar et al. (2017) in contrast find a positive relationship between activated macroprudential policy measures and both stability and the level of GDP growth in 64 countries, presumably because higher stability brings smaller negative shocks.

Our model is not macroeconomic so we restrict the analysis to household consumption volatility and (in Appendix B) average consumption over the house price cycle. Macroprudential policies leading to lower house prices may decrease consumption due to the wealth effect (Attanasio et al., 2011; Campbell and Cocco, 2007) while rising wealth inequality can lead to a reduction in consumption due to lower marginal propensities to consume out of wealth for wealthier households (Carroll et al., 2014; Dyman et al., 2004). As both the wealth effect and the wealth inequality effect depend on the level of house prices, reducing house price volatility via LTV caps can limit the plunge in consumption after a house price bust—an effect that otherwise prolongs recessions. On the other hand, Alam et al. (2019) find that reducing LTV by one percentage point reduces private consumption growth by 0.1 percentage points after a year. Similar, Richter et al. (2019) find that a one percentage point reduction in the LTV caps reduces consumption by about 0.1% after two to four years for a set of 56 economies.

2.2. Agent-based models on macroprudential policy

There is an emerging literature on agent-based models of macroprudential policy effects on financial stability. Lalitis et al. (2020) use wealth, income, Loan-to-Value and Loan-to-Income distributions from the Household Finance and Consumption Survey for fifteen EU-countries to simulate the effect of LTV caps on house prices and credit growth. They find that introducing an LTV cap of 85% decreases house prices on average by 9% and mortgage credit by 10%, with significant heterogeneity in the country-level results. Axtell et al. (2014) model the Washington D.C. housing market, where boom-bust cycles emerge endogenously. They find that limiting households’ leverage is more effective than interest-rate policies in preventing house price bubbles. Ozel et al. (2019) expand the agent-based macroeconomic model EURACE by a simple housing market and find that increasing households’ maximum equity-to-asset ratio from 0.6 to 0.8 almost halves average house price levels while reducing credit growth by 2.3 percentage points. Fire sales are almost entirely eliminated, and write-offs are reduced by almost 80%.

Baptista et al. (2016) build an agent-based housing market model calibrated using UK household survey data. They show that introducing an LTI cap of 3.5 decreases the standard deviation of house prices from 1.21 to 1.09. Cokayne (2019) applies the model of Baptista et al. (2016) to the Danish housing market. He finds that both LTI and LTV restrictions reduce house price volatility significantly. Reducing LTI from 4 to 2 reduces house price volatility by around 40%. Comparing the reductions in LTV caps for first-time buyers (FTB) and second and subsequent buyers (SSB) shows that the former has a stronger impact on the housing cycle.5 Bringing the LTV cap of FTB agents down from 98% to 86% reduces the standard deviation of house price growth by nearly 40%. The same restriction on SSB agents, who use the revenue from the previous home sale for larger down payments so that they can borrow less, shows almost no effect.

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4 Also, the effect of LTVs on the Gini coefficient is not significant for the Netherlands and Portugal, the countries with the largest LTVs in their sample.

5 In Denmark, investors are often public companies and, thus, not subject to these measures.
The aforementioned agent-based models concentrate on the effect of macroprudential policies on financial stability. In order to also analyse the side effects of macroprudential policy, we enrich the model of Baptista et al. (2016) by implementing a more complex household consumption function, allowing for wealth effects. This enables us to investigate the borrower-specific effects of LTV caps on Debt-to-Income ratios but also on consumption volatility and wealth inequality, affected by changes in the transaction patterns of the housing market.

3. Model description and modifications

Building on Baptista et al. (2016), we develop an agent-based housing market model populated with heterogeneous households, interacting on ownership and rental markets, and a commercial bank providing mortgage credit subject to central bank policies. The model contains a fixed housing stock, where each house is characterised by a quality variable (a proxy for location, size, and condition). The model variables evolve over discrete time, where each unit is supposed to stand for a month.

Households can be: renters, owner-occupiers, or buy-to-let investors. Change of status is possible in each period. Households change their housing status through market interactions. They enter the ownership market by placing bids for houses or offering their home or investment property for sale. When households enter the model, 8% of them can become BTL agents, all by design in the upper half of the income distribution. They are able to buy and sell investment property. Agents who are not renting or owning a house form a ‘social housing’ residual in the model.

Households age and die, while new households enter the model. When households die, a randomly selected household inherits their wealth (keeping long-term wealth inequality constant). The population size remains constant and the age structure is selected to be close to the 2014 British age distribution. New households are randomly assigned to an income percentile when they enter the model. Combined with their age, this determines their wage and pension income over their lifetime.

At the beginning of each period, households can place a bid on the housing or the rental market, depending on their individual characteristics. At the end of each period, bids and offers are cleared by an auction mechanism. Households with unsuccessful bids or offers consider re-entering the market the following period.

This is a partial model, without the broader macroeconomy with firms or the government sector (apart from the central bank). The larger part of disposable income (wages) is given exogenously; only income from renting is endogenous in the model. This design implies that consumption decisions do not feed back to wages and effective demand, an important limitation we discuss in Section 7.

3.1. Household decisions

3.1.1. Household consumption

Households’ desired consumption consists of an essential part (fixed to UK monthly income support which is always fully consumed) and a non-essential part. It is calculated as:

$$\text{c}_{it}^{desired} = c_0 + \alpha x_{it}^{m, disp} + \beta_i (b_{it} + y (w_{hi} - q_{it})),$$

where $c_0$ is essential consumption, $y_{it}^{m, disp}$ monthly disposable income, $b_{it}$ deposits, $w_{hi}$ housing wealth and $q_{it}$ mortgage debt, which is the only type of debt in the model. Parameters $\alpha_i$ and $\beta_i$ depend on the agent’s income quartile, allowing for lower-income households to consume a higher proportion out of disposable income and wealth per monetary unit. $\beta_i$ is set to match the UK’s top 10% total wealth share (excluding pension wealth) of the years 2008–2018 (45%) and the corresponding ratio of households’ financial wealth to mortgage debt. To account for the empirical fact that financial wealth

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6 The code for Baptista et al. (2016) can be found here: https://github.com/INET-Complexity/housing-model ; the code of our adaptation here: https://github.com/RubenTarne/wealth-effect/tree/Tarne-Bezemer-Theobald. For a complete description of the original model see Baptista et al. (2016) and for the complete model specification of our model adaption—including equations, variables and parameter values—see: https://github.com/RubenTarne/wealth-effect/blob/Tarne-Bezemer/Theobald/Equations%20-%20Overview%20-%20Tarne%20Bezemer%20Theobald.pdf

7 For the sake of brevity, we will not describe the details of the rental market, but in principle it works similar to the ownership market.

8 On average, these 8% lead to effectively 6% of households holding investment property, which is the share of households in the Wealth and Assets Survey of 2011 that earn rental income. This share of “active” BTL agents moves procyclically with the housing cycle.

9 Specifically, the propensity $\alpha_i$ is set to 0.99 for the lowest income quartile, 0.96 for the second, 0.93 for the third, 0.9 for the highest excluding the top 10% for which it is 0.85 and 0.6 for the top 1%. These values are close to US data following Dynan et al. (2004), where the first quintile has a marginal propensity to consume of 0.99, and the others in ascending order, 0.9, 0.89, 0.83, and 0.76. The top 5% have an MPC of 0.63 and the top 1% of 0.49. As the model does not incorporate a pension scheme, which usually absorbs a significant part of household savings, we account for this by increasing the consumption propensities slightly. Calibration values for all parameters introduced in the text can be found in Table A5 in the Appendix.

10 We refer to model version c) from Section 5.1 to match these values, as it resembles the post-crisis years better than the baseline model. The average top 10% total wealth share (excluding pension wealth) in the UK is around 45% and financial wealth to mortgage debt relation is about 1.6 (Wealth and Assets Survey: https://www.ons.gov.uk/file?uri=/peoplepopulationandcommunity/personalandhouseholdfinances/incomeandwealth/datasets/totalwealthwealthingreatbritain/july2006tojune2016andapril2014omarch2018/totalwealthtablesfinal.xlsx). The UK real house price index moves between 98% - 112% in 2011-prices between Q1-2008 – Q2-2018 (OECD, 2022). The top 10% wealth share of the model for the corresponding subset of periods with house prices between 98% and 121% is 43%, the financial wealth to mortgage debt relation 1.7. For aforementioned income quartiles, $\beta_i$ is set in ascending order to 0.0075, 0.006, 0.005, and 0.004, with the top 10% set to 0.002 and the top 1% to 0.0002 (monthly values). This calibration follows from the fact that wealthier households tend to have a lower propensity to consume out of wealth than poorer households (Arrondel et al., 2019).
has a larger effect on household consumption than housing wealth, $\gamma$ dampens the impact of net housing wealth on the household's desired consumption (Arrondel et al., 2019; Chauvin and Mullbauer, 2018; Christelis et al., 2015; Jawadi et al., 2017). Desired consumption can be constrained by wealth effects, so that realised consumption is:

$$c_{i,t} = \begin{cases} 
    c_0 + \alpha \gamma_{i,t}^{\text{disp}} & \text{if } b_{i,t} + y_{i,t}^{\text{disp}} - c_{\text{desired}} < \zeta \gamma_{i,t}^{\text{disp}} \\
    c_{\text{desired}} & \text{if } c_{\text{desired}} < c_0 \\
    \text{else} & 
\end{cases}$$

where $\zeta$ reflects precautionary saving and is set to two. If desired consumption falls below essential consumption, which can happen when debt levels are very high or disposable income turns negative, realised consumption is constrained to essential consumption so that a significant part of income will be saved.

### 3.1.2. Placing bids on the ownership market

New households enter the model in social housing (SH in Fig. 1). Whenever households are in social housing, they either place a bid on the ownership market (arrow 1 in Fig. 1) or on the rental market (arrow 5). The decision is made by comparing the cost of renting and buying. The probability of entering the ownership market ($SH \rightarrow OO$) is given by:

$$Prob(\text{placing a bid})_{SH \rightarrow OO}^{SH \rightarrow OO} = \frac{1}{1 + \exp \left\{ - \eta \left[ 12T_{Q,i} - (12m_{SH \rightarrow OO}^{SH \rightarrow OO} - p_{SH \rightarrow OO}^{SH \rightarrow OO} \cdot g_t) \right] \right\}}$$

where $12T_{Q,i}$ are the yearly costs of renting a house of quality $Q$ and $(12m_{SH \rightarrow OO}^{SH \rightarrow OO} - p_{SH \rightarrow OO}^{SH \rightarrow OO} \cdot g_t)$ is the yearly cost of buying a house of the same quality. The latter term consists of the expected monthly mortgage payment $m_{SH \rightarrow OO}^{SH \rightarrow OO}$, less the expected appreciation or depreciation of the given house, calculated by the product of the bid price $p_{SH \rightarrow OO}^{SH \rightarrow OO}$ and the expected yearly growth rate in house prices:

$$g_t = \lambda \left[ \frac{H_{t-1} + H_{t-2} + H_{t-3}}{H_{t-25} + H_{t-26} + H_{t-27}} \right]^{1/24} - 1 - \mu$$

\[11\] $\gamma$ is set to 0.25. Some sensitivity analyses for this parameter are presented in Appendix E.

\[12\] See for a sensitivity analysis of this parameter Appendix E.
$g_t$ is calculated as the average quarterly house price growth rate over the last two years, dampened by households’ sentiment parameters $\gamma$ and $\mu$. $HPI_t$ is the house price index at period $t$, where 1 equals the UK house price level of 2011. The households’ bid price $p_{i,t,k}^{\text{SH-OO}}$ for house $k$ of a certain quality increases with expected rising house prices. It is a noisy ($\varepsilon$) multiple ($\sigma$) of the household’s yearly wages $12y_{i,t}^{\text{m,emp}}$:

$$p_{i,t,k}^{\text{SH-OO}} = \min \left( q_{i,t}^{\text{SH-OO}} + b_{i,t}, \frac{12y_{i,t}^{\text{m,emp}} \exp(\varepsilon)}{1 - \varphi g_t} \right).$$

(5)

The bid price might be limited by the maximum mortgage $q_{i,t}^{\text{SH-OO}}$ the bank is willing to lend, applying an internal LTV cap of 80%. If the resulting bid price is too low to bid for a house of even the lowest quality, then the agent automatically enters the rental market.

BTL investors first become owner-occupiers before they decide to buy investment property. The investment decision (arrow 3 or 4 in Fig. 1) differs from an owner-occupier’s decision to buy a home. The BTL agent’s probability to place a bid on the market is given by:

$$\text{Prob}(\text{placing a bid} | \text{BTL}) = \begin{cases} 0, & \text{if } \sum m_{i,t,k} > 0.5y_{i,t}^{\text{m,net}} \\ 1 - \left( 1 - \frac{1}{1 + e^{-(\alpha^{\text{BTL}}_{i,t} \varphi)}} \right)^\frac{1}{12}, & \text{if else} \end{cases}$$

(6)

Eq. (6) states that a BTL investor does not place a bid, if monthly mortgage payments are higher than 50% of monthly post-tax income. This internal restriction is introduced to limit bankruptcies, as BTL investors can own more than one rental property. There are two types of BTL investors. Trend-following investors buy when capital gains are high. Expectations are formed adaptively. Fundamentalist investors buy when the expected rental yield is high, deciding on investment according to its (investor-class specific) perceived return $\Omega_{i,t}$. The BTL agent’s bid price is the sum of the household’s deposits and the maximum mortgage loan the bank is willing to grant, when applying the internal LTV limit:

$$p_{i,t,k}^{\text{BTL-OO}} = q_{i,t}^{\text{BTL-OO}} + b_{i,t}.$$ 

(7)

3.1.3. Placing offers on the ownership market

In line with the English House Survey from 2011 (Department for Communities and Local Government, 2013), owner-occupiers in our model sell their home on average every 17 years as they move (see arrow 2 in Fig. 1). Their offer price depends on the historic average realised transaction price, which they observe on the market for houses of the same quality. This price is adjusted by a mark-up and the expected time the house was on the market before being sold. If the expected sale price is below the principal of the remaining mortgage, the household will not sell the house. Each month, BTL investors decide if they want to sell their property according to the following probability:

$$\text{Prob}(\text{placing an offer} | \text{BTL}) = \begin{cases} 0, & \text{if i has only 2 houses} \\ 1 - \left( 1 - \frac{1}{1 + e^{-(\alpha^{\text{BTL}}_{i,t} \varphi)}} \right)^\frac{1}{12}, & \text{if else} \end{cases}$$

(8)

based on the expected equity yield of their property $k$, $\Psi_{i,t,k}$. For simplicity reasons, investors always keep at least one investment property. This implies that the number of BTL investors over the cycle is more stable than in reality, where the number of BTL investors increases significantly in a boom (see also Fig. A3 in the Appendix). The price-setting mechanism of BTL investors selling properties is basically the same as for owner-occupiers selling their home.

3.2. Market mechanism

When all bids and offers are made, they are matched in a double-auction process. In the first step, bids of FTB and SSB agents are matched with the cheapest house of the highest quality they can afford. BTL agents’ bids are matched with the real estate providing highest rental yield that they can afford. All offers that are matched with only one bid are cleared. The realised price is the offer price.

At the second step, all offers that have been matched with more than one bid increase the offer price by a small fraction. The house is then randomly sold to one of the bids still qualifying. After this first iteration, all uncleared bids and offers

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13 These dampening factors are set according to the direct price expectation responses of households NMH survey by Bank of England and are than compared to the past house price movements in the households’ region, gained from the Land Registry data between 2014 and 2018. $\lambda$ is set to 0.44 and $\mu$ to 0.007.

14 This value is randomly drawn from a normal distribution with $\mathcal{N}(0, 0.5)$.

15 $\sigma$ is set to 4.5. While the model reacts sensitively to this scaling parameter, qualitatively, our results do not change for other parameter values.

16 Fundamentalists and trend-followers weigh the perceived rental yield and capital gain differently to calculate $\Omega_{i,t}$. Fundamentalists weigh both gains equally, while trend-followers weigh the capital gains with 90%. For further details see the online appendix.
go through the same matching process as before. This procedure is repeated until either no offers or no bids are left. A household whose bid did not match any offer will decide in the next period whether to bid on the housing market again. A household whose offer did not match any bid can reduce the offer price and decide, in the case of BTL agents, whether to remove it from the market.

The present model builds on Baptista et al. (2016) in several areas with several innovations. In Baptista et al. (2016), the consumption function is what fixes the distribution of financial wealth relative to the distribution of income, leading to large swings in consumption generally and specific to SSB agents, implying larger leverage when they want to buy their subsequent home. This is addressed by our consumption function. Further, households in our model do not receive an additional financial endowment at “birth” and BTL agents do not bid on the ownership market above a debt-service-to-income threshold (50% of net income). Moreover, BTL agents only take on mortgage debt where interest and principal are repaid over the entire mortgage term, so as to limit the number of bankruptcies.

Another change is that the commercial bank pays out its interest income as “dividends” to households with deposits (rather than paying fixed-rate interest on deposits) and banks receive fixed-rate interest on loans, rather than increasing rates with increasing debt as in Baptista et al. (2016). For other changes we refer to Appendix D.

4. Baseline dynamics

In this section, we present baseline model dynamics without macroprudential policy in order to study the interconnectedness of transactions in the housing market, the house price cycle and the three target variables—household debt-to-income-ratio, absolute deviation of consumption between through and peak (as a proxy for consumption volatility) and top 10% total net wealth share.

4.1. Dynamics of key housing market indicators

After the burn-in phase of the model (not shown), we observe regular synchronised real estate price and mortgage cycles that last about 100 months (8.3 years). This is shorter than the house cycle estimated for the United Kingdom (13 years; Strohsal et al. 2017). The cycle length is sensitive to the price expectation of households (parameter g, in Eq. (4)). If households look further back in time when forming their house price expectation, it takes longer for house price swings to affect household decisions, slowing down house price growth and lengthening cycles (i.e. lowering cycle frequency).

The length and frequency are also sensitive to the share of buy-to-let (BTL) agents in the population and to parameters influencing the bid price formation of first-time-buyer (FTB) and second and subsequent (SSB) agents. A higher percentage of BTL agents in the population leads to increasing house price peaks, prolonging the cycle.

Importantly, the model matches key UK housing market indicators reported by the Bank of England. These include the average mortgage-debt-to-income and house-price-to-income ratio, the number of monthly housing transactions and mortgage loans (Table A1 in Appendix A). Already at this point, we may also note several differences between the model and UK data. In the model, upswings last shorter than downturns (see Fig. 2), while the UK house price cycle—especially from the mid-1990s on—exhibits longer upswings than downturns (see left panel of Fig. A2 in the Appendix). House prices fall to lower levels in the model than in British data and tend to stay low for longer. This difference may be due to the absence of stabilising mechanisms that exist in reality in the downturn, such as the ‘Help to Buy’ scheme. These differences do not undermine the model results with respect to the research question; we will return to them in Section 7.

The model gives rise to agent-type-specific transaction patterns which drive the house price cycle, where prices rise when there is excess demand for housing and fall when there is excess supply, while house prices again feed back into agents’ decisions to enter the housing market. Tracing the transactions over the house cycle is central to understanding how different macroprudential rules can affect agent-specific behaviour, as we now show.

The left panel of Fig. 2 shows each type of agents’ ratio of transactions to the housing stock. Starting in the “upswing first half”, for FTB and SSB agents positive price expectations lower their perceived cost of buying relative to renting (Eq. (3)) so that they bid on the ownership market. BTL agents (especially fundamentalists) are also entering the market as their expected property yields increase. Their bids are met by a relatively large housing supply accumulated over the last downturn and, for the most part, already on the market for several months. As a result, more houses are sold than in previous periods, including, and this is crucial for the price mechanism, those houses of a given quality that are relatively expensive. That is the reason that realized sale prices are above their current expected values, so that the house price index rises, increasing in turn price expectations. In the first half of the upswing the market turnover is at its maximum: FTB agents purchase on average 4.5%, SSB agents 9.0% and BTL agents 11.6% of the total housing stock.

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17 To increase model tractability compared to Baptista et al. (2016) loan-to-income ceilings were replaced by loan-to-value caps and psychological costs of renting are removed. Note that the central bank in both model versions does not change the base rate. For a sensitivity analysis of different interest rate levels, see Appendix E.

18 When halving the backward-looking time horizon that agents have to build their price expectations from two years to one year, the average cycle length shortens by around 20%.

19 Recall that the desired purchase price of FTB and SSB agents is a multiple of their income (parameter σ in Eq. (5)). Increasing this multiplier leads to higher bid prices, resulting in higher house price peaks.

20 The ‘Help to Buy’ scheme subsidises FTB home purchases with a government loan.
In the second half of the upswing, the rise in price expectations and perceived capital gains lead to BTL agents (especially trend-followers) entering the market. The increasing demand is now met by a shrinking supply since once prices are trending up, BTL agents stop selling their properties, reinforcing the upward price trend. FTB agents (mostly young and with little savings) are increasingly constrained by their deposits available for down payment relative to prices. In contrast, SSB agents place more bids at the higher prices, which might seem counterintuitive in a simple supply-and-demand framework. The reason is their history: in the preceding downturn (especially in the second half), there was an oversupply. SSB agents responded to their need to sell their house with a lag by selling their houses in the first half of the upswing that followed. Only in the second half of the upswing, with a high price regime, are they in a position to buy. These kinds of dynamics can only be gleaned from a historical-time agent-based model. The offers and bids over the house price cycle are shown in Fig. A5 in the Appendix\textsuperscript{21}. The turnover in the second half of the price upswing is lower than in the first half, because the supply of houses is only a fraction of that at the beginning of the upswing.

House price growth diminishes and then turns negative as bids by BTL and SSB agents decrease due to falling deposits and rising debt service, and, eventually, SSB agents’ desired purchase prices fall below market prices. As price expectations follow falling house prices, BTL agents start selling due to negative perceived yields while FTB and SSB buyers increasingly prefer renting. These changes accelerate the price downturn and the fall in market turnover\textsuperscript{22}. When prices are low enough, first FTB agents enter the market again, while SSB agents must first sell their home. FTB bids turn the cycle\textsuperscript{23}.

British data on the volume of mortgages taken out by households (see Fig. A6 in the Appendix) between 2007 and 2018 widely confirm the transaction pattern differences between BTL agents and the owner-occupiers (FTB and SSB households). With falling prices after 2007, loans to BTL borrowers fell to their lowest levels and, with rising prices from 2013 on, increased fastest (taking up a larger share of total advances). We will revisit the transaction pattern of BTL and FTB agents in detail in Section 7. The real-world difference between FTB and SSB borrowers is not as pronounced as in our model. This could be partly explained by the fact that the price level in 2018 (the end of our observation period) was still well below the house price peak in the model; and at lower prices, SSB and FTB purchases are closer together. Another part of the explanation might be the missing of an agent-specific saving motive for FTB in our model, which would otherwise enable them to enter the housing market at higher prices).

\textsuperscript{21} The difference in purchasing patterns between FTBs and SSBs (movers) is not driven by their desired purchase prices (Eq. (5)), which are mainly determined by their income. For that to be true FTB agents should have lower income on average than SSB agents (which would make them exit the market earlier). Yet, they are concentrated towards the upper half of the income distribution, while movers are equally distributed along the income distribution (see Fig. A4 in the Appendix). This is due to their age differences, as a significant share of movers is already in retirement, which reduces their income.

\textsuperscript{22} For a comparison between the lead-lag structure of the model and the U.K. with regards to the house prices and property transactions, see the right panel of Fig. A2 in the Appendix.

\textsuperscript{23} The time it takes BTL agents to enter the market after the prices turn depends on the lag of the price expectation formation, i.e. on the average price increase from t-27, t-26 and t-25 to t-3, t-2 and t-1 in Eq. (4).
The right-hand panel of Fig. 2 shows the ownership pattern resulting from these transactions over a representative cycle (100 periods). BTL investors' housing stock increases in the upswing, as they only buy but do not sell houses. In the downturn, they sell their property to FTB and SSB agents who increase their share accordingly. During the upswing, the shares in the housing stock of FTB and SSB agents decrease as they sell their homes. Of course, the limited rationality of BTL agents has to do with the fact that their binding behaviour is widely trend-chasing and thus procyclical – a behaviour that has been described in finance literature for a long time (Shleifer and Summers, 1990).

4.2. Baseline results for the target variables

Recall that we study the evolution of three variables that could be affected by the policy of the central bank. These ‘target’ variables are the household debt-to-GDP ratio, the top 10%24 total net wealth share and the gap between highs and lows of per household consumption in monetary units (consumption volatility).

Fig. 3 shows how leverage (the debt-to-income ratio) evolves procyclically. Fast rising house prices about 30 percentage points per year25 are initially driven by transaction dynamics of agents; the price upswing of the model is more condensed than the observable UK data. The procyclicality of leverage is driven by the transactions of BTL and SSB agents (Fig. 3 top-left panel). As soon as prices start to rise, BTL agents enter the market as buyers. This increases their leverage heavily. When prices start falling, they stop buying property and start selling. This and their mortgage payments reduce their indebtedness.

The transaction pattern of SSB agents is less pronounced. While they buy almost as many houses as BTL agents in the first half of the upswing, they initially sell even more and repay debt, resulting in the observed decline in homeownership (see the right panel-hand in Fig. 2) and leverage. FTB agents buy at low prices so that their leverage rises much less. Recall that they cannot enter the market at high prices due to limited deposits. Subsequently their indebtedness decreases due to debt repayments and (when house prices start rising) increasing home sales.

The top right-hand panel in Fig. 3, depicts the total net wealth share of the wealthiest 10% over the house cycle. In the model, net wealth equals housing wealth plus financial wealth (deposits) minus mortgage loans. In line with the literature, the total net wealth share of the richest 10% decreases with rising house prices. The fluctuation of the wealth share in the model is stronger than in the UK data mainly because model house prices fluctuate stronger. Also the model has no other asset price fluctuations which can balance some of the impact of the house price fluctuations on total net wealth inequality (Kuhn et al. 2020).

BTL agents’ total net wealth is very sensitive to changes in house prices because BTL agents are highly leveraged. Therefore, in a house price upswing, the increase in the stock of BTL housing wealth (also net wealth) is large. When prices are falling, the highly indebted BTL agents become increasingly part of the bottom 90% of the net wealth distribution.

It is noteworthy that transactions between agent-classes affect wealth inequality along the house price cycle. At low prices, FTB agents enter the market, while BTL agents sell their property. This leads to lower total net wealth inequality at high prices, primarily because BTL agents, with their procyclical buying behaviour, allow home sellers to move up the wealth distribution.

The bottom panel of Fig. 3, shows the consumption in monetary units per households, divided into three subcomponents—consumption induced by income, by financial wealth and by net housing wealth. Since most households’ income consists mainly of employment income, which, in the model, is stable over the house price cycle, this subcomponent shows little fluctuations. Higher fluctuations stem from changes in net housing wealth and, to a lesser extent, changes in aggregate deposits (financial wealth). Both changes, in turn, are caused by the cyclicality of the housing market. There is considerable consumption volatility induced by house price changes and by agents’ subsequent transactions (which change their wealth portfolio, and hence their consumption). For about a third of the simulation period (periods 30 to 60), housing wealth adds more than 200 monetary units of consumption (more than 10% of total consumption) to the relatively stable level of income- and financial-wealth-induced consumption. As noted, wealth in the model fluctuates a little more than in the real-world data, and also the standard deviation of consumption is with 5.7% larger than in the UK data (Attanasio et al. 2011).

5. Effects of macroprudential policies on debt, wealth inequality and consumption volatility

We now move from the benchmark results to the simulations including macroprudential policies. We explore three regimes of credit conditions linked to different regulatory stances (Section 5.1) and their effects on the three target variables (Section 5.2). In section 5.3 we study in detail how transaction patterns change the target variables.

5.1. Three policy regimes

Fig. 4 presents simulation results for different credit conditions. The baseline ‘traditional banking’ regime (top-left panel) reflects banking behaviour before the late 1970s when financial liberalisation started to ease credit conditions (Fernandez-Corugedo and Muellbauer, 2006). The commercial bank applies a maximum LTV of 80% for all households, independent of

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24 We use the top 10% total net wealth share as indicator for wealth inequality as we are primarily interested in the upper part of the wealth distribution, where the GINI is relatively insensitive.

25 Note the x-axis in Fig. 3 shows months.
the state of the house price cycle. Each of the sub-figures shows the house price cycle and the maximum LTV over 200 months\(^{26}\).

From the late 1970s on, financial markets were increasingly de-regulated. As a consequence, credit supply conditions became more procyclical (Hardie and Howarth, 2013; Lindner, 2014; Muellbauer et al., 2015) and there was strong growth in residential mortgage credit (Jordà et al., 2016). We incorporate these changes by making the maximum LTVs of the commercial bank procyclical:

\[
LTV_t = \psi g_t + \tilde{LTV}, \quad \text{for } 0 \leq LTV_t \leq 100\%.
\]

where \(\psi\) denotes a dampening parameter to the expected changes in house prices \((g_t)\). To ensure that LTVs move around observed LTV ratios, \(\tilde{LTV}\) is set to 0.8\(^{27}\) for all borrower types. It represents the commercial bank’s internal LTV limit (i.e. not the regulatory cap imposed by the central bank) if it is expected that prices are stable. For model consistency, the maximum value of the LTV here is 100%.

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\(^{26}\) The simulation has a burning-in period of 1500 periods (not shown). Simulation results are selected to start with a house price trough.

\(^{27}\) This value is taken from van der Heijden et al., (2011, p. 308).
The liberalised financial market regime is shown in the top-right panel, (‘pre-crisis banking’). We observe that compared to the traditional banking regime, the cycle is longer. House price peaks almost double in value, but the house price trough increases only somewhat: as it turns out, the effect of procyclical credit conditions is asymmetric.
Table 1
Target variables for different regimes.

<table>
<thead>
<tr>
<th>Regime</th>
<th>Debt-to-income ratio (%)</th>
<th>Top 10% total net wealth share (%)</th>
<th>Per household consumption volatility (amplitude = max-min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a) constant max LTV = 80%</td>
<td>max = 116%, mean = 96%</td>
<td>max = 68.6%, mean = 49.6%</td>
<td>amplitude = 348</td>
</tr>
<tr>
<td>b) max LTV = 100%, procyclical credit conditions</td>
<td>max = 249%, mean = 170%</td>
<td>max = 93.2%, mean = 53.7%</td>
<td>amplitude = 759</td>
</tr>
<tr>
<td>c) procyclical credit conditions, anticyclical macroprudential LTV caps (90%, all agents)</td>
<td>max = 135%, mean = 106%</td>
<td>max = 82.2%, mean = 53.7%</td>
<td>amplitude = 400</td>
</tr>
<tr>
<td>d) 70% FTB, 90% SSB, 90% BTL</td>
<td>max = 128%, mean = 101%</td>
<td>max = 83.1%, mean = 54.8%</td>
<td>amplitude = 371</td>
</tr>
<tr>
<td>e) 90% FTB, 70% SSB, 90% BTL</td>
<td>max = 124%, mean = 99%</td>
<td>max = 78.5%, mean = 53.1%</td>
<td>amplitude = 380</td>
</tr>
<tr>
<td>f) 90% FTB, 90% SSB, 70% BTL</td>
<td>max = 102%, mean = 87%</td>
<td>max = 76.3%, mean = 51.9%</td>
<td>amplitude = 310</td>
</tr>
</tbody>
</table>

In panel c) we introduce macroprudential anticyclical LTV caps. They result from making \( LTV_{t, cap} \) dependent on observed past house price movements:

\[
LTV_{t, cap} = \begin{cases} 
0.9, & \text{if } \Delta HP_{Q_{0:t-1}} > 0 \wedge LTV_{t-1, cap} = 1.0 \\
1.0, & \text{if } \Delta HP_{Q_{0:t}} < -0.2 \wedge LTV_{t-1, cap} = 0.9 
\end{cases} 
\tag{10}
\]

In the simulation, initially, macroprudential policy is inactive. The lower 0.9 LTV cap (the solid line) is activated once quarterly price changes become positive. Conversely, the higher 1.0 \( LTV_{t, cap} \) (purple dotted line) is then activated once yearly prices drop by more than 20%, and so on. The internal lending rule of the commercial bank remains procyclical, but the credit supply is restricted in the house price upswing by the external rule of the central bank. As a result, the level of house price peaks and the cycle frequency are again close to the ‘traditional banking’ results in panel a).

In panels d), e) and f) we study the effects of borrower-specific macroprudential rules. Here, we assume that the central bank sets \( LTV_{t, cap} \) of one agent class to 70% instead of 90%. Results are shown for first-time buyers (FTB) in panel d), for subsequent buyers (SSB) in panel e) and for buy-to-let (BTL) investors in panel f). We observe the strongest effects on dampening peaks when BTL agents are restricted.

Because of stochastic influences, the outcome of the model is path-dependent so that Monte-Carlo runs are needed to ensure generality of the results (Fig. A7 in the Appendix). All results are based on 50 Monte-Carlo runs while each run comprises 1000 periods.

5.2. Effects on the target variables

This section examines the effects of the different macroprudential policy regimes on the target variables (household indebtedness, wealth inequality and consumption volatility). In 5.2, we study the procyclicality of credit supply conditions given the regimes a), b) and c) of Fig. 4. In Section 5.2.2, we analyse agent-specific credit limitations given the regimes d), e) and f) of Fig. 4.

5.2.1. Influence of procyclical credit conditions

The simulation of the liberalised banking regime suggests large effects on debt, wealth inequality and consumption volatility, in line with the literature. Table 1 shows that average debt-to-income (DTI) ratios increase from 96% in regime a) ‘traditional banking’ to 170% in regime b) ‘pre-crisis banking’, with peak values rising from 116% to 249% (see also in Fig. 5, top-left). The transition from ‘traditional’ to ‘pre-crisis’ liberalised banking also leads to higher maximum and average total net wealth inequality, higher average monthly consumption, and rising consumption volatility; the difference between the maximum and minimum consumption values\(^{28}\) (the amplitude of the consumption cycle) rises from 348 to 759 per household.

These observed increases in leverage, wealth inequality and consumption volatility by liberalised banking contributed to the introduction of macroprudential rules, with debt development usually seen as the primary target and the other two as secondary at best. Limiting the LTV caps to 90%, brings the debt-to-income ratio close to the levels in the ‘traditional banking’ regime (first column of Table 1). The DTI maximum is reduced to 135% (relative to 116% in the traditional banking regime) and the average to 106%—relative to 96% in the traditional banking regime; the consumption amplitude falls to 400 monetary units relative to 348 before. These strong effects on the variables that feed into financial stability are in line with Kelly and O’Toole (2018), who find that above an LTV of 75%, default rates of mortgages increase steeply.

Total net wealth inequality is less affected by macroprudential regulation. The wealth share of the richest 10% of households is almost the same as in the ‘pre-crisis’ regime b). This finding is in contrast to the results of Carpentier et al. (2018),

\(^{28}\) To estimate volatility of consumption we use the absolute distance between minimum and maximum values and not its standard deviation. The distribution of monthly consumption per household is bimodal and higher volatility does not lower minimal consumption (see Fig. A12, where the distributions show similar minimal values, but maximum values differ). This happens mainly because changes in the LTV caps affect house price peaks and only marginally house price troughs (see Fig. 3), because at low house prices macroprudential credit restrictions do not affect the turning point as such.
who suggest that limiting LTVs would also decrease wealth inequality. One reason is that with macroprudential measures active, less wealthy households no longer benefit strongly from the rise in house prices. In the macroprudential regime c, this effect balances the wealth-inequality-reducing impact of lower debt at low prices (see the top-right panel of Fig. A9 in the Appendix).

5.2.2. Agent-specific macroprudential policy

Given the substantial differences in housing market transaction behaviour between household types, borrower-specific LTV caps might be efficient (Carpantier et al., 2018). They are already applied in several countries, including Ireland, Israel, New Zealand, and Finland (IMF-FSB-BIS, 2016).

The results in Table 1 (d)–(f) show that reducing BTL agents’ ability to access credit in the housing market upswing leads to the strongest effect on maximum and average debt-to-income ratios. In the right-hand panel in Fig. 5, reflecting the change from regime c) to f), maximum DTI values fall from 135% to 102%. When restricting FTB and SSB agents, the decline is only to 128% and 124%, respectively. Overall, the effect of additional agent-specific credit restrictions is significantly smaller than the effect of reducing LTV caps to 90% compared to the liberalised ‘pre-crisis’ regime with its LTV limit of 100%. This reveals a non-linearity also reported by Alam et al. (2019). The non-linearity arises because deposits (i.e. potential down payments) are very unevenly distributed over households. This implies that LTV reductions (of a given size) starting from higher LTV levels exclude a larger share of the population from being able to enter the housing market than the same reduction at lower LTV levels.

The size of the effects of limiting FTB and SSB agents is in line with those found by Alam et al. (2019) a year after the implementation of LTV caps. Translating the 20 percentage point decrease in the LTV cap of one agent-class to an average decrease of 20/3=6.7 percentage points and applying Alam’s et al. (2019) coefficients, this results in a decline in household credit growth after one year of 4.4 percentage points. In comparison, restricting FTB agents’ access to credit in our model yields a reduction of peak DTI values by 6.8 percentage points, while the SSB restriction leads to a reduction by 10.8 percentage points. The 32.9 percentage points decline in peak DTI values of the BTL restriction, however, is significantly larger.

Fig. 5 shows that lower DTI ratios are not merely the results of reductions in maximum house prices; the mean values also shift downward. Over the entire house price cycle one can observe lower household debt levels. Again, this effect is strongest when restricting BTL agents, where the mean-line is not only shifted downwards but also flattened. This suggests that strong restrictions on BTL agents make the development of DTI-ratios less dependent on the house price cycle.

Limiting BTL agents’ access to credit also reduces the maximum and average values of total net wealth inequality, as Table 1 shows. As BTL agents have less opportunity for buying houses when prices are high, housing wealth becomes less concentrated, leading to lower total net wealth inequality at high prices. At low prices, the overall lower indebtedness leads to fewer households suffering from negative equity—a situation where liabilities are higher than assets and wealth-induced consumption turns into savings for debt-repayments. The limitation of SSB agents has only limited equalising effects on the wealth distribution while the limitation of FTB agents even increases wealth inequality. With fewer (and lower) bids by FTB agents on the housing market in the upswing, BTL agents are without competitors and hence even more successful in buying property. BTL agents concentrate housing wealth more, and thereby, increase total net wealth inequality—at least at high prices.

The final target variable in Table 1 is consumption volatility. Here, transactions in the housing market drive fluctuations in consumption through both housing wealth and financial wealth (Fig. 3). Dampering the house price cycle should, therefore,
reduce average consumption and consumption volatility. Since the macroprudential restrictions mainly affect house price peaks and house price troughs hardly at all, it follows that mainly consumption volatility should be affected and less average consumption. We see in Table one, third column that reducing BTL agents’ access to credit again has the strongest impact. Alam et al. (2019) find for a reduction in LTV caps of 6.7 percentage points a reduction of about 1 percentage point in consumption growth (after one year). In our model the equivalent LTV cap reductions (i.e. the 20 percentage points defining each policy regime) lead to a reduction in the consumption peak (not the amplitude) equal to 1.3 percentage points when first-time buyers are restricted and 0.9 percentage points in the case of second and subsequent buyers. The corresponding restriction of buy-to-let agents yields a stronger reduction in the consumption peak, 4.5 percentage points.

Overall, the simulation results, suggest that restricting BTL agents’ access to credit represents an effective regulatory instrument. In Section 6, we expand our analysis by comparing the currently applied LTV caps of the Irish Central Bank with a setup where, in line with our results, more focus is put on BTL agents. In Appendix C, we also run statistical tests to make sure that the difference between the results in Table 1 is statistically significant, overall confirming their robustness.

5.3. Transmission mechanism

The model outcomes are driven by the effects of macroprudential regulation on agents’ transaction patterns in the housing market and the mortgage market. Fig. 6 shows the average number of sales as a percentage of the total housing stock for different phases of the house price cycle and for different macroprudential regimes. The numbers shown for regimes c) to f) are LTV caps applied to FTB, SSB and BTL households.

5.3.1. From traditional banking to pre-crisis banking: regimes (a)–(c)

With the introduction of procyclical maximum LTVs by commercial banks (pre-crisis regime b)) house price peaks increase substantially, while the frequency of their occurrence decreases. The risk of over-indebtedness grows compared to the traditional banking regime where house price peaks are less pronounced and the house price cycle turns downwards sooner. In Fig. 6 we see that especially first-time-buyer (FTB) agents increase their access to the housing market in the upswing, where they purchase 13.5% of the housing stock in the pre-crisis regime as opposed to only 4.9% in the traditional banking regime. Second and subsequent buyer (SSB) agents’ purchases increase as well, but less as they were not as credit-constrained as FTB agents in the traditional banking regime. In the second half of the downturn, FTB agents are even more credit constrained in the pre-crisis regime than they were in the traditional banking regime. Pro-cyclically, their maximum LTV drops sharply in this phase.

From the ‘traditional banking’ to the ‘pre-crisis banking’ regime, the average debt-to-income ratio (DTI) rises mainly because of FTB and BTL agents. SSB agents, on the other hand, hardly change their realised LTVs and the prices they bid for their new homes. In both regimes, they receive enough deposits from sales to make bids without extensive borrowing (Eq. (5)). When more households sell more properties, then given the larger consumption response to financial wealth than to housing wealth, this increases consumption in the pre-crisis regime relative to the traditional banking regime. Also, the higher DTI ratios allow stronger house price growth, inducing further wealth effects on consumption.

Introducing macroprudential policy (regime c) reverts the transaction patterns on the housing market so that the buying behaviour of many agents comes close to that of the traditional banking regime. A notable difference between the traditional banking and the macroprudential regime is fewer purchases by FTB agents in the second half of the house price downturn, where commercial banks’ procyclical maximum LTVs drop below the 80% of the traditional banking regime. At this point, especially buy-to-let investors sell their property while fewer FTB agents can buy property from BTL agents. Overall, there is less selling from households at the upper end of the wealth distribution (BTL) to households at the lower end of the wealth distribution (FTB). As a consequence, when prices rise again, housing wealth concentration remains stronger in the macroprudential regime than in the traditional banking regime.

5.3.2. Restricting classes of agents individually: regimes (d)–(f)

In regime (d) the central bank restricts, in addition to the macroprudential regime (c), only FTB agents’ access to credit. This causes them to purchase more in the second half of the downturn than in the first half of the upswing. The new credit restrictions especially exclude low-income FTB agents from purchasing homes. As a consequence, there are also fewer low-income SSB agents in the population, since, by definition, an FTB agent can only become an SSB agent through successful transactions in the housing market. BTL agents benefit from restrictions to FTB agents and the lower number of SSB agents in the market. They buy more property at a given price. Their ownership share of the total housing stock increases from an average of 25.1% (in regime c) to 27.6% (in regime d)). At the same time the share of households who are in social housing or renters increases from 41.3% to 43.2%.

29 Restricting BTL agents reduces consumption volatility most, but the effect on average consumption is significant as well. See Appendix B for an analysis of the combined effects on average and consumption volatility.
30 Investors move across the total net wealth distribution over the house price cycle. On average, however, they are found in the upper half of the total net wealth distribution (Fig. A4).
31 The average housing stock held by BTL investors as investment stock increases from 22.3% to 25.1%.
Fig. 6. Transactions over the house price cycle. The regimes depict different regulatory stances. In regime (c), the LTV caps for FTB, SSB and BTL buyers are all 90%. In models (d), (e) and (f) the LTV cap is reduced to 70% for FTB, SSB and BTL buyers, respectively.

In regime (e) the central bank restricts, in addition to the macroprudential regime (c), SSB agents’ access to credit. This has little effect on transaction patterns in the housing market. SSB agents are least reliant on credit due to their high stock of deposits from previous sales, which are used as a down payment for house purchases.

In regime (f) the central bank restricts, in addition to the macroprudential regime (c), BTL agents’ LTV caps. This shifts part of the BTL agents’ purchases, from the second to the first half of the house price upswing when prices are lower. Due
to lower prices paid and the increasing use of down payments (built up by longer saving periods), BTL agents can partially compensate the loss in credit access. But overall, the share of property they own as investment decreases (on average, from 25.1% in the macroprudential regime (c) to 22.4% in regime (f) where only BTL agents are restricted). The buying patterns of FTB and SSB agents remain almost unchanged in this regime.

Turning to the effects on the target variables, we find that the different behaviours of the agent classes, and their different income and wealth positions, influence the impacts of LTV caps on house prices, household leverage and portfolio reshuffling, which in turn affects the target variables. DTI ratios change the most when in macroprudential regime (f) BTL agents’ LTV caps are additionally lowered to 70%. The share in household debt held by BTL investors is not larger than the share of SSB agents but on average at the time of purchase, they have smaller deposits, increasing their sensitivity to credit availability. A reduction of SSB agents’ LTV caps in regime (e) has little effect, since their LTVs are mostly already below the 70% threshold in the upswing when the macroprudential restriction starts to bite. Also restricting FTB agents in regime (d) affects DTI ratios only slightly, as these agents are largely buying at low prices with limited borrowing capacity (see Fig. 3, top left).

Restricting BTL agents leads to significantly lower wealth inequality, consistent with Carpantier et al. (2018). Since BTL agents’ leverage is sensitive to credit restrictions, their lower indebtedness leads to fewer households with negative equity, and credit restrictions limit the number of houses BTL agents can own. These effects are strong enough to offset the wealth inequality increasing effects of LTV caps on house prices (a channel absent in Carpantier et al. (2018)). For FTB agents, lower LTV caps reduce their leverage and the number of transactions from richer to poorer households at lower prices. This leads to overall more concentrated housing wealth, hence higher wealth inequality. For SSB agents, wealth inequality effects are small (see Appendix C).

Consumption volatility falls most when restricting BTL agents’ access to credit. The house price cycle becomes less debt-fuelled as BTL agents borrow most in the late phase of the house price upswing. The more they borrow, the more they increase the amplitude of the house price cycle, thereby affecting housing-wealth-induced consumption. In the model, mortgage lending creates deposits held by the seller. Consequently, with lower debt levels in case of a BTL-specific LTV cap, the stock of deposits tends to be lower and so does consumption induced by financial wealth. The effect is somewhat reduced as lower rental and dividend payments (than in the uniform macroprudential regime (c) imply a shift of disposable income from on average higher-income households with lower marginal propensities to consume to lower-income households with higher marginal propensities to consume. The same shift but in the opposite direction is reducing aggregate consumption when FTB agents are restricted. Here, rental payments increase, compared to regime (c), which shifts income towards high-income households with lower MPCs.

### 6. An application to Irish policies

In order to demonstrate the macroprudential policy relevance of borrower-specific credit constraints, we run additional simulations in this section and compare the results to those from similar policies already implemented by the Central Bank of Ireland (Central Bank of Ireland, 2021a). The aim is to explore if additionally increasing LTV caps for BTL investors turns out to be more effective, as suggested in the previous analysis. Policy regime g) represents the present Central Bank of Ireland LTV caps (see Fig. 7). They are 90% for FTB, 80% for SSB and 70% for BTL agents. In policy regime h) we introduce more restrictive caps on BTL investors (to 60%) while loosening those on SSB agents by the same amount (to 90%). Consistent with previous insights, such requirements lead to slightly lower house price peaks than the original LTV caps applied by the Central Bank of Ireland.

The simulation results in Table 2 show that in regime h) household debt-to-income ratios respond more strongly, consumption is more stable, and total net wealth inequality falls slightly in this scenario compared to the previous regimes. Compared to regime f), in the Irish policy regime g), transaction patterns on the housing market and consumption volatility are only slightly affected. Fig. 8 shows sales to the respective agent classes over the house price cycle for policy regimes f) and h).

---

32 Fig. A5 in the Appendix supports this view, as BTL agents are the ones with the highest number of bids in the late phase of the house price upswing, after SSB agents. SSB agents can provide a high down payment and are therefore less likely to apply for large loan amounts because they have recently moved and sold a house.

33 A possible restriction of bank money creation through capital requirements is beyond the scope of this paper.
Fig. 7. House price cycles in the Irish policy regime and with additional LTV requirements for BTL investors.

Fig. 8. Transactions over the house price cycle, Irish and additional policy regimes.

Table 3

<table>
<thead>
<tr>
<th></th>
<th>1st Half Credit Cycle Downturn</th>
<th>2nd Half Credit Cycle Downturn</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BTL</td>
<td>FTB</td>
</tr>
<tr>
<td><strong>UK</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nominal</td>
<td>2,424.7</td>
<td>2,212.6</td>
</tr>
<tr>
<td>change to prev. cycle phase</td>
<td>13.7%</td>
<td>-24.4%</td>
</tr>
<tr>
<td><strong>Model</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nominal</td>
<td>4,053.8</td>
<td>1,280.4</td>
</tr>
<tr>
<td>change to prev. cycle phase</td>
<td>107.0%</td>
<td>-71.6%</td>
</tr>
<tr>
<td><strong>UK</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nominal</td>
<td>801.8</td>
<td>1,577.4</td>
</tr>
<tr>
<td>change to prev. cycle phase</td>
<td>-20.7%</td>
<td>29.2%</td>
</tr>
<tr>
<td><strong>Model</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nominal</td>
<td>0.9</td>
<td>1,470.5</td>
</tr>
<tr>
<td>change to prev. cycle phase</td>
<td>-99.8%</td>
<td>117.0%</td>
</tr>
</tbody>
</table>

The differences between regime (f) and regime (h) are more pronounced. The strongest effect is the reduction of BTL purchases in the first part of the upswing reducing the share of the housing stock held as investment property, from 22.4% to 21.0%, and also reducing DTI overall ratios. As with the reduction of BTL agents’ LTV caps from regimes c) to f), total net wealth inequality decreases due to less housing wealth concentrated in the hands of investors. Similarly, consumption volatility diminishes due to lower debt-levels and lower house price peaks. Statistical test results of Appendix C support the
overall impression that differences between the policy regimes are significant, but in some rare cases the hypothesis that the outcome stems from the same probability distribution cannot be rejected.

7. Contributions and limitations

In this section we reflect on the contributions of our analysis and critically discuss the limitations. First, in terms of macroeconomic policy, the main contribution of our model is to jointly analyse the effects of borrower-specific macroprudential measures with respect to household debt, wealth inequality and consumption volatility. Liu and Molise (2021) mention that ‘very few studies examine a borrower-specific counter-cyclical loan-to-value regulation in a model where borrowers of more than one type from distinct sectors of the credit market co-exist’. In contrast, the effectiveness of countercyclical macroprudential policies has been extensively researched in an aggregate financial accelerator setting with a representative agent (see among others Kannan et al. 2012). Compared to us, Liu and Molise (2021) distinguish between the household and the corporate sector and therefore do not focus on mortgage loans. One of the few other studies investigating the effectiveness of household borrower-specific macroprudential policies is that of Punzi and Rabitsch (2018). While they distinguish borrower types by their leverage, we implement the distinction based on the motivation for the house purchase, which is usually considered by central banks (Central Bank of Ireland, 2021a).

Second, from the perspective of the growing agent-based literature in economics, we contribute to the strand of studies that examines the effect of macroprudential policies using an agent-based model calibrated on key variables of an economy’s financial cycle (Cardaci, 2018; Catapano et al., 2021; Cokayne, 2019). This type of economic model is particularly appropriate for our research questions related to mortgage measures because, in addition to borrower heterogeneity, it allows us to study the effect of macroprudential policies on the household wealth distribution (Carpantier et al., 2018). Although the effect on the wealth distribution is not the main focus of macroprudential intervention by a central bank, it can be important for the acceptability of such measures (Central Bank of Ireland, 2021b). A limitation here is that we only study the overall wealth distribution. While the model does in principle allow for researching inequality within and between age-cohorts, and reductions in overall wealth inequality are likely to go hand in hand with distributional changes within or between certain age cohorts, such an analysis is beyond the scope of this paper.

Third, we contribute to the research on transaction patterns in the real estate market. Despite its limitations (noted below), the model-generated agent-specific target variables influenced by the transaction patterns share key features with observable data. We illustrate this by comparing new monthly mortgage borrowing in the UK, depicted in Fig. A6, to the model output over the four credit growth cycle phases (first half upswing, second half upswing, first half downturn, second half downturn). The first peak in new borrowing in the UK can be observed in 2007M7 while new borrowing is lowest in 2009M1, before peaking again in 2017M7. The model output is the average of ten Monte-Carlo runs. For comparison, new loans in the model are re-scaled to match the observable UK values of the respective agent group34, so that the sum of new loans (in monetary units) over the different credit cycle phases is the same in the model as in the UK data. Re-scaling does not affect the percentage change of new loans between the cycle phases.

Table 3 shows the results. BTL agents’ average monthly sum of new mortgage loans during the first half of the credit cycle downturn amount to £2,425 million per month in the UK and £4,054 million in the model (Table 3, column 3). In this cycle phase, average monthly borrowing has increased by 13.7% (from £2,133 million) in the UK and 107.0% (from £1,958 million) in the model compared to the second half of the upswing. Table 3 then lists, in columns 4 – 6, for both BTL and FTB agents, the average monthly new loans for the other credit growth cycle phases. Overall, the model is able to reproduce fairly well the relative changes over the cycle phases for each of the agent classes.

In the UK as in the model, new mortgages for BTL investors fall stronger than for FTB agents from the first to the second half of the downturn (-58.3% < -44.8% and -91.2% < -47.1%). From the second half of the downturn to the first half of the upswing, FTB agents increase their new mortgage borrowing, while BTL investors reduce it, in the UK as well as in the model. In the second half of the credit growth cycle phase, both FTB and BTL investors increase their new borrowing, while the increase for BTL agents is stronger. Again, this applies to both the UK and to the model. While in some cases model values are outside the observable range, the sign of percentage change from the model output matches the one from UK data for all the eight cycle phases for two types of agents.

We also note several limitations of our analysis, which could be addressed in future research. There is no public-sector stabilising mechanism in a house price bust—either institutionalized, such as the Dutch national mortgage guarantee, or incidental and discretionary—so that house prices fall to relatively low levels compared to the UK data. This has a negative impact on expected returns. Another limitation is a missing explicit savings motive of relatively young FTB agents for entering the ownership market (Aron et al., 2012). Both issues (the lack of an agent-specific savings motive and the lack of stabilization) may lead to an underestimation of FTB agents’ indebtedness in certain housing cycle phases, as most of the FTB agents enter the housing market at low prices instead of venturing into high-priced purchases.

34 Specifically, the model output is re-scaled as follows: \[
\sum_{t=1}^{4} \text{amnl}_{t,\text{BTL}} \times k_{\text{BTL}} = \sum_{t=1}^{4} \text{amnl}_{t,\text{BTL}}^{\text{model}} \times \sum_{k=1}^{4} (\text{amnl}_{t,\text{BTL}} \times \text{nHouseholds}^{\text{BTL}}(t,k) + k_{t}),
\] where \(\text{amnl}_{t,\text{BTL}}\) are average monthly new loans per credit cycle phase \(t=1,...,4\). \(\text{nHouseholds}\) stands for the number of households. The rescaling factor, \(k_{t}\), depends on the type of agent, i.e. \(k_{\text{BTL}} = 0.32\), \(k_{\text{FTB}} = 2.1\).
An important limitation also is that due to its partial nature, the model underestimates adverse effects on average household consumption, which might arise from negative feedback loops due to falling wages and rising unemployment (see Appendix B for a joint analysis of consumption volatility and average consumption, which has been absent from the main analysis). It is important to emphasize that our model is not a macroeconomic model but a housing market model including some macroeconomic variables, but no feedback effects.

Furthermore, interest rates are fixed in the model, whereas in the UK, the central bank’s lowering of interest rates post-crisis combined with flexible rate mortgages meant that more households were able to service their debts and fewer went bankrupt in the face of negative income shocks during the financial crisis (Aron and Muellbauer, 2016). While this model simplification increases tractability of the results, it clearly reduces model realism. Therefore, it is important to gauge what this does to our findings. In the model set up, the closest we can mimic effects of variable interest rates is to vary the level of the fixed interest rate and compare results (Table A4). Our main findings appear to be robust to this exercise. Importantly however, in this sensitivity analysis the interest rate does not change endogenously in response to the house price or the business cycle. Nevertheless, the model is calibrated to reflect low levels of household bankruptcies as was the case in the UK after the 2007 crisis (see Section 3.1.2). Indeed, compared with the US, the low delinquency rate in the UK may be largely attributed to the fact that the Bank of England not only cut interest rates decisively, but also that mortgage rates quickly adjusted precisely because many mortgages were variable-rate loans (Coles and Hardt, 2000). So while probably the largest bias resulting from having no variable rates in the model is in delinquencies, it is reassuring to see that this variable tracks UK reality quite well.

Another simplification in the model is that we neglect transaction costs incurred as a result of a house purchase. Theoretically, there may be differences between BTL investors and FTB agents in this respect, just as is the case for variable interest rates. To the best of our knowledge, however, there is so far no analysis or evidence to confirm that depending on the house purchase motive (BTL or FTB status), there are significant differences in the variable-rate portion of the total mortgage loan volume or in real estate transfer taxes, in brokerage fees and other transactions costs. This means that while these two features are undoubtedly simplifications, it is not clear that and how they affect the models’ results with respect to the differences between household types.

It is worthy of note that the consumption function used in the model does not include an explicit collateral channel, where households withdraw equity in a house price upswing (Aladangady, 2017; Cloyne et al., 2019; Mian et al., 2013). The housing wealth coefficient in the consumption function might be viewed as a reduced-form representation of the collateral channel. But the model does not allow re-mortgaging for the same house. It hence operates under the assumption that this and other forms of withdrawals are not systematically more common among first-time buyers than among buy-to-let agents. Modelling this explicitly would significantly complicate the model. Also, we have no borrower-specific data on equity withdrawals over time. Some central bank studies provide insightful illustrations of how housing equity withdrawals turned into injections after the 2007 housing bubble burst. There is however no data showing whether the withdrawal were mainly made by fist-time buyers or a buy-to-let agents, and whether the pattern of the past can be transferred to the new regulatory regime more than ten years after the financial crisis (Lydon and O’Leary, 2013; Reinold, 2011). In this sense there is very little external validation to go on when including this feature in the model.

While its absence is certainly a limitation, it should also be noted that in the model, households can sell their property without buying a new one, thereby withdrawing equity in form of deposits. This mechanism has been found to be most important channel of withdrawing equity in Australia in the mid-2000s (Schwartz et al., 2010) and in Ireland between 2005 and 2009 (Lydon and O’Leary, 2013). In the model, this kind of equity withdrawal leads to higher deposits in the house price upswing and hence to higher consumption out of financial wealth, which can be visually inspected in Fig. 3. This is still quite different from an explicit equity-withdrawal collateral channel. It might be surmised that including this would lead to top-up loans or over-mortgaging, which could increase the volatility of debt-to-income ratios, shift consumption between households, alter the distribution of deposits and so ultimately change the ability of households to be active in the housing market.

Finally, the time series properties of the house price cycle in the model deserve a critical look. Fig. A2 in the Appendix shows that the fit of the model to the data in terms of the cross-correlation between house prices and house transactions is quite good. But the phase duration of the house price cycle in the model is quite different from the observable data in the UK (or elsewhere). The duration of upswing and downswing in the traditional banking regime is almost identical, while the liberalization and macroprudential regimes show a house price upswing which lasts shorter than the downturn; in reality, house price upswings last longer than downturns. One reason is the neglect of macroeconomic feedback effects which hasten the decline—such as bankruptcies in the construction sector or rising risk premia on loans during downturns15. Whatever the reasons, simplifying the model by omitting them is unlikely to bias model results, because there is no reason to expect the feedback effects influence the policy regimes differently. The model replicates the critical mechanism generating a turnaround in house prices that can also be observed in the UK. This mechanism is that FTBs re-enter the housing market on the buyer side earlier in the credit cycle. Table 3 shows this to be the case both in the model and the UK data.

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15 In the model the maximum LTVs of the commercial bank work as a form of risk-premium, where perceived risk increases when prices are falling (in all but the traditional banking regime, see Fig. 4).
Alternatively, one can evaluate reasons for the (too short) upswing phase relative to the (too long) downturn phase in model-generated data. A natural candidate to answer is the simplifying assumption of a constant housing stock in the model. Here, using a growth model would be more realistic, but at the same time significantly more complex. Based on empirical evidence, one would expect new construction to move pro-cyclically with the house price cycle. Compared to our model with a constant housing stock, this could lead to real estate prices rising less rapidly than in the current model without construction dynamics. However, this simplification of our model can only be critical to the extent that BTL investors are more responsible than FTBs for new construction and thus expansion of the housing stock.

Evaluating quantitatively to what extent the simplifications of the model bias the key results that the BTL-focused measure proves most efficient, requires extensive model expansion aiming at the lack of a time-varying house stock. For a qualitative assessment however, note that BTL-focused measures are most effective because their expectations formations frequently exclude price drops leading to longer continuation of the house price upswing (local trend chasing). Another reason is the positioning of BTL investors in the distribution of (financial) wealth (Fig. A4), which enables a significant proportion of them to make additional purchases despite considerable down payments when prices are high. Neither of these two factors are much affected by the simplification of leaving out construction dynamics and macro feedbacks.

8. Conclusions

Recent literature in the wake of the financial crisis has identified excessive household debt, particularly in the form of mortgages, as a key cause of macroeconomic instability. Macroprudential policies such as caps on the Loan-to-Value ratios have been introduced in response. Recently, to increase the efficiency of such policies, central banks have applied borrower-specific credit requirements. The effect of borrower-specific macroprudential requirements remains largely unexplored. The purpose of this paper is to help fill this gap.

We provide an in-depth analysis of the effect of borrower-specific LTV caps on debt-to-income ratios, wealth inequality and consumption. The heterogeneity of borrower types and the importance of households’ individual asset and income positions for their credit eligibility led us to employing an agent-based model. We built on the model by Baptista et al. (2016) developed to reflect the types of households active on the UK housing market. We add a wealth term and income-dependent propensities to consume to the original consumption function. This modification makes consumption move pro-cyclically with house prices, a stylized fact observed in many economies. We study the consequences under macroprudential policies.

In model simulations calibrated on UK data, we reproduce the fact that commercial banks in financial liberalisation regimes tend to employ procyclical maximum LTVs as part of their credit assessment. From a stability perspective, this lending behaviour should be opposed by the central bank. In this context, it is worth examining the consequences of macroprudential policies on household debt, wealth inequality and consumption volatility.

Our simulations show that the most effective approach for central banks is to limit Loan-to-Value (LTV) ratios borrower-specifically, in particular those of buy-to-let (BTL) investors. In specific, in our model a reduction of the LTV cap of BTL agents by 20 percentage points leads to a significant reduction in aggregate debt-to-income ratios (-19 percentage points), in total net wealth inequality (-2 percentage points) and in consumption volatility (-23%). Restricting fist-time-buyer (FTB) agents’ access to credit has a relatively low overall impact on household indebtedness and consumption volatility, while even increasing wealth inequality (+1 percentage point). Restricting second and subsequent buyer (SSB) agents shows minor effects on the target variables. SSB agents are least reliant on mortgage credit, due to higher financial wealth (deposits) from previously sold homes.

Finally, we discuss several limitations of our model analysis. It is left for future research to extend the economic modelling accordingly. While this will help to improve the empirical fit of the model and to approach the quantitative optimum of borrower-specific mortgage measures, we are confident that the core message of our analysis will remain the same. This is the importance for macroprudential policy to distinguish between different types of borrowers based upon their motivation for house purchases. Especially, our results suggest that prioritising macroprudential requirements for buy-to-let investors, turns out to be most effective in reducing indebtedness, wealth inequality and consumption volatility for all households.

Data availability

The link to the model code is provided in the article.

APPENDIX

Appendix A. Model output and the Bank of England core indicators

Table A1 compares the housing market core indicators by the Bank of England with the output of the baseline model. The indicators of the model are averages over the 50 Monte-Carlo runs. Green cells mark indicators that lie in between the UK minimum and maximum values. The numbers of housing transactions and mortgage approvals in the model are adjusted for the UK population and housing stock.
Appendix B. Effects on consumption volatility and average consumption

Lowering debt-fuelled consumption volatility can be part of a central bank mandate. Whenever a policy measure is taken, the average level of consumption is not supposed to be affected adversely. In this section we evaluate the policy regimes from the main text by comparing their effects on both average consumption and consumption volatility. The resulting ratio of both for the different policy regimes tells us how ‘costly’ the reduction in consumption volatility is in terms of reducing the average level of consumption.

We motivate this ratio by assuming that a reduction in average consumption in monetary units is utility improving for households as long as it goes in hand with a bigger reduction in consumption volatility in monetary units—reflecting a high degree of risk-aversion. We define the utility of a representative household as $U = a \ast \hat{C} - b \ast (\text{max}(C) - \text{min}(C))$, where the ratio $a/b$ then provides insights into the degree of households’ risk-aversion.

From Table 1, the consumption amplitude is most sensitive to changes in BTL agents’ access to credit. It drops from 400 to 310 monetary units per household and month, as opposed to only 380 (SSB reduction) and 371 (FTB reduction). However, average consumption also drops lowest with restricting BTL agents in policy regime f) (from 1924 to 1888 monetary units). From regime c) to regime f), reflecting a restriction on BTL agents, the $a/b$ ratio is $-36/-90 = 0.4$. For reducing FTB agents’ LTV cap, this ratio is $-13/-29 = 0.45$ and for SSB agents $-6/-20 = 0.3$. The larger the ratio, the more expensive is the reduction in the consumption amplitude with regards to the reduction in the average consumption level. Thus, in contrast to the primary focus on consumption volatility in the main text, for the given example of a simple utility function, results imply that the strong effects of restrictions on BTL investors only appear the most effective under the assumption of a certain degree of households’ risk aversion. This assumption, however, does not seem far from reality.

Appendix C. Statistical tests

In this section, we test if the numerical differences between policy regimes reported in Table 1 are statistically significant. In detail, we test whether the numerical differences are large enough that the values for each target variable generated by the different policy regimes can be assigned to different probability distributions. We use a two-sided Kolmogorov-Smirnov test, as the distributions are not normally distributed, and we pay special attention to the maximum values. However, if we were to test the aggregated target variable distributions (i.e. aggregating over all 50 Monte-Carlo (MC) paths of each policy regime) all policy regime are reported to be significantly different from each other, merely due to the high number

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Table A1

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Average 1987-2006</th>
<th>Minimum since 1987</th>
<th>Maximum since 1987</th>
<th>Previous value (oya) 2018</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household mortgage debt to income</td>
<td>68.7%</td>
<td>49.3%</td>
<td>109.6%</td>
<td>98.5%</td>
<td>96%</td>
</tr>
<tr>
<td>Owner-occupier mortgage LTI ratio (mean above the median)</td>
<td>3.8</td>
<td>3.6</td>
<td>4.2</td>
<td>4.2</td>
<td>3.13</td>
</tr>
<tr>
<td>Owner-occupier mortgage LTV ratio (mean above the median)</td>
<td>90.6%</td>
<td>81.6%</td>
<td>90.8%</td>
<td>87.5%</td>
<td>79.9%</td>
</tr>
<tr>
<td>Buy-to-let mortgage LTV ratio (mean)</td>
<td>n.a.</td>
<td>56.6%</td>
<td>75.4%</td>
<td>61.0%</td>
<td>72.8%</td>
</tr>
<tr>
<td>Housing Transactions</td>
<td>129,508</td>
<td>51,660</td>
<td>221,978</td>
<td>101,100</td>
<td>118,421</td>
</tr>
<tr>
<td>Approvals of loans secured on dwellings</td>
<td>97,905</td>
<td>26,284</td>
<td>132,709</td>
<td>65,742</td>
<td>97,569</td>
</tr>
<tr>
<td>Advances to homemovers</td>
<td>48,985</td>
<td>14,300</td>
<td>93,500</td>
<td>32,100</td>
<td>37,497</td>
</tr>
<tr>
<td>Advances to first time buyers</td>
<td>39,179</td>
<td>8,500</td>
<td>55,800</td>
<td>30,800</td>
<td>24,514</td>
</tr>
<tr>
<td>Advances to buy-to-let purchasers</td>
<td>10,128</td>
<td>3,600</td>
<td>29,100</td>
<td>6,400</td>
<td>35,559</td>
</tr>
<tr>
<td>House price to household disposable income ratio</td>
<td>2.9</td>
<td>2.1</td>
<td>4.6</td>
<td>4.5</td>
<td>3.3</td>
</tr>
<tr>
<td>Rental yield</td>
<td>5.8%</td>
<td>4.8%</td>
<td>7.6%</td>
<td>4.8%</td>
<td>12%</td>
</tr>
</tbody>
</table>

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36 If the focus was more on differences in means, the Wilcoxon signed-rank test would have been an alternative.
of observations involved. We, therefore, conduct a pairwise comparison of individual MC paths, delivering fifty individual distributions for each target variable and policy regime.

The specific testing procedure is set up as follows: first, we test the individual MC paths of one policy regime against each other and record the share of tests which do not reject the null hypothesis of the same probability distribution. In Table A2, the diagonals (in bold) document these benchmark values for each policy regime and target variable. For instance, the top left cell reads that 43% of the intra-policy-regime tests for the debt-to-income ratios of the traditional banking regime may come from the same probability distribution. This distribution can be regarded as true as its values stem from the same policy regime (i.e. the same model parametrisation).

Table A2 shows the individual tests resulting in the 43% of non-significant cases, including also the corresponding critical and p-values. In a second step, we compare these benchmark values (diagonal values) to those of testing the MC paths of one policy regime against the MC paths of another policy regime (pairwise comparison).

For the debt-to-income ratio, the test shows substantial differences between the diagonal and the off-diagonal values, apart from the comparisons between policy regimes d) and e). Here, the 46% and 43% benchmark values are close to the 30% comparative value. This could be expected, as the corresponding DTI ratios in Table 1 are close to each other. The aggregated distributions are illustrated in Fig. A10. Test results for total net wealth inequality also show meaningful differences between policy regimes, with the exceptions of the comparison between regimes b) and c), c) and e) as well as those of the Irish banking version. Fig. A11 shows the aggregated distributions.

Testing the consumption path distributions yields quite similar results to those of wealth inequality, while the benchmark values tend to be lower. Differences seem to be significant between c) and f) as well as f) and h), supporting the consumption-volatility reducing effect of BTL restrictions. Non-significant differences arise between d) and e), f) and g), and g) and h). The aggregated distributions are shown in Fig. A12.

Overall, the test results support the hypotheses that borrower-specific macroprudential policy regimes matter. For the Irish case, the differences between the policy regimes, with regards to wealth inequality and consumption, are less robust.

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37 The corresponding values for all other tests are available upon request.

38 This is partly because consumption is subject to stronger memory effects than total net wealth inequality. Consumption is in large parts induced by employment income, which is not stable over individual M.C. runs. The mechanism of birth and the allotment of income percentiles is stochastic. As households live for around 50 years, aggregate employment income can be subject to small long-term oscillations, different for each M.C. run. The lower the house price peaks, the lower the influence of house prices and financial wealth on overall consumption and, therefore the larger the influence of these oscillations, explaining the lower benchmark values of model regime f), g) and h).
Table A3: Detailed breakdown of Kolmogorov-Smirnov test results the Debt-to-income ratio in Monte-Carlo runs under the traditional banking regime. If H0 is rejected, the field is coloured green; H0 is rejected with $\alpha=1\%$ if critical value $K_\alpha = \sqrt{\frac{\ln r}{n+m}}$ with $K_\alpha = \sqrt{\frac{\ln 0.01}{m+n}} = 1.628$ and $n=m=1000$. Overall, there are 1225 tests between different Monte-Carlo paths. From the 1225 tests, 522 tests (or 43% of the cases) do not reject the null hypothesis and therefore cannot confirm that the results are significantly different.

<table>
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**Appendix D. Additional changes to the original model**

This Appendix presents additional model modifications compared to Baptista et al. (2016), not discussed in the main text. Some are based on the continuous improvement of the original model by Adrián Carro from the Bank of Spain. Most changes aim at a greater correspondence with real-world data. The behaviour of BTL agents has been redefined in the following ways. When BTL agents offer their properties on the ownership market, tenants keep their contract and are only evicted before their contract expires if the house is bought by an owner-occupier. In addition, BTL agents now reconsider each month whether they still want to sell the property they are currently offering on the ownership market. In the original model, BTL agents kept their property on the market even if they considered it a better investment if they kept it. Another change is the removal of a special rule for BTL households who do not yet own a property—other than the one they live in—to automatically bid for properties, regardless of their perceived investment yield.
Table A4
Sensitivity analyses results. Parameter settings in benchmark model, interest rates = 6.5%, \( \gamma = 0.25 \), and \( \zeta = 2 \); interest rates low = 4.5%; results based on 50 Monte-Carlo simulations for each sensitivity regime.

<table>
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<tr>
<th>Sensitivity Regime</th>
<th>Policy Regime</th>
<th>Changes compared to 90% FTB, 90% SSB, 90% BTL</th>
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<td>LTV cap FTB, SSB, and BTL</td>
<td>Average DTI (ppts)</td>
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<td>low interest rates, ( \text{int} = 4.5% )</td>
<td>70%, 90%, 90%</td>
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<td>90%, 70%, 90%</td>
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<td>90%, 90%, 70%</td>
<td>-22.1</td>
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<td>high interest rates, ( \text{int} = 8.5% )</td>
<td>70%, 90%, 90%</td>
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<td>90%, 70%, 90%</td>
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<td>low housing wealth term, ( \gamma = 10% )</td>
<td>70%, 90%, 90%</td>
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<td></td>
<td>90%, 90%, 70%</td>
<td>-19.1</td>
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<td>high housing wealth term, ( \gamma = 40% )</td>
<td>70%, 90%, 90%</td>
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<td>90%, 70%, 90%</td>
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<td>90%, 90%, 70%</td>
<td>-19.9</td>
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<td>low precautionary saving, ( \zeta = 1 )</td>
<td>70%, 90%, 90%</td>
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<td>high precautionary saving, ( \zeta = 3 )</td>
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<td>90%, 90%, 70%</td>
<td>-19.2</td>
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Additional changes include setting the price mark-up for offered properties. Previously, this was 4% above the expected selling price for a house of the same quality, adjusted for the expected time the property would remain unsold and for the difference between current interest rates and long-term interest rates. Now the mark-up is a function of an underlying probability distribution calibrated using observed mark-ups on the online housing market platform Zoopla. Another change is that non-BTL owners who have inherited a property now rent it out, while they wait for the property to sell. Previously, these houses were empty. In addition, in the current model, households in social housing pay a monthly rent based on the 2013-14 average local authority rents in the UK. Finally, the long burn-in period was significantly shortened by setting the target number of households (according to the age and income demographics of the UK) in the first phase, rather than going through a slower build-up process.

Appendix E. Sensitivity analysis

To assess the sensitivity of our findings in chapter 5, we run a series of model simulations with different parameter settings and compare the outcomes to those in Table 1. To this end, Table A4 shows the effects of the policy regimes that restricted each agent class individually compared to the regime where the LTV cap was 90% for all agent classes.

Three different parameters were varied: interest rates, the strength of the housing wealth effect in relation to the financial wealth effect \( \gamma \) from Eq. (1), and the precautionary saving parameter \( \zeta \). There are six sensitivity regimes—by decreasing and increasing each of the three parameters—which are compared to the policy runs reported in chapter 5.

The results show that, qualitatively, the outcomes of the policy experiments in chapter 5 are insensitive to the parameter changes introduced here. Restricting BTL agents leads to the strongest reduction in average debt-to-income ratios, in wealth inequality and in consumption amplitude. Also, the LTV restriction of FTB agents increases total net wealth inequality in all sensitivity regimes by a similar rate.

Regarding the effects of different parameterisations on house price cycles, Fig. A1 shows that low interest rates lead to higher house price peaks and high interest rates reduce house price peaks. The other variations do not have much impact on the house price cycle.

Appendix F. Additional Figures and Tables

Table A5, Figs. A2–A12
Fig. A1. Density curves and median values (dotted lines) of monthly house price indexes for the different sensitivity regimes. Based on 50 Monte-Carlo runs with 1000 periods based on model (c) in chapter 5, each.

Table A5
Calibration Values for Model Parameters Presented in the Paper. Complete list of parameters, variables and equations can be found in the online Appendix.

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<td>$\alpha_i$</td>
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<td>$\beta_i$</td>
<td>0.0075 for the lowest income quartile, 0.006 for the second, 0.005 for the third, and 0.004 for the highest excluding the top 10% set to 0.002 and the top 1% to 0.0002</td>
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Fig. A2. Detrended UK real house prices (1977–2018) and cross-correlation of house prices and number of housing transactions, where transactions are held constant. House prices seem to peak about seven quarters after peaks in in the number of housing transactions, for both the model and the UK. Source: UK monthly housing transactions 1977–2018 from Bank of England; UK quarterly constant house prices 1977–2018, OECD (2022) OECD Economic Outlook. Housing transactions are transformed to quarterly data, time series were detrended using (Hamilton, 2018).
Fig. A3. Number of agents over the house price cycle.

Fig. A4. Home ownership of different agent-classes as a function of the wealth distribution-average value over the house price cycle.
Fig. A5. Monthly offers and bids over the house price cycle. The upswing is defined as the time period between lowest and highest house price. For visibility, the durations of the upswing and downturn are halved.

Fig. A7. House price indices of fifty Monte-Carlo runs for 300 periods starting with the first trough after the 1500 periods burn-in phase (benchmark model).
Fig. A8. Scatterplots of house prices and debt-to-income ratios (in %) for different credit regimes (50 Monte-Carlo runs).
Fig. A9. Scatterplots of house prices and top 10% total net wealth shares for different credit regimes (50 Monte-Carlo runs).
Fig. A10. Histograms of debt-to-income ratios (in %) in different policy regimes.
Fig. A11. Histograms of top 10% total net wealth shares in different policy regimes.
Fig. A12. Histograms of consumption in monetary units per household in different policy regimes.