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HOUSING AFFORDABILITY IN A MONETARY ECONOMY: AN AGENT-BASED MODEL OF THE DUTCH HOUSING MARKET

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ABSTRACT

This paper is motivated by the global housing affordability crisis. Housing shortages in monetary economies are defined by affordability, which is the balance between money (income and borrowing) to access housing and the price (purchase prices and rents) that provides access. This balance is governed by real variables (demography and housing supply) and by monetary and financial variables (interest rates, mortgage debt subsidies, and loan-to-value norms). We study the trade-offs between policies addressing real and financial causes of affordability dynamics. We use a heterogeneous-agent housing market model calibrated to the Netherlands. We find that a 10% reduction in the peak house price level is achieved by reducing the bank's loan-to-value cap from 96.9% to 93.3%, or by increasing the interest rate from 4.0% to 5.4%, or by increasing the ratio of private properties to households from 69% to 74%. This corresponds to building 420,000 housing units, an effort that faces substantial political, regulatory, and capacity constraints. Higher income inequality weakens the benefits of more construction for first-time buyers, as more of the housing stock is bought as a second home or by buy-to-let investors.

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1 Introduction

What are the causes of housing shortages and housing affordability? This question is highly relevant as Europe, the US, China, and many other OECD and middle-income societies are in the grip of severe housing affordability crises (Wetzstein 2017; Hallett 2021). For instance, in 2015 one in two U.S. households was paying more than 30 percent of their income in rent (Gabriel and Painter 2020) and a quarter of owner-occupied households were paying more than 30 percent of their income in housing costs (Molloy 2020) – with both these percentages substantially higher than in earlier decades.

In this paper, we study affordability dynamics in an agent-based model calibrated to The Netherlands, the 17th largest economy in the world. Much of housing affordability research is on the US, and there is a paucity of research on other economies. Since national housing markets are often highly specific, country studies have a large potential to offer insights (perhaps generalizable) on the causes of the affordability crisis. The Netherlands (and other European countries) experienced a steep acceleration of house price growth between 2015 and 2021 (Dieckelmann et al. 2023). In 2015, a Dutch median-income renter household could buy any housing unit in the bottom 38% of the Dutch housing stock, ranked on increasing price. In 2022, to do this one had to be in the top 30% incomes of the renter population (Groot, 2022). In these years, the current global affordability crisis accelerated.

Affordability concerns, high house prices, and high rents are often attributed to insufficient housing supply and, in turn, frequently viewed as caused by supply regulation (Glaeser and Gyourko 2012; Hilber and Vermeulen 2016; Meen and Whitehead 2020; Hilbers and Eijking 2022). But increases in housing-related expenditures need not occur because of changes in the quality or amount of housing consumed, or physical supply factors (Albouy et al. 2016). This motivates the present paper.

In illustration, the number of households per one hundred housing units in the Netherlands was the same in 2020 in the midst of the affordability crisis (namely, 101) as in 2014 (also 101) when the house price boom got underway. It was only marginally higher than the post-2000 minimum in 2008 when it was 100 (Groenemeijer 2021). But while the housing stock per population hardly moved, house prices and affordability have gyrated wildly. In other countries, there are similar disconnects between stable or even rising per capita living spaces and dwelling, and Even allowing for the regional nature of shortages, this begs the question what, then, are the causes of the dynamics of house prices, housing affordability and housing shortages, if not only housing supply and population trends?

Attempts to answer this question run into the conundrum that shortages are an ostensibly physical concept, yet are irreducibly monetary in nature. In addition, houses are not only durable consumption goods but also investible and leveraged assets. Because of these two features, money (payment flows) and finance (leverage and capital gains) must be part of any model explaining house prices. For instance, buyers' borrowing capacity is a driver of house prices in the Netherlands (DNB 2020); but at the same time the borrowing capacity of renters has over 2013-2020 lagged house prices, reducing their housing affordability (Nordman 2020).

During the rising affordability crisis over 2013-2020, about 90 thousand housing units of the Dutch housing stock came into investor ownership, sold by owner-occupiers. This was a third of the 300 thousand housing shortage in 2022 (De Vries and Hans 2023). Historical research shows that investors' yield-seeking behavior can cause large booms and busts in house prices (Korevaar 2023), and therefore in affordability.

The monetary and financial nature of housing markets is among the reasons that their development is nonlinear, characterized by cycles that last around two decades (Jadevicius and van Gool 2020). The underlying transaction dynamics in upswings are markedly different from the downswings.

Markets for both property and credit do not typically clear so there is no price-mediated quantity equilibrium. Agents in housing markets (owner-occupiers, buy-to-let investors, renters) are heterogeneous and they interact to produce housing market features ('emerging' properties) that cannot be observed or analyzed at the level of representative agents.

For all these reasons, modeling and analysis need to reflect interacting, heterogeneous agents acting in historical time, producing system-level nonlinearities such as cycles and tipping points. Standard models in economics are timeless or two-period; they employ representative agents; and they often omit money and credit. The assumption is that markets move from one price-mediated quantity equilibrium to the next, without modeling the transition paths.

A model class that is more suited to reflect the complex-system nature of housing markets is agent-based models. In this paper, we employ an agent-based model to analyze the trade-offs between physical supply responses and monetary-financial policies, calibrated to 2017 Dutch data. We estimate the effects of interest rates and loan-to-value caps on housing prices, and we compare this to the effect of changes in housing supply.

Previewing the results, we find that a 10% reduction in the peak house price level is achieved by reducing the bank's loan-to-value cap from 96.9% to 93.3%, or by increasing the interest rate from 4.0% to 5.4%, or by increasing the ratio of private properties to households from 69% to 74%. The model highlights how these policies are alternatives in reducing housing prices. We also trace the consequences for affordability in terms of first-time buyers' down payments, debt service, and their share of all properties. A key insight is that bank credit dynamics are central to understanding the relative (in) effectiveness of construction in increasing first-time buyers' share of the housing stock, relative to financial policies such as LTV caps.

This is highly relevant to current policy challenges. Increasing the model ratio of private properties to households from 69% to 74% is the model equivalent of adding about 420,000 residential units in the Netherlands. This model estimate is consistent with Dutch Central Bank estimates that every 80,000 houses would lead to a 1-2% price drop. Extrapolating this (linearly) to achieve the price decline of 10%, the housing stock would need to grow by 400,000 - 800,000 units (on a 2017 housing stock of 8 million), enclosing the estimated 420,000 units. Construction on this scale is challenging in terms of spatial planning, administrative procedures, and the environment. The policy relevance is that construction is not necessarily the most effective response to the affordability crisis. Housing shortages are not only physical but also monetary and financial in nature, and financial policies must be part of the solution.

In the next section, we explore this monetary and financial nature. We then discuss the housing market and affordability crisis in the Netherlands, and we survey the academic and policy literatures on the effects of interest rates and financial policies (LTV and LTI caps) on credit and house prices. We then introduce the agent-based model in section 3, simulation results in section 4, and a discussion and concluding remarks in section 5.

2. Connections to the Literature

2.1 The Nature of Shortages

Economic intuition suggests that housing shortages exist due to a rise in demand for housing relative to the supply of housing, reflected in rising house prices. Shortages are then viewed as a quantity concept, traced to a lack of balance between two other quantities, supply and demand of housing. The drivers of physical demand and supply of housing are presumed to be population growth, lifestyle preferences, and income growth on the demand side, and construction, location, and local amenities on the supply side. This leads to an analytical model explaining housing shortages in terms of 'fundamentals' (Hort 1999). In that model, prices may stand in for physical shortages or surpluses, since variations in prices are viewed as exclusively reflecting variations in excess demand or surplus supply. What is missing in this conception is the notion that capitalism is monetary and financial capitalism (Keynes 1933), more than a system of physical production and consumption.

Consider the measurement of shortages. The unit in which statistical housing shortages are expressed is a physical quantity concept: the number of houses that a population lacks in seeking to fulfill its housing needs. But what is in fact counted are not houses, but people A housing shortage is defined as the number of individuals (scaled by household size) who want to form an independent household but cannot. This includes homeless people, people above 25 years of age who are living with their parents, immigrants living in institutions, and people living in non-residential housing such as office buildings (MBZK 2021)[3, 4].

Therefore a housing shortage means that too many prospective buyers are confronting too high ask prices. What is labeled 'shortage' in the statistics, and expressed (but not counted) as a quantity of housing units, is in fact not a deficit in physical housing units. It is a shortfall in purchasing power which may or may not be related to a deficit in physical housing. This is better called an affordability problem than a shortage, which presumes that affordability can only be caused by (and therefore, must be equal to) having too few physical housing units. This frames the problem as having only one solution: more construction. But there are other possible causes of an affordability crisis and different solutions.

Experienced shortage, then, is not just the experience of missing a house, it is the experience of missing the money to pay the price or the rent. A housing shortage in a monetized society, whatever its causes, is in the first place about the balance between money (income and borrowing) to access housing and the price (purchase prices and rents) that provides access. These are all monetary and financial variables, influenced by monetary and financial policies and norms such as interest rate

[3] For instance, in 2020 the supply of dwellings was 99,000 and the demand was 378,000, resulting in a 279,000 shortage. The demand is based on the 521,000 households without their own house, composed of different groups: 89,000 living in living spaces other than residential buildings (office space, boats, caravans, institutions) and 432,000 living in shared households (e.g. with their parents). Based on an assumption of how many of the 521,000 households voluntarily do not have their own household in a residential building, the non-voluntary group is estimated to be 378,000, and this is the housing demand in 2021. The supply of 99,000 is computed as the 246,000 dwellings which are not occupied for more than a year and which are not second homes. Of 441,000 empty dwellings in 2021, 195,000 were unavailable mostly because they were second homes (a substantial reduction in the supply) and 147,000 were frictionally and temporarily non-occupied, mostly due to moving and renovations. See MBZK 2021, p. 27, Figure 2.8.

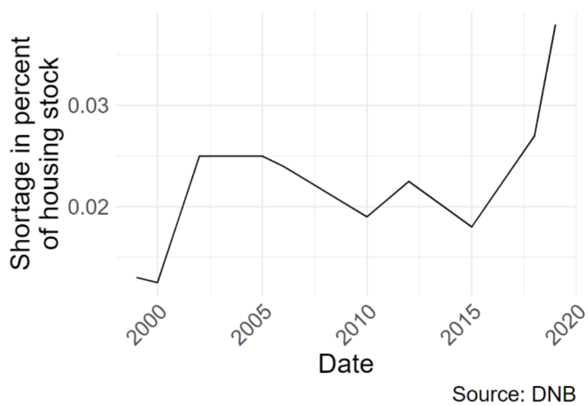
[4] This makes clear that the statistical housing shortage is governed, as much as physical supply and financial conditions, by social norms. For instance, welfare state policies in psychiatric care and in social housing construction may push people into homelessness or prevent them from falling into homelessness. For another example, 25 years as the age threshold to form an independent household is a cultural norm; the younger that age, the bigger the statistical housing shortage in an otherwise identical society. Statistical practice, then, recognizes that the housing shortage is not some physical number of dwellings that should be built to solve the problem. It is the balance of social, cultural, and political influences on unmet housing demand. Change in those norms and policies - such as the privatization of social housing units - might solve or create a housing problem, just as much as housing construction does.

policies, mortgage debt subsidies, and banks' loan-to-value norms (Duca et al, 2021). Would it not be logical to look here for the solution as well?

For instance, rising mortgage debt flows push up housing prices independently of the physical supply of housing. There is "a causal chain going from an expansion in credit to house prices" (Favara and Imbs, 2015:984; Adelino et al, 2012). Landvoigt et al (2015) find that cheaper credit for poor households was a major driver of prices in San Diego County during the 2000s boom, especially at the low end of the market. Mortgage debt can be constrained by financial policies such as loan-to-value caps (Gatt, 2023), which may therefore help resolve housing shortages, quite apart from house building and monetary policies[5].

In the Netherlands, low interest rates, mortgage debt subsidies, and high loan-to-value norms contributed to increasing house prices since the Great Financial Crisis (DNB 2020). Jointly with a slowdown of construction activity, this has resulted in an official 2021 housing shortage of 279 thousand units. This was 4 percent of the 8 million housing stock, the largest shortage since the 1960s. It was double the 2 percent that is considered frictional shortage in a market where all demand is met (MBZK 2021:45); see Figure 1.

Figure 1: Housing shortage in the Netherlands



The increase in reported shortages and double-digit house price increases was matched by double-digit growth of newly issued mortgage credit plus an inflow of investor money (Bezemer and Schoenmaker 2021). These trends are suggestive of financial factors underlying the shortages.

2.2 Modelling the Dutch Housing Market

Dutch house price and housing shortage outcomes have been modeled by, among others Boelhouwer (2005) and Boelhouwer et al (2021). This follows a literature in which a long-run relationship between house prices and borrowing is posited, with temporary deviations from a long-run equilibrium (e.g. McQuinn et al (2008) on Ireland). In Boelhouwer et al (2021), mortgage credit supply and demand are determined by interest rates. This determines the debt-service-to-income ratio and the long-term equilibrium between credit and house prices. Bezemer and Schoenmaker

[5] Glaeser et al (2012) ask "can cheap credit explain the housing boom" and conclude that only 20% of the early 2000s US house price boom was attributable to low interest rates. However, despite the title, Gleaser et al (2012) do not actually study a 'credit' variable. This and other research equates credit flows to interest rates; but there is considerable variation in credit flows for the same interest rate, as experience in the eurozone attests.

(2021) argue that credit may drive price directly, rather than through interest rates or debt service ratios, since credit variations are not fully determined by interest rate variations.

This is modeled by Van der Drift et al (2023) as an equilibrium between mortgage credit and house prices. The advance on earlier literature is agent heterogeneity. The market equilibrium depends on the behaviour of two types of households, those constrained by LTV caps and unconstrained households with equity in their homes. A striking result is that more housing supply will not necessarily reduce the price of housing. Additional demand is still purchased at high prices because demand fuelled by credit is still constrained, in line with Bezemer and Schoenmaker (2021). What could reduce the house price in this model is lower debt-service-to-income (DSTI) caps.

These results presume that there is a long-term equilibrium between credit and house prices and that the demand elasticity of housing is equal to one. However, the assumption of price-induced equilibrium may be inappropriate in the housing market, where credit determines access, since credit is quantity rationed (Stiglitz and Weiss 1981)[6]. If only for this reason, housing markets do not normally clear[7] so the neoclassical price-driven equilibrium mechanism may not be the appropriate conceptual framework.

Other drawbacks of neoclassical theorizing are discussed in, for instance, Colander (2000), Bouchaud (2008), and Lawson (2013), among many others. A key problem is the modeling of representative agent(s) instead of agents interacting with each other. As a result, the economy has no emerging properties such as periods with high and low price volatility. There are no endogenous nonlinearities, as opposed to the complex-system behavior or real-world housing market. There is no role for historical time (instead of e.g. a two-period model) different from the large role of cyclicality and of history in housing markets. The build-up of agents' liquidity in the past determines their current purchasing power, as we find in this paper.

The present paper advances the literature by introducing a different (agent-based) model in which these assumptions - equilibrium tendency, representative agents, no nonlinearities, no historical time - are not necessary, while distinguishing between types of households. We model credit as a variable that is not fully determined by interest rates. We trace the nonlinear market process over time, distinguishing analytically between the upswing and downturn phases. We support the policy implication in Van der Drift et al (2023) that the solution to housing shortages lies in monetary and financial policies, not necessarily only in construction. Therefore, in the next sections, we review literature on the effects of interest rates and financial policies.

2.3 Effect of Interest Rates

There are only a few long-term studies of interest rate effects, capturing one or several cycles. Jordà, Schularick, and Taylor (2020) find for a sample of 17 advanced economies from 1870 to 2006 that a 1 percentage point increase in interest rates causes a drop in real house prices of 5% (4% post-WWII).

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[6] The definition of rationing is that prospective buyers cannot purchase at the going price. Groot (2022) writing on the Dutch housing market that "[f]or first-time buyers, the maximum mortgage is the decisive constraint; once they own a house, they usually can well afford the monthly debt service." (authors' translation). This is rationing of housing by the banks' credit decisions, not price-induced equilibrium mediated by either house prices or interest rates.

[7] There are other reasons, including regulations, why housing markets need not clear. The 2021 report on the Dutch hosing markets states that "experience shows that in some regions, demand will always exceed supply" (MBZK 2021:26).

This value is close to our results in section 4 (a 4.1% decrease in average house prices and a 7.3% decrease in peak prices).

Sutton et al (2017) analyze house price responses to changes in short- and long-term interest rates in 47 economies. They find a role for short-term interest rates as a driver of house prices, but the rate impact is gradual rather than immediate, and not observable in each quarter after the rate shock. Up to five years after short-term rates increase, there are negative house price impacts (Sutton et al 2017, Table 3). However, the quarterly lagged coefficients (some of them positive) vary too much for a reliable quantitative estimate.

Wong et al (2003) is a long-term study using 1981-2001 data on Hong Kong that illustrates this heterogeneity of causal relations over time. They find a moderate correlation between house prices and interest rates in the deflationary 1998-2001 years and then a clear relation between reduced interest and higher housing prices until 1997, which however disappears thereafter when, in the authors' interpretation, negative effects on house prices of anticipated capital losses after the Asian crisis balance lower interest rate effects. This highlights the relevance of the asset nature of housing.

Studying housing as assets also underpins the shorter period that Dieckelmann et al (2023) analyze. They study the acceleration of house price growth in euro area countries between 2015 and 2021. They report non-linearities in the house price response to interest rate, consistent with asset pricing theory. An increase in real interest rates from ultra-low levels could lead to much larger house price reductions than the literature suggests. This finding is in line with the substantial rebounds in house prices in many developed economies after the outbreak of COVID-19, when inflation rose and real rates dropped. Similarly, in an analysis of Australia, Canada, the European Union, New Zealand, the United Kingdom, and the United States from 2017Q1 to 2021Q1, Yiu (2021) finds that a 1% fall in the real interest rate caused a 1.5% increase in house prices in this period.

But Shi et al (2014), working with data on New Zealand during 1999–2009, estimate that both policy rates and real retail mortgage rate rises did not decrease but increased real housing prices. Dokko et al. (2011) find for data on 17 OECD countries in the mid-2000s that falling rates were not the main reason for rising house prices. Miles (2014) and Glaeser et al (2012) find only weak effects of US monetary policy rates on house prices.

Given nonlinearities over time and over interest rate levels in the house price – interest rate relation, it is unsurprising that the evidence is mixed[8]. Another frequent reason must be that most studies are shorter-term than the five-year lagged impacts which Sutton et al (2017) report; shorter-period studies miss the full impact. In the present paper, we analyze impacts as averages over the full cycle, which is estimated at 22 years in the Netherlands (Jadevicius and van Gool 2020) and which includes the ultralow real interest rate levels studied by Dieckelmann et al (2023).

2.4 Effects of Financial Policies

Much research equates credit flow variations to interest rate fluctuations, leaving credit out of the interest rate model. But in a quantity-rationed mortgage credit market (Stiglitz and Weiss 1981),

[8] Dieckelmann et al (2023:3) report enormous variation in the percentage change in real house prices for a given percentage point change in the real interest rate (the semi-elasticity) across the literature. This ranges from -3.6 (Cihák and Shanghavi 2008), between -1.2 and -9.1 (Adelino et al 2012), -20, (Himmelberg et al, 2005), between -1.0 and -6.8 (Glaeser, et al 2012), between -3.2 to -3.3 (Sherlund 2021), to -12 to positive (Havranek et al 2021). Cihák and Shanghavi (2008) review more than 20 studies and find values between zero and -8.

price changes need not necessarily correspond to quantity changes, or have decisive impacts. It is therefore unsurprising that monetary policy is not necessarily effective in constraining house prices (Crowe et al. 2011). Variations in credit growth may move out of sync with changes in interest rates.

Indeed there is much stronger evidence on credit flows and house prices (Adelino et al, 2012; Favara and Imbs, 2015; Duca et al 2011, 2021). Therefore it makes sense to consider ways to constrain credit flows other than by monetary policy, by limiting loan-to-value or loan-to-income ratios. However, the literature is ambiguous on the quantitative effects of LTV caps. This is only to be expected in a highly nonlinear market with cycles and tipping points, and markedly different transaction patterns over the cycle. For instance, "tightening of LTV and DTI limits [is] more effective when credit is expanding quickly or when house prices are high relative to income" (Jácome and Mitra, 2015:24, referring to the McDonald (2015) overview study). These nonlinearities suggest the use of agent-based models. Laliotis et al (2020) calibrate an agent-based model with European data from the Household Finance and Consumption Survey and find that LTV caps lead to reductions in property prices and debt levels.

An illustration of the diversity of experiences even within one country is Igan and Kang (2011) who estimate that an LTV intervention (dummy variable) in South Korea was associated with a 50-70% decrease in the growth of house price change (log change of house prices) after three to six months of the intervention. In addition, Yun and Moon (2020, table 5) estimate for the South Korean housing market in a later boom stage compared to Igan and Kang (2011) that a one percent increase in LTV reduces the house price index by 2 percent. But overall, cross-country studies show that LTVs and DTIs have substantial and long-term effects on credit and on real house price growth". Jácome and Mitra (2015:24), citing Crowe et al (2011) and Duca et al (2011), note that the "empirical evidence suggests that a ten percentage point increase (decrease) in the maximum-allowed LTV ratio is associated with a 13 percent increase in nominal house prices (ten percentage point decline in the house price appreciation rate)".

Other studies are consistent with the direction of the effect, although its strength varies greatly. Alam et al. (2019) estimate that a 0.65 percentage point decrease in household credit growth results from one percentage point tightening of LTV caps (but they do not estimate the effect on house prices.) Hodula et al (2023) research the introduction of LTV limits in the Czech housing market. They find no significant change in mortgage loan sizes and a positive effect (an 8.5% increase) on house prices in transactions – likely because the cap reduced bank lending for cheaper properties. Strikingly they find no separate effect on BTL property prices. Jácome and Mitra (2015) offer an overview of experiences in Brazil, Hong Kong SAR, Korea, Malaysia, Poland, and Romania. They also find in a panel regression that a ten percentage point tightening of LTV has a maximum cumulative impact of lowering the level of mortgage credit by only about 0.7 percent, but "panel estimates for real house price growth yield small and counterintuitive effects" (which are not reported).

The policy and practitioner consensus in the Netherlands is that large-scale housing construction is not feasible due to policy, administrative, societal, and environmental limitations (BB 2022). Perhaps construction is less of a solution to housing shortages than is commonly assumed. With abundant liquidity, new construction might be purchased by others than by those experiencing the shortages, so that shortages need not fall (Van der Drift et al 2023). The literature suggests that limiting debt growth or investor cash for residential investment might reduce financially-driven demand and create the space for housing-needs-driven demand to be met, as prices fall.

3 Model Description

The model we employ to analyze this is based on Tarne (2022) and Tarne, Bezemer, and Theobald (2022), which are both based on Carro et al. (2022). In this section, we discuss the model structure. To preserve the flow of the paper, we relegate the estimation, calibration, and validation procedures to Appendices A, B, and C, respectively.

The model is an agent-based housing model with a bank and 10,000 households of three types: owner-occupier (OO) households, 'buy-to-let' (BTL) households, and households living in social housing. Note that what are BTL 'households' in the model, in reality also subsumes professional real estate investment firms. There are three types of residences: social housing, owner-occupied properties, and privately owned rental properties. Each is heterogeneous in housing qualities, represented in price differences.

The model is not a full macroeconomic model: household wages are determined exogenously, calibrated on 2017 Dutch household data. Consumption expenditures do not feed back as spending into household incomes. The model is also non-spatial and non–physical: location and household features (such as size and amenities) are not fully modeled, apart from a stylized quality-price link. These simplifications allow us to focus on the financial dynamics.

The model is defined in discrete time. In each period, which can be thought of as one month, households receive wages and rental income (if they are BTL households) and they pay mortgages, rent, and consumption. Each month also they make buy/sell/rent decisions and portfolio (save/spend/borrow) decisions. There is one commercial bank that issues mortgage loans according to an internal and pro-cyclical loan-to-value (LTV) rule (Kelly, Le Blanc, and Lydon 2019). LTV is capped, and calibrated to match Dutch housing market variables (see Appendix B).

3.1 Housing Supply

A decrease (increase) in the housing supply in the model means that less (more) of the population can access privately owned housing, either as renter or owner. This is represented in the model as an increase of the share of households in 'social' housing, since this is the residual sector. In the translation to real-world conditions, the model's 'social' housing sector represents not only the real-world official social housing sector but also any other residence situation other than occupying privately owned housing. This includes adults (or adult households) living with their parents, on the streets, and in institutions. Because in the model social housing is a residual category, it passively adapts to conditions in privately owned housing. Changes in the distribution of the population between social housing and privately owned housing can only occur because of changes in the supply of privately owned housing (since by definition in the model, there are no social housing shortages).[9] In the model, an increase in the housing supply by one percentage point means an increase of one percentage point in the share of private properties owned by households.

For example, the shortage of 2.4% in 2017 - the model is calibrated on 2017 data, see Appendix A, - corresponds to 69% of all households having access to privately owned housing, as renters or owners

[9] This is different from real–world conditions, where households can have second (and more) owner-occupied houses. In the model, only buy-to-let investors can hold more than one property, but they rent these out. Therefore, in the real world, more of the population can be forced into social housing without any changes in the privately owned housing stock, but just because of an increasing concentration of privately owned housing with the section of the population owning multiple properties.

(and therefore 31% of the population are in social housing). Between 1999 and 2020, the lowest value of the housing shortage in the Netherlands was 1.25%. This is represented in the model as 70.4% of all households having access to privately owned housing. Likewise, the peak shortage value over 1999-2020 (3.80%) translates in the model to 67.85% of the population in privately owned housing.

Having a social housing sector in addition to renting and owning on the private market increases the model's realism. However, the model still abstracts from social housing constraints (which are assumed absent) and second homes – both factors with potentially substantial effects on shortages and affordability.

In the model, all households in the social housing sector in each period may enter the rental and ownership markets. With a large share of households in the social housing sector, this demand could lead to an unrealistically large demand for housing, with impacts on price formation. In practice, however, the majority of bids made by households in the social housing sector are very low, with no or little effect on market dynamics. Their principal effect is to place a floor under house prices.

3.2 Demographics, Income, Consumption

Each period, households age. Old households die and new households are born. This demographic process with calibrated parameters ensures that the age structure mimics that of the Netherlands in 2017. Households that die, bequest their wealth randomly to some other (living) household. Newly born households are assigned randomly to an income percentile, which is fixed over the course of their life. This simplification avoids the need for modeling defaults (which are rare in the real data). For consistency reasons (and in contrast to Carro et al. (2022)), households do not receive an endowment but start with zero wealth.

A (calibrated) percentage of households above a threshold income percentile is given a "BTL flag". This means they are potential (but not necessarily actual) BTL-type households. These households can purchase property to let and so become BTL-type households.

Each household is now allocated wage income (based on their income percentile and age[10]) and BTL households receive rental income. After paying their mortgage or rent, each household determines its desired consumption based on disposable income, marginal propensity to consume (which decreases with rising income), and net financial and housing wealth. Desired consumption is capped to a maximum, reflecting a precautionary savings motive (Tarne et al. 2022).

3.3 Housing Decisions

In each period, households go through a decision tree regarding their housing situation.

Households entering the simulation start in social housing. They first decide whether to buy or rent by weighing the cost of purchasing and renting a home of the same quality. The cost of purchasing is determined by their desired purchasing price, a function of the household's income, and their backward-looking house price expectations (both calibrated to Dutch household data, row 15 and 20 of Table A.2 and row 10 of Table A.4 in Appendix A). This desired purchase price can be limited by the mortgage amount that the commercial bank is willing to lend. This amount is limited either by the

[10] Income percentiles are estimated for each ten-year age bracket. So a household (head) n percentile 100 aged 20 gets the highest income of 20-year-olds. A top percentile head of household aged 50 has the highest income of 50-year-olds, which is higher than the income of the 20-year-old top percentile. Note that income, while fixed within each percentile, changes in money terms over time.

LTV limit or the households' internal debt-service-to-income ratio (calibrated to Dutch household data, row 34 in Table A.4).

The cost of renting is the expected monthly rent of a home of the same quality as the maximum house quality the household's bid price could afford. Then the household compares the monthly mortgage expenditures and expected house appreciation – the net costs or gains from buying - to the net costs of renting, viz. the rent of a home of the same quality on the private rental market. This comparison results in the probability of putting in a purchase bid or rent bid, with higher probabilities for houses with higher net gains or lower net costs. If the desired purchase price is too low to afford a home of the lowest quality, households will enter the private rental market.

On the ownership market, the bid price is the desired purchase price or the maximum mortgage, whichever is smaller. On the rental market, the bid price is a function of the households' income, calibrated to Dutch household data (row 11 in Table A.2 in Appendix A).

Owner-occupiers decide each month on moving, with the probability calibrated to Dutch data (on average once every 17 years). If they sell, the model places them in the default social housing category before making further decisions on renting or buying, as described above.

A pre-determined subset of households can purchase property to let on the private rental market[11]. BTL households purchase based on expected yields. They are either trend-following or fundamentalist investors, who compute their expected yields as, respectively, expected property price increases and expected rental income (based on past rental prices). BTL households always place empty rental properties on the rental market.

If expected yields turn negative, BTL households are more likely to sell. Selling may also happen with positive expected yields because of liquidity constraints and/or credit constraints (calibrated to Dutch household data), or because mortgage servicing payments are above the internal debt-service-to-income limit. Different from Tarne (2022), owner-occupiers have an internal (desired) debt-service-to-income (DSTI) limit for given incomes and mortgage interest rates. The model interest rate is fixed. In the experiments below we introduce interest rate shocks. (Note that there is also an internal *rent*-to-income ratio.)

3.4 The Market Mechanism

After households make their purchasing and selling decisions, bid and ask prices are matched in a double-auction mechanism.[12] In the first step, each bid is matched with the lowest ask price of the highest possible quality. This usually results in several bids matching one offer. In this case, the ask price increases slightly, some bids may drop out and the buyer is randomly selected from the group of remaining bids. BTL bids are matched with bids that have the highest expected yield, regardless of their quality. Once all houses with at least one bid are sold, any offers or bids left are matched again. The process repeats until no match can be made anymore because the market has cleared (this is rare), because there are no bids left for the remaining offers, or because the bid and ask prices that are left are too far apart (this happens regularly).

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[11] To simplify the model, only owner-occupiers can rent out, ensuring there are no renters renting out properties.

[12] Due to space constraints, we focus here only on the ownership and not the rental market, which works very similarly.

Households that could not buy, then go back to step 1 in the next period. Owner-occupiers who could not sell keep their property on the market in the next period, with some probability of reducing the asking price. BTL sellers will in the next period decide again if they want to sell their property.

The house price level h_t in period t is calculated as the ratio of the sum of all transactions in t-1 to the sum of the reference prices of the sold properties in t-1:

$$h_t = \frac{\sum_{j=1}^{n_{t-1}^{hm\ sales}} p_{k,t-1,j}}{\sum_{j=1}^{n_{t-1}^{hm\ sales}} p_{Q,t-1,j}^{ref}}. \qquad (1)$$

With $\sum_{j=1}^{n_{t-1}^{hm\,sales}} p_{k,t-1,j}$ being the sum of transaction prices of all j transactions of properties k in $t-1$ and $\sum_{j=1}^{n_{t-1}^{hm\,sales}} h_{t-1}\, p_{Q,t-1,j}^{ref}$ being the sum of the reference prices of each of the sold properties (based on their quality band), adjusted for the price level in $t-1$. The base reference prices ($h = 1$) are taken from the house price distribution of 2017, with $\ln\left(p_Q^{ref}\right) = N(13.40201{,}0.414925)$ (see also Table A.2 (Appendix)) and then adjusted by the current house price index. In the model each of the 35 quality bands has the same number of houses. Transactions contribute to increasing prices when the purchase price is above the reference price of the previous period.

The 69 free parameters of the model are plausibly postulated, estimated, and calibrated using Dutch data from 2017, mainly from the European Household Survey (HFCS). The procedure follows Carro (2023) with some changes and is described in detail in Appendix A. The model is run with 10,000 households for 9000 steps (which represent a month), where the first 1000 steps are discarded as the transition phase. All model results are based on ten Monte-Carlo simulation runs. The model best fitting the stylized facts of the Dutch housing market is selected (see Table A.5).

How well does the calibrated model match the data? In Appendix B we undertake a careful comparison of model and reality in five areas: the shape of the cycle, loan-to-value ratios, age distribution, distribution over household types, trading intensity, and differences in trading intensity between household types. We find that the calibrated model matches key housing market indicators and housing dynamics, but some distributions show significant deviations. Upon further exploration, the deviations can be explained by structural simplifications in the model, such as the absence of interest-only loans; the absence of family support for FTB households; and the aggregation of commercial and household investors into one BTL class of 'households'. Each of these model choices adds tractability.

4 Analysis

Having ascertained the validity of the model, we turn to analysis. We conduct experiments to examine the impact of monetary, financial, and construction policies. In line with the paper's focus, we consider the effects on house price peaks (section 4.1) and on first-time buyers' affordability in terms of down payments and debt-to-income ratios (section 4.2).

We simulate changes in three parameters: the number of housing units, interest rates, and loan-to-value caps. We examine the required changes in each parameter needed to realize a 10% reduction in the cyclical peak value of the house price index (HPI). Table 4.1 summarizes the effects on affordability metrics. It shows that increasing the housing supply has mixed effects, decreasing the average debt-service-to-income ratios of first-time buyers, and decreasing their average downpayments, yet the overall first-time buyer ownership goes down. This is mainly due to buy-to-let investors being able to buy up the additional properties.

Some of the findings are not robust, as indicated in the footnotes. Robustness checks with the second-best fitting model of the calibration exercise, which exhibits important differences in the calibrated parameters, and the fifty-best fitting models are performed in Appendix D.

Table 4.1: Policy effects on house price peaks and affordability

Outcomes / **Policy reducing house price peaks by 10% vs baseline**	effects on affordability				
	Age of FTB	Income of FTB	DSTI of FTB	Down-payment of FTB	FTB ownership fraction
Increasing housing supply by 400.000 units (NDL equivalent)	o	o	↓	↓	↓(*)
Increasing interest rates from 4.04% to 5.38%	o	o	o(**)	↓(**)	o
Reducing LTV caps for all borrowers from 96.9% to 93.3%	↑	↑	↓	↑	↓(***)
Reducing LTV caps only for BTL households from 96.9% to 92.8%	o	o	o	↓(*)	o

↑↓ = worsening or improving affordability of first-time buyers (FTB). For example, reducing LTV caps for all borrowers increases the average age and income of FTB (i.e. excluding younger and lower-income households from becoming FTB), increases their downpayments, and reduces the share of owners that are FTB. These are all indications of falling affordability. On the other hand, it reduces the debt service burden, which increases affordability.
*: when the share of BTL investors is higher, as described in Appendix D: o
**: In the second-best fitting model, where the share of BTL investors is lower (Appendix D.1), this turns to: ↑
***: In the second-best fitting model, where the share of BTL investors is lower (Appendix D.1), this turns to: o

4.1 Three Ways to Manage House Prices

Figure 4.1 shows the simulation results that support these conclusions. For each of the three parameters, we report the peak (purple line), trough (blue line), and mean (green line) house price index (in 2017 prices) across increases and decreases of the parameter value. We use Monte-Carlo simulations with 9,000 steps, discarding the first 1,000 as a burn-in phase, and averaging the results across ten simulation runs.

In Figure 4.1, grey error bars represent the trough and peak values across the simulation runs. The parameter values in the baseline model are indicated as a red dashed line. The yellow dashed line indicates the value of the parameters for which the peak HPIs of the models are 10% lower than in the baseline. The pink shaded areas are observed empirical values in the Netherlands, where available (not for LTV caps).

In a baseline simulation, the housing shortage is set equal to the Dutch housing shortage of 3.4% in 2017. Figure 4.1 shows that in this simulation the 10-year mortgage interest rate in the data ranges from 1.7% in 2003 to 5.6% at the end of 2022. LTV caps range between 80 and (close to) 100 percent.[13]

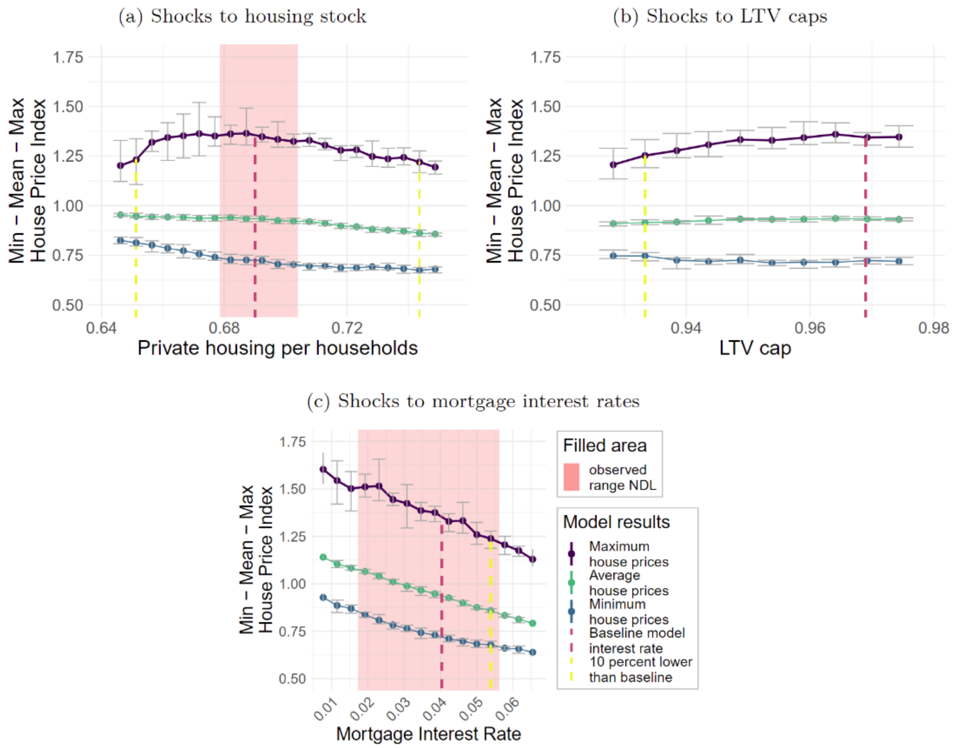


Figure 4.1: Effects on house prices of housing stock, LTV caps, and interest rates

The simulation results in Figure 4.1 (top left) show that a 10% change in the peak house price level (vertical axis) is achieved by increasing the physical supply, raising the ratio of private properties to households from 69% (the red dotted vertical line) to 74% (the right-hand yellow dotted vertical line). This change in the model is equivalent to adding about 420,000 housing units in the Netherlands).

An advantage of agent-based models is that the – often counter-intuitive - transmission mechanisms leading to such results can be studied in detail. For instance, the peak house price level also falls if the private housing stock is *reduced,* as the Figure shows. The reason is that, under the given circumstances, BTL investors, who are otherwise responsible for intensifying the house price upswing, are crowded out of the market. At the same time, it must be said that in this case the model works under extreme conditions, which is evident from the fact that the house price upswing and downswing flatten out considerably (see also Figure C.1 in Appendix C). We explore this in detail in Appendix C.

Figure 4.1 similarly shows that the 10% change in the peak house price level would be achieved by reducing the LTV cap from 96.90% to 93.3% (top right), or by increasing the interest rate from 4.0%

[13] The LTV caps imposed by the central bank exceed 100%, where our model becomes inconsistent; so, we use values just under 100 per cent at most. That the model does not allow for LTVs above 100% implies lower model debt levels than in the Netherlands (Table A.5).

to 5.4% (bottom). These numbers are averages over the entire cycle. In this way, the model shows that the peak house prices can be tempered by increasing supply, LTV caps, and interest rates.

The estimated increase of the housing stock by around 420,000 housing units in the Netherlands lies just inside the estimated effects of new housing on house prices by the Dutch Central Bank (DNB 2020). This estimate suggests that an increase of 80,000 houses would lead to a drop in prices by 1-2%, so extrapolating this effect (linearly) to achieve the price drop of 10%, the housing stock would need to grow by 400,000 - 800,000 units. If anything, the calibrated model is conservative in its estimation of construction needs. Also, the simulated effects of interest rates and LTV caps are well within the wide range of findings in the literature, reviewed in section 2.

We also estimate the effect of only reducing BTL investors' LTV caps, while leaving those for FTB and SSB households unchanged (Figure 4.2). Since affordability is mostly a concern for FTB households, this borrower-specific policy might be more effective; it has been implemented in e.g. Ireland (Central Bank of Ireland 2022). We found that applying a BTL-households-only LTV cap (left panel), a reduction in that cap from 95.7% to 92.8% is required for the 10% house price reduction – a number only slightly lower than the reduction to 93.3% in the case of an all-households LTV cap.

In Appendix D, we probe the robustness of these results, by examining simulations using a sample of the next best-fitting models from the calibration.

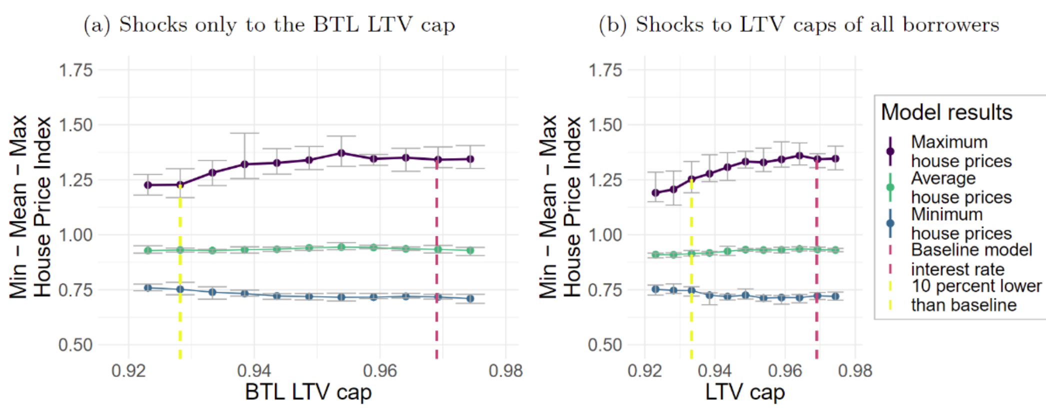


Figure 4.2: Effects on house prices of BTL-households-only LTV caps

4.2 Affordability

Even if changes in interest rates or LTV caps reduce house price peaks, this need not solve affordability problems. For some households, notable first-time buyers, affordability may actually fall with lower house prices, if an increase in down payments or in debt service limits their access to credit, and therefore housing. In this section, we assess first-time buyers' housing affordability as measured by the required down payments and monthly debt service.

Note that since we keep interest rates fixed in the model, changes in income and loan size determine the debt service burden. Since the other element of affordability is the size of the down payment, affordability is not determined only by household variables but also by bank behavior. With larger loans for the same house price, debt service rises (lower affordability) and down payments fall (higher affordability). Variations in bank lending across the credit cycle will then influence the affordability of housing. This can lead to counterbalanced results, as we will now see.

Table 4.2 shows the age and average income of FTB households; the higher the average income, the more lower-income households are apparently excluded from becoming FTB households (since income itself is exogenously set). We also report loan-to-income (LTI) and debt-service-to-income ratios as well as the Loan to Value (LTV) ratio. In Table C.1 in the Appendix, we report additional outcomes of these policy experiments.

Table 4.2: First-time buyers' affordability in five policy scenarios leading to house price peaks 10% lower than in the baseline

	average values for FTB at purchase							average homeownership distribution				
Model version	Age	Monthly income	LTI	DSTI	LTV	Purchase price	Downpayment	Share of FTB hh	std of av share of FTB hh	std of share of FTB hh	Share of SSB hh	Share of BTL hh property
baseline	32.72	6'177	2.700	0.1733	0.9054	183'341	21'315	0.189	0.00150	0.0101	0.361	0.0912
less housing	32.21	6'092	3.012	0.1932	0.9242	197'138	17'370	0.203	0.00119	0.0055	0.368	0.0493
more housing	32.73	6'199	2.524	0.1619	0.9127	170'576	18'577	0.182	0.00133	0.0063	0.363	0.1446
lower LTV cap	33.02	6'236	2.623	0.1685	0.8965	181'413	22'027	0.183	0.00088	0.0069	0.355	0.1049
lower BTL LTV cap only	32.60	6'150	2.804	0.1799	0.9136	187'603	19'825	0.188	0.00140	0.0060	0.363	0.0934
interest rate up	32.61	6'161	2.455	0.1807	0.9036	167'652	20'321	0.192	0.00228	0.0111	0.371	0.0819

Note: The results stem from 10 Monte-Carlo Simultions run with 3000 periods for each model version, where the first 1000 periods have been discarded. Std. of av. share of FTB hh gives the standard deviation of the FTB ownership share between MC runs; std. of share of FTB hh gives standard deviation of the FTB ownership share when averaged over all 10 MC runs, indicating their variability within a simulation run.

Table 4.2 shows these measures for the baseline model and five experiments. In the baseline model, the average downpayment of a first-time buyer is 21,315€. Counter-intuitively, with less housing (fewer private properties in the model) this falls to 17,370€. The reason is that less housing increases the average price an FTB household pays, and their debt rises by more than the house price rises so their down payments fall. They can borrow more: the LTI in this scenario (3.0) is higher than it is in the baseline (2.7). This is due to the higher availability of credit in a housing market with shorter downturns and longer upswing phases. Table C.1 in the Appendix shows that the share of 'upswing years' in all years increases from one-third to one-half in this scenario, a result of BTL households driving the cycle less than they did in the baseline (see for more detailed results section C.1 in the Appendix). So due to the procyclicality of credit conditions for FTB households, in the regime with longer upswings, housing becomes more affordable in terms of down payment, even while more expensive. The average income of FTB households falls, indicating that housing becomes more accessible to lower-income households. The effect is not symmetric, as Table 4.2 shows. With more housing, down payments *also* decrease compared to the baseline, because purchase prices fall, while the average income of FTB agents does not fall. To state once again, it is not the case that housing supply reduction decreases the housing availability for FTB households in the model.

The right-hand panel of Table 4.2 shows that when the housing supply is reduced, the share of FTB households in all households rises somewhat (from .19 to .20), while with the other policies the changes are insignificant relative to the standard deviations reported. The rise of FTB households among owners when the housing supply falls is balanced by a strong reduction of the BTL households' share (from .09 to .05). Conversely, BTL households increase their share of all properties quite strongly when the housing supply rises (from .09 to 0.15). This reduces the supply to FTBs, which helps explain the limited effectiveness of housing supply expansion on FTB affordability. This limited supply effect can be studied through the lens of inequality in income, as we explore in the next section.

Table 4.2 further shows that lower LTV caps for all reduce housing affordability for FTB households: they borrow less and pay down more, at purchase prices that are only marginally lower. This excludes households at income levels that gave access to housing in the baseline, as signified by the higher average income level of successful FTB households.

Moreover, Table 4.2 also shows that in the BTL-only LTV reduction scenario, FTB households' average down payment falls and their loan amounts rise, so that housing affordability for them rises and lower-income households can now purchase housing[14]. Their average leverage rises, but only marginally. To the extent that FTB households' affordability is the focus of policy, by this metric this is a highly effective intervention.

Finally, Table 4.2 shows that increasing interest rates increase housing affordability for FTB households by reducing their average down payments. While the share of FTB households increases slightly, this is just above one standard deviation above the baseline (0.189 + .0015 = 0.1905).

4.3 Inequality Weakens the Supply Effect on Affordability

A final key finding of the experiments is that the distribution of housing over BTL and other households matters to the housing supply's effect on affordability. We take the share of FTB households in the population (i.e., access to owned housing for those who do not own) as the metric for affordability.

Recall from section 3.1.1 that a (calibrated) percentage of households above a threshold income percentile are potential (but not necessarily actual) BTL-type households. Since both a higher income and more wealth make buying a property to let more likely, variation in the share of such 'dormant' BTL households represents variations in top income inequality. Here we study what such variations in inequality mean for affordability.

We consider results from the fifty best-fitting models from the calibration exercise in Appendix A, where the share of dormant BTL households can vary between 2.2% and 11%. In Figure 4.3 we report the effects of construction (housing supply growth) on affordability (the share of FTB households in the population). We do this separately for the top and bottom quartiles of model results, ranked by their dormant BTL share.

In the Figure, we plot FTB ownership share (vertical axis) against the housing stock per population (measured as private housing units per household on the horizontal axis). The dotted lines are one-standard-deviation confidence intervals. The green graph shows that increasing the housing supply when the share of potential BTL households is large (i.e. with high income inequality), the share of FTB households in the population tends to fall. Conversely, in simulations where the share of BTL households is low (the purple graph), more housing does not negatively affect the share of FTB households. But equally, even with few BTL households, representing more equal income and wealth distributions, more housing does NOT increase affordability.

The intuitive explanation is that with more potential BTL investors – that is, more rich households and professional investors - more of any increase in the housing supply will be snapped up by those rich households and investors, leaving a lower share of the additional properties for FTB households. This is consistent with the results in Van der Drift et al. (2023).

[14] The higher affordability for FTB households is only partly replicated in a model version where cycle dynamics are less driven by BTL households (Table D.3 in Appendix D).

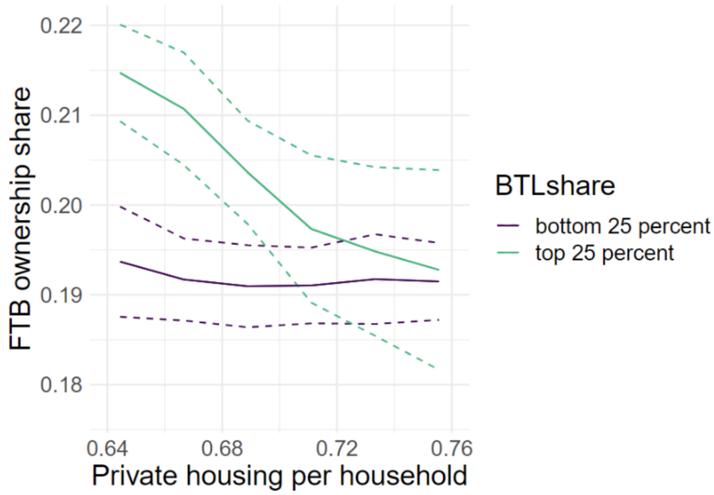


Figure 4.3: The income distribution matters to the effect of housing supply on affordability

Notes: 'BTL shares' are the top and bottom quartiles of the potential BTL population shares across simulations. Results are based on the 50 best-fit models. Dotted lines indicate one-standard-deviation confidence intervals.

Again, the ABM nature of the model helps us to understand more fully the mechanisms leading to the result. It turns out that there is a positive feedback loop that amplifies the effects of lower FTB shares. The higher BTL share in the property market leads to stronger house price cycles and therefore lower LTVs for FTB households in the longer downturn phases, where they are the main buyers on the market. Since FTB households are more credit-constrained than BTL households, who enjoy rental incomes, in the upswing even more of the housing supply goes to BTL investors. This is a self-sustaining loop, since the larger housing share of BTL amplifies credit cycles. Ultimately this loop is weakened by the FTB demand for housing when prices are low, but the result is that the income distribution matters more to the effect of housing supply on affordability than would be the case without this capital-gain-cum-credit constraints loop.

5 Summary and Conclusion

This paper was motivated by the global housing affordability crisis since the mid-2010s (Hallett 2021). The study is undertaken in the context of the Netherlands, a medium-sized highly developed economy. Dutch house prices increased sharply over the period of 2014-2021 and the official 2021 housing shortage of 300,000 housing units (4% of the housing stock) is double the level where non-frictional demand for housing can be met (MBZK 2021).

The paper addressed the monetary nature of the economy. The statistical definition of the housing shortage shows that this key statistic is not only physical in nature, even though expressed in the number of dwellings. A housing shortage is the widespread shortfall of purchasing power for given house price levels, with both purchasing power and prices being monetary variables. This paper developed the argument that not only the nature but also the causes of a housing shortage are not necessarily solely physical (demographics and housing supply). They are also monetary and financial, features that cannot be reduced to macroeconomic 'fundamentals' (preferences and incomes).

This was explored in an agent-based model with heterogeneous households and differentiating between private (owned or rented) properties and the social housing sector. The model, calibrated to 2017 Dutch data, produces cycles that map reasonably well onto the Dutch housing cycle. We further validated the model's realism in terms of loan-to-value ratios, age distribution, distribution over household types, trading intensity, and differences in trading intensity between household types.

We estimated the effects of interest rate rises and loan-to-value cap policies on housing prices and shortages, and we compared this to the effect of changes in housing supply. In the model simulations, a 10% change in the peak house price level is achieved by reducing the banks' loan-to-value cap from 96.90% to 93.3%, or by increasing the interest rate from 4.0% to 5.4%, or by increasing the ratio of private properties to households from 69% to 74%. The real-world equivalent of this would be adding about 420,000 residential units in the Netherlands. Since housing construction on this scale appears not feasible in the medium term due to policy, societal, and environmental limitations, it seems worthwhile to explore further the option to limit debt growth by interest rate and loan-to-value cap policies.

Future analysis and policy applications should take into account the limitations of the present analysis. Importantly, the supply side of the housing market is not modeled but exogenously given. This means that any negative private-sector supply response to the proposed policies is still to be incorporated, along with the policy response in the social housing sector that could ameliorate a private-sector construction slowdown.

Also, this is a market model, not a macroeconomic model. It has no economy-wide effects on housing market developments – these tend to be substantial, also in the Netherlands (Bezemer and Schoenmaker 2021) – nor their feedback into housing markets through sentiment and valuation effects.

APPENDICES

APPENDIX A: ESTIMATION AND CALIBRATION

For the estimation and calibration, we mostly follow the procedure used by Carro (2023) on Spanish data. Table A.1 shows the five postulated model design parameters.

Table A.1: Model design parameters

Parameter	Value
Seed for the random number generation	1
Number of simulation runs	9000
Number of periods per simulation run	10
Number of periods after which to record	1000
Number of households	10000

Table A.2 reports the 30 parameters in the model which were set exogenously, based on data taken from the third wave of the European Central Bank Household Finance and Consumption Survey (HFCS) (ECB 2020). The HFCS includes data on households' income, their financial and housing wealth, their debt, and their mortgage payments. This wave includes 2,556 Dutch households, surveyed around 2017.[15] Therefore, where possible, other data from 2017 is used to motivate parameters and calibration targets, and the model is made consistent with 2017 Dutch institutional features where possible.[16]

Importantly, the HFCS also includes data on the purchase price of the households' properties and the mortgage amounts at origination. In combination with other sources[17], this allows us to estimate a number of model parameters, as reported in Table A.2. The Table also reports the estimation procedure.

Some model parameters could not be motivated from the data. These are reported in Table A.3. Seven parameters are set equal values of the UK calibration of this model (Tarne 2022) and 11 parameters were plausibly postulated. The remaining 16 parameters were calibrated using the method of simulated moments (Franke 2009; Franke and Westerhoff 2012).

[15] The age of a household in the HFCS survey is defined as the age of the household member with the highest personal income.

[16] For instance, tax rates are Dutch 2017 tax brackets of 2017, see https://belastingdienst.nl. The minimum monthly income is set to the 2017 social security payment for a married couple which is 1247€, see https://www.nibud.nl/.

[17] The other sources include the Ministerie van Binnenlandse Zaken en Koninkrijksrelaties (2018) (here abbreviated MBZK2018), Ministerie van Binnenlandse Zaken en Koninkrijksrelaties (2017) (MBZK2017) or the ECBUsed here: the time series of gross disposable income of Dutch households with the code "QSA.A.N.NL.W0.S1M.S1.N.B.B6G._Z._Z._Z.XDC_R_POP._T.S.V.CY._T".

Table A.2 Parameters estimated with data

Parameter	Value	Source
Rent paid by households in social housing	529	www.government.nl, HFCS[a]
Average years that owner-occupiers move housing	17	HFCS[b]
Ratio of private to social housing	0.69	MBZK2018, MBZK2017[c]
Government monthly income support	1247	https://www.nibud.nl/[d]
Distribution of employment income by age	Estimated distribution	HFCS
Age distribution	Estimated distribution	HFCS
Minimum income percentile for BTL investors	0.6	HFCS[e]
Tenancy length distribution of households in private renting		
average	95	HFCS[f]
standard deviation	119	HFCS[f]
Desired rent-to-income fraction		
Intercept	7.028643	HFCS[g]
Beta	0.1707986	HFCS[g]
standard deviation of the residuals	0.3430468	HFCS[g]
Desired purchase price for owner-occupied property		
Intercept	6.244125	HFCS, ECB[h]
Beta	0.557319	HFCS, ECB[h]
standard deviation of the residuals	0.3613434	HFCS, ECB[h]
Monthly consumption induced by housing wealth	0.0021738	Zhang (2019)
House price expectation as multiple of past house prices	0.3573437	HFCS[i]
House price distribution		
Scale parameter	12.40201	HFCS, OECD[j]
Standard deviation	0.414925	HFCS, OECD[j]
Rental price distribution		
Scale parameter	6.800651	HFCS, OECD[k]
Standard deviation	0.2163964	HFCS, OECD[k]
Desired downpayment distribution of owner-occupiers		
FTB Scale parameter	10.77896	HFCS[l]
FTB Standard deviation	1.225692	HFCS[l]
SSB Scale parameter	11.4721	HFCS[m]
SSB Standard deviation	1.082031	HFCS[m]
Maximum age by which a mortgage of an owner-occupier has to be repaid	79	HFCS[n]
LTV cap of commercial bank when expected price change = 0	0.957	HFCS[o]
Owner-occupiers' maximum debt-service-to-income ratio	0.3993453	HFCS[p]
BTL agents' maximum DSTI above which they abstain from purchasing new property	0.3721952	HFCS[q]
Mortgage interest rate	0.0404128	DNB[r]

[a] Median rent of rents paid below social rent limit of 710.68 (in 2017). [b] Average tenure of owner-occupiers (in years). [c] Calculated as the ratio of social to private housing, while dropping institutional for-profit investors' housing (5% of all housing), as they are not represented in the HFCS. [d] Social security per month of married couple. [e] Calculated as the cutoff above which 80% of investors are found. [f] Distribution of current years in rented residence above social housing limit, lowest value is 12 month. [g] Estimated on the log-log relationship of income and current rental payments of households; households with rent-to-income ratios above 1 are excluded. [h] Estimated on the log-log relationship of income and owner-occupied purchase price; for purchases in previous years households' income is adjusted by the average change in disposable gross income in the Netherlands (ECB); only includes mortgages still unpaid, and restricted to ratios within the 90% interpercentile range. [i] Calculated as ratio of households' average expected house prices for the next year (2.3%) to average price increases over the past three years. [j] Calculated from the purchase prices of property from 2000 on; Purchase prices have been adjusted to 2017 prices with the OECD house price index. [k] Calculated from households' rental payments above the social rent limit of 710.68€. [l] Realised downpayments of owner-occupiers aged 35 and younger, as FTB mortgages are not identifyable in the HFCS. [m] Realised downpayments of owner-occupiers older than 35. [n] Maximum age of non-BTL household with mortgage, top 98% quantile. [o] Average median LTV (at origination) of each of the past 20 years of currently non-repayed mortgages loans (i.e. observable) in 2017, maximum values restricted to the maximum value of 2017 (1.925). [p] 95% quantile of current DSTI, counting only mortgage payments for main residence and dropping all ratios over 1. [q] Maximum mortgage payments to income ratio of BTL investors. [r] Average mortgage interest rate between 2003 - 2022.

Table A.3 Postulated parameters

Parameter	Value	Source
Monthly probability of reducing the property offer price	0.055	Postulated[a]
Mean percentage of offer price reduction	1.603	Postulated[a]
Standard deviation of percentage reductions of offer price	0.617	Postulated[a]
Distribution of mark-ups of offer prices over realised property transaction prices	Estimated UK distribution	Postulated[a]
Distribution of mark-ups of offer prices over realised rental transaction prices	Estimated UK distribution	Postulated[a]
Monthly percentage reduction of offered unsold rentals	0.05	Postulated[a]
Mortgage duration in years	25	Postulated[a]
Monthly propensity to consume out of disposable income for households in income percentiles [$\leq 0.25; > 0.25 \leq 0.5; > 0.5 \leq 0.75; > 0.75 \leq 0.9; > 0.9 \leq 0.99; > 0.99$]	[0.9; 0.7; 0.6; 0.575; 0.55; 0.5]	Postulated[b]
Monthly propensity to consume induced by finanical wealth for households in income percentile [$\leq 0.25; > 0.25 \leq 0.5; > 0.5 \leq 0.75; > 0.75 \leq 0.9; > 0.9$]	[0.03; 0.015; 0.0125; 0.0135; 0.0075]	Postulated[b]

[a] Same as Tarne (2022). [b] Close to Tarne (2022), and adjusted pre-calibration to match the median and the mean financial wealth of households.

In this method, calibration targets are motivated from statistical moments in empirical data such as the average, standard deviation, and kurtosis of, for instance, house prices (all shown in Table A.5). Within upper and lower limits (reported in Table A.4) a set of parameter values is efficiently sampled using the Latin-Hypercube method (McKay, Beckman, and Conover 1979). Then the model is run using these values.

In this way, 4,000 parameter sets are drawn and the model is run for 3,000 periods. The first 1,000 (the burn-in phase) are discarded. For the remaining 2,000 periods, the sum of the absolute relative distances (i.e. over- and undershooting are treated the same) to the target variables gives an overall score[18]. None of the models is able to match all target variables (see Table A.4), so all scores are positive. The parameter set with the lowest score (=1.370) is then selected for the experiments in this paper. For robustness, we also explored simulations using parameter sets with the next 50 best scores[19] (score second-best model = 1.375, score of the fifty-best model = 1.586, score of the worst fitting model = 54.713).

[18] Very close to the target variable the score remains zero, as to allow for a certain threshold of targets being good enough. The specific values can be provided by demand.

[19] The 50 best scores are selected due to computational reasons.

Table A.4 Parameter values after calibration

Parameter	Value	Range for calibration
Weight of transaction prices in t-1 on t	0.858	[0.25 - 1]
Deposit-to-purchase-price ratio above which hh pays in cash	1.808	[1 - 3]
Income percentile value above which FTB agents save extra for a downpayment	0.734	[0 - 1]
Propensity to consume out of disposable income for FTB agents above specific income percentile	0.752	[0.1 - 1.0]
Precautionary buffer (multiple of monthly net income)	1.002	[0 - 5]
Fundamentalist BTL agents' weight on capital gains vs rental yield	0.188	[0 - 0.5]
Trend-follower BTL agents' weight on capital gains vs rental yield	0.555	[0.5 - 1]
Share of BTL agents being fundamentalists	0.916	[0 - 1]
Loan-to-value cap	0.969	[0.957 - 0.9999][a]
Years that backward-looking price expectations take into account	2	[0 - 10]
Distribution of desired downpayments for BTL agents		
Scale parameter	0.124	[0.1 - 0.5]
Standard deviation	0.03	[0.01 - 0.1]
Probability of household having a BTL flag	0.076	[0.0221 - 0.11]
Sensitivity parameter for the choice between renting and buying	0.01454	[ln(0.00001) - ln(0.1)][b]
Intensity of choice parameter for BTL investors on effective yield	21.40809	[ln(0.1) - ln(1000)][b]
Sensitivity parameter for the changes in house prices affecting LTV cap	0.535	[0 - 1]

[a] The minimum is set to the neutral LTV limit by the commercial bank; by design the maximum LTV in the model has to be below 1. [b] The logarithm is used to sample more equally over the different orders of magnitude.

Table A.5: Calibration targets

	Model	NLD	Source
Avg. net financial wealth	25351	20704	HFCS
Median net financial wealth	93412	83392	HFCS
Aggregate debt-to-Income	0.722	0.845	HFCS[a]
Aggregate NFW / mortgage debt	2.118	1.81	HFCS
Share owner-occupied housing	0.585	0.6	MBZK2018
Share privat rental property	0.091	0.09	MBZK2018
total net wealth share of whealthiest 10 percent	0.438	0.561	HFCS[b]
Average monthly transactions per household			
Total	0.00324	0.00211	Kadaster[c]
FTB	0.00099	0.00068	Kadaster[d]
SSB	0.00198	0.00112	Kadaster[d]
BTL	0.00027	9.2e-05	Kadaster[d]
House price index			
Mean	0.938	1.0	OECD[d]
Min	0.721	0.796	OECD[d]
Max	1.358	1.272	OECD[d]
Std.	0.132	0.121	OECD[d]
Kurtosis	2.712	2.028	OECD[d]
Avg. cycle length	22.4	22	@JadeviciusvanGool2020
Share buy-to-let households	0.036	0.022	HCFS
Share private unrented property	0.001	0.01	Source

[a] Only including mortgage debt and adjusted for the model not including interest-only loans by estimating the hypothetical repayment of interest-only mortgages in the HFCS with the average annual repayment rate from amortizing mortgages in the HFCS. [b] Consisting of net housing wealth and net financial wealth. [c] 1995-2022, adjusted for number of households in the Netherlands. [d] 2009-2021, adjusted for number of households in the Netherlands.
[e] Quarterly Data, de-trended with the Hodrick-Prescott filter with the smoothing parameter of = 400'000.

APPENDIX B: VALIDATION

B.1 Approach

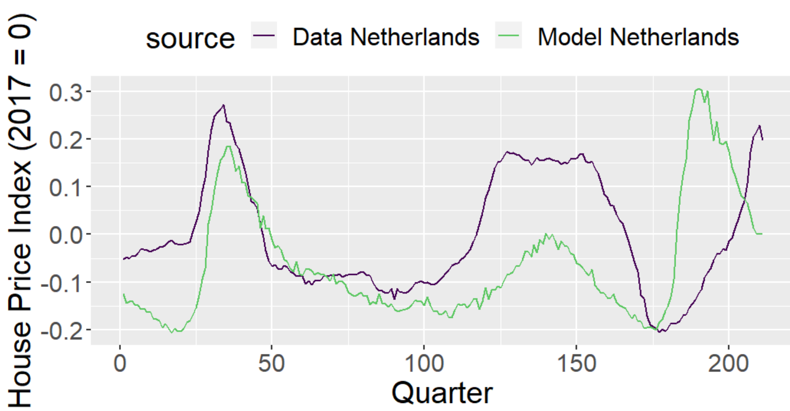
The 69 free parameters of the model are plausibly postulated, estimated, and calibrated using Dutch data from 2017, mainly from the European Household Survey (HFCS). The procedure follows Carro (2022) with some changes and is described in detail in Appendix A. The model is run with 10,000 households for 9000 steps (which represent a month), where the first 1000 steps are discarded as a transition phase. All model results are based on ten Monte-Carlo simulation runs. The model best fitting the stylized facts of the Dutch housing market is selected (see Table A.5).

How well does the calibrated model match the data? In this section, we undertake a careful comparison of model and reality in five areas: the shape of the cycle, loan-to-value ratios, age distribution, distribution over household types, trading intensity, and differences in trading intensity between household types.

While all this is part of the model validation, we also begin to use the agent-based nature of the model to better understand some of its features – for instance, to understand why first-time buyers' transactions vary less with the state of the housing cycle than those of other households.

B.2 The Cycle

In the literature, the Dutch housing cycle has been estimated to last about 22 years (Jadevicius and van Gool 2020), longer than, for instance, the US or the UK (see also Deelen et al. (2020)). Figure B.1 compares the de-trended Dutch housing cycle from 1970Q1 - 2022Q3 to a representative cycle phase of the model. The model recreates the first cycle and then the long house price depression quite well. The second cycle is more subdued in the model than it is in the data, while the upswing that follows is faster and goes higher.



Source: OECD Quarterly Data, de-trended with the Hodrick-Prescott filter with the smoothing parameter of = 400'000.
Model house price index is shifted to zero.

Figure B.1: Detrended Dutch Housing Cycle 1970Q1-2022Q3 vs the model

B.3 Loan-to-Value Ratios

The top-left panel of Figure B.2 compares the current loan-to-income ratios of mortgage holders. The model undershoots the LTIs of Dutch households at high LTV values. The most likely reason is that in the model there are no interest-only mortgages and households do not withdraw equity. Due to the absence of forced repayment until maturity, mortgage volumes remain larger over time relative to income, than is the case for repayment mortgages. The large amount of interest-only mortgages and equity withdrawals (about half of the households in the HFCS in 2017 was in one of both categories[20]) is a special feature of Dutch household debt that should be borne in mind, and which is absent in the model.

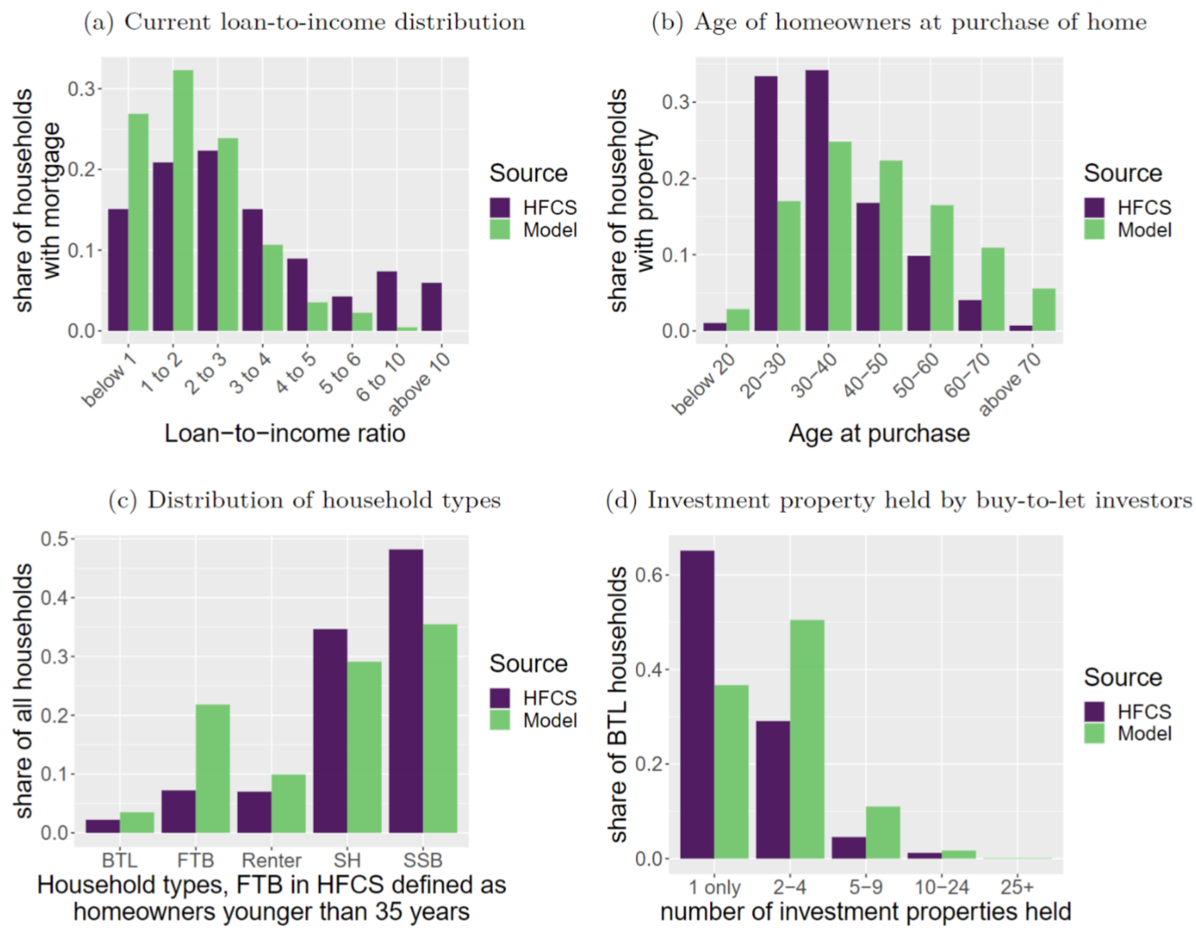


Figure B.2 Validating the model against HFCS data

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[20] In fact, 52% of all mortgages. We inferred this from the HFCS data as mortgages of which the principal from origination to the time of observation did not decrease (35%) or increase (17%). This compares to research showing that about half of first-time buyers had an interest-only mortgage in 2009–2011. Following new legislation, this dropped to one in ten in 2016 (Zijlstra en Bolscher 2021).

B.4. Age Distribution

The top-right panel shows the age of households at purchase. Model households are generally older when they purchase a property than is the case in reality. This could be due to model households starting out without any financial assets and without inter-household cash transfers (except the random inheritance mechanism.) In reality, households are supported by prior savings and transfers from family so that they can earlier in life buy a property than would otherwise be the case. The earlier start of indebtedness also feeds into higher LTV ratios in the Netherlands than in this model version.

B.5 Distribution over Household Types

The bottom-left panel of Figure B.2 shows the distribution of the population over different household types (the bottom-right panel is discussed in section B.7). The HFCS data does not distinguish between FTB and SSB households, nor between private and social-housing renters in the Figure. We, therefore, estimate FTB households as homeowners younger than 35 years (as also in Table A.2 in the Appendix) and we use the statutory rent limit of 529€ (see Table A.2) as the cut-off point below which households are assumed to be in social housing. The first proxy may be imprecise as it results in more FTB households in the model than is the case in the HFCS. The second works better but not perfectly: more households are now identified as in social housing in the HFCS than what can be inferred from aggregate data on social housing (MBZK 2018, Table 1.4.1).

B.6 Transactions

There are significantly more monthly property transactions in the model than in reality in the Netherlands, (Table A.5 in Appendix A shows an average number of sales per month per household of 0.00324 in the model versus 0.00211 in the Netherlands). The housing market turnover in the model is driven by the average tenure of owner-occupiers. Reasons for moving housing (changing jobs, a divorce) are not explicitly modeled; owner-occupiers in the model simply put their home on the market on average every 17 years. Assuming that this value does not drastically change over time and that a change in tenure of owner-occupiers always implies selling property leads to an average number of sales per household per month around 0.0028, i.e., the monthly sale probability times the population share of owner-occupiers. These assumptions – especially that a change in tenure of owner-occupiers always implies selling property - are quite restrictive, and this might be the reason why the model outcome is higher than the official statistics in the Netherlands[21].

B.7 Differences Between Household Types

We now focus on the owner-occupier market where three types of households operate: owner-occupiers who are first-time buyers (FTB), owner-occupiers who are second-home and subsequent-homes buyers (SSB), and buy-to-let (BTL) households. The distinction between SSB and FTB households within the group of owner-occupiers is motivated by differences between SSB and FTB households in income and credit and liquidity constraints, which will turn out to be very relevant to this paper's research question. The distinction is also relevant to the public debate in the current

[21] With the data sources used in this paper, we cannot resolve this discrepancy. Perhaps the data on tenure is less reliable than the transaction data in the official Land Registry (Kadaster) source. Part of the difference is due to owner-occupiers changing tenure who do not in reality always sell their home, as in inheritance situations or families combining homes. This involves moving, but not selling.

affordability crisis in the Netherlands (as in other countries) where a major concern is the position of FTB households.

In Figure B.3 we compare the number of transactions per quarter for each owner type over time for the Netherlands (left panel) and in the model data (right panel). The data goes back to 2009Q1, encompassing a downturn and upswing that we can match to a downturn and upswing in the model data.

In the Dutch data, the downturn is faster down and the upswing less steeply up, than is the case in the model data. Further, in the Dutch data FTB households' transactions vary less with the state of the house cycle than those of SSB and BTL households. Especially, SSB households increase their purchases significantly once prices stop falling. In the model, SSB purchases increase somewhat earlier, at the end of the downturn. But overall, the model can replicate the low sensitivity of FTB households to the housing cycle, as well as SSB and BTL purchasers' procyclical behavior.

After this validation, we now use the agent-based nature of the model to better understand why FTB households' transactions vary less with the state of the housing cycle than those of SSB and BTL households. The reason is that when prices rise, FTB households are priced out due to their limited savings, while SSB agents have financial wealth from selling their previous home. Note also that with continuously rising house prices, the number of transactions falls both for the Netherlands (slightly) and the model (more pronounced). Further, the Figure shows that BTL borrowers increase their purchases once prices stop falling, both in the Dutch data and in the model.

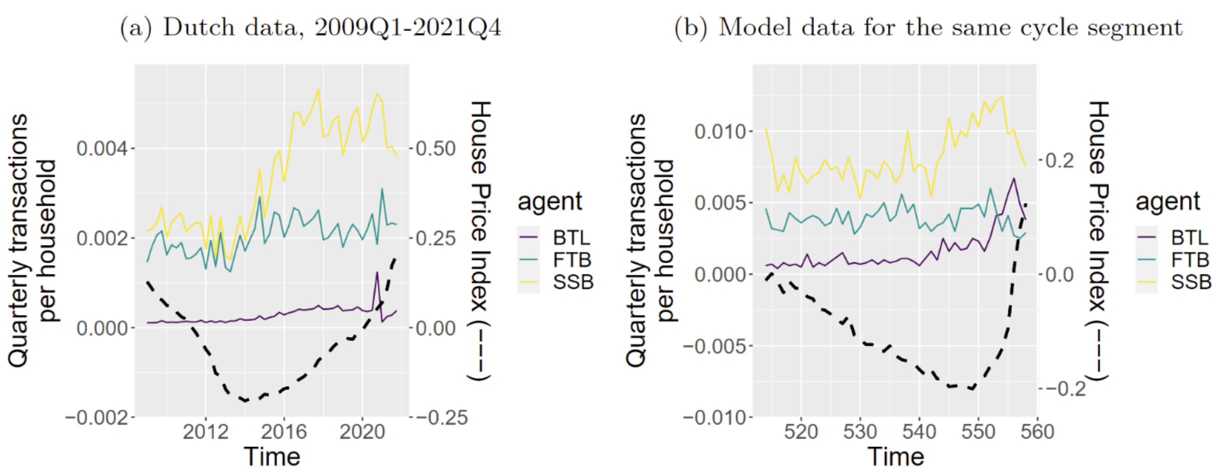

Figure B.3 Number of transactions per quarter for each owner type for the Netherlands (left panel) and in the model (right panel).

Household types also differ in the number of properties held. The bottom-left panel of Figure B.2 shows that BTL model households tend to hold more than one property to let, while in the Netherlands most BTL households hold only one. At face value, this seems to imply that the role of BTL households in price formation is larger in the model than in reality.

However, comparison to external data suggests that the HFCS data in fact understate the role of investors, which may be better captured in the model. Buy-to-let households in the HFCS data account for 3.3% of all houses, but the share of properties held by investors (households and others) in the Netherlands is 9%, according to MBZK (2018). The number of BTL investors in the model matches this number quite well (see the calibration targets in Table A.5). BTL ’households’ in the model could be viewed as standing in for all investors in the owned-housing market.

In summary, the calibrated model matches key housing market indicators and housing dynamics, but some distributions show significant deviations. Upon further exploration, the deviations can be explained by structural simplifications in the model, such as the absence of interest-only loans; the absence of family support for FTB households; and the aggregation of commercial and household investors into one BTL class of ‘households’. Each of these model choices is defensible, adding tractability.

APPENDIX C: TRACING AGENT-BASED MECHANISMS

In this appendix, we analyze agent-specific model dynamics. This will allow us to better understand in what way, for instance, more housing leads to lower price peaks. This involves tracing the model simulation outcomes at the level of transactions and agents. While laborious, this is rewarding as it allows for a better assessment of the plausibility of the underlying mechanisms in the model, as follows.

C.1 Housing Stock Changes

A first finding of note is that with a large housing stock (a higher private-housing-to-households ratio) more properties are traded, leading to lower average demand per unit. The number of monthly bids per property on offer falls from 0.89 on average in the baseline model to 0.61 in the model with higher private housing supply (fifth line in Table C.1). This leads to lower transaction prices and, therefore, lower price levels. The fall in the bids-per-offer ratio is driven by fewer bids rather than by more offers on the market, since the increased supply of housing is almost exclusively bought up by BTL households. As Table C.1 (fifteenth line) shows, they now hold 14.5% of all properties compared to 9.1% in the baseline model[22]. The last line in the table indicates the variation of the ownership share over the housing cycle, by subtracting the minimum from the maximum ownership share over all simulation runs. While the baseline model already shows considerable variation in the BTL ownership share (5.3%), with more housing this variation increases (to 7.3%).

Table C.1: Additional outcomes of the policy experiments

	Model version				
Variable (average monthly values)	baseline	less housing	more housing	lower LTV cap	interest rate up
average bid price	152'002	156'301	157'641	155'084	140'377
average offer price	346'735	372'642	322'059	358'840	311'533
bids on ownership market by FTB per household	0.0100	0.0110	0.0080	0.0114	0.0091
bids per private rental offered	145	277	83	134	154
bids per property offered	0.89	0.73	0.61	0.76	0.69
BTL bids per BTL purchase	3.72	6.16	2.40	3.02	4.07
house price index	0.934	0.952	0.865	0.919	0.854
maximum LTV offered by commercial bank	0.951	0.956	0.952	0.933	0.952
monthly bids on property market	177	206	143	193	161
monthly offers on property market	492	316	496	386	478
monthly purchases by BTL investors	2.7	1.6	4.1	3.0	2.7
non-BTL bids per non-BTL purchase	5.58	6.27	4.47	6.17	4.86
purchases by FTB per household	9.91	10.13	9.75	9.80	9.94
purchases by SSB per household	19.7	20.9	20.0	19.7	20.6
share of all properties owned by BTL agents	0.091	0.049	0.145	0.105	0.082
share of households being active BTL agents	0.036	0.024	0.041	0.038	0.033
share of months with max LTVs by commercial bank	0.202	0.089	0.251	0.000	0.185
share of months with positive annual house price growth	0.35	0.48	0.40	0.43	0.36
volatility (max-min) of share of properties owned by BTL agents	0.053	0.037	0.073	0.052	0.052

Note: The results stem from ten Monte-Carlo Simultion run with 3000 periods for each model version, where the first 1000 periods have been discarded. All experiment versions represent those where house price peaks fell by 10%.

[22] BTL households do not sell their properties as often as homeowners; moving households keep their property on the market until it is sold, while BTL investors only put their property on the market when their expected yield on their property becomes negative. They take it off the market as soon as they expect it to be positive again.

Second, why do price peaks also fall if the number of private properties is *reduced*? The resulting increase in relative demand leads to higher house price troughs, but not to higher house price peaks. The reason for this in turn is that it is mainly BTL households' purchases that drive the house price upswing.

Figure C.1 shows this. We trace the contribution of each agent class to the percentage change in the house price index over the property cycle for all three model versions (see the calculation of the house price index in Equation (1)). The overall change in prices is depicted by the yellow line (lhs.); the black line represents the house price index (rhs.).

The Figure shows that purchases by BTL and FTB households increase house prices (positive purple and blue bars), while purchases by SSB households dampen them (negative green bars). Each bar gives the price changes induced by each agent class. Upswings with annual price increases above 10% are almost exclusively driven by BTL households' purchases. These are only observed in the baseline model and the model with more housing, not in the model with less housing. In both these model versions, the BTL purchases clear the market: each property offered is sold, even properties offered above the expected transaction price for a house of the same quality. These transactions push up the house price consistent with Equation (1).

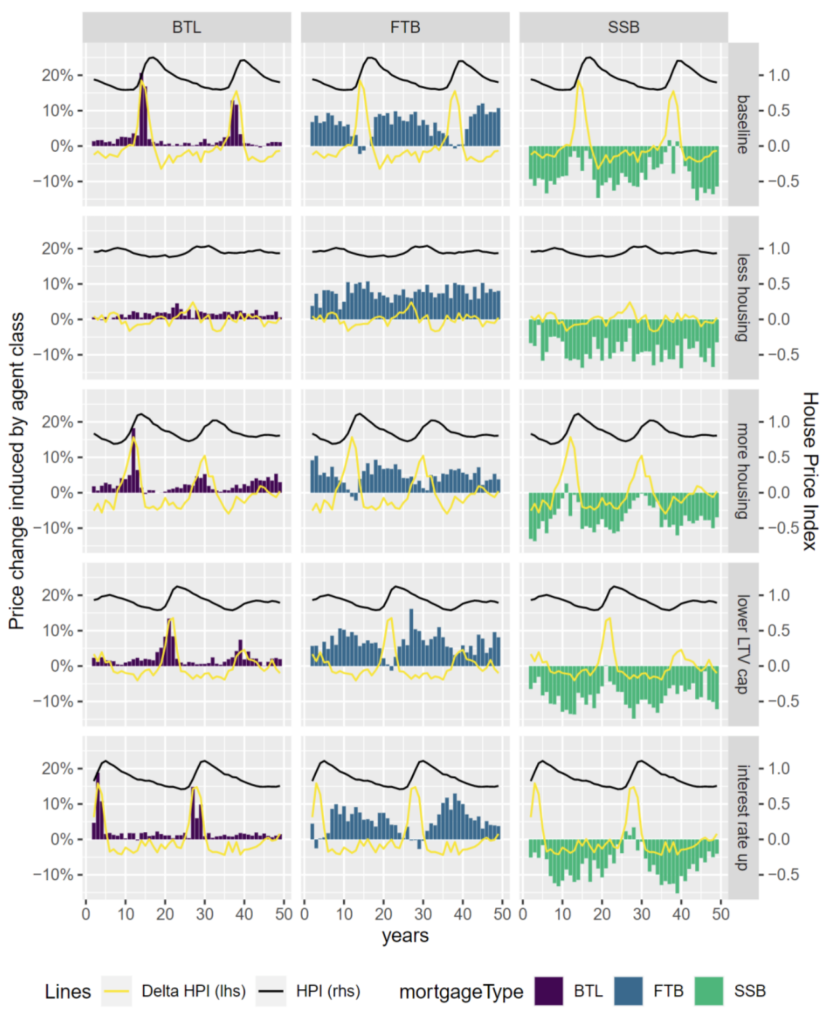

Figure C.1: Agents' contributions to price changes by household type for different policies

In the simulation with less private housing supply, fewer BTL households purchase rental property priced considerably above their expected purchase price. As a result, the market does not clear. In this model world, there are fewer BTL households due to increased competition from FTB and SBB households, leading to BTL households having to make more bids on the housing market to purchase a property. This is clear from Table C.1. In the baseline model, BTL agents bid on average 3.72 times before they purchase. But with fewer housing, this rises to 6.16 bids per purchase. For FTB and SSB households the rise is merely up to 5.58 and 6.27, respectively. This difference causes the share of actual BTL households (i.e. not only prospective, of the BTL type, but actually property-owning) to decrease from 3.6% to 2.4%.

This analysis also clarifies the active role of SSB households in causing downturns while FTB households dampen the downturn. The reason is that these household types are purchasing at different ends of the housing quality distribution. Recall that FTB households are more financially constrained than SSB agents so FTB households crowd into the lower quality and cheaper end of the housing stock, where they push up the prices SSB agents, who have more savings from selling their previous properties, therefore bid for higher-quality properties, where demand is lower so that they can buy cheaper, pushing down prices. This serves to show how the evolving liquidity distribution shapes house price dynamics.

C.2 Lower Loan-to-Value Caps

Reducing the LTV cap affects the distribution of LTVs. Figure C.2 shows the histograms of LTVs over the course of one Monte-Carlo run for each transaction involving mortgage credit. It shows that property purchasers are actually restricted by the reduced LTV cap (from 95.7% in the baseline to 93.3%).

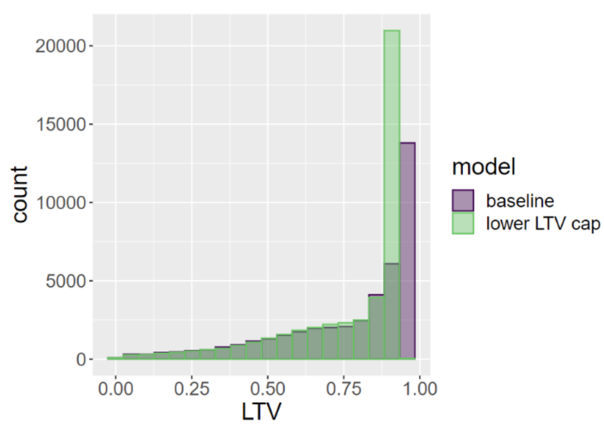

Figure C.2: Impact of LTV caps on realized LTVs

However, this aggregate result does not explain which type of household is restricted, and when. While FTB agents are restricted by the LTV cap, their "contributions to price changes" (Figure C.1) show that FTB households are not driving the upswing, BTL households are. Therefore, for the policy to be effective in reducing prices, we need to see that in the baseline version, BTL households are more often constrained by the LTV cap in the house price upswing. Figure C.3 confirms this. BTL households that purchase properties in the baseline scenario often have LTVs that are above the lower-LTV-cap experiment value of 93.3%. Therefore, in this experiment, they become credit-constrained. As a consequence, market clearing does not happen and prices rise less than in the baseline scenario[23].

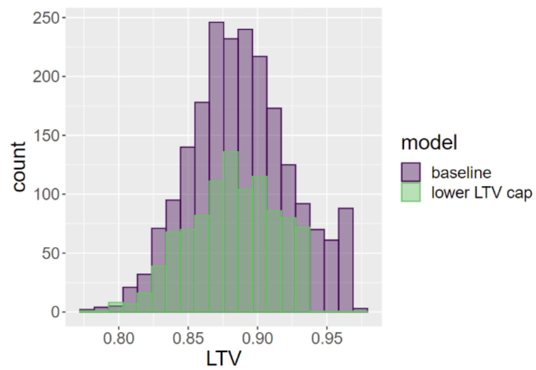

Figure C.3: Buy-to-Let agents' LTV values at origination in the house price upswing when LTV caps decrease

C.3 Higher Interest Rates

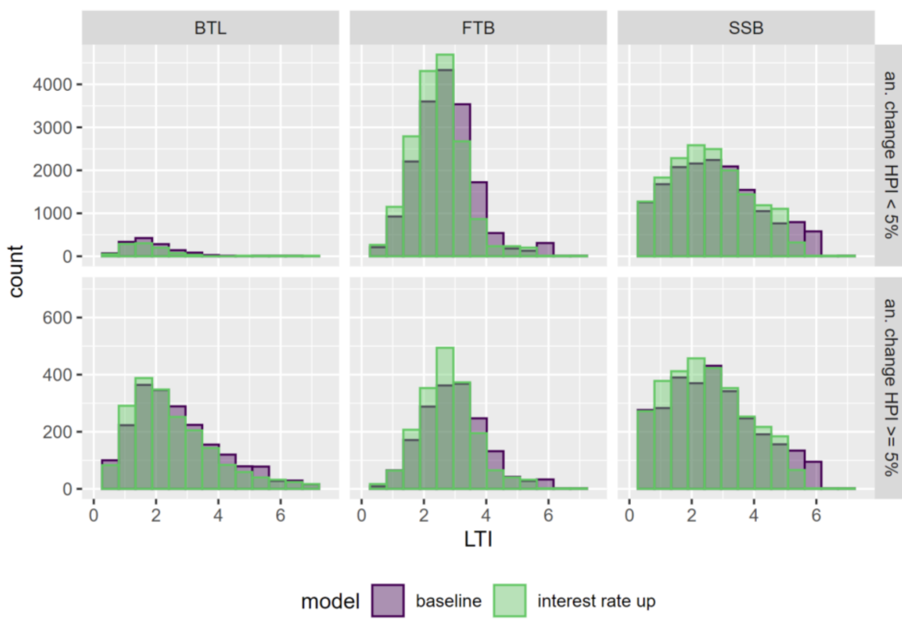

Figure C.4: Lower interest rates (green) than in baseline (purple) reduce LTIs of all household types in upswing phases (lower panels) and other cycle phases (upper panels)

Our final exploration concerns the interest rate experiment. The effect on house prices works through internal debt-service-to-income limits of BTL and owner-occupier households. The exogenous employment income of owner-occupiers is very stable but BTL households also receive variable

[23] The result here hinge on the behaviour of BTL agents, but the model shows qualitatively similar results when there are fewer BTL households, provided FTB households have higher LTV caps. This is shown for a model version with fewer BTL households but higher overall LTV caps in Appendix D.1.

rental income. Compared to the upswing-only effect of LTV caps and supply changes, higher interest rates affect the price formation throughout the cycle - see Figure C.4 where LTIs are lower both in upswings and other cycle phases.

Figure C.1 shows that both in the baseline and higher-interest-rate simulation, BTL investors cause price rises in the upswing. But prices start each cycle at lower levels and peak prices are also lower.

APPENDIX D: ROBUSTNESS

To test the robustness of the model we re-do the analyses for different model parametrisations by studying the second-best (section D.1) and the fifty best-fitting models (section D.2), out of the 4,000 calibration runs described in Appendix A. By ranking on fit, the sensitivity analysis includes those models that are validated with the Dutch data.

D.1 Second-Best Model

The second-best-fitting model has significantly different parametrizations in areas identified as central for the dynamics of the best-fitting model (Table D.1). For instance, the LTV cap is higher (just below 100%) while the share of BTL households is significantly lower. This changes the dynamics of the model. While BTL households are central in the dynamics in the best-fitting model, here less so, simply because there are fewer BTL households. Since this is an important difference we focus on this rather than one of the other 49 best-fitting models. A key takeaway on robustness is that the results hold up qualitatively, even though the BTL household influence on the housing cycle is replaced by more influence of FTB households, due to the higher LTV caps.

Table D.1: Parameters calibrated of second-best model for robustness checks

Parameter	Second-best model	Best model	Range for calibration
Weight of transaction prices in t-1 on t	0.907	0.858	[0.25 - 1]
Deposit-to-purchase-price ratio above which hh pays in cash	2.656	1.808	[1 - 3]
Income percentile value above which FTB agents save extra for a downpayment	0.935	0.734	[0 - 1]
Propensity to consume out of disposable income for FTB agents above specific income percentile	0.409	0.752	[0.1 - 1.0]
Precautionary buffer (multiple of monthly net income)	1.514	1.002	[0 - 5]
Fundamentalist BTL agents' weight on capital gains vs rental yield	0.366	0.188	[0 - 0.5]
Trend-follower BTL agents' weight on capital gains vs rental yield	0.587	0.555	[0.5 - 1]
Share of BTL agents being fundamentalists	0.817	0.916	[0 - 1]
Loan-to-value cap	0.997	0.969	[0.957 - 0.9999][a]
Years that backward-looking price expectations take into account	4	2	[0 - 10]
Distribution of desired downpayments for BTL agents			
Scale parameter	0.408	0.124	[0.1 - 0.5]
Standard deviation	0.049	0.03	[0.01 - 0.1]
Probability of household having a BTL flag	0.039	0.076	[0.0221 - 0.11]
Sensitivity parameter for the choice between renting and buying	0.00052	0.01454	[ln(0.00001) - ln(0.1)][b]
Intensity of choice parameter for BTL investors on effective yield	0.26639	21.40809	[ln(0.1) - ln(1000)][b]
Sensitivity parameter for the changes in house prices affecting LTV cap	0.934	0.535	[0 - 1]

[a] The minimum is set to the neutral LTV limit by the commercial bank; by design the maximum LTV in the model has to be below 1. [b] The logarithm is used to sample more equally over the different orders of magnitude.

Table D.2: Calibration targets of the second-best model for robustness checks

	Second-best model	best model	NLD	Source
Avg. net financial wealth	23291	25351	20704	HFCS
Median net financial wealth	94444	93412	83392	HFCS
Aggregate debt-to-Income	0.788	0.722	0.845	HFCS[a]
Aggregate NFW / mortgage debt	1.967	2.118	1.81	HFCS
Share owner-occupied housing	0.6	0.585	0.6	MBZK2018
Share privat rental property	0.078	0.091	0.09	MBZK2018
total net wealth share of whealthiest 10 percent	0.434	0.438	0.561	HFCS[b]
Average monthly transactions				
Total	0.00345	0.00324	0.00211	Kadaster[c]
FTB	0.00099	0.00099	0.00068	Kadaster[d]
SSB	0.00224	0.00198	0.00112	Kadaster[d]
BTL	0.000215	0.00027	9.2e-05	Kadaster[d]
House price index				
Mean	0.964	0.938	1.0	OECD[d]
Min	0.763	0.721	0.796	OECD[d]
Max	1.274	1.358	1.272	OECD[d]
Std.	0.106	0.132	0.121	OECD[d]
Kurtosis	2.192	2.712	2.028	OECD[d]
Avg. cycle length	24.8	22.4	22	@JadeviciusvanGool2020
Share buy-to-let households	0.022	0.036	0.022	HCFS
Share private unrented property	0.001	0.001	0.01	Source

[a] Only including mortgage debt and adjusted for the model not including interest-only loans by estimating the hypothetical repayment of interest-only mortgages in the HFCS with the average annual repayment rate from amortizing mortgages in the HFCS. [b] Consisting of net housing wealth and net financial wealth.
[c] 1995-2022, scaled for model size. [d] 2009-2021, scaled for model size.
[e] Quarterly Data, de-trended with the Hodrick-Prescott filter with the smoothing parameter of = 400'000.

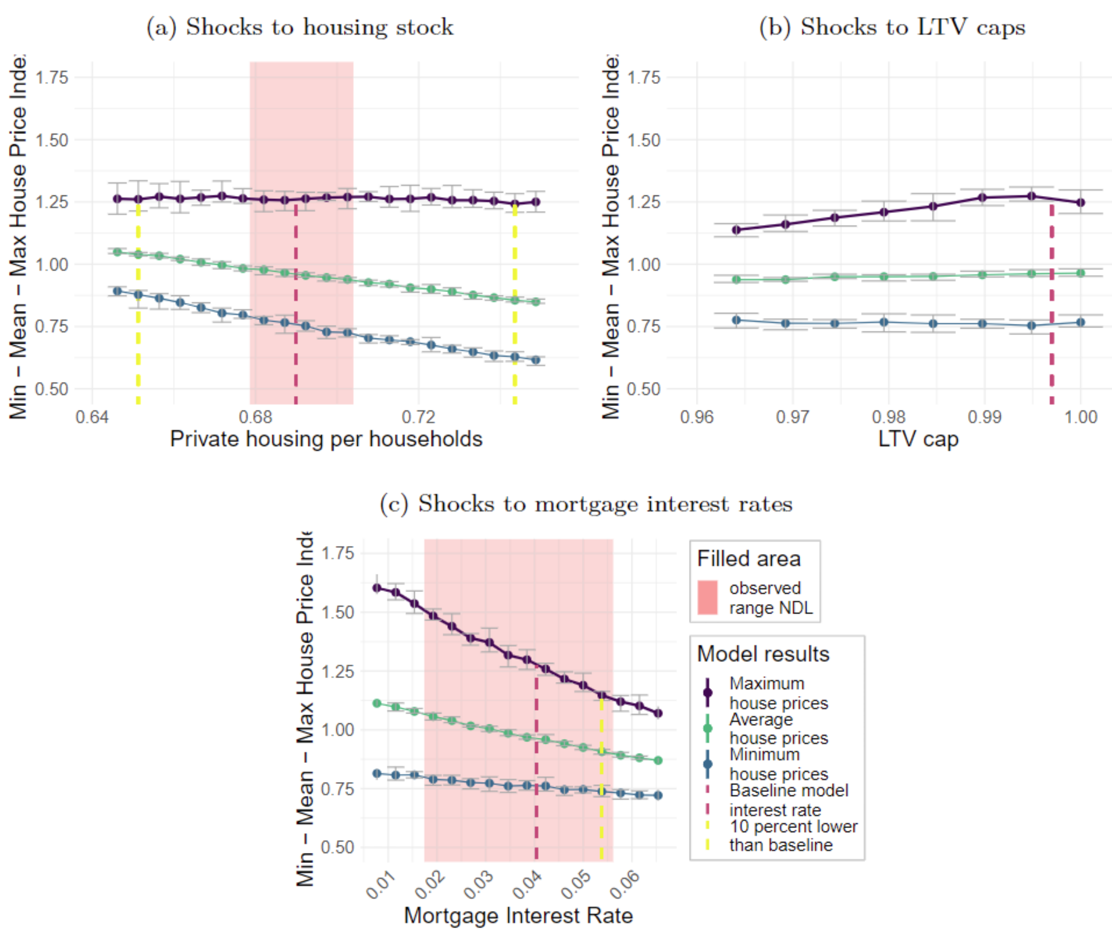

Figure D.1: Effects on house prices of housing stock, LTV caps, and interest rates

We observe that the shocks have similar effects here and in the main analysis (Figure D.1). However, increasing the private housing stock has no impact on maximum prices while reducing average and minimum prices even more strongly. Figure D.2 shows that this is again due to BTL investors increasing their share of properties (as in the main analysis), leading to them inducing strong upswings (purple bars). Whereas less housing reduces peaks in the main analysis, here it only increases mean and trough prices.

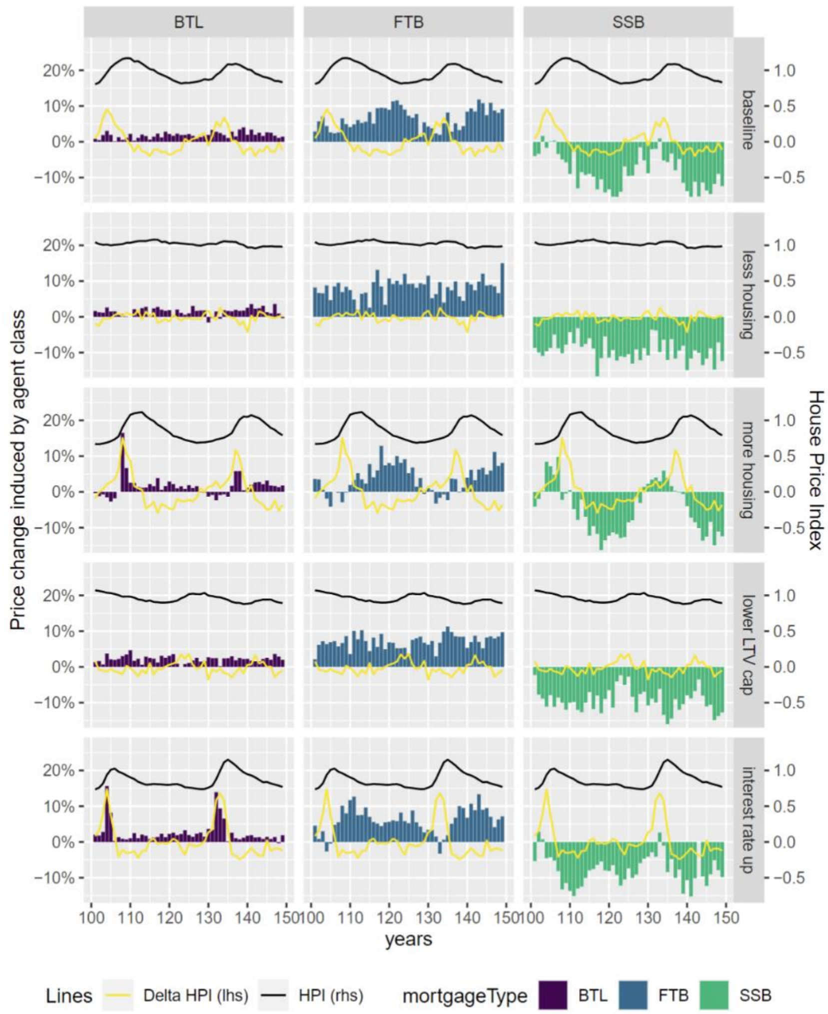

Figure D.2 Agents' contributions to price changes by household type for different policies (second-best model)

Table D.3 shows that the effects on affordability are muted (as discussed in section 4.3). With the lower BTL share in this model version, increasing the housing supply does have a more limited effect on the share of FTB households, which goes in the expected direction (it rises from 0.189 to 0.192, instead of falling from 0.189 to 0.182 as reported for the best-fitting model in Table 4.2).

Table D.3: Affordability for the second-best model

	average values for FTB at purchase							average homeownership distribution				
Model version	Age	Monthly income	LTI	DSTI	LTV	Purchase price	Downpayment	Share of FTB hh	std of av share of FTB hh	std of share of FTB hh	Share of SSB hh	Share of BTL hh property
baseline	32.34	6'121	3.070	0.1968	0.9236	202'207	17'785	0.189	0.0008	0.0052	0.393	0.0759
less housing	32.68	6'177	3.361	0.2158	0.9150	226'710	21'915	0.187	0.0014	0.0037	0.371	0.0649
more housing	32.32	6'149	2.604	0.1667	0.9234	171'860	15'753	0.192	0.0021	0.0051	0.405	0.1061
lower LTV cap	32.75	6'266	2.627	0.1686	0.9076	181'518	19'182	0.180	0.0015	0.0044	0.392	0.0877
lower BTL LTV cap only	32.36	6'106	3.062	0.1963	0.9223	201'769	18'051	0.190	0.0014	0.0049	0.393	0.0753
interest rate up	32.40	6'186	2.868	0.2109	0.9163	192'898	19'374	0.187	0.0017	0.0048	0.398	0.0741

Note: The results stem from 10 Monte-Carlo Simultions run with 3000 periods for each model version, where the first 1000 periods have been discarded. Std. of av. share of FTB hh gives the standard deviation of the FTB ownership share between MC runs; std. of share of FTB hh gives standard deviation of the FTB ownership share when averaged over all 10 MC runs, indicating their variability within a simulation run.

D.2 Fifty-Best Models

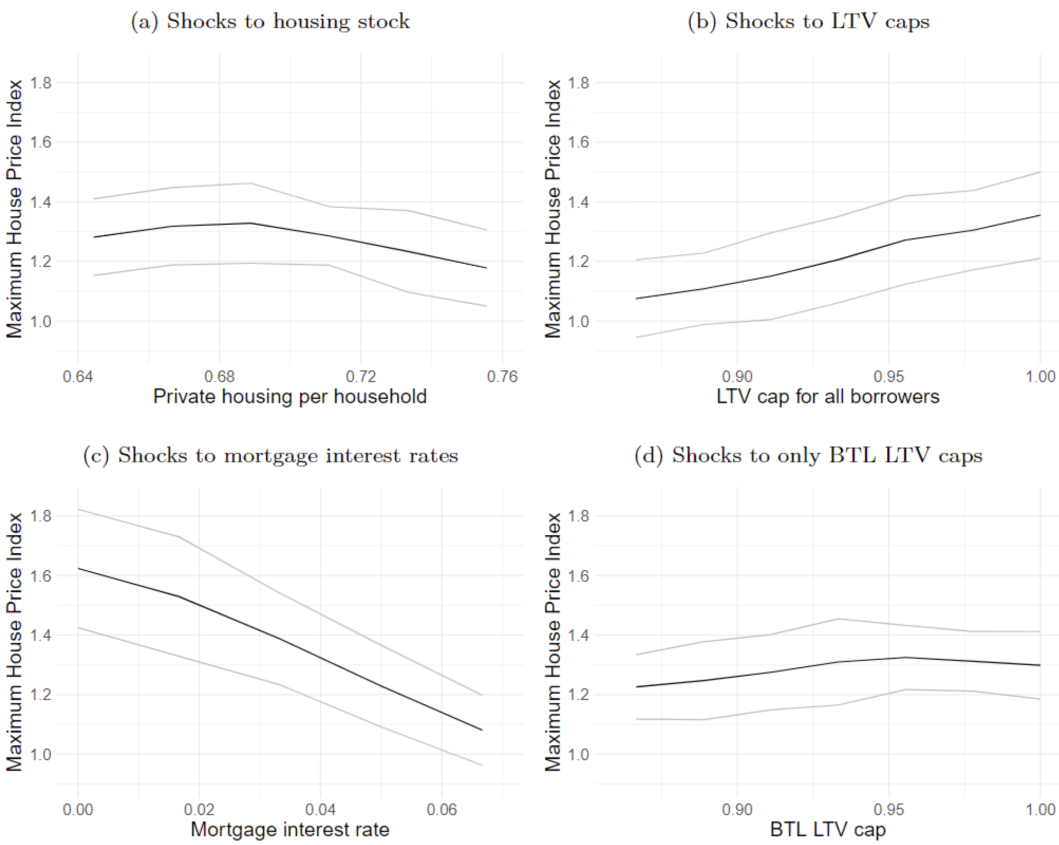

Figure D.5 Effect of policies on house price peaks of the fifty best-fitting models (standard deviation in grey)

Notes: Instead of dividing the range of the shocked parameters into forty steps, due to computational reasons, ten are used, and instead of ten Monte-Carlo runs per step one simulation run is performed. Only the peak prices per simulation run are presented.

Figure D.5 repeats the experiments with the fifty best-fitting models, to be able to average over a sufficient number of different models. Instead of dividing the range of the shocked parameters into forty steps, ten are used, and instead of ten Monte-Carlo runs per step one simulation run is performed. Only the peak prices per simulation run are presented.

Over the fifty best-fitting models, increasing housing tends to decrease peak prices, while decreasing LTV caps limits peak prices. Limiting LTV caps for BTL households only seems to have some dampening effect on peak prices. Here the baseline model used in the main analysis seems to be uncharacteristic for the less well-fitting model versions.

Turning to affordability, Figure D.6 presents the average share of FTB households in the population, as in section 4.3, but without grouping the models by the share of BTL households. The top-left panel of the figure is this ungrouped equivalent to Figure 4.3 and shows that overall, with increasing the rate of private housing per household, affordability (as measured by the share of FTB households) decreases. LTV caps on all borrowers decrease housing affordability as well, as does raising the interest rates. Limiting LTV caps of BTL investors only has only a muted effect.

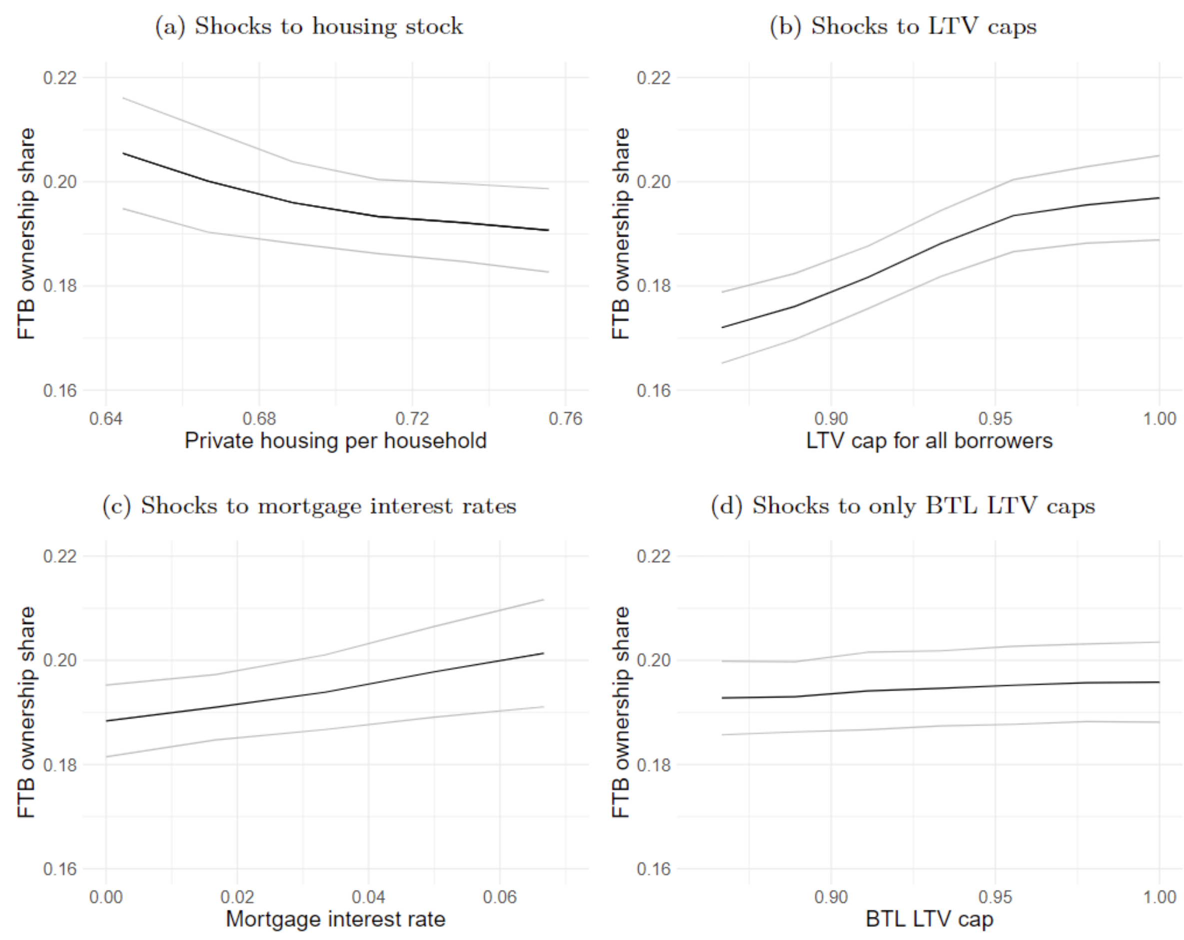

Figure D.6: Affordability: Average FTB ownership share

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