THE EFFECT OF BORROWER-SPECIFIC LOAN-TO-VALUE POLICIES ON HOUSEHOLD DEBT, WEALTH INEQUALITY AND CONSUMPTION VOLATILITY: AN AGENT-BASED ANALYSIS

Ruben Tarne[1], Dirk Bezemer[2], Thomas Theobald[3]

ABSTRACT

This paper analyses the effects of borrower-specific credit constraints on macroeconomic outcomes in an agent-based housing market model, calibrated using U.K. 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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Abstract

This paper analyses the effects of borrower-specific credit constraints on macroeconomic outcomes in an agent-based housing market model, calibrated using U.K. 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.

1 Introduction

Many advanced economies experienced a massive rise in household mortgage debt in recent decades and especially before the Great Financial Crisis that began in 2007. Household debt has been found to increase the probability of financial crises and to enhance the severity of recessions (Bezemer & Zhang, 2019; IMF, 2012; Jappelli, Pagano, & di Maggio, 2008; Jordá, Schularick, & Taylor, 2016; Sutherland, Hoeller, Merola, & Ziemann, 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 & Moessner, 2018).

As these measures directly intervene in the wealth accumulation of households, they are very likely to affect other economic outcomes, including economic growth (Richter, Schularick, & Shim, 2019) and the wealth distribution (Colciago, Samarina, & de Haan, 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 economic 'side effects', including weak consumption and economic growth (Fontan, Claveau, & Dietsch, 2016; Furceri, Loungani, & Zdzienicka, 2018; Hansen, Lin, & Mano, 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)[1]. However, the effects of such rules on macroeconomic outcomes (intended and unintended) are largely unexplored as data is limited (Kelly, O'Malley, & O'Toole, 2015). Furthermore, tools that can investigate such questions need to model both micro- and macroeconomic dynamics and require therefore a high degree of heterogeneity which increases their complexity considerably. This heterogeneity should extend to the specific borrower types as well as their individual asset and income positions as these affect credit eligibility.

To address these challenges, we analyse the effects of borrower-specific LTV caps on household debt, wealth inequality and consumption volatility[2] in an agent-based housing market model. We seek to find an efficient macroprudential policy intervention (i.e. achieving a substantial reduction of household debt and consumption volatility) without negative 'side-effects' (i.e. avoiding a significant increase of wealth inequality). For this objective, it is essential to understand how changes in the three 'target variables' (household debt, consumption volatility, and wealth inequality) result from the interactions between individual households (reflecting different types of borrowers) and a commercial bank. This is at the heart of the so-called the 'housing cycle', as house prices and, correspondingly, credit conditions change with time. The U.K. experienced pronounced housing cycles in recent decades, making it a suitable country for this analysis. Therefore, our model is a modification of Baptista et al. (2016), calibrated to the U.K. using micro data sources, including the Wealth and Asset Survey and housing market data from Zoopla. The model matches a number of key housing market indicators. We improve the model fit by enriching the households' consumption function with wealth-dependent and income-dependent marginal propensities to consume. These changes generate consumption cycles moving with the housing cycles, which allows us to study

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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.

consumption volatility. The model also reflects institutional specificities, notably the different types of agents active in the U.K. 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, as these distinguish between FTB, SSB and BTL borrowers. Such credit restrictions give rise to changes in the transaction patterns of the housing market which explain the dynamics of the aforementioned target variables.

We find that borrower-specific LTV caps differ strongly in their efficiency in reducing debt, wealth inequality and consumption volatility. 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 even increases wealth inequality. The significant effect of restrictions to BTL investors' credit access can be reconciled with the role they played in the run-up to the Great Financial Crisis as their search for yield resulted in a different motivation for house purchases than in the case of owner-occupied homes (Haughwout, Lee, Tracy, & van der Klaauw, 2012). Such a restriction also reduces wealth inequality, as expected by Carpantier et al. (2018), even though house prices are generally lower when BTL investors are restricted, which in itself could suggest higher wealth inequality (Domanski, Scatinga, & Zabai, 2016). 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 selected literature analysing the effect 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 and explain how these results arise from granular changes in the transaction patterns of the housing market. Section 6, guided by the results from section 5, proposes a modification of the borrower-specific LTV rules applied by the Irish Central Bank. Its current policy forms a prominent example of adopting borrower-specific macroprudential measures. In section 7, 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 on household debt, consumption volatility, and wealth inequality. Our goal is also to deepen the understanding of the potential 'side-effects' of macroprudential policies (Alam et al., 2019; Cardaci, 2018; Richter et al., 2019) and of agent-based models simulating the emergence of financial instability.

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 & 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, Grydaki, & Zhang, 2016) and restricting household consumption (Mian, Rao, & Sufi, 2013). These effects can be long-lasting (Drehmann, Juselius, & Korinek, 2018).

Several studies estimate the effect of macroprudential policies on credit growth, which should be negative if targets are met[3]. Most of the empirical studies add dummy variables to their model specifications to control for the effect of macroprudential policies. For instance, Cerutti, Claessens and Laeven (2017) find for 119 countries from 2000-2013 that introducing LTV caps is associated with reductions of 1.5 percentage points in household credit growth and 1.2 percentage points in real house price growth. We are especially interested in the reaction of macroeconomic target variables to specific changes in Loan-to-Value caps. Due to data limitations, only few studies deliver such estimates. For instance, 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 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 household credit growth after one year. LTV cap reductions between 10 and 25 percentage points lead to credit reductions of 0.36 percentage points. These magnitudes are comparable to the credit response of 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.

More recently, an increasing number of studies address the consequences of macroprudential policy on economic outcomes, although these so-called 'side-effects' are not the priority of macroprudential policy (Alam et al., 2019; Richter et al., 2019). For instance, increases in wealth inequality can affect aggregate demand through wealth effects (Arrondel, Lamarche, & Savignac, 2019; Carroll, Slacalek, & Tokuoka, 2014). Here, the first effect, the distributional effect, may initially be mentioned as a side effect from a central bank perspective; however, the effect on aggregate demand and thus economic growth falls within the core tasks of all central banks. The relationship between macroprudential policy and wealth inequality needs further research (Colciago et al., 2019). One mechanism through which macroprudential policy might affect wealth inequality is via the effect on house prices, given the fact that corporate shares and real estate ownership do not show the same distribution across households (Domanski et al., 2016; Kuhn, Schularick, & Steins, 2020). While equities are concentrated at the top, real estate is more equally distributed. In the run-up to the financial crisis, house prices rose faster than equity prices, leading to a decline in wealth inequality in the U.S. (Kuhn et al., 2020), France (Garbinti, Goupille-Lebret, & Piketty, 2017) and Spain (Martínez-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, Carpantier, Olivera, and Van Kerm (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

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[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).

results (the effect of LTVs is persistent when average house price changes are accounted for)[4]. Moreover, the study does not account for the effects of borrower-specific LTV rules, which is at the heart of this paper.

A direct effect of macroprudential policy can be a dampening of economic growth, due to lower household expenditures, in particular residential investment. Sánchez and Röhn (2016) find for a panel of mostly OECD countries that macroprudential policies go together with lower average economic growth but also less extreme positive growth shocks, i.e. lower volatility. Boar et al. (2017), however, find a positive relationship between activated macroprudential policy measures and both stability and the level of GDP growth in 64 countries. The positive effect on the level of the average growth rate may be explained by the fact that higher stability represents not only a refraining of positive growth shocks but also an avoidance of negative ones. The effect of macroprudential policies on growth is therefore not clear. As our model does not encompass a wider macroeconomy, in this context we focus mainly on household consumption volatility. In Appendix B we take average consumption into account as well.

Macroprudential policies aim at lowering house prices which can lead to lower consumption due to the wealth effect (Attanasio, Leicester, & Wakefield, 2011; Campbell & Cocco, 2007). Moreover, the aforementioned 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; Dynan, Skinner, & Zeldes, 2004). As both the wealth effect and 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 restricting LTV caps by one percentage point reduces private consumption growth by 0.1 percentage points after a year, which also limits economic growth. Similar to these findings, 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. Laliotis 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% reduces house price growth on average by 9% and credit growth 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 12%. 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 U.K. 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

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[4] Also note, that for the Netherlands and Portugal, the countries with the largest LTVs in their sample, the effect of LTVs on the Gini coefficient are not significant.

LTI and LTV restrictions reduce house price volatility significantly. Reducing LTIs 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.

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, both originating 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 bank providing mortgage credit subject to central bank policies[6]. 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, and buy-to-let investors. This means that agents can principally go through three different regimes. Regime change is possible in each period. Agents who are not renting or owning a house form a residual in the model called social housing. 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. Our model is a partial model, hence it does not encompass the broader macroeconomy with firms or the government sector, apart from the central bank setting macroprudential requirements. The larger part of disposable income (wages) is given exogenously; only income from renting is endogenous in the model. Wage income is determined exogenously, and there is no firm sector. This design implies that consumption decisions do not feed back to wages and effective demand.

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.

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[5] In Denmark, investors are often public companies and, thus, not subject to these measures.

[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-%20WP%20-%20Tarne%20Bezemer%20Theobald.pdf

3.1 Household Decisions

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[7] for sale. When households enter the model space 8%[8] of them become BTL agents — given they are in the upper half of the income distribution — and are able to buy and sell investment property.

3.1.1 Household Consumption

Households' desired consumption consists of an essential part (fixed to U.K. monthly income support which is always fully consumed) and a non-essential part. It is calculated as[9]:

$$c_{i,t}^{desired} = c_0 + \alpha_i y_{i,t}^{m,disp} + \beta_i \left(b_{i,t} + \gamma \left(w_{i,t}^h - q_{i,t} \right) \right), \tag{1}$$

where c_0 is essential consumption, $y_{i,t}^{m,disp}$ monthly disposable income, $b_{i,t}$ deposits, $w_{i,t}^h$ housing wealth and $q_{i,t}$ mortgage debt, which is the only type of debt in the model. Parameters α_i and β_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[10]. β_i is set to match the U.K.'s top 10% wealth share of the years 2008-2018 (45%) and the corresponding ratio of households' financial wealth to mortgage debt[11]. To account for the empirical fact that financial wealth has a larger effect on household consumption than housing wealth, $\gamma < 1$ dampens the impact of net housing wealth on the household's desired consumption (Arrondel et al., 2019; Chauvin & Muellbauer, 2018; Christelis, Georgarakos, & Jappelli, 2015; Jawadi, Soparnot, & Sousa, 2017). For model consistency, $c_{i,t}^{desired}$ is bounded at 0. Further, desired consumption can be constrained by wealth effects, so that realised consumption is:

$$c_{i,t} = \begin{cases} \text{if } b_{i,t} - \left(c_{i,t}^{\text{desired}} - y_{i,t}^{m,\text{disp}} \right) < \zeta y_{i,t}^{m,\text{disp}}, & \beta_i = 0 \\ \qquad\qquad \text{if } c_{i,t}^{\text{desired}} < c_o, & \beta_i = \alpha_i = 0 \\ \qquad\qquad\qquad\qquad \text{else }, & c_{i,t} = c_{i,t}^{\text{desired}} \end{cases}, \tag{2}$$

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

[8] These 8% lead to effectively 6% of households holding investment property, which is the share of households in the Wealth and Asset Survey of 2011 that earn rental income.

[9] In the model version by Baptista et al. (2016) the consumption function serves to keep the financial wealth distribution in a certain relationship with household income. This results in unrealistically high fluctuations of aggregate consumption, as households selling a house usually consume large parts of the revenue in the following period. These transactions are concentrated to the middle of a housing market upswing. Such consumption behaviour has adverse impacts on households' leverage as this would require them to take on new loans later when they decide to buy a new house, which happens rather frequently according to UK data. To address these issues, we decide in favour of a more elaborated consumption function.

[10] Specifically, the propensity α_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, Skinner, & Zeldes (2004), where the first quintile has a marginal propensity to consume (MPC) 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.

[11] 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% wealth share in the UK is around 45% and financial wealth to mortgage debt relation is about 1.6 (Wealth and Asset Survey 2020). The UK constant house price index moves between 98% -121% in 2011-prices (OECD Economic Outlook). 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, β_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).

where ζ reflects liquidity preference and is set to twice the monthly disposable income. In the case that desired consumption turns negative, which can happen when debt levels are very high, 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 Figure 1). Whenever households are in social housing, they either place a bid on the ownership market (arrow 1 in Figure 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:

$$Prob(\text{placing a bid})_{i,t,k}^{SH \rightarrow OO} = \frac{1}{1 + \exp\{-\beta_3[12\overline{r_{Q,t}} - (12m_{i,t,k}^{SH \rightarrow OO} - p_{i,t,k}^{SH \rightarrow OO} \cdot g_t)]\}}, \tag{3}$$

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

$$g_t = \alpha_4 \left[\left(\frac{HPI_{t-1} + HPI_{t-2} + HPI_{t-3}}{HPI_{t-25} + HPI_{t-26} + HPI_{t-27}} \right)^{1/24} - 1 \right] - \gamma_4, \tag{4}$$

g_t is calculated as the average quarterly house price growth rate over the last two years, dampened by households' expectations α_4 and γ_4[12]. The households' bid price $p_{i,t,k}^{SH \rightarrow OO}$ for house k of a certain quality increases with expected rising house prices. It is determined by yearly wages $12y_i^{m,emp}$ adjusted by α_5[13], and stochastic characteristics ε_5:

$$p_{i,t,k}^{SH \rightarrow OO} = \min \left(q_{i,t}^{SH \rightarrow OO} + b_{i,t}, \frac{\alpha_5 12y_{i,t}^{m,emp} \exp(\varepsilon_5)}{1 - \beta_5 g_t} \right), \tag{5}$$

The bid price might be limited by the maximum mortgage $q_{i,t}^{SH \rightarrow OO}$ the bank is willing to give. 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.

An owner-occupier's decision to buy a home differs from a BTL agent's decision to buy an investment property (arrow 3 or 4 in Figure 1). The BTL agent's probability to place a bid on the market is given by:

$$Prob(\text{placing a bid})_{i,t,k}^{\substack{BTL \rightarrow BTL \\ OO}} = \begin{cases} 0, & \text{if } \sum m_{i,t,k} > 0.5 y_{i,t}^{m,net} \\ 1 - \left(1 - \frac{1}{1 + e^{(-\beta_6 \Omega_{i,t,k})}} \right)^{\frac{1}{12}}, & \text{if else} \end{cases}, \tag{6}$$

Equation (6) states that a BTL investor does not place a bid, if monthly mortgage payments are higher than 50% of monthly post-tax income. There are two types of BTL investors. Trend-following investors basically 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 $\Omega_{i,t}$[14]. The BTL agent's bid price is only limited by the household's deposits and maximum mortgage the bank is willing to grant:

$$p_{i,t,k}^{OO \to BTL} = q_{i,t}^{OO \to BTL} + b_{i,t} \ . \tag{7}$$

3.1.3 Placing Offers on the Ownership Market

In line with the 'English Housing 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 Figure 1). Their offer price depends on the 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 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:

$$Prob(\text{placing an offer})_{i,t,k}^{BTL \to BTL} = \begin{cases} 0, & \text{if } i \text{ has only 2 houses} \\ 1 - \left(\frac{1}{1+e^{\left(-\beta_7 \Psi_{i,t,k}\right)}} \right)^{\frac{1}{12}}, & \text{if else} \end{cases}, \tag{8}$$

based on the expected equity yield of their property k, $\Psi_{i,t,k}$. 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 Figure A 2 in the Appendix). The price-setting mechanism of BTL investors selling properties is 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 increases 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 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, in the case of BTL agents, whether to remove it from the market.

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[14] 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%.

Figure 1: Households' states and decisions in the housing market model
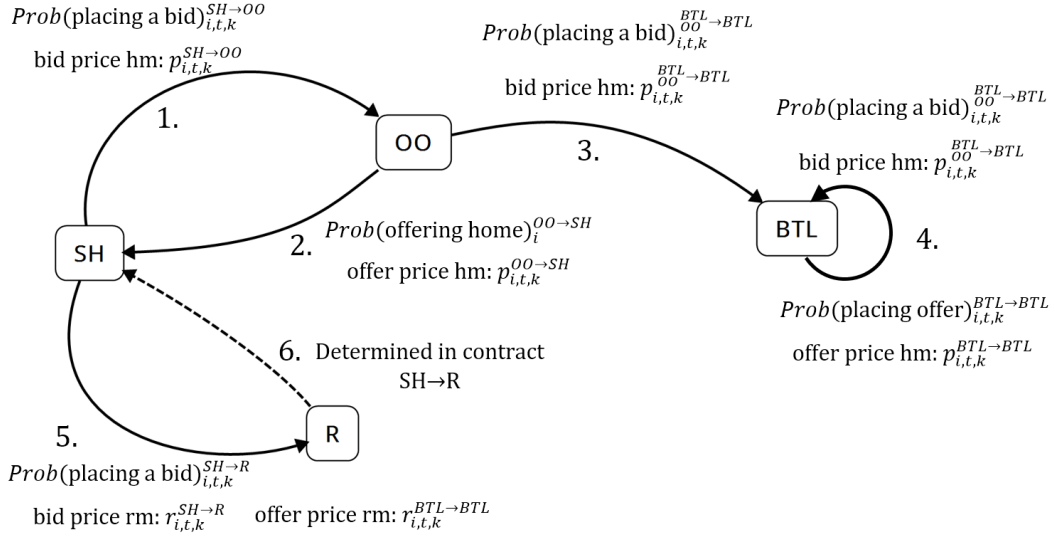
Notes: hm – housing market, rm – rental market, S.H. – social housing, O.O. – owner-occupier, BTL – buy-to-let, R – renter, p – price, Prob – probability, i – the individual agent, t – time, k – index for an individual house of a certain quality. For instance $Prob(placing\ a\ bid)_{i,t,k}^{SH\to OO}$ reads "the probability of placing a bid on the housing market by an agent in social housing in order to become an owner-occupier".

4 Baseline Dynamics

In this section, we present the baseline dynamics of our model in order to study the interconnectedness of transactions in the housing market, the house price cycle and the three target variables. The baseline version of our model is not subject to macroprudential policy effects. It can therefore serve as a benchmark for those scenarios in which macroprudential requirements become binding for the agents' credit approvals.

4.1 Dynamics of Key Housing Market Indicators

The model generates a house price cycle consisting of synchronised real estate prices and mortgages that lasts about 100 months, or 8.3 years. The cycle length is shorter than that observed in the United Kingdom, estimated to last around 13 years (Strohsal, Proaño, & Wolters, 2017). The cycle frequency of the model is itself sensitive to the price expectation of households (parameter g_t in Equation (4)). The more years in the past households take into account when forming their house price expectation, the longer it takes for house price swings to affect households' decisions, slowing down house price growth and lowering the frequency of the cycles. The frequency is also quite sensitive to the overall share of BTL agents and to the bid price of FTB and SBB agents. A higher percentage of BTL agents in the population leads to increasing house price peaks[15] and prolonging the cycle.

The upswings of the model are shorter than the downturns (see Figure 2), while the U.K. house price cycle — especially from the mid-1990s on — exhibits longer upswings than downturns (see left panel of Figure A 1 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 is due to a lack of stabilising mechanisms in the downturn (like the 'Help to Buy'[16] scheme). Some

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[15] Recall that the desired purchase price of FTB and SSB agents is a multiple of their income (parameter α_5 in Equation (5)). Increasing this multiplier leads to higher bid prices, resulting in higher house price peaks.

[16] The 'Help to Buy' scheme subsidises FTB home purchases with a government loan.

implications of this — which we don't consider to invalidate the findings of our study — are discussed in the conclusion of the paper. Importantly, the model matches a variety of key U.K. housing market indicators determined 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 A 1 in Appendix A).

The model gives rise to agent-type-specific transaction patterns along the house price cycle, driven by different motives of the agents to buy and sell houses. Such market interactions, in turn, 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' decision to enter the housing market. Following the transactions is central to understanding how different macroprudential rules can affect agent-specific behaviour.

The top-left panel of Figure 2 shows the agents' share of real estate sales, i.e. the ratio of transactions to the housing stock, disaggregated by the buyers' agent-class. The largest turnover can be found in the first half of the upswing. The number of sales drops steadily until the first half of the downturn. When prices are low, the number of transactions rises again[17].

FTB agents buy mostly at low prices. Due to their age and their limited savings, FTB agents cannot buy when house prices are high (because of the necessary down payment). During the first half of the upswing and the second half of the downturn, they purchase on average 9.6% of the total housing stock, while at high prices (i.e. during the second half of the upswing and the first half of the downturn) they purchase only 1.1% of the housing stock.

Figure 2: Transactions and ownership along the house price cycle
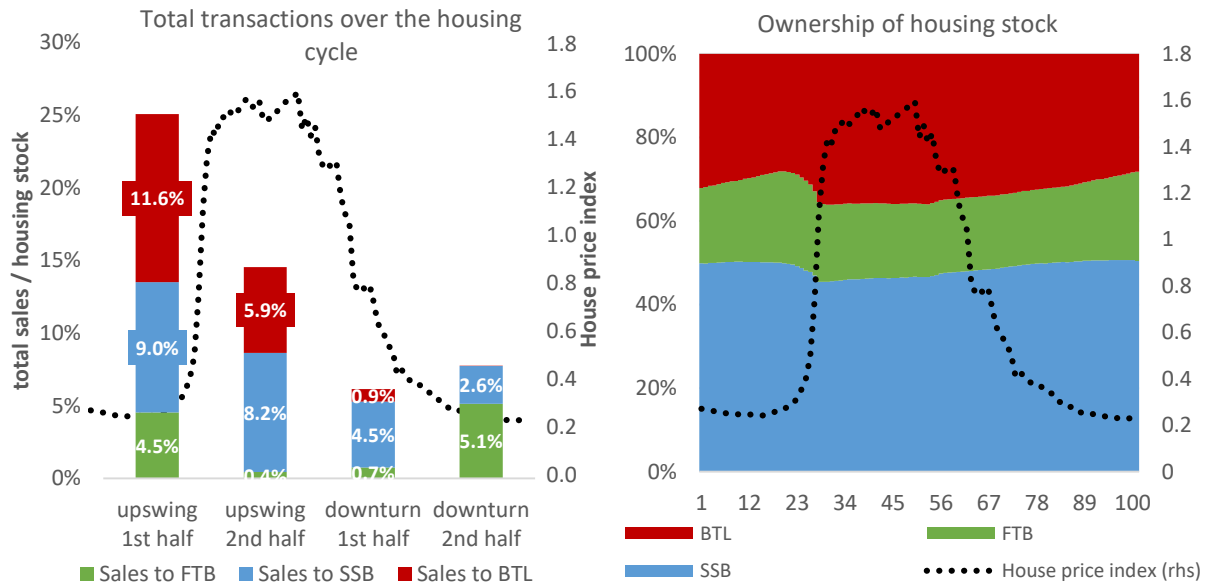
SSB agents buy mainly in the upswing. High-income SSB agents even have bid prices above the realised peak prices. Although such buying behaviour sounds counterintuitive at first, the cause is to be found in the deposits received from previous sales and used for the new purchases. In the downturn (especially the second half), there is an oversupply of houses on the market so that SSB agents have to wait longer until they can sell their homes. With rising prices, SSB agents start selling their homes Only after a delay, SSB agents can buy a house at the new place

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[17] 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 Figure A 1 in the Appendix.

where they have moved to. Their offers and bids over the house price cycle are shown in Figure A 4 in the Appendix[18].

BTL agents buy property when house prices are rising, and they sell when prices are falling. Different from SSB agents, BTL agents take their unsold property off the market as soon as prices begin to rise again. Fundamentalist BTL investors buy property early in the upswing. With stronger rising prices, trend followers enter as well.

British data on the volume of mortgages taken out by households (see Figure A 5 in the Appendix) between 2007-2018 confirm the transaction pattern differences between BTL agents and the owner-occupiers (FTB and SSB households). With falling prices after 2007 advances 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). The difference between FTB and SSB borrowers is not as pronounced as in our model. However, this could be partly explained by the price level in 2018 being still well below the house price peak in our model (at lower prices SSB and FTB purchases are closer together) and by a missing saving motive for FTB in our model (which would enable them to enter the housing market at higher prices).

To include both sides of the transactions, the right panel of Figure 2 shows the ownership of the housing stock by agent-class 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. At the beginning of the upswing, the shares in the housing stock of FTB and SSB agents decrease as they sell their homes not only to FTB and other SSB agents but also to BTL agents.

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% wealth share and the gap between highs and lows of per household consumption in monetary units (consumption volatility). These variables change throughout the house price cycle, as Figure 3 shows.

Leverage, proxied by the debt-to-income ratio, evolves procyclically. When house prices rise, the yearly growth rates of about 30 percentage points[19] are driven by fast transaction dynamics of agents, hence the price upswing of the model is more condensed than the observable U.K. data. The procyclicality of leverage is driven by the transactions of BTL and SSB agents (Figure 3, top-left panel). As soon as prices start to rise, BTL agents enter the market as buyers, while not selling property. This increases their leverage heavily. With falling prices, their market behaviour turns into the opposite, as they stop buying property and start selling it due to their adaptive expectations. Combined with their monthly mortgage payments, this reduces the indebtedness of the BTL agent class. The transaction pattern of SSB agents is less pronounced. While they buy almost as many houses in the first half of the upswing like BTL agents, they initially sell even more, resulting in the observed decline in homeownership (see the right panel in Figure 2). The debt-repayments from their sales limit the overall effect on the indebtedness

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[18] The difference in purchasing patterns between FTBs and SSBs (movers) is not driven by their desired purchase prices (Equation (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 in the upper half of the income distribution, while movers are equally distributed along the income distribution (see Figure A 3 in the Appendix). This is due to their age differences, as a significant share of movers is already in retirement, which reduces their income.

[19] Note the x-axis in Figure 3 shows months.

of the SSB agent class. FTB agents buy at low prices as they cannot enter the market at high prices due to their limited equity financing in the form of deposits. The favourable purchase prices result in only a small increase in the indebtedness of the FTB agent class. Their indebtedness decreases due to steady debt repayments and in addition, when house prices rise, due to increasing home sales.

Figure 3: DTI, top 10% wealth share and consumption per household
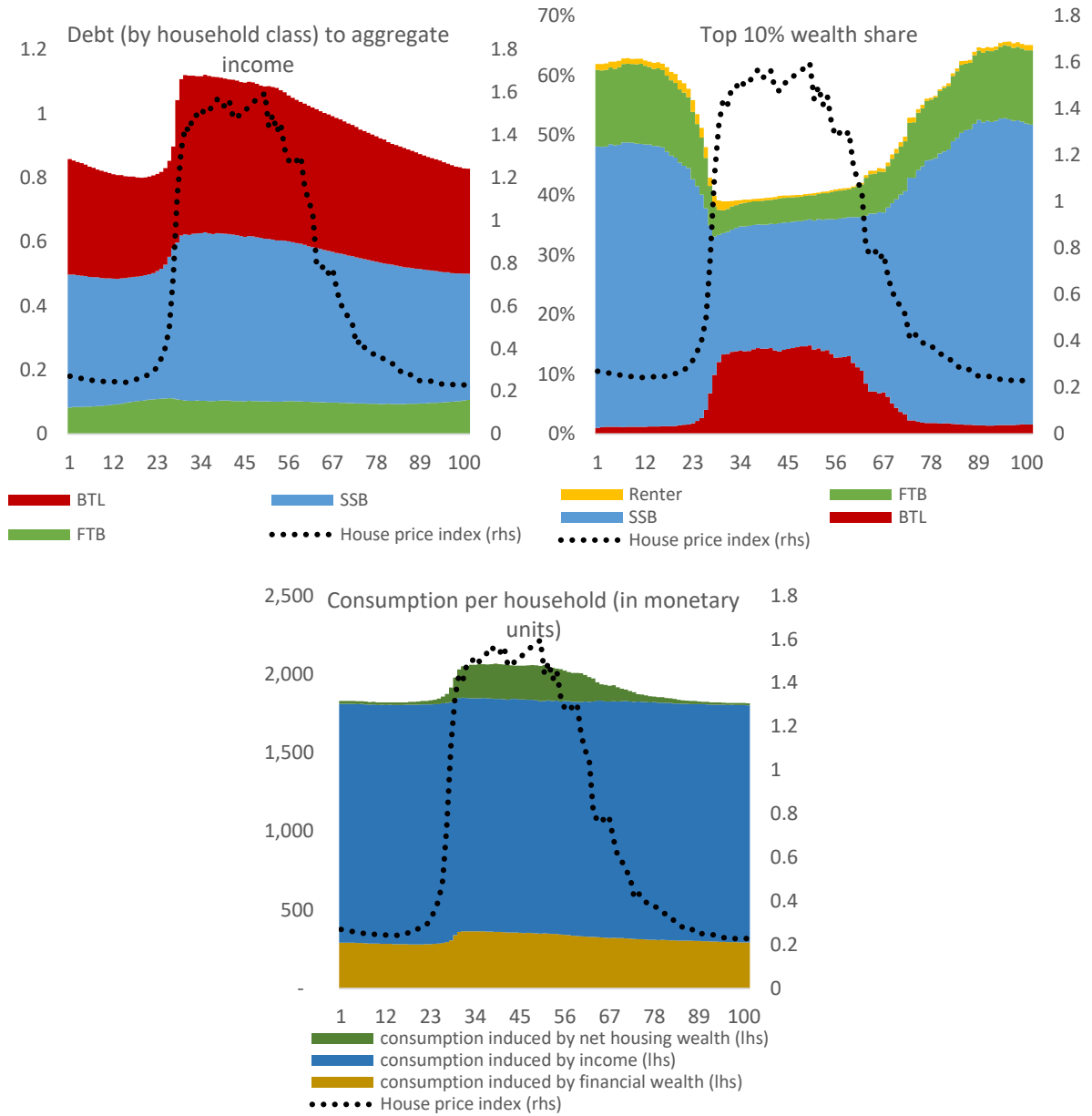
The second indicator of our interest is wealth inequality. Figure 3, top right, depicts the net wealth share of the wealthiest 10% in conjunction with the house price cycle, broken down into the shares owned by the different agent-classes. In line with the literature, the wealth share of the richest 10% decreases with rising house prices. The fluctuation of the wealth share is stronger than in the U.K. mainly because house prices fluctuate stronger than in British data. Moreover, the model does not generate financial asset price fluctuations (it only contains deposits) which can offset some of the impact of the house price fluctuations on wealth inequality (Kuhn et al., 2020). In a house price upswing, especially BTL agents benefit. Their increasing stock of housing wealth results in higher net

wealth than is the case for SSB and FTB agents, despite their high level of borrowing. When prices are falling, BTL agents become increasingly part of the bottom 90%, as their high level of borrowing is now only matched by low gross asset values on the housing market. 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 a lower wealth inequality at high prices, primarily because BTL agents, with their procyclical buying behaviour, allow home sellers to move up the wealth distribution.

The third indicator we are interested in is consumption volatility. Figure 3, bottom, 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 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. The consumption volatility induced by house price changes and agents' subsequent transactions — which affect agents' consumption via the changing composition of assets — is considerable. 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. Overall the standard deviation of consumption is 5.7%, a little bit higher but close to the 3.0% of the U.K., reported in Attanasio et al. (2011).

5   Effects of Macroprudential Policies on Debt, Wealth Inequality and Consumption Volatility

The previous sections emphasised the nexus between households' interactions on the housing market, the house price cycle and the target variables. We now analyse how macroprudential policies, affecting agents' ability to access credit, influence the transaction patterns in the housing market and thereby the house price cycle and the target variables (debt-to-income levels, wealth inequality and consumption volatility). We explore three regimes of credit conditions linked to different regulatory stances (section 5.1) and their effects on the target variables, taking into account the agent-specific dynamics (section 5.2). In section 5.3 we study in detail how transaction patterns change the target variables.

5.1   Three Policy Regimes

Figure 4 presents simulation results for different credit conditions. The baseline 'traditional banking' regime (top-left panel) reflects banking behaviour before the late 1970s when credit conditions started to be liberalised (Fernandez-Corugedo & Muellbauer, 2006). The commercial bank applies a maximum LTV of 80% for all households, independent of the state of the house price cycle. Each of the sub-figures shows the house price cycle and the maximum LTV over 200 months[20].

From the late 1970s on, financial markets were increasingly de-regulated. As a consequence, credit supply conditions became more procyclical (Hardie & Howarth, 2013; Lindner, 2014; Muellbauer, St-Amant, & Williams,

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[20] The simulation has a burning-in period of 1500 periods (not shown). Simulation results are selected to start with a house price trough.

2015) and there was strong growth in residential mortgage credit (Jordá et al., 2016). We incorporate these changes by making the maximum LTVs of the commercial bank procyclical, i.e. dependent on the change in house prices:

$$LTV_t = \alpha_9 g_t + \widetilde{LTV}, \quad \text{for } 0 \le LTV_t \le LTV_{cap} = 100\%, \tag{9}$$

where α_9 denotes a dampening parameter to changes in house prices over the last two years (g_t). To ensure that LTVs move around observed LTV ratios, $\widetilde{LTV}$ is set to 0.8[21] for all borrower types. For model consistency, LTV_{cap} restricts maximum LTVs at the upper end to 100%.

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, and the house price through increases somewhat: as it turns out, the effect of procyclical credit conditions is asymmetric.

In panel (c) we add anticyclical LTV caps, by also making $LTV_{t,cap}$ dependent on the house price cycle:

$$LTV_{t,cap} = \begin{cases} 0.9, & \Delta HPI_{QoQ,t} > 0 \\ 1, & \Delta HPI_{YoY,t} < -0.2 \end{cases}. \tag{10}$$

In a simulation run, initially, macroprudential policy is inactive. The lower LTV cap (the solid line) is activated when quarterly price increases become positive. Conversely, the higher $LTV_{t,cap}$ (purple dotted line) is activated once yearly prices drop by more than 20%. The internal lending rule of the commercial bank remains procyclical, but the credit supply is restricted in the house price upswing by the external rules 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 $LTV_{i,t,cap}$ 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). One observes the strongest effects on dampening peaks when BTL agents are restricted. However, this observation should only serve as a first indication.
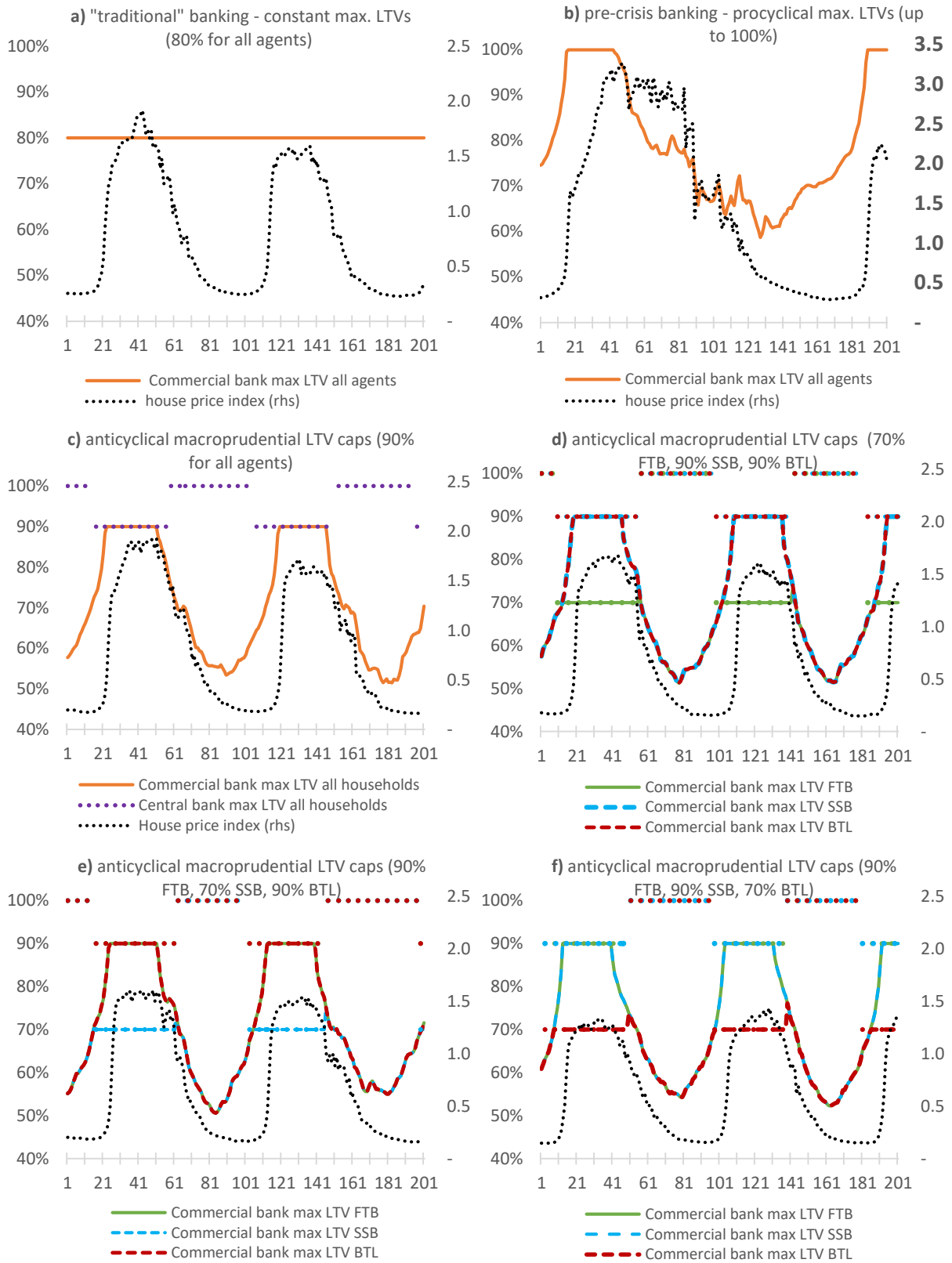
Because of stochastic influences, the outcome of the model is path-dependent so that, additionally, Monte-Carlo runs are needed for the generality of the results (Figure A 6 in the Appendix). To ensure robustness, all following results are based on 50 Monte-Carlo runs while each run comprises 1000 periods.

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 5.2.1, we study the procyclicality of credit supply conditions given the regimes a), b) and c) of Figure 4. In section 5.2.2, we analyse agent-specific credit limitations given the regimes d), e) and f) of Figure 4.

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[21] Following van der Heijden, Dol, & Oxley (2011), p. 308.

Figure 4: House price cycles with constant and procyclical maximum LTVs, agent-specific and identical LTV caps (all 200 Months)

a) "traditional" banking - constant max. LTVs (80% for all agents)

b) pre-crisis banking - procyclical max. LTVs (up to 100%)

Commercial bank max LTV all agents
house price index (rhs)

c) anticyclical macroprudential LTV caps (90% for all agents)

Commercial bank max LTV all households
Central bank max LTV all households
House price index (rhs)

d) anticyclical macroprudential LTV caps (70% FTB, 90% SSB, 90% BTL)

Commercial bank max LTV FTB
Commercial bank max LTV SSB
Commercial bank max LTV BTL

e) anticyclical macroprudential LTV caps (90% FTB, 70% SSB, 90% BTL)

Commercial bank max LTV FTB
Commercial bank max LTV SSB
Commercial bank max LTV BTL

f) anticyclical macroprudential LTV caps (90% FTB, 90% SSB, 70% BTL)

Commercial bank max LTV FTB
Commercial bank max LTV SSB
Commercial bank max LTV BTL

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 171% in model b) 'pre-crisis banking', with peak values rising from 116% to 243% (see also in Figure 5, top-left). In addition to the changes in DTI ratios, the transition from 'traditional' to 'pre-crisis' liberalised banking also leads to higher maximum and average wealth inequality, higher average monthly consumption, and rising consumption volatility: the difference between the maximum and minimum consumption values[22] (the amplitude of the consumption cycle) rises from 318 to 694 per household.

Variations in household consumption caused by a reallocation of households' assets can have large effects on macroeconomic stability (Mian et al., 2013). The same applies to the rise in wealth inequality (Jones, 2015) and to the rise in DTI ratios (Schularick & Taylor, 2012). These effects have contributed to the introduction of macroprudential rules, with debt development usually seen as the primary target and the other two as secondary at best.

Table 1: Target variables for different regimes

Regime	Debt-to-income ratio (%)	Top 10% wealth share (%)	Per household consumption volatility (amplitude = max-min)
a) constant max LTV = 80%	max = 116% mean = 96%	max = 67.8% mean = 49.9%	amplitude = 318
b) max LTV = 100%, procyclical credit conditions	max = 243% mean = 171%	max = 84.0% mean = 53.6%	amplitude = 694
c) procyclical credit conditions, anticyclical macroprudential LTV caps (90%, all agents)	max = 130% mean = 107%	max = 81.0% mean = 53.8%	amplitude = 368
d) 70% FTB, 90% SSB, 90% BTL	max = 124% mean = 101%	max = 82.3% mean = 55.2%	amplitude = 359
e) 90% FTB, 70% SSB, 90% BTL	max = 121% mean = 99%	max = 78.2% mean = 52.8%	amplitude = 356
f) 90% FTB, 90% SSB, 70% BTL	max = 102% mean = 87%	max = 74.1% mean = 51.7%	amplitude = 295

Limiting the LTV caps to 90%, brings the debt-to-income ratio close to the levels in the 'traditional banking' regime, as can be seen in Table 1. The DTI maximum is reduced to 130% — relative to 116% in the traditional banking regime — and the averages to 107% — relative to 96% in the traditional banking regime; the consumption amplitude falls to 368 monetary units relative to 318 before. These strong effects on the variables that feed into

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[22] 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 Figure A 11, 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 Figure 3), because at low house prices macroprudential credit restrictions do not affect the turning point as such.

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. Wealth inequality is less affected by aforementioned macroprudential regulation; The wealth share of the richest 10% of households is almost the same as in the pre-crisis regime. This finding is in contrast to the results of Carpantier et al. (2018), who suggest that limiting LTVs would also decrease wealth inequality. One reason is that with macroprudential measures active, prices tend to be lower, which, in the model, leads to higher wealth inequality. The predominant effect is that less wealthy households now no longer benefit strongly from the rise in house prices. In the macroprudential regime c), this predominant effect balances out the wealth-inequality-reducing impact of lower debt at low prices (see the top-right panel of Figure A 8 in the Appendix).

5.2.2 Agent-Specific Macroprudential Policy

Given the substantial differences in housing market transaction behaviour across 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 Figure 5, reflecting the change from model c) to f), maximum DTI values fall from 130% to 102%. When restricting FTB and SSB agents, the decline is only to 124% and 121%, respectively. The effect size is significantly smaller compared to previously discussed restriction of LTV caps from 100% to 90%. This reveals a non-linearity also reported by Alam et al. (2019). The non-linearity arises due to deposits (i.e. potential down payments) being very unevenly distributed among households. This implies that LTV reductions (of a given size) from comparatively higher levels exclude a larger share of the population from being able to enter the housing market.

The effect sizes of limiting FTB and SSB agents is basically in line to 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 overall decrease of 20/3, Alam's et al. (2019) results imply a DTI reduction of 4.4%. Similarly, restricting FTB agents' access to credit in our model yields a reduction of peak DTI values of 4.6% while the SSB restriction leads to a reduction of 6.9%. The effect of the BTL restriction, however, is with 21.5% significantly larger. Figure 5 shows that lower DTI ratios are not merely the results of reductions in maximum house prices; the means also shift downward. All along the 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. Empirical results of LTV caps might also be driven by the restriction on BTL agents due to their different investment motive (at least in countries with a significant investors' share).

Limiting BTL agents' access to credit also reduces the maximum and average values of 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 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. Limiting SSB agents has almost no effect on the wealth distribution while limiting 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 wealth inequality — at least at high prices.

Figure 5: Debt-to-income ratios (in %) and house prices for different credit regimes
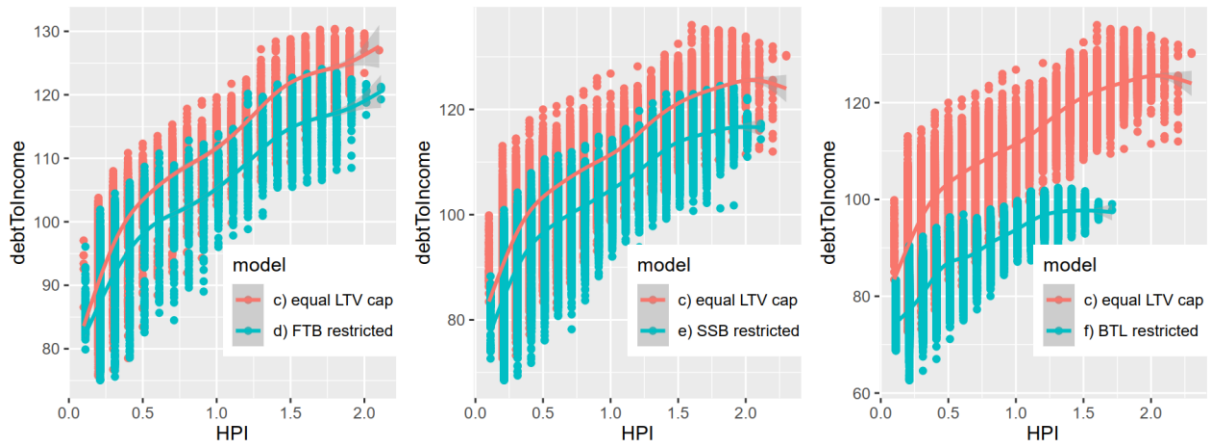
Note: We show the results of 50 Monte-Carlo runs for different regulatory regimes. In model c), the LTV caps for FTB, SSB and BTL buyers are all 90%. In models d), e) and f) the LTV caps is reduced to 70% for FTB, SSB and BTL buyers, respectively.

As can be seen in Figure 3, transactions in the housing market drive fluctuations in consumption by affecting housing wealth through house prices and financial wealth through changes in the portfolio composition. Both factors influence household consumption through the housing wealth and the financial wealth term in the consumption function, respectively. Smoothing the transaction patterns in the housing market should, therefore, reduce consumption volatility without reducing average consumption by as much, as house price minima and, correspondingly, minimum consumption is less affected. Again, reducing BTL agents' access to credit has the strongest impact[23]. Alam et al. (2019) find for a reduction in LTV caps of about 7 percentage points a reduction of about 1 percentage point in consumption growth (after one year). This result is similar to the overall reductions in maximum consumption (not in the amplitude) of 1.6 percentage points and 2.1 percentage points we find for a corresponding reduction in LTV caps of FTB and SSB agents in our model, but it is significantly below the 4.9 percentage point reduction we find for limiting BTL investors.

Overall, the simulation results, suggest that restricting BTL agents' access to credit represents an efficient 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 different model outcomes are driven by how macroprudential regulation affects agents' ability to get a mortgage loan and to place a certain bid in the housing market, hence changing the transaction patterns in this market. In this section, we analyse these changes in detail and explain how they lead to the results in Table 1. To this end, Figure 6 shows the average number of sales as a percentage of the total housing stock for different phases of the

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[23] 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.

house price cycle (upswing first half, upswing second half, downturn first half, downturn second half) and for different macroprudential regimes (LTV caps correspond to the regimes c) to f) in Figure 6).

Figure 6: Transactions along the house price cycle
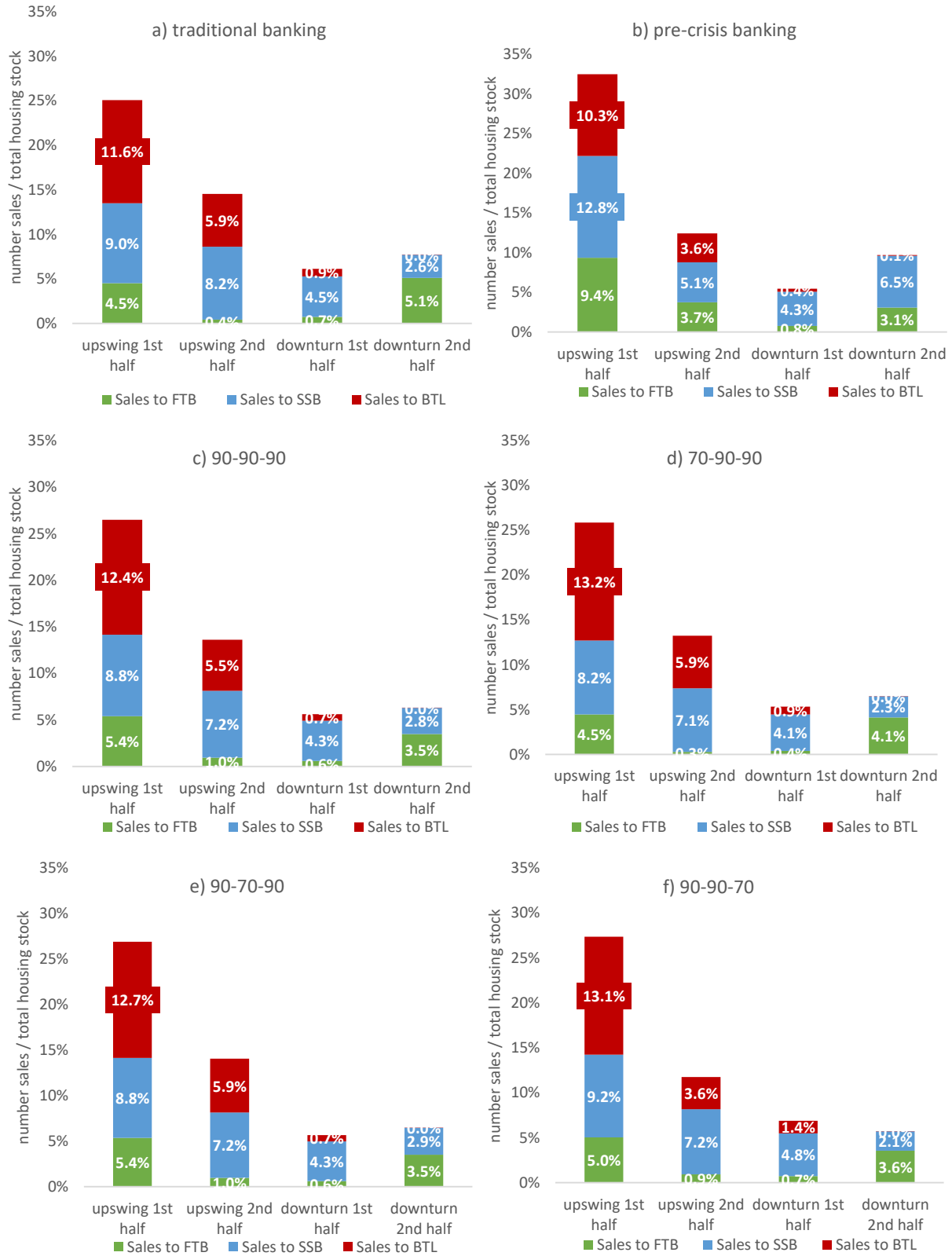
Note: The regimes depict different regulatory stances. In regime c), the LTV caps for FTB, SSB and BTL buyers are all 90%. In models d), e) and f) the LTV cap is reduced to 70% for FTB, SSB and BTL buyers, respectively.

5.3.1 From Traditional Banking to the Crisis and Back

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. By allowing to buy a house almost entirely financed by mortgages, 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. Figure 6 shows the changes in housing market transaction patterns for different macroprudential regimes. Especially FTB agents can 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. SSB agents' purchases increase as well, but less as they are not as credit-constrained as FTB agents. In the second half of the downturn, FTB agents are even more credit constrained in the pre-crisis regime than in traditional one, due to the procyclicality introduced, i.e. their maximum LTV drops sharply in this phase.

From the 'traditional banking' to the 'pre-crisis banking' regime, the average DTI rises mainly because of FTB and BTL agents. With the same down payment from their deposits they are allowed to take out more loans and to buy houses at higher prices. SSB agents, on the other hand, hardly change their realised LTVs and the prices they bid for their new homes. In both regimes, the high stock of deposits from the sale of the house in those places from which the SSB agents want to move, allows them to make the maximum bid they want, even without additional borrowing (Equation (5)). Wealth inequality increases from the traditional to the pre-crisis regime due to a higher share of households suffering from a negative net asset position, i.e. their gross debt exceeds their gross assets. In the model, the following applies: the more households hold a (larger) negative wealth stock, the higher the wealth share of the top 10% (see Figure A 8 in the Appendix for the relation of house prices and top 10% wealth share). Consumption increases from the traditional to the pre-crisis regime due to the higher DTI ratios, which increase the financial wealth holdings of mainly households selling property, which thereby increase their consumption due to the higher consumption response to financial wealth than to housing wealth. Further, the higher DTI ratios allow stronger house price growth, inducing 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 — due to the commercial banks' procyclical LTV rule — maximum LTVs in the macroprudential regime drop below the 80% of the traditional banking regime. At this point, especially BTL investors sell their property. Due to this lower maximum LTV of the commercial bank fewer FTB agents can buy property from BTL agents. Summarising, there is less trading from households at the upper end of the wealth distribution (BTL) to households at the lower end of the wealth distribution (FTB)[24]. As a consequence of this special effect, when prices rise again, housing wealth concentration remains stronger in the macroprudential regime than in the traditional banking regime[25].

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[24] Investors move across the wealth distribution along the house price cycle. On average, however, they are found in the upper half of the wealth distribution.

[25] The average housing stock held by BTL investors as investment stock increases from 22.3% to 25.1%

5.3.2 Restricting Classes of Agents Individually

This sub-section analyses how transaction patterns in the housing market change by additional macroprudential requirements that restrict the LTV cap of each class of agent individually. We then trace how the different macroprudential specifications affect our target variables (household indebtedness, wealth inequality, consumption volatility) through the transactions in the housing market.

5.3.2.1 Effects on Transaction Patterns

Restricting, in addition to the macroprudential regime c), only FTB agents' access to credit does not completely decrease their spending on houses. Rather than in the first half of the upswing, they purchase more in the second half of the downturn — where prices are lower. The credit restrictions, however, 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%.

Restricting, in addition to the macroprudential regime c), SSB agents' access to credit has little effect on transaction patterns in the housing market. SSB agents are least reliant on credit due to high stock of deposits from previous sales, which are used as a down payment for house purchases.

An additional lowering of BTL agents' LTV caps by the central bank shifts part of the BTL agents' purchases to lower prices, from the second to the first half of the house price upswing. Due to lower prices paid and the increasing use of down payments (built up by longer saving periods), BTL agents can partially compensate for 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 to 22.4% in the regime in which only BTL agents are restricted). The buying patterns of FTB and SSB agents remain almost unchanged in this regime.

5.3.2.2 Effects on Target Variables

DTI ratios change most when BTL agents' LTV caps are additionally lowered to 70%. BTL investors contribute as much as SSB agents to aggregate household debt. But on average, they have lower deposits, increasing their sensitivity to credit availability. A further reduction of SSB agents' LTV caps remains almost without effect since their LTVs are mostly below the 70% threshold in the upswing when the macroprudential restriction starts to bite. Restricting FTB agents in addition to the macroprudential regime c) only, also affects DTI ratios only marginally as these agents are largely buying at low prices with limited use of mortgages (see Figure 3, top left).

The effects we find for wealth inequality are generally in line with the results by Carpantier et al. (2018), implying that stricter credit conditions can reduce wealth inequality. Restricting BTL agents' LTV caps even more basically limits the housing stock they can own. This corresponds to a lower concentration of net housing wealth and therefore lower wealth inequality. Especially at lower prices, the BTL LTV cap helps to reduce wealth inequality as reduction in the DTI ratio leads to fewer households with (less) negative net asset position. Interestingly, in the case of the additional BTL restriction, the fact that house price peaks are lower does not coincide with higher, but

lower wealth inequality[26]. While some households with real estate holdings from the bottom half of the wealth distribution benefit less, the dominant effect comes from the prevention of over-indebtedness among households that buy during the price upswing. In this context, the LTV cap matters not only directly for BTL agents, but also for the other classes of agents because part of the upward pressure on prices from competition is absent. Restricting FTB agents produces an inequality-increasing effect as it reduces the number of transactions from richer to poorer households at lower prices. Housing wealth will be overall more concentrated so that wealth inequality increases.

Consumption volatility falls most when restricting BTL agents' access to credit. The house price cycle becomes less debt-fuelled as BTL agents are the ones that borrow the highest amounts in the late phase of the house price upswing. The more they can borrow, the more they stretch the amplitude of the house price cycle, thereby affecting housing-wealth-induced consumption[27]. In the model, credits for house purchases create deposits with the seller[28]. 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[29] (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 (MPC). 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 Bank of Ireland. The aim is to explore if additionally increasing LTV caps for BTL investors turn out to be more efficient, as suggested in the previous analysis. Policy regime g) represents the present Bank of Ireland LTV caps (see Figure 7). They are 90% for FTB, 80% for SSB and 70% for BTL agents. In model version h) we introduce more restrictive caps on BTL investors while keeping the overall limitation relative to the uniform macroprudential restrictions in policy regime similar to those of the Bank of Ireland (i.e., 30 percentage points lower). We relax the constraint on SSB agents to 90% and restrict BTL agents more to 60%. Consistent with previous insights, such requirements lead to slightly lower house price peaks than the original LTV caps applied by the Bank of Ireland.

Measured against the outcome of the previously defined target variables (Table 2), it becomes evident that additionally restricting BTL investors' access to credit, while SSB agents are only subject to less stringent requirements, yields preferable outcomes. Household debt-to-income ratios respond more strongly, and wealth inequality falls slightly. Consumption amplitudes are also additionally reduced by limiting BTL agents. In the Irish policy regime, transaction patterns on the housing market and consumption volatility are hardly affected. Figure 8 shows sales to the respective agent classes as a function of the different phases of the house price cycle for policy

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[26] When real estate assets are less unequally distributed than financial assets (Kuhn et al., 2020).

[27] Figure A 4 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.

[28] A possible restriction of bank money creation through capital requirements is beyond the scope of this paper.

[29] In the model, the mortgage interest payments the commercial bank receives are paid out as dividends to owner households. The dividends are distributed according to the share of deposits a household holds.

regimes f) and h). At first glance, it is admittedly difficult to uncover significant differences. However, the strongest effect is the reduction of BTL purchases in the first part of the upswing from regime f) to regime h). As a consequence, this reduces the share of the housing stock held as investment property, from 22.2% to 21.0%, at the same time it reduces DTI ratios. As with the reduction of BTL agents' LTV caps from regimes c) to f), wealth inequality decreases due to housing wealth being less 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 cases the hypothesis that the outcome stems from the same probability distribution cannot be rejected.

Figure 7: House price cycles with in the Irish policy regime and the one with additional LTV requirements for BTL investors (all 200 Months)
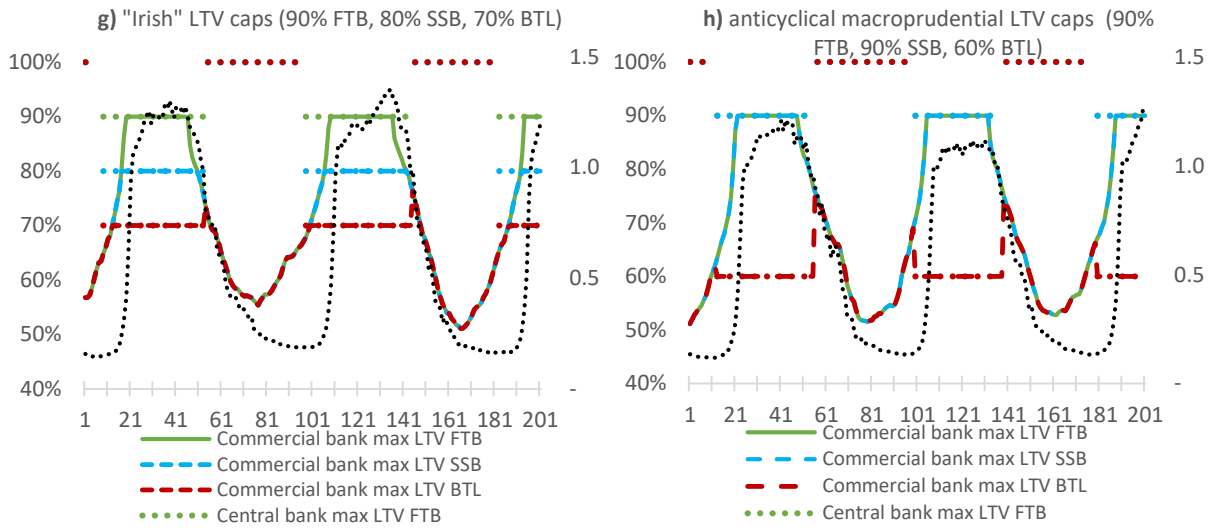
Table 2: Target variables for Irish and additional policy regimes

Regime	Debt-to-income ratio (%)	Top 10% wealth share (%)	Per household consumption volatility (amplitude = max-min)
f) 90% FTB, 90% SSB, 70% BTL	max = 102% mean = 87%	max = 74.1% mean = 51.7%	amplitude = 295
g) 90% FTB, 80% SSB, 70% BTL	max = 99% mean = 85%	max = 72.4% mean = 51.5%	amplitude = 301
h) 90% FTB, 90% SSB, 60% BTL	max = 95% mean = 82%	max = 71.9% mean = 51.2%	amplitude = 260

Figure 8: Transactions along the house price cycle, Irish and additional policy regimes
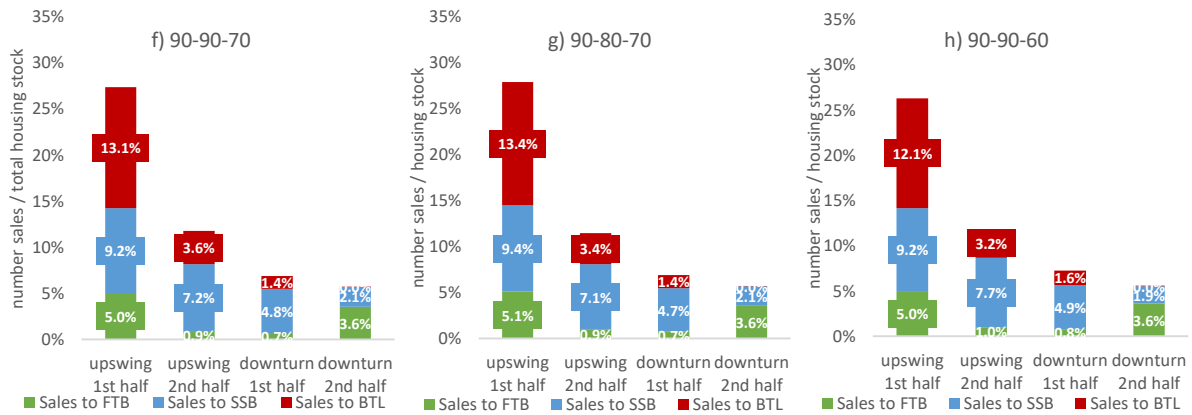
7 Conclusions

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. To address excessive household indebtedness, central banks started to implement housing-market-related macroprudential policies, like caps on the Loan-to-Value ratios limiting the amounts of credit households can borrow. Recently, to increase the efficiency of such policies, central banks have applied borrower-specific credit requirements. At present, however, the effect of borrower-specific macroprudential requirements on important economic variables is not sufficiently explored. 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 their individual asset and income positions lead us to employing an agent-based model. We built on the model by Baptista et al. (2016) and add a wealth term and income-dependent propensities to consume to the original consumption function. This modification makes consumption move procyclically with house prices, a stylized fact observed in many economies before and after the recent financial crisis.

In model simulations, we can also reproduce the fact that commercial banks in financial liberalisation regimes tend to apply procyclical maximum LTVs as part of their credit assessment, a lending behaviour that the central bank should oppose from a stability perspective. In this context, it is worth examining the consequences of macroprudential policies on household debt, wealth inequality and consumption volatility. In principle, fine-tuned macroprudential tools should be able to move the economy back to the pre-crisis state in terms of target variables such as household debt-to-income ratios as well as collateral effects in terms of consumption volatility and wealth inequality.

Simulations show that the most effective approach for central banks is to limit Loan-to-Value (LTV) ratios borrower-specifically, in particular BTL agents' LTV. According to our model results, a reduction of 20 percentage points in BTL agents' LTV cap leads to a reduction in aggregate DTI ratios (-20 percentage points), in wealth inequality (-2 percentage points) and in consumption volatility (-20%). Restricting FTB agents' access to credit had a low overall impact on household indebtedness and consumption volatility, while even increasing wealth inequality (+1 percentage point). Restricting 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.

While our partial model reveals a bundle of considerable results, it is also characterised by some limitations that may be the subject of future research. There are no stabilising mechanisms in a house price bust, like the Dutch national mortgage guarantee, so that house prices fall sharply. Another limitation might be the missing savings motive of FTB agents for an initial deposit (Aron et al., 2012). Both effects can lead to an underestimation of FTB agents' indebtedness, as most of them enter the housing market at low prices. Moreover, due to its partial nature, the model might underestimate adverse effects on average household consumption, which might arise from negative feedback loops through the firm sector, lower wages and higher unemployment (see Appendix B for a joint analysis of consumption volatility and average consumption).

Our analysis emphasises the importance for macroprudential policy to distinguish between different types of borrowers. Especially, our results suggest prioritising macroprudential requirements for buy-to-let investors. Their profit motive as well as (initially) favourable position in the wealth distribution fundamentally affect the policy outcomes.

APPENDIX

Appendix A. Model output and the Bank of England Core Indicators

Table A 1 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 U.K. minimum and maximum values. The numbers of housing transactions and mortgage approvals in the model are adjusted for the U.K. population and housing stock.

Table A 1: Comparison of the model output with the Bank of England Housing Market Core Indicators for U.K.

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

Source: (Bank of England, 2018)

Appendix B. Effects on Consumption Volatility and Average Consumption

It can be part of a central bank mandate to lower debt-fuelled consumption volatility. Whenever a policy measure is taken, it is always hoped that the average level of consumption will not be adversely affected. In this section we provide some details about the policy regimes from the main text when looking at both average and consumption volatility. We, therefore, set the reduction in volatility in relation to the reduction in average consumption, resembling risk-aversion of households. The assumption is 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 $U = a * \bar{C} - b * (\max(C) - \min(C))$, where a/b then provides an insight 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 368 to 295 monetary units per household and month, as opposed to only 356 (SSB reduction) and 359 (FTB reduction). Average consumption also drops lowest with restricting BTL agents in policy regime f) (from 1920

to 1889 monetary units). From regime c) to regime f), reflecting a restriction on BTL agents, the $^a/_b$ ratio is $\frac{-31}{-73} = 0.42$, for reducing FTB agents' LTV cap, this ratio is $\frac{-11}{-9} = 1.22$ and for SSB agents $\frac{-3}{-12} = 0.25$. The larger the ratio, the stronger the effect that a reduction in the consumption amplitude by one monetary unit has on the average consumption level along the house price cycle. Thus, in contrast to the primary focus on consumption volatility in the main text, for the given simple utility function, results imply that the strong effect of restrictions on BTL investors only appear the most efficient under the assumption of a certain degree of households' risk aversion.

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 numerical differences are large enough so that values can be assigned to different probability distributions. We use a two-sided Kolmogorov-Smirnov (K.S.) test, as the distributions are not normally distributed, and we pay special attention to the maximum values[30]. However, if we were to test the aggregated target variable distributions — i.e. aggregating over all fifty Monte-Carlo (M.C.) paths of each model version — the policy regimes are reported to be significant for each of the pairwise comparisons, merely due to the high number of observations involved. We, therefore, conduct a pairwise comparison of individual M.C. 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 M.C. 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 A 2, 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-model 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 A 3 shows the individual test results resulting in 43% of non-significant cases, the table also includes critical- and p-values[31]. In a second step, we compare these benchmark values (diagonal values) to those of testing a M.C. path of one policy regime against the M.C. paths of another policy regime (pairwise comparison).

For the debt-to-income ratio, the test results in clear 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. The latter could be expected, as the corresponding DTI ratios in Table 1 are close to each other. The aggregated distributions are illustrated in Figure A 9. Test results for wealth inequality also show meaningful differences between policy regimes, apart from the comparison between models b) and c), c) and e) as well as those of the Irish banking version tests. Figure A 10 shows the aggregated distributions. Testing the consumption amplitude distributions yields quite similar results than for wealth inequality, while the benchmark values tend to be lower[32]. Apparently, differences seem to be significant between c) and f) as well as f)

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[30] If the focus was more on differences in means, the Wilcoxon signed-rank test would have been an alternative.

[31] The corresponding values for all other tests are available upon request.

[32] This is partly because consumption is subject to stronger memory effects than 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 higher frequency of the house price cycles is, the larger the influence of these oscillations, explaining the lower benchmark values of model versions f), g) and h).

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 Figure A 11.

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.

Table A 2: Share of two-sided Kolmogorov-Smirnov tests of the single Monte-Carlo runs of each regime where the null-hypothesis cannot be rejected

	Regimes	a) traditional banking	b) pre-crisis banking	c) 90-90-90	d) 70-90-90	e) 90-70-90	f) 90-90-70	g) 90-80-70	h) 90-90-60
DTI	a) traditional banking	**43%**							
	b) pre-crisis banking	0%	**57%**						
	c) 90-90-90	0%	0%	**41%**					
	d) 70-90-90	0%	0%	0%	**46%**				
	e) 90-70-90	0%	0%	0%	30%	**43%**			
	f) 90-90-70	0%	0%	0%	0%	0%	**45%**		
	g) 90-80-70	0%	0%	0%	0%	0%	0%	**51%**	
	h) 90-90-60	0%	0%	0%	0%	0%	0%	0%	**58%**
Wealth inequality	a) traditional banking	**47%**							
	b) pre-crisis banking	0%	**40%**						
	c) 90-90-90	0%	21%	**45%**					
	d) 70-90-90	0%	0%	2%	**49%**				
	e) 90-70-90	0%	8%	23%	1%	**46%**			
	f) 90-90-70	0%	1%	1%	0%	7%	**36%**		
	g) 90-80-70	0%	0%	0%	0%	2%	27%	**36%**	
	h) 90-90-60	0%	0%	0%	0%	0%	15%	25%	**34%**
Consumption	a) traditional banking	**17%**							
	b) pre-crisis banking	0%	**44%**						
	c) 90-90-90	0%	0%	**24%**					
	d) 70-90-90	0%	0%	4%	**19%**				
	e) 90-70-90	0%	0%	10%	17%	**21%**			
	f) 90-90-70	7%	0%	0%	0%	0%	**19%**		
	g) 90-80-70	4%	0%	0%	0%	0%	17%	**23%**	
	h) 90-90-60	0%	0%	0%	0%	0%	1%	4%	**16%**

Table A 3: Detailed breakdown of Kolmogorov-Smirnov test results the Debt-to-income ratio in Monte-Carlo runs under the traditional banking regime

a) traditional banking

MC-run	1	2	3	4	5	6	7	8	...	50
					$d_{n,m}$					
1	0									
2	0.099	0								
3	0.125	0.043	0							
4	0.034	0.071	0.096	0						
5	0.075	0.085	0.065	0.085	0					
6	0.065	0.047	0.063	0.058	0.088	0				
7	0.057	0.110	0.149	0.069	0.127	0.104	0			
8	0.088	0.128	0.166	0.081	0.147	0.118	0.045	0		
...	...	...	...	...	...	...	...	...	...	
50	0.109	0.050	0.041	0.080	0.088	0.051	0.122	0.147	...	0
					$\sqrt{\frac{nm}{n+m}}d_{n,m}$					
1	0									
2	2.21	0								
3	2.79	0.96	0							
4	0.76	1.59	2.15	0						
5	1.68	1.90	1.45	1.90	0					
6	1.45	1.05	1.41	1.30	1.97	0				
7	1.27	2.46	3.33	1.54	2.84	2.32	0			
8	1.97	2.86	3.71	1.81	3.29	2.64	1.01	0		
...	...	...	...	...	...	...	...	...	...	
50	2.44	1.12	0.92	1.79	1.97	1.14	2.73	3.29	...	0
					p-value					
1	1									
2	0.000	1								
3	0.000	0.314	1							
4	0.611	0.013	0.000	1						
5	0.007	0.001	0.029	0.001	1					
6	0.029	0.220	0.038	0.069	0.001	1				
7	0.078	0.000	0.000	0.017	0.000	0.000	1			
8	0.001	0.000	0.000	0.003	0.000	0.000	0.264	1		
...	...	...	...	...	...	...	...	...	...	
50	0.000	0.164	0.371	0.003	0.001	0.149	0.000	0.000	...	1

Notes: If H0 is rejected, the field is coloured green; H0 is rejected with $\alpha=1\%$ if critical value $K_\alpha < \sqrt{\frac{nm}{n+m}}d_{n,m}$ with $K_\alpha = \sqrt{\frac{\ln\left(\frac{2}{\alpha}\right)}{2}} = 1.628$ 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.

Appendix D. Additional Figures

Figure A 1: Detrended U.K. real house prices (1977-2018) and cross-correlation of house prices and number of housing transactions.
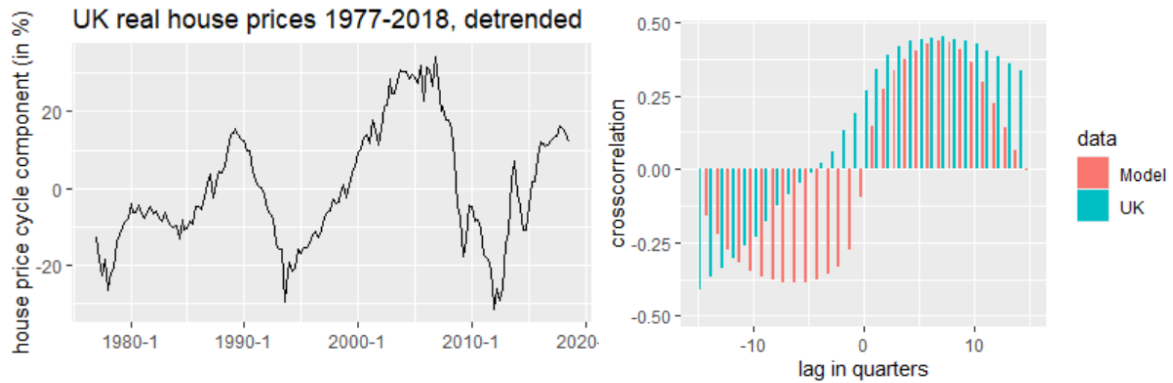
Source: U.K. monthly housing transactions 1977-2018 from Bank of England[33]; U.K. quarterly constant house prices 1977-2018, OECD Economic Outlook
Notes: Housing transactions transformed to quarterly data, time series detrended using Hamilton (2018)

Figure A 2: Number of agents along the house price cycle

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[33] https://www.bankofengland.co.uk/-/media/boe/files/core-indicators/housing-tools.xlsx
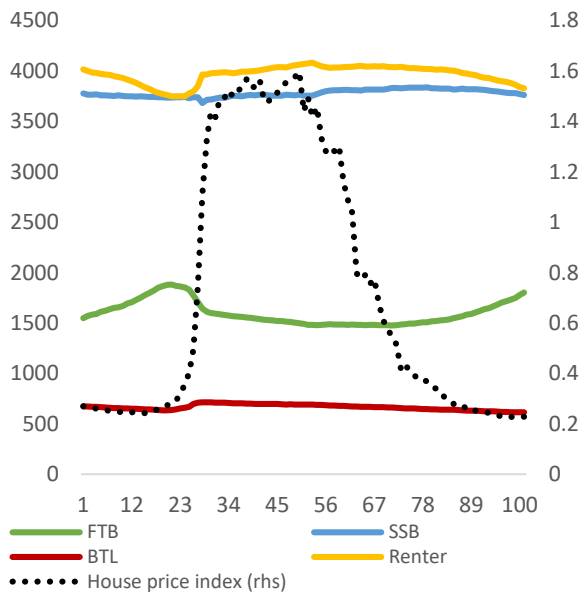
Figure A 3: Home ownership of different agent-classes as a function of the wealth distribution — average value over the house price cycle
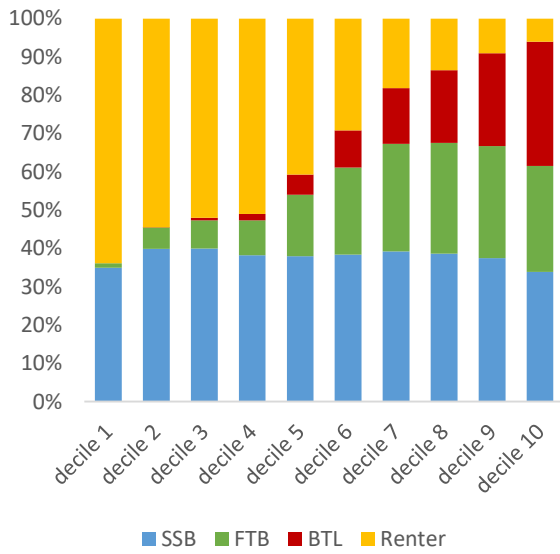
Figure A 4: Monthly offers and bids over the house price cycle
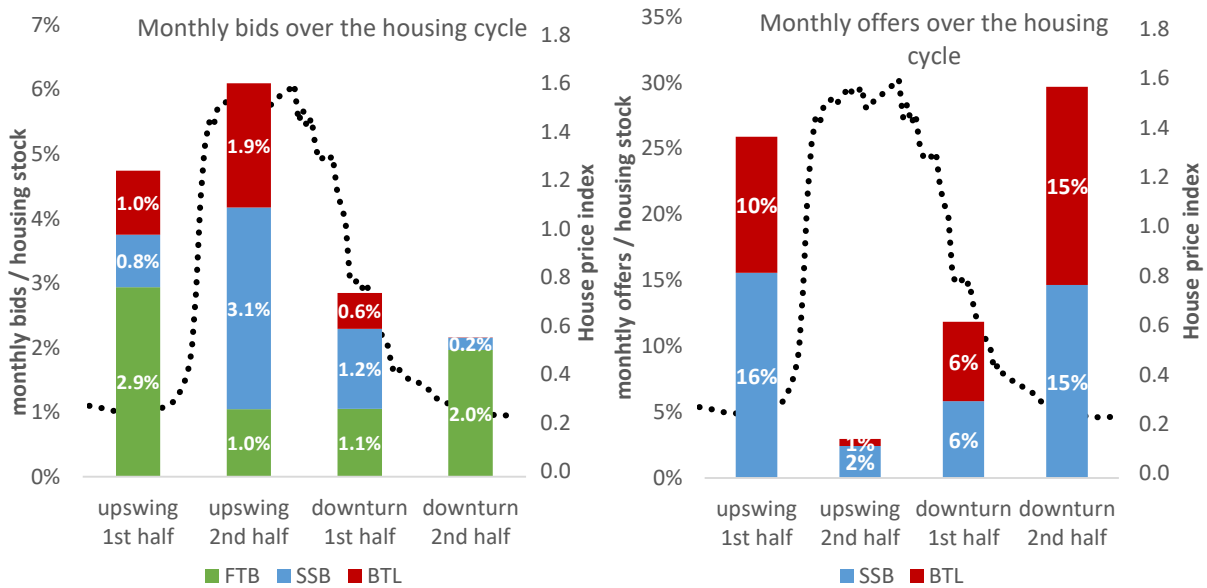
Notes: The upswing is defined as the time period between lowest and highest house price. The upswing and downturn are halved by total duration (not by the price). Upswing and downturn differ in length. Note that the focus is on bids and offers per month, as offers and bids tend to be made for several months in a row.

Figure A 5: Advances for residential loans by loan purpose in £ millions (in 2011 prices) and house price index (index 2011 prices) from 2007-2018
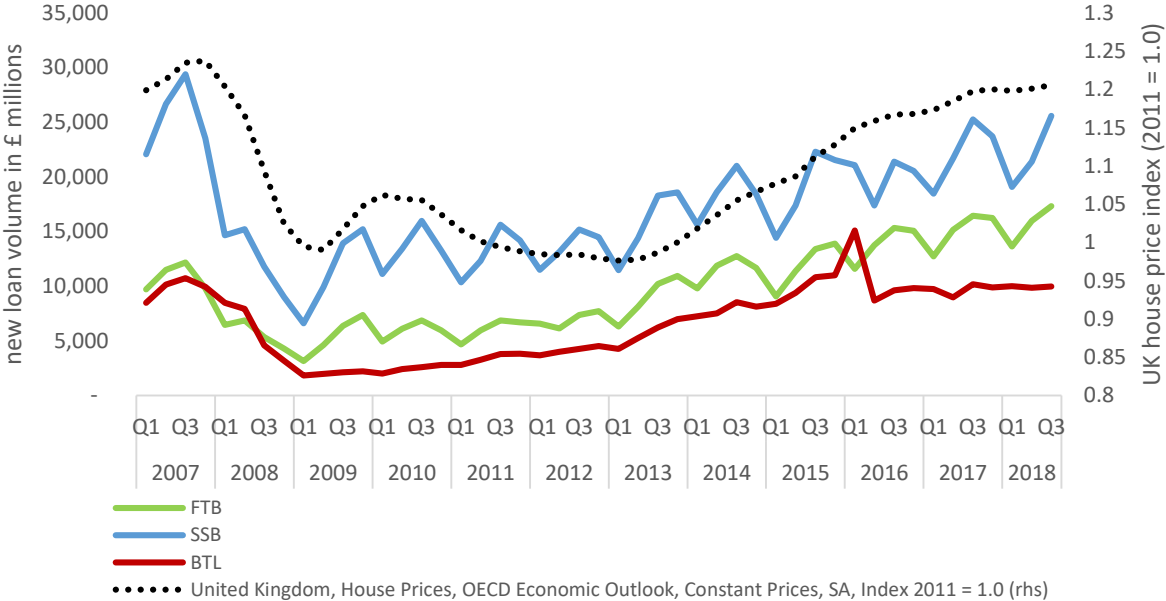
Notes: Residential loan provisions from Bank of England and the FCA in 2011 prices, not seasonally adjusted, taken from https://www.fca.org.uk/data/mortgage-lending-statistics/previous-editions; Source of house price index: OECD Economic outlook

Figure A 6: Monte-Carlo runs and house price cycle regularities
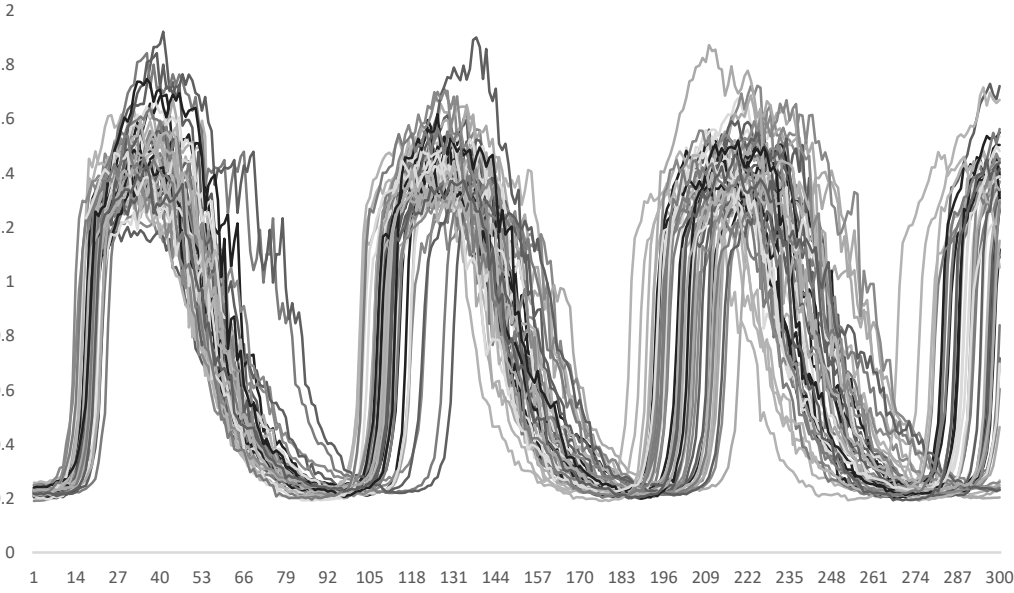
Notes: House price indices of fifty Monte-Carlo runs for 300 periods from the first trough on after the 1500 periods burn-in phase (benchmark model).

Figure A 7: Scatterplots of house prices and debt-to-income shares (in %) with different credit regimes policies (50 Monte-Carlo runs)
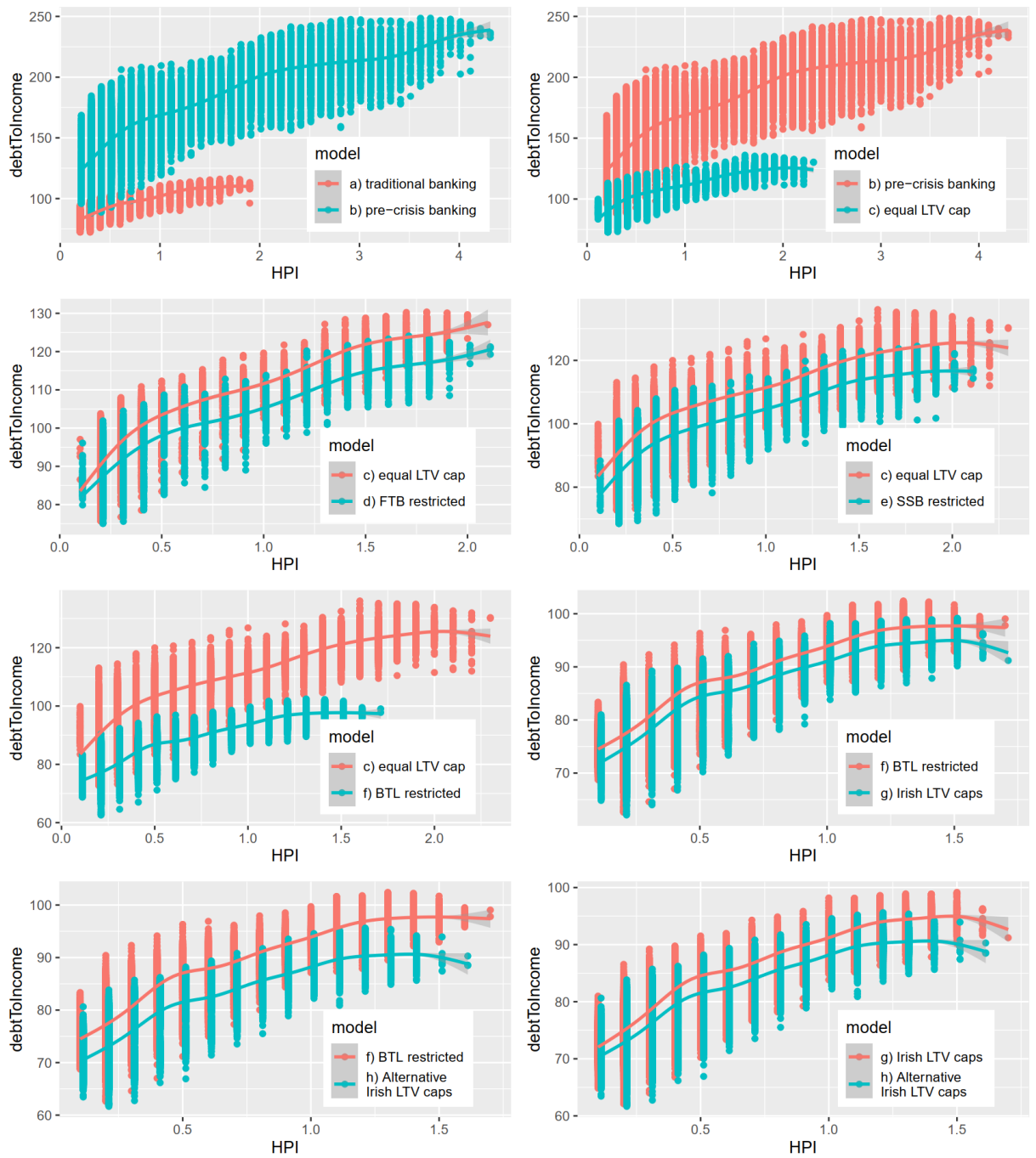
Figure A 8: Scatterplots of house prices and top 10% wealth shares with different credit regimes policies (50 Monte-Carlo runs)
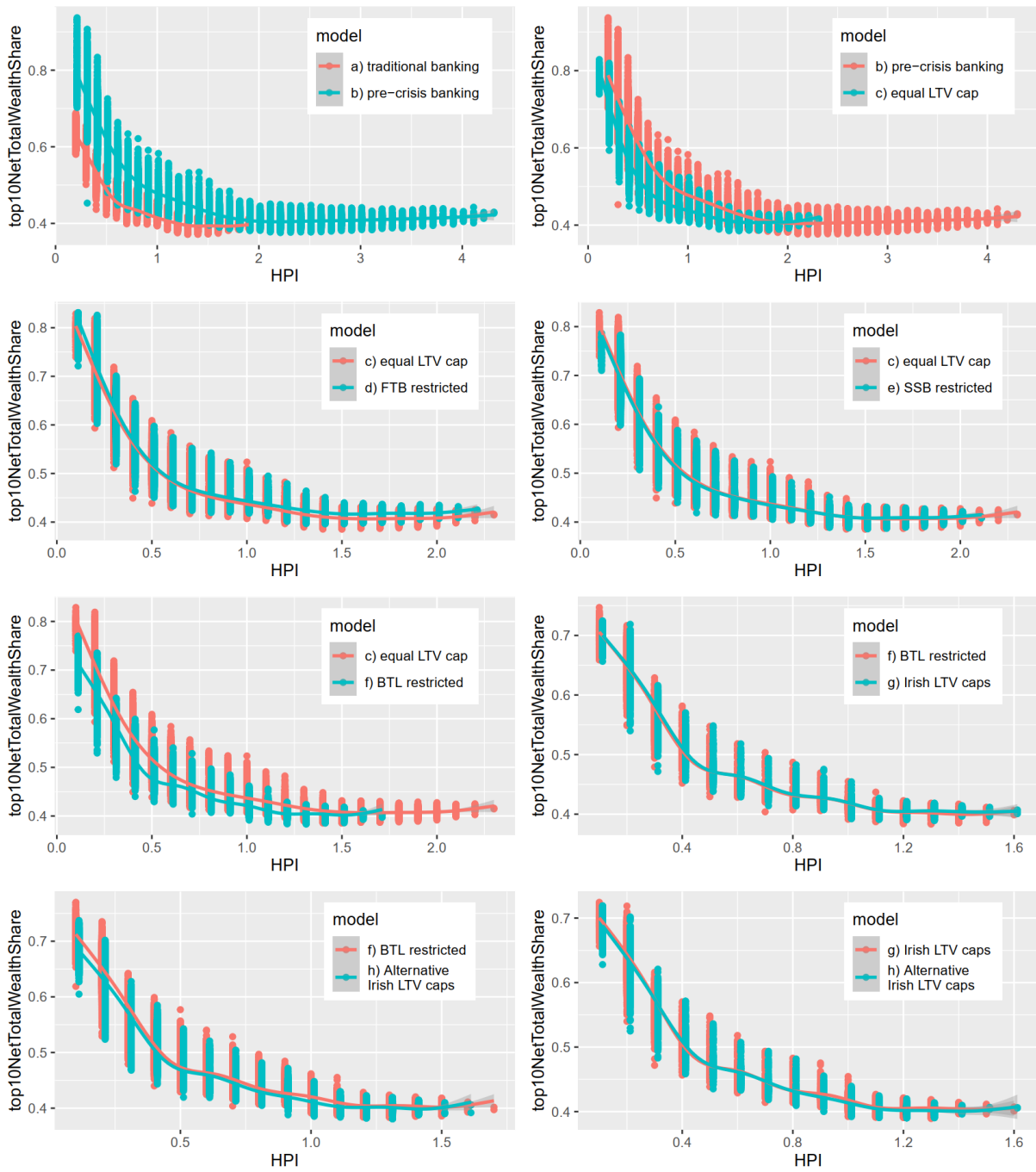
Figure A 9: Histograms of debt-to-income ratios (in %) in different policy regimes
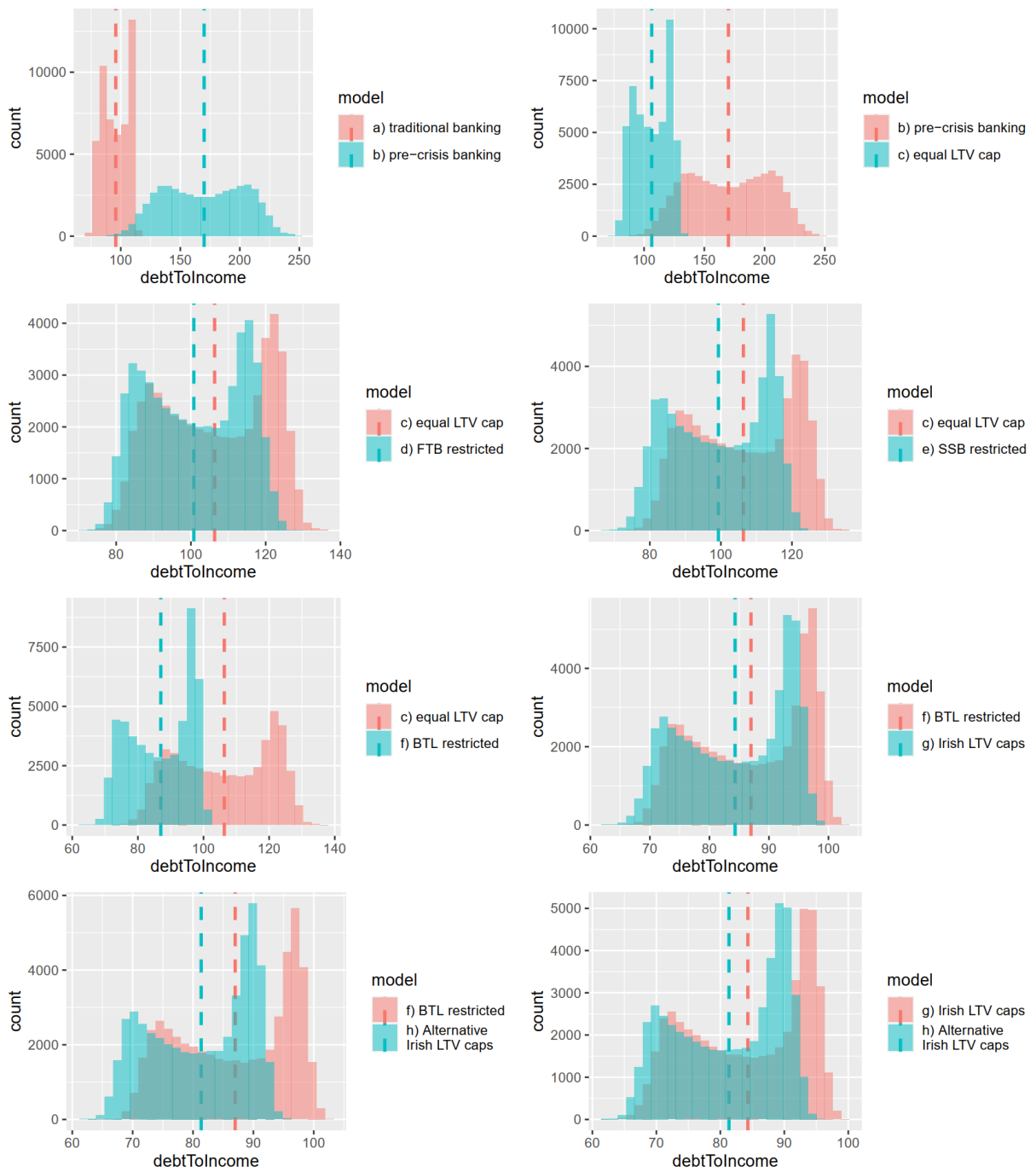
Figure A 10: Histograms of top 10% wealth shares in different policy regimes
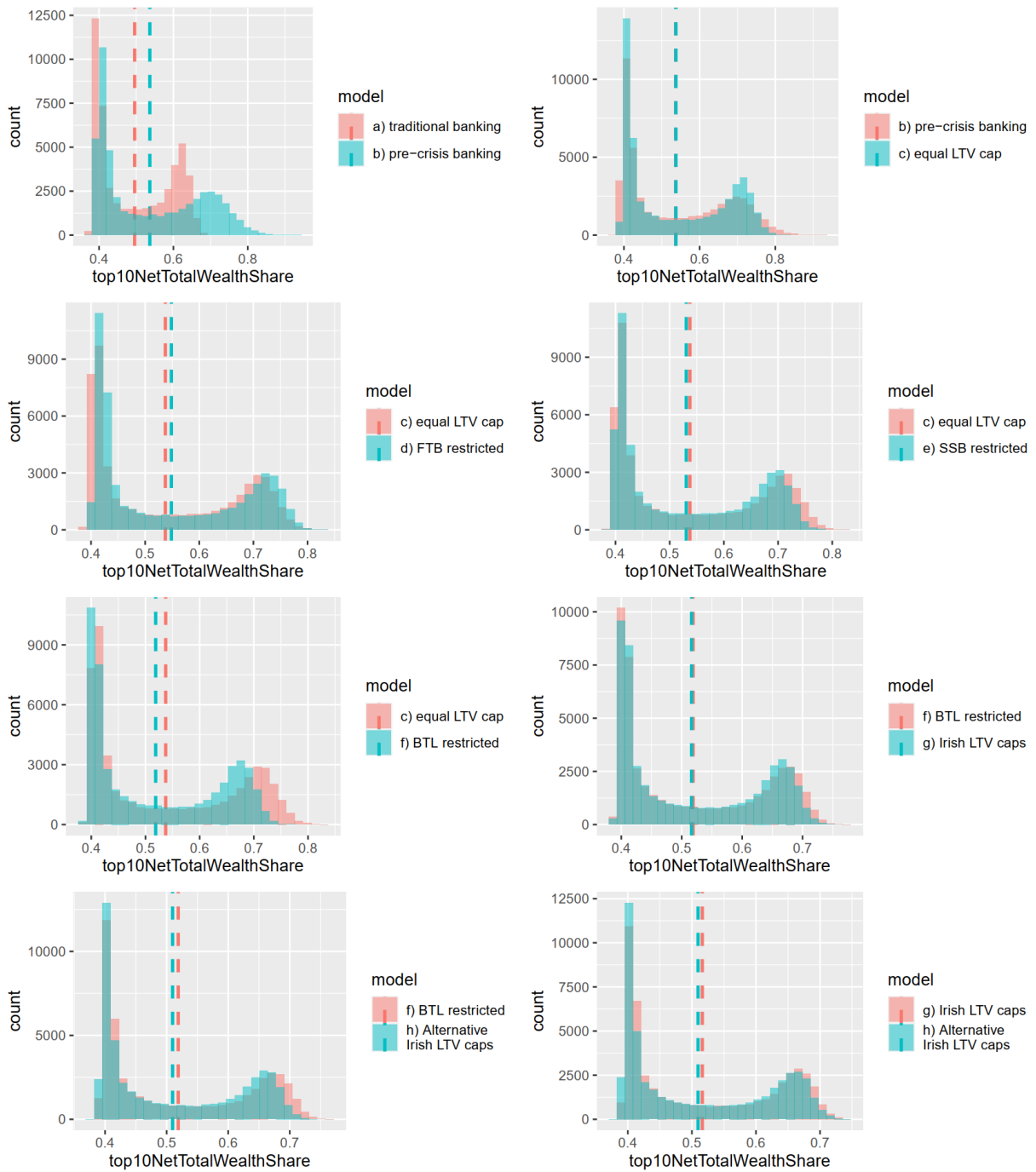
Figure A 11: Histograms of consumption in monetary units per household in different policy regimes
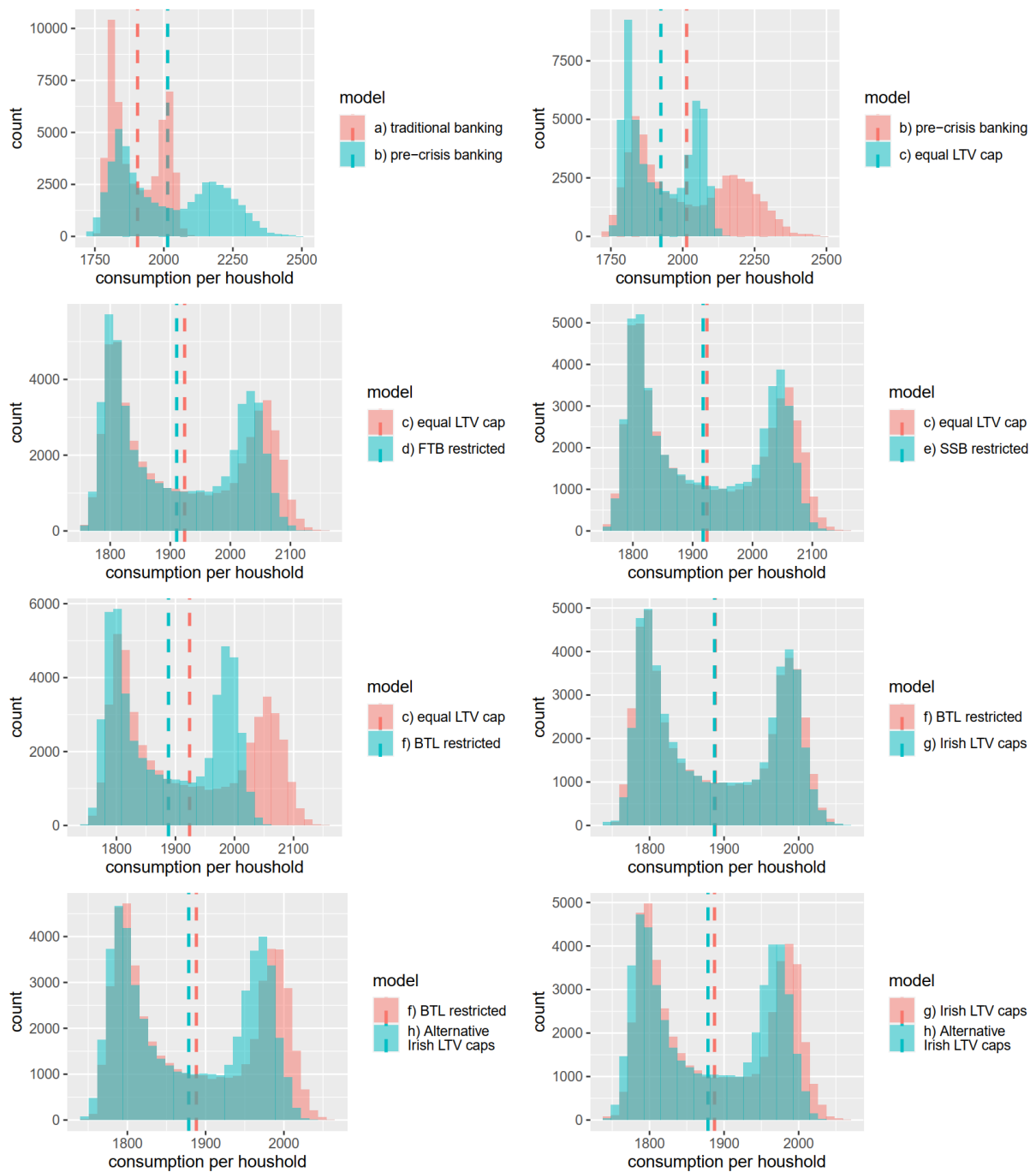
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