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Buy to let: Investment buyers in a housing search model

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Abstract:
In this paper, I explore and explain how buy-to-let investors affect housing price dynamics. The impact of buy-to-let investors on the housing market is much discussed by policy makers, but previously not considered in the literature. I develop a structural search model that allows housing owners to buy second houses to let out, and let rents be determined endogenously. To motivate the model, I present empirical evidence from the city of Oslo showing that a significant share of buyers are buy-to-let investors, and both rents and the share of second house buyers are positively correlated with housing prices. The model introduces two mechanisms that affect volatility compared to a model with no landlords and constant rents. 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 rents on housing prices and transaction volumes. The model is calibrated using data from Oslo, and is able to match quantitatively the high investor share and housing price volatility of a housing boom.

Keywords: Housing, Search, Rental market

JEL classification: D83, R21, R31

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Sammendrag

Hvordan utleieinvestorer påvirker boligmarkedet er mye diskutert i Norge, og i flere andre land. Sentralbankene i Norge, England, Nederland, Australia og New Zealand har alle uttrykt bekymring over at utleieinvestorer bidrar til ekstra press på boligprisene. Media kobler også investorer med høy boligprisvekst. Å modellere et boligmarked med investorer kan tydeliggjøre hvorvidt disse bekymringene er reele.

I denne artikkelen utforsker og forklarer jeg eksistensen av utleieinvestorer, og hvordan de påvirker boligprisdynamikken. Utleieinvestorer er definert som privatpersoner som kjøper sekundærbolig for med tanke på utleie (altså ikke investorer som pusser opp for raskt videresalg). Data fra Oslo viser at ca 20 prosent av boligkjøp i perioden 2007 - 2014 foretas av utleieinvestorer. Andelen investorer er positivt korrelert med boligprisvekst. Boligpriser og leiepriser er også positivt korrelert.

Basert på empirien presenterer jeg en søkemodell hvor boligeiere kan investere i bolig nummer to for utleie. Boligpriser og husleie bestemmes endogent i modellen. Modellen inneholder to mekanismer som øker boligprisvolatiliteten sammenlignet med en standard søkemodell uten utleiere. For det første fører endogen korrelasjon mellom boligpriser og husleie til at kjøpere er villig til å betale mer for boligen i opphetede markeder, for å komme seg unna høy husleie. For det andre blir det mer attraktivt å investere i utleieboliger når leien er høy, noe som øker antallet investorer. En økning av antallet kjøpere forsterker søkefriksjonene i markedet og presser prisene opp.

Modellen kalibreres for å treffe et antall empiriske momenter fra boligmarkedet i Oslo. Den kalibrerte modellen er i stor grad i stand til å forklare den høye andelen utleieinvestorer, og økningen av boligpriser i Oslo over perioden 2007 - 2014, som et resultat av høy innflytting. Jeg simulerer også en alternativ modell uten investorer. Prisøkningen i denne modellen er halvparten så høy. I tillegg ser jeg på mulige tiltak for å begrense andelen utleieinvestorer. En økning av kostnaden ved å investere i utleiebolig (tilsvarende innstramningen i boligpakken i 2016) øker velferd marginalt, og er svært effektivt for å redusere boligprisvolatilitet. En slik politikk kan dog føre til at sårbare leietakere mister muligheten til å leie, noe som ikke fanges opp av min modell.

1 Introduction

This paper provides empirical evidence and a theoretical model exploring an interaction between the market for owner-occupied and rental housing not previously considered in the literature: 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.

While the impact of buy-to-let investors on the housing market has not yet been considered in housing market models, it has been a concern in policy circles. The Bank of England (2015) worries that buy-to-let buyers drive the prices up in good times, and may be more vulnerable to negative interest rate and price shocks, and similar concerns are also 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 Næringsliv 2014; NRK, 2015) and Australia (Bloomberg, 2017), also connect investment buyers with housing price booms. Modeling this mechanism helps understanding whether these concerns are valid or not, and clarifies the role investment buyers play in housing market cycles.

I focus on buy-to-let investors, a class of investors that usually invests in housing for a longer time frame (Bracke, 2016). They are thus a separate and different type of investors than "flippers" (investors who buy and quickly resell houses). In contrast to flippers, buy-to-let investors mainly look for a return from rents, not from price appreciation. The role of flippers is not explored in this paper, as the way I define investors requires them to hold their houses for a certain period.[1] The coexistence of flippers and buy-to-let investors is likely.

In the empirical part of this paper, I investigate the number of investment buyers, and whether the investment buyer share of transactions is related to the housing cycle. The Norwegian housing register allows me to identify ownership of all Norwegian houses (including apartments). Using housing transaction data from the city of Oslo in the period 2007 - 2013, I show that the share of buyers who buy a second (or subsequent) house is significant, fluctuating between 10 and 25 percent of total transactions. Moreover, the investor share seems to be pro-cyclical.

I also use a rental asking price index and a house price index for Oslo to provide evidence that rental prices are pro-cyclical. It is not surprising that housing prices and rents are correlated. A house can be occupied by either an owner or a renter. The markets are not separate and an increase in population puts pressure on both markets.

I then build a structural search and matching model that is consistent with these empirical facts, by incorporating the opportunity for housing owners to become landlords. Most housing market search models let agents enjoy returns from only one house, while any

[1] Bayer et al. (2011) show that flippers represent a significant and pro-cyclical share of buyers in the Los Angeles housing market in the period 1988-2009.

other houses are for sale. In models where a rental market exists, rents are usually constant over time. In reality, some people buy a second or even further houses to let out, while rents vary over time.

If rents were constant, investing in a rental house would be less attractive in "hot" markets, when housing prices are high. In that case, second houses would be bought at times when the housing market were cold, and investment buyers could help stabilize market volatility. However, the empirical evidence presented here indicates that rents are correlated with housing prices, and that second houses are bought more often when the market is hot. In my model, consistent with this evidence, the increased numbers of buyers with investment motives in tight markets drive housing prices further up.

It is worth noting that my model has two different mechanisms that affect volatility compared to a model without landlords and endogenous rents. 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 further increase the number of buyers and amplify the effect of high rents on housing prices and transaction volumes.

In the calibrated model, investment buyers exist, even as the expected return to owner-occupation is higher than the expected return from rents, and with no liquidity constraints in the model. This may seem surprising, as prospective owner-occupiers could be expected to outbid landlords, due to a higher per-period utility of owning. However, the mean return of being a renter is higher than the mean rent. Thus, housing prices do not fully reflect the difference between rents and owner utility; the value of changing from being a renter to being an owner is less than the value of being an owner.

The paper fits in a large and increasing literature on search and matching in the housing market. This has become a popular way to introduce frictions as a response to observed features of the housing market (such as high price volatility and persistence of booms and busts) that are hard to reconcile with fluctuations in fundamentals in a frictionless market. 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.[2] Assuming search frictions seems reasonable for the housing market, as houses are heterogeneous goods, and transactions of houses are often drawn-out processes. Search models are well suited to explain a number of well-known empirical facts about housing markets, such as the correlation of high prices with high transaction volumes and short time on market for vacant houses.

As standard housing market search and matching models typically provide lower price volatility than observed in data, a number of model variations have also been suggested.[3]

[2] See e.g. Carrillo (2012), Anenberg and Bayer (2015), Diaz and Jerez (2013) and Head et al. (2014). For a recent survey of the use of housing market search models, see Han and Strange (2015).

[3] See e.g. Caplin and Leahy (2011), Diaz and Jerez (2013), Ngai and Tenreyro (2014) and Anenberg and Bayer (2015)

A main feature of these models is the search for mechanisms that add price volatility, to achieve large enough volatility of prices.

The paper most related to mine is Anenberg and Bayer (2015). In a dynamic equilibrium search model with internal[4] and external movers, the decision to buy before selling or sell before buying is endogenous and there is a cost to holding two houses. 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, where prices are low and houses sell slowly, internal movers want to sell before buying. If they buy first, they may end up holding a costly second house for sale for a long period. This adds to the already large supply of sellers, and prices decrease even more.[5]

While my model has certain similarities to the model in Anenberg and Bayer (2015), the main mechanisms involved are quite different. Anenberg and Bayer add extra volatility by having agents who switch between being buyers and sellers, dependent on the market situation, while here it comes through having a larger or smaller share of owners also being investors. The rental market in my model is another novel mechanism, which creates a direct link from market conditions to the value of being buyer and landlord.

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 and transactions may well be due to a combination of all these factors.

A couple of previous papers have expanded on the standard assumption of constant, exogenous rents. Head et al. (2014) develop a search model where construction, entry of buyers, housing prices, rents and transactions are determined endogenously to study the impact of income shocks on housing markets. They allow for quick, costless conversions from rental housing to houses for sale and back. In their model, rents actually fall at first when population inflow increases, due to sellers anticipating higher housing prices in the future and deferring sales by moving vacant houses into the rental sector. This is contrary to empirical evidence.

Kashiwagi (2014) looks at the properties of a tractable theoretical search model with both renters and owners. In his model, a real estate sector immediately buys all houses for sale, and decides each period how many houses to rent out and how many to sell. Neither of these models allow households to invest in rental housing, which removes the amplifying effect on prices that the buying decision of owners provides in my model.

The buy-to-let model is calibrated using the method of simulated moments.[6] As in Anenberg and Bayer (2015), the model I calibrate is a dynamic equilibrium model, where

[4]Internal movers are defined as people both buying and selling in the area within a certain time.

[5]Another model of the timing of buying and selling is developed in Moen et al. (2016). This is a model of multiple equilibria, with large, endogenous fluctuations in prices and number of transactions as the equilibrium switches.

[6]Similarly to Anenberg and Bayer (2015), simulated moments from the model are matched with moments from housing market data

I use the dynamics of housing market variables to fit the model. The calibrated model fits data moments fairly well. I also show how the model performs compared to a standard search model, without the buy-to-let aspect. It is able to explain a larger amount of housing price volatility than a standard search and matching model. It achieves 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 is a period of very high population inflow. The buy-to-let model displays a price increase twice as high as the standard model, matching the high observed price increase over the period. Simulations of a low inflow period indicates that prices in the buy-to-let model will also fall more than in the standard model.

In the last part of the paper, the model is used to look at welfare and price implications 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 leads to a larger decrease in housing prices and price volatility than a general tax on landlords. Both policies slightly increase welfare.

2 Data and motivating empirics

As a motivation for the following model, I here present empirical evidence on the relation between housing and rental prices, and on the share of housing transactions conducted by investment buyers. This empirical investigation of buy-to-let investors adds information on a subject barely covered in the literature. Some institutional aspects of the housing market in the source data location are also mentioned, to better understand from which setting the results emerge.

I use data for the municipality of Oslo, the largest city in Norway, with around 600,000 inhabitants in the period studied. Norwegian register data allows me to know the ownership of almost all houses and apartments in the city of Oslo,[7] and also if the owners own any other housing in Norway. The reason for only using data for Oslo is twofold. Most rental apartments in Norway is concentrated in large cities, thus any effects of investment buying should be most visible in the largest city.[8] Also, data on rental prices are not widely available; but for Oslo, I have a source that provides me with rental 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 11,000 housing units in Oslo (less than four percent of the housing stock) are municipally owned

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

[8] Bracke (2016) shows that this holds in England and Wales, with London having the clearly highest share of buy-to-let investors.

(Statistics Norway, 2017b). The remaining rental market is commercial, with asking rent unregulated, as Norwegian rents are generally not affected by rent control.[9]

2.1 Data

Transaction data for housing for the year 2007 - 2014 come from Statistics Norway. Statistics Norway gathers the data from Finn.no, the main web page for housing listings in Norway and from The Norwegian Mapping Authority (NMA) which holds the register of real property transfers (*Tinglysning)*. The data on ownership of non-transacted houses for the same period are from the Norwegian cadastre (*Matrikkelen*), which holds information about 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 hold ownership of houses from the cadastre.[10]

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, and to add tax information, which I use to add information on reported rental income for a robustness check.

Thus, I am able to study how the share of buyers from households that already own a home change over time. I do not use transactions where the buyer is a company or organization, as they do not fit within my model framework.

Rental price data are harder to find than data for housing transactions. To my knowledge, there exists no rental microdata for the Oslo area. Instead, I use an aggregated statistic, which is made for Boligbygg[11] (the housing department of the municipality of Oslo), using hedonic regression on all housing units advertised for rent at the webpage Finn.no. Advertised rental prices and characteristics are used to calculate rental prices for typical apartments with 0, 1, 2, 3, 4 and 5+ bedrooms in the city of Oslo, split into five different geographical zones. 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 measure.

2.2 Housing and rental prices

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,[12] based on transacted houses that have been

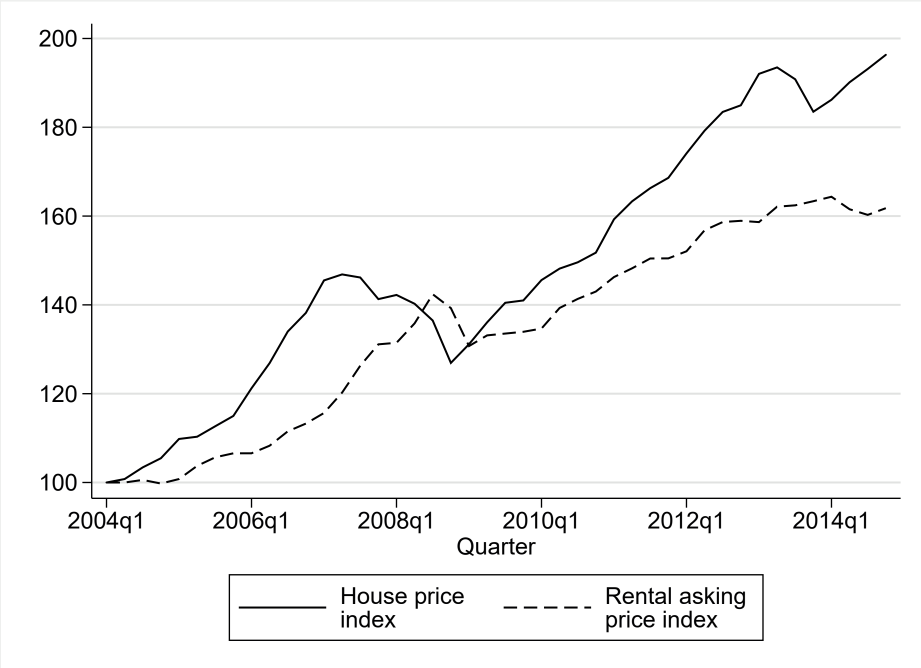
[9]There are restrictions on the increase of rents within a rental term, but rental terms are generally short, and there are no restrictions on asking rent.

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

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

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

Figure 1: Housing and rental prices in Oslo



Notes: Q1 2004=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. Rental asking prices are calculated as the average over all apartment types and geographical zones of the Boligbygg rental price statistic. The prices are adjusted for inflation, and indexed to Q1 2004.

advertised at Finn.no.[13] 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 prices 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.[14] Rental price growth over the period is also somewhat lower, and less volatile, than housing price growth.

The correlation of housing prices and rents is expected, as increased demand for housing services would affect both owner-occupied and rental housing. In the literature on 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, if implied rents and real rents follow the same path, prices and rents should be

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

[14] 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, appraisal values (which are mostly similar to asking prices) and transaction prices of transacted housing closely co-move, suggesting that the lag might not only be an artifact of the different data sources.

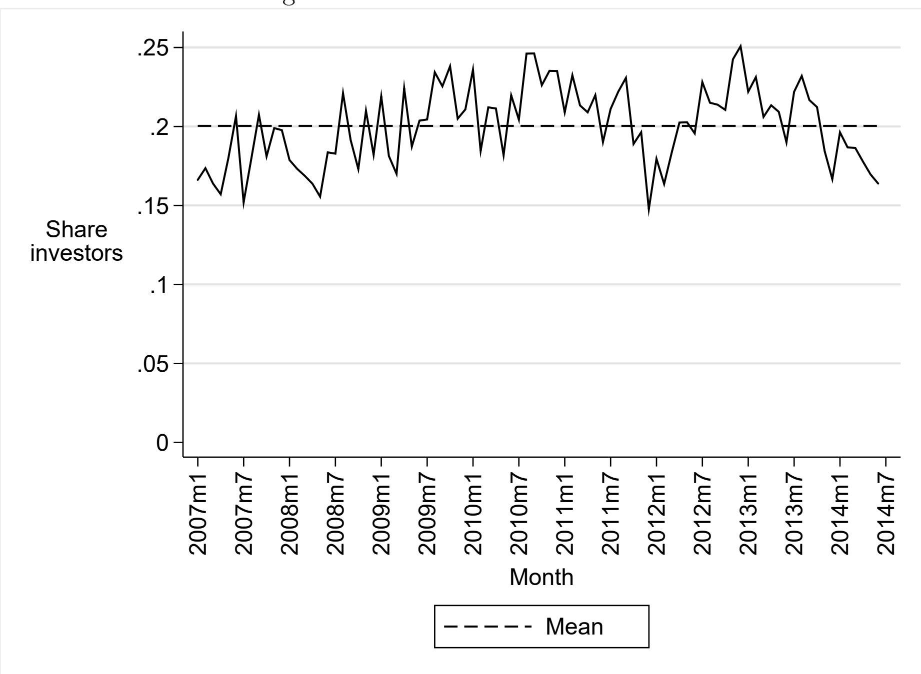
correlated.

There is a literature which shows that the price-to-rent ratio is highly pro-cyclical, e.g. Favilukis, Ludvigson, Van Nieuwerburgh (2017). A very high price-to-rent ratio could imply that prospective landlords are priced out in booms, if prices increase more than the returns to renting out. But usually, the rental data in these papers come from national accounts or measures of all renters' rent. However, the most relevant measure for prospective investors is the current asking rent; measures based on all rents likely underestimate the pro-cyclicality of rents.

2.3 Investment buyers

Next, I look at how the share of investment buyers fluctuate over the housing price cycle. The only previous paper which empirically explores buy-to-let, Bracke (2016), 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, the my data allow for estimation of the buy-to-let investor share based on full housing transaction coverage.

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.

Buyers are defined at the household level, as distribution of housing ownership between spouses may reflect tax considerations more than real ownership. I define buy-to-let as the purchase of a house by a buyer who already owns at least one house, and who still owns at least two houses at the end of the year following the year in which they bought a secondary house.[15] More on creating the dataset of investment buyers can be found in Appendix A. To test the robustness of the investment buyer measure, I explore the use of a definition which requires an investor to keep two houses for a period of at least 24 months.

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.

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 Oslo, in Panel B only apartment transactions are used. Standard errors in parentheses.
** $p<0.01$, * $p<0.05$

Figure 2 show that buyers buying investment homes represent a significant share of all housing purchases in Oslo. The mean share over the period is 20 percent.[16] While the

[15]That is, a household who owns at least two houses for a period of over 12 months.
[16]This share is comparable to Amsterdam and Rotterdam in the Netherland, where De Nederlandsche

share varies, it is never below 10 percent, and often above 20 percent. There are significant seasonal spikes in the share, which is highest during autumn.[17]

To measure the correlation between house price growth and the share of investment buyers, I regress the monthly share of investment buyers on the housing price growth in 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.[18]

Table 2: Housing price growth and alternative investor share

All housing	(1)	(2)	(3)
Quarterly growth	0.113	0.347**	0.043
	(0.081)	(0.100)	(0.075)
Monthly dummies		yes	yes
Yearly trend			0.010**
			(0.001)
R-squared	0.028	0.199	0.520
Observations	60	60	60

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. ** $p<0.01$, * $p<0.05$

As a robustness check, I also use a second measure of investment buyers, which is the measure of investment buyers defined above who additionally report rental income in their tax returns (in the year following the buying year).[19] As reported in Table 2, the results are similar to those using the main measure, though weaker, and significance does not survive in the specification with a yearly trend.

Bank (2018) reports an investor share of almost 25 percent for 2017q3.

[17]Ngai and Tenreyro (2014) show that seasonal fluctuations may appear in a model with a matching function with increasing returns to scale. In that model, match quality is lower in "cold" seasons. As investors may care less about match quality, it is possible to imagine that investors may prefer buying in the cold season. I do not include this seasonality in my model.

[18]86.4 percent of buy-to-let purchases are apartments.

[19]I only have tax data available through 2012, which means that this measure covers a shorter period than the main measure.

3 Model

Here I develop a search and matching model where owners are allowed to buy a second house, to let out.[20] This feature is introduced to explain the existence and timing of purchases of investment houses, which are commonly observed in the data. The possibility of buying investment houses adds more volatility to housing prices, which is consistent with empirical patterns.

The model is similar to standard housing search and matching models in many ways. The 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 a market for rental houses, and a rental market. Owners can buy a second house to let, but searching for a second house is costly. Rents are determined in the model by the supply and demand of rental housing in a frictionless rental market.

3.1 Agents

There are five possible states for agents in this model. The states depend 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 are those who do not own a house. All non-owners want to buy housing. In their first period, new entrants are not allowed to buy.

Housing owners are hit by mismatch shocks at rate δ, in which case they turn into sellers.[21] 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.[22] Note that landlords only

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

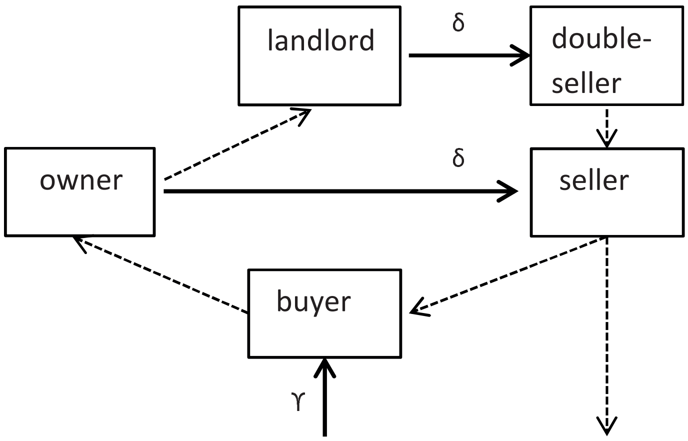
[21] As in Piazzesi et al. (2015), I impose selling before buying.

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

sell when hit by a mismatch shock, meaning that they can not act as flippers by selling if 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 an investment cost, κ. The investment cost κ may reflect e.g. financing cost, or the search effort. Owners who buy a second house become landlords.

Figure 3: Graphical representation of the model



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 a utility $u < \varepsilon_i$. 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.

Sellers (both normal and double-sellers) meet with buyers (buyers and owners) 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.

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.

Buyers rent housing through the rental market. Those who do not find a match try to buy again in the next period. 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.[23] 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,[24] which does not depend on the rental match, but on the renter, and is redrawn every year. They also have to pay the 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.

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 of new agents is announced.

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 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 measure 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.

[23] Saiz (2003) documents how an inflow of poor Cuban immigrants to Miami in 1980 immediately increased rents, particularly for low-quality housing, but not housing prices.

[24] 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.

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 subscript t in the value functions is a parsimonious way of showing that a function depends on Ω_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. A match with a seller occurs with probability 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. Depending on the type of seller j, $\Pi_t^{o,j}$ gives the expected surplus of the meeting, conditional on the surplus being positive, of which the buyer share is $1-\theta$. The expectation is over γ', which is the inflow of agents in next period.

As in Anenberg and Bayer (2015), the value function can be split into two additively separable components; one which depends on the individual match quality and one which does not:[25]

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

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

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:

[25] See Appendix B for details.

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

The value of being a buyer:

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

Here, 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 M/B, in which case they receive their bargaining share, $(1-\theta)$, of the surplus, in addition to their value of remaining buyers, V_{t+1}^b.

The value of being a seller:

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

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 transaction surplus if a transaction occurs. The probability of meeting a buyer for a seller is 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 utility flow of a rental house is also received, and that the outside option and transaction surpluses are those of a double seller.

3.4 Meetings

The housing market, where houses are transacted, is modeled with search frictions. Match quality is heterogeneous.

3.4.1 Matching function

The number of matches is determined through a matching function by the total number of buyers, $B = b + o_b$,[26] and the total number of sellers, $S = s + d$. The matching function, as in Anenberg and Bayer (2015), is given as:

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

[26]Where o_b is the number of owners not hit by a mismatch shock who choose to search for second houses in the current period, as described below.

I limit the number of matches to $min(B, S)$, though for the calibrated parameter values in my model, this limitation does not bind. 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 matches 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 without a house 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 (and price).[27]

3.4.2 Transactions

A match results in a transaction if the expected surplus is greater than 0. Thus the actions for buyers and sellers are: transact if a match 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 $E_{\gamma'}\Pi^{i,j}$, where 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 surplus of the buyer shifting state to owner in next period, plus the surplus of the seller being a buyer instead of a seller in the 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 change of state for the different combinations of buyers i and sellers j. They are:[28]

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

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

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

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

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

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

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.[29] 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 as $\sim N(0, \tilde{\sigma}^2)$). The conditional surplus, given the probability that the surplus is positive, can be found; 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

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 $(1-\theta)$.[30] The bargaining process determines the price of the house, P, which is thus dependent on the type of both buyer and seller: $P = [P^{b,s}, P^{b,d}, P^{o,s}, P^{o,d}]$.

The price is found from the surplus in the following way, dependent on type of buyer and seller:

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

[29] 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 e.g. agents with high match quality to be in the state with the lowest probability.

[30] 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.

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

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

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

Here, $\tilde{\varepsilon}^{b,j}$ is the random match quality, truncated from below by the minimum value which allows for 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 $P_t^{o,d}$.

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.[31] Owners will want to buy as long as the expected return of searching for an extra house to buy is higher than the cost κ.

All owners are similar. The equilibrium strategy of owners will be a mixed strategy, where all owners assign a similar probability $\rho_b \in [0,1]$ of searching. The share of owners who are buyers can then be calculated 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 owners set, for which the expected benefit of searching is equal to the cost of searching.[32] 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 thus given as $o_b = \rho_b(1-\delta)o$, 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 transactions, possible renters, with measure $b+\gamma$, meet landlords, with measure $l+d$, in the rental market.

[31] 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 the price is high.

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

Renters are given 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, rent would (theoretically) be equal to the maximum willingness to pay, $\bar{r}$. With more landlords than renters, rental prices are driven to zero by competition.

3.7 Laws of motion

The movements of state variables depend both on the transactions happening endogenously in the model, and by exogenous movements from shocks or inflows. Below, the laws of motion for the different state variables are split into movements from these sources.

3.7.1 Transition of state variables in equilibrium:

In the equations, $T^{i,j}$ is the probability that a match 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.[33]

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

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.

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

Similarly, sellers consist of last period's sellers, minus the sellers who sold, plus double sellers who sold one of their houses.

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

The number of landlords is increased by buyers who bought a second house, either from sellers or double-sellers.

[33] A description of how $T^{b,s}$ and $T^{b,d}$ depend on the transaction surplus is given in Appendix B.

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

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

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

Owners can be found from the remaining 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.

3.7.2 Exogenous transitions:

$$b' = b + \gamma - \tau \tag{27}$$

Last period's inflow are buyers in the next period. A number τ of last period's sellers exit the economy and do not become buyers.

$$s' = s + \delta o = s + \delta(1 - 2l - s - 2d) \tag{28}$$

Sellers are supplemented by owners receiving a mismatch shock.

$$l' = l - \delta l \tag{29}$$

A share of landlords also receive a mismatch shock.

$$d' = d + \delta l \tag{30}$$

The mismatched landlords are double-sellers in the next period.

$$o' = o - \delta o \tag{31}$$

Again, for completion: exogenous transition from the owner state occurs due to owners becoming mismatched.

3.8 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 been matched, 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

I first calibrate parameters with direct comparisons in the data. A number of parameters are also set to have values commonly used in the literature. The remaining parameters are found using the method of simulated moments (MSM).

4.1 A priori calibration

Each period in the model is assumed to be 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 (that is, symmetric bargaining), and use the value of η in the matching function from Genesove and Han (2012).

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).[34] The parameters are presented in Table 3, 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 five targets:

- The mean rent to housing price ratio.[35]

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

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

- 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 share of transactions over housing stock.

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. Note that 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. See Appendix A for details, including Figure C.3 which shows that this housing price index is quite similar to the housing price index by Eiendom Norge presented in Section 2.2.

Table 3: 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 (2015)

B) Parmeters calibrated by MSM

Parameter	Value	Description	
$\bar{\varepsilon}$	1	Mean matched utility	(Normalization)
u	0.7765	Mismatched utility	
σ	0.1448	Standard dev. of match quality	
$\bar{r}$	1.7900	Maximum rent	
κ	0.2196	Cost of finding second house	
δ	0.0289	Prob. of mismatch shock	

Notes: The parameters are quarterly.

The mean share of transactions over housing stock is calculated as the number of housing transactions divided by the housing stock of Oslo over the years 2007 - 2013. More details on the numbers behind this moment can be found in Appendix A.[36]

[36] 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, a direct calibration would underestimate the mismatch rate.

For each combination of parameters, the model is solved,[37] and then simulated over a sequence of inflow shocks.[38] 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.[39] Moments are calculated from the simulations and compared with data moments. The chosen parameter vector is the one that minimizes the distance to the data moments.

5 Results

5.1 Model fit

The parameter values found through MSM are presented in Table 3, Panel *B*. The mismatch utility, u, is 0.78 of mean matched utility (mean matched utility, $\bar{\varepsilon}$, is the unit that other values are measured in). 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 0.78 is somewhat lower than in Anenberg and Bayer (2015), but much higher than the 0.1 assumed by Diaz and Jerez (2013). The standard deviation of match quality, σ, is higher than the 0.0787 found by Anenberg and Bayer (2015).

The maximum theoretical rent, $\bar{r}$, is 1.79 times the mean utility of owning. 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, 39.5 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 0.83 times the mean utility of owning. The value of κ implies that the search cost of prospective investment buyers is equal to a little less than 1 month of rent. This may seem quite low, but the Norwegian tax system gives incentives to invest wealth in secondary housing. This is not reflected in my model, and may help explain the low search cost of investors.[40]

The mismatch shock, δ is 0.029 With this mismatch rate, mismatch occurs roughly once every 10 years. This gives a fairly similar housing tenure to e.g. Anenberg and Bayer (2015) and Ngai and Tenreyro (2014), who calibrate housing tenure against surveys of US, and US and the UK respectively.

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

[38]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 200 different draws of starting values, and take the median of the moments over the 200 simulations.

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

[40]For more on Norwegian housing taxation, see Bø (2015).

Table 4: Moments

Moment	Data	Simulations
Mean rent/housing price	0.0135	0.0100
Mean investor share	0.1999	0.1990
Housing prices (σ/μ)	0.1021	0.1010
Rents (σ/μ)	0.0573	0.0517
Investor share (σ/μ)	0.0915	0.0894
Housing transaction rate	0.0247	0.0265

Notes: Data moments are from the period 2007q1 - 2014q2. Simulated moments are the medians of 200 simulations.

Table 4 shows how the simulated moments from the calibrated model compare with the moments from data. It is clear that the model is able to hit the high share of investors well, however, the volatility of the investor share is somewhat too high. The model is not able to fully fit the volatility of housing prices and rents. The model is also unable to fully capture how high prices are relative to rents. This may also be influenced by real world tax incentives to own instead of rent.

5.2 Sources of friction

To see how the features of the buy-to-let model are affecting the functioning of the housing market patterns, I here compare the full model with a model without a buy-to-let sector (presented in Appendix C). The model is a "standard" search model, with three types of agents (owners, buyers and sellers), that closely follows the modeling choices of the buy-to-let model, and have the same parameters.

Next, I try to separate the effects of the two mechanisms that my model features. The full 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 owners are more willing to become landlords in periods of high rents.

In the constant rent model, the buy-to-let sector still exists, but there is no rent change channel for buyers. Owners can still invest in second houses, and the rent achieved by landlords is set as in the baseline model, in a frictionless market where buyers compete for rental houses. However, rents paid by renters are constant. 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 removes the increased incentives for buyers to buy in high-rent periods.

A number of moments, empirical, and simulated from the main model, the standard search 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

Table 5: Comparing different models

A) Moments	Data	Buy-to-let model	Standard model	Constant rent model
Housing prices (σ/μ)	0.1021	0.1010	0.0639	0.0812
Transaction volume (σ/μ)	0.1503	0.0143	0.0037	0.0250
Price autocorrelation	0.9514	0.9938	0.9936	0.9939
Corr. price/rents	0.7640	0.9971	.	0.9911
Corr. price growth/share investment	0.2864	0.5376	.	0.7955

B) Values relative to baseline model				
	Price	1.0000	0.4408	0.7585
	Rent (landlords)	1.0000	.	1.0224
	Rent (renters)	1.0000	.	0.9704
	Owners	1.0000	1.2074	1.0013
	Match quality	1.0000	1.0032	0.9969

Notes: Data moments are from the period 2007q1 - 2014q2. Simulated moments are the medians of 200 simulations. Coefficient of variation of housing prices is a matched moment, the other moments are unmatched. Owners are agents in owner and landlord states.

the calibrated parameter values, is able to hit the volatility of housing prices quite well. The standard model displays 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 consistent with what Diaz and Jerez (2013) and Anenberg and Bayer (2015) report from their models. A possible explanation observed in my simulations is that in periods with many buyers, relatively few matches lead to transactions. In these cases, the option value of being a seller is high. Unless the match quality draw is very high, sellers defer sales to the next period in the hope of achieving a higher price. 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).

This problem is connected to the high price to rent ratio observed in data, as mentioned in Section 5.1. To achieve high prices in the model, match quality has to be high. And high match quality decreases the number of matches leading to a transaction. Another way of increasing the transaction volatility in the model would be to increase prices without increasing match quality. This could be done e.g. by allowing bargaining weights to depend on market conditions. Due to e.g. bidding wars (Han and Strange, 2014), sellers may have higher bargaining power when there are many buyers relative to sellers.[41] Modeling a version of the buy-to-let model with a varying bargaining weight is however not straightforward, and I defer it to future research.

[41] Carrillo (2013) presents a search model with that feature. Diaz and Jerez (2013) also discuss how a Nash bargaining version of their model displays only half the volatility than when prices are set in competitive equilibrium.

The last two rows of Panel A of Table 5 show the correlation of prices and rents and the correlation of the investment share of buyers with the growth in housing prices from last to current quarter. The model in both cases have the right sign on the correlation, but it is too strong.

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 the 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 75% of the baseline model. Not surprisingly, the standard model, without landlords, have a clearly higher share of matched owners than the other two models.

To the extent the constant rent model captures one, and not the other of the mechanisms in the buy-to-let model, some conclusions can be drawn. The existence of investment buyers, and their crowding in at times of high-rent, contribute to 47 percent of the increase in price volatility, 57 percent of the housing price increase, and negatively to the transaction volatility separating the buy-to-let and the standard model.

5.3 Different levels of population inflow

The data period 2007q1 - 2014q2 coincided with a period of unusually high population inflow to Oslo. It is interesting to also explore how buy-to-let investors affect the housing market in different market conditions. For that purpose, I simulate the model, as well as the standard and constant rent model, for periods of normal and low population inflow, and compare simulation results with the high inflow data period.

Table 6: Different inflow levels

Model	Inflow	Price change	Rent change
Data		1.4558	1.2274
Buy-to-let	High	1.3998	1.1852
	Medium	1.0050	1.0024
	Low	0.4676	0.6293
Standard	High	1.2113	.
	Medium	1.0022	.
	Low	0.6476	.
Constant rent	High	1.3138	1.0991
	Medium	1.0031	1.0005
	Low	0.5912	0.7639

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 200 simulations. Changes in housing price and rent are calculated as value in period 30 over value in period 1.

Table 6 shows the impact of different levels of inflow shocks on the housing prices and rents in the three models previously presented. The buy-to-let model is affected more by both high and low inflow shocks than the standard model.[42] 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: Reduced expectations for the resale price, and lower expected rental income. Buyers are also affected by lower resale price, but their return from owning a house is not affected. Investors thus react more strongly to inflow shocks than ordinary buyers. And as investors and buyers compete for houses, prices in general will be more affected in a model with investors.

Though my model does not contain credit constraints or debt, the strong price and rent falls in a low inflow period indicate that central banks may be may be right in their worries that a large buy-to-let sector could pose risks to financial stability.

5.4 Model mechanisms

Due to the complicated nature of the value functions, the model cannot be solved analytically. To help understanding the model mechanisms, I here present some graphs showing simulations of the model, and discuss how certain features of the model operate.

Figure 4 shows the co-movements of inflow, rents and housing prices, over a simulated time period of 60 quarters. The results come from a representative simulation of the model. The first 30 periods are from the burn-in phase (burn-in period 171 - 200) with inflow shocks drawn from the pre-period distribution. The last 30 are from the simulation period, with inflow from the real inflow sequence. Variables are displayed as the percentage deviation from the pre-period mean values.

The figure demonstrates how the inflow shocks influence the prices in the model. Inflow is clearly positively correlated with housing prices and rents. It is also noticeable that housing prices are more volatile than rents, which corresponds with the empirical evidence in Figure 1. The sequence of high inflow shocks over the period 2007q1 - 2014q2, is shown to strongly increase housing prices, while leading to a more moderate rent increase.

The relationship between inflow and the share of investment buyers is shown in Figure 5. The correlation between the two variables is very strong (0.95). In fact, the strong correlation between inflow shocks and housing prices and investment share shown in Figure 4 and Figure 5 are examples of the high correlation of the investment share of buyers and housing prices growth shown in Table 5. The model features an influence from inflow shocks to other elements of the model which is a bit too strong compared to data.

By looking at the value functions (3) $-$ (9), it is possible to draw some conclusions about how rents, r, and the mismatch utility, u, affect housing prices. A rent increase will increase the value of being both landlord and double seller (V^l and V^d). V^l will be affected more, through a longer expected letting tenure (if a landlord changes state, it

[42] The effect on prices in the constant rent model is in between the two other models.

Figure 4: Inflow, rents and prices

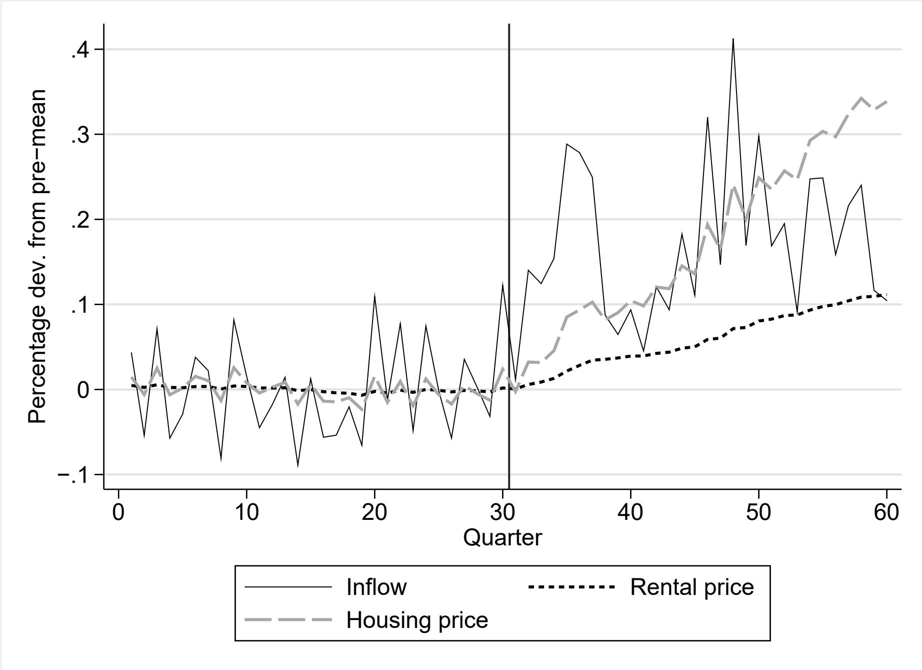
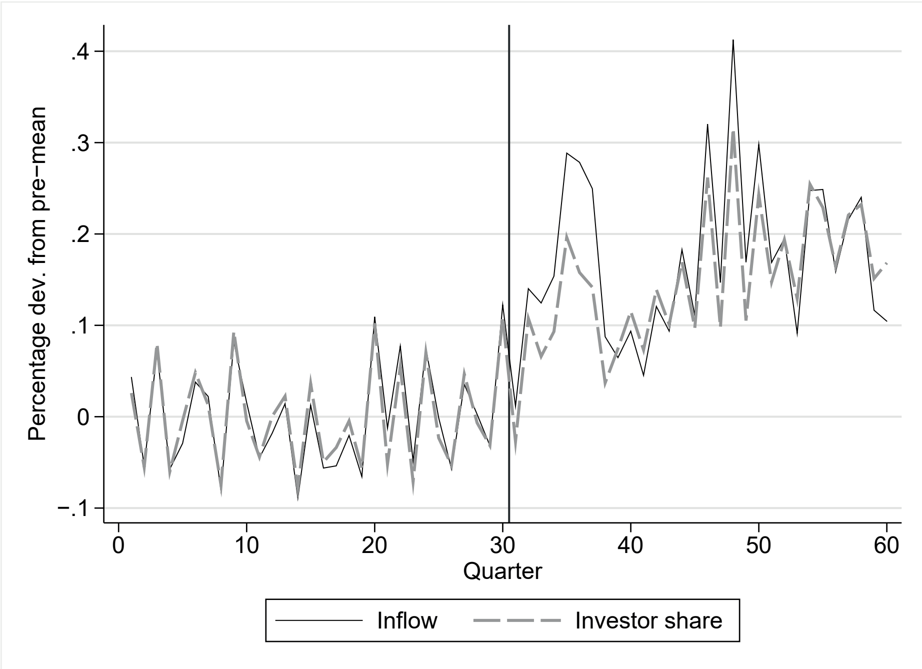


Figure 5: Inflow and investment buyers



Notes: These two graphs show simulations of the model over a period of 60 quarters. The first 30 periods are from the burn-in phase with inflow shocks drawn from the pre-period distribution. The last 30 are from the simulation period, with inflow matched to real inflow.

will be to being double-seller, also receiving rents). At the same time, buyer value (V^b) will decrease, as buyers have to pay the higher rent.

These changes in value functions will directly drive up $P^{b,d}$ and $P^{o,d}$, while the effect on $P^{o,s}$ is ambiguous. As all prices are connected through the option value of deferring a sale to the next period, a rent increase drives up all prices, though $P^{b,d}$ and $P^{o,d}$ will see the largest increases. The correlation between rents and housing prices thus arises because the willingness to pay for housing for first-time buyers increase with rents, as the alternative cost of not buying (i.e. renting) is higher.

Simultaneously, as V^l increases, the surplus of a transaction involving an owner becoming a landlord ($\Pi^{o,s}$ or $\Pi^{o,d}$ depending on seller type) goes up. This will increase the search probability of owners, leading to a larger number of buyers.

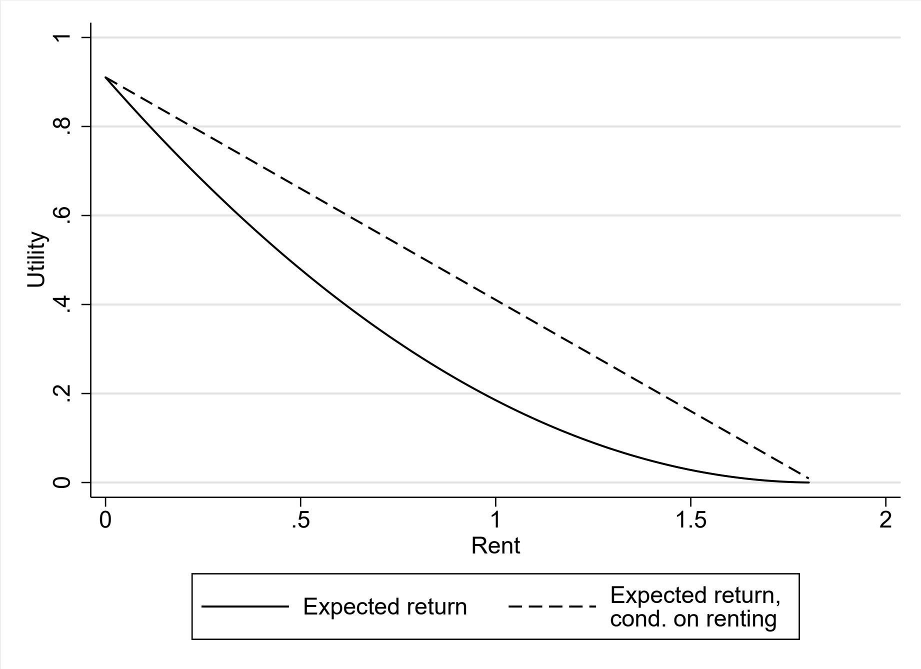
The lower the value of u relative to the value of $\bar{\varepsilon}$, the more costly it is for an agent to be mismatched. Thus, a lower u allows for a larger dispersion of prices, as it is less profitable for sellers to defer a transaction if the current match gives a low price. In general, a lower u will also mean lower prices, through two different mechanisms. First, sellers are more motivated to sell (their reservation value is lower), which drives down the price sellers achieve through Nash bargaining. And with a higher motivation to sell, and lower prices, a larger share of match quality draws lead to transactions, which also pushes down average prices.

Inflow shocks affect the stock of buyers relative to sellers. After a sequence of high shocks, there can be a seller's market, with a large number of buyers relative to sellers. In my model, the high number of buyers will also drive up rents, which, as earlier argued, increase housing prices. Higher prices increase the minimum match quality required, $\tilde{\varepsilon}^{b,j*}$, leading to a lower number of transactions. Thus, the existence of a rental market both increases price reaction to a seller's market, and also persistence, as there will be more buyers in next period.

The calibrated model features a fairly high share of investment buyers. It may seem surprising that owners are able to compete with buyers in the housing market when their return (the expected rent) on average is markedly lower than buyers' return (with expected value 1). However, buyers on average get an expected return of renting which is positive, because rent equals the return to rent of the marginal renter. All other renters get a positive return.

In a market with many landlords, a large share of buyers will be able to rent, at low rents. Thus, the return of changing from buyer to owner will be low, and investment buyers will be able to compete on price, even though their return is low. This is shown in Figure 6, which presents the expected return of renting, both unconditional and conditional on being in the set of renters, for different levels of rent. As fewer renters find a place to rent, rents increase, and the expected return is decreasing. Not only because the rents increase, but also due to the lower probability of finding a rental match (remember that the utility of being a non-renter is 0).

Figure 6: Expected return from renting



Notes: 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.

Finally, the model gives heterogeneity in housing prices. The heterogeneity arises both from the different types of buyers and sellers, and from differing prices within transactions involving buyers, dependent on the realization of match quality. While it is hard to say analytically which prices should be higher, the simulated prices from the model can be compared to empirical data on sales prices for different buyer groups. In the baseline simulation, investors pay 0.02 percent less than buyers, while Bracke (2016) reports an investor discount of at least 1.6 percent.

6 Policy and welfare

Could the government increase welfare, and reduce volatility by increasing the cost of buying second houses? Having calibrated the buy-to-let search model, I will now look at the implications of some possible policy interventions for welfare and the workings of the housing market. I will look at two different ways for the government to increase the cost of buying (or owning) buy-to-let housing.

1. Reform 1: Increasing the cost of searching for a secondary house. This could be done by e.g. increasing the cost of financing secondary housing, which has been suggested 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 10 percent (or 0.02).[43]

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 can 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 0.002.[44] This equals 0.24 percent of quarterly rental income.

In both cases, the extra costs imposed are thrown away, i.e. not returned to agents in any form. Before presenting the impacts of the two policies, I explain how welfare is defined and calculated. It should be noted that agents in the model are risk-neutral. In reality, most agents are probably risk-averse. Policies reducing price volatility, which does not affect welfare in the model, would thus lead to an additional real-life increase in welfare.

6.1 Welfare

Welfare is the discounted sum of housing utility, that is all current and future returns from owning and renting houses, for all types of agents. 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:

$$\begin{aligned} W &= \sum_{t=0}^{\infty} \beta^t E(min(b_t, l_t + d_t)\bar{r}^*_{it} + (s_t + d_t)u + \frac{M}{B_t S_t}(b_t s_t E[\tilde{\varepsilon}|\tilde{\varepsilon} > \tilde{\varepsilon}^{b,s*}]Pr(\tilde{\varepsilon} > \tilde{\varepsilon}^{b,s*}) \\ &\quad + b_t d_t E[\tilde{\varepsilon}|\tilde{\varepsilon} > \tilde{\varepsilon}^{b,d*}]Pr(\tilde{\varepsilon} > \tilde{\varepsilon}^{b,d*}))), \end{aligned} \tag{32}$$

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 terms $E[\tilde{\varepsilon}|\tilde{\varepsilon} > \tilde{\varepsilon}^{b,j*}]Pr(\tilde{\varepsilon} > \tilde{\varepsilon}^{b,j*})$ define 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 cannot be affected by policy. Welfare is measured in terms of the present value of 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.

[43] In the model, κ consists of several elements, many of them outside of government control, such as the time cost of looking for a second house. It is thus unclear how large the policy change would have to be to achieve a ten percent increase in κ.

[44] The per-period tax is set to be equal in amount, in the pre-tax state, to the total increase in search cost.

I find total welfare by simulating the model over a long time. As t goes to a large number, β^t gets very small, and adding extra periods has only infinitesimal effect on total welfare. When calculating welfare effects, I let the baseline model run for 200 periods to settle, then through the 30 periods of data. Thereafter, I simulate 1000 periods for the baseline model, and for each new policy, and compare the resulting welfare.[45] Any gains or losses from the transaction from one policy path to another are thus included in the results.

6.2 Policy implications

Table 7 presents results from the policy changes, 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 10 percent (Reform 1) and a per-period tax of rental housing, $rc = 0.002$ (Reform 2).

Both reforms increase welfare, though the increases are small, below 0.2 percent. It is noticeable though, that welfare increases even if the costs imposed are not returned to agents. However, the reforms have strong effects on prices. There are also noteworthy differences between the reforms. The welfare increase is slightly larger for Reform 1, and it induces a stronger, negative effect on housing prices and on the volatility of housing prices and transaction volume. Reform 2, on the other hand, leads to a smaller increase in rents and consequently a higher share of renters being able to let. Reform 1 also gives a larger increase in the number of owners and decrease in the number of buyers.

Table 7: Policy implications, percentage change

	Reform 1	Reform 2
Welfare	0.14	0.05
Housing prices	-13.03	-2.04
Rents	0.37	0.15
Transaction volume	-0.04	0.00
Housing prices (σ/μ)	-4.25	-1.42
Rents (σ/μ)	0.63	-0.26
Transaction volume (σ/μ)	1.45	0.64
Investors in market	-1.71	-0.55
Matched owners	0.19	0.08
Renter share of buyers	-0.42	-0.17
Buyers	-0.39	-0.15
Match quality b,s	0.00	-0.00
Match quality b,d	0.12	-0.00

Notes: The effect of each reform is calculated as the median of 200 simulations, each over 1000 periods. Percentage change is compared to baseline model.

[45] In the last 1000 periods, both expected and realized inflow shocks have mean and variance that are the averages of both pre and data period: Mean $\gamma = 0.0167$, var. $\gamma = 0.0000032$. Outflow matches mean inflow.

The surprisingly strong effect of Reform 1 on prices and volatility is due to the policy having 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. The marginal buyer who is pushed out by investment buyers has a higher match quality in a seller's market, as sellers are more willing to postpone a transaction to next period. The fact that the reform hits hardest in hot markets also explains the strong effect on housing prices and price volatility.

Reform 2 only affects those who actually buy, and it is similar over all market conditions, lessening its effect on prices. The reform is also imposing a cost on landlords in each period, which explains why its effect on rents are relatively larger compared to reform 1 than its effect on prices. The welfare increases caused by both policies come from the 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.

The reason that Reform 1 performs better in welfare terms is that it allows a larger number of buyers to become owners. 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 0.83), a higher level of ownership is welfare-improving. However, as long as $\bar{r} > 1$, 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.

When considering these results, it is important to remember the assumptions of my model. Renters are assumed to be 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, policies which increase rents may push poor people into homelessness, even if their need for housing is very high, because ability to pay may not match willingness to pay. 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 adds to a growing literature which takes housing market search models to empirical data.

The model is motivated by empirical evidence on rents and investment buyers in Oslo, the largest city of Norway. First, I show that rental price growth is correlated with housing price growth, though somewhat lower, and less volatile. Second, investment buyers consistently represent a significant share of all housing buyers in Oslo, on average almost 20 percent. Finally, investors buy 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 volatility 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, in times when the large number of buyers already push prices up. Second, owners' expected return of becoming landlords increase in periods of high rents, adding to the number of buyers and amplifying the effect of high rents on housing prices and transaction volumes.

I calibrate the model partially against direct comparisons in the data and partially 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. It is able to explain a larger amount of housing price volatility than a standard search and matching model, though not all. It 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 periods of high population inflow are consistent with data.

Finally, two different policy reforms are simulated. There are small, but positive welfare gains in 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 the reform taxing the search for investment houses, as it alleviates the crowding in of investors in hot markets. The welfare analyses may underestimate welfare gains; due to risk-neutral agents, 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 those buyers 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 other house, or resell the new house. To do this, I need to 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 allows me to use 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 thus match housing transactions on housing identifier, as well as 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. I 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 within buyer-id multiple 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 id-number). If one 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 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. Also discarded are matches where the floors recorded in NMA and Finn do not match. The remaining matches are exposed to the processes described above to make sure that only one 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

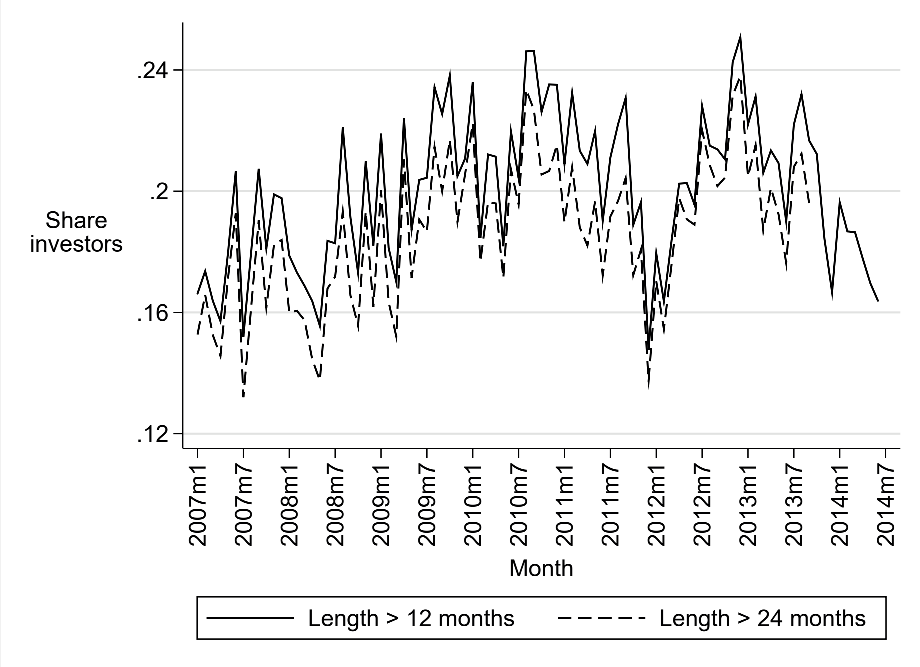
The personal identifier which identifies ownership can also be used to add information on the household of owners, through the dataset Income and wealth statistics for households (Statistics Norway, 2018a), where I have data available from 2006 - 2012. The ownership of houses is aggregated from personal 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 more 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 2.

Alternative definition

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 C.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 C.1: Investors - ownership length

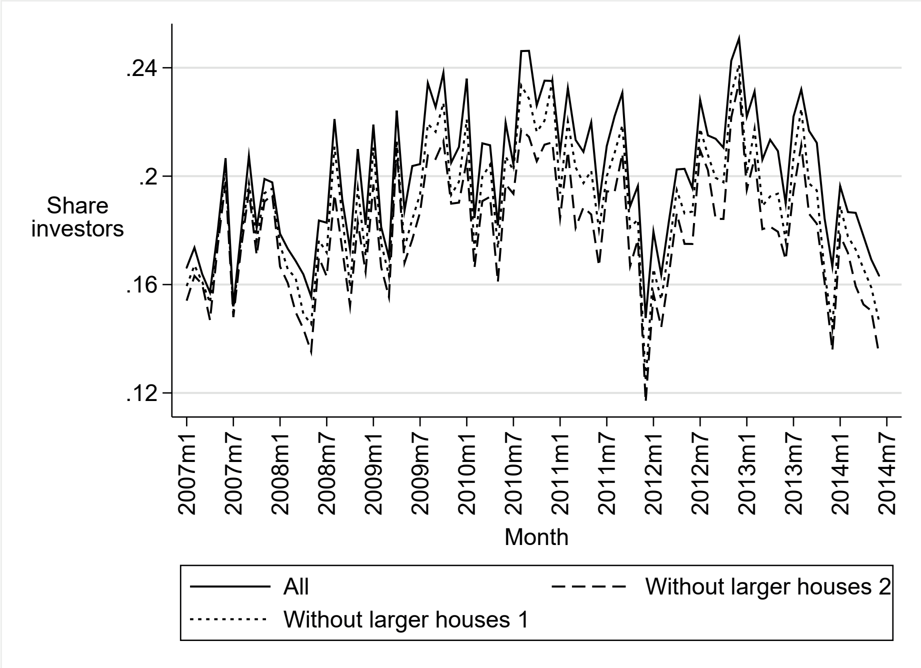


Notes: The monthly share of houses bought by buy-to-let investors are calculated as the share of houses bought by a person who already owns another house, and who owns at least two houses for a period of over respectively 12 and 24 months. Only purchases by private buyers.

Some of the buyers defined as buy-to-let buyers 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 is owned by the buyer 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.[46] These two measures are shown, along with the baseline, in Figure C.2. Both alternative measures are strongly correlated to the baseline, with correlation at respectively 0.98 and 0.96.

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

Figure C.2: Investors - size of new housing

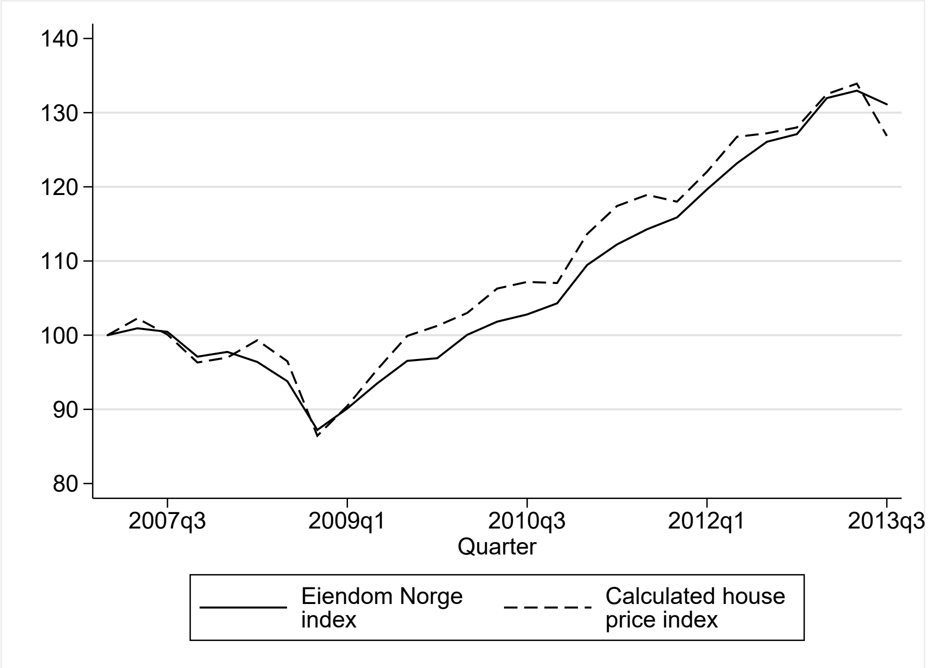


Notes: The monthly share of houses bought by buy-to-let investors are calculated as the share of houses bought by a person who already owns another house, and who owns at least two houses for a period of over 12 months. Only purchases by private buyers.

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 C.3: Housing index and aggregated data



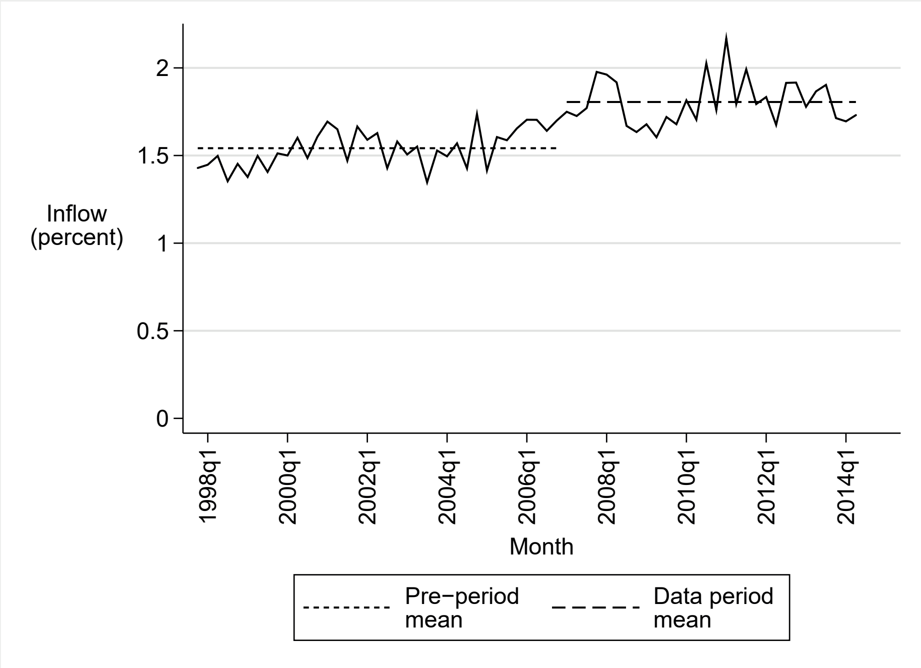
Notes: Q1 2007=100. The house price index is made by Eiendom Norge, the interest group for Norwegian real estate agents. It is a hedonic index based on transacted houses that have been advertised at Finn.no (see also Figure 1). The calculated housing price index is based on the data in my sample. It 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 C.3 compares the hedonics 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 appear to be minor.

Population inflow

The years for which I have housing transaction data coincides with a period with 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). Population in Oslo grew by 18 percent in the period 2007 - 2014, or above 2 percent per year on average (Statistics Norway, 2018b).

Figure C.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, which is what I calibrate my model against, was also much higher than in previous years, as shown in Figure C.4.

The mismatch rate

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

The number of housing units (including apartments) for 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, rowhouses, apartments and other housing.[47] 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 houses types are included in this dataset, but it excludes houses that are not listed through Finn.no.[48] Thus, I use the second source, the NMA register of real property transfers to find

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

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

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, organized as a limited company (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.[49] By dividing the imputed total number of transactions on the housing stock, I find the yearly transaction share of houses, shown in Table C.1. The calibration target is the quarterly rate that gives mean yearly transaction rate of 0.0986.

Table C.1: 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.

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 more frequent than that of owners, and which does not affect the number of housing transactions.

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

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:

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

Share of transactions with positive surplus

In the laws of motion, $T^{b,s}$ and $T^{b,d}$ are the shares of matches involving buyers and respectively sellers and double-sellers with positive transaction surplus. Given the properties of the truncated normal distribution, the shares 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.

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 r in rent which equals 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 for a better comparison with housing prices in the buy-to-let model. Without it, buyers would be worse off, leading 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.