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We use a unique data set of individual transaction histories from Norway to show that temporary shocks to the buyer-to-seller ratio (or market tightness) caused by the transaction sequence decisions of moving homeowners -- whether to buy first and then sell or vice versa -- impact house prices. Using a shift-share IV design motivated by a simple theoretical model, we estimate that a 10 percentage point increase in the aggregate buy-first share causes house prices to increase by around 5 percent, time-to-sell to decrease by around 17 percent, and market tightness to increase by around 15 percent more in a local housing market that has a one standard deviation higher share of locally moving owners. Our empirical strategy allows us to estimate an elasticity of price to market tightness of around 0.4 and an elasticity of matching with respect to buyers of around 0.86.

JEL Classification: N/A

Keywords: housing markets, trading frictions, market tightness, transaction order, shift-share design, transaction-level data, transaction histories, search theory

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Transaction Sequencing and House Price Pressures*

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Abstract

We use a unique data set of individual transaction histories from Norway to show that temporary shocks to the buyer-to-seller ratio (or market tightness) caused by the transaction sequence decisions of moving homeowners – whether to buy first and then sell or vice versa – impact house prices. Using a shift-share IV design motivated by a simple theoretical model, we estimate that a 10 percentage point increase in the aggregate buy-first share causes house prices to increase by around 5 percent, time-to-sell to decrease by around 17 percent, and market tightness to increase by around 15 percent more in a local housing market that has a one standard deviation higher share of locally moving owners. Our empirical strategy allows us to estimate an elasticity of price to market tightness of around 0.4 and an elasticity of matching with respect to buyers of around 0.86.

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1 Introduction

Housing markets are the prime example of a frictional asset market, characterized by a slow and asynchronous arrival of trading counter-parties and substantial trading delays. But how important are these trading frictions for house prices and housing market dynamics more generally? According to theory, such trading frictions imply that temporary positive shocks to the ratio of buyers to sellers exert upward pressure on prices and lead to reduced selling times, and vice versa when the ratio is temporarily low. Nevertheless, there has been little empirical evidence to corroborate these effects of the buyer-to-seller ratio, or the market tightness as this ratio is sometimes called.

Recent theoretical work (Moen et al., 2019) has shown that the transaction sequence of moving homeowners – whether to buy a new dwelling first and then sell the old ("buy first") or vice versa ("sell first") – mechanically impacts the buyer-to-seller ratio in a housing market. This happens both in the short run, because of a crowding effect on the buyer side of the market but also in the long run, because of a relative decline in the for-sale inventory. Hence a shock to the share of moving owners that buy first, or the buy-first share for short, gives rise to a shock to market tightness, and through this *tightness channel* influences prices and selling times. Importantly, as we show in this paper, when moving owners constitute a larger share of transacting agents in a local housing market, changes in the buy-first share have larger effects on tightness, and hence, on local prices and selling times.

We use these insights to construct a novel empirical strategy to estimate how changes in the buy-first share affect house prices and time-on-market for sellers through the tightness channel. We implement this strategy on a unique data set of individual homeowner transaction histories. Consistent with theory, we find that the aggregate buy-first share has strong heterogeneous effects on local housing markets. These heterogeneous effects enable us to estimate the effects of the local buy-first share on local prices and time-on-market, which are significant. The heterogeneous effects also allow us to construct an instrument for market tightness and estimate how it affects housing prices. In particular, we obtain an elasticity of local house prices with respect to market tightness of around 0.4. Therefore, our empirical analysis shows that temporary shocks to the buy-first share in a small geographical area influence house prices in that area via the local tightness. This finding points to limits to arbitrage across space and time.

In the first part of the paper we briefly analyze the relationship between the buy-first share and market tightness using a simple model, and discuss the drivers of the buy-first share. We then document substantial heterogeneity among households in their propensity to buy first. Theoretically, households who face a high (subjective) cost of living in temporary quarters, and households in a strong financial position, are more likely to buy first. This is confirmed by data, as older households (who tend to be more wealthy) and couples with children (for whom presumably living in temporary quarters is more costly) are more likely to buy first compared to younger or single households (or couples without children).

At the aggregate level, we show that the buy-first share varies strongly over time and co-moves with changes in house prices and consumer sentiment. However, this time variation is not due to compositional effects arising from changes in household structure, age or location.

Next, we move on to our main empirical analysis, a shift-share IV design based on the aggregate buy-first share and the shares of locally moving owners. We define locally moving owners as owners who buy and sell in the same housing market. As shown in the theory section, a higher fraction of locally moving owners in a housing market implies that the *same* change in moving owners' propensity to buy first exerts a *larger* effect on market tightness compared to a housing market with a lower fraction of locally moving owners. Therefore, we compute the (time-averaged) ratio of locally moving owners to other transacting agents in a local housing market and interact it with the quarterly changes in the *aggregate* buy-first share, which proxy for economy-wide shocks to the buy-first propensity (and which we argue are plausibly exogenous from the perspective of a local housing market).

We then use quarterly neighborhood-level data on prices and time-to-sell for the four largest Norwegian cities to estimate the dynamic response of prices, time-to-sell, time-to-buy, and a measure of market tightness, computed as the ratio of time-to-buy and time-to-sell, to changes in our shift-share regressor using local projections (Jordà, 2005). Our baseline specification controls flexibly for neighborhood-specific seasonality and city-specific time trends through fixed effects, and also allows for arbitrary local market sensitivities to the aggregate house price cycle, i.e. for an arbitrary correlation between a local market's share of locally moving owners and its house price "beta". Our identifying assumption is that, conditional on these controls, in periods when the aggregate buy-first share increases, city-neighborhoods that tend to have relatively more locally moving owners do not experience faster house price growth for other, un-modeled, reasons.

Qualitatively, our empirical results strongly confirm the importance of moving owners' transaction order for housing markets. In terms of magnitudes, a 10 percentage point increase in the aggregate buy-first share increases house prices by around 5 percent and lowers time-to-sell by 17 percent more in a neighborhood that has a one standard deviation larger share of locally moving owners. Similarly there is a differential effect in our market tightness measure of around 15 percent but no differential effect on time-to-buy. It takes up to one year for these effects to build up, reflecting momentum in the housing market (Guren, 2018). These effects are highly robust to a battery of robustness tests, which include removing or adding other shift-share controls, controlling for heterogeneous price dynamics for apartments versus houses, not weighting our regressions, excluding the moving owners in a given city when computing the shift-share for that city, using local neighborhoods based on postal codes, using a different sample period, etc.

Finally, we use our shift-share instrument to estimate the effect of tightness on prices and time-to-sell using IV estimation. We estimate an elasticity of prices to tightness of around 0.4 and an elasticity of time-to-sell to tightness of -0.86. The latter estimate implies that the elasticity of matching with respect to buyers, a key parameter in models of housing search, is 0.86. Intriguingly, this coincides with the only other estimate of this parameter in the literature reported in Genesove and Han (2012).

Related literature. Our paper bridges several strands of the economics and finance literature. First, we contribute to the growing literature on search models of housing market dynamics (Wheaton (1990), Williams (1995), Krainer (2001), Novy-Marx (2009), Caplin and Leahy (2011), Diaz and Jerez (2013), Head et al. (2014), Ngai and Tenreyro (2014), Guren (2018), Guren and McQuade (2019), Ngai and Sheedy (2019), Moen et al. (2019), Piazzesi et al. (forthcoming), among others). Many of these papers study price and liquidity fluctuations in housing markets due to fluctuations in market tightness.[1] Wheaton (1990) models a housing market consisting only of moving owners that always choose to buy before selling. All sellers have two homes, and their reservation prices depend on expectations about time-to-sell. A higher buyer-to-seller ratio thus leads to reduced sales time, higher seller reservation prices, and higher market prices. Based on the Wheaton (1990) model, Diaz and Jerez (2013) develop and calibrate a search model in which market tightness fluctuates randomly depending on the stochastic arrival of sellers and buyers. The model thus generates a cyclical time series pattern of house prices and a negative co-movement of prices with time-to-sell.[2] Guren and McQuade (2019) study the U.S. foreclosure crisis following the 2008 financial crisis. In their model foreclosed homes are immediately put on the market, which depresses market tightness, and by dramatically increasing time-to-sell also lowers house prices for non-foreclosed properties. Quantitatively, they simulate a decrease in tightness of around 60% which is associated with an up to 30% drop in house prices, giving an elasticity that is similar in magnitude to our estimate.

[1] Apart from fluctuations in market tightness, market liquidity can vary because of scale or thick-market effects as in Ngai and Tenreyro (2014). Since market tightness and market size may be positively correlated, it follows that some of our estimated price effects of changes in tightness may be due to thick-market effects. Separately identifying thick-market from market tightness effects is a promising venue for future research.

[2] In Arefeva (2020) a higher buyer-seller ratio is associated with more buyers bidding for one house, which tends to amplify the price effect from higher seller reservation prices.

Moen et al. (2019) (henceforth, MNS) argue that the transaction order of moving owners is a key determinant of housing market tightness, and changes to that transaction order can have a powerful influence on tightness. In their model mismatched owners always participate in trading. In contrast, Ngai and Sheedy (2019) model the moving decision as investment in match quality, which is endogenous to market conditions. This endogenous participation decisions is important for explaining key empirical facts during the housing boom of the late 90s and early 2000s. Relative to these papers, we are the first to provide an estimate of the elasticity of house price to market tightness, a key parameter for any search model of the housing market. In addition, we provide direct evidence on the link between moving owners' transaction order and housing market dynamics. Our paper is also related to work by Anenberg and Bayer (2020) and Anenberg and Ringo (2020). Anenberg and Ringo (2020) also examine empirically the importance of transaction sequence decisions for the housing market. We differ from them in our empirical approach and how we map our empirical findings to housing market counterfactuals.

Our approach is to consider local housing markets as "segments" within a larger housing market and focus on the behavior of owners searching locally within these segments. These assumptions bring our work close to the work of Piazzesi et al. (2020) on segmented housing search. The authors analyze the search patterns of many buyers in the San Francisco Bay Area and document the presence of both *narrow* searchers (those searching within just a few neighborhoods) and *broad* searchers (those searching within a whole city) at the level of market segment characterized by geography and property characteristics. Broad searchers tend to equalize differences in the buyer-to-seller ratio across market segments, by entering more (less) often in segments with higher (lower) inventory. Our evidence of a differential effect on market tightness across neighborhoods due to changes in the buy-first share, implies that in Norwegian housing markets broad searchers are not able to fully equalize these differences in the short run.

The second literature we contribute to is the literature on Bartik or shift-share instruments (Bartik, 1991) and their application to the study of housing markets. There has been a recent resurgence of using shift-share instruments to analyze the link between the housing and labor markets. Liebersohn (2017) shows that local industry composition (across US Core Based Statistical Areas) affects local house prices via a housing demand channel. Howard (2017) uses a Bartik instrument for inter-regional migration inspired by Altonji and Card (1991) to argue that migration raises local house prices and housing demand and lowers unemployment. Guren et al. (2018) use a shift-share instrument based on the sensitivity of local house prices to the regional housing cycle to estimate the housing wealth effect over a long time period. Loutskina and Strahan (2015) and Greenwald and Guren (2020) instrument for the effects of credit supply on house prices using a shift-share instrument based on an interaction of the local share of subsidized housing loans that are close to the conforming loan limit (CLL) with nationwide changes in CLLs in the US. We relate to these papers by also using a shift-share analysis to understand changes in house prices. However, our analysis is at a much more disaggregated level (neighborhoods within cities rather than whole cities) and at a higher frequency. Moreover, we also use local exposure to aggregate house prices as a shift-share *control* that absorbs shocks to housing demand and thus strengthens our identification.

Finally, our empirical findings on price effects of changes in market tightness bring our paper close to a large literature in finance on the limits to arbitrage. Such limits can arise due to constraints on equity capital (Shleifer and Vishny, 1997), amplified by leverage constraints (Gromb and Vayanos (2002), Brunnermeier and Pedersen (2008), Gromb and Vayanos (2010)) and frictions in reallocating capital across asset markets (Duffie and Strulovici, 2012).[3] Empirically, there is evidence for a price impact of asset demand‘ shocks (the so called *price pressures* effect) in stock markets (Shleifer (1986), Harris and Gurel (1986), Coval and Stafford (2007), Deuskar and Johnson (2011), Gabaix and Koijen (2020)), bond markets (Greenwood and Vayanos (2014)), mortgage-backed securities markets (Gabaix et al., 2007), options markets (Garleanu et al., 2008), and foreign exchange markets (Abbassi and Bräuning, 2020). We contribute to this growing literature by showing that demand effects matter in housing markets, arguably the most frictional and hardest to arbitrage of all asset markets.

2 The buy-first share and the buyer-to-seller ratio

A key element in our empirical analysis is the relationship between the buy-first share and the tightness in the market. In this section we analyze this relationship with the help of a simple model.

Our starting point is that there are frictions in the housing market which cause trade to be a time-consuming process. How much time it takes depends on the ratio of buyers to sellers in the market (the market tightness). Normally, one would expect that a high tightness facilitates faster selling but leads to slower buying.

We consider a local housing market. Locally moving owners, who want to move from one house to another house in the same local housing market, have to make two transactions: buying a new home and selling the old home. Hence they are both buyers and sellers in the local market, and have to make a sequence decision of whether to buy first and then sell or

[3] In the context of housing, short-sale constraints may also be particularly important (Miller, 1977).

vice versa.[4]

The model is set in continuous time. There is a continuum of agents on both sides of the market. Let $B_1(t)$ denote the measure of local moving buy-first owners, who have a house and are searching to buy a new one before selling it. Let $S_1(t)$ denote the measure of local moving sell-first owners, who have a house and are searching to sell it before buying a new one. The total measure of locally moving owners in this first "stage" of the transaction process is denoted by $Z(t)$. Similarly, for the second stage, let $S_2(t)$ denote locally moving owners who bought first earlier and are now selling off their old home, and $B_0(t)$ the measure of locally moving owners who sold first and are now looking for a new home in the same local housing market. In addition, let $S_m(t)$ denote the measure of houses for sale owned by people who are leaving the area (and who are not buying in the local market), and $B_m(t)$ denote the measure of buyers who have moved to the area (and who are not selling in the local market). Finally, let $B^{tot}(t)$ and $S^{tot}(t)$ denote the total measure of buyers and sellers, respectively.

The tightness θ in the market can then be written as:

$$\theta(t) = \frac{B^{tot}(t)}{S^{tot}(t)} = \frac{B_0(t) + B_1(t) + B_m(t)}{S_1(t) + S_2(t) + S_m(t)} \tag{1}$$

It follows immediately that *cet.par*, increasing $B_1(t)$ at the expense of $S_1(t)$ increases $\theta(t)$.[5] Let τ denote the fraction of the moving owners in the first stage that buy first. Suppose that τ shifts up, for instance because some sell-first moving owners change their mind and switch to buying first. Thus, keeping $B_1(t) + S_1(t)$ constant, the immediate effect on $\theta(t)$ is then

$$\frac{d\log\theta}{d\tau} = \frac{Z(t)}{B^{tot}(t)} + \frac{Z(t)}{S^{tot}(t)} > 0 \tag{2}$$

Suppose for instance that $B_0 + B_m = S_2 + S_m = aZ_1$, and that τ goes from zero to one. Then tightness increases by a factor of $\frac{(a+1)^2}{a^2}$. If $a = 1$, this is a factor of 4.

These are the instantaneous effects of a change in the stock of locally moving owners who buy first. As time goes by, an increase in the buy-first share will influence all the stocks in non-trivial ways, before the market reaches a new steady state equilibrium. In order to

[4] An alternative hypothesis is that the moving owners are on both sides of the market simultaneously, and buy or sell first depending on which opportunity comes first. However, as pointed out in MNS, this is not consistent with data. If most agents did search this way, a high buy-first share should be associated with a low buyer-seller ratio, as that is when a buy opportunity is likely to come before a sell opportunity. However, empirically a high buy-first share is correlated with a high buyer-to-seller ratio (short time on market for houses).

[5] $S_2(t)$ and $B_0(t)$ remain unaffected at that point in time, since it takes time for the changes in the transaction sequence in the first stage to influence the respective stocks of buyers and sellers in the second stage of the move.

study these long run effects, we specify the following additional details about the housing market.

We assume that the rate at which buyers meet and trade with sellers can be written as $q(\theta)$, and the rate at which sellers meet and trade with buyers – as $\mu(\theta)$. In a small time interval, dt, a measure $B^{tot}q(\theta)dt$ of buyers and a measure $S^{tot}\mu(\theta)dt$ of sellers trade. Since every trading buyer has a trading seller as counter-party, it follows that $B^{tot}q(\theta)dt = S^{tot}\mu(\theta)dt$, or that

$$\theta = \frac{\mu(\theta)}{q(\theta)}. \tag{3}$$

There is an inflow γ of locally moving owners who either buy first or sell first. Suppose that a constant fraction x of them decide to buy first. Below we will study how the steady-state tightness depends on x.[6] In addition there is a flow of people moving out of the local area who list their house for sale. The intensity of this flow is denoted by g and assumed constant. There is an equal flow of people who enter the local area from outside and start looking for a house. We assume that g is independent of local housing market conditions.[7]

The total measure of people that ultimately want a house in the local market – which we refer to as local dwellers or just dwellers, is $D^d = B_m + B_0 + B_1 + S_1 + S_2$. The total measure of available houses is $D^s = B_1 + S_1 + 2S_2 + S_m$. Since the entry and exit flows into and out of the area are equal, and local movers and houses exit/enter the market in pairs, it must be true that $\dot{D}^s = \dot{D}^d$, where the dot represents a time derivative. It follows that $D^s - D^d \equiv k$, where k is a constant. Hence

$$S_2 + S_m - (B_m + B_0) \equiv k \tag{4}$$

We assume that $k = 0$, in which case there are equally many houses and local dwellers. In the appendix we show that the steady state tightness is given by

$$\theta = \frac{1 + x\kappa}{1 + (1 - x)\kappa} \tag{5}$$

where $\kappa = \gamma/g$ is the ratio of the inflow of internal movers to the inflow/outflow from the local area.

Note that with $x = 0$ ("sell-first" steady state) (5) tells us that the tightness is given by $\underline{\theta} = 1/(1 + \kappa)$. With $x = 1$ ("buy-first" steady state), it is $\overline{\theta} = 1 + \kappa$. The ratio of the two is $(1 + \kappa)^2$. For example, if $\kappa = 1$ (i.e. $\gamma = g$, so there are equally many local and non-local

[6] Above we defined τ as the fraction of the *stock* of locally moving owners in the first stage of the transaction process that were buying first. This is generally different from the fraction of *newly transacting* moving owners that buy first, since the outflows from B_1 and S_1 are different.

[7] This assumption is discussed in section 6.

movers), the ratio is 4. Hence the steady state tightness is 4 times higher when all locally moving owners buy first compared with when they all sell first.[8] Note that the effect of a higher buy-first share on the buyer-to-seller ratio is purely mechanical, that is, it is the result of mechanical changes to the stocks and flows in the market.

In the empirical exercise we will utilize the fact that the responsiveness of θ to the buy-first share depends on κ. To illustrate this, note that

$$\frac{d\log\theta}{dx} = \kappa\left[\frac{1}{1+x\kappa} + \frac{1}{1+(1-x)\kappa}\right] \tag{6}$$

The expression is 0 for $\kappa = 0$, strictly increasing in κ, and goes to infinity as κ goes to infinity (g goes to zero).

So far we have only considered steady-state comparative statics. In the appendix we briefly discuss the dynamic properties of the model. We show that if moving owners in the first stage of the transaction process in the "buy-first" steady state suddenly decide to sell first, then market tightness jumps directly to the "sell-first" steady state value. We also show that if the share of newly entering moving owners into the market that decide to buy first jumps from x to $x + \Delta x$, $\Delta x > 0$, the market tightness will immediately start to grow.

Finally, we relate the buyer-to-seller ratio to house prices. Economic theory tells us that market tightness matters for house prices. In Norway, dwellings are sold in auctions. A higher buyer-to seller ratio implies that there will be more buyers at each auction, which results in more intense bidding and higher house prices. If buyers and sellers bargain over the price (which would be the case in Norway if there is only one potential buyer present), a higher buyer-to seller ratio will improve the outside option of the seller and worsen that of the buyer, and according to standard bargaining theory this leads to higher prices.[9] Hence we write the house price p as a function of market tightness θ, as well as a vector of other variables X, $p = f(\theta; X)$, where $f_\theta > 0$. Thus a shock to the buy-first share x increases θ, and hence, p. We call this the effect of the buy-first share on house prices through the *tightness channel*. By equation (6) this tightness effect is stronger the higher is κ.

3 Data

We use housing transaction data for the four largest cities in Norway: Oslo, Bergen, Stavanger, and Trondheim plus the contiguous urban municipalities that are part of the metropolitan areas of these cities. In terms of population, our data set covers housing markets that

[8] If the flow of non-local movers, g, goes to zero, $\overline{\theta}$ goes to infinity and $\underline{\theta}$ goes to zero.

[9] MNS shows that a higher buy-first share (in steady state) is associated with higher prices, both if bargained over or if posted as in competitive search equilibrium.

represent around 40% of the total population of Norway in 2015. The data come from the official registry of all housing transactions in Norway (the Land Register). The data consist of information on the housing unit transacted, which includes a unique housing unit identifier, basic hedonics, the transaction price and closing date, and unique individual identifiers for the buyers and sellers in the transaction.[10] We use the unique individual identifiers and unique property identifiers to construct individual transaction histories, which we then utilize to identify *moving owners*. The definition of a moving owner is straightforward: she buys a property and will be its owner-occupier, and sells a property which she previously occupied. Next, a moving owner is said to *buy first* if her first transaction in the transaction sequence is a buy and her second transaction is a sell and, conversely, for a *sell-first* moving owner. The *buy-first share* is then defined as the share of moving owners in a local housing market or population group who buy first in a given time period. Finally, a *locally moving owner* is a moving owner who only buys and sells a property within a specific geographic location. Conversely, a *non-locally moving owner* is a moving owner who buys and sells properties in different geographic locations.

In addition, we construct hedonic price indices, sales, time-to-sell and time-to-buy series. The construction of the hedonic price indices is standard and is described in the Appendix. Since we do not have information on when a property was put on the market for sale, we construct time-to-sell in the following way: We follow MNS and use the fact that for buy-first moving owners, the average time difference between the first (buy) and the second (sell) transaction equals the average time-to-sell. We proceed analogously for time-to-buy, equating it to the average time difference between the first (sell) and second (buy) transactions for sell-first moving owners.

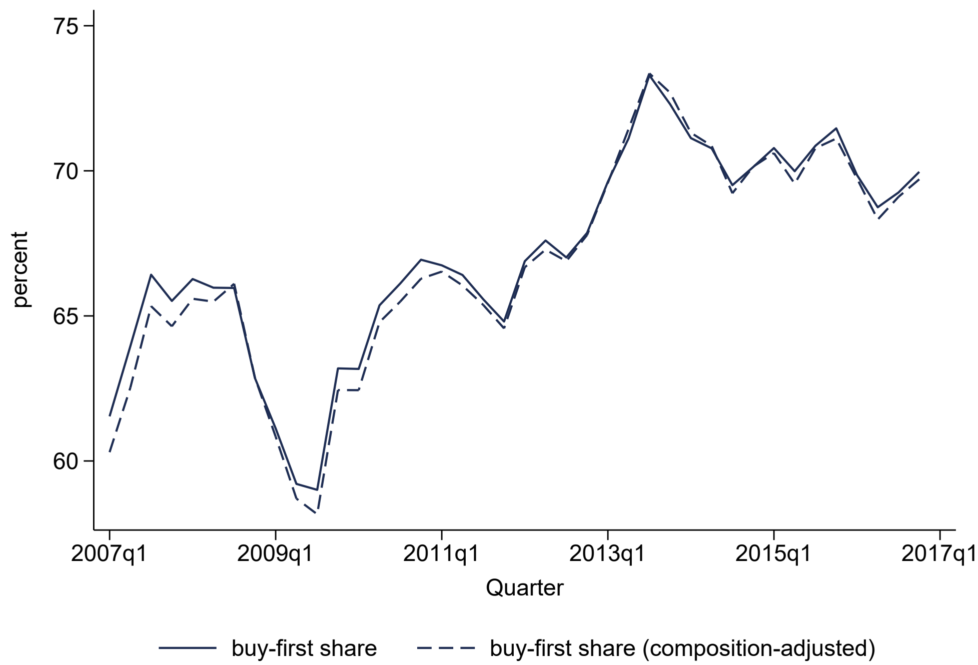
We do not observe market tightness directly, since we do not observe the stocks of buyers and inventory. Instead, we combine the time-to-sell and time-to-buy series together with Equation (3) to compute market tightness as the ratio of time-to-buy over time-to-sell.[11]

Our baseline local housing markets are the city parishes or neighborhoods ("bydeler") of the 4 cities plus their surrounding municipalities using the 2005 administrative partition of parishes and municipalities. In addition, we drop local housing markets with less than 1,000 total sales. This leaves us with a total of 49 local housing markets. Our time unit of analysis is a quarter, and our main empirical analysis covers the period 2007Q1-2016Q4.

[10] The Appendix includes further details about our data, sample selection, and variable construction.

[11] Formally, if $q(\theta)$ is the rate at which buyers meet and trade with sellers, then time-to-buy is $1/q(\theta)$. Similarly if $\mu(\theta)$ is the rate at which sellers meet and trade with buyers, then time-to-sell is $1/\mu(\theta)$. Therefore, by Eq. (3), $\theta = \mu(\theta)/q(\theta) = (1/q(\theta))\,/\,(1/\mu(\theta))$ =time-to-buy/time-to-sell.

Figure 1: Buy-first share in Norwegian housing markets, 2007Q1-2016Q4.



Notes: The figure plots the aggregate buy first share and the composition adjusted aggregate buy first share over the period 2007q1-2016q4. The buy first share is defined as the share of moving owners that buy first. The composition adjusted series is constructed by aggregating the estimated propensity to buy first after controlling for individual demographic characteristics and seasonality specific to the different local housing markets.

4 Drivers of the buy-first share

The share of moving owners that buy first varies substantially over time. Figure 1 illustrates this fact by showing the evolution of the aggregate buy-first share during 2007Q1-2016Q4.[12] In addition, we plot the evolution of a composition-adjusted buy-first share, which is constructed by aggregating the individual buy-first propensity after controlling for a number of individual demographic characteristics and local housing market-specific seasonality factors.

The buy-first share varies considerably over this period, from less than 60 % to almost 75 %, with a notable dip during the Financial crisis of 2008-2009, a large increase in 2014 and subsequent decrease in late 2015/early 2016. The composition-adjusted buy-first share follows a very similar pattern, suggesting that the dynamics of the buy-first share are not due to changes in the composition of moving owners (at least based on observables).

[12]"Aggregate" here and below refers to the aggregate for Oslo, Bergen, Stavanger, Trondheim, and their surrounding municipalities.

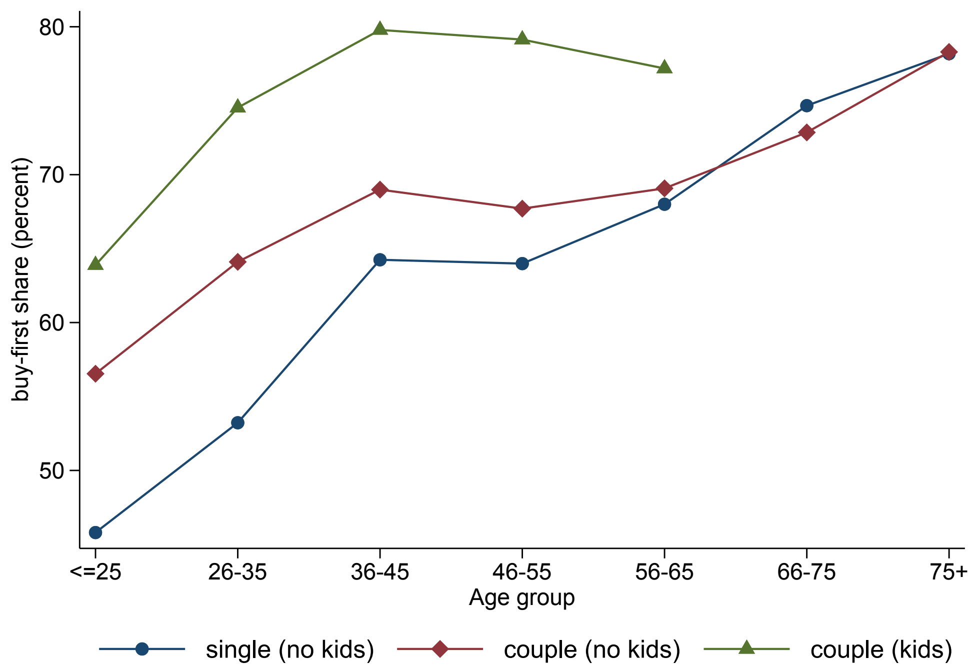
The large time variation in the buy-first share is consistent with MNS, who find even larger fluctuations in the buy-first share in the Copenhagen region, where it was below 25 % in 1994, increased to 80 % in 2006, and then fell to 40 % again in 2008. Similarly, for the Netherlands Rouwendal et al. (2019) show that the buy-first share varies over time from around 80% in the early 2000s to below 50% after the Financial crisis.

There are advantages and disadvantages with the buy-first and sell-first strategies. An advantage of buying first is that the process of moving from one home to the next is likely to be smoother and less costly. Households who buy first can presumably move directly from the old house to the new house without having to reside in temporary quarters, something sell-first moving owners may have to do. On the other hand, buying first is financially more demanding, as it typically requires that the household in question obtain a bridge loan to finance the new house. Agents who sell first, in contrast, can use the sales value of their old house to pay for (part of) the new house. Bridge loans can be costly and difficult to obtain. In addition there is a financial risk of owning two houses for a period of time, for instance, because house prices may fall.

Hence we expect that households for whom staying in temporary quarters is particularly inconvenient, like households with children, have a higher propensity to buy first than other households. Furthermore, we expect that household with good access to credit have a higher propensity to buy first than other households. We provide empirical evidence for these determinants. Figure 2 shows how the buy-first share varies with age and also by household type. There is a clear age pattern associated with the propensity to buy first – it is substantially lower for younger individuals and increases with age. Moreover, couples, and especially couples with children are more likely to buy first at any age. The lower propensity to buy first associated with younger and single-member households can be both due to credit market imperfections that limit the ability of such households (who are more likely to have low net worth) to buy first or that make it more risky to buy first should their old property be worth less than they anticipate. Indeed, as we show in the Appendix, household balance sheet composition, particularly in the year prior to the transaction, correlates with the probability to buy first. In addition, these patterns may reflect lower costs of going through a short-term rental period compared to older households or households with children. Overall, these facts suggest that households steer their transaction sequence in response to household-specific heterogeneity in the costs of holding two properties or going through a short-term rental period, in line with the theoretical considerations laid out above.

We further expect that the buy-first share depends positively on expected house price growth, as buy-first (sell first) agents then will expect a capital gain (loss). In addition the buy-first share may depend positively on consumer sentiment and expected income growth

Figure 2: Buy-first share by age and ownership status.



Notes: The figure plots the share (percent) of moving homeowners that are buying first for different age groups stratified by their household type. The share is computed for couples with children, couples without children and singles without children over the sample period 1994-2016.

because it may make the moving owners more willing to accept the risks associated with buying first. Table 2 in Section 5.2 provides empirical support for these drivers.[13]

Finally, there can exist strategic complementarities associated with the moving owners' choice of transaction sequence. This was particularly emphasized in MNS. Arguably, being in the second stage of the transaction sequence – owning two houses and trying to sell the old house if buying first or living in temporary quarters and trying to buy a house if selling first – is particularly costly. If there are more buyers relative to sellers in the market, the process of selling becomes quicker and simpler, while the process of buying becomes more time-consuming and demanding. Hence a high buyer-to-seller ratio favors buying first and vice versa. This is what induces strategic complementarities and multiplier effects: If more people decide to buy first, this will increase market tightness, and make it more attractive to buy first for other moving agents. Hence a small initial shock to the buy-first share can give rise to large changes in the equilibrium buy-first share.[14]

MNS demonstrate that the house price *level* as such has only a modest or no impact on the choice of transaction sequence. For a given interest rate, high housing prices in isolation will make it more costly to finance the necessary bridge loan if buying first. However, high house prices (for a given interest rate) typically mean a high rental price, which make it more costly to sell first.[15]

5 Shift-Share Analysis

In this section we implement a shift-share design to test if changes in the buy-first share affect local housing markets. Specifically, we test a salient prediction of the effects of changes in the buy-first propensity on tightness and prices as discussed in Section 2. The prediction is intuitive and concerns the interaction effect between the share of moving owners and changes in their propensity to buy first. Specifically, by equation (6), the larger the ratio of moving owners involved in local housing market transactions relative to other transacting agents, the larger the (equilibrium) effect of changes in their transaction sequence on the local housing market. This prediction gives us a natural shock exposure measure for a local housing market. This shock exposure measure has a structural counterpart in the parameter $\kappa = \gamma/g$ introduced in Section 2.

[13]The buy-first share can also depend on conditions in the rental market. For example, low rental prices and good access to short-term renting may reduce the buy-first share.

[14]MNS show that the multiplier effects can be so strong that they lead to multiple equilibria.

[15]MNS show conditions under which the two effects cancel each other out exactly.

5.1 Shock exposure measure

Our shock exposure measure for local housing market i is given by,

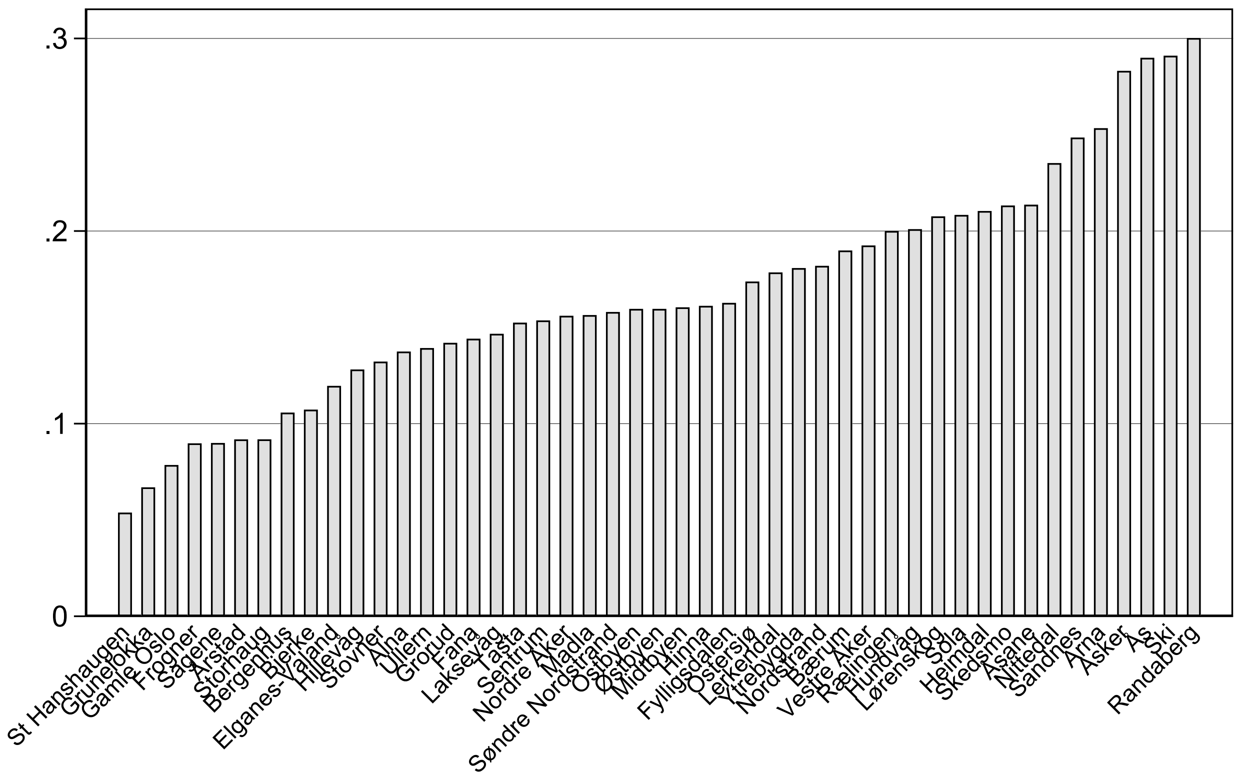
$$\hat{\kappa}_i = \frac{\overline{locally\,moving\,owners_i}}{\overline{sales_i} - \overline{locally\,moving\,owners_i}}, \tag{7}$$

where $\overline{x}$ denotes the time-averaged value of x. Figure 3 shows the values of $\hat{\kappa}_i$ for the different local housing markets in our analysis. There is substantial variation in the shock exposure even within cities, which we will utilize. A lower value of $\hat{\kappa}$ is associated with neighborhoods that have fairly homogeneous housing stock (primarily small apartments), which implies a low importance of *locally* moving owners. On the other extreme are local housing markets with greater heterogeneity in the housing stock in terms of apartments and houses. This relation is confirmed in Table 1 where we correlate the shock exposure measure with local characteristics. A local housing market with a higher value of $\hat{\kappa}$ has higher median household income, fewer households, a smaller share of single households (or small apartments), and a larger share of couples with children (or houses) and smaller share of first-time buyers. The correlation with household income appears to be driven by the household composition in a neighborhood – since single households mechanically have lower household income than couples. Indeed, income has a small and insignificant effect on $\hat{\kappa}$, after including all demographic variables.

We conclude that our local shock exposure measure is correlated with local household/housing composition. This correlation is arguably mechanical, since by construction a location with a higher value of $\hat{\kappa}$ has a greater share of moving owners and, hence, a lower share of first-time buyers. Similarly, a location with a more heterogeneous housing stock in terms of a larger share of houses will have a larger share of owners that move locally within the neighborhood when moves are induced by preference heterogeneity over different types of housing.

We account for this housing composition when constructing our local house price indices by including indicators for types of housing (and interactions of those with other hedonics) and controlling for size. In addition, as we explain further in Section 5.4 below, we control for the heterogeneous sensitivity of local house prices to the aggregate housing cycle, which should absorb additional variation in local house prices due to housing stock composition. In practice, there is a small negative correlation between our shock exposure measure and the local house price "beta" (the coefficient from regressing local house price growth on aggregate house price growth), as we show in Figure 4.

Figure 3: Shock exposure by local housing market.



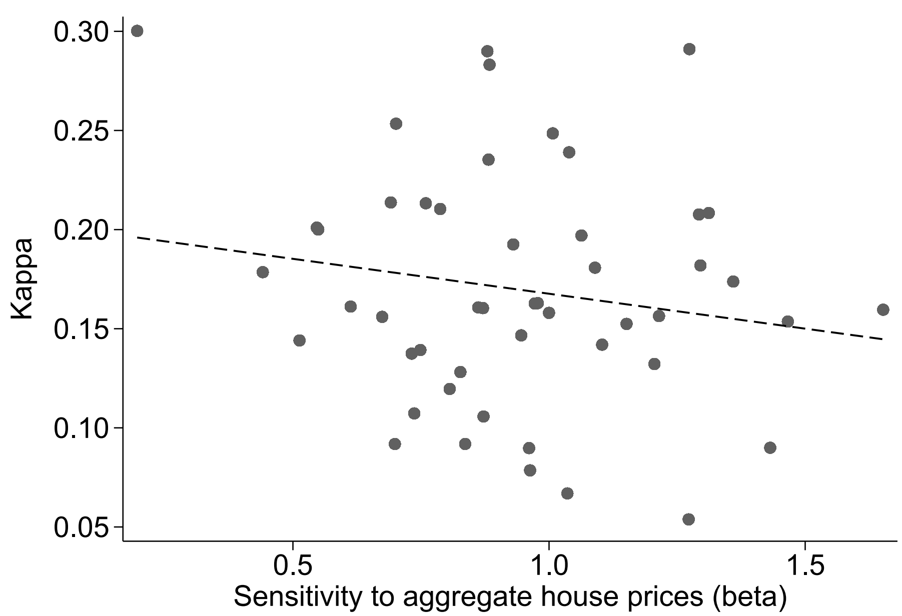
Notes: The figure plots the values of $\hat{\kappa}_i$ for the different local housing markets we use in the analysis. $\hat{\kappa}_i$ is defined as the share of transactions made by moving owners in each local market and is computed according to equation (7).

Table 1: Shock exposure and local demographic variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
household income	0.204***										-0.0695
	(0.0358)										(0.136)
number of households		-0.0221*									-0.0149
		(0.0126)									(0.0107)
single households			-0.366***								-0.0856
			(0.0527)								(0.391)
couples w/ children				0.606***							-0.0495
				(0.0939)							(0.506)
houses					0.188***						0.163**
					(0.0250)						(0.0751)
small apts.						-0.254***					-0.00237
						(0.0520)					(0.0969)
first-time buyers							-0.472***				-0.604***
							(0.159)				(0.197)
investors								-0.320			-0.614
								(0.434)			(0.512)
average price (log)									0.0478		-0.0757
									(0.0528)		(0.0734)
N	46	46	46	46	46	46	46	46	46	46	46
R^2	0.425	0.065	0.523	0.486	0.563	0.352	0.168	0.012	0.018	0.472	0.705

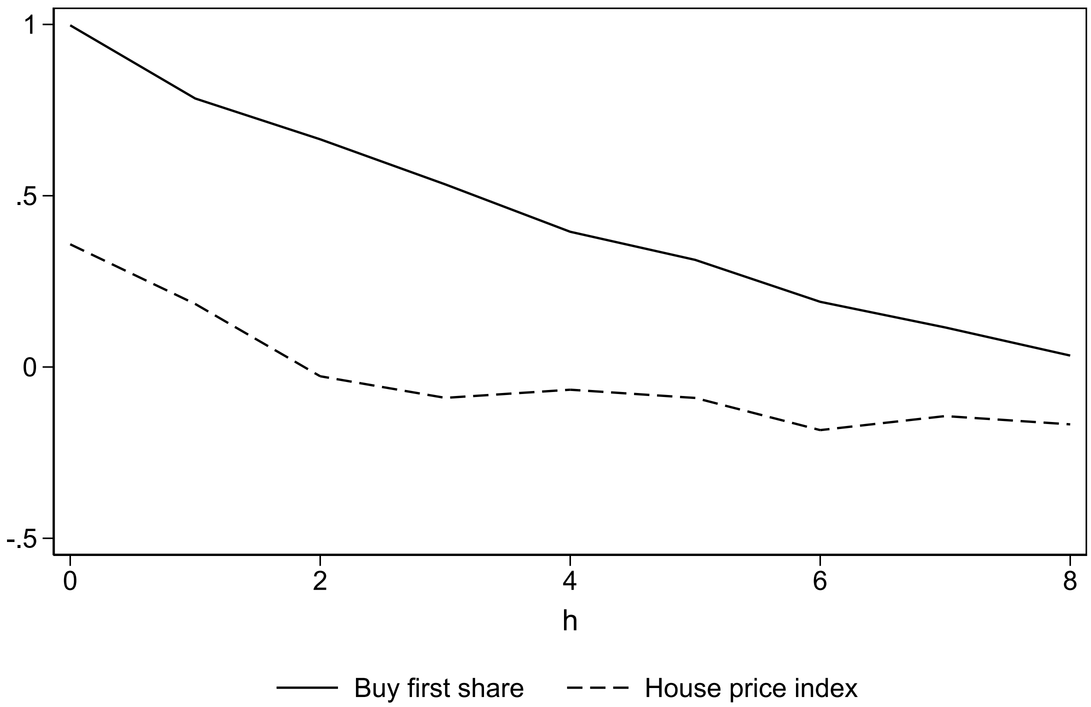
Standard errors in parentheses. $\hat{\kappa}_i$ is defined as the share of transactions made by moving owners in each neighborhood and is computed according to equation (7). Household income is log of median disposable household income, averaged over 2004-2014; Total households is log of number of households, averaged over 2004-2014; Single households is the share of single-member households, averaged over 2004-2014. Couples with children is the share of households with children, averaged over 2004-2014. Houses is the share of properties that are single-family houses, semi-detached houses, or row houses and small apts. is the share of properties that are apartments with up to 2 rooms. Properties in a location are determined based on all unique properties that have transacted in a location in the period 1993-2017. First-time buyers is the share of buyers over the period 2007-2016 who are observed to buy for the first time in the data and are 40 years old or younger. Investors is the share of buyers who hold more than one property at the time of a transaction and who are not classified as a moving owner in that transaction. Average (log) price is computed over the period 2007-2016. Note that there are only 46 observations as demographic variables are only available for Bærum as a whole. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 4: Correlation between local shock exposure and local house price beta.



Notes: The figure plots the correlation between the local housing markets sensitivity to aggregate house price changes and $\hat{\kappa}$, the share of transactions made by moving homeowners. The local sensitivity is estimated as the log change in local housing prices on the log change of aggregate house prices over our sample period 2007Q1 to 2016Q4.

Figure 5: Cumulative responses of buy first share and house prices to quarterly changes in the buy first share.



Notes: The figure plots the correlation between ΔBF_t, the quarterly change in the aggregate buy first share, and the cumulative changes in the aggregate house price index and buy-first share for different horizons h, computed as $\ln y_{t+h} - \ln y_{t-1}$, $h \in 0, 8$. The correlations are estimated over the sample period 2007Q1-2016Q4.

5.2 Aggregate shifter

We interact our local shock exposure $\hat{\kappa}_i$ with the quarterly change in the aggregate buy-first share, denote by ΔBF_t.

Figure 5 plots the cumulative response of the buy-first share and of aggregate house prices to quarterly changes in the buy-first share. Changes in the buy-first share tend to be mean-reverting and mostly die down 6 quarters after the initial shock. In addition, although there is a positive correlation with house price changes, the correlation is well below one. We will use these properties of the buy-first share to control for local housing markets having differential sensitivity to the aggregate housing cycle and also to facilitate the interpretation of our estimated impulse responses.

Beyond a positive correlation with aggregate house prices, Table 2 shows that the buy-first share is also positively correlated with consumer sentiment and with GDP and interest rates.

Table 2: Correlations between quarterly changes in the aggregate buy-first share and quarterly changes in aggregate variables.

Variable	Full sample	20 highest-weighted quarters
House price index	0.370	0.380
Consumer confidence index	0.435	0.521
GDP (log)	0.292	0.341
Interest rate	0.270	0.327
Price expectations	0.119	0.0629
Credit conditions index	-0.137	-0.0896

This table plots the contemporaneous correlation between quarterly changes in the buy first share and quarterly changes in the different variables over the sample period. The first column reports the correlation for the full sample and the second column reports the correlation for the top one-half of quarters by decomposition weight. See Appendix A.2.7 for the decomposition exercise and Figure A.5 for quarters with the highest weights. The house price index is the hedonic price index (see Appendix) from the housing transaction data. The Consumer confidence index (TNS Kantar) measures households expectations for their own economy and the national economy. GDP is real mainland GDP, the interest rate is the average interest rate on lending for all households, price expectations measures the share of households that expect higher house prices one year ahead from a survey from Prognosesenteret. Credit conditions reports changes in the access to loans for the household sector relative to previous quarter based on a survey among banks done by Norges Bank. We compute the correlations by shifting back the buy-first share series by one quarter to account for the average time difference between agreement and closing dates. See the Appendix for details.

The correlation with consumer sentiment is particularly high in quarters that contribute a high share of the variation in our regressor based on a decomposition we do in Appendix A.2.7.

5.3 Econometric methodology

Based on our theoretical analysis in section 2, we assume that the dynamic response of local housing market outcomes to shifts in the aggregate buy-first share is given by the following model

$$\Delta y_{i,t-1,t+h} = \alpha_i + \beta_h \hat{\kappa}_i \Delta BF_t + \Gamma'_h X_{i,t-1} + u_{i,t-1,t+h}, \tag{8}$$

where $\Delta y_{i,t-1,t+h}$ is the log change in variable y in local housing market i between quarter $t-1$ and quarter $t+h$, $\hat{\kappa}_i$ is the shock exposure of local housing market i, ΔBF_t is the change in the aggregate buy-first share, $X_{i,t-1}$ collects a number of additional covariates, and $u_{i,t-1,t+h}$ is a mean-zero error term. We estimate equation (8) for separate horizons by the method of local projection (Jordà, 2005).

Our main outcome variables of interest are the local house price index, time-to-sell, time-to-buy and market tightness. Our baseline specification includes controls for local seasonality, city-specific factors (as county-by-quarter fixed effects), and 8 lags of our main regressor (to control for its mean-reversion (cf. Figure 5)).[16] Finally, we control for the interaction between $\hat{\kappa}_i$ and aggregate house price changes at the estimation horizon, namely $\hat{\kappa}_i \times \Delta P_{t-1,t+h}$, where P_t denotes the aggregate house price index in quarter t. Below we explain why we include this particular control.

Finally, we weight our regressions by the average number of sales in the local housing market. Additionally, standard errors are two-way clustered by local housing market and quarter (Adão et al., 2019).[17]

5.4 Identification

We write the identifying assumption for $plim\hat{\beta}_h \rightarrow \beta_h$ as a time-series moment, as in Borusyak et al. (2018) and Chodorow-Reich et al. (2019):

$$E\left[\Delta BF_t \varepsilon_{t,h}\right] = 0, \tag{9}$$

where $\varepsilon_{t,h} = E\left[\hat{\kappa}_i u_{i,t-1,t+h}\right]$ is a weighted-average of the time t, horizon h error terms across local housing markets. Informally, condition (9) requires that when the aggregate buy-first share increases, house prices in high-κ locations do not grow faster for other reasons than the effect of the higher buy-first propensity.[18] Put differently, Eq. (9) holds if other aggregate variables that correlate with the time t change in the buy-first share do not impact differentially the high- vs. low-κ locations (at any horizon h).

Note that it is not a problem for identification if the change in the buy-first share correlates with other aggregate variables as long as they *do not* impact differentially high- vs. low-κ locations. As shown in Table 2, the buy first share correlates with a number of aggregate variables. It correlates most strongly with house prices and consumer sentiment. Therefore, a threat to identification is if aggregate shocks that increase the (current and future) demand

[16] Counties are large administrative divisions, which comprise a number of municipalities. There are 5 counties in our data set with each city corresponding to a separate county. In addition, Oslo's surrounding municipalities are part of a different county (Akershus).

[17] Table A.2 in the Appendix shows summary statistics for all of the variables in our sample.

[18] Note that this identifying assumption does not require exogeneity of $\hat{\kappa}$, which is the identification condition studied in Goldsmith-Pinkham et al. (2018).

for housing (and house prices) correlate positively with contemporaneous changes in the buy-first share *and* at the same time impact more strongly high-κ markets.[19] This in itself is not a problem unless the high-κ markets are more sensitive to the aggregate housing cycle (more cyclical). In other words, this channel would confound our results, if high-κ housing markets were also high "beta" housing markets. Figure 4 suggests that this is likely not the case. Nevertheless, to alleviate any concerns, we include in our baseline specification the interaction between $\hat{\kappa}$ and aggregate house price changes at the estimation horizon, $\hat{\kappa}_i \times \Delta P_{t-1,t+h}$.[20] Thus, we effectively consider only variation in the buy-first share that is "orthogonal" to aggregate house price changes at the estimation horizon.

5.5 Results

5.5.1 Baseline results

Figure 6 plots the estimated impulse responses for our baseline specification (8) (the estimated coefficients β_h) for prices and time-to-sell while Figure 7 plots the response of time-to-buy and market tightness. In addition, Table 3 presents the coefficient estimates at one particular horizon for the Jordà regressions. We have normalized κ_i by its standard deviation to facilitate interpretation of magnitudes. The figures also include the estimated pre-trends for 4 quarters prior to the shock period as a placebo. There are no pre-trends in the outcome variables, consistent with high and low κ markets being on parallel trends prior to the change in the buy-first share.

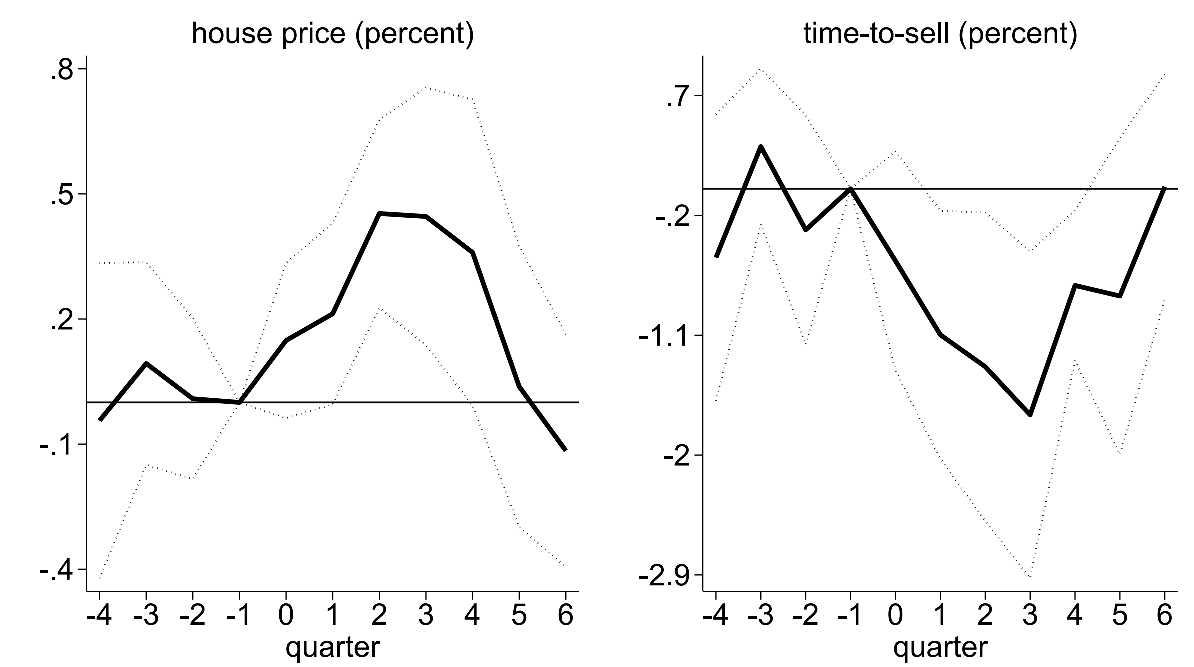
House prices begin to increase, while time-to-sell begins to fall immediately after the shock. However, it takes a couple of quarters for these effects to build up, reflecting momentum in the local housing markets (Guren, 2018). Using the estimated response at quarter 3 (4 quarters after the shock), we find that a one percentage point increase in the aggregate buy-first share is followed by house prices increasing by around 0.45 percent *more* in a local housing market with a one-standard deviation *higher* value of κ compared to the average. Similarly, time-to-sell falls by around 1.7 percent more in that local housing market. We interpret the hump-shaped response in both prices and time-to-sell as reflecting the mean-reverting nature of the aggregate buy-first shock (cf. Figure 5).

Turning to the response of time-to-buy and market tightness, there is no significant response of time-to-buy, while market tightness increases and is around 1.5 percent higher

[19] The possibility that the buy-first share reacts to changing expectations about future house prices, and thus acts as a forward indicator for housing demand shocks, was first pointed out and analyzed in MNS.

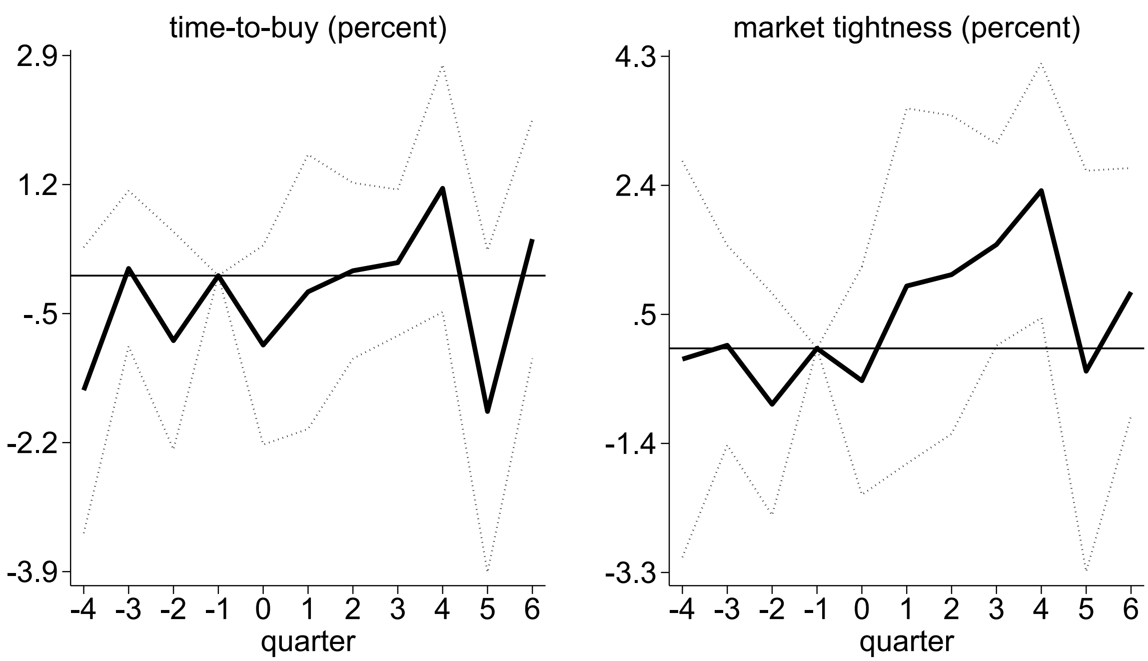
[20] Note that interacting with $\hat{\kappa}_i$, rather than with the estimated local sensitivity to aggregate house prices at horizon h, implies that we allow for *any* correlation between κ_i and the sensitivity of local housing markets to the aggregate housing cycle – including a perfect correlation. In the robustness section below we also explore alternative shift-share controls.

Figure 6: House price and time-to-sell response.



Notes: The figure plots the coefficients from estimating Equation (8) at each horizon shown on the x-axis. House prices are based on a hedonic price index (see the Appendix for details). Time-to-sell is the average time between the (first) buy and the (second) sell transactions for moving owners that buy first trimmed at the 5th and 95th percentiles by quarter. The local exposure κ_i is normalized by its standard deviation. The dashed line shows a 95% confidence interval based on two-way clustered standard errors with clustering on local housing market and quarter.

Figure 7: Time-to-buy and market tightness response.



Notes: The figure plots the coefficients from estimating Equation (8) at each horizon shown on the x-axis. Time-to-buy is the average time between the (first) sell and the (second) buy transactions for moving owners that sell first trimmed at the 5th and 95th percentiles by quarter. Log market tightness is equal to the difference between log time-to-buy and log time-to-sell. The shock occurs in quarter 0 and is equal to an increase in the aggregate buy first share of one percentage point. The local exposure κ_i is normalized by its standard deviation. The dashed line shows a 95% confidence interval based on two-way clustered standard errors with clustering on local housing market and quarter.

Table 3: Estimation results, horizon $h = 3$.

Dep. var	house price	time-to-sell	time-to-buy	market tightness
$\kappa_i \Delta BF_t$	0.446***	-1.698***	0.171	1.528**
	(0.157)	(0.624)	(0.485)	(0.741)
Horizon h	3	3	3	3
Sales-weighted	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
County x time FE	Yes	Yes	Yes	Yes
House price control	Yes	Yes	Yes	Yes
Shock lags	Yes	Yes	Yes	Yes
R^2	0.630	0.420	0.200	0.260
Locations	49	49	49	49
Quarters	40	37	37	37
N	1,960	1,565	1,556	1,377

Notes: Standard errors in parentheses. Standard errors are two-way clustered on location and quarter. The table shows the coefficient estimates from estimating Equation (8) at horizon $h = 3$, that is the dependent variable is the 4-quarter log change in house price index, time-to-sell, time-to-buy, and market tightness. House prices are based on a hedonic price index (see the Appendix for details). Time-to-sell is the average time between the (first) buy and the (second) sell transactions for moving owners that buy first trimmed at the 5th and 95th percentiles by quarter. Time-to-buy is the average time between the (first) sell and the (second) buy transactions for moving owners that sell first trimmed at the 5th and 95th percentiles by quarter. Log market tightness is equal to the difference between log time-to-buy and log time-to-sell. The shock equals an increase in the aggregate buy first share of one percentage point. The local exposure κ_i is normalized by its standard deviation. *** p<0.01, ** p<0.05, * p<0.1

in a local housing market with a one-standard deviation higher value of κ. [21]

5.5.2 IV estimation

Next, we use our shift-share variable $\hat{\kappa}_i \Delta BF_t$ as an instrument to consistently estimate the effect of changes in (log) market tightness on (log) prices, time-to-sell and time-to-buy. As shown in Section 2, $\hat{\kappa}_i$ corresponds to a structural parameter that determines the responsiveness of the local market tightness to changes in the buy-first propensity of locally moving owners. In addition, equation (6) shows that for small values of κ and close to steady state, our shift-share variable $\hat{\kappa}_i \times \Delta BF_t$ is proportional to the *predicted* (log) change in local

[21] Figure A.7 in the Appendix includes the estimated response of the local buy-first share and sales. We find suggestive evidence that sales respond more in high-κ local markets though the pre-trends in that case suggest that high and low-κ housing markets are not on parallel trends in terms of sales growth. The local buy-first share is not differentially affected in high- and low-κ markets.

market tightness given *aggregate*-level shocks to the local buy-first share.[22] Therefore, we estimate the following model,

$$\Delta y_{i,t-1,t+3} = \alpha_i + \beta_\theta \Delta \log \theta_{i,t-1,t+3} + \Gamma_h' X_{i,t-1} + u_{i,t-1,t+h}, \tag{10}$$

using 2SLS, where the outcomes Δy are log changes in prices, time-to-sell and time-to-buy and θ denotes market tightness. We focus on the 4-quarter changes in the variables, since they have fully adjusted at that horizon. The vector of controls is as in Eq. (8) and again we two-way cluster on quarter and location. Table 4 shows the 2SLS estimates, together with the first-stage and reduced-form estimates.[23]

We find that the elasticity of the house price with respect to market tightness is around 0.4, while the elasticity of the matching function with respect to buyers – the negative of the estimated coefficient on (log) time-to-sell – is around 0.86.[24] This latter estimate equals the estimate of the same elasticity in Genesove and Han (2012), which to our knowledge has so far been the only estimate of this key parameter in the housing search literature.[25] The first-stage regression is somewhat weak, so the IV estimates should be interpreted with some caution. Still, it is reassuring that the estimate of the elasticity of the matching function with respect to buyers is so close to the other reported estimate in the literature.

[22] This empirical strategy can be formally motivated as follows: as in Section 2, we write the house price level in a local market as a function $p = f(\theta)$ of the local market tightness (we suppress the dependence on other variables). Also we have $\theta(x, \kappa)$, where x is the buy-first share, and κ is the exposure in the market in question. From equation (5), we know that, for small values of κ,

$$\log \theta = \log(1 + \kappa x) - \log(1 + \kappa - \kappa x) \approx 2\kappa x - \kappa.$$

Therefore, close to steady state, and for small values of κ, we can write $p = f(\theta(z, \kappa))$, where $z = \kappa x$. Let η_z^p denote the semi-elasticity of the price with respect to z. Similarly, let η_θ^p denote the elasticity of the price with respect to θ. Finally, let η_z^θ denote the semi-elasticity of θ with respect to z. Then $\eta_z^p = \eta_\theta^p \eta_z^\theta$, or $\eta_\theta^p = \eta_z^p / \eta_z^\theta$. Consider then Table 4. The IV estimate for the elasticity of p with respect to θ (corresponding to η_θ^p) is equal to the reduced-form coefficient (corresponding to η_z^p) divided by the first-stage coefficient (corresponding to η_z^θ.)

[23] In the table we have restricted the sample to only observations with non-missing values of the 4-quarter log change in market tightness. Therefore, the first-stage is as in Table 3 but the reduced-form estimates for the other variables differ slightly.

[24] With a Cobb-Douglas matching function $AB^\alpha S^{1-\alpha}$, where B and S are the stocks of buyers and sellers respectively, time on market is $S/(AB^\alpha S^{1-\alpha}) = A^{-1}\theta^{-\alpha}$. The elasticity of time-on market with respect to θ is thus $-\alpha$.

[25] Note that the coefficient on (log) time-to-buy minus the coefficient on (log) time-to-sell equals one by construction, since log market tightness is constructed as the difference between log time-to-buy and log time-to-sell. Therefore, we cannot test for constant returns to scale in the matching function using our empirical approach.

Table 4: First-stage, reduced-form and IV estimates.

	First stage (market tightness)		
$\kappa_i \Delta BF_t$		1.528**	
		(0.643)	
F-statistic		5.636	
	house price	time-to-sell	time-to-buy
Reduced form	0.608***	-1.314**	0.214
	(0.188)	(0.513)	(0.587)
IV estimate	0.398*	-0.860***	0.139
	(0.213)	(0.307)	(0.307)
N	1,377	1,377	1,377

Notes: Standard errors in parentheses. Standard errors are two-way clustered on location and quarter. The first stage and reduced form estimates are from estimating Equation (8) at horizon $h = 3$, that is the dependent variable is the 4-quarter log change in market tightness (for the first stage regression), house price index, time-to-sell, and time-to-buy. The IV estimates are the coefficient estimate in Eq. (10) using 2SLS. House prices are based on a hedonic price index (see the Appendix for details). Time-to-sell is the average time between the (first) buy and the (second) sell transactions for moving owners that buy first trimmed at the 5th and 95th percentiles by quarter. Time-to-buy is the average time between the (first) sell and the (second) buy transactions for moving owners that sell first trimmed at the 5th and 95th percentiles by quarter. Log market tightness is equal to the difference between log time-to-buy and log time-to-sell. *** p<0.01, ** p<0.05, * p<0.1

5.6 Robustness

We perform a number of exercises to assess the robustness of our main findings. Figures 8 and 9 include the estimated responses of house prices and time-to-sell, respectively, for these robustness exercises. First we remove the house price shift-share control $\hat{\kappa}_i \times \Delta P_{t-1,t+h}$ (row 1, column 2), and then we replace it with a house-price shift share control based on the estimated local "beta", i.e. $\hat{\beta}_i \times \Delta P_{t-1,t+h}$, where $\hat{\beta}_i$ is the estimated sensitivity of local house prices changes to aggregate house price changes (row 1, column 3). Both of these exercises produce responses that are nearly identical to the baseline.

In another robustness exercise (row 1, column 4), we allow for local prices to have heterogeneous sensitivity to *housing-type specific* demand shocks. For example, if both the buy-first decision and a single-family house are luxury goods, an increase in household income could increase both the aggregate buy-first share and the prices of single-family houses over apartments.[26] If our regressions have not absorbed sufficiently the time-varying changes in the hedonic values of single-family houses, and different local markets vary in their composition of different housing types, then differential sensitivity to demand shocks for single-family houses would confound our results.

Therefore, we construct housing-type specific price indices (see the Appendix for details), distinguishing three types of housing: single-family and other houses, small apartments, and large apartment. We then use these price indices to construct three shift-share controls of the form $\hat{\kappa}_i \times \Delta P^d_{t-1,t+h}$, where P^d denotes a housing-type specific price index, for each of the three types just mentioned. Finally, use include these three shift-share controls in equation (8). The results from this exercise suggest that housing-type specific demand shocks should not be a concern.

We further address this same concern (row 2, column 1) by saturating our model with interaction fixed effects of time and an indicator taking the value 1 for local markets that are in the top half in terms of the share of single-family and other houses. If local housing markets with high vs. low share of single-family and other houses are evolving along different time trends, then this control would absorb this variation. Again, the results are in line with our baseline, further supporting the notion that housing-type specific demand shocks are not a confounder for our estimates.

In our next robustness exercise we remove the county-specific factors (no county-by-quarter fixed effects) (row 2, column 2). This also has a limited impact on our estimates. We also estimate responses if we do not weight local markets by mean sales (row 2, column 3). The price response is now noisier and possibly smaller, suggesting that smaller local

[26] However, we view this particular mechanism as unlikely, since as Table 1 shows κ does not vary with the *level* of house prices, i.e. high-κ locations do not have more expensive housing.

markets could be somewhat less responsive to changes in the buy-first share. Next, we present estimated responses using values of $\hat{\kappa}_i$ constructed using data up to 2007 (row 2, column 4). Again, our results are mostly unchanged, reflecting the fact that $\hat{\kappa}_i$ is quite stable over time.

In row 3, column 1 of Figures 8 and 9 we estimate the responses of prices and time-to-sell using a "leave-one-out" buy-first share. Specifically, we construct aggregate buy-first shares for each county, by removing the moving owners transacting in that specific county, and use this leave-one-(county)-out buy-first share as the aggregate shifter. As Figure A.6 in the Appendix shows, these leave-one-out buy-first shares are highly correlated, which implies that they are mostly responding to common aggregate-level shocks rather than any local shocks. Consequently, our results are also robust to using this regressor.

Next, we show that our results are robust to other definitions of housing markets. Specifically, we construct local housing markets using the first three digits of a property's 4-digit post code. This leads to 132 much smaller local housing markets.[27] The estimated responses (row 3, column 2) are quite similar to the baseline though a bit noisier.[28]

Finally, we estimate our model using different samples – from 2000 to 2016 (row 3, column 3) as well as our full sample from 1994 to 2016 (row 3, column 4). The results are in line with those for our baseline sample.[29]

6 Discussion: are local housing markets segmented?

Economic theory tells us that the buyers-to-seller ratio matters for house prices. Key to our analysis is the idea that shocks to the aggregate buy-first share lead to differentiated shocks to the local buyer-to-seller ratios, and hence, to differentiated house price responses in these locations. However, there are (at least) two mechanisms that could constrain the differentiated effects of local market tightness and local housing prices.

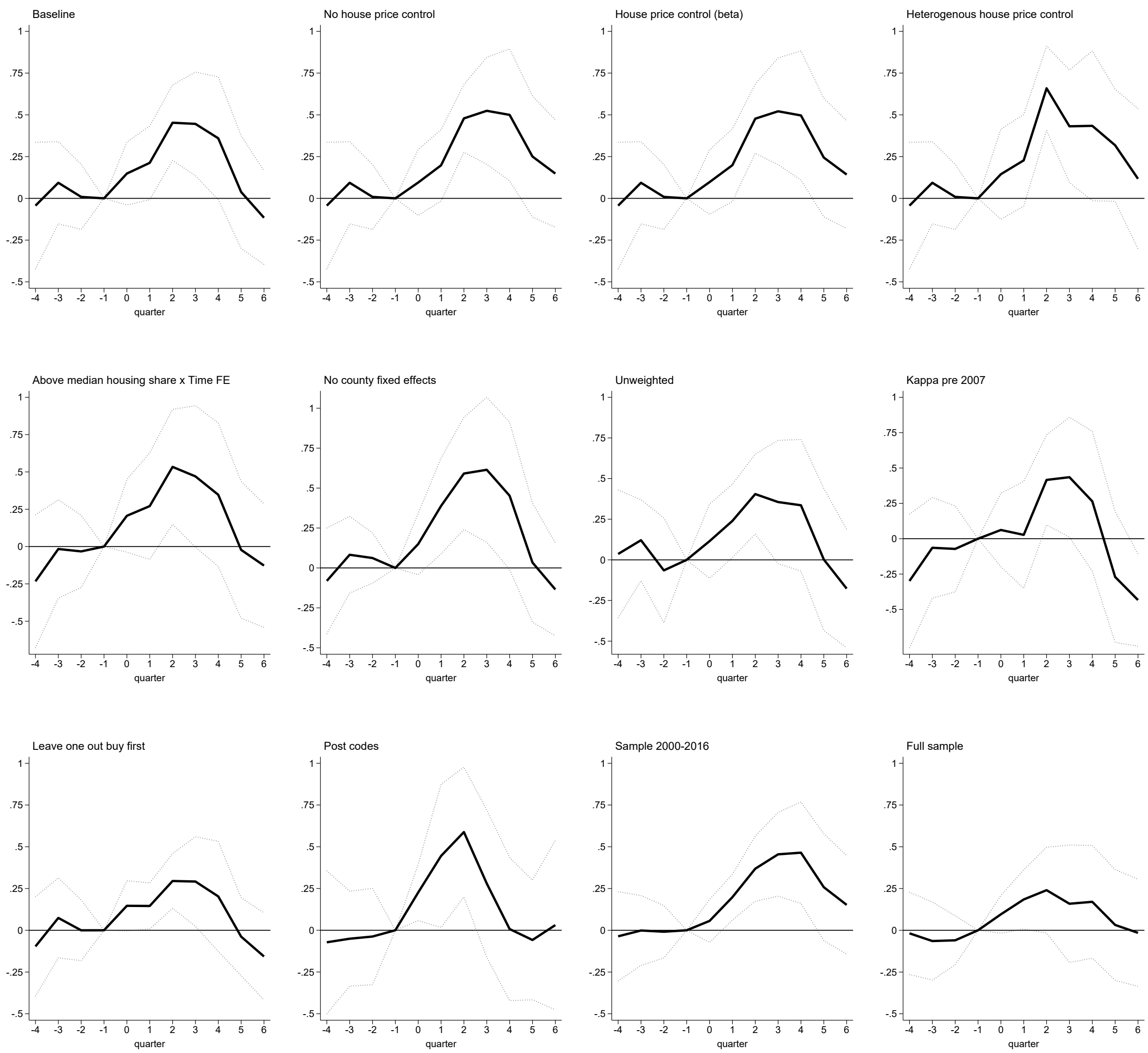
The first mechanism is associated with mobility between local housing markets – arbitrage across space. If local housing market conditions create an upward pressure on prices in one local housing market, buyers would tend to relocate to other local housing markets. In our model setup from Section 2, this would mean that the inflows and outflows of agents to and from the local area (the g parameter) are not exogenous and constant, but endogenous

[27]In unreported results we also consider one more alternative partition of local housing markets using the 2001 municipality and city parish subdivisions (which were smaller in size to the 2005 parishes that we use for our baseline results). Our results are again robust to such alternative partitions.

[28]This and the previous exercises alleviate concerns about reverse causality, whereby the aggregate buy-first share responds more to local shocks in high-κ markets.

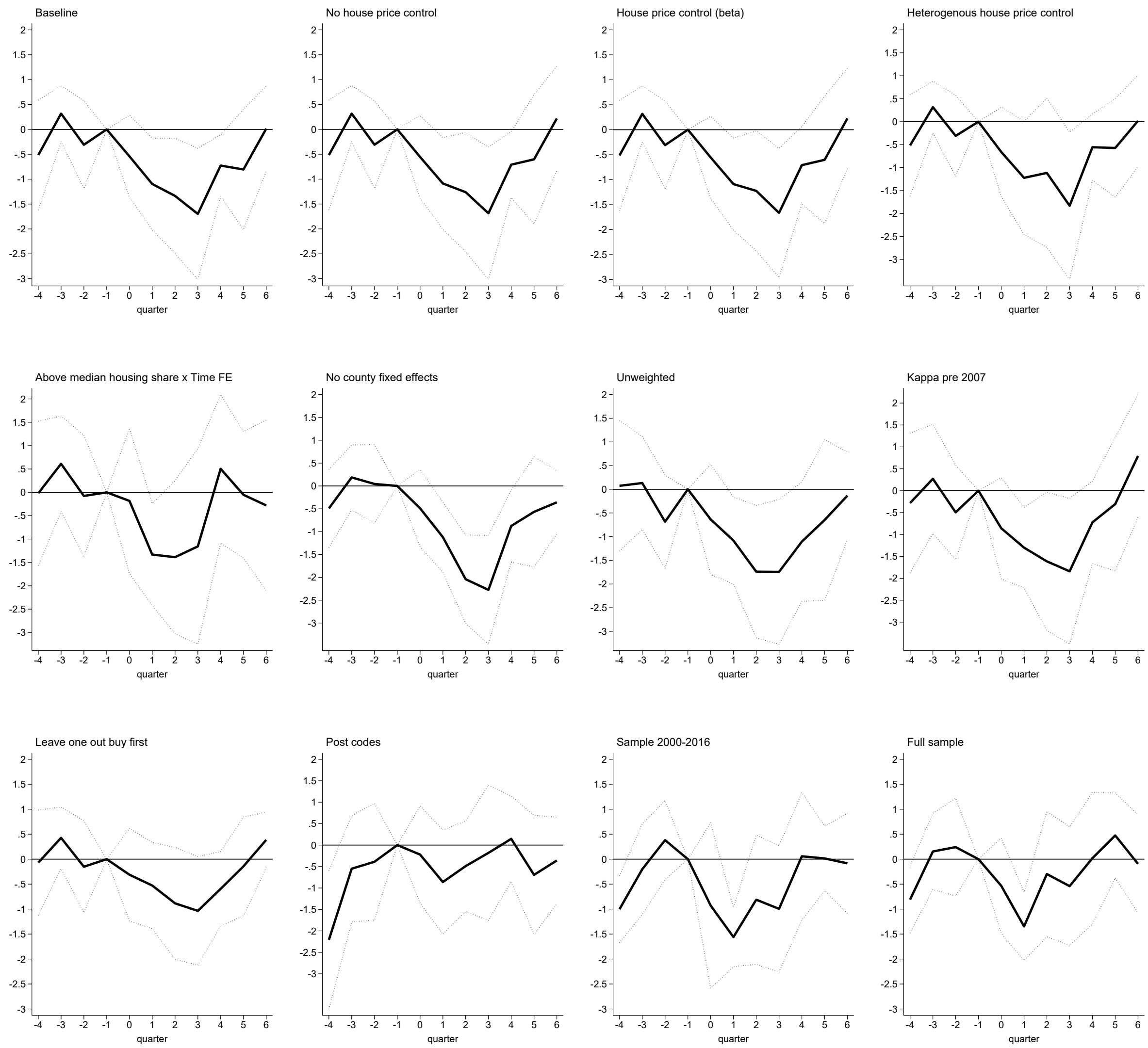
[29]In the Appendix (Figures A.8) we include the responses to a number of additional robustness exercises, where we exclude one city at a time. Those exercises show that our results are not driven by one single city.

Figure 8: Estimated response of prices (robustness exercises)



Notes: The figure plots the coefficients from estimating Equation (8) for quarterly house prices at each horizon shown on the x-axis for different robustness exercises. House prices are based on a hedonic price index (see the Appendix for details). The shock occurs in quarter 0 and is equal to an increase in the aggregate buy first share of one percentage point. The local exposure $\hat{\kappa}_i$ is normalized by its standard deviation. The dashed line shows a 95% confidence interval based on two-way clustered standard errors with clustering on local housing market and quarter.

Figure 9: Estimated response of time-to-sell (robustness exercises)



Notes: The figure plots the coefficients from estimating Equation (8) for quarterly house prices at each horizon shown on the x-axis for different robustness exercises. Time-to-sell is the average time between the (first) buy and the (second) sell transactions for moving owners that sell first trimmed at the 5th and 95th percentiles by quarter. The shock occurs in quarter 0 and is equal to an increase in the aggregate buy first share of one percentage point. The local exposure $\hat{\kappa}_i$ is normalized by its standard deviation. The dashed line shows a 95% confidence interval based on two-way clustered standard errors with clustering on local housing market and quarter.

and reacting to local housing market conditions. If these responses are sufficiently strong, for instance because different local housing markets are considered to be perfect substitutes, and if buyers are fully informed about prices, all local housing markets must be equally attractive in equilibrium (the "law of one price" in this context). Hence any local housing market shock would be neutralized by the endogenous mobility responses of agents, and only aggregate shocks would matter for housing prices. Note that the fact that moving owners disproportionately move within the area they live in indicates that different locations are not considered perfect substitutes, for at least some potential buyers.

The second mechanism is associated with changes in housing market conditions being temporary – arbitrage across time. The willingness to pay for a house today depends on the expected future value of the house. In markets with rational, forward-looking agents this would reduce (but not eliminate) the local effects of temporary shocks to the buy-first share.

Hence, our finding that local housing market conditions matter for local house prices indicates that there must be frictions in the housing market that prevent arbitrage across space and time from eliminating the effects of these shocks. Furthermore, since there are reasons to believe that some of the effects are partly undone by arbitrage across time and space, we expect that, in the aggregate, shocks to the buy-first share would have larger effects on house prices than locally. Similarly, if shocks are permanent, rather than temporary, then we would expect larger effects. Hence, the aggregate effects of permanent shocks to the buy-first share could be (substantially) larger than what our findings based on the local effects of temporary shocks suggest.

7 Concluding Comments

In this paper we provide empirical evidence for the importance of the transaction sequence of moving owners for housing markets. Our estimates show that changes in this transaction sequence (whether due to a choice on the side of moving owners or because of constraints imposed on them) are a first-order driver of house price dispersion and volatility. Since the mechanism through which such transaction sequence choices operate in housing markets is changes in market tightness, our results also provide evidence for the effect of tightness on prices and time-to-sell – a central prediction of essentially all search models of the housing market. Our approach allows us to back out the elasticity of house prices with respect to market tightness, a parameter that can be used to calibrate quantitative models of the housing market that include trading frictions. However, our approach does not allow us to identify the multiplier effect associated with the local equilibrium feedbacks between the local buy-first share, market tightness, and prices. Identifying these multipliers in the data is a promising venue for future research.

We study the impact on local housing markets of aggregate shocks to the buy-first share in response to changes in economy-wide conditions, such as shocks to consumer sentiment or house price expectations. However, such shocks could also be institutional. Since the 2008 Financial crisis, a number of macro-prudential regulatory tools have been implemented in credit markets. These could impose constraints on moving owners, among others. In particular, our analysis indicates that transaction sequence decisions could be significantly affected: for instance, the aggregate buy-first share declined in 2016, when several tightening measures were introduced on homebuyers in Norway (see Figure 1). This is unsurprising given that such regulations could increase banks' costs of extending bridge loans, either via borrower-level restrictions (debt service to income or loan-to-income caps), or bank-level tightening of regulatory capital. If this increased cost is passed through to moving owners seeking bridge loans, it would affect the cost-benefit analysis associated with buying vs. selling first, reducing the aggregate buy-first share. Therefore, from a policy perspective, our results suggest possible unintended price effects across housing markets, that may have to be taken into account when designing future regulatory interventions.

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Appendix

A.1 Model details

Deriving (5) For a given x, the dynamics of the model is given by the following equations (dependence on time suppressed):

$$
\begin{aligned}
\dot{B}_1 &= x\gamma - q(\theta)B_1 \\
\dot{B}_m &= g - q(\theta)B_m \\
\dot{B}_0 &= \mu(\theta)S_1 - q(\theta)B_0 \\
\dot{S}_1 &= (1-x)\gamma - \mu(\theta)S_1 \\
\dot{S}_m &= g - \mu(\theta)S_m \\
\dot{S}_2 &= q(\theta)B_1 - \mu(\theta)S_2
\end{aligned}
$$

In steady state, all the derivatives are zero. Hence it follows readily that $B_1 = \frac{x\gamma}{q}$, $S_1 = \frac{(1-x)\gamma}{\mu}$, $B_0 = \frac{(1-x)\gamma}{q}$, $B_m = \frac{g}{q}$, and $S_m = \frac{g}{\mu}$.

With these simple observations in hand we can use (4) to solve for the steady state value of θ. It follows that

$$\frac{x\gamma}{\mu(\theta)} + \frac{g}{\mu(\theta)} = \frac{(1-x)\gamma}{q(\theta)} + \frac{g}{q(\theta)}$$

Multiplying with $\mu(\theta)$ and using that $\mu(\theta) = \theta q(\theta)$ gives that $x\gamma + g = \theta\left((1-x)\gamma + g\right)$, or that

$$\theta = \frac{1 + x\kappa}{1 + (1-x)\kappa}$$

hence we have derived (5).

Dynamics It follows from (2) that if some moving owners switch from selling first to buying first, this will momentarily shift the tightness up.Over time, this will reduce the inflow into B_0 and increase the inflow to S_2. Furthermore, the outflow rates from all the "buying states" will decrease and from all the "selling states" will increase. Hence the dynamics of the system is generally not trivial.

However, in some cases the dynamics is simple. Suppose we are in the sell-first steady state. Suppose then that at a given point in time, all locally moving owners at the sell first stage switch and start buying first. That is, if S_1^* is the steady state number of sell first-individuals, then $B_1 = S_1^*$ just after the switch while $S_1 = 0$. The tightness after the switch is given by (after inserting 4 into 1 with $k = 0$)

$$
\begin{aligned}
\theta &= \frac{B_m + B_0 + S_1^*}{B_m + B_0} \\
&= \frac{\frac{g+\gamma}{q} + \frac{\gamma}{\mu}}{\frac{g+\gamma}{q}} \\
&= 1 + \frac{\gamma}{\theta^s(\gamma + g)} \\
&= 1 + \kappa
\end{aligned}
$$

where θ^s is the sell-first steady state equilibrium tightness. Hence the tightness jumps directly to the buy-first steady state tightness.

Consider then a situation where the market is in steady state equilibrium for a given x, and that x at some point in time shifts up to a new constant level $x + \Delta x$. This will momentarily increase the flow into B_1 and reduce the flow into S_1. There will be no momentary effect on the stocks, and hence no momentary increase in the flow into S_2 or reduction in the flow into B_0. Hence, just after the shock, we have that

$$
\begin{aligned}
\frac{d \log \theta(t)}{dt} &= \frac{\dot{B}_1}{B^{tot}} + \frac{\dot{S}_1}{S^{tot}} \\
&= \frac{\gamma \Delta x}{B^{tot}} + \frac{\gamma \Delta x}{S^{tot}}
\end{aligned}
$$

Hence the tightness will immediately start to grow after the shift in x. After a while, all the flows will be affected.

A.2 Data details

A.2.1 Data description

We start with individual level housing transaction data for the period 1993-2017 for the four main cities in Norway: Oslo, Bergen, Stavanger and Trondheim plus surrounding municipalities in the cases of Oslo and Stavanger.[30] The data comes from the official registry of all housing transactions in Norway (the Land Register). From 2007 onward it includes all housing transactions. Prior to 2007 it excludes transactions in shares of housing cooperative

[30] In Norway cities tend to be administratively separated into distinct municipalities. However, the metropolitan areas of these cities often contain contiguous urban municipalities, as is the case with Oslo and Stavanger. In these two case the surrounding municipalities are urban areas that are closely integrated into the metropolitan city with municipal public transportation of the specific city extending into them.

associations (“borettslag”).

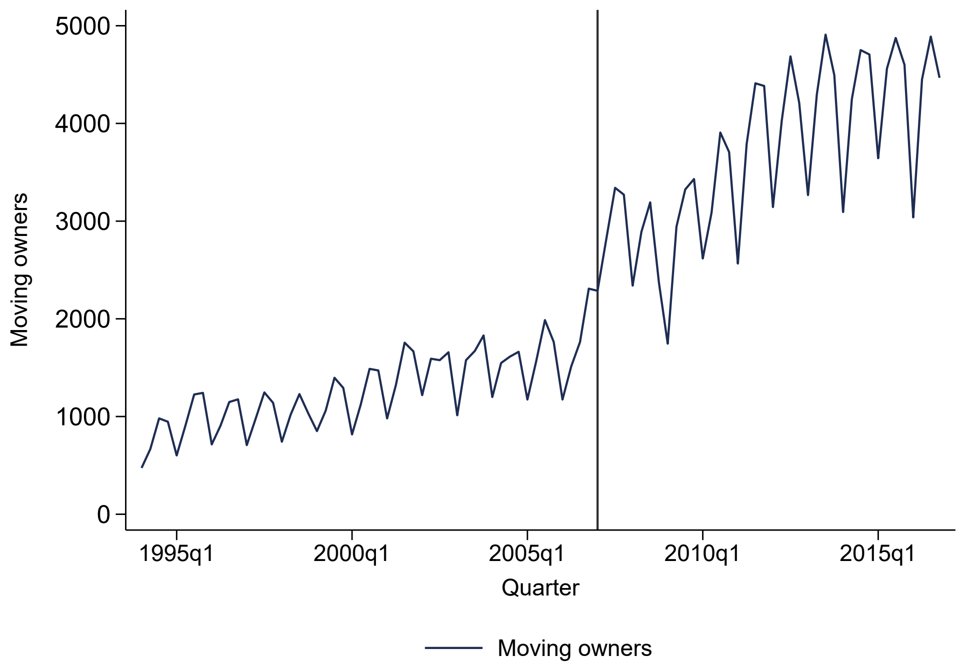
The data consists of information on the housing unit transacted, which includes a unique housing unit identifier and basic hedonics such as location (in terms of the postal code of the property), type of the housing unit (apartment vs. row house vs. semi-detached house vs. single-family house), the ownership structure (independently owned vs. a part of a housing cooperative association), size, number of bedrooms, floor (for apartments), year of construction. It also includes information on the date of the transaction, the type of transaction (whether it is a market transaction or other transfer of ownership rights) and unique individual identifiers of the buyers and sellers in the transaction, together with information on the share of the property that a buyer acquires or a seller relinquishes. Finally, it includes information on the transaction price. Moreover, for a subset of our transaction data we can merge with household information from Statistics Norway and identify the household type that an individual belongs to. We restrict attention to individuals (i.e. we drop firms) and use the unique individual identifiers and unique property identifiers to construct the transaction histories of individuals over time.

A.2.2 Identifying moving owners

We use these individual transaction histories to identify *moving owners*. The definition of a moving owner is straightforward: she buys a property and will be its owner-occupier, and sells a property which she previously occupied. Since we do not have information on residency, we identify an individual as a moving owner for a specific pair of housing transactions as follows: given two consecutive housing transactions in an individual's transaction history, we call the individual a moving owner (for these two transactions) if the individual buys and sells two different properties within a year in a market transaction. Moreover, she must have owned the property she sells for at least one year and will own the property she buys for at least one year. We refer to the two transactions over which we identify an individual as a moving owner as the *transaction sequence* of the moving owner.

Since we examine two consecutive transactions at a time we also impose that the second transaction in a transaction sequence cannot be the first transaction in another transaction sequence. Thus individuals who have been identified as a moving owner in two transactions and who transact again within a year of the second transaction are not identified again as a moving owner. In addition, we only restrict attention to individuals that have transacted at most 10 times in our data set. In unreported analysis, we consider only individuals that own at most 3 properties at any given time. Our results remain mostly unchanged. Since we do not observe ownership prior to 1993 or after 2017, we can only consistently identify an individual as a moving owner over the period 1994-2016. In addition, note that if an

Figure A.1: Moving owners, 1994Q1-2016Q4.



Notes:The figure plots the number of identified moving owners in the period 1994q1-2016q4. A moving owner is defined as an individual who buys a property and will be its owner-occupier, and sells a property which she previously occupied.

individual also transacts in markets that we do not have data for, then we cannot identify that individual as a moving owner. Therefore, given the limited geographical span of our data we will be under-counting the total number of moving owners for all of Norway. This, however, is not a major problem, since our geographic coverage is relatively broad in terms of population as already mentioned. Additionally it is not a problem when considering moving owners *within* a specific geographic housing market. Not observing cooperatives prior to 2007 is a bigger source of concern, since we may substantially under-count moving owners also within geographic housing markets. Figure A.1 shows that this is indeed an issue as it shows a clear break in the number of moving owners in 2007Q1. Specifically, there are 2 to 3 times more identified moving owners after 2007Q1 compared to the period from 1994Q1-2006Q4. This should not be surprising as housing cooperatives constitute a large share of housing units in large Norwegian cities. For this reason we will start our baseline analysis in 2007Q1.

A moving owner is said to *buy first* if her first transaction in the transaction sequence is a buy and her second transaction is a sell and, conversely, for a *sell-first* moving owner. The *buy-first share* in a local housing market or in a population segment (e.g. defined by age group or household type) is defined as the share of moving owners in that market/population segment who buy first. Furthermore, we use the date of the first transaction to create a time series of the buy-first share in the aggregate. Specifically, we compute a weighted series where we use the property share of the individual as weight. In principle, this could lead to some over- or under-estimation of the true buy-first share. For example, if an individual that is identified as a moving owner buys together with another individual that has not owned a property before (and hence is not identified as a moving owner), then the buy-first moving owner's property weight is only one-half (while the property weight on her sell transaction is one). In unreported analysis, we use the maximum of the property weight over the two transactions. This hardly changes our results.

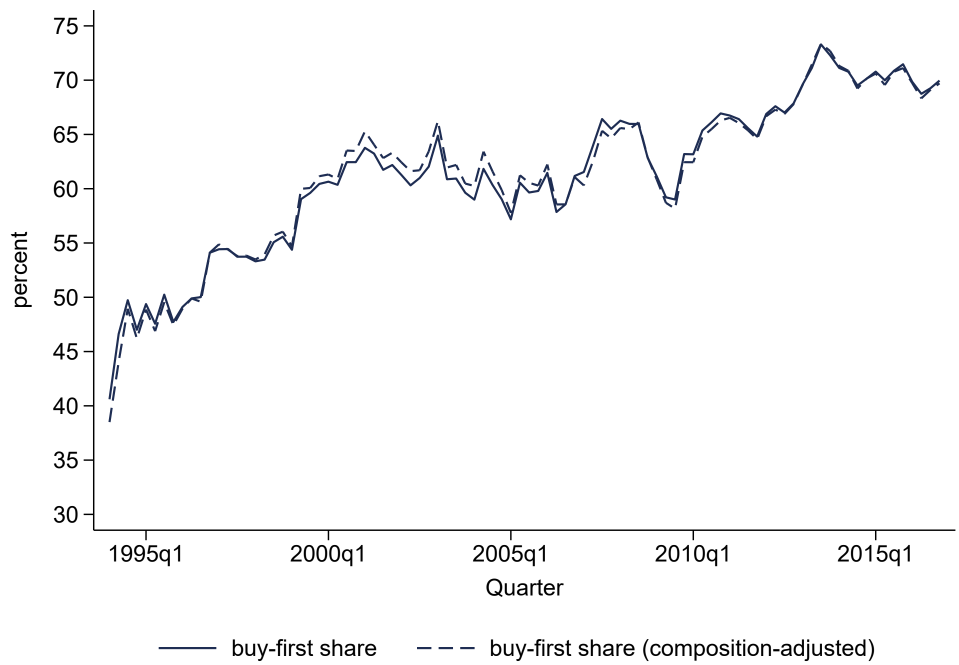
Finally, a *locally moving owner* is a moving owner who only buys and sells a property within a specific geographic location. Conversely, an *non-locally moving owner* is a moving owner who buys and sells properties in different geographic locations. Similarly, a *buy first* locally moving owner is a locally moving owner that buys first, while a *buy first* non-locally moving owner is a non-locally moving owner that buys first. These definitions mirror the way we construct the respective variables using our transaction-level data.

Figure A.2 plots the buy-first share for the whole period 1994Q1-2016Q4 together with composition-adjusted buy-first share, which is constructed by aggregating the estimated propensity to buy first after controlling for individual demographic characteristics and seasonality specific to the different local housing markets

A.2.3 Constructing relevant variables

We also construct price indices, sales, and a time-to-sell and time-to-buy series for specific local housing markets and time periods. We describe how we construct our hedonic price indices in a separate section below. Sales are defined as the total number of transactions in a local housing market and time period. We construct time-to-sell in the following way: Since we do not have information on when a property was put on the market (and only observe the closing date for the transaction), we follow MNS and use the fact that for a buy first moving owner, the time between the (first) buy and the (second) sell transactions is proportional to the time-to-sell. We then compute the mean time between these two transactions in a particular local housing market and time period as our time-to-sell. Specifically, we construct monthly series for time-to-sell and sales, seasonally adjust them using the X11 method, compute a symmetric 3-month moving average and aggregate them up to the quarterly frequency. We proceed analogously for time-to-buy, using the time between the first sell and second buy transactions for a sell first moving owner and averaging for a given location and

Figure A.2: Buy-first share, 1994Q1-2016Q4.



Notes:The figure plots the aggregate buy first share and the composition adjusted aggregate buy first share over the period 1994q1-2016q4. The buy first share is defined as the number of moving homeowners that buy first. The composition adjusted series is constructed by aggregating the estimated propensity to buy first after controlling for individual demographic characteristics and seasonality specific to the different local housing markets.

time period. Finally, as described in the main body of the paper, we combine the time-to-sell and time-to-buy series together with a simple observation from search theory to compute market tightness as the ratio of time-to-buy and time-to-sell.

A.2.4 Use of closing dates rather than agreement dates

In our data we observe transaction or closing dates rather than actual agreement dates. In practice there is a two to three month difference between these dates on average. This leads to two issues. First, there is an offset in the timing of important downturns such as the house price decline during the 2008-2009 Financial Crisis. To deal with this issue, when we correlate our constructed variables with other aggregate variables like GDP and interest rates, we shift back all of our constructed series by one quarter. This, however, is not an issue for our main analysis, since we use the same data to construct all our variables. Second, since the difference between agreement and closing dates is not a constant we may be introducing measurement error in our main variables of interest. This is particularly important for the buy-first share which will be part of our main regressor as we explain in Section 5. We believe that the measurement error we are introducing is small based on previous findings in Moen et al. (2019) using data for Copenhagen, Denmark, where they observe both the agreement and closing dates. In practice, there is a very high correlation (more than 90%) between being classified as a buy first moving owner based on agreement dates and based on closing dates in the cross-section. There is a similar high correlation between the buy-first share based on closing and agreement dates in the time series. Additionally, whether we are measuring the buy-first share based on agreement or closing dates is irrelevant for our identification assumptions and our empirical results and only concerns the structural interpretation of our estimates.

A.2.5 Baseline sample

Our baseline local housing markets are the city parishes ("bydeler") of the 4 cities plus their surrounding municipalities using the 2005 administrative partition of parishes and municipalities.[31] In addition, we drop local housing markets with less than 1,000 total sales. This leaves us with a total of 49 local housing markets.

Our time unit of analysis is a quarter. Given the break in the data for moving owners in 2007Q1 and the fact that we can consistently identify moving owners only up to 2016Q4

[31] The municipality of Bærum, which is contiguous to Oslo, is very large with population comparable to that of the second largest city in Norway, Bergen. Therefore, in our baseline definition we split Bærum in four approximately equally-sized segments (in terms of sales) by allocating contiguous postal areas within that municipality. Our results continue to hold if we keep B ærum as one (large) local housing market.

our main empirical analysis covers the period 2007Q1-2016Q4 (2007Q1-2017Q4 for house prices).[32]

A.2.6 House price indices

We construct house price indices for each local housing market using hedonic regression with detailed controls on housing characteristics. We construct price indices both for the 49 local housing markets as defined in our baseline analysis as well as for the 132 local housing markets based on the first 3 digits of the property postal codes that we use in one of our robustness exercises. We construct local price indices using properties transacted in each local market excluding properties in housing cooperatives, since for those properties there is a transfer of a share of common debt in the housing cooperative that is not reflected in the price of the property. For each local housing market, we estimate the following specification:

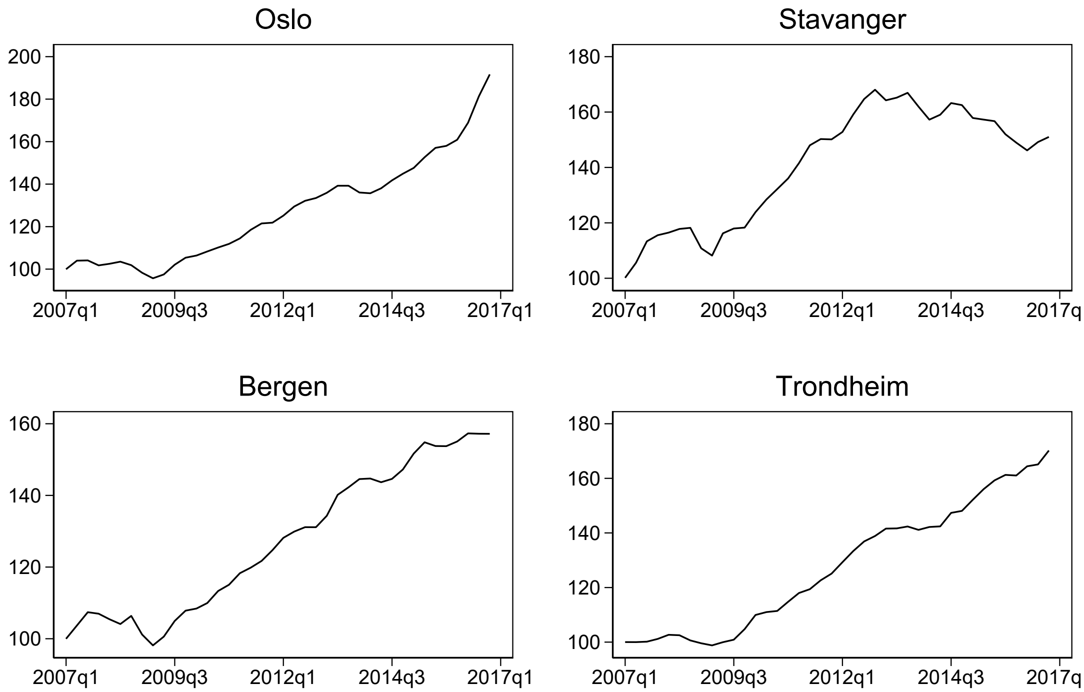
$$\log P_h = \alpha + \sum_j \beta_j log(area_h) * zip_{j(h)} + \sum_j \gamma_j zip_{j(h)} * age_h + \delta X_h + \psi_{t(h)} + \varepsilon_h \qquad \text{(A.1)}$$

where $\log P_h$ denotes the log price of transaction h, zip_j denotes fixed effects for the zip codes within the region, *area* stands for the livable area of the sold unit (in square meters), *age* is a categorical variable based on the age of the building, with groups including up to 5, 15, 25, 35, and above 35 year old units. X_h includes other categorical controls, such as the number of rooms, floor, the type of the unit sold (multi-dwelling home, semi-detached homes, etc.), and month fixed effects, while ψ_t denote month-year fixed effects. The month-year fixed effects include the (logarithm of) house price developments over time for each local housing market, controlling for the observables. To construct the local index, we revert from logarithm to house price level by exponentiating the time fixed effects and adjusting by the root mean square error (as the regression is estimated in logs, the expected price of a log-normal distribution should be adjusted by the standard deviation which is approximately the RSME). We then take a 5-month symmetric moving average. Finally, we aggregate up to construct city-level and national house price indices by weighting the local indices by the number of sales in a local housing market in a given time period. Figure A.3 plots the resulting house price indices for Oslo, Bergen, Trondheim and Stavanger.

In addition to this index, we also construct local price indices for different property types, namely small apartments (defined as apartments with up to 2 rooms), large apartments (apartments with more than two rooms) and houses (single-family homes, semi-detached houses and row houses). To construct these indices we again estimate hedonic models as

[32]Since we include 8 lags of the regressor in our baseline specification, we also use the buy-first share in 2005Q1-2006Q4.

Figure A.3: House price indices for 4 largest cities in Norway.



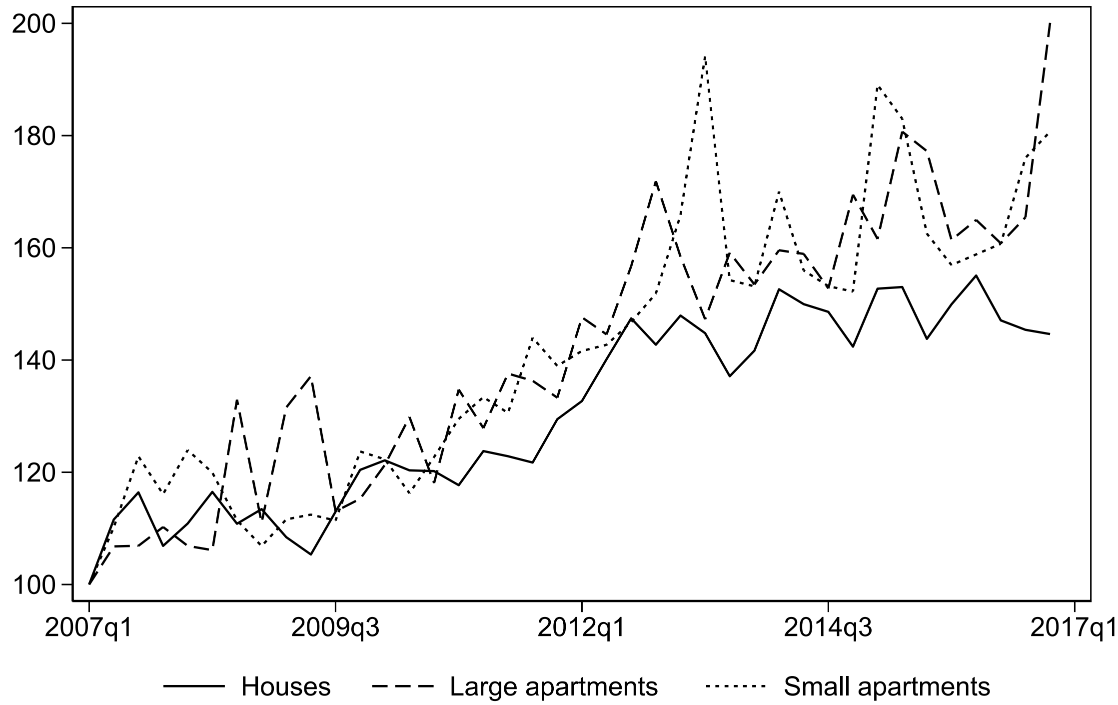
in Eq. (A.1) but include property-type times month-year fixed effects. We then follow the same procedure for the month-year fixed effects for each property type. We seasonally adjust using the ARIMA X-11 seasonal filter and also take a 5-month symmetric moving average. As a part of the seasonal filter, we remove outliers (that are 100 percent larger or smaller than the previous observation). Finally, we trim the type-specific series at the 5th and 95th percentiles. We use these house price indices in one of our robustness exercises.

A.2.7 Decomposition

To shed light on which time periods are important for our estimated effects, we perform a decomposition of the variation in the regressor as in Chodorow-Reich et al. (2019). Specifically, we let $\tilde{x}_{i,t}$ denote the residualized regressor after partialling out the controls and fixed effects from equation (8).[33] $\beta = \sum_t w_t \beta_t$, where β_t is the regression coefficient obtained from using only data for quarter t, and w_t is a weight that equals the contribution of quarter t to

[33]Below we suppress the dependence on the estimation horizon h, since we perform out decomposition only for $h = 3$, i.e. for the 4-quarter change as in our IV regression. Also, for simplicity, we exclude the house price shift-share control in the decomposition exercise, since it has a minor effect on the coefficient estimate as we show in Section 5.6. Then the coefficient of interest β in equation (8) can be decomposed as

Figure A.4: House price indices for different types of housing.



the total (residual) variation in the regressor, that is

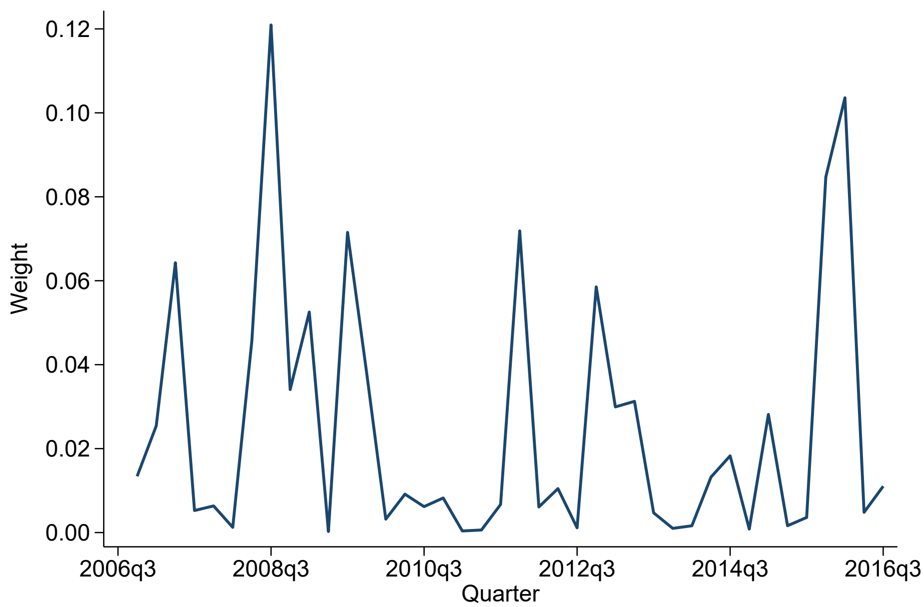
$$w_t = \left(\sum_i \sum_s \omega_i \tilde{x}_{i,s} \right)^{-1} \left(\sum_i \omega_i \tilde{x}_{i,t} \right), \tag{A.2}$$

where ω_i denotes the mean number of sales in location i. The weights w_t naturally sum to one, and a higher value of w_t corresponds to a quarter with larger contribution to the total residual variation. Consequently, the coefficient estimate for that quarter would have a greater impact on the overall coefficient estimate. Figure A.5 plots the resulting weights. Even though the quarters around the 2008 Financial crisis have relatively high weights, there are also many other periods with high weights, particularly in 2016. Therefore, there is not just one specific period in our sample that "drives" our results.

A.3 Transaction sequence decisions and household balance sheets

We use household level balance sheet information from the Norwegian Tax Authority and Statistics Norway linked with information on housing transactions from the Land Register provided by Ambita AS for the municipalities Oslo, Bærum, Bergen, and Stavanger, in order

Figure A.5: Regressor decomposition weights.



Notes: The figure plots the decomposition weights for our main regressor computed according to Eq. (A.2). We offset the observations by one quarter (for example, the observation in 2015Q3 is attributed to 2015Q2.) to account for the fact that the buy-first share is computed based on closing dates rather than at the time the transaction order decision is made.

to understand how moving owners' balance sheet composition affects their propensity to buy first or sell first. Our sample period is 2004-2016 and we restrict attention to households that have at most 10 transactions in the period 1993-2017.

We are particularly interested in how liquid wealth (in the form of bank deposits), total indebtedness, and household income correlate with whether a household buys first or sells first. Since we have information on balance sheets on 31 Dec. of a given year, we examine how the balance sheet position at the end of the previous year affects the transaction sequence of moving owners in a given year (whether they buy first or sell first). Specifically, we estimate the following regression equation

$$BF_{it} = \alpha + \beta_1 \log deposits_{iy(t)-1} + \beta_2 \log debt_{iy(t)-1} + \beta_3 \log incme_{iy(t)-1} + X_{it}'\gamma + \varepsilon_{it}, \quad \text{(A.3)}$$

where t denotes a quarter, and $y\,(t) - 1$ denotes the calendar year prior to quarter t. Table A.1 includes estimated coefficients for different specifications of this model. Overall, bank deposits in the year prior to the transaction have a positive effect on the probability of buying first, while debt (or leverage in the specifications that include total assets) has a negative effect on the probability of buying first. Finally, previous year's income has a positive effect on the probability of buying first. These facts square well with how households obtain mortgage loan pre-approvals in Norway (a "finansieringsbevis") and the factors that bank officials include in their loan consideration – i.e. total amount of non-housing equity that is available in the household's bank accounts, total housing equity, and information on past income.

A.4 Additional figures and tables

Table A.1: Household balance sheets and transaction order.

	(1)	(2)	(3)	(4)	(5)	(6)
L1.Bank deposits (log)	0.0115**	0.0259**	0.0106**	0.0265**	0.0265**	0.0217**
	(0.0012)	(0.0014)	(0.0015)	(0.0017)	(0.0015)	(0.0026)
L2.Bank deposits (log)						0.0090**
						(0.0025)
Bank deposits (log)		−0.0254**	0.0000	−0.0273**	−0.0252**	−0.0293**
		(0.0014)	(0.0016)	(0.0017)	(0.0014)	(0.0021)
L1.Total debt (log)	−0.0164**	−0.0377**	−0.0165**	−0.0378**	−0.0375**	−0.0321**
	(0.0015)	(0.0016)	(0.0018)	(0.0020)	(0.0016)	(0.0038)
L2.Total debt (log)						−0.0118**
						(0.0039)
Total debt (log)		0.0548**	0.0033	0.0532**	0.0548**	0.0533**
		(0.0016)	(0.0019)	(0.0019)	(0.0016)	(0.0023)
L1.Total income (log)	0.0289**	0.0150**	0.0282**	0.0112*	0.0165**	0.0166*
	(0.0035)	(0.0035)	(0.0039)	(0.0044)	(0.0037)	(0.0082)
L2.Total income (log)						0.0025
						(0.0076)
L1.Total assets (log)				0.0054		−0.0198**
				(0.0035)		(0.0070)
L2.Total assets (log)						0.0016
						(0.0056)
L1.Total assets (acc.) (log)					−0.0034	
					(0.0027)	
L1.Other financial assets (log)						0.0019
						(0.0025)
L2.Other financial assets (log)						−0.0030
						(0.0025)
Local seasonality	Yes	Yes	Yes	Yes	Yes	Yes
Location-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Household type-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Age group-by-type FE	Yes	Yes	Yes	Yes	Yes	Yes
Household type-by-Location FE	Yes	Yes	Yes	Yes	Yes	Yes
Both transactions in same year	No	No	Yes	No	No	Yes
R^2	0.07	0.09	0.06	0.09	0.09	0.10
Observations	72,833	71,566	60,424	47,987	71,544	35,247

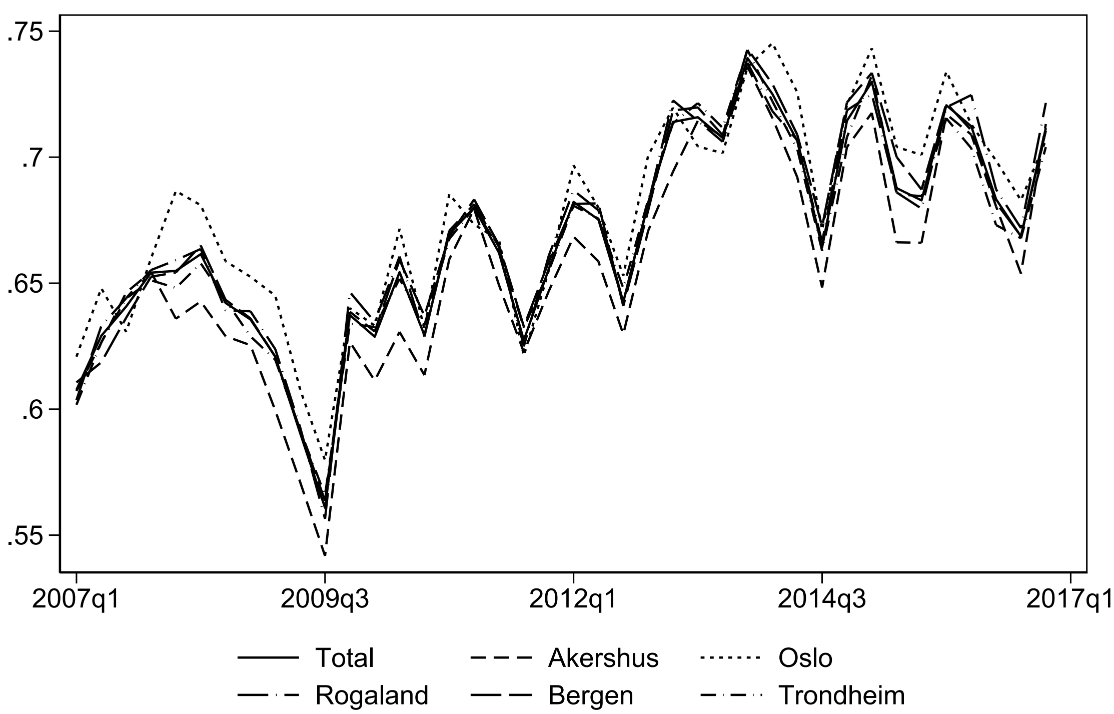
Notes: The table reports coefficients and standard errors from a linear probability model for the probability to buy before selling on liquid assets, debt, income, and other controls. Standard errors in parentheses are clustered at the household level. * denotes significance at the 5% level, and ** denotes significance at the 1% level.

Table A.2: Summary Statistics

Shock exposure					
	Mean	Std.Dev.	Min	Max	Locations
$\hat{\kappa}$	0.17	0.06	0.05	0.39	49

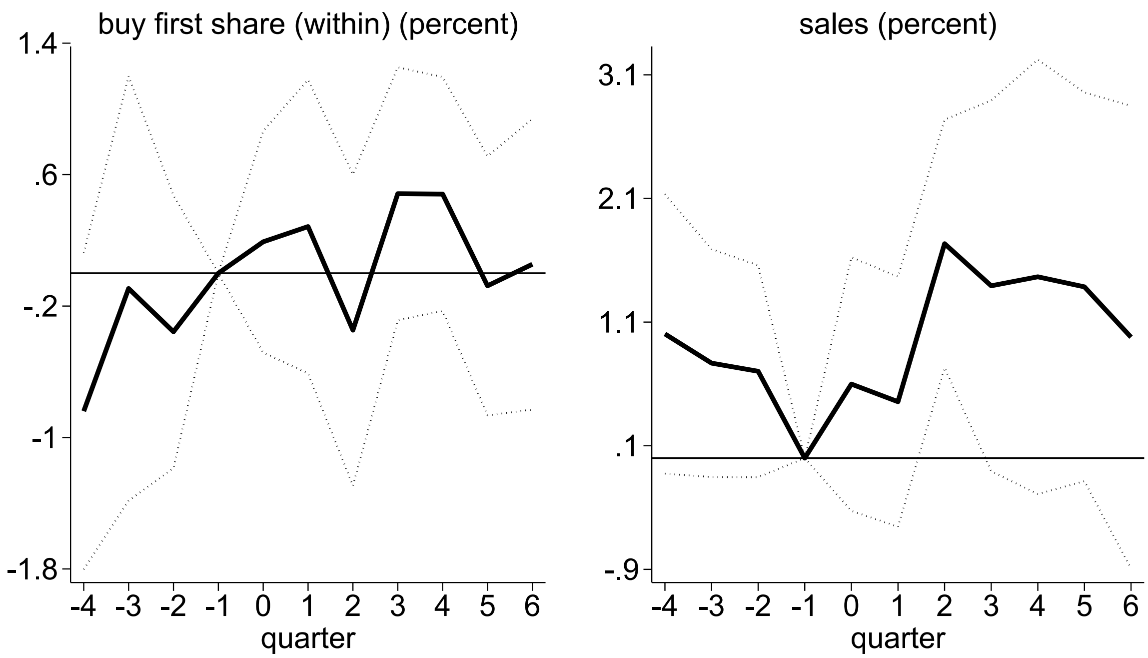
Variables					
	Mean	Std.Dev.	Quarters	Locations	N
log house price index	4.890	0.210	44	49	2,156
log sales	5.120	0.760	44	49	2,156
log time to sell	3.880	0.300	40	49	1,960
log time to buy	4.460	0.630	40	49	1,960
log tightness	0.550	0.370	40	49	1,960
aggregate buy-first share (%)	66.77	4.010	40		40

Figure A.6: Leave-one-(county)-out buy-first share.



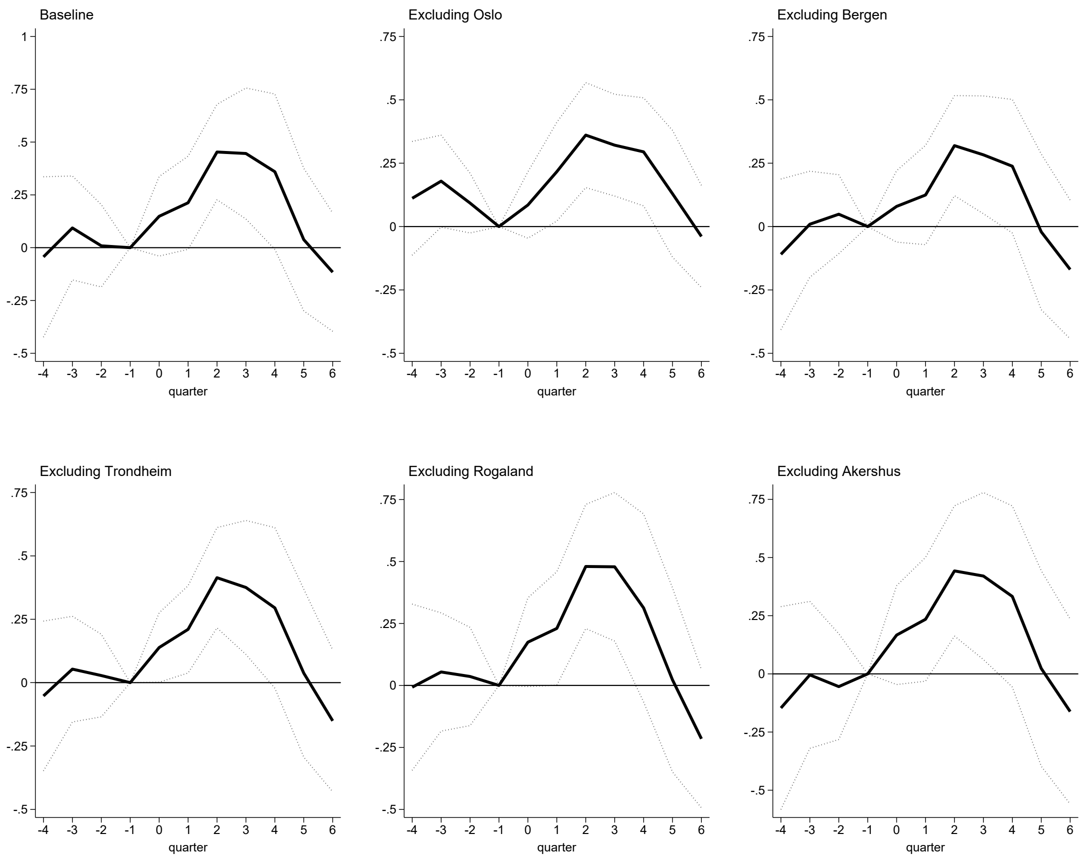
Notes: ”Total” refers to the buy-first share including all locations. ”Akershus” refers to the buy-first share computed after leaving out all moving owners transacting in the county of Akershus. ”Rogaland” refers to the buy-first share computed after leaving out all moving owners transacting in the county of Rogaland, which includes the city of Stavanger and its surrounding municipalities. ”Oslo” refers to the buy-first share computed after leaving out all moving owners transacting in the city of Oslo, etc.

Figure A.7: Estimated effects for local buy-first share and sales.



Notes: The figure plots the coefficients from estimating Equation (8) at each horizon shown on the x-axis. House prices are based on a hedonic price index (see the Appendix for details). Local buy-first share is defined as the share of locally moving owners that buy first in a given quarter. Sales is the total number of local transactions in a quarter. The local exposure $\hat{\kappa}_i$ is normalized by its standard deviation. The dashed line shows a 95% confidence interval based on two-way clustered standard errors with clustering on local housing market and quarter.

Figure A.8: Estimated house price response (additional robustness)



Notes: The figure plots the coefficients from estimating Equation (8) for quarterly house prices at each horizon shown on the x-axis for different robustness exercises. House prices are based on a hedonic price index (see the Appendix for details). The shock occurs in quarter 0 and is equal to an increase in the aggregate buy first share of one percentage point. The local exposure $\hat{\kappa}_i$ is normalized by its standard deviation. The dashed line shows a 95% confidence interval based on two-way clustered standard errors with clustering on local housing market and quarter.