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Buy to let: The role of rental markets in housing booms

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Abstract

How do rental markets affect housing price dynamics? I develop a structural search model that allows housing owners to invest in rental housing, and let rents be determined endogenously. To motivate the model, I present empirical evidence that a significant share of buyers are buy-to-let investors, and rents and the buy-to-let share are positively correlated with housing prices. The calibrated model matches the high investor share and housing price increase of a housing boom. A buy-to-let sector in a search framework is able to explain much of the observed increase in price-to-rent ratio, without shocks to credit or over-optimistic expectations. The model introduces two mechanisms that increase prices compared to a standard search model. First, the endogenous correlation of rents and housing prices makes it attractive for non-owners to buy in "hot" markets, to avoid paying high rents. Second, the increased incentives to become landlords in high rent periods further increase the number of buyers and amplify the effect of high demand on housing prices.

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1 Introduction

This paper explores the interaction between the market for owner-occupied and rental housing. I model the connection between ownership and rental marktes through the possibility for housing owners to invest in a second house to let out (buy-to-let). The incentives to invest depend on the achievable rent, which is endogenous in the model. The modelling choices are influenced by empirical patterns of buy-to-let investors in Oslo. How rental markets affect housing prices has rarely been considered in the literature, but the influence is shown here to be important for housing price dynamics.

Housing prices have been growing quickly in many developed countries over the last decades (Knoll et al., 2017). This has particularly been an urban phenomena, affecting what Gyourku et al. (2013) call "Superstar cities". In the Norwegian capital Oslo, housing prices almost doubled over the period 2004 - 2014 (with real growth of 60 percent). In this paper I consider how rental demand and supply contribute to high housing price growth. I also show that a model of buy-to-let investors in a search framework can explain the rapid increase of housing prices compared to rents, the so-called "price-rent puzzle" (Liu et al., 2019).

There is ample evidence that the price-to-rent ratio increases during housing booms (e.g. Campbell et al., 2009; Favilukis et al., 2017; Liu et al., 2019). Housing market models often struggle to account for the full extent of that increase. Because housing prices usually depend on the present value of rents, the price-to-rent ratio is quite stable. To break this close connection, different papers introduce mechanisms such as shocks to credit supply[1] or over-optimistic housing buyers (Landvoigt, 2017). The buy-to-let model creates an economy where the price-to-rent ratio increases in booms, without any role for credit constraints, and with rational price expectations. While credit supply is convincingly implicated in the US housing boom, and likely relevant also for housing price increases in Oslo, it is interesting that most of the price-to-rent increase can be matched in a model without credit shocks. The boom is instead driven by an exogenous increase in population inflow, which increases demand for both owned and rented housing.[2] Increased rental demand induces more buy-to-let investors to enter the market, which, through search frictions, amplifies the housing price increase.

The impact of buy-to-let investors on the housing market has been a concern in policy circles in many countries. The Bank of England (2015) worries that buy-to-let investors drive up prices in good times, and may be vulnerable to negative interest rate and price shocks. Similar concerns have also been voiced in New Zealand (Reserve Bank of New Zealand, 2016), Australia (Reserve Bank of Australia, 2017) and the Netherlands (De Nederlandsche Bank, 2018). The media, in e.g. the UK (The Guardian, 2013), Norway (Dagens

[1] Changes in credit is the favored explanation in a large literature on the recent US housing boom and bust. See Favara and Imbs (2015), Di Maggio and Kermani (2017), Favilukis et al. (2017), Garriga et al., (2019), Liu et al., (2019) and Greenwald and Guren (2019).

[2] Thus, it is related to Kaplan et al. (2020), where shocks to housing demand beliefs are the main drivers of the price-to-rent ratio.

Næringsliv 2014; NRK, 2015) and Australia (Bloomberg, 2017), also connect investment buyers with housing price booms. Chinco and Mayer (2016), Gao et al. (2020) and Garcia (2021) show empirically that second house buyers exacerbate the boom-bust-cycle, but neither deal directly with buy-to-let investors nor explores the mechanisms driving this result. Modeling a housing market with buy-to-let helps understanding whether the concerns about buy-to-let are valid or not, and clarifies the role investment buyers play in housing market cycles.

Buy-to-let investors are a different type of investors than "flippers", who buy and quickly resell houses.[3] In contrast to flippers, buy-to-let investors mainly look for return as landlords, not from price appreciation. They usually invest in housing for a longer time frame (Bracke, 2021). The role of flippers is not explored in this paper. The way I define investors empirically requires them to hold their houses for a certain period. The coexistence of flippers and buy-to-let investors in the housing market is likely.[4]

In the empirical part of this paper, I investigate how common investment buyers are, and whether the investment buyer share of transactions is related to the housing cycle. Using housing transaction data from the city of Oslo in the period 2007 - 2014, I show that the share of buyers who buy a second (or subsequent) house is significant, fluctuating between 15 and 25 percent of total transactions. Moreover, the investor share seems to be pro-cyclical. The period I investigate had extraordinarily high growth in housing prices, coinciding with high population inflow. I also use a rental asking price index and a house price index for Oslo to show that housing prices and rents are correlated, though housing prices increase faster and are more volatile.

I then build a structural search and matching model that is consistent with these empirical patterns, by incorporating the opportunity for housing owners to become landlords, and by letting rents be set in the model. These features interact. If rents were constant, investors would buy second houses when demand was otherwise low, and investment buyers could help stabilize price volatility. To match the data indicating that rents are correlated with housing prices and buy-to-let is pro-cyclical, having endogenous rent driving investments is important. The increased number of buyers with investment motives in tight markets drives housing price volatility.

The buy-to-let model has two different mechanisms that increase price volatility compared to a "standard" search model with constant rents and no landlords. First, the endogenous correlation of rents and housing prices makes it more attractive for non-owners to buy in "hot" markets, to avoid paying high rents. Second, the increased incentives for owners to become landlords in periods with high rents amplify the effect of high demand on housing prices by further increasing the number of buyers. Compared to non-search models, the search frictions in this model drive housing prices and price-to-rent ratio as match quality

[3] Bayer et al. (2020) shows that flippers represent a significant and pro-cyclical share of buyers in the Los Angeles housing market in the period 1988-2012, and also in other US metro areas.

[4] Though Norwegian tax rules, which tax capital gains unless a house has been owner-occupied by the seller at least 12 of 24 months before the sale makes flipping less attractive.

increases with hot markets.

The model is calibrated using the method of simulated moments. I use the dynamics of housing market variables to find the parameters of the dynamic equilibrium model. The calibrated model matches the high share of investment buyers found in the data, and fits qualitatively with the correlation of rents and housing prices and a number of unmatched moments, though it severely underestimates transaction volatility. The data period I try to match has very high population inflow, and high growth in prices and rents. The buy-to-let model displays a price increase of around 40 percent and a more moderate rent growth, very close to values observed in the data. The price increase in a standard search and matching model, without the buy-to-let aspect, is only half as large. Simulations of a low inflow period indicate that prices in the buy-to-let model will also fall more than in the standard model if housing demand is low.

In the calibrated model, a significant share of buyers are investors, even though the expected per-period return to owner-occupation is higher than the return from rents, and buyers do not face credit constraints. This may seem surprising, as prospective owner-occupiers might have been expected to outbid landlords due to the higher return of owning. The explanation is that the mean utility of being a renter is positive in the model. Thus, housing prices do not fully reflect the difference between rents and owner utility; the net value of changing status from renter to owner is lower than the value of being an owner.

In the last part of the paper, the model is used to look at welfare and price effects of two policy interventions in the buy-to-let market. In particular, I show that in this model, a tax that discourages investment buyers in hot markets is more effective in reducing housing price growth during a housing boom than a general tax on landlords. Both policies slightly increase welfare.

Only a few papers have previously discussed the role of housing investors when housing prices and rents are endogenous. Sommer et al. (2013) lets prices and rents be connected by household investment decisions. The model explores the role of credit constraints. When access to credit increases (through lower mortgage interest and downpayment requirements), more renters want to own. Simultaneously, buying becomes more attractive for prospective landlords as the interest on their bank holdings decrease. This leads to an increase in housing prices, and a decrease in rents. Combined with higher incomes, the model generates higher housing prices and a modest increase rents, but only explains half the increase in price-to-rent during the US housing boom 1995-2006.

In Head et al., (2014), search and matching is added to a dynamic housing model with a rental market, endogenous entry and construction to understand how income shocks drive housing market dynamics. A positive income shock leads to an immediate increase in inflow and housing demand. Construction of new housing takes time, thus market tightness and housing prices increase, and the search frictions creates housing price momentum. The tightness is further increased by the shift of some housing for sale to the rental market, both to meet demand from new entrants, and in anticipation of future house price growth.

Kaplan et al. (2020) develops an equilibrium overlapping-generations incomplete markets model with a rental sector. There are three sources of shocks: to aggregate income, credit and housing beliefs. The US boom-bust is modeled as positive realizations followed by reversals of all three shocks. Rental prices are determined by the user cost of housing. The main driver of changes in price-to-rent is found to be beliefs of higher future housing demand. In the calibrated model, housing prices are almost unaffected by credit shocks, as the rental state strongly reduces the number of households with housing demand constrained by credit supply. Credit shocks and income shocks are however important to match further moments in consumption and ownership growth.

This paper has a more narrow focus on how the interaction between rents, housing investors and search frictions affect housing prices. The interaction is able to explain 70 percent of the increase in price-to-rent. There is no role for income or credit shocks driving the boom in Sommer et al (2013). Unlike Kaplan et al. (2020), the housing demand shock that drives prices is not calibrated but based on empirically data on inflow. Head et al. (2014) and Kaplan et al. (2020) features rental companies that can obtain rental housing without costs or frictions. My paper shows that the interaction between rental investors and other buyers may be important.

The paper also fits in an increasing literature on search and matching in the housing market. Search frictions have become a popular way to match observed features of the housing market (such as high price volatility and persistence of booms and busts) that are hard to explain in models with a frictionless market. Assuming search frictions seems reasonable for the housing market, with very heterogeneous goods and long-lasting transactions processes. Following the seminal paper by Wheaton (1990), which introduced search and matching in a housing setting, there have been a number of papers taking an empirical approach to housing market search models.[5] As standard housing market search and matching models typically display lower price volatility than observed in data, a number of model variations have been suggested, with mechanisms that add price volatility.[6]

The model most related to mine is in Anenberg and Bayer (2020). In a dynamic equilibrium search model with internal[7] and external movers, the decision to buy before selling or sell before buying is endogenous and holding two houses is costly. Estimating the model on transaction data from Los Angeles, they find that internal movers' timing of buying and selling can explain a large fraction of housing market volatility. In e.g. a market with few buyers and many sellers, prices are low and houses sell slowly. Thus internal movers want to sell before buying to avoid a long period of holding a house for sale. This adds to the already large supply of sellers, and prices decrease even more.[8]

[5] For a recent survey of the use of housing market search models, see Han and Strange (2015).

[6] E.g. Caplin and Leahy (2011), Diaz and Jerez (2013), Ngai and Tenreyro (2014) and Anenberg and Bayer (2020).

[7] People both buying and selling within the same area.

[8] Another model of the timing of buying and selling is developed in Moen et al. (2019).

While my model has similarities to Anenberg and Bayer (2020), the main mechanisms involved are quite different. Anenberg and Bayer add extra volatility by having agents who are either buyers and sellers, dependent on the market situation, while here it comes through having a larger or smaller share of owners also being investors. Previous search models mostly feature constant rents, or lack a rental state. The rental market in my model is thus another novel mechanism, creating a additional link from market conditions to the value of owning houses.[9] I do not model the decision of buying or selling first, correlated shocks (Diaz and Jerez, 2013) or thick markets (Ngai and Tenreyro, 2014), but these mechanisms are complimentary to mine. The high observed volatility of housing market prices may well be due to a combination of all these factors.

Next, in Section 2, I describe the data sources used in the paper, and show empirical patterns that motivate my model. Section 3 develops the model, while the calibration process is described in Section 4. Results and discussion of model mechanisms are presented in Section 5. In Section 6, the implications for welfare and housing prices of two different policies discouraging buy-to-let are discussed. Section 7 concludes.

2 Data and motivating empirics

As a motivation for the following model, I here present empirical facts on the relation between housing and rental prices, and on the share of housing transactions conducted by investment buyers.[10] This empirical investigation of buy-to-let investors adds information on a subject barely covered in the literature. To better understand the setting from which the results emerge, I also cover some institutional aspects of the housing market.

I use data for the municipality of Oslo, the largest city in Norway, with around 600,000 inhabitants. Norwegian register data allows me to know the ownership of almost all houses and apartments in the city of Oslo,[11] and also if the owners own any other housing in Norway. The reason for only measuring buy-to-let in Oslo is twofold. Most rental apartments in Norway are concentrated in large cities, thus any effects of investment buying should be most visible in the largest city.[12] Also, data on rental prices are not widely available; but for Oslo, I have average asking prices of new rental contracts at a quarterly level.

In the municipality of Oslo, around 30 percent of households are renters (Statistics Norway, 2017a). There is only a small non-commercial rental sector: Around 12,500 housing

[9]Head et al. (2014) and Kashiwagi (2014) expand on the standard assumption of constant, exogenous rents. Neither of their models allow households to invest in rental housing, which amplifyes the effect of rents on prices in my model.

[10]The relations I find between housing prices, rents and investment buyer share are correlations. I am not able, with the available data, to identify any causal effects. Still, a model of buy-to-let investors should be able to recreate these correlations.

[11]Units in housing cooperatives organized as listed companies are not included in the data. They make up around 5 percent of yearly transactions (see Appendix A).

[12]Bracke (2021) shows that this holds in England and Wales, with London having the clearly highest share of buy-to-let investors.

units (less than four percent of the housing stock) are municipally owned (Statistics Norway, 2017b). The remaining rental market is commercial, with unregulated asking rents, as Norwegian rents are generally not affected by rent control.[13] Most rental housing is owned by small scale private landlords.[14] Housing units are generally sold freely on the market, using English auctions.[15]

2.1 Data

Transaction data for housing for the year 2007 - 2014 come from Statistics Norway.[16] Statistics Norway gathers data from Finn.no, the main web page for housing listings in Norway and from the Register of real property transfers at The Norwegian Mapping Authority (NMA). Data on ownership of non-transacted houses for the same period are from the Norwegian cadastre, which contains the ownership history of all housing in Norway. I can observe when properties are bought from the Finn.no data, the identity of buyers from the NMA data, and how long they own houses from the cadastre.[17]

The transaction data are connected with data from the Income and wealth statistics for households (Statistics Norway, 2018a) through a personal identifier. These data are used to aggregate housing ownership at the household level. Thus, I am able to identify the share of buyers from households that already own a home. I do not use transactions where the buyer is a company or an organization, as they do not fit within my model framework. I also add tax information on reported rental income for a robustness check.

Rental price data are harder to find than housing transaction data. To my knowledge, there exists no rental microdata for the Oslo area. Instead, I use an aggregated statistic, which is made for Boligbygg[18] (the housing department of the municipality of Oslo), based on all housing units advertised for rent at the webpage Finn.no. Using advertised rental prices and characteristics in a hedonic regression, rental prices are estimated for typical apartments with 0, 1, 2, 3, 4 and 5+ bedrooms, for five geographical zones in Oslo. The rental price statistic is available at a quarterly level for the period 2004 to 2014. I average prices over all apartment types and geographical zones to get a rental asking price index.

It is notable that this statistic shows new rental contracts. Most measures of rent used in the literature come from national accounts or surveys of all renters' rent. However, for prospective investors the most relevant measure is the current asking rent, not the average rent of rental contracts entered into over a longer period.[19]

[13] There are restrictions on the increase of rents within a rental term, but rental terms are generally short, and there are no restrictions on asking rent.

[14] Nationally, only around 10-15 percent of rental housing is owned by firms or organizations (Sandlie and Sørvoll, 2017).

[15] I do not model the auction process, but see Arefeva (2017) for a housing search model with auctions.

[16] Before 2007, transaction data did not include the personal identifier used to get information on previous housing ownership.

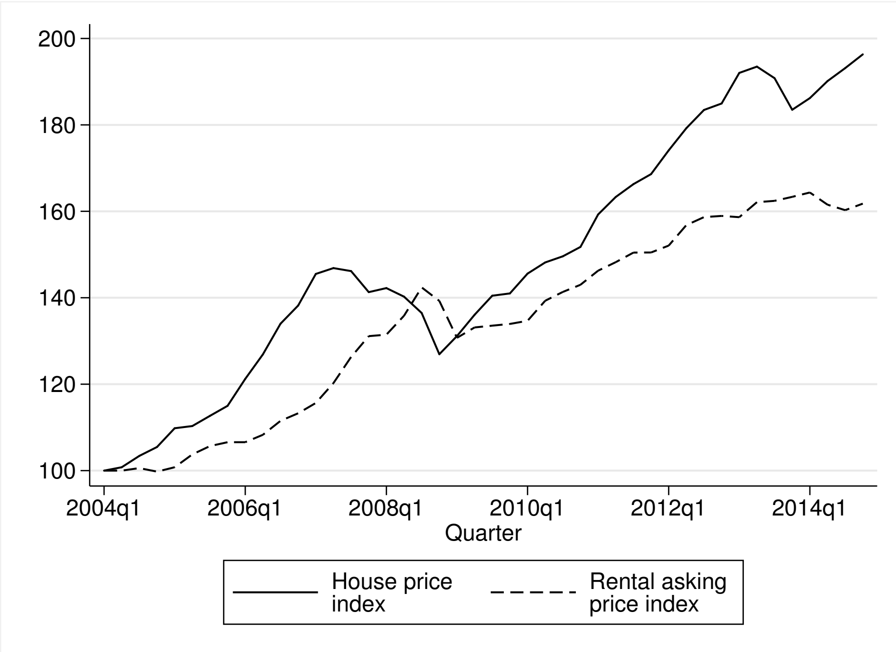
[17] More on the datasets, and how they are merged, can be found in Appendix A.

[18] http://boligbygg.reeltime.no/.

[19] To the extent that rent prices are sticky within contracts, as suggested by Genesove (2003), measures based on all rents likely underestimate the pro-cyclicality of rents.

2.2 Housing and rental prices

Figure 1: Housing and rental prices in Oslo



Notes: The housing price index is made by Eiendom Norge, an interest group for Norwegian real estate agents. It is a hedonic index based on transacted houses that have been advertised at Finn.no. Rental asking prices are calculated as the average over all apartment types and geographical zones of the Boligbygg rental price statistic. The prices are indexed to Q1 2004.

Figure 1 shows the housing price index and the development of asking prices for rental housing over the period 2004 - 2014, at a quarterly frequency. The housing price index is a hedonic index made by Eiendom Norge,[20] based on transacted houses that have been advertised at Finn.no.[21] Housing prices grow quickly over the period, with a small dip during the financial crisis of 2008. Rental prices roughly follow housing prices, quickly increasing until 2008, then falling for a couple of quarters, before increasing until around 2013, when they stabilize for the rest of the period. While the indices follow a fairly similar path, it is noticeable that rental prices appear to be lagging a little.[22] Rental price growth over the period is also lower, and less volatile, than housing price growth.

The correlation of housing prices and rents is expected, as increased demand for housing services should affect both owner-occupied and rental housing. In the literature on the

[20] Eiendom Norge (www.eiendomnorge.no) is an interest group for Norwegian real estate agents.

[21] A housing price index calculated on the dataset used to find investor share in this paper, is very similar for the period of overlap. See Appendix A.

[22] As the rental index is composed of asking prices, not achieved prices, the lag may result from backward looking price setting from landlords. It could be that achieved prices more closely follow the housing price index. Still, for transacted housing, appraisal values (which are mostly similar to asking prices) and transaction prices closely co-move, suggesting that the lag is not only an artifact of the different data sources.

user cost of housing (Poterba, 1984) this is incorporated as the assumption that housing prices are the net present values of implied rents. There are reasons to believe that differences between rents and prices may not be fully arbitraged away (Glaeser and Gyourko, 2007). Still, prices and rents should be correlated, assuming implied and actual rents follow the same path.

2.3 Investment buyers

Next, I look at how the share of investment buyers fluctuates with housing price growth. The only previous paper which empirically explores buy-to-let, Bracke (2021), shows that buy-to-let investments in England and Wales are pro-cyclical, and concentrated around small houses in well-performing markets. In addition to analyzing a different location, my data allows for estimation of the buy-to-let investor share based on full housing transaction coverage, while Bracke (2021) is able to identify 20 - 25 percent of buy-to-let transactions.

Buyers are defined at the household level, as distribution of housing ownership between spouses may reflect tax considerations rather than real ownership. I define buy-to-let as the purchase of a house in year t by a buyer who already owns at least one house, and who still owns at least two houses at the end of year $t + 1$.[23] More on creating the dataset of investment buyers can be found in Appendix A. To test the robustness of the investment buyer measure, I also explore a definition which requires an investor to keep two houses until the end of year $t + 2$.

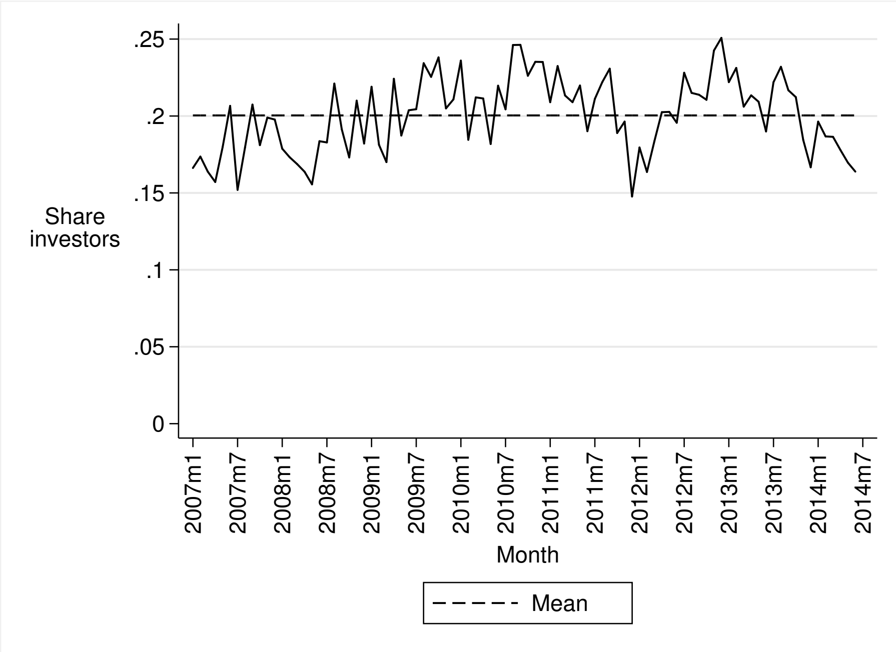
It may be that some households I define as investors do not actually rent out their investment property, but instead uses it as e.g. an urban holiday cottage. There may also be cases of subsidized rent to children or other family members. For the mechanisms described in this paper, it is not essential that houses are actually rented out at market price. The implicit rent still follows the market rent; i.e. the value parents ascribe to providing children with subsidized housing depends on how much the children would otherwise pay to rent in the market.

Figure 2 shows that buyers of investment housing represent a significant share of all housing purchases in Oslo.[24] The mean share over the period is 20 percent.[25] While the share varies, it is never below 15 percent, and often above 20 percent. There are significant seasonal spikes in the share, which is highest during autumn.[26]

To measure the correlation between housing price growth and the share of investment buyers, I regress the monthly share of investment buyers on the housing price growth in

[23] That is, a household who owns at least two houses for a period of over 12 months.
[24] The monthly number of investment buyers is shown in Appendix E, Figure A.5.
[25] This share is comparable to Amsterdam and Rotterdam in the Netherlands, where De Nederlandsche Bank (2018) reports an investor share of almost 25 percent for 2017q3.
[26] Ngai and Tenreyro (2014) shows how seasonal fluctuations appear in a model with a matching function with increasing returns to scale. Match quality is lower in "cold" seasons. As investors may care less about match quality, it could be that investors may prefer buying in the cold season. I do not include seasonality in my model.

Figure 2: The investor share of transactions



Notes: The monthly share of houses bought by buy-to-let investors are calculated as the share of houses bought by a person who already owns another house, and who owns at least two houses for a period of over 12 months. Only purchases by private buyers.

Oslo over the three previous months. The results are shown in Table 1, Panel A. When month of year dummies are included (to control for the observed seasonal variation in investor share), there is a positive and significant correlation between the share of investors in a month and the price appreciation in the three previous months. The correlation is also significant when including a yearly trend in investor share. The correlation is even stronger when only looking at apartments (Table 1, Panel B), where buy-to-let investments are concentrated.[27]

As a robustness check, I also use another measure of investment buyers, which is investment buyers defined as above, who additionally report rental income in their tax returns (in year $t+1$ after buying). The results (Table A.3) are qualitatively similar to those using the main measure, though somewhat smaller and less significant. See Appendix D for results and details.

3 Model

Here, I develop a search and matching model in which rents are endogenous and owners are allowed to buy a second house, to let out.[28] These features are introduced to explain

[27] 86.4 percent of buy-to-let purchases are apartments.

[28] I do not allow ownership of more than two houses, to keep the model tractable.

Table 1: Housing price growth and investor share

A) All housing	(1)	(2)	(3)
Quarterly growth	0.088	0.376**	0.331**
	(0.90)	(0.109)	(0.108)
Monthly dummies		yes	yes
Yearly trend			0.002*
			(0.001)
R-squared	0.011	0.292	0.339

B) Apartments only	(1)	(2)	(3)
Quarterly growth	0.136	0.436**	0.398**
	(0.096)	(0.116)	(0.116)
Month dummies		yes	yes
Yearly trend			0.002
			(0.001)
R-squared	0.023	0.299	0.441
Observations	90	90	90

Notes: This table presents the results of OLS-regressions where the dependent variable is the monthly share of investment buyers. Independent variables are housing price growth over previous quarter, and in some specifications, month of year dummies and a time trend. In Panel A, the variables are found by aggregating over all housing transactions, in Panel B only apartment transactions are used. Standard errors in parentheses.
** p<0.01, * p<0.05

the existence and timing of investment house purchases, which are commonly observed in the data.

The model is similar to standard housing search and matching models in many ways. Agents are homogeneous and risk-neutral, and houses are homogeneous. Agents get utility from renting or owning houses. They search for houses in a housing market with search frictions. Prices are set by complete information Nash bargaining. Time in the model is discrete, and agents discount the future at the common rate β.

The additional features are the inclusion of buy-to-let investors and a rental market. Owners can buy a second house to let out, but searching for a second house is costly. Rents are determined in the model by the supply of, and demand for rental housing in a frictionless rental market.

3.1 Agents

There are five possible states for agents in this model. The state depends on how many houses the agent owns (zero, one or two) and whether the agent is matched or mismatched with the primary house.

The five states are summarized below:

1) Owners (o). Matched housing owners, who may also invest in a second house.

2) Landlords (l). Matched with one house, and own another house which they let out.

3) Double-sellers (d). Landlords who have been hit by a mismatch-shock, selling first one, then the other house.

4) Sellers (s). Owners who have been hit by a mismatch-shock, or double-sellers who have sold one house.

5) Buyers (b). Buyers do not own a house. All non-owners want to buy housing.

Housing owners are hit by mismatch shocks at rate δ, in which case they turn into sellers.[29] Landlords are hit by mismatch shocks at the same rate δ, in which case they turn into double sellers, selling first one, then the other of their houses.[30] Note that landlords only sell when hit by a mismatch shock, meaning that they cannot act as flippers by actively choosing to sell when prices are high.

Owners who do not receive a mismatch shock may search for a second house to invest in. If they choose to do so, they face a search cost, κ. The search cost reflect e.g. financing cost and search effort. Owners who buy a second house become landlords.

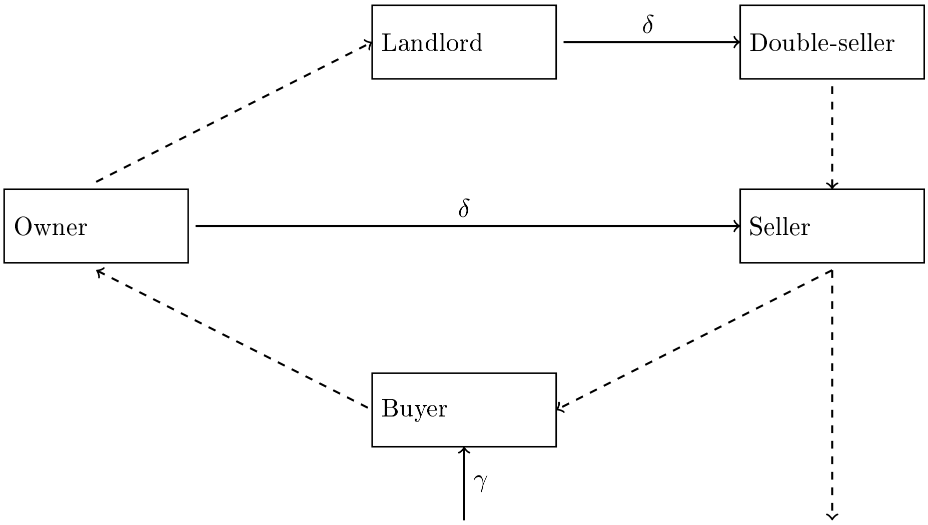
Sellers (both normal and double-sellers) meet with buyers (normal buyers and investors) in a housing market with search frictions. Following housing transactions, a share of successful sellers disappear (move out of the city or die), while the rest turn into buyers. Double-sellers become sellers.

Inflow to the economy, γ_t, fluctuates over time, and is assumed to be iid. Outflow equals average inflow, so the population is stable over time. The housing stock in the economy is fixed.

[29] As in Piazzesi et al. (2020), I impose selling before buying.

[30] To simplify, I do not allow Rental-sellers (landlords only selling their rental house). I also assume that landlords hit by mismatch shocks will not match with their second house.

Figure 3: Graphical representation of the model



Notes: Fully drawn lines are exogenous movements, dotted lines are endogenous. Inflow is denoted γ, mismatch shock δ.

A graphical representation of transitions between states in the model is given in Figure 3. In the figure, fully drawn lines are exogenous movements, while dotted lines are endogenous movements.

Matched owners get a flow utility equal to the match quality ε_i, which is idiosyncratic for each owner-house match, and time invariant. Mismatched owners (i.e. sellers) all get utility $u < \bar{\varepsilon}_i$. Landlords get utility ε_i for owning a matched home, plus rental income r_t. Mismatched landlords (double-sellers) get the mismatch utility u, plus rental income r_t.

Buyers rent housing through the rental market. In each period they search for a house to buy. New entrants to the economy are not able to buy in their first period. The reasoning for excluding new entrants from buying is that recent arrivals lack the knowledge, bank connections or equity required to buy a house. In the model, this assumption gives prospective landlords some knowledge about future renter demand. The group of prospective renters thus consist of buyers and new entrants: $b + \gamma$.

Renters get an individual utility r_{it} from renting,[31] which does not depend on rental match, but on the renter. It is redrawn every period.[32] This heterogeneity reflects rental needs that differ depending on age, children and non-rent opportunities. All renters pay a common rent r_t, which is determined in the frictionless rental market. The individual return to rent is only known after housing transactions, to avoid selection into buying based on returns to rent (which would make the solution more complex), but the distribution of returns to rent is common knowledge.

[31]If renters did not have heterogeneous returns to renting, rents would only have two possible values, either r or 0, depending on whether there were more renters or landlords.

[32]This is a simple way of getting heterogeneity in the distribution of otherwise homogeneous agents, similar to e.g. Greenwald and Guren (2019).

Those who neither own nor rent get a housing utility of $nr = 0$. They represent people e.g sharing flats with others or living in their parents' household. They do not pay any rent.

3.2 Timing

The timing of a period in the model is as follows:

1) Inflow shock is drawn.

2) Housing owners decide whether to search for a second house or not.

3) Sellers (both normal and double-sellers) meet buyers (buyers and searching owners) in a housing market with search frictions. Match quality is revealed, and transactions are agreed if expected surplus is positive.

4) Inflow arrives (i.e. new entrants are not able to buy in their first period).

5) Non-owners learn their return to rent

6) Buyers and new entrants meet landlords and double-sellers in a frictionless rental market.

7) Utility flows to agents.

8) Houses are transacted.

3.3 Value functions

The state variables in the model are the measures of agents in different states: o, l, d, s and b. Normalizing the housing stock to 1 allows the reduction of state space by one dimension. Since $o = 1 - 2l - s - 2d$, there are four state variables: l, d, s, b.

The vector $\Omega_t = (l_t, d_t, s_t, b_t, \gamma_t)$ reflects the knowledge of agents at the beginning of period t; of current state variables and the stochastic inflow of the period. The model presented above can be characterized by the following Bellman equations, which show the value of being an agent in a certain state, given Ω_t. The dependence of a function on Ω_t is in the following abbreviated to the subscript t.

The value of being an owner:

$$\begin{aligned} V_t^o(\varepsilon_i) \quad &= \quad \varepsilon_i + \beta E_{\gamma'}[\delta V_{t+1}^s + (1-\delta)(\rho_t^b(V_{t+1}^o(\varepsilon_i) + \frac{M}{B}(1-\theta)(\frac{s_t}{S_t}\Pi_t^{o,s} \\ &+ \frac{d_t}{S_t}\Pi_t^{o,d}) - \kappa) + (1-\rho_t^b)V_{t+1}^o(\varepsilon_i))] \end{aligned} \tag{1}$$

The owner receives utility ε_i from being matched in the current period. A mismatch shock arrives with probability δ, in which case the owner becomes a seller in the next period. If not, the agent decides with which probability to search for a second house. This probability, ρ^b, is set so that the expected value of searching is equal to the cost, κ. A match with a seller occurs with probability $\frac{M}{B}$; the number of meetings divided by the total number of buyers. The matching function M is defined below. As search is random, the probability of meeting a seller, s, or a double seller, d, is determined by their respective shares in the seller pool S. $\Pi_t^{o,j}$ gives the expected surplus of the meeting, (dependent on seller type, j), conditional on the surplus being positive. The buyer share of the surplus is $1-\theta$. The expectation is over γ', which is the inflow of agents in next period.

As in Anenberg and Bayer (2020), the value function (1) can be split into two additively separable components; one which depends on the individual match quality and one which does not:[33]

$$V_t^o(\varepsilon_i) = \tilde{\varepsilon} + U_{t+1}^o, \tag{2}$$

in which $\tilde{\varepsilon} = \frac{\varepsilon_i}{1-\beta(1-\delta)}$.

The value of being a landlord can be denoted as:

$$V_t^l(\varepsilon_i) = \varepsilon_i + r_t + \beta E_{\gamma'}[\delta V_{t+1}^d + (1-\delta)V_{t+1}^l(\varepsilon_i)] \tag{3}$$

Landlords receive utility ε_i for living in a matched home, plus rental income r_t from their second house. With probability δ they become mismatched in the next period, becoming double sellers, otherwise they remain landlords.

As for owners, the value function for landlords can be separated into one element dependent on match quality and one that is not:

$$V_t^l(\varepsilon_i) = \tilde{\varepsilon} + U_{t+1}^l \tag{4}$$

The value of being a buyer:

$$V_t^b = max(r_{it} - r_t, 0) + \beta E_{\gamma'}[V_{t+1}^b + \frac{M_t}{B_t}(1-\theta)(\frac{s_t}{S_t}\Pi_t^{b,s} + \frac{d_t}{S_t}\Pi_t^{b,d})] \tag{5}$$

Buyers receive a current utility which is either the return from rent minus rent payment or 0, depending on whether they are renters or non-renters. Buyers meet sellers with probability $\frac{M}{B}$, in which case they receive their bargaining share, $(1-\theta)$, of any surplus, in addition to their value of remaining buyers, V_{t+1}^b.

The value of being a seller:

[33] See Appendix B for details.

$$V_t^s = u + \beta E_{\gamma'}[V_{t+1}^s + \frac{M_t}{S_t}\theta(\frac{b_t}{B_t}\Pi_t^{b,s} + \frac{o_t}{B_t}\Pi_t^{o,s})] \tag{6}$$

The value of being a seller consists of the flow utility from owning a mismatched house, u, the value of being a seller in next period, plus the seller share of the transaction surplus if a transaction occurs. The probability of meeting a buyer is $\frac{M}{S}$.

The value of being a double seller:

$$V_t^d = u + r_t + \beta E_{\gamma'}[V_{t+1}^d + \frac{M_t}{S_t}\theta(\frac{b_t}{B_t}\Pi_t^{b,d} + \frac{o_t}{B_t}\Pi_t^{o,d})] \tag{7}$$

The value function of a double seller is quite similar to that of a seller. The difference is that the rent from a rental house is also received, and that the outside option and transaction surpluses are those of a double seller.

3.4 Meetings

3.4.1 Matching function

The number of meetings (or matches) is determined through a matching function by the total number of buyers, $B = b + o_b$,[34] and the total number of sellers, $S = s + d$. The matching function, as in Anenberg and Bayer (2020), is given as:

$$M(B, S) = AB^{\eta}S^{(1-\eta)} \tag{8}$$

I limit the number of matches to $min(B, S)$. Each buyer and seller is assumed matched maximum one time per period. The probability for a seller to meet a buyer is then $\frac{M}{S}$. Similarly, a buyer meets a seller with probability $\frac{M}{B}$.

There are four types of meetings in the model: Buyer meets seller, buyer meets double seller, owner meets seller and owner meets double seller. Search is random; buyers cannot choose to look for sellers of a specific type.

Each buyer b who get matched to a seller's (or double seller's) house receives a match quality draw, ε_i, which reflects how well that particular house suits the buyer's preferences. Match quality is distributed normally:

$$\varepsilon \sim N(\bar{\varepsilon}, \sigma^2) \tag{9}$$

I assume homogeneous match quality for owners who buy second houses, which means that all matches involving owners, given seller type, result in the same transaction surplus

[34] Where o_b is the number of owners who search for second houses in the current period, as described in Section 3.5.

(and price).[35]

3.4.2 Transactions

A meeting results in a transaction if the expected surplus is greater than 0. Thus the actions for buyers and sellers are: transact if a meeting happens and the surplus is positive; do not transact if the surplus is negative, or if a match does not occur. The expected surplus of a type i buyer meeting a type j seller is defined as $E_{\gamma'}\Pi^{i,j}$, in which the surpluses, $\Pi^{i,j}$, of the four types of matches are given by the change of state of the respective agents, times the probability of a transaction. The surplus of e.g. a buyer meeting a seller is the gain of the buyer shifting state to owner in next period, plus the gain of the seller being a buyer instead of a seller in next period, multiplied by the probability that the transaction will have a positive surplus.

As the surpluses are defined in terms of next period values, they all depend on the state variables and inflow of next period, Ω_{t+1}.

3.4.3 Transaction surpluses

The transaction surpluses, $\Pi_t^{i,j}$, of the four types of matches can be written in terms of the agents' value functions defined in Section 3.3. First, I define the value of the changes of state for the different combinations of buyers i and sellers j. They are:[36]

$$\pi_t^{b,s} = U_{t+1}^o + \tilde{\varepsilon} - V_{t+1}^b + V_{t+1}^b - V_{t+1}^s \tag{10}$$

$$\pi_t^{b,d} = U_{t+1}^o + \tilde{\varepsilon} - V_{t+1}^b + V_{t+1}^s - V_{t+1}^d \tag{11}$$

$$\pi_t^{o,s} = U_{t+1}^l - U_{t+1}^o + V_{t+1}^b - V_{t+1}^s \tag{12}$$

$$\pi_t^{o,d} = U_{t+1}^l - U_{t+1}^o + V_{t+1}^s - V_{t+1}^d \tag{13}$$

The surpluses in (10) and (11) depend on the match quality achieved by the buyer. In (12) and (13), the match quality is unchanged from V^o to V^l and its value does not affect the surplus.[37] In (10) and (11), the only idiosyncratic term is $\tilde{\varepsilon}$, which has a variance of $\tilde{\sigma}^2 = \frac{\sigma^2}{(1-\beta(1-\delta))^2}$. I define $\bar{\pi}$ as the non-idiosyncratic term of π (π minus a term distributed

[35] As second houses are rented out, not lived in, there is less need for landlords to find houses that fits their personal preferences.

[36] I assume that sellers who exit the economy has a utility similar to buyers' utility.

[37] This depends on my assumption that the probability of being hit by a mismatch shock is similar for both owners and landlords. If the probability of mismatch were different for the two states, there would be strategic incentives for agents with high match quality to be in the state with the lowest probability.

as $\sim N(0, \tilde{\sigma}^2)$). The conditional surplus, given the probability that the surplus is positive, can be found; by using the properties of a truncated normal function for (10) and (11), and the fact that the probability is either 0 or 1 for (12) and (13):

$$\Pi^{b,j} = E[\pi^{b,j}|\pi^{b,j} > 0]Pr(\pi^{b,j} > 0) = \Phi(\frac{\bar{\pi}^{b,j}}{\tilde{\sigma}})\bar{\pi}^{b,j} + \phi(\frac{\bar{\pi}^{b,j}}{\tilde{\sigma}})\tilde{\sigma} \tag{14}$$

$$\mathit{\Pi}^{o,j} = E[\pi^{o,j}|\pi^{o,j} > 0]Pr(\pi^{o,j} > 0) = max(\pi^{o,j}, 0), \tag{15}$$

for $j = d, s$. In equation (14), Φ is the standard normal cdf, and ϕ is the standard normal pdf.

3.4.4 Prices and laws of motion

The surplus of a transaction is shared between buyer and seller through Nash bargaining, with the bargaining weights of seller and buyer respectively θ and $(1-\theta)$.[38] The bargaining process determines the price of the house, P, which depends on the type of both buyer and seller: $P = [P^{b,s}, P^{b,d}, P^{o,s}, P^{o,d}]$.

The prices are related to the value functions in the following way:

$$P_t^{b,s} = \theta(U_{t+1}^o + \tilde{\varepsilon}^{b,s} - V_{t+1}^b) - (1-\theta)(V_{t+1}^b - V_{t+1}^s) \tag{16}$$

$$P_t^{b,d} = \theta(U_{t+1}^o + \tilde{\varepsilon}^{b,d} - V_{t+1}^b) - (1-\theta)(V_{t+1}^s - V_{t+1}^d) \tag{17}$$

$$P_t^{o,s} = \theta(U_{t+1}^l - U_{t+1}^o) - (1-\theta)(V_{t+1}^b - V_{t+1}^s) \tag{18}$$

$$P_t^{o,d} = \theta(U_{t+1}^l - U_{t+1}^o) - (1-\theta)(V_{t+1}^s - V_{t+1}^d) \tag{19}$$

Here, $\tilde{\varepsilon}^{b,j}$ is the random match quality, truncated from below by the minimum value which gives positive surplus in a meeting between a buyer b and a seller j. There will thus be a distribution of the prices $P_t^{b,s}$ and $P_t^{b,d}$, while all transactions of type o, s and o, d have the same prices, respectively $P_t^{o,s}$ and $P_t^{o,d}$.

The movements of state variables depend both on the transactions happening endogenously in the model, and by exogenous movements from inflow and mismatch shocks. The laws of motion for the different state variables are presented in Appendix B.

[38] Diaz and Jerez (2013) double the volatility of prices by setting prices through competitive equilibrium (Moen, 1997) instead of Nash bargaining. In competitive equilibrium, sellers compete by posting non-negotiable prices, which seems unrealistic, at least for the Norwegian housing market where transaction prices in hot markets are often much higher than asking prices.

3.5 The investor share

Owners can choose to search for a second house. The expected return of searching will depend on the probability of finding a house if searching, the house price and the rent that can be achieved by letting out the house.[39] Owners will want to buy as long as the expected return of searching for an extra house is higher than the cost κ.

All owners are similar. The equilibrium strategy of owners is a mixed strategy, where all owners assign the same probability $\rho_b \in [0,1]$ of searching. The share of owners who search is then given as:

$$\rho^b =: E_\gamma[\frac{M(B(\rho^b),S)}{B(\rho^b)}(1-\theta)(\frac{s}{S}\Pi^{o,s}+\frac{d}{S}\Pi^{o,d})]-\kappa=0, \tag{20}$$

which defines the search probability for which the expected benefit of searching is equal to the cost.[40] The expected benefit is the probability of finding a match, $\frac{M}{B}$, times the seller share, $(1-\theta)$, of the surplus of a match with either a seller (s) or a double-seller (d).

The measure of owners who want to buy is given by $o_b = \rho_b(1-\delta)o$, or the probability of owners wanting to buy, times the measure of owners who did not receive a mismatch shock.

3.6 Rental market

After the housing market matching, possible renters, with measure $b+\gamma$, meet landlords, with measure $l+d$, in the rental market.

Renters draw a willingness to pay for rental housing from a uniform distribution $U(0,\bar{r})$. The rental market is frictionless; rental prices equal the willingness to pay for the marginal renter.

The marginal renter is given by $b+\gamma-(l+d)$, and the rent is:

$$r = max(\bar{r}\frac{(b+\gamma-(l+d))}{b+\gamma},0). \tag{21}$$

If there were no landlords, the rent would (theoretically) equal the maximum willingness to pay, $\bar{r}$. If there are more landlords than renters, rental prices are driven to zero by competition.

[39] There is also a return from selling the house, but since selling depends on being hit by a mismatch shock, owners cannot buy with the intention of selling when prices are high.

[40] Finding the search probability of owners can be solved as a Complementarity problem, as the share is constrained to be in $[0,1]$.

3.7 Equilibrium

Each agent, dependent on the information set Ω, and state i, has a policy rule, $\zeta_i(\Omega)$, which determines the agent's action. The action set A_i consists of three elements $A_i \subset (s, T, r)$. For owners, s is the choice of probability to search for a second house. For all other agents, s is empty. For agents who have had a meeting, T is transact or not transact. The third possible action is relevant for agents who are buyers, r is the choice whether to rent or not given the rental price and the draw of willingness to rent. Each agent also has a belief over the probability of other agents' policy rules: $\sigma_{ij}(\Omega) \rightarrow Pr(\zeta_i = j|\Omega, i)$.

An equilibrium is a set of policy rules, ζ_i and beliefs σ_{ij}, for all agents, actions and states which ensures that:

1. Policy rules are optimal
2. Agents have correct beliefs about the policy rules of other agents.

4 Calibration

A number of parameters are given values commonly used in the literature, and I calibrate parameters with suitable matches in the data directly. The remaining parameters are found using the method of simulated moments (MSM).

4.1 A priori calibration

Each period in the model is a quarter of a year. The discount rate, β, is set to get an annual discount rate of 0.95. As is common in the housing search literature, I set the bargaining power of sellers, θ, to 0.5. The value of η in the matching function is from Genesove and Han (2012) and the matching constant A from Anenberg and Bayer (2020).

The inflow process is given as a normal distribution, with mean 0.0154 and variance 0.0000012. The population inflow is calibrated on the mean and variance of the quarterly gross migration to Oslo, from other municipalities and abroad, as a share of total population over the period 1997q4 - 2006q4 (Statistics Norway, 2018b).[41] The parameters are presented in Table 2, Panel A.

4.2 Method of simulated moments

The remaining unknown parameters are: $\bar{\varepsilon}$, u, σ, $\bar{r}$, κ and δ. The value of mean match quality, $\bar{\varepsilon}$, is normalized to 1. The remaining parameters are calibrated using MSM against the following six targets:

[41] I do not have any information on the number of households moving to Oslo, which would be a preferable measure.

Table 2: Calibration of parameters

A) Parameters calibrated a priori

Parameter	Value	Description	Method
β	0.987	Discount rate	Common in literature
θ	0.5	Bargaining power of seller	Common in literature
Mean γ	0.0154	Mean inflow	From data
Variance γ	1.2E-6	Variance of inflow	From data
η	0.84	Exponent of matching function	From Genesove and Han (2012)
A	0.5	Matching constant	From Anenberg and Bayer (2020)

B) Parameters calibrated by MSM

Parameter	Value	Description	
$\bar{\varepsilon}$	1	Mean matched utility	(Normalization)
u	0.7581	Mismatched utility	
σ	0.1544	Standard dev. of match quality	
$\bar{r}$	1.8326	Maximum rent	
κ	0.3303	Cost of finding second house	
δ	0.0280	Prob. of mismatch shock	

Notes: The parameters are quarterly.

- The mean rent to housing price ratio.[42]
- The coefficient of variation of rents.
- The coefficient of variation of housing prices.
- The mean investor share of buyers.
- The coefficient of variation of the investor share of buyers.
- The mean housing turnover rate.

As described in Section 2, my micro data only cover a limited period of time: the 30 quarters 2007q1 - 2014q2. The data used for calculating moments are adjusted for inflation and for quarterly seasonal effects, as there is neither inflation nor seasons in my model.

The housing price target is based on a hedonic index of housing prices. The index is calculated on the housing transactions included in my sample, and control for e.g. size, age and location, to account for possible composition differences over time in transacted housing units. See Appendix A for details, including Figure A.3 which shows that this housing price index is quite similar to the housing price index by Eiendom Norge presented in Figure 1.

The housing turnover rate is calculated as the number of housing transactions divided by the housing stock of Oslo over the years 2007 - 2013. More details on creating this moment can be found in Appendix A.

[42] Measured as the quarterly mean rent divided by the quarterly mean value of apartment prices.

For each combination of parameters, the model is solved,[43] and then simulated over a sequence of inflow shocks.[44] Moments are calculated from the simulations and the chosen parameter vector is the one that minimizes the distance to data moments. Importantly, the inflow shock vector corresponds to the real sequence of inflow shocks over the 30 quarters 2007q1 - 2014q2. This is a period of significantly higher inflow than the calibration period 1997q4 - 2006q4, which means that I simulate results for a period of higher than expected population inflow.[45] I have also calibrated the model on iid shocks with mean and variance taken from the period 2007q1 - 2014q2 (instead of the real shocks). The results, which are very similar to baseline results, are presented in Appendix D.

5 Results

5.1 Model fit

The parameter values calibrated by MSM are presented in Table 2, Panel *B*. The mismatch utility, u, is 0.76 of mean match quality.[46] The higher the mismatch utility, the more willing sellers are to postpone transactions, if they are not satisfied with the current match. The value of 0.76 is somewhat lower than in Anenberg and Bayer (2020), but much higher than the 0.1 assumed by Diaz and Jerez (2013). The standard deviation of match quality, σ, is around twice the 0.0787 found by Anenberg and Bayer (2020).

The maximum theoretical rent, $\bar{r}$, is 1.83 times the mean match quality. It seems realistic that some renters have high willingness to pay for a rental house when the alternative is neither owning nor renting. With uniform distribution of return to rent, 42 percent of buyers are willing to pay more than the mean per-period utility of owning a house for the ability to stay in a rental house. In the simulated model, mean rent is 0.93 times the mean utility of owning.

The value 0.33 of κ implies that the search cost of prospective investment buyers is equal to a little more than 1 month of rent. It may seem quite low, but the Norwegian tax system gives incentives to invest in secondary housing. This is not reflected in my model, but may help explain the low calibrated search cost.[47]

The mismatch rate, δ, is 0.028. With this rate, mismatch occurs roughly every 10 years. This gives a fairly similar housing tenure to Ngai and Tenreyro (2014) and Anenberg

[43] Given the equations in Section 3, the model can be solved by value function iteration. I use linear interpolation in the iterations, as the state variables are continuous.

[44] I start from random starting values of the state variables, then simulate 200 periods with the standard inflow process to let the model settle before calculating moments, to remove the influence of starting values. I use 1000 different draws of starting values, and take the median of the moments over the 1000 simulations.

[45] Additional information on the inflow process is found in Appendix A.

[46] Mean match quality, $\bar{\varepsilon}$, is the unit that other values are measured in. Though note that mean realized match quality will be higher, as low draws leads to smaller transaction probabilities.

[47] For more on Norwegian housing taxation, see Bø (2020).

Table 3: Moments

Moment	Data	Simulations
Mean rent/housing price	0.0114	0.0111
Mean investor share	0.1999	0.1972
Housing prices (σ/μ)	0.1021	0.1020
Rents (σ/μ)	0.0573	0.0502
Investor share (σ/μ)	0.0915	0.0883
Housing transaction rate	0.0247	0.0255

Notes: Data moments are from the period 2007q1 - 2014q2. Simulated moments are the medians of 1000 simulations.

Table 4: Price changes

Model	Inflow	Price change	Rent change	Pric-to-rent change
Data		1.4558	1.2274	1.3752
	Baseline	1.3920	1.1778	1.2628
Buy-to-let	Medium	1.0011	0.9998	1.0016
	Low	0.4341	0.5770	0.7328

Notes: Data moments are from the period 2007q1 - 2014q2. The model is simulated for different levels of inflow. Changes in housing price and rent are calculated as max value over min value over the period (or min value over max value in the low inflow case, with decreasing prices). Simulated moments are the medians of 1000 simulations.

and Bayer (2020), who calibrate against surveys of respectively US and the UK, and US housing tenure.

Table 3 shows how the simulated moments from the calibrated model compare with the data moments. The model is able to hit the high share of investors well, as well as most other moments. Notably, housing price volatility is well matched. Though it is not able to fully fit the volatility of rents.

To see how well the model is able to recreate the Oslo housing boom, I compare the actual and simulated housing price and rental increases over the period 2007q1 - 2014q2 in Table 4 (the first two rows). The buy-to-let model displays a price increase of 39 percent, almost matching the 46 percent increase in observed prices over the period. The rental increase in data was 23 percent, while the buy-to-let model achieves 18 percent. Additionally, the model captures 70 percent of the increase in the price-to-rent ratio.

5.2 Population inflow and housing prices

The data period 2007q1 - 2014q2 coincided with a period of unusually high population inflow to Oslo. It is interesting to explore how buy-to-let investors would affect the housing market in different market conditions. For that purpose, I simulate the buy-to-let model, for periods of normal (or medium) and low population inflow, and compare simulation results with the high inflow data period.[48]

Table 4 shows the impact of different levels of inflow shocks on housing prices and rents. Both rents and housing prices in the buy-to-let model are very sensitive to the level of inflow.[49] In the low inflow scenario, housing prices more than halve and rents almost halve. Though my model does not contain credit constraints or debt,[50] the strong price and rent falls in a low inflow period indicate that central banks may be right to worry that a large buy-to-let sector poses risks to financial stability.

5.3 Model mechanisms

The model cannot be solved analytically. To help understanding the model mechanisms, I here present graphs showing impulse functions following increased inflow, and discuss how certain features of the model operate.

The impulse functions show a one-period increase in inflow of 10 percent, followed by the mean inflow for the rest of the period. In Figure 4a, the inflow, as well as the response of investors, and the investor share of buyers is shown. When a positive inflow shock arrives, investors immediately enter the market in large numbers. This is to preempt the new entrants, who are commonly known to be entering the market as buyers in next period. The investor share of transactions also increases, meaning that the investors that enter the market displace some ordinary buyers. In period 1, there is a dip in investors, as such a large number bought in period 0. Thereafter the number of investors stabilize at a slightly higher level than before the shock, while the investor share is almost similar to the pre-state.

As the number of investors increase the buyer mass in period 0, this drives up housing prices and the number of transactions, shown in Figure 4b. Rents are also impacted, as there are more prospective renters, but less than the housing prices. After period 0, with inflow at the mean inflow, prices stabilize at a new, higher level. Because of the high level of investor purchases in period 0, rents drop a little in period 1 before converging to a new and higher level. The high transaction number in period 0 leads to fewer houses for sale, and fewer transactions, in the next few periods. After a few periods, there is convergence to a new, slightly higher level of transactions.

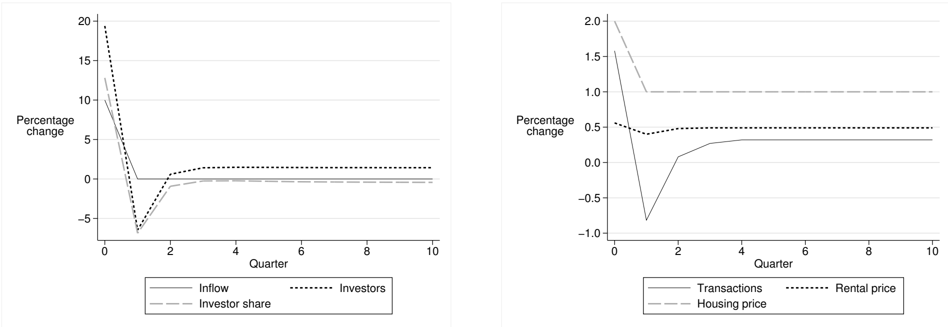
Figure A.6, in the Appendix, shows the underlying movements of the agent states. After the large investor inflow in period 0, there is a wave of new buyers in period 1, coinciding with a dip in sellers. Thereafter, the states converge towards a larger number of buyers and landlords, and a slightly lower number of total sellers.

The correlation of housing prices and rents as a result of an inflow shock contrasts with Head et al. (2014), where landlords are not buy-to-let investors, but sellers who decide to

[48] Medium and low inflow is defined in Appendix A.
[49] Section 5.4 explores how central the buy-to-let mechanisms are to this result.
[50] Implicitly, all agents have access to as much housing credit as they want.

Figure 4: Impulse functions

(a) Inflow, investors and investor share (b) Transactions, rents and prices



Notes: These two graphs show how different aspects of the model react over a period of 10 quarters following an inflow shock 10 percent above mean inflow. Percentage change is from the pre-shock period. The graphs show median values of 1000 simulations.

defer sales to a later period. In their model, rents actually fall at first when population inflow increases, as sellers anticipate higher housing prices in the future and move vacant houses into the rental sector. Head et al. (2014) note that their empirical results do not support this prediction. The data from Oslo presented in Section 2 seem to support the positive correlation of housing prices and rents.

In non-search models with a rental sector (e.g. Kaplan et al., 2020), the implicit role of landlords is often to stabilize housing prices by absorbing excess supply. With frictionless housing markets, risk-neutral landlords without credit constrains have perfectly elastic demand for housing.[51] In the buy-to-let model, landlords have to compete with buyers for housing in a market with search frictions, and thus add to price pressure. As the competition for housing increases, a higher match quality is required for a transaction to happen, which again translates to a higher price.

The calibrated model features a fairly high share of investment buyers, almost 20 percent of transactions. It may seem surprising that investors are able to compete with buyers in the housing market when their flow return (the expected rent) on average is markedly lower than buyers' return (with expected value respectively 0.93 and 1). However, buyers have a positive expected return of renting, because the rent equals the return to rent of the marginal renter. All other renters get a positive return. This is shown in Figure A.7 in Appendix E, which presents the expected return of renting, both unconditional and conditional on being in the set of renters, for different levels of rent.

In a market with many landlords, a large share of buyers will be able to rent, at low rents. Thus, the return of changing state from buyer to owner will be low, and investment buyers will be able to compete on price, even though their return is low. As rents increase (with a higher buyer-to-landlord ratio), the expected rental return for buyers is decreasing, both due to the rent increase, but also to the lower probability of finding a rental match (as

[51] This is discussed in further detail in Greenwald and Guren (2019).

the utility of being a non-renter is 0).

The costly search of investors, and search frictions, means that investors who actually become landlords earn a positive expected return.[52] In the calibrated model, the expected return for an investor becoming a landlord is 2.54 percent, and it remains similar over the boom.[53]

5.4 How important is buy to let?

To see how the unique features of the buy-to-let model affect the housing market, I find it useful to introduce two further models as comparisons. First, I compare the full model with a model without the buy-to-let sector (presented in detail in Appendix C). The model is a "standard" search model, with three types of agents (owners, buyers and sellers), that have the same parameters as the buy-to-let model. Implicitly, the standard model can be seen as a model with a rental sector that is fully separated from the owner-occupier market, and with completely elastic supply.

Next, with the "constant rent" model, I try to separate the effects of the two mechanisms that my model features. The buy-to-let model both makes it more attractive for non-owners to buy in hot markets, because of the correlation of rents and housing prices, and increases the number of buyers in those periods, as more owners want to become landlords in high rent periods. In the constant rent model, the buy-to-let sector still exists, but there is no rent change channel for buyers.[54] As in the baseline model, the return to landlords is determined by supply and demand in a rental market. However, rents paid by renters are constant.[55] Buyers, ranked by willingness to pay for rental housing, are assigned to fill all rental houses, but the price they pay is always similar. The constant rent model thus keeps the crowding effect of more investment buyers, but lacks the increased incentives for buyers to buy in high-rent periods.

A number of moments, empirical, and simulated from the main model, the standard model without landlords and the constant rent model are presented in Table 5, Panel A. Comparing data moments with model moments, it is clear that the buy-to-let model, at the calibrated parameter values, is able to hit the volatility of housing prices quite well. The standard and constant rent models display much lower price volatility.

None of the models fit transaction volatility particularly well, though the buy-to-let model achieves somewhat higher volatility than the standard model. The lacking ability to match transaction volatility is also a noted in the models of Diaz and Jerez (2013) and Anenberg and Bayer (2020). A possible explanation observed in my simulations is that

[52] The entry of prospective investors set the expected return of searching for an investment house to 0. Thus, the return for those who are actually able to buy a house is positive.

[53] Return is calculated as the change in value from being a owner to becoming a landlord, minus the average purchase price of investors, divided by the purchase price.

[54] This model does not represent a realistic market situation, as rents paid by renters are not equal to rental income of landlords. It is a modeling exercise to look at mechanisms separately.

[55] The rent is set to be similar to the mean rent paid over the simulation period in the baseline model.

Table 5: Comparing different models

A) Moments	Data	Buy-to-let model	Standard model	Constant rent model
Housing prices (σ/μ)	0.1021	0.1020	0.0693	0.0586
Transaction volume (σ/μ)	0.1503	0.0147	0.0043	0.0235
Price autocorrelation	0.9514	0.9935	0.9949	0.9946
Corr. price/transactions	0.7811	-0.1931	-0.7263	-0.1254
Corr. price/rents	0.7640	0.9973	.	0.9944
Corr. price growth/share investor	0.2864	0.7972	.	0.5721
Rent-to-price (σ/μ)	0.0748	0.0500	.	0.0268*
Corr price/price-to-rent	0.8250	0.9988	.	0.9875*

B) Values relative to baseline model				
	Price	1.0000	0.4653	0.7770
	Rent (landlords)	1.0000	.	0.9831
	Rent (renters)	1.0000	.	0.9052
	Owners	1.0000	1.2073	0.9921
	Match quality	1.0000	1.0010	0.9993

Notes: Data moments are from the period 2007q1 - 2014q2. Simulated moments are the medians of 1000 simulations. Coefficient of variation of housing prices is a matched moment, the other moments are unmatched. Owners are agents in owner and landlord states.
* Rent to landlords.

the restriction on one match per seller per period is often binding.[56] A higher number of buyers thus does not lead to more meetings. As the option value of being a seller is high in hot markets, a higher minimum match quality, $\tilde{\varepsilon}^{b,j*}$, is required for a transaction. Otherwise sellers defer sales to the next period in the hope of achieving a better match. Thus, in hot markets, a lower share of meetings lead to transactions, which is not balanced by a higher number of meetings due to the binding limit on the number of meetings.

Possible ways to increase transaction volatility could be to implement increased expected match quality when there are many matches, as in Ngai and Tenreyro (2014), or allow multiple matches per period per seller, as in Albrecht et al. (2016) and Arefeva (2017). With multiple matches per seller, and bidding wars (Han and Strange, 2014) transactions would be more likely in hot markets. Modeling a version of the buy-to-let model with multiple matches per seller is however not straightforward, and I defer it to future research.

Rows 5 and 6 of Table 5, Panel A show the correlation of prices and rents and the correlation of the investor share of buyers with housing price growth from last to current quarter. The model in both cases have the right sign on the correlation, but it is too strong. The last two rows of Panel A show the coefficient of variation of the rent-to-price ratio, and the correlation between price-to-rent and prices. The buy-to-let model captures around two-thirds of the observed volatility of the price-to-rent ratio, and a

[56]This restriction is used in several other housing match papers as well. However, the rental sector in the buy-to-let model leads to a higher share of buyers compared to sellers than in a standard search model.

strong positive correlation with prices. The constant rent model explains around half as much of the volatility.

Table 5, Panel B shows how housing prices, rents, share of matched owners and match quality compare in the standard and constant rent model compared to the baseline. Of notice is housing prices which are over twice as high in the buy-to-let model as in the standard model. The constant rent model has prices at 78% of the baseline model. Not surprisingly, the standard model, without landlords, have a clearly higher share of matched owners than the other two models.

Then, I simulate the price increases during the housing boom in the alternative models. Table A.5 in Appendix D shows the change in housing prices, rents and price-to-rent ratio over the simulation period for the two alternative models, and different inflow levels.[57] The price increase in the buy-to-let model with high inflow is almost twice as high as in the standard model, while the constant rent model is close to the standard model. The rental increase in data was 23 percent, while the buy-to-let model achieves 18 percent, and the constant rent model 11 percent.[58]

The buy-to-let model is also affected more by both high and low inflow shocks than the standard model.[59] This is due to the rent channel, which does not operate in the standard model. For prospective investors, a low inflow shock has two negative effects on their return: Reduced expectations for the resale price, and lower expected rental income. Buyers are only affected by the lower resale price; their return from owning a house is not affected. Investors thus react stronger to inflow shocks than ordinary buyers. As investors and buyers compete for houses, prices in general will be more affected in a model where investor number fluctuates.

To the extent the constant rent model captures one, and not the other mechanism in the buy-to-let model, some conclusions can be drawn. Table 5 shows that the existence of investment buyers, and their crowding in at times of high-rent, contribute to 8 percent of the increase in price volatility, 66 percent of the higher house price level, and negatively to the transaction volatility separating the buy-to-let and the standard model. The simulations indicate that price levels are affected by buy-to-let investors, while the price response to inflow mostly comes from the rental change channel. Understanding the separate mechanisms may be important when choosing how to regulate buy-to-let investors. The role of housing market institutions and rental regulations on the buy-to-let sector is further discussed in Bø (2021). Many other cities do not have the prevalence of small-scale buy-to-let investors that Oslo has, but the response of rents to demand pressures is likely more widespread.

[57] The comparable results for the baseline model are shown in Table 4

[58] While rent in the constant rent model is constant for renters, for landlords it varies with market conditions.

[59] The effect on prices in the constant rent model is intermediate.

6 Policy

Could the government increase welfare, and reduce price growth over a housing boom by increasing the cost of buying or owning second houses? Having found that buy-to-let investors add to housing price volatility, I now simulate two different ways for the government to increase the cost of buy-to-let.

1. Reform 1: Increasing the cost of searching for a second house. This could be done by e.g. increasing the cost of financing secondary housing, which has been done recently in Norway (Ministry of Finance, 2016) and New Zealand (Reserve Bank of New Zealand, 2016). In my model, this will be reflected by an increase in κ. I show simulations where I increase the value of κ by 5 percent (or 0.017).[60]
2. Reform 2: Increasing the running cost of being a landlord. A possible way to achieve this is increasing the weight of secondary housing in a wealth tax, as has been done lately in Norway. I approximate this in my model by including a per-period cost, rc, of owning a rental house. Simulating this reform, I add a per-period cost of 0.0023[61]. This equals 0.25 percent of quarterly rental income.

Both reforms are assumed to be permanent, and in both cases all tax revenue is thrown away, i.e. not returned to agents in any form. Welfare in this model is the sum of housing utility; returns from owning and renting houses for all types of agents, over the 30 periods of simulation. As rents and housing prices are transfers between agents, they do not affect welfare. On the other hand, the share of prospective renters who are able to rent is relevant, as renters achieve higher utility than non-renters. The social welfare function is defined in Appendix B. It should be noted that agents are risk-neutral. In reality, most agents are probably risk-averse. Policies reducing price volatility, which do not affect welfare in the model, would thus lead to an additional real-life increase in welfare. When calculating price and welfare effects of the policies, I let each model run for 200 periods to settle. Thereafter, I simulate 30 periods with the same, high inflow (based on 2007q1 - 2014q2), and compare the resulting moments and price increases.[62]

6.1 Policy implications

Results from the policy changes are presented in Table 6, panel A, as the percentage change from the baseline model for a number of measures. As previously mentioned, the two policy changes I consider are an increase of the investment buyer search cost κ by 5 percent (Reform 1) and a per-period tax on rental housing, $rc = 0.002$ (Reform 2).

[60] In the model, κ consists of several elements, some of which are outside government control, such as the time cost of searching. It is thus unclear how large the policy change would have to be to achieve a 5 percent increase in κ.

[61] The per-period tax is set to be equal in amount, over the baseline simulation, to the total increase in search cost from Reform 1.

[62] Thus, I simulate what would happen in a high-inflow period if the policies were already in place, not what would happen if the policies were enacted during the housing boom.

Table 6: Policy implications

A) Percentage change		Reform 1	Reform 2
Welfare		0.26	0.02
Housing prices (σ/μ)		-6.55	-0.93
Rents (σ/μ)		0.42	-0.72
Investors in market		-3.84	-0.54
Investor transactions		-1.87	-0.25
Matched owners		0.20	0.06
Renter share of buyers		-0.68	-0.21
Buyers		-0.81	-0.25
Match quality b,s		0.05	-0.01
Match quality b,d		0.18	-0.01
B) Price increases	**Baseline**	**Reform 1**	**Reform 2**
Housing prices	1.3920	1.3643	1.3880
Rents	1.1778	1.1783	1.1764

Notes: Panel A: The effect of each reform is calculated as the median of 1000 simulations, each over 30 periods. Percentage change is compared to baseline model. Relative increase is increase in price over period relative to baseline model. Panel B: Prices in period 30 (max.) over price in period 1 (min.).

Both reforms increase welfare, though the increases are small (below 0.3 percent). It is however noticeable that welfare increases even though the tax costs are not returned to agents. The reforms have larger effects on prices and price volatility. Housing price volatility decreases by almost 7 percent and 1 percent under Reform 1 and Reform 2, respectively.

In Table 6, panel B, the housing price and rent increases over the simulation period are presented. Both reforms lessens the price increases. There are noteworthy differences between the reforms. The welfare increase is slightly larger for Reform 1, and it induces a stronger, negative effect on housing price growth and on the volatility of housing prices. Reform 2, on the other hand, leads to a decrease instead of an increase in rents and rent volatility.

The welfare increases caused by both policies come from redistribution of houses from low-value renters to owners. Investors do not consider the impact they have on the tightness of the housing market. Increased entry of investors leads to lower match probability of non-owners, which is a negative externality.

As long as the return from rent for the marginal renter is lower than the expected utility of owning a house for a buyer (remember, average rent in the calibrated model is 0.93), a higher level of ownership is welfare-improving. However, as long as the maximum willingness to pay for renting, $\bar{r} > 1$, there will be some renters who have a utility of renting that is higher than the expected utility of a prospective owner. Thus, a social planner would not want a society completely without rental housing.

The surprisingly strong effect of Reform 1 on prices and volatility is because it has the strongest effect in a seller's market. With many buyers relative to sellers, there is a low probability of finding a match. Thus, an increase in the search cost, which is paid even if no match is found, will represent a larger share of expected surplus. A reduction in investors in this condition has a strong moderating effect on prices. Reform 2 only affects those who actually buy, and it is similar over all market conditions, lessening its effect on prices.

The reason that Reform 1 performs better in welfare terms is that the marginal buyer who is pushed out by an investor has higher match quality in a seller's market, as sellers are more willing to postpone a transaction to next period. This can be seen in Table 6, as an increase in match quality.

When considering these results, it is important to remember the assumptions of my model. Renters are assigned to rental houses if their return to renting is higher than the current rent. Implicitly, there are no credit constraints, i.e. all agents are able to pay their present value for rental or owned housing. All buyers who are not able to rent get the same utility, and there are no dynamic negative effects of being a non-renter in a period.

In reality, ability to pay may not match willingness to pay. Policies which increase rents or reduces rental supply may push poor people into homelessness, even if their need for housing is very high. Additionally, one could imagine that being a non-renter instead of a renter in one period could drive some people into debt or long term homelessness with lasting negative consequences.

7 Conclusion

In this paper, I present a search and matching model exploring an interaction between the market for owner-occupied and rental housing not previously considered in the literature: buy-to-let, or the possibility for housing owners to invest in a second house to let out. I also let rents be determined endogenously in the model.

The model is motivated by empirical evidence on housing prices, rents and investment buyers in Oslo, the largest city of Norway. First, I show that rental price growth is correlated with housing price growth. Second, investment buyers consistently represent a significant share of all housing buyers in Oslo, on average almost 20 percent. Finally, investors buy more in periods of housing price growth: There is positive and significant correlation between the share of investors in a month and price appreciation in the three previous months.

My model introduces two mechanisms that affect housing prices compared to a standard housing search model. First, the endogenous rents are high when there are many buyers, because of competition for rental housing. To avoid paying the high rents, buyers are willing to pay more than if rents were constant. Second, owners' expected return from becoming landlords increase in periods of high rents, adding extra investors to the number of buyers and amplifying the effect of high rents on housing prices.

I calibrate the model using the method of simulated moments. The calibrated model fits data moments fairly well, and performs better in almost all dimensions than a standard housing search model with the same parameters. In particular, it is able to explain the high housing price volatility observed in the data. It also matches the high share of investment buyers found in the data, and fits qualitatively with a number of unmatched moments, such as the correlation of rents and housing prices, though it severely underestimates transaction volatility.

Simulated price and rent increases in a period of high population inflow are consistent with data. Notably, the model fully matches the price growth, and much of the increased price-to-rent ratio in a housing boom, without the need for exogenous shocks to credit supply which is the main explanatory factor in a large literature on the housing boom in the US. In this model, the boom is instead driven by an exogenous increase in population inflow, which increases demand for both owned and rented housing, with the housing price increase amplified by search frictions as more investors enter the market.

Finally, two different policy reforms are simulated. There are small, but positive welfare gains from taxing second house ownership. The welfare gains are achieved through the redistribution of houses from low utility renters to higher utility owners. Housing prices and price volatility are reduced, particularly by taxing the search for investment houses, as it alleviates the crowding in of investors in hot markets. The welfare analyses may underestimate welfare gains; as agents in the model are risk-neutral, the large decreases in housing price volatility are not valued. However, there may also be negative effects which are not captured by the model on the welfare of non-owners who lose the possibility to rent.

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Appendix A: More on data

Defining investment buyers

Finding the share of investment buyers requires the identification of buyers who are already owning at least one housing unit, and who do not immediately sell their previous house, or resell the new house. To do this, I merge together several data sets.

Information on the date properties are bought, as well as price and housing characteristics, comes from Finn.no, the main web page for housing listings in Norway. Data are identified through a housing unit identifier. A second source of transaction data is The Norwegian Mapping Authority (NMA), via Ambita, which holds the register of real property transfers (*Tinglysning).* From NMA data, I can observe the identity of buyers (and sellers) for each transacted housing unit. The data on ownership of non-transacted houses are from the Norwegian cadastre (*Matrikkelen*), which holds information about housing ownership history. However, the cadastre does not contain ownership of cooperative apartments. Ownership of these are imputed from transaction data.

Combining transaction data from Finn.no and NMA with ownership information from the cadastre, I am able to study the share of buyers already owning a house. The data I have available allow me to observe the time period from 2007q1 until the end of 2014q2. This gives me 90 months, or 30 quarters of observations.

Transaction data

There are, however, some complications in the merging of these three datasets. In many cases, the housing unit identifier does not uniquely identify separate apartments, only the apartment building. I therefore match housing transactions on the housing identifier and transaction price, which is a variable in both Finn and NMA data. I do not allow any matches where the registration date is before the transaction date, as registration is done with a lag. I also drop transactions where the buyer is a company or organization, as they do not fit within my model framework.

For a number of observations, one transaction from Finn.no is still matched with several observations from the NMA. First, I deal with multiple within buyer-id observations. Here, one problem is that a house can have several entries in the NMA register (i.e. basement or annexes can have their own entries). If a buyer-housing-id-price combination is found more than once, only the observation with the registration date closest after the transaction date is kept. If there are still multiple observations, I first discard observations where listed floor does not match with the floor given in Finn data. Thereafter, I discard observations listed as basement or loft. Then, I keep the observation with the largest living area.

Once there is only one observation per buyer-housing-id-price, I make sure that the each Finn observation is only matched to one ownership by summing over the ownership share of all matched observations from NMA. If the total ownership share is higher than 1, I discard observations where the floor from NMA does not match with the floor given in Finn. Then the observation with the registration date closest after the transaction date are kept.

Thereafter, I try to merge any observations from Finn that were not matched in the first round (i.e. no direct match on transaction price). I match these remaining observations only on the housing identifier. If transaction price is observed from both datasets, matches with a price discrepancy of above five percent are discarded. Similarly, matches with observed difference of living area of above 25 percent are dropped. Matches where the floors recorded in NMA and Finn do not match are also discarded. The remaining matches are exposed to the processes described above to make sure that only one buyer-housing-id-price combination exists per transaction and that each Finn observation is only matched to one ownership.

Ownership data

The cadastre holds the ownership history of all self-owned housing units in Norway from 2004. I drop housing units not owned by persons, and ownerships which lasts for less than a calendar year (for my purpose, I want ownership at year-end). Ownership exit is set to the end of the year before the registered end of ownership date.

Cooperative apartments are not covered by the cadastre. However, from the NMA, I have transaction data, including seller and buyer id, for coops from 2007 - 2015. Using this data, I am able to add the ownership history of all coops that have been transacted at least once during that period. Because I am not able to identify ownership of coops purchased before 2007 and held through the whole period, my measure of investors will be somewhat downward biased

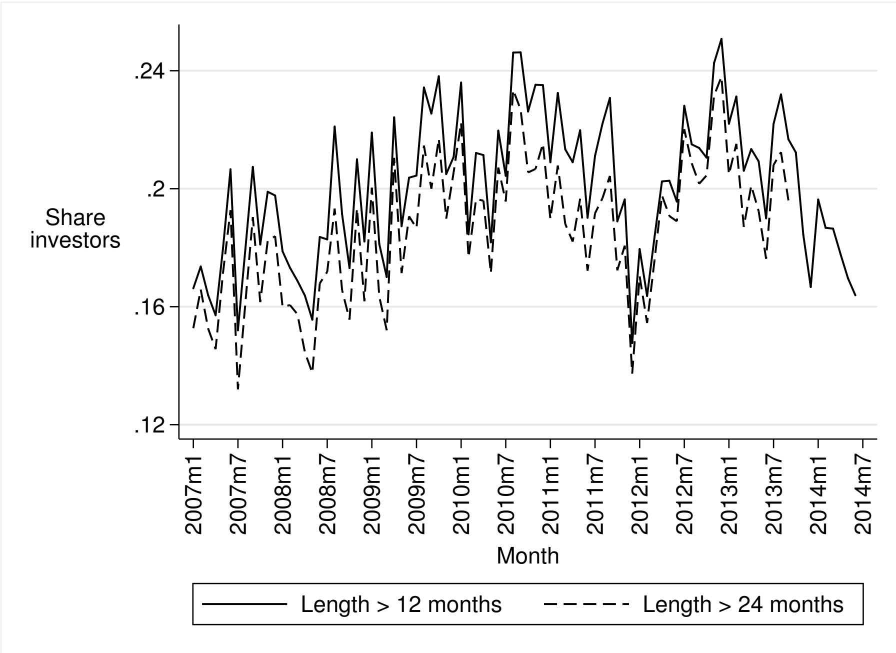
The personal identifier which identifies ownership can be used to add information on the household of owners, through the dataset Income and wealth statistics for households (Statistics Norway, 2018a), where I have data available from 2006 - 2012. The ownership of houses is aggregated from personal to household level, and investors are defined at the household level. I chose to use ownership at the household instead of individual level, because the distribution of housing ownership between spouses may reflect tax considerations rather than real ownership. A household is counted as the owner of a housing unit if its ownership share is larger than 0.5.

Through the personal identifier, transaction data can also be connected with tax information, which I use to add information on reported rental income for the robustness check in Table A.3.

Alternative definitions

I make a model of buy-to-let investors. These investors should hold on to their houses for a period of time. My main definition of investors require a ownership length of at least 12 months. Here, I use an alternative measure where ownership length is at least 24 months. The main reason for not using this definition as my main measure is due to the limited time covered by my data. With ownership data for 2007 - 2015, using the alternative definition of investors limits data to the years 2007 to 2013, and due to slowness in the registration of property transfers, I am not able to utilize the last quarter of 2013. With my main measure, I am able to utilize data until 2014q2. As shown in Figure A.1, the two measures are very similar (the correlation is 0.97). While the alternative measure is obviously a little bit lower than the main measure (as the restrictions are stronger), there seems to be no pattern in the difference.

Figure A.1: Investors - ownership length



Notes: The monthly share of houses bought by buy-to-let investors is calculated as the share of houses bought by a person who already owns another house, and who owns at least two houses for a period of over respectively 12 and 24 months. Only purchases by private buyers.

Some of the buyers defined as buy-to-let investors may in fact buy a new home, while keeping the old house as an investment. In this case, the timing of the purchase may not be dependent on the expected return at the buying time. To explore whether these buyers make a difference, I make two alternative investor measures. The first measure classifies buyers who buy a secondary house which is larger than any other house which they own as non-investors. Around 16 percent of the sample lacks information on housing size. While the first measure requires size on all houses to be available, the second counts buyers who do not own any other house where housing size is known to be larger as non-investors.[63] These two measures are shown, along with the baseline, in Figure A.2. Both alternative measures are strongly correlated to the baseline, with correlation at respectively 0.98 and 0.96.

[63]In other words, Measure 1 interprets a missing size house as larger than the new house, Measure 2 takes missing as smaller.

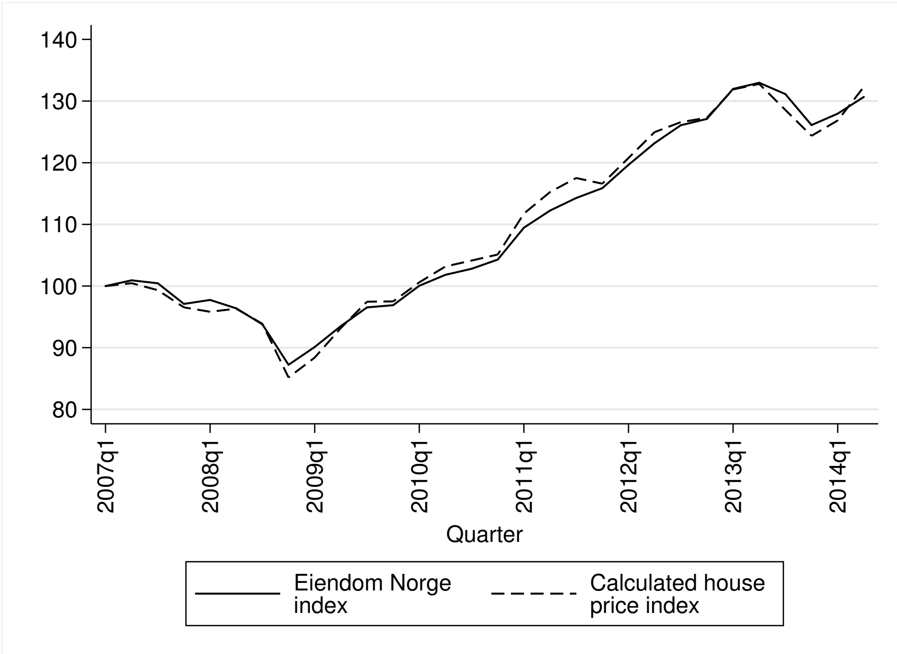
Figure A.2: Investors - size of new housing

Notes: The monthly share of houses bought by buy-to-let investors is calculated as the share of houses bought by a person who already owns another house, and who owns at least two houses for a period of over 12 months. Only purchases by private buyers.

Housing price index

The housing price index used to calculate prices in the calibration is a time-dummy hedonic index. It is calculated as a linear model with transaction price as the dependent variable, and size, floor, type of housing, joint property debt, and dummies for building age and city district as independent variables.

Figure A.3: Housing index and aggregated data



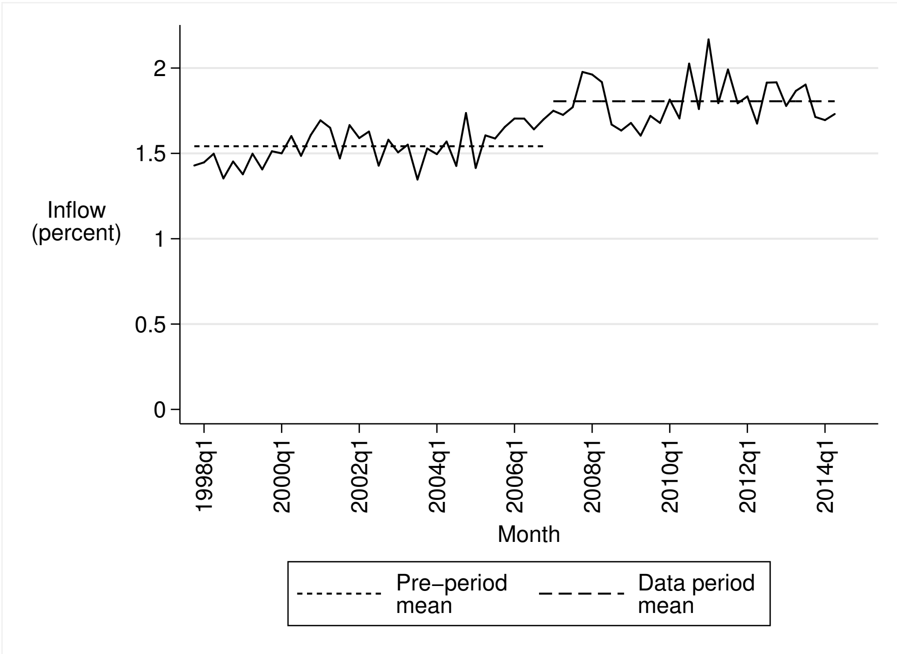
Notes: Q1 2007=100. The house price index is made by Eiendom Norge, the interest group for Norwegian real estate agents. It is a hedonic index based on transacted houses that have been advertised at Finn.no (see also Figure 1). The calculated housing price index is based on the data in my sample. It is a linear time-dummy hedonic index, with size, floor, type of housing, property debt, and dummies for building age and city district as control variables.

Figure A.3 compares the hedonic based housing price index from Eiendom Norge with the calculated index based on housing transactions included in my sample. Both indices are set to 100 in 2007q1. The differences between the indices are minor.

Population inflow

The population inflow parameter, γ, is calibrated on the mean and variance of quarterly gross migration to Oslo, from other municipalities and abroad, as share of total population over the period 1997q4 - 2006q4 (Statistics Norway, 2018b). However, the years for which I have housing transaction data coincides with a period of historically high population inflow to Oslo. Following the EU-expansions of 2004 and 2007, there was a boom of Eastern European labor immigration to Norway, starting in 2007 (Barne-, likestillings- og inkluderingsdepartementet, 2012; OECD, 2015: Table B.1). This was also a period of relative economic prosperity in Norway compared with the rest of Europe. Oslo was strongly influenced by this development, as well as high birth rates (BBC, 2014). The population in Oslo grew by 18 percent in the period 2007 - 2014, or above 2 percent per year on average (Statistics Norway, 2018b).

Figure A.4: Popuation inflow 1997-2014



Notes: Population inflow to Oslo over the period 1997q4 to 2014q2. The inflow is adjusted for quarterly seasonal effects. Averages for the pre-period (1997q4-2006q4) and the period covered by other data moments (2007q1-2014q2) are also shown.

The gross inflow of people to the city over the data period, which is the source of the inflow shocks used in the baseline simulations, was much higher than in pre–period years, which I calibrate my model against, as shown in Figure A.4.

Medium and low inflow

The medium inflow process is the same as the one used in the calibration of the model. It is an iid process with the mean and variance of the quarterly gross migration to Oslo, from other municipalities and abroad, as a share of total population over the period 1997q4 - 2006q4.

The low inflow process has a mean which is 20 percent below the medium inflow (high inflow is almost 20 percent above), and the variance is also 80 percent of the medium inflow process. Means and variances in all inflow processes are shown in Table A.1.

Table A.1: Inflow variants

	High, baseline	High, alternate	Medium	Low
Mean	0.0181	0.0181	0.0154	0.123
Var.	1.8E-6	1.8E-6	1.2E-6	1.0E-6
Process	Observed values	Iid	Iid	Iid

Notes: Mean, variance and description of the inflow processes used.

The mismatch rate

One of my calibration moments is the mean share of housing transactions over the total private housing stock. There are a number of considerations involved in arriving at this number, which will be explained here.[64]

The number of housing units (including apartments) in the housing stock comes from the Norwegian cadastre, as described in Statistics Norway (2016). The statistic on dwellings is yearly, and I include single-family housing, row houses, apartments and other housing.[65] Municipal housing (Statistics Norway, 2017b) is excluded from this total. The housing stock number may be somewhat inflated, as it includes uninhabited houses. But in a city like Oslo, with high housing prices and growing population, there should not be too many empty dwellings.

As mentioned previously in this appendix, there are two sources of transaction data available to me. The first comes from Finn.no, the main web page for housing listings in Norway. All kinds of housing types are included in this dataset, but it excludes houses that are not listed through Finn.no.[66] Thus, I use the second source, the NMA register of real property transfers to find data for the number of housing transactions. As the registration of property transfers takes a few months, the number of houses registered in a year will not correctly measure the number of houses sold in the same year. But for the purpose of measuring transactions over a number of years, the exact assignment of transaction to year should not matter. However, the NMA register does not include transactions of a certain kind of cooperative apartments, where the coops are organized as limited companies (hereafter stock apartments).

By comparing the number of transacted cooperative apartments from Finn.no and from the NMA register, I find that the share of transactions advertised through Finn.no is 0.72. I assume that the ratio of transactions advertised through Finn.no to total transactions is similar for stock apartments and other cooperative apartments, which allows me to impute the number of transactions for stock apartments, and the total number of transactions.[67] By dividing the imputed total number of transactions on the housing stock, I find the yearly transaction share of houses, shown in Table A.2. The calibration target is the quarterly rate that gives mean yearly transaction rate of 0.0986.

The housing transaction numbers show that a little less than a tenth of houses in Oslo are transacted each year. On the other hand, Statistics Norway (2015) reports that roughly a fifth of the population in Oslo moved during the year 2014. The difference between these numbers may come from the moving rate of renters, which can be expected to be higher than that of owners, and which does not affect the number of housing transactions.

[64] It would maybe seem reasonable to calibrate the rate of mismatch directly against the transaction share. However, as the mismatch shock only hits matched housing owners, not mismatched owners waiting to sell, this would underestimate the mismatch rate.

[65] The only type of housing I exclude is dwellings in shared housing, which contains e.g. retirement homes.

[66] This could be houses which are e.g. inherited or sold through personal contacts.

[67] I use the average rate for all years in the imputations. Using yearly rates instead makes no noticeable difference in the calibrated transaction rate.

Table A.2: Housing transaction numbers

Year	Reg., non-coop	Reg., coop	Adv., coop	Share adv., coop	Adv., stock	Imputed tot., stock	Total transactions	Housing stock	Transaction share
2007	14,148	13,977	9,854	0.7050	1,287	1,798	29,923	280,996	0.1065
2008	13,270	12,467	7,438	0.5966	1,017	1,421	27,157	284,279	0.0955
2009	12,893	11,935	8,674	0.7268	1,068	1,492	26,215	288,764	0.0908
2010	14,355	12,240	9,171	0.7493	1,215	1,697	28,270	291,529	0.0970
2011	14,956	12,345	9,177	0.7434	1,279	1,787	29,086	294,174	0.0989
2012	15,867	12,532	9,281	0.7406	1,215	1,697	30,046	296,472	0.1013
2013	16,134	12,244	9,173	0.7492	1,243	1,736	30,114	300,497	0.1002
Average	14,518	12,534	8,967	0.7158	1,189	1,661	28,687	290,959	0.0986

Notes: Registred transactions are from the NMA register of property transactions. Advertised, coop are cooperative houses sold through Finn.no. The number of advertised stock apartments are inflated by the mean share of advertised cooperatives to impute total number of stock housing transactions. Total transactions sums registred transactions and imputed total for stock apartments. Housing stock is all housing units except municipal and shared housing. Transaction share is total transactions over housing stock.

Appendix B: Model details

Value functions for owners and landlords

Here, I go through the process of getting from equation (1) to equation (2). The value function for owners, equation (1), is:

$$\begin{aligned} V_t^o(\varepsilon_i) &= \varepsilon_i + \beta E_{\gamma'}[\delta V_{t+1}^s + (1-\delta)(\rho_t^b(V_{t+1}^o(\varepsilon_i) + \frac{M}{B}(1-\theta)(\frac{s_t}{S_t}\Pi_t^{o,s} \\ &\quad + \frac{d_t}{S_t}\Pi_t^{o,d}) - \kappa) + (1-\rho_t^b)V_{t+1}^o(\varepsilon_i))] \end{aligned}$$

By iterating on the equation, it can be rewritten as:

$$\begin{aligned} V_t^o(\varepsilon_i) &= \varepsilon_i + \beta(1-\delta)\varepsilon_i + \beta E_{\gamma'}\left[\delta V_{t+1}^s \right. \\ &\quad +(1-\delta)(\frac{M_t}{B_t}(1-\theta)\rho_t^b(\frac{s}{S}\Pi_t^{o,s} + \frac{d}{S}\Pi_t^{o,d}) - \kappa) \\ &\quad +\beta(1-\delta)E_{\gamma''}[\delta V_{t+2}^s + (1-\delta)(\frac{M_{t+1}}{B_{t+1}}(1-\theta)\rho_{t+1}^b(\frac{s}{S}\Pi_{t+1}^{o,s}) \\ &\quad \left. + \frac{d}{S}\Pi_{t+1}^{o,d}) - \kappa)) + ...]\right] \end{aligned}$$

and finally as:

$$V_t^o(\varepsilon_i) = \frac{\varepsilon_i}{1-\beta(1-\delta)} + U_t^o$$

where none of the terms in the second part of the equation depend on ε_i.

The same transformation can be done on the value function for landlords:

$$\begin{aligned} V_t^l(\varepsilon_i) &= \varepsilon_i + r_t + \beta E_{\gamma'}[\delta V_{t+1}^d + (1-\delta)V_{t+1}^l(\varepsilon_i)] \\ &= \frac{\varepsilon_i}{1-\beta(1-\delta)} + r_t + \beta E_{\gamma'}\left[\delta V_{t+1}^d + (1-\delta)(r_{t+1} + \beta E_{\gamma''}[\delta V_{t+2}^d + ...]\right] \\ &= \frac{\varepsilon_i}{1-\beta(1-\delta)} + U_t^l. \end{aligned}$$

Transition of state variables in equilibrium:

In the following equations, $T^{i,j}$ is the probability that a meeting between buyer of type i and seller of type j has a positive surplus, and leads to a transaction. For transactions involving draws of match quality ($T^{b,s}$ and $T^{b,d}$), the probability is continuous, while $T^{o,s}$ and $T^{o,d}$ are indicators taking the value 0 or 1. Given the properties of the truncated normal distribution, the shares of matches involving buyers and, respectively, sellers and double-sellers with positive transaction surplus can be written as $T^{b,i} = \Phi(\frac{\bar{\pi}^{b,i}}{\tilde{\sigma}})$, $i = s, d$, where Φ is the standard normal cdf.

$$b' = b - b\frac{M}{B}(\frac{s}{S}T^{b,s} + \frac{d}{S}T^{b,d}) + s\frac{M}{S}(\frac{b}{B}T^{b,s} + \frac{o_b}{B}T^{o,s}) + \gamma - \tau \tag{22}$$

Buyers equal last period's buyers, minus those who bought (either from sellers or double sellers), plus sellers who sold, either to buyers or owners. Last period's inflow, γ, are buyers in the next period. A number τ of last period's sellers exit the economy and do not become buyers.

$$s' = s - s\frac{M}{S}(\frac{b}{B}T^{b,s} + \frac{o_b}{B}T^{o,s}) + d\frac{M}{S}(\frac{b}{B}T^{b,d} + \frac{o_b}{B}T^{o,d}) + \delta o \tag{23}$$

Similarly, sellers consist of last period's sellers, minus the sellers who sold, plus double sellers who sold one of their houses and owners receiving a mismatch shock.

$$l' = l + o_b\frac{M}{B}(\frac{s}{S}T^{o,s} + \frac{d}{S}T^{o,d}) - \delta l \tag{24}$$

The number of landlords is increased by buyers who bought a second house, either from sellers or double-sellers, and decreased by the share who receive a mismatch shock.

$$d' = d - d\frac{M}{S}(\frac{b}{B}T^{b,d} + \frac{o_b}{B}T^{o,d}) + \delta l \tag{25}$$

Double-sellers who do not transact with a buyer or owner remain double-sellers in the next period. Mismatched landlords are double-sellers in the next period.

$$o' = o - o_b\frac{M}{B}(\frac{s}{S}T^{o,s} + \frac{d}{S}T^{o,d}) + b\frac{M}{B}(\frac{s}{S}T^{b,s} + \frac{d}{S}T^{b,d}) - \delta o \tag{26}$$

The measure of owners can be inferred from the other states, but for completion, I present the movement of the owner state. Next period's owners are reduced by owners buying second houses, and replenished by buyers who transact with sellers or double-sellers. Exogenous transition from the owner state occurs due to owners becoming mismatched.

Welfare

Welfare is the sum of housing utility, that is, all returns from owning and renting houses, for all types of agents over the 30 periods of simulation. As rents and prices are just transfers between agents, they do not affect welfare. On the other hand, the share of prospective renters who are able to rent is relevant, as non-owners who rent achieve higher utility than non-renters. The social welfare function is defined as:[68]

$$\begin{aligned} W \quad = \quad & \sum_{t=0}^{T} E(min(b_t, l_t + d_t)\bar{r}^*_{it} + (s_t + d_t)u + \frac{M}{B_t S_t}(b_t s_t E[\tilde{\varepsilon}|\tilde{\varepsilon} > \tilde{\varepsilon}^{b,s*}]Pr(\tilde{\varepsilon} > \tilde{\varepsilon}^{b,s*}) \\ & + b_t d_t E[\tilde{\varepsilon}|\tilde{\varepsilon} > \tilde{\varepsilon}^{b,d*}]Pr(\tilde{\varepsilon} > \tilde{\varepsilon}^{b,d*}))), \end{aligned} \tag{27}$$

[68] Welfare is usually discounted by β, but to be consistent with other moments presented, here it is not. Over a simulation of 30 periods, the difference is negligible.

where $\bar{r}^*_{it}$ is the mean return to rent for buyers who are renting, and the number of buyers who rent is given by $min(b_t, l_t + d_t)$. The welfare function includes the present value of all matches, as the term $E[\tilde{\varepsilon}|\tilde{\varepsilon} > \tilde{\varepsilon}^{b,j*}]Pr(\tilde{\varepsilon} > \tilde{\varepsilon}^{b,j*})$ defines average present value of a match, $\tilde{\varepsilon}$, conditional on the match resulting in a transaction. The welfare of owners at $t = 0$ is not included, as it is not affected by policy. Welfare is measured in housing consumption equivalents.

Transactions involving owners investing in second homes does not produce any welfare directly. But the first term of equation (32) shows that an increased number of rental houses does increase welfare, as long as there are more buyers than rental houses.

Appendix C: Model without landlords

In this section, I present a model without the opportunity for owners to turn into landlords and without a rental market. This is to see what difference the inclusion of a rental sector makes. Buyers who do not buy and new entrants will pay a constant sum in rent which is lower than their (homogeneous) willingness to pay, instead of renting in a competitive market. This simplifies the value functions as follows:

Owner:

$$\begin{aligned} V_t^o(\varepsilon_i) &= \varepsilon_i + \beta E_{\gamma'}[\delta V_{t+1}^s + (1-\delta)V_{t+1}^o(\varepsilon_i))] \\ &= \frac{\varepsilon_i}{1-\beta(1-\delta)} + U_t^o, \end{aligned}$$

Buyer:

$$V_t^b = r_c + \beta E_{\gamma'}[V_{t+1}^b + \frac{M}{B}(1-\theta)(\Pi_t^{b,s}(\Omega))],$$

where r_c is the "rental return" for buyers. It is set to be equal to the median expected rental return for buyers in the baseline model in the first simulation period after the burn in. This rental return is set to get a better comparison with housing prices in the buy-to-let model. Without the rental return, buyers in this model would be worse off, leading automatically to lower housing prices.

Seller:

$$V_t^s = u + \beta E_{\gamma'}[V_{t+1}^s + \frac{M}{S}\theta(\Pi_t^{b,s}(\Omega))]$$

There is now only one possible type of transaction. The surplus of a transaction is given as:

$$\pi_t^{b,s} = U_{t+1}^o + \tilde{\varepsilon} - V_{t+1}^b + V_{t+1}^b - V_{t+1}^s = U_{t+1}^o + \tilde{\varepsilon} - V_{t+1}^s,$$

thus, the rental return described earlier does not affect the number of transactions in the model, as V^b is netted out.

As explained in Section 3.7, the conditional expectation of a surplus is

$$\Pi^{b,s} = E[\pi^{b,s}|\pi^{b,s} > 0]Pr(\pi^{b,s} > 0) = \Phi(\frac{\bar{\pi}^{b,s}}{\tilde{\sigma}})\bar{\pi}^{b,s} + \phi(\frac{\bar{\pi}^{b,s}}{\tilde{\sigma}})\tilde{\sigma}$$

Movements of state variables in equilibrium:

$$b' = b - MT^{b,s} + MT^{b,s} + \gamma = b + \gamma$$

$$s' = s - MT^{b,s} + \delta o = s - MT^{b,s} + \delta(1-s)$$

$$o' = o + MT^{b,s}$$

where $T^{b,s}$ is the share of matches with positive transaction surplus.

Appendix D: Additional results

Investors with taxable rental income

Here, I present a regression similar to Table 1 in Section 2, using another measure of investment buyers as independent variable. The measure is investment buyers defined as before, who additionally report rental income in their tax returns (in year $t + 1$ after buying).

This could be seen as a more pure measure of Buy-to-let investors, than the baseline definition. However, there are some issues with this measure which restricts is usefulness. First, rental income is not third party reported, which means that there may be substantial tax evasion (Kleven et al., 2011). Second, reported taxable rental income is net of maintenance and other costs. Particularly for the first year of ownership, there may be renovation or reconstruction needs which could drive net earnings to zero. Third, if buy-to-let is done at some scale (as a rule-of-thumb five or more properties), rental income should be reported as business income, not as rental income. The data does not allow for identification of the share of business income that comes from rental income. Finally, I only have tax data available through 2012, which means that this measure covers a shorter period than the main measure. I use housing transactions through the third quarter of 2011.

Table A.3, show that the results are similar to those using the main measure, though weaker, and significance does not survive in the specification with a yearly trend.

Table A.3: Housing price growth and alternative investor share

All housing	(1)	(2)	(3)
Quarterly growth	0.119	0.296**	0.026
	(0.069)	(0.94)	(0.058)
Monthly dummies		yes	yes
Yearly trend			0.010**
			(0.001)
R-squared	0.051	0.254	0.783
Observations	57	57	57

Notes: This table presents results of OLS-regressions similar to Table 1, Panel A, except that the dependent variable is the share of investment buyers also reporting taxable rental income. Standard errors in parentheses.
** p<0.01, * p<0.05

Simulations

Table A.4 shows the simulation moments when inflow shocks are iid, instead of observed shocks. There are no large differences.

Table A.5 shows the change in housing prices, rents and price-to-rent ratio over the simulation period, for the constant rent and standard model (defined in Section 5.4), dependent on inflow process.

Table A.4: Moments

Moment	Data	Simulations, observed inflow	Simulations, iid inflow
Mean rent/housing price	0.0114	0.0111	0.0108
Mean investor share	0.1999	0.1972	0.1985
Housing prices (σ/μ)	0.1021	0.1020	0.1005
Rents (σ/μ)	0.0573	0.0502	0.522
Investor share (σ/μ)	0.0915	0.0883	0.815
Housing transaction rate	0.0247	0.0255	0.248

Notes: Data moments are from the period 2007q1 - 2014q2. Simulated moments are the medians of 1000 simulations. The first two columns repeated from Table 3.

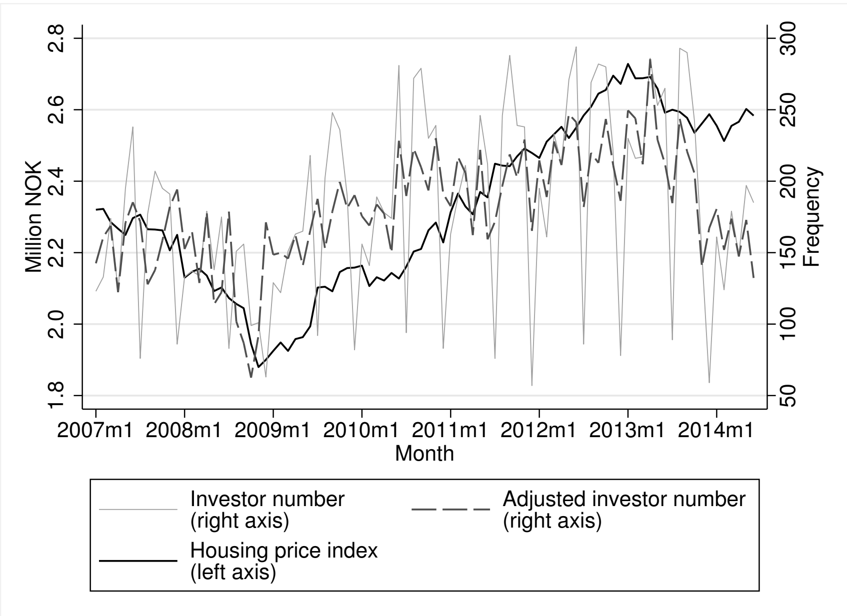
Table A.5: Different inflow levels

Model	Inflow	Price change	Rent change	Pric-to-rent change
Data		1.4558	1.2274	1.3752
Standard	High	1.2169	.	.
	Medium	0.9999	.	.
	Low	0.6117	.	.
Constant rent	High	1.2110	1.1075	1.1486
	Medium	1.0004	1.0001	1.0000
	Low	0.5973	0.7067	0.7644

Notes: Data moments are from the period 2007q1 - 2014q2. Changes in housing price and rent are calculated as max value over min value over the period. Simulated moments are the medians of 1000 simulations.

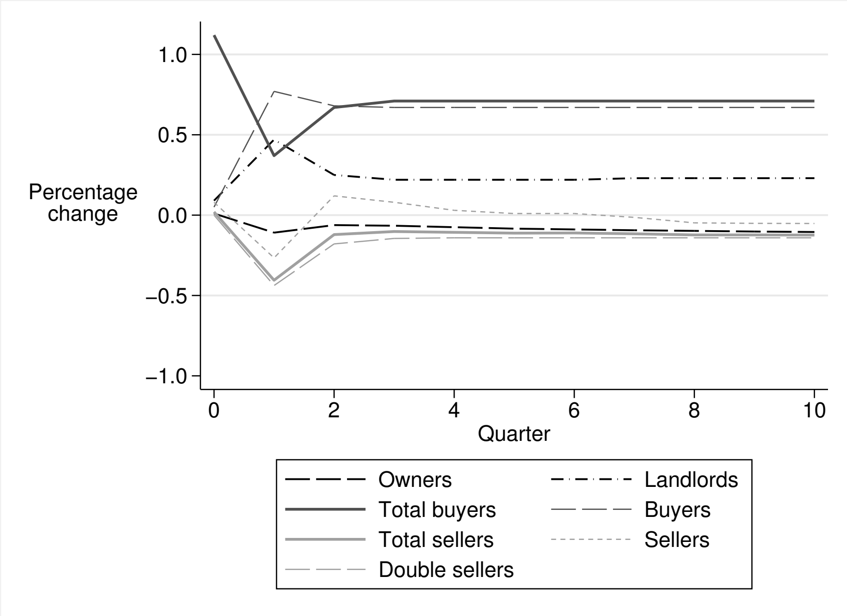
Appendix E: Additional figures

Figure A.5: Investor transactions



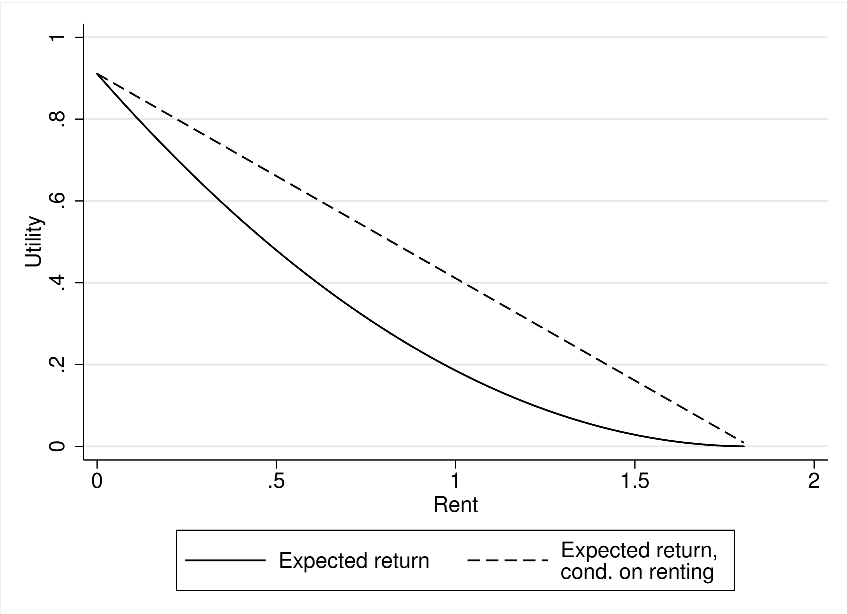
Notes: This graph shows the raw number of buy-to-let transactions for each month, as well as the number of transactions adjusted for monthly seasonal effects. The housing price index described in Appendix A is shown for comparison.

Figure A.6: Impulse function: Agent types



Notes: This graph shows the percentage change in the number of agents in different states for 10 quarters following an inflow shock 10 percent above mean inflow. The graph shows median values of 1000 simulations.

Figure A.7: Expected return from renting



Notes: Values based on the calibrated baseline model. Expected return is the unconditional return from renting that a buyer can expect before knowing own willingness to rent. Expected return to rent, conditional on renting is the return given that own return to rent is higher than the rent.

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