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The Effects of Macro-prudential Policies on House Price Cycles in an Agent-based Model of the Danish Housing Market

Graeme Cokayne
gsc@nationalbanken.dk

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Abstract

Following the global financial crisis, many countries have introduced or tightened macroprudential policies. Using an agent-based model (ABM), this paper seeks to measure the impact on house price cycles of two distinct borrower-based macroprudential instruments, namely loan-to-income and loan-to-value ratios. The use of an ABM allows for the consideration of the effects of these policies on the distribution of heterogeneous households. The paper shows that the relation between tightening an instrument and its effect on house price fluctuations may be highly non-linear, depending on the distribution of households for which the instrument becomes binding. Furthermore, the paper demonstrates that the marginal effect of tightening one instrument generally depends on the calibration of the other instrument. From a policy perspective, these findings highlight the importance of using granular data – preferably at the household level – when calibrating borrower-based macroprudential instruments. Likewise, the findings demonstrate the importance of macroprudential authorities establishing a coherent framework where the effects of different measures are evaluated together.

Resume

Efter den globale finanskrise har mange lande indført eller strammet makroprudentielle tiltag. Ved hjælp af en agentbaseret model (ABM) søger dette papir at måle indvirkningen på boligpriscyklerne af to forskellige låntagerbaserede instrumenter, nemlig grænser for lån i forhold til indkomst og lån i forhold til boligværdi. Anvendelsen af denne type model gør det muligt at overveje virkningerne af disse tiltag i forhold til fordelingen af heterogene husholdninger. Papiret viser, at forholdet mellem at stramme et instrument og dets effekt på boligprisudsving kan være meget ikke-lineært afhængigt af fordelingen af husholdninger, for hvilke instrumentet bliver bindende. Desuden viser papiret, at den marginale effekt af at stramme et instrument generelt afhænger af kalibreringen af det andet instrument. Fra et regulatorisk perspektiv fremhæver disse resultater vigtigheden af at bruge granulære data - helst på husstandsniveau - når man kalibrerer låntagerbaserede makroprudentielle instrumenter. Ligeledes viser resultaterne vigtigheden af, at makroprudentielle beslutningstagere evaluerer virkningerne af forskellige tiltag i sammenhæng.

Key words

Housing; Agent-based model; Macro-prudential Policies; Regulation

JEL classification

D1; D31; E58; G18; G21; R2; R21; R31

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The author alone is responsible for any remaining errors.

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Graeme Cokayne

Danmarks Nationalbank, DK-1093 Copenhagen, Denmark, gsc@nationalbanken.dk

Wednesday 22$^{\text{nd}}$ May, 2019

Abstract

Following the global financial crisis, many countries have introduced or tightened macroprudential policies. Using an agent-based model (ABM), this paper seeks to measure the impact on house price cycles of two distinct borrower-based macroprudential instruments, namely loan-to-income and loan-to-value ratios. The use of an ABM allows for the consideration of the effects of these policies on the distribution of heterogeneous households. The paper shows that the relation between tightening an instrument and its effect on house price fluctuations may be highly non-linear depending on the distribution of households for which the instrument becomes binding. Furthermore, the paper demonstrates that the marginal effect of tightening one instrument generally depends on the calibration of the other instrument. From a policy perspective these findings highlight the importance of using granular data – preferably at the household level – when calibrating borrower-based macroprudential instruments. Likewise, the findings demonstrate the importance of macroprudential authorities establishing a coherent framework where the effects of different measures are evaluated together.

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1 Introduction

Housing is an important part of most major economies. Given that it is the largest single investment for most households, fluctuations in house prices significantly affect household wealth and hence demand in the economy (Berger et al. 2018, Liu et al. 2016, Mian and Sufi 2011). Housing is also a significant source of collateral used by economic actors (Bahaj et al. 2017, Liu et al. 2013, Chaney et al. 2012). Furthermore, cycles in the construction of housing have a significant impact on the economic cycle. Therefore, analysis of how macroprudential policies can moderate housing fluctuations has been an important part of the overall analysis of macroprudential regulation.

Since the recent financial crisis, monetary authorities have been particularly focused on macroprudential policies. Most of these policies are aimed at curbing the supply of loans in boom times in order to reduce some of the pain in an eventual bust (Cerutti et al. 2017). While the policies employed to reduce the pro-cyclicality of the financial cycle vary greatly across countries (Masciandaro and Volpicella 2016), macroprudential policies appear to be an essential part of the financial stability toolkit (Korinek and Sandri 2016). Macroprudential policies can broadly be considered to target banks (such as capital adequacy requirements) or borrowers (such as loan-to-value (LTV) and loan-to-income (LTI) ratios). Following the global financial crisis, monetary authorities placed a great deal of focus on macroprudential policies aimed at the housing sector. As a result, efforts to examine the effects of these policies on housing have increased (Bruno et al. 2017, Benigno et al. 2013). This paper adds to the effort to investigate the effects of borrower-based macroprudential policies on the housing market.

In moderating the effects of asset-price cycles, economic and financial policy strategies can be grouped broadly into 'leaning against the wind' and 'cleaning up afterwards' (Filardo and Rungcharoenkitkul 2016, p. 3). Policies that 'lean against the wind' attempt to moderate the boom phase of the cycle in order to reduce the probability of a crisis occurring and/or constraining the depth of any bust that might occur. On the other hand, the rationale behind 'cleaning up afterwards' is that moderating the boom often imposes significant costs on the economy to avoid a crisis that might not occur, and so it is better to deal with any negative consequence when and if they appear.

Prior to the global financial crisis (GFC), policy strategies by and large took the approach of cleaning up afterwards. The arguments in favor of this approach stated that monetary policy was best focused on inflation as a means of stabilizing the economy, and that it would require considerably contractionary policies to significantly reduce the likelihood of a financial crisis, which would impose greater costs than would occur following the bursting of an asset price bubble (Gourio et al. 2017). Following the GFC, policymakers increasingly looked for ways to reduce the probability of future crises (Gerba and Żochowski 2017). Part of this push was to introduce policies aimed at leaning against the wind, because this was seen to reduce the losses that would be incurred after any crisis happened as evidence suggested that the losses following a crisis were more significant than previously suggested and that better data might make predicting crises easier (Filardo and Rungcharoenkitkul 2016, p. 3).

There is some evidence that macroprudential policies are better suited to leaning against the wind than monetary policy (Kockerols and Kok 2019). The use of both bank- and borrower- focused tools can help tighten financial conditions as imbalances begin to develop and so mitigate the losses that might occur following a crisis (Adrian and Liang 2018, p. 75). As the model in this paper does not have mechanisms for debt overhang to affect households following house price falls, this paper focuses on borrower-targeted macroprudential policies and assesses their effects on house-price cycles through 'leaning against the wind'.

In an attempt to evaluate the effects of macroprudential policies on the housing market, traditional economic analysis might miss some of the nuances because of housing market peculiarities. Firstly, housing is heterogeneous. One house or apartment can be very different to another along various dimensions. Therefore, any model that assumes a homogeneous product might miss some important details (Chen et al. 2009). Secondly, agents in the housing market are also heterogeneous, and so models that assume a representative agent, for example, will not be able to capture how prudential policies might affect some agents differently to others (Chen et al. 2009).

Thirdly, housing is local. If there is an excess of demand in a city, it is not possible to buy a house in another part of the country and move it to the city to sell it there. Fourthly, housing is a relatively illiquid asset. These two factors mean that any disequilibrium in supply and demand will take longer to solve than some economic models traditionally assume. This is especially so when housing cycles often exist within these disequilibria (Wong and Ho 2017, Olszewski et al. 2016). Finally, housing is often leveraged, which can exacerbate cycles in housing in ways that traditional analysis might not take account of (Favara and Imbs 2015, Iacoviello 2005).

For this model an agent-based approach was preferred as it allows for greater heterogeneity among agents and more dimensions in the model than other models, e.g. DSGE models (Fagiolo and Roventini 2017). ABMs also allow agent interactions to lead to macroeconomic outcomes without imposing any sort of equilibrium conditions (Farmer and Foley 2009). ABMs can model more chaotic variables such as house prices in a way that more closely resembles reality than comparable non-ABM models. The assumptions about agents' (in this case households') behavior are more flexible and hence can be more closely aligned to reality in ABMs than comparable non-ABMs (Fagiolo and Roventini 2017).

The use of ABMs in economic modeling has been growing over the past decade or so. This has been particularly strong in applications for research in finance (Chen et al. 2009). Furthermore, ABMs have been used across a range of systemic-risk subject areas (see, for example, Halaj (2018), Teplý and Klinger (2018), Thurner (2011)). More recently ABMs have also been used for analyzing the housing market (see, for example, Erlingsson et al. (2014), Filatova et al. (2009)).

While ABMs can provide insight into housing, there are some drawbacks of using them (Farmer and Foley 2009). For example, the models will only be as good as their calibrations. Furthermore, it needs to be checked that the equations underlying the decisions accurately reflect the decisions made by people in the real world. More recent innovations in DSGE modeling can overcome some of these shortcomings, such as including a full equilibrium with production and the supply side of housing. Furthermore, more recent DSGE models can provide more heterogeneity among households and firms than previous models. Therefore, there is a role for traditional economic modeling alongside DSGE and ABMs, but for the purposes here an agent-based approach was chosen.

The model I use in this paper is demand-driven and based on the Baptista et al. (2016) model. From their base, it has been adapted for the idiosyncrasies of the Danish housing market compared with the UK market. Heterogeneous households choose to buy or rent houses based on the relative costs of owning versus renting. In the Baptista et al. (2016) model, investor households own additional houses which they rent out to other households. Baptista et al. (2016, pp. 34-36) state that the house price cycles in their model are exacerbated by the behavior of investor households entering and leaving the ownership market. However, in my model, all houses for rent are owned by rental property owners that are not households. This aligns more closely with the Danish housing market in which most rental properties are owned by large investment companies. The house price cycles in this model would suggest that households deciding whether to buy or rent on its own has a significant effect.

My model does not include a mechanism through which debt overhang can cause disruptions following a hous price boom. Households do not cut back on expenditure following house price falls, nor is there a channel for household spending to influence future household income. While these mechanisms are not included in the model, the model can still point to ways in which macroprudential policy can constrain house price cycles without a debt overhang channel. As a result, the results of the model are likely to be somewhat conservative compared with the real economy.

The aim of the model is to assess the effects of various macroprudential policies on house price cycles. In particular, I assess how tightening policies reduces the amplitude of house price growth cycles. This is assessed by using policies that affect the supply of loans (namely loan-to-value (LTV) and loan-to-income (LTI) ratios). I find that small shifts in the LTI or LTV ratios can have significant dampening effects on house price cycles through the reduction of the peaks. Furthermore, because the model allows for the consideration of the distribution of households, I can link these results to the distribution of households' income and debt to show when they are binding.

Section 2 describes the model that is used. Section 3 details how data were used to calibrate the model and reports how well the outcomes of the model align with real world data. The results are given in Section 4 and conclusions in Section 5.

2 Model

This model is based on the one presented in Baptista et al. (2016). Similarly to the Baptista et al. (2016) model, in this model households make decisions about whether they want to buy or rent their accommodation, enter bids on the relevant market following that decision and then move in if their bids are matched to offers. Households age and earn income and then die, at which point they pass on their wealth to another household. The buying decisions of the households are subject to policies of a macroprudential authority regulating the mortgage market.

Nonetheless, there are some significant differences from that model which reflect various pertinent differences between the Danish housing market and that in the UK. The main differences to the UK model presented in Baptista et al. (2016) are that rental accommodation is not owned by investor households but rather by "rental property owners" who do not buy or sell the rental properties but simply rent them out. This reflects the market in Denmark where most rental properties are owned by large investment funds that mainly own them to receive the stream of rental income rather than seeking a capital gain from selling them to households. Furthermore, rental contracts are open-ended, and there are two types of rental accommodation, namely controlled rental accommodation (CRA) and non-controlled rental accommodation (NCRA).

2.1 Types of agents

In this model, there are four types of agents: households, rental property owners, a bank and a macroprudential authority. Households buy, rent and sell houses. Rental property owners manage the rental properties. The bank issues mortgages to households to buy houses and the macroprudential authority controls the macroprudential policies that the bank has to adhere to when issuing mortgages.

2.1.1 Households

There are three different types of households: renters, first-time buyers and owner-occupiers. Households can shift between these categories over their lifetime depending on the decisions they make with regard to housing. These types of households differ in terms of the decisions they make about their housing situations and the conditions that are imposed on them relating to those decisions. Across these types, households are heterogeneous in characteristics such as age, income, and bank balances.

The age of a household refers to the reference person in the household and so households are born at a random age in their twenties. When they are born, households are randomly assigned an age, income percentile and initial wealth. The probability distributions of the households' income percentiles and wealth are calibrated to the income distribution of Danish households. The households age as the model progresses, and hence their incomes change with their age in line with those of the Danish population, but the households always remain in their income percentile.

The number of households starts at zero and then expands as new households are born. The number of households expands until it reaches the target population, which in this model is 10,000 households. Households die according to an age-dependent distribution, so they are more likely to die the older they get. This age-dependent death rate is based on Danish demographic data but is adjusted so that the population of households remains around the target population. Given the randomness of the births and deaths, the population will not necessarily be exactly equal to the target population but will fluctuate to a small degree around it.

When households die, their wealth is inherited by a randomly chosen household. If the deceased household owned a house, the mortgage is annulled and the ownership of the house is transferred to the beneficiary. If the beneficiary owns their own home, they immediately sell the house they inherited. If the beneficiary is renting, they leave their rental accommodation and move into the house they have inherited.

2.2 Houses

In this model, 'houses' is a generic term for all types of accommodation that households might rent or own to live in on a long-term basis. That is, no distinction is made between houses and apartments or any other types of long-term accommodation. When houses are constructed they are assigned to one of 48 'quality bands'. These quality bands are intended to summarize all possible dimensions of quality that a house might possess, e.g. whether it is a house or apartment, the number of rooms it has, its floorspace, whether it is close to the city or further out, the neighborhood in which it is located, etc. While assuming the existence of an objective measure of house quality that all households agree with, this seems to be an acceptable means of introducing heterogeneity into the quality of houses.

As the number of households expands, houses are constructed so that the number of houses is around 85 per cent of the number of households. The remaining 15 per cent of households are in 'social housing' (see Section 2.3.1). When houses are constructed, in addition to the quality band, they are randomly assigned to one of three categories of housing; owner-occupier (O-O), controlled rental accommodation (CRA), and non-controlled rental accommodation (NCRA). The houses do not leave the category to which they are assigned. This is consistent with the housing market in Denmark, where houses rarely shift between these categories. In the model, 65 per cent of houses are O-O, with the remainder of houses being rental accommodation. Once the steady state of households is reached, the supply of houses in each category is fixed.

2.3 Household behavior

The periods in the model are meant to represent months. Each month, the household gets paid income according to its age that month and its income percentile. They then pay non-housing consumption. This non-housing consumption is based on:

- a minimum level of expenditure that all households must pay for subsistence purposes, and
- a discretionary level of consumption that causes the remaining wealth at the end of the period to approach a desired wealth goal.

The desired wealth goal is set for each household so that the overall distribution of wealth approximates that of the Danish society. After they have spent their money on non-housing consumption, households make housing decisions based on their current housing status. If the household is in 'social housing', they decide whether they want to rent or buy a new house. If they are renting, they decide whether they want to continue to rent, and if they are living in a house that they own, they decide whether they want to sell the house. After making their decision, households that wish to rent or buy will place bids on the relevant market, and households that decide to sell will place offers on the ownership market. The markets then clear, and households with successful bids move into their new house. Renters then pay rent and owners with mortgages pay their mortgages. Any extra income remaining at the end of the period is put into a "bank account" and earns 0.2 per cent interest. Figure 1 presents a stylized version of the decision-making process in the model.

2.3.1 Social housing

Following the Baptista et al. (2016) model, 'social housing' is a special category of housing for households that are between houses. These households are either waiting to move into their first home just after being 'born', or they have left rental accommodation or have sold their house but have not yet purchased (or rented) a new house. They can be thought of as either children who are ready to move out of their parents' house or people in transition between two homes. Households in social housing always wish to move out

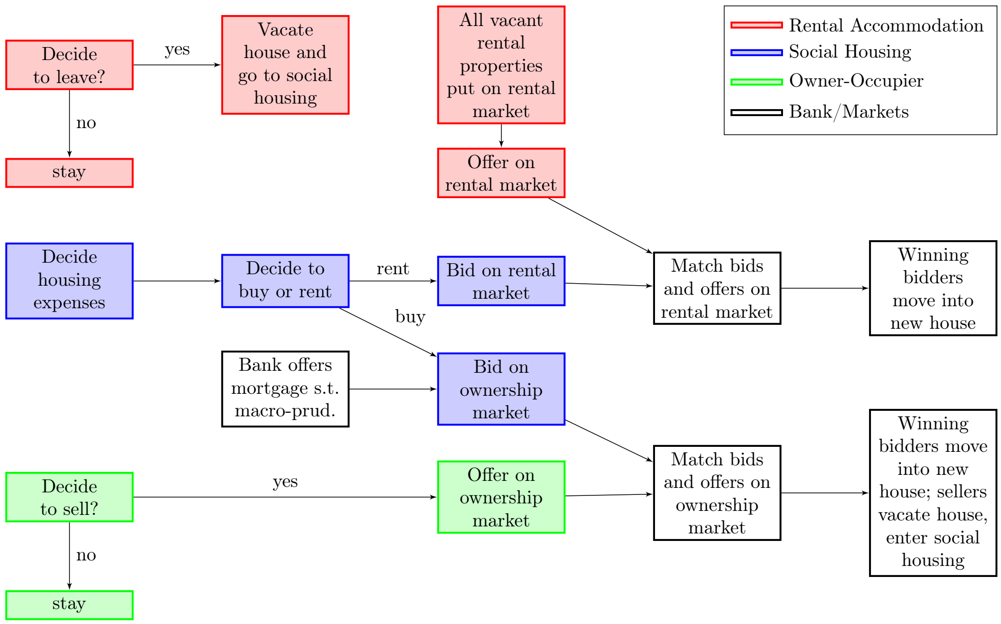


Figure 1: Flowchart of the dynamics of the decision-making process for each household per time step. Households in social housing decide how much they wish to spend on housing, and then decide whether to buy or rent. If they decide to rent, they bid on the rental market. If they decide to buy, they bid on the ownership market subject to the mortgage offered by the bank. Non-controlled rental accommodation (NCRA) tenants decide if they want to leave their house. If they do, they vacate the property and move into social housing. The NCRA owner then puts all vacant NCRA on the rental market. Owner-occupier households decide if they want to sell their house. If they do, they offer it on the ownership market. Bids and offers are then matched on the rental and ownership markets. Winning bidders move into their new houses, sellers on the ownership market vacate their house and move into social housing. Controlled rental accommodation is not featured in this flowchart.

of social housing, and so will always make a decision to rent or buy and then make a bid on the relevant market.

The decision to buy or rent is based on the costs of those two choices given the quality of house that the household wishes to move into. The household first decides how much it wishes to spend on housing. This is based on their income and the expected house price appreciation (Equation 1).

$$p_{desired} = \frac{\gamma\, y\, exp(\epsilon)}{1 - \beta g} \tag{1}$$

where $p_{desired}$ is the household's desired expenditure, y is income, γ and β are parameters, ϵ is noise, and g is the expected house price appreciation defined in Equation 2.

Central to households' decision-making with regard to renting and owning property is their expectation about the course of house prices. This is consistent with empirical evidence that expectations are a significant contributor to house price cycles both in Denmark and in other countries (Hetland and Hetland 2017). In the model, expectations affect housing decisions through two channels. The first is how much money households are willing to devote to housing expenditure; the faster house prices are expected to grow, the more money households will devote to housing expenditure. The second channel is, in assessing the cost of owning versus renting, households will assess owning as cheaper (and hence they are more likely to opt to buy a house) if the household expects house prices to grow faster.

In line with Baptista et al. (2016), the expected house price appreciation is a backward-looking expectation, based on the annual growth in the house price index from the most recent quarter, compared with the relevant quarter a year earlier.

$$g_t = \alpha \left(\frac{h_{t-1} + h_{t-2} + h_{t-3}}{h_{t-13} + h_{t-14} + h_{t-15}} - 1 \right) \tag{2}$$

where g_t is the expected house price appreciation estimated in period t, α is a constant parameter, and h_t is the house price index in period t.

Having determined how much it wishes to spend, the household then finds out the house quality that it can afford given its desired expenditure and recent house sale prices. The household then estimates the cost of renting a house of a similar quality (r_Q). The rental cost of such a house is inflated by a 'psychological cost of renting' (ϕ), while the cost of owning a house is computed as the difference between the monthly mortgage payment (m) and the expected house price appreciation, assuming that a house is bought at a price equal to the desired expenditure.

The difference between the two costs is inputted into a logistic function to produce a discrete choice to rent or buy. The logistic function is given by: $\sigma(\delta x) = 1/(1 + e^{-\delta x})$, where x is the difference in the cost of buying and renting, and δ is a shape parameter that determines how deterministic the decision is with respect to x. The behavior rule is shown in Equation 3.

$$\begin{aligned} P(buy) &= \sigma\left(\delta\left[RentingCost - BuyingCost\right]\right) \\ &= \sigma\left(\delta\left[r_Q(1+\phi) - 12(m - pg)\right]\right) \end{aligned} \tag{3}$$

If the household chooses to buy, it bids its desired expenditure on the ownership market. If the household decides to rent, it bids a fixed fraction of its income (set at 33 per cent) on the rental market.

While the ownership and rental markets are separate, they are indirectly linked through households' decisions to buy or rent. If the cost of buying a house increases, one would expect that, other things remaining equal, the demand for rental accommodation would increase as households view them to be relatively cheaper. This should then push up rents as the supply of rental properties is fixed.

If the household decides to buy, it will either pay the price outright or take out a mortgage. If the household's bank balance is greater than twice the cost of the house, it will purchase the house outright. Otherwise, it will take out a mortgage from the bank. The minimum down payment that the household pays is determined by the mortgage conditions set by the bank (see Section 2.5).

2.3.2 Owner-occupiers

Households that own their own home make a decision about selling their property each period. The probability that the household will decide to sell their house is set so that owner-occupiers will sell their house on average every 11 years, which is consistent with observations from the Danish housing market. This probability is moderated by whether the number of houses on the market is above or below 5 per cent of the number of households so that there is no large build-up of houses on the market at any given time.

$$p(Sell) = \frac{1}{11 \times 12} \times \left[1 + 4\left(0.05 - \frac{housesOnMarket}{Households}\right)\right] \tag{4}$$

Where $p(sell)$ is the monthly probability that a household decides to sell their house.

If the household decides to sell their house, they will offer it on the ownership market at a price based on:

1. the average price of houses of similar quality, and
2. the average days on the market for houses of all qualities.

The higher the average price of houses of similar quality, the higher will be the price the household offers their house for, and the longer houses have been on the market, the lower the offer will be. The function governing the offer price is as follows:

$$Initial\ Offer\ Price = \exp\left[\psi + \ln(\bar{p}) - \eta \ln\left(\frac{(d+1)}{31}\right) + \epsilon\right] \tag{5}$$

Where ψ is the initial mark-up from the average price, $\bar{p}$ is the average sale price of houses of similar quality, η is the size of days on market effect, d is the average number of days on the market for houses of all qualities, ϵ is noise.

If a house remains on the market from the previous time step, its price is reduced with a 6 per cent probability. If the price is reduced, it is reduced by a random percentage, with a mean of 5 per cent.[1] If the price falls below the amount required to pay off its mortgage, it is withdrawn from the market.

[1] These numbers are broadly consistent with the data from the Danish housing market.

2.3.3 Market clearing

After households have made their housing decisions for the month, the ownership market is cleared in an auction-style process. The market clearing is a two-step process. In the first stage of the process, all of the bids are matched with the best quality house for which the offer is less than or equal to the bid. Offers will, thus, be matched to zero, one or multiple bids.

In the second stage of the process, offers matched to a single bid are sold to that buyer at the offer price. Offers that are matched to multiple bids will have the sale price bid up by a random amount and sold to one of the bidders chosen at random. This process is repeated for a number of rounds, after which any offers that are still not matched to any bids are returned to the sellers, who will decide in the following period whether to re-offer the house at the same price, reduce the price or withdraw the offer. Any bids not matched to any offers are deleted.

2.4 Rental properties

In Denmark, less than 25 per cent of rental properties are directly owned by households. Instead, the majority of rental properties are owned by pension and investment funds. Furthermore, most rental properties built prior to 1991 have controlled rent, while those built after that date are subject to free market pricing for rents. Reflecting these two facts about the Danish rental market, the model has two separate markets for rents: namely the controlled rental market and the non-controlled rental market. Properties in each of these markets are owned by a single owner, reflecting the investment funds that tend to own rental properties.

2.4.1 Controlled rental market

Rental properties tend not to become owner-occupied dwellings and so, in our model, when houses are created, a proportion of them are designated controlled rental accommodation (CRA). Rental properties built prior to 1991 are subject to controlled rent, and households get assigned to these houses by means of a waiting list. In our model, households are put on the CRA waiting list when they are born. If a household enters CRA, buys their own house or dies, they are removed from the CRA waiting list. If a household sells their house or leaves CRA, they are put back on the CRA waiting list.

Each period, the CRA owner's only action is to assign any vacant CRA to households at the top of the waiting list. These households then move in to the CRA and pay a fixed fraction of median income in rent. In Denmark, if a household rents an entire house, they tend to have an open-ended rental contract and so can generally stay in the house as long as they wish. Therefore, in our model, households residing in CRA have a fixed probability each month of deciding to leave their CRA, such that, on average, households will leave CRA every 10 years, consistent with data from the Danish rental market.

2.4.2 Non-controlled rental market

A proportion of houses are designated non-controlled rental accommodation (NCRA). These houses are rented by households and owned by the NCRA owner. In line with the open-ended nature of rental contracts in Denmark, households in NCRA have a fixed probability of deciding to leave their NCRA in any given month. Each month, the NCRA owner offers any vacant NCRA on the rental market for a price determined in a similar way to those houses offered on the ownership market. Namely,

$$\textit{Initial Rental Offer} = \exp\left[\theta + \ln(\bar{r}) - \kappa \ln\left(\frac{(d+1)}{31}\right) + \epsilon\right] \tag{6}$$

Where θ is the initial mark-up from the average rent, $\bar{r}$ is the average rent of houses of similar quality, κ is the size of days on market effect, d is the average number of days on the rental market for houses of all qualities, ϵ is a noise term. Putting vacant NCRAs on the rental market is the NCRA owner's only role. Households that have decided to rent bid a fixed fraction of their income on the rental market. Bids and offers on the rental market are cleared in the same way as for the ownership market.

2.5 The bank and macroprudential authority

The only role of the bank in the model is to provide mortgages to households that require them. All mortgages are 25-year fixed rate repayment mortgages. Monetary policy in Denmark is focused on maintaining a fixed exchange rate against the euro, and so interest rates are not directly affected by the demand for credit in Denmark. As such, the model's mortgage interest rate is unaffected by the demand for credit. The bank will approve any mortgage that meets the prudential constraints, namely:

1. loan to value (LTV),
2. loan to income (LTI), and
3. affordability constraints.

The maximum mortgage the bank offers is equal to whichever of the above constraints is binding. In order to explore the differing effects of the LTV ratio on different types of borrowers we allow the LTV ratio to be set to different ratios for first-time buyers and owner-occupiers. When banks grant mortgages, there is often flexibility to allow some mortgages above the LTI limit. To reflect this in the model, the bank can approve a certain percentage of mortgages above the set ratio, usually set at 15 per cent. The affordability constraints are set so that a household's monthly mortgage payments are no greater than a fixed share of its disposable income. Formally, the affordability constraint is:

$$MaximumLoan = Y_d \nu \frac{1-(1+r)^{-N}}{r} \tag{7}$$

Where Y_d is the household's disposable income, ν is the share of household disposable income available for mortgage payments, r is the monthly interest rate, and N is the number of monthly payments (equal to 300 for a 25-year loan).

The prudential constraints differ in how they affect mortgagees and how they relate to the house price cycle. LTV ratios determine how much of the value of a house mortgagees can borrow, or put another way, how much of the value of the house the mortgagee must save as a down payment. If the LTV ratio is kept steady, as house prices increase, the absolute amount the mortgagee must save for the down payment will increase too (though this increase will only be a fraction of the increase in house prices). As house prices fall, so will the amount the mortgagee must save. In this way the LTV requirement is countercyclical as the restraints on the household increase in the boom and relax in the bust.

LTI ratios determine how many multiples of a household's annual income it is able to borrow (in this case to buy a house). Given that income tends to be less cyclical than house prices, LTI ratios set a limit on the size of the loan a household can borrow that is relatively unaffected by the house price cycle. Therefore, as house prices rise, LTIs are more likely to become a binding constraint. LTIs are then expected to restrict the top of a cycle but have relatively little impact at the bottom of a cycle.

As stated above, affordability constraints set a limit on the share of monthly disposable income that can be used for mortgage payments. In a regime of fixed interest rates, they will act much like an LTI ratio.

The macroprudential authority's role is to set the prudential constraints on the bank's mortgages.

3 Calibration

The ABM results are only valuable if the models reflect reality. The process of ensuring that they do reflect reality as closely as possible involves the calibration of the model and then the validation of the model against actual economic statistics from the area in question. See Table 3 in the Appendix for a list of the values and sources of the model parameters.

3.1 Calibration

The parameters for the model have been calibrated at the micro as well as macro level. The micro-calibration of the model involves attempting to match the parameters of the model to the actual distributions of data from the Danish economy. The richness of the model relies on heterogeneous agents being affected by and reacting to conditions in the model in heterogeneous ways. As such, distributions of agent characteristics that are important. Therefore, for the most part the aim of the model calibration is to match the distributions of the model to those of the real world rather than just a small set of descriptive statistics, such as means or medians. So, for example, the income by age distributions used in the model are matched to those of the Danish economy.

In other contexts, it is not possible to get data on the full distributions of variables. For these variables we instead attempt to calibrate the model in such a way that the decisions made through the decision equations result in statistics that match up with those of Danish society. So, for example, data on sales of homes and rental terms of apartments have been used in the decision equations around selling houses and leaving rental accommodation to ensure that the length of time households remain in their properties in the model matches those seen in reality.

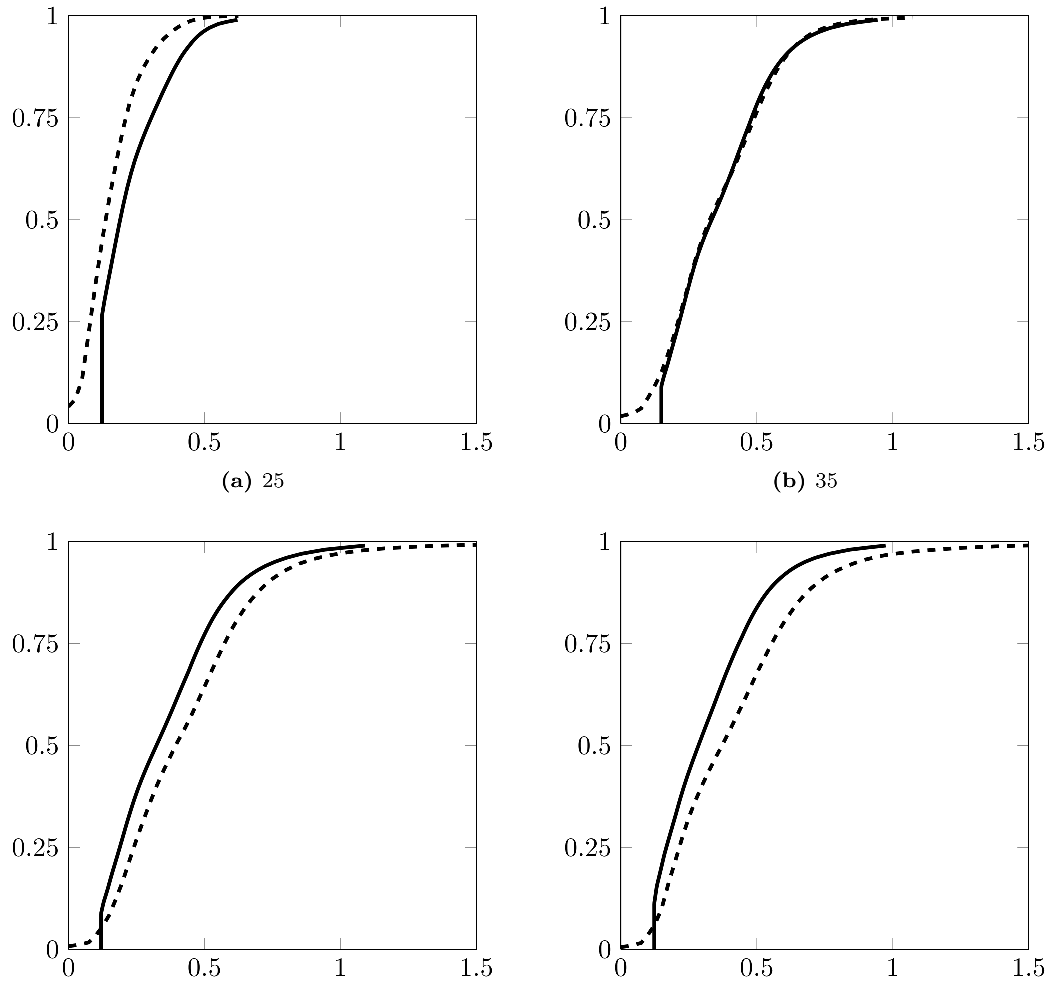
3.2 Validation

To confirm that the model was accurately reflecting reality, numerous data were extracted from it to compare with actual data from the Danish housing market. The closer the data from the model align with those of the Danish economy, the more confident we can be in the conclusions of the model.

The post-tax income distributions for different ages in the model have a reasonably tight fit with the comparable distributions in the Danish economy (Figure 2). When comparing the results of the simulations with that we see in Denmark, Figure 3 shows a typical 47-year run of the simulated data matched against actual house price data for Denmark since 1971.[2] The simulated data have been transformed into quarterly data from the original monthly series. The Danish data are seasonally adjusted data, which have been de-trended with a linear trend. As can be seen, the simulated data are qualitatively similar to the real data. The amplitude of the cycles in the simulated data is approximately on a par with that in the actual data. Similarly, the number of cycles is approximately the same in both data sets. The standard deviation of the Danish house price index (as shown in Figure 3) is 7.26, which is larger than that recorded in the baseline model of 6.43. Nonetheless, the house price data from the model appear to do a reasonable job of replicating the data seen in Denmark.

Further control indicators can be seen in Table 1. The housing measures taken from the Danish economy were recorded over the time period from 1973 until 2018, except for household credit growth, which was recorded from 2004 to 2018. The measures taken from the model were based on the baseline model with an LTV limit of 98 per cent and an LTI of 6 times income. As can be seen from the table, the aggregates appear to match the Danish economy reasonably closely, providing additional confidence in the model.

[2] The simulated data in Figure 3 are not specifically meant to line up with the cycles in this particular time period.



(a) 25 **(b)** 35 **(c)** 45 **(d)** 55

Figure 2: Cumulative distributions of post-tax income (in million DKK) in the model (- - - -) and real data for Denmark for comparison (——) for four different ages.

We can also compare the growth in credit in the model with the growth in house prices. We should expect that house price and credit growth are positively correlated, as strong house price growth will tend to necessitate larger mortgages for households. Reassuringly, we find that the simulated credit growth is positively correlated with house price growth (Figure 4). While the R-squared value for credit growth and house price growth is comparatively low at 18.5, the relationship is highly significant with a correlation coefficient of 0.43. Therefore, the relationship between credit growth and house price growth is significant and positive. However, other factors are clearly needed to explain the values.

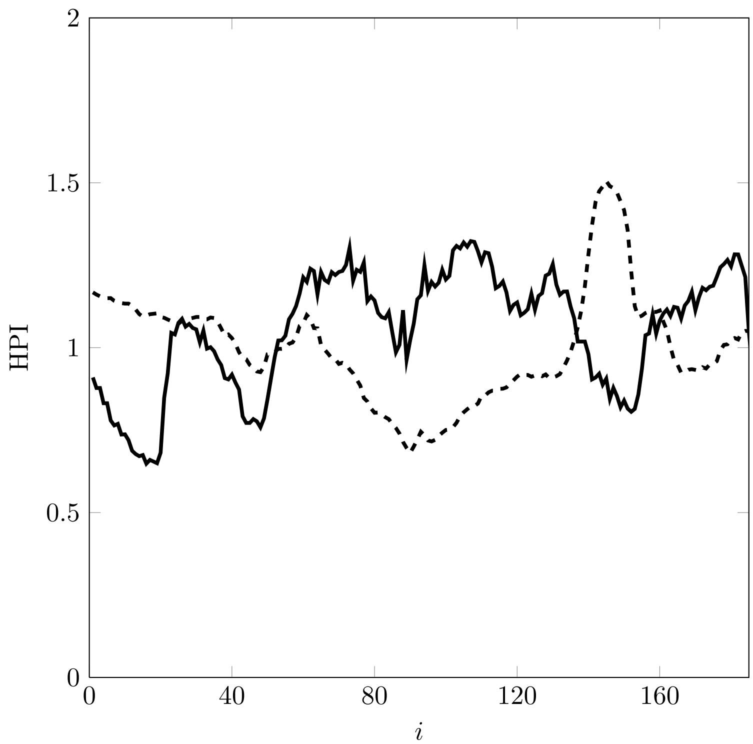


Figure 3: A typical simulation (——) of the house price index versus the actual (- - - -) Danish house price index, seasonally adjusted and de-trended

4 Results

The main purpose of using the model in this analysis is to examine how alternative macroprudential policies affect house price cycles. In this section, I explain how I analyze the effects of these policy measures on the housing market, and present results of the effects of house price expectations and the macroprudential policies on the model. In the results that follow, each data point is based on 10 simulations of 10,000 periods.

Indicator	Denmark's official variables			Housing ABM Simulations
	Minimum	Average	Maximum	
Mortgage LTV ratio	24.8%	40.7%	57.4%	26.5%
Household credit growth	0.2%	4.9%	15.5%	3.5%
Debt to income ratio	117.1%	198.1%	326.3%	199.8%
House price growth	-15.3%	6.0%	27.5%	0.8%

Table 1: Comparison of various housing indicators from the simulation results with those from the Danish economy. Date ranges for values: LTV: 1973 Q1 to 2018 Q2; household credit growth: Jan 2004 to Dec 2018; debt to income: 1973 Q1 to 2018 Q2; house price growth: 1973 Q4 to 2018 Q3.

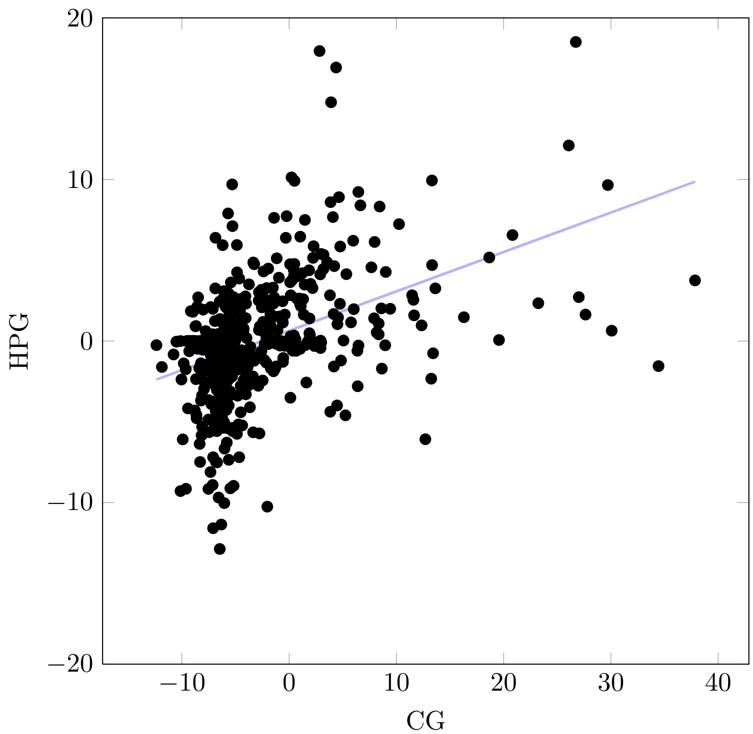


Figure 4: Scatter plot of credit growth vs house price growth in simulations.

4.1 Macroprudential policy measures and house price cycles

In general, the goal of macroprudential policy with respect to housing is to reduce vulnerabilities of households to systemic risks through their investments in housing. Macroprudential policies such as LTI and LTV ratios will affect households' access to credit. These policies are also likely to have flow-on effects on the house price cycle. The assessment of these effects on the house price cycle is the main focus of this paper.

In particular, the measure that is central to the assessment is the standard deviation of house price growth. The advantage of this approach is that it is a simple measure that can be calculated from the house price data with minimum need for subjective assumptions. I also consider the distribution of house price growth with particular emphasis on viewing the extreme values of the distribution. That is, whether the probability of recording extreme values of house price growth is reduced through the application of macroprudential policies.

I have chosen not to use other measures of house price cycles such as growth rates from peak to trough, or trough to peak, or peak-to-peak length of cycles as these naturally involve assumptions about how to determine which points in the data are peaks and troughs. The simulation data did not always lend itself to an uncomplicated determination of which points should be considered peaks or troughs, and so I have settled on using the standard deviations of house price growth and distribution of house price growth as these appear to capture the information about house price cycles with fewer subjective assumptions.

The baseline model has an LTI of 6 times income and an LTV of 98 per cent. In the model, very few households have an LTI greater than 6 (Figure 8) and so the baseline model's policies are not especially binding. Since 2015, Denmark has had an LTV constraint of 95 per cent, and, since 2018, lending conditions are placed on new borrowing by households with a debt-to-income ratio above 4 times income and an LTV above 60 per cent. Prior to this, Denmark did not have national legally binding LTV or LTI limits, though some regulatory initiatives were put in place in 2016 in main urban areas, and banks individually may have implemented these policies themselves nationwide. Therefore, the baseline model is generally in line with the policies in place in Denmark for most of the past few decades.

The standard deviation of the Danish house price index, seasonally adjusted and de-trended (as shown in Figure 3), is 7.26. This is somewhat higher than that recorded in the baseline model of around 6.43. The higher standard deviation for the actual data possibly reflects the lack of debt overhang in the model (see Section 4.3), leading to smaller troughs in the model compared with actual data. Furthermore, there are many influences on the house price index in the real world that are not fully captured in the model. Therefore, the more valid interpretation of the effect on the standard deviation of house price growth in the model is to reflect the direction and comparative scale of the reduction rather than the exact number.

4.2 The role of house price expectations

The baseline of the model simulates the house price cycles observed in Denmark. The main mechanism through which these cycles are produced is the house price expectations that households in the model have. As mentioned in Section 2, house price expectations are backward looking expectations, i.e. households expect house prices to continue to grow at the same rate that they did over the previous year. This expectation is moderated through a coefficient defining how much of the current growth households expect to be realized in future house price growth.

House price expectations affect the model through their effect on the amount of money households are willing to spend on housing, and on households' assessment of the cost of housing relative to renting, and hence their decisions about whether to buy or rent. The stronger households expect house price growth to be, the more money they will be willing to spend on buying a house, and the cheaper will they consider the cost of buying a house relative to renting.

The central role of house price expectations is illustrated in Figure 5. This figure shows typical simulations of the model, with the coefficient on house price growth at zero and at 0.5 for the reference simulation. As can be seen, with the coefficient equal to zero, which essentially removes house price expectations from

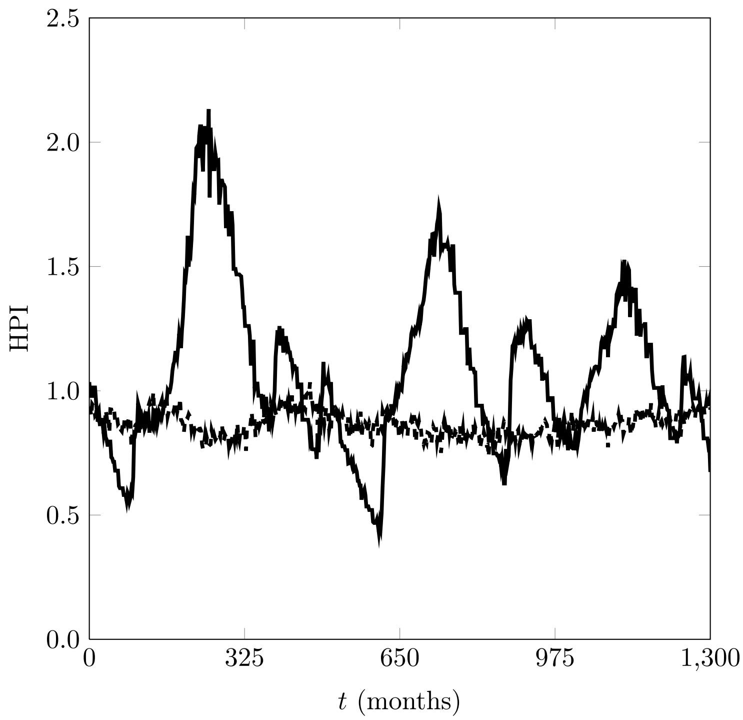


Figure 5: Typical simulations of the house price index (HPI), with the coefficient on house price expectations g at zero (- - - -) and 0.5 (——).

the model, the cycles in house prices disappear. The reduction in house price cycles mainly occurs when the house price appreciation coefficient falls below 0.3 (Figure 6). At levels higher than 0.3, the standard deviation of house price growth remains fairly flat, suggesting that house price cycles are unaffected by households expecting more of past house price growth to be realized in future house price growth. However, when the house price appreciation coefficient is below 0.3 (that is, households expect that less than 30 per cent of the current house price growth will be realized again in the future), the standard deviation in house price growth falls dramatically.

4.3 No debt overhang

In the model there is no debt overhang. In general, debt overhang occurs when households take on debt during a boom when they expect asset prices to continue to rise strongly. After the peak, households then have more debt than they would otherwise wish for given the now lower-than-expected asset prices. This leads households to reduce expenditures to service their debt. As a number of households retract expenditures at the same time, this leads to a reduction in income in the economy, leading to further retraction of expenditures.

In the model, there is no mechanism for households to reduce expenditures in the face of falling house

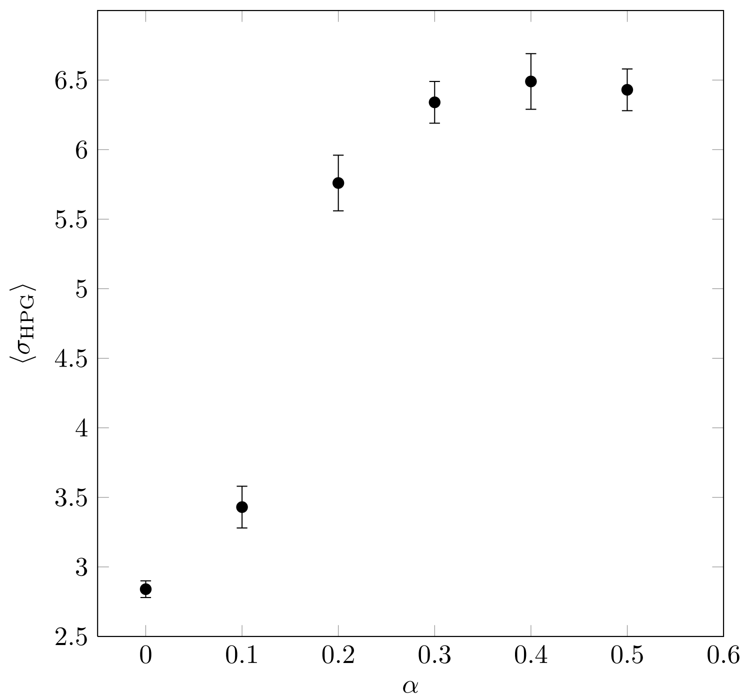


Figure 6: Standard deviation of annual growth of the House Price Index across simulations under different house price appreciation coefficients α.

prices, beyond that which they otherwise would have done to service the mortgages that they have taken on. Furthermore, there is no feedback loop for expenditures to affect household incomes. Given these factors, the effects of the macroprudential policies will mainly affect the top of the cycle, or 'leaning into the wind', but will not affect the bottom of the cycle. As Figure 7 shows, when the LTI constraint is tightened the maximum value of the house price index is reduced, while the minimum and median values remain unchanged. Ultimately, this suggests that the results reported are likely to be conservative compared with a model that features debt overhang.

4.4 Loan-to-income (LTI) and loan-to-value (LTV) ratios

The main focus of this paper is to investigate the effects of tightening macroprudential policies on house price cycles. In this assessment, I tighten the LTV ratio from 98 per cent of the value of the house to 86 per cent, and the LTI from 6 times income to 2 times income. Compared with historical policies in Denmark, these tightenings could be considered to be quite extreme, but nonetheless they give an insight into how much the house-price cycle would be affected by a broad range of tightenings.

The loan-to-value (LTV) ratio constrains more mortgage applications than the other macroprudential policies. In the baseline model, around half of mortgage applications are constrained by the loan-to-value ratio. Almost all of the other mortgage applications in the baseline model are not constrained by any of

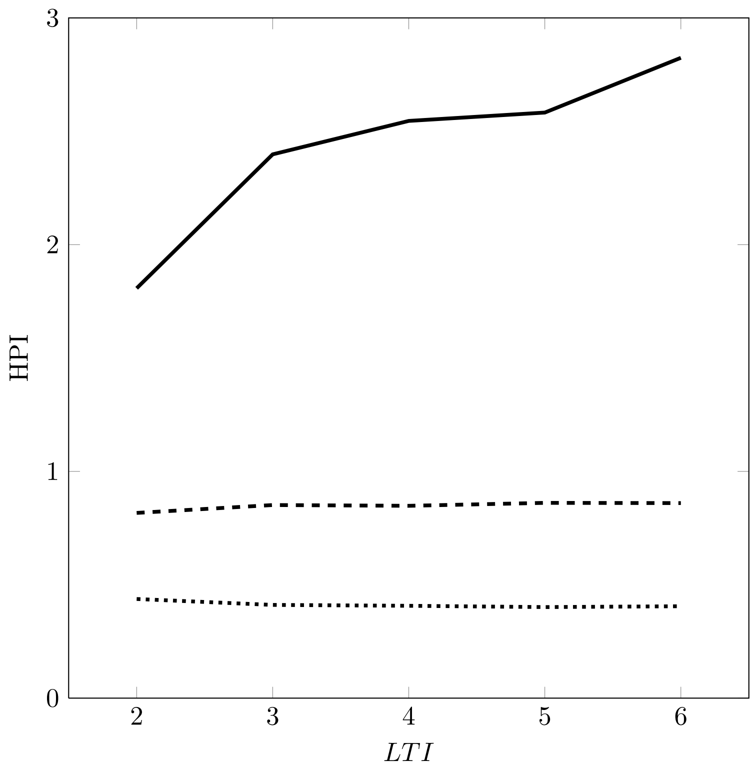


Figure 7: Average maximum, minimum and median values of the house price index (HPI) across simulations under different values of the loan-to-income (LTI) constraint.

the macroprudential policies. As the prudential policies are tightened, the share of mortgage applications constrained by the policies increases. The share of mortgage applications constrained by the LTV constraint rises to 95 per cent as it is tightened to 86 per cent of the value of the loan. The share that is constrained by the loan-to-income (LTI) constraint rises from around zero per cent to 30 per cent as it is tightened to 2 times the household's income.

The LTI ratio places a ceiling on the amount that a household can borrow to buy a house. This in turn constrains the extent to which house prices can rise during a housing boom. Figure 8 shows how the distribution of LTI across households changes as the measure is tightened. There is a shift down the scale, with a significant increase just below the new target measure, 3.0, as those households that would otherwise have LTIs greater than 3.0 are restricted to the new constraint. Some households' LTI ratios are above the band as it is not a hard ceiling, with 15 per cent of loans allowed to be above the band to reflect real-world flexibility.

Figure 9 shows histograms of the recorded year-ended house price growth under regimes of LTI ratios of 6.0 and 3.0. Clearly, the distribution of house price growth recorded under the tighter LTI regime is narrower than that under the looser regime. This indicates that the extremes of house price growth become less likely

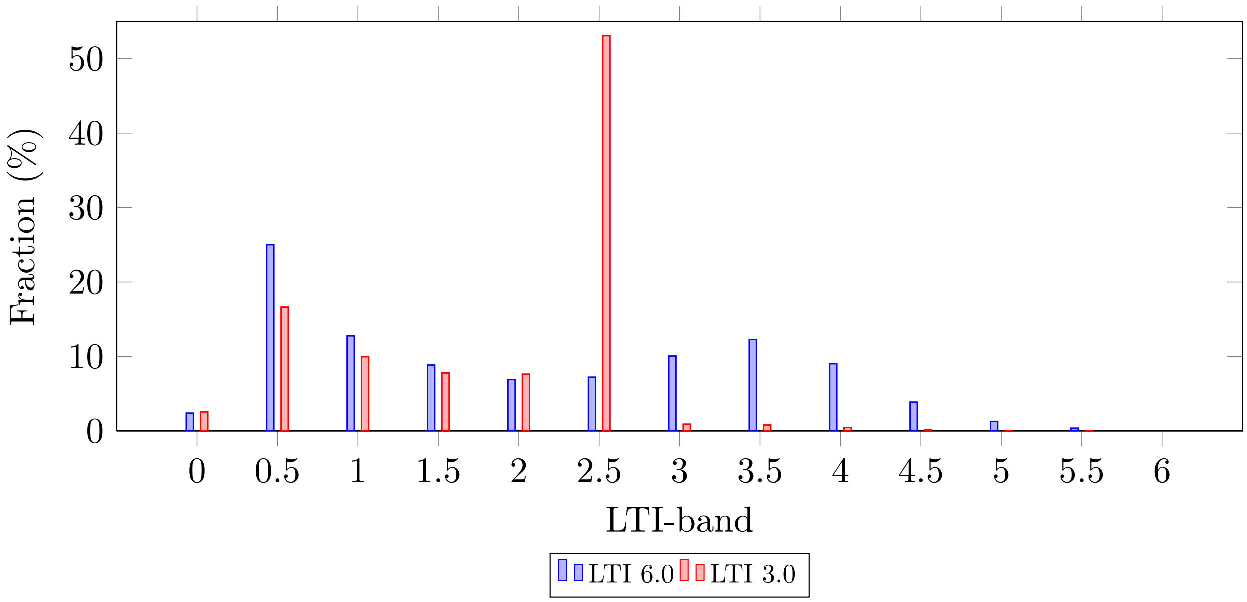


Figure 8: Histograms of owner-occupiers' loan-to-income ratios (LTI) under regimes of LTI ratios of 6.0 and 3.0

LTI	Standard deviation HPG	LTV	Standard deviation HPG
6	6.43	0.98	6.43
5	6.43	0.94	5.74
4	6.37	0.90	4.73
3	5.85	0.86	3.94
2	3.96		

Table 2: Comparison of the standard deviation of house price growth (HPG) for different values of the loan-to-income (LTI) and loan-to-value (LTV) constraints.

with tighter loan-to-income regimes. I take this to indicate that house price cycles are reduced when the LTI requirement is tightened.

Further evidence of this reduction in house price cycles can be seen when looking at the standard deviation of house price growth under different LTI regimes (Table 2 and Figure 10). As the LTI condition is tightened from 6 times income, there is initially little movement in the standard deviation of house price growth until the LTI is reduced below 4 times income. Between an LTI of 4 and 2 there is a rapid tightening of house price cycles with the standard deviation reduced by around 40 per cent between these values. As Figure 8 shows, even in the relatively unrestricted case of an LTI constraint of 6, there was only a small share of households with LTI ratios above 4. Therefore, tightening the LTI constraint does not affect many households until it is reduced below 4, at which point, as more households are affected, the effect on house price cycles increases, resulting in a non-linear response to policy tightening. What these results show is that policy makers need to be well aware of the distribution of LTI ratios among households before implementing policies.

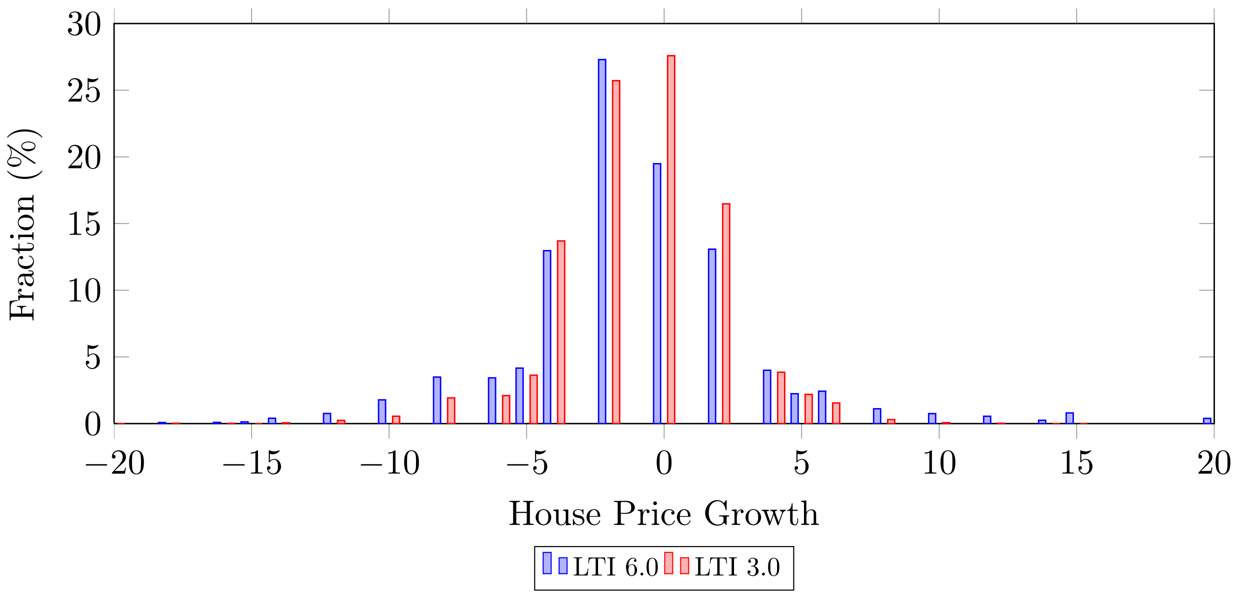


Figure 9: Histograms of yearly house-price growth recorded under regimes of loan-to- income (LTI) ratios of 6.0 and 3.0.

Similarly to the LTI constraint, as the LTV condition is tightened, the standard deviation of house price growth falls (Table 2 and Figure 11). The LTV ratio is always a binding constraint for a significant share of households, and so any tightening in this constraint will restrict fluctuations in house price cycles, resulting in a more linear response than that of the LTI.

As the LTV can be set at different rates for first-time buyers (FTB) and owner-occupiers (O-O), it can be determined that the effect on the house price cycle from tightening the LTV largely affects the market through its effects on FTB (Figure 11). This is because the constraint is more binding on FTB, as O-O can use the proceeds from the sale of their previous house to have a larger down-payment on their new house. Tightening the LTV ratio for FTB from 98 per cent causes a steady reduction in the standard deviation of house price growth. The standard deviation of house price growth is reduced by nearly 40 per cent between LTVs of 98 per cent and 86 per cent. These results are similar to those in comparable studies such as that of Ingholt (2019). While Ingholt (2019) was looking at housing credit growth rather than house price growth, he found that tightening LTV ratios can reduce the standard deviation of credit growth by 48 per cent.

When more than one macroprudential policy is tightened at the same time, if both policies are in the zones where they become individually binding, the two policies can combine to reduce the standard deviation of house price growth further than if only one of the policies had been tightened (Figure 12). That is, when the LTI ratio is reduced below 4 times income and the LTV is tightened as well, the effect on house price cycles is enhanced. This is because the policies become binding for different households, and so constrain a broader share of the population compared with a situation where just one of the policies is tightened.

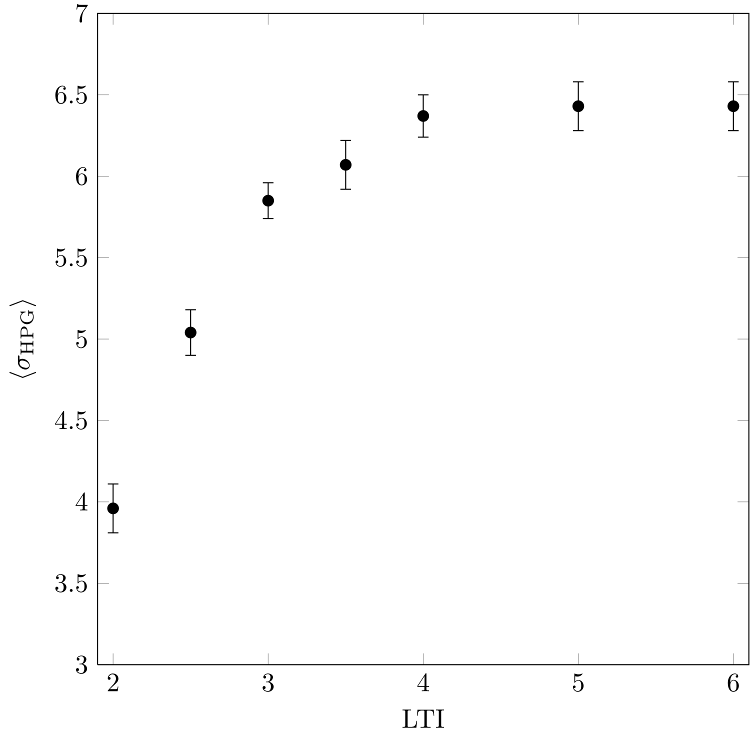


Figure 10: Effect of LTI on house price growth. Average standard deviation of house price growth (HPG) under varying values of the LTI constraint.

Nonetheless, when one of the macroprudential policies is tightened to a large extent, the extra effect from the other policy appears to mostly disappear as most households become constrained, leaving little for the extra policy tightening to do. In these cases the LTV constraint tends to be the more dominant policy.

These results suggest that macroprudential policymakers need to be aware of the distribution of households with regard to their debt when implementing macroprudential policies. Loan-to-value ratios are likely to be binding for a significant share of households and so tightening the LTV ratio will most likely have a linear effect. However, the LTI ratio is likely to be less binding for households and so the response to its tightening can be quite non-linear. Policy makers also need to be aware that there might be a particular zone of policy settings which will allow the two measures to produce a combined effect. However, outside of this zone there is not likely to be any greater effect compared with tightening just one of the measures.

5 Conclusion

This paper has presented an agent-based model of the Danish housing market for the purposes of examining the effects of macroprudential policies on housing cycles. The model takes into account the idiosyncrasies of the Danish market. In particular that the Danish market has sizable non-market-based and market-

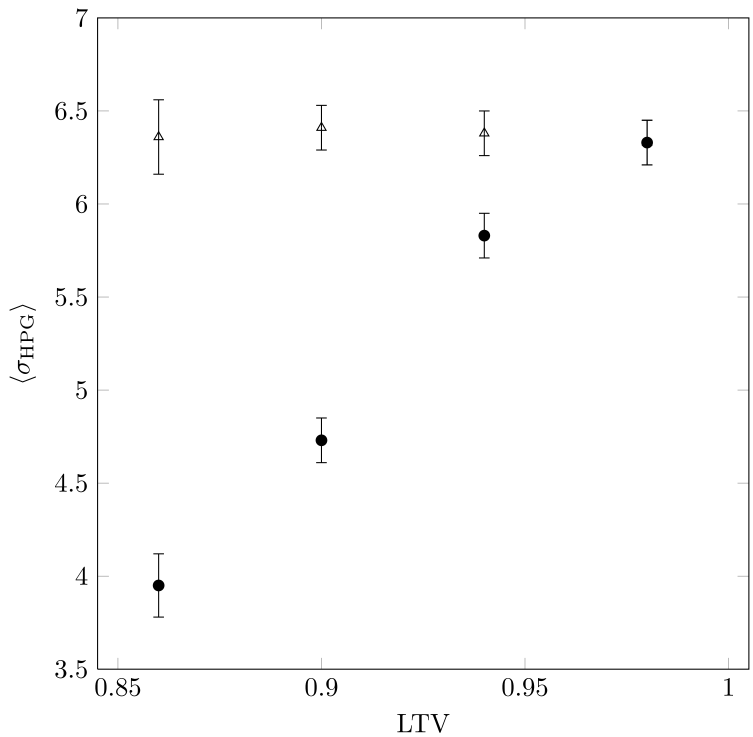


Figure 11: Effect of LTV on house price growth. Average standard deviation of house price growth (HPG) under varying values of first-time-buyer and owner-occupier LTV (first-time-buyer □; owner-occupier △).

based systems for distributing rental accommodation, combined with minimal household ownership of rental properties. Incorporating these factors into an agent-based model resulted in a system with housing cycles reflecting the cycles apparent in the actual Danish market.

By applying different macroprudential policies to the model, I was able to determine the extent to which these policies reduce Danish house price cycles. The policies examined were loan-to value (LTV) and loan-to income (LTI) ratios. Tightening the LTI constraint caused a reduction in house price cycles that was particularly pronounced between LTIs of 4 times income and 2 times income. Similarly, reducing LTV ratios from 98 per cent to 86 per cent reduced house price cycles significantly. Combining these policies was shown to have an extra effect over and above that of the individual effects, as the policies restricted a different set of households. Nonetheless, this combined effect was restricted to a certain joined range of policy settings.

As this paper has shown the efficacy of the agent-based model being used, it would be possible to use it to analyze other aspects of the Danish housing market. For example, it could be used to look at how various policy variables affect households in different parts of the income and age distributions, examine how changes in the size of the non-market rental sector relative to the market-based rental sector affect the system as a whole, or consider the effects of non-standard mortgage products on the housing market.

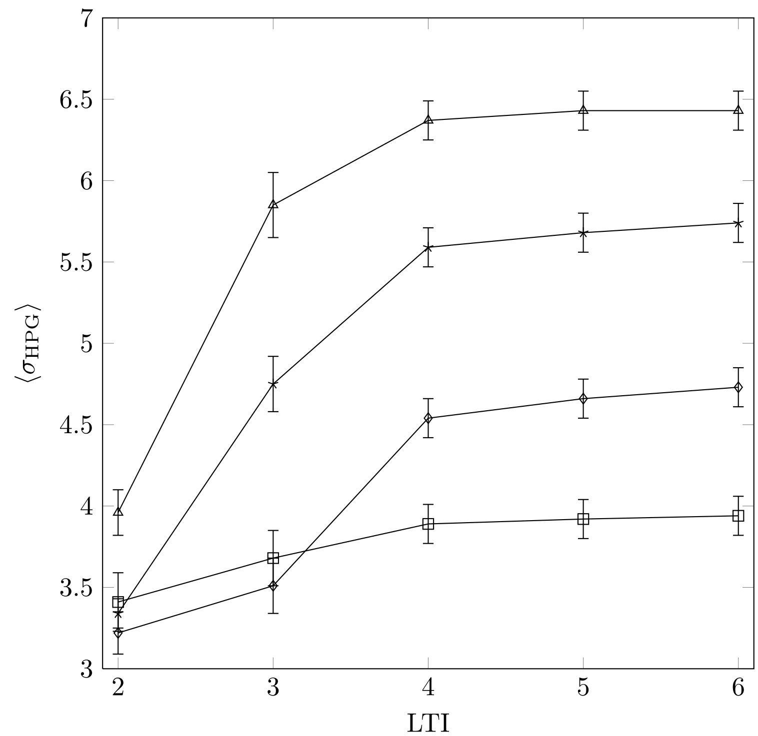


Figure 12: Effect of LTI on house price growth for different values of the LTV. Average standard deviation of house price growth (HPG) under varying values of LTV and LTI. Legend for above figure (LTV = 0.86 □; LTV = 0.90 ⋄; LTV = 0.94 ⋆; LTV = 0.98 △)

In all, this paper adds to the evidence that ABMs contribute to the study of economic markets as an adjunct to more traditional economic analysis.

6 Appendix

A Parameter Values and Data Sources

Table 3: Parameter values and sources Medians are denoted by M, ith percentile by P_i.

Model component or Equation	Parameter Values	Sources	Notes
Panel A: Demographics			
Number of households	10 000	Model input	
Birth rate	1.80%	Danmarks Statistik	
Mortality	1.80%	Danmarks Statistik	The pdf was multiplied by a constant factor to ensure that the overall number of households remained around the target population.
Panel B: Income and financial wealth			
Income given age and income percentile		Danmarks Statistik	
Minimum Income	11,282 DKK/month	Danmarks Statistik	Married couple's monthly lower earnings from income support.
Essential consumption fraction	80%	Rockwool Fonden	Percentage of the minimum income spent by every household each month as "essential consumption."
Return on financial wealth	0.2%		Interest rate on bank deposits.
State Income tax	Tax bands DKK 43 442 5.83%; DKK 479 600 15%	skat.dk	State tax is charged on total taxable income at the given rate on income earned above the related band limit.
Municipal Income tax	24.9%	skat.dk	Municipal tax is charged at a rate on taxable income less the employment allowance.
Employment Allowance	8.3%	skat.dk	Employment allowance is 8.3% of gross income, to a maximum allowance of 28,000 DKK
Panel C: Behavioural rules			
Equation 1, Desired expenditure on housing	$\gamma = 4.5; \beta = 0.08; \epsilon = N(0, 0.14)$	Baptista et al. (2016)	γ is the multiple of income households want to spend on housing, β is the adjustment to spending due to expected price appreciation, ϵ is a noise term.
Equation 2 House price appreciation expectation	$\alpha = 0.5$	Baptista et al. (2016)	α represents the share of the past year's house price growth that is expected to manifest in future growth.
Equation 3 Rent or buy decision	$\delta = 1/3500; \phi = 1.1/12$	Baptista et al. (2016)	δ is the sensitivity of the rent or buy decision to the difference in costs; ϕ is the psychological cost of renting.
Renting Fraction	0.33	Rockwool Fonden	Fraction of income bid as rent.
Equation 5 House offer price	$\psi = 0.04; \eta = 0.011; \epsilon = N(0, 0.5)$	Baptista et al. (2016)	ψ is the mark-up on the average sale price; η is the size of the "days on market" effect.
Price decline if unsold	Probability of reducing the price = 5.5%, Distribution of price change = N(1.603, 0.617)	Boliga	Normal distribution of price declines is bounded at zero.
Multiple of house price for cash payment	2	Baptista et al. (2016)	If the household's bank balance is more than this multiple of the price, the households does not take out a mortgage.
Equation 6 Initial Rental offer	$\theta = 0.0; \kappa = 0.0; \epsilon = N(0, 0.05)$	Baptista et al. (2016)	
CRA rent fraction	0.3	Rockwool Fonden	CRA rent as a share of median income.
Price reduction on rental market	5.0%	Boliga	Reduction in demanded rent each month until house is occupied.

Continued on next page

Table 3 – *Continued from previous page*

Model component or Equation	Parameter Values	Sources	Notes
Panel D: Housing markets			
Initial HPI	0.8	Baptista et al. (2016)	
Length of rental agreements	unlimited	Landsbyggefonden	Both NCRA and CRA rental agreements last as long as the household wishes to remain the house.
Probability of leaving rental property	0.008	Landsbyggefonden	The probability each month that a household will leave a rental property (both for NCRA and CRA). Average length of tenancy 11 years.
Panel E: Bank			
Mortgage interest rate	2.0%		
Baseline LTV	0.98		The maximum share of the value of a house that a household can borrow.
Baseline LTI	6.0		The maximum multiple of a household's income that a household can borrow.
Baseline affordability coefficient	0.5		Maximum share of income to be spent on housing in stressed conditions.

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DANMARKS NATIONALBANK
HAVNEGADE 5
DK-1093 COPENHAGEN K
WWW.NATIONALBANKEN.DK

DANMARKS NATIONALBANK