The Housing Phillips Curve*

Andreas Benedictow[†],
Erling Røed Larsen[‡], and Dag Martin Sundelius[§]

December 30, 2021

Abstract

Using a high-resolution housing transaction data set, we examine the relationship between price changes and the unsold rate in the Norwegian housing market within a Phillips curve framework. We find that price changes and the unsold rate are associated, but our results indicate a reversed causality, from price changes to the unsold rate. We interpret our findings in a framework based on micro-foundations in which households decide on the sequence of buying and selling, i.e. whether to hold two or zero houses in the transition period. Data on individual sellers and buyers support the hypothesis that the propensity to hold two houses is pro-cyclical.

Keywords: Housing Phillips curve, Buying-before-selling, Unsold rate, Granger causality, Hedonic price index

JEL Codes: C20, D44, R21

*The authors are grateful to Eiendomsverdi for data. We also thank Ragnar Nymoen, André K. Anundsen, and Dag Einar Sommervoll for comments and suggestions. We are grateful for input from participants at the 93rd annual conference of the Western Economic Association International.

[†]Housing Lab, Oslo Metropolitan University and Samfunnsøkonomisk Analyse.

[‡]Housing Lab, Oslo Metropolitan University and BI Norwegian Business School.

[§]Eiendomsverdi.

1 Introduction

The Phillips curve is one of the most studied and well-known relationships in economics. In its simplest form, it refers to a relationship between the level of unemployment and the rate of subsequent wage inflation. That relationship is easy to grasp and useful in practice. After all, it may function as a gauge of how scarcity is priced. Whenever a commodity is scarce, economists believe the price of the commodity tends to increase. Conversely, when the commodity is plentiful, the price increase is modest, absent, or even reversed. While the original Phillips curve was sourced from the labor market, such curves would, could, and should be expected in other markets. This article asks a simple question: Is there a housing Phillips curve?

Yes. This answer is clearly warranted by data for Norway's capital Oslo, and supported by evidence from other large cities. We propose to use the "unsold rate" as a pressure gauge of the housing market, corresponding to the unemployment rate of the labor market. The unsold rate is the number of unsold units as a share of units for sale in the market. This article documents that there is a clear association between price changes and the unsold rate. However, the direction of causality appears to be reversed: While the causality in the labor market goes from unemployment to wage changes, the housing Phillips curve indicates that in the housing market price changes move before the unsold rate.

Scarcity may move prices, but it could also be the other way around: Prices are also a signal that people may act on and thus affect scarcity through changes in demand and supply. This article uses an interpretative framework based on micro-foundations to explain a component of this reversed causality. The core content of this framework is this: While the labor market is characterized by a search-and-match activity between employees and employers that leads to one match, the housing market is characterized by a search-and-match activity between buyers and sellers that lead to two matches. After all, an owner-occupier needs to find both a buyer of his old house and a seller of his new house. This dual search-and-match activity comes with financial implications most easily understood by keeping in mind that a moving owner-occupier needs to choose between owning two houses or no houses in the transition period. If he buys first, he owns two houses and pays two mortgages in the transition period and experiences a capital gain in a rising market or a loss in a falling market. If he sells first, he owns no houses and needs to rent in the transition period. Studying the target value functions, we observe that price developments represent a powerful influence on the relative values of buying first or selling first. When prices rise, owning two houses is more tempting. When prices fall, owning zero houses is more tempting. The implication is that sudden changes in the relative values between buying first and selling first may lead to changes in the unsold rate (Anundsen and Røed Larsen (2014)).

Our contribution lies in bringing novel data to an old idea. The data contain two key dates: the date on which a unit is announced for sale and the date on which the seller accepts the bid from the buyer. These two dates allow us to obtain a complete overview over what is in the market, and distinguish between what is for sale and what has just been sold, at any given point in time. Thus, we are able to construct a temporal grid of price changes and unsold rates with high granularity, which create an opportunity we exploit in the Granger causality regressions and in the documentation of the supporting evidence for our proposed explanation.

There are several reasons why economists should care about these findings. First, houses are assets with an aggregate value that is sufficient to move other markets (Leamer (2015)), and so we seek insights into the mechanisms governing the price formation and the consequences of the price formation. If one can compare price changes with unsold rates and use this to evaluate the overall condition of the housing market, we would like to know.

Second, it is possible that price changes have momentum and lead to feedback loops. A price change may induce a shift in the relative values of the decisions to buy first or sell first, which in turn can re-inforce the very price change that triggered it. Rising house price inflation could initiate a rush among moving owner occupiers to buy first, which increases relative demand and fuels further inflation. The presence of such dynamics in the housing market bears several policy implications that we would like to inspect more closely. On the one hand, it is useful to know that moderately-behaved house prices may allow heterogeneity in decisions to buy or sell first. On the other hand, if or when a feedback loop is triggered, it may be exacerbated if financial regulation makes it difficult to own two houses for a (short) period of time, i.e. disallows access to interim credit for moving owner-occupiers who want to buy before selling.

This article is organized as follows: In the next section, we describe the literature on Phillips curves and related work on the housing market and our thoughts on taking the Phillips curve framework to the housing market. Section 3 defines the housing Phillips curve. Section 4 describes data and the institutional arrangements of the Norwegian housing market. In section 5, we present our empirical techniques and in section 6 our findings. Section 7 lays out our interpretative framework based on micro-foundations that is consistent with reversed causality. Section 8 summarizes and discusses policy implications.

2 Literature and motivation

2.1 The Phillips curve

It is not within the scope of this article to give a full review of the vast Phillips curve literature that followed Phillips' (1958) seminal article. Instead, we outline a few key features of the early contributions and add some recent perspectives in order to set the stage for introducing the housing Phillips curve (HPC).

The Phillips curve describes an observed empirical relationship between unemployment and wage inflation. Phillips (1958) found this relationship when he studied a long time series for the UK. When unemployment was high, wages increased slowly. When unemployment was low, wages increased more rapidly. Subsequently, economists estimated Phillips curves for several countries and the Phillips curve became part of the toolkit of macroeconomics (Samuelson and Solow (1960)).

The Phillips curve's lack of theoretical foundation was subject to considerable criticism, notably by Phelps (1967, 1968) and Friedman (1968, 1977, 1995). They argued that the government could not trade higher inflation for lower unemployment permanently. The difference between nominal and real wages was pointed out. Instead, they suggested, the Phillips curve is vertical in the long run. Gordon (2018) present recent perspectives of the Friedman-Phelps approach. Gordon also proposes a framework within which one may explain how adverse supply shocks like the oil crises in the 1970s led to high unemployment and high inflation. The presence of information asymmetry was debated. Lucas (1972, 1973) and Sargent and Wallace (1975) argued that expectations are rational, so that economic agents will anticipate expansionary economic policies based on a known rule for monetary policy and adapt immediately.

The short-run Phillips curve is also known as the expectations augmented Phillips curve because an increase in expected inflation makes it shift up. Under this name it also appears in a more recent class of macroeconomic models with sticky prices, the New Keynesian dynamic stochastic general equilibrium models. In these models, there is a positive relation between the rate of inflation and the level of demand, and thus a negative relation between the rate of inflation and the rate of unemployment. This is often called the "New Keynesian Phillips curve". The New Keynesian Phillips curve implies that the government can reduce unemployment temporarily by increasing inflation, but not permanently (Clarida et al. (1999) and Blanchard and Galí (2007)).

Several other explanations of a short run trade-off have been suggested: long-term labor contracts (Fischer (1977)), sticky prices (Rotemberg (1982) and Mankiw (1985)), and non-rational expectations (Akerlof and Yellen (1985)). Other contributions reject the idea of the Phillips curve, arguing that wages and prices are determined by the market, and that competitive firms cannot just raise prices to compensate for higher wages, see e.g. Herbener (1992).

There is a more recent branch of more micro-oriented empirical analyses of the Phillips curve, which exploits disaggregated or high-frequency data. Kumar and Orrenius (2016) use state-level data from 1982 to 2013 to study the curvature of a wage-price Phillips curve using spline specifications, in which short-term unemployment is associated with increases in average and median wages while long-term unemployment is associated with the latter. Coibion and Gorodnichenko (2015) study the difference between inflation and expected inflation and the unemployment rate to explain the disinflation during the Great Recession. Antoine and Boldea (2018) study a Phillips curve at monthly frequencies and argue that this is more appropriate given the twice-quarterly monetary policy meetings. Galbács (2015) and Gordon (2018) present recent overviews of the Phillips curve literature and Bhattarai (2016) offers empirical evidence for the presence of Phillip's curves in 28 out of 35 OECD countries in the period from 1990 to 2014.

2.2 Phillips curves in other markets

The standard Phillips curve emerges from studies of the labor market and reflects the changes in the price of labor when there are changes in the scarcity of labor. A low unemployment rate mirrors a tight labor market, in which firms compete with other firms over labor. Wages increase faster when unemployment is reduced and vice versa. Since prices reflect scarcity in every market, it is reasonable to expect Phillips curve-type relationships in other markets as well. In this article, we study the housing market through a Phillips curve framework.

An early contribution can be found in Rosen and Smith (1983) who study the U.S. rental market. They find that rents are connected to excess supply or demand and estimate a natural vacancy rate for U.S. cities. They found that the natural vacancy rate ranged over a considerable spectrum, and was estimated at 6 percent for New York and 14.6 for Denver.

Gabriel and Nothaft (2001) study U.S. rents and vacancies and obtain evidence that supports the idea that rent changes reflect equilibrium deviations of the probability that a unit becomes vacant and the length of the vacancy. Lerbs and Teske (2016) find that, in Germany, a doubling of the vacancy rate at the municipality level is associated with a 5-8 percent discount in quality-controlled house prices. Zabel (2016) uses MSA level data for 1990–2011 to develop a dynamic model of the housing market. He finds that when there is excess demand, prices rise as vacancies are reduced. However, he finds an asymmetry since prices do not decline when there is excess supply and vacancies increase.

This study contributes to this literature by combining data on dates of announcements for sale and dates of acceptances of highest bid. This combination allows us to measure the number of units for sale and the number of units sold within a given period. Using transaction data, we construct a price index that allows us to study quality-controlled price changes before, within, and after the same period. This enables us to test whether a housing Phillips curve exists.

3 The Housing Phillips curve

We start out by defining the housing market equivalents to the components in the standard Phillips curve, i.e. wage inflation and the unemployment rate. The equivalent to the price for labor, the wage level, is a quality-controlled house price level. The equivalent to the unemployment rate is the ratio of available housing units to the total number of units in the housing market. The "housing market" could be defined as the housing stock. We dismiss this definition because it would not keep the analogy to the original Phillips curve intact, as the housing stock is the population of housing units and is similar to the population in an economy, not the labor force. In the labor market, the unemployment rate is the ratio of the for-hire workers to the sum of for-hire and hired workers. We let the housing market equivalent be the ratio of for-sale houses to the sum of for-sale houses and sold houses.

More precisely, the unemployment rate in period t, UR_t, is defined as the number of unemployed workers, U_t, as a share of the labor force, LF_t:

$$UR_t = U_t/LF_t. \tag{1}$$

Similarly, the unsold rate of housing units in period t, $UR_{H,t}$, is the number of unsold units as a share of units for sale in the housing market H, which is the sum of unsold units, $U_{H,t}$, and sold units in the same period, $(S_{H,t})$:

$$UR_{H,t} = U_{H,t}/(U_{H,t} + S_{H,t}). \tag{2}$$

The analogy is obviously not perfect, but we argue that it is close enough to be a useful proxy. Even in the labour market there are competing definitions: In Norway, the unemployment rate measured by the registered unemployed (by the Norwegian Labour Authority) and the labour market survey (Statistics Norway, including unregistered unemployed) may at times differ substantially.

To be a precise analogy of the unemployment rate, our definition of the unsold rate (unsold properties as a share of *properties put up for sale*) rests on the assumption that the labour force consists of people continuously looking for a new job, i.e. are on the market. This may be a bold assumption. However, in Norway, the median time spent in the same job is approximately 3,5 years, see Sørlie et al. (2012). This indicates that most people in the labor force (the denominator of the unemployment rate) are searching the labour market for better options most of the time.

In its simplest form, the housing Phillips curve represents the empirical trace of an association between the unsold rate at time t, $UR_{H,t}$, and the rate of house price change (measured as an index, in order to control for composition) at time t, $\Delta P_t = (P_t - P_{t-1})/P_t$:

$$UR_{H,t} = \alpha + \beta \Delta P_{t+s} + u_t, \tag{3}$$

in which the subscript s represents a difference in timing. It is an empirical question whether is is positive, zero, or negative. The coefficient β represents the relationship between house price changes and the levels of the unsold rate and is expected to be negative: a low unsold rate goes hand in hand with high house price inflation and vice versa. u represents the error term, assumed to be mean-zero, constant variance.

Causality may go from scarcity to prices, but it could also be the other way around. To see this, keep in mind that even though scarcity may push prices up, prices are also a signal that people may act on and thus affect scarcity through changes in demand and supply. In the original Phillips curve for the labor market, causality is normally found to go from scarcity to prices, i.e. from unemployment to wages. Here we investigate the direction of causality between housing prices and the unsold rate, and a negative s in equation (3) would represent reverse causality, i.e. that house price changes are leading the levels of the unsold rate. The relationship between the unsold rate and price change and the direction of causality are empirical questions, to which we will return in section 6. We also need a dosage of caution since what we search for, and test for, is Granger causality, which essentially is a matter of timing of the two variables, not an underlying causality mechanism.

4 Data and institutional arrangements

We use data from Eiendomsverdi, a firm that specializes in acquiring housing market data and collaborates with Real Estate Norway (the association of real estate brokerages), Finn.no (an online advertising platform), and other firms that source housing information, and combines these data with public records. About 70 percent of all transactions pass through Finn.no and real estate agents. Examples of transactions that do not pass through such market places are within-family transactions and other non-arms-length transactions.

4.1 Transaction data

Our transaction data set comprises sell price, ask price, date on which the highest bid was accepted by seller, attributes of the unit, date of advertisement registration on the online platform Finn.no, and appraisal value (for some, not all, units that have been transacted). The original data file consists of 445,810 observations and 41 variables. We study owner-occupied units, and exclude co-ops.

We trim on sell price, size, and the ratio of sell price on size, using 1 and 99 percentiles. We also trim after having estimated our hedonic model on the 0.1th and 99.9th percentile residuals and we trim on missing data. After trimming, we are left with 378,294 observations covering January 2010 - October 2017.

While the public registration date and unit attributes are sourced from official registers, we have access to three additional unique variables: the ask price, the date on which the unit was registered online, and the date on which the highest bid is accepted. The ask price is the last ask price a seller sets, and it is entered into an electronic registering system by a realtor. Typically, an ask price is not revised during the first three weeks of the sales process and only a fraction of sales involve revised ask prices. In the period before 2014, reports indicate that less than 10 percent were revised. In the period after 2014, the practice may have increased somewhat in frequency.

4.2 Data on unsold units

Eiendomsverdi registers advertisements on Finn.no. It compares every registered advertisement with the next nine months of transactions. As long as there is no match, the advertised unit is classified as "for sale" and is counted in the stock of unsold units. If it has not been registered as sold after nine months, it is removed from the for-sale stock.

4.3 Data on the buy first rate

To test for a presence of a link between observed prices and households' decisions about selling or buying first, we employ survey data for the proportion of households who reports that if they were to move, they would buy a new dwelling before selling their existing one. The survey data is collected by the analytics firm Prognosesenteret on behalf of the real estate company Eiendomsmegler 1. The survey is based on a sample of approximately 1400 households all over the country. The survey has been done at varying intervals over the years, from four to twelve times each year. We construct a quarterly time series based on monthly averages when available, otherwise a quarter is represented by a corresponding monthly observation[1].

4.4 Institutional arrangements

The home is the most important asset of most Norwegian households. Almost 80 percent of Norwegians are owner-occupiers at any given time (Røed Larsen and Sommervoll (2009)) and more than 90 percent own during their lifetime. The high proportion of owner-occupiers separates Norway from many countries, including its neighbors Sweden and Denmark. As early as 1920, more than 50 percent of Norwegian households were homeowners (see e.g. Benedictow et al. (2020)). The share was boosted after World War II, in part due to tax incentives. The incentives have been eased in latter years, but the aim of a high share of homeowners still has broad political support.

The Norwegian housing market is liquid and transparent. It is arranged as electronic auctions of houses. A brief description of the sales process would start with a seller contacting a realtor. The realtor and the seller discuss when to put the unit on the market and at what ask price. Then, the unit is announced for sale on the online platform Finn.no and sometimes, but increasingly rarely, also in national and local newspapers. There is some geographical

[1]Only data on a national level have been available to us. However, the national housing market is highly correlated with the Oslo market, with an R^2 of 0.97

variation in the process, although the basic 'rules of the game' are the same. In Oslo, the public posting of advertisement on Finn.no typically occurs on a Friday, with an announced public showing nine or ten days later, i.e. on a Sunday and a Monday. Included in the ad is an ask price, which is called a 'price suggestion' rather than a reservation price, pictures, and a detailed description of the unit. Historically, advertisements would also include an appraisal value, but recently this practice has waned. Even if sellers often hire an appraiser, the role of the appraiser is to deliver a technical report. The assessment of the market value is left to the realtor.

During the public showings, interested parties inspect the unit while the realtor is present. The seller may or may not be present. The day after the last showing, the auction commences. The auction is arranged as an ascending bid (English) auction. Bids are delivered digitally, and the first bid is usually accompanied by a proof of financing issued by a bank. The proof of financing is done in a way that masks what the maximum bid potential is. Bids may or may not include an expiration time or date. The realtor continuously informs the participants of developments in the auction. All bids are legally binding. A seller accepts the bid by making a formal acceptance through informing the realtor. This acceptance is legally binding, i.e. after acceptance the seller has essentially granted transfer of ownership. The signature meeting is often a few weeks later and the registration into public registers is done after an additional few more weeks.

5 Empirical techniques

To construct the house price index, we employ our own version of the Sale Price Appraisal Ratio (SPAR) method (Bourassa et al. (2006), de Haan et al. (2009)), in which we use a predicted price from a hedonic model in stead of the appraisal value. The SPAR-approach involves first estimating a hedonic model for a base year, then predicting each house price based on the hedonic model. Then, we compute the ratio of the sell price on the predicted price and use the median ratio for each month. This set-up has the advantage that all observations includes the sell price (the numerator), controls for type and attributes by dividing by the hedonic price (the denominator), and handles outliers by using the median, not the mean, ratio each month.

5.1 The hedonic model

To measure price growth, we first employ a price index setup that is based on a hedonic regression model. A hedonic pricing model for houses, relies on the assumption that the price for a home is a function of the marginal prices of its attributes, and that it is possible to estimate these attribute prices, see Rosen (1974).

Our model corrects for differences in the distributions of house attributes over time. For example, there is a tendency for a relatively large share of small apartments being sold in July than June in Oslo, due in part to students rushing to buy apartments before semester start. A model not adjusting for size would therefore yield a wrong estimate of the underlying growth in the price level. The construction of a hedonic model depends on the goal of the model. For example, if the goal is to obtain a price index in the classical hedonic model set-up, it might be preferable to use the logarithm of the sell price as a dependent variable so that one focuses attention of percentage growth. If the goal is to predict prices, it might be preferable to use the sell price itself as the dependent variable since the logarithm is a non-linear transformation and Jensens inequality implies that applying the exponential function to convert a predicted log(sell) to a nominal level leaves us with a bias. If the goal is to obtain a price index, one might also be reluctant to add variables that are not likely to vary over time because of the degrees of freedom the estimation of the coefficients would require.

Our hedonic model is a regression of observed sell price[2] onto a space consisting of a

[2]We use the sell price, not the logarithm of the sell price since in our SPAR set-up we model the sell price, the predicted of which is to function as an adjustment (A) in the denominator to the observed sell price.

second order polynomial of the logarithm of size, dummy variables for type, interaction variables between apartment and the second order polynomial of size, dummy variables for plots above 1000 square meters and construction epochs. Notice the lack of temporal components in equation (4).[3]

$$\begin{aligned}\hat{P}_i = \alpha + \beta_1 logSize_i + \beta_2(Sq(logSize_i) + \gamma Type_i + \delta_1(logSize \times Ap_i) \\ + \delta_2(Sq(logSize) \times Ap_i) + \epsilon Plot_i + \tau Epoch_i + u_{it},\end{aligned} \tag{4}$$

in which 'Ap' is short notation for Apartment, a dummy variable that takes on the value 1 if the unit is an apartment, and 'Sq' for squared. Subscript i refers to unit i, t time, Plot a dummy variable that is 1 if the plot is larger than 1,000 square meters, and Epoch is a vector of construction period dummies. The error term u_{it} is assumed to be mean-zero and constant variance.

5.2 The SPAR-index

Instead of explicitly estimating a time coefficient to measure growth, we use a Sale Price Appraisal Ratio (SPAR) method (see Bourassa et al. (2006) and de Haan et al. (2009)), in which the 'appraisal is the adjustment performed by diving by the predicted value in the base period, $\hat{P}_1$ from equation 4. By calculating the coefficients in 4 at a base year (we use 2014), we can get an estimate of what the value of a unit i was at that moment in time. We use this as a benchmark. This leads us to a SPAR for unit i at time t:

$$SPAR_{it} = \frac{P_i}{\hat{P}_i} = \frac{f(A_i)\lambda_t}{f(A_i)}, \tag{5}$$

[3] We are modeling the hedonic model for a base period. In a SPAR set-up, the price level increase is seen through the development of the nominator, the sell price itself, as it is measured against a base rate of the value of the combination of attributes.

in which $f(A_i)$ is the the value of the combination of attributes of unit i and λ_t is the time component in the price level, which is not directly observable. We set λ to unity for the base period and calculate the price growth from period t to $t+1$ as the growth in median SPAR ratios in period t and $t+1$.

$$\Delta P_{it+1} = \frac{median(SPAR_{it+1})}{median(SPAR_{it})} - 1 = \frac{\frac{f(A)\lambda_{t+1}}{f(A)}}{\frac{f(A)\lambda_t}{f(A)}} - 1 = \frac{\lambda_{t+1}}{\lambda_t} - 1, \tag{6}$$

in which median is the function that identifies the median across the transactions $i \in I$ at a given point in time. Thus, from using our hedonic model in a SPAR set-up we identify the price growth not caused by differences in attributes over time. Estimation results and the price index are presented in section 6.1.

5.3 Granger causality

As outlined in Section 3, economic theory does not guide us on the direction of causality between a house price index and the unsold rate. Either direction is possible. Because we are interested in the timeline of events, we employ the standard Granger causality set-up.[4] Granger (1969) provides a commonly used approach for empirical testing, in which a time series X is said to Granger-cause another time series Y if it can be shown that X provide statistically significant information about future values of Y. More specifically, we say that Y is Granger-caused by X if the coefficients on the lagged X's are statistically significant in a specification in which lagged values of Y are also included. Thus, Granger causality measures precedence, a necessary condition for causation. We also note that two-way causation is frequently found, i.e. that X Granger causes Y and Y Granger causes X.

[4]More generally, we would think of tightness and prices as being co-determined by a variety of other supply and demand factors. Thus, an alternative set-up is a VAR model determining the housing price and the unsold rate simultaneously. In this paper, we are mainly searching for the housing market Phillips curve, and regard the Granger set-up as simple and efficient for our purpose. Thus we use the simpler tool.

Therefore, we test both directions.[5] We run bi-variate regressions for UR[6] and ΔP:

$$UR_t = \alpha_{0,1} + \sum_{n=1}^{N} \alpha_{n,1} UR_{t-n} + \sum_{n=1}^{N} \beta_{n,1} \Delta P_{t-n} + u_t, \tag{7}$$

$$\Delta P_t = \alpha_{0,2} + \sum_{n=1}^{N} \alpha_{n,2} \Delta P_{t-n} + \sum_{n=1}^{N} \beta_{n,2} UR_{t-n} + w_t, \tag{8}$$

in which u and w are assumed to be nicely-behaved error terms. We test the null hypothesis that $\beta_{1,k} = \beta_{2,k} \; ... = \beta_{N,k} = 0$ for $k = 1, 2$.

We say that price changes, ΔP, Granger cause levels of the unsold rate, UR, if there are βs significantly different from zero in the first equation. This means that we reject a null hypothesis of all βs equal to zero. Likewise, we say that levels of the unsold rate, UR, Granger cause price changes if any βs in the second equation are significantly different from zero.

6 Empirical results

6.1 The hedonic price index

Table 1 shows the estimation results from equation 4 and figure 1 the corresponding hedonic price index for Oslo.

We observe in Table 1 that the hedonic model has high explanatory power. The Ajdusted R-square is 0.756 so three fourths of the variation in sell price is explained by variation in the attributes. Our model is similar in spirit to[7], and uses the same data source as, Anundsen and Røed Larsen (2018). We decided a priori, in order to preserve identical set-

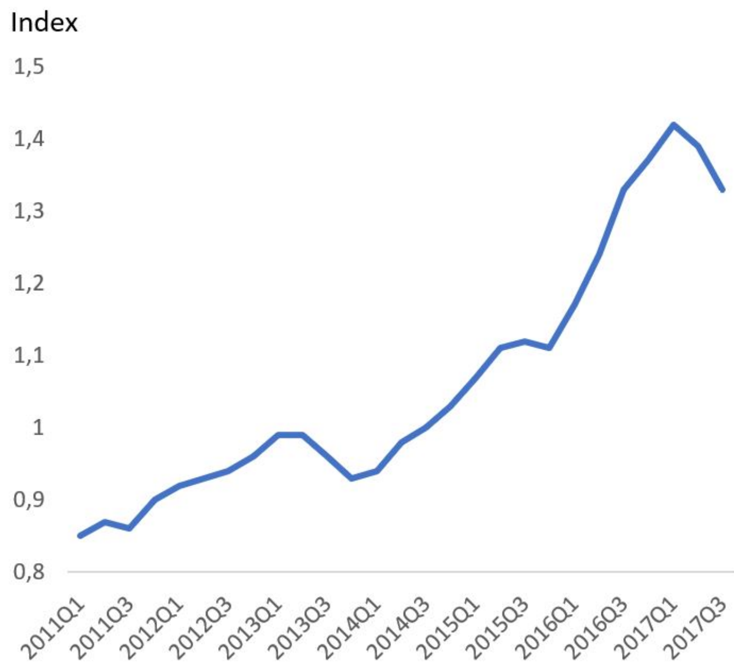
[5]We also test for different leads and lags of ΔP when estimating the Housing Phillips curve in Section 6

[6]For the sake of simplicity, we skip the subscript H on the unsold rate, UR, onwards.

[7]Their aim was high predictive power across areas, while our aim is to construct a price index for a given geographical segment, so there are differences. They used a high number of zip code dummies, which we do not need to.

ups across geographical areas, which key attributes to include in the specification, e.g. size (a second degree polynomial), type, plot size, dummies for construction period, and interaction variable.[8]

Figure 1: Hedonic house price index. Quarterly. Oslo, 2011(1) - 2017(3)



Notes: The index is constructed using a SPAR-approach (Sell Price on Appraisal Ratio) while using a hedonic model in stead of the appraisal value. The index level is relative to the index base of 2014(3), which is set equal to unity.

6.2 Causality

Panel A of Figure 2 plots UR (inverted) and quarterly changes in the house price, ΔP, from 2011 to 2017. By visual inspection, we see that they are highly correlated. High house price inflation is accompanied by low unsold rates and vice versa. As a visual supplement to the Granger causality testing, panel B displays the Adjusted R^2 of regressions of the two variables for different lags (one lag for each regression) of UR on ΔP. The horizontal axis indicates the

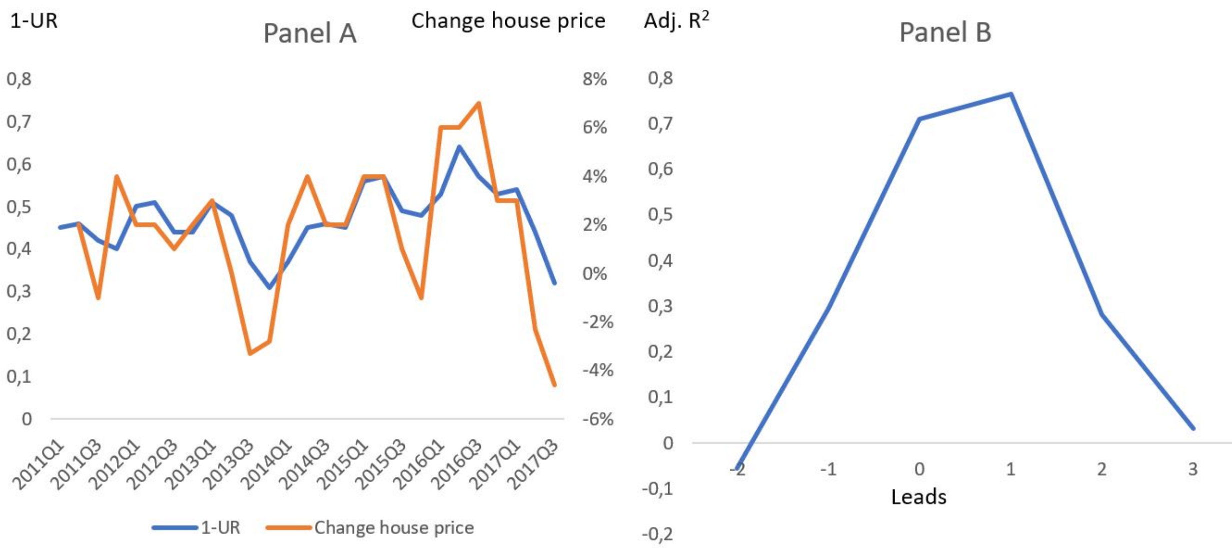
[8]To avoid any sense of data mining and to maximize simplicity, we did not perform downwards model selection for each geographical area, so we did not remove the two variables that had estimated coefficients with low statistical significance in Oslo. Thus, for Oslo, we kept the dummy for detached units and dummy for plot size above 1,000 square meters. Similarly, we made sure that the specification was shared across areas.

Table 1: Estimation results, hedonic model in equation 4

	Dependent variable:
	$\hat{P}_i$
LogSize	$-9{,}887{,}664^{***}$
	(2,072,431)
LogSizeSQ	$1{,}473{,}730^{***}$
	(211,059)
Type:Detached	6,114
	(68,848)
Type:Row House	$-192{,}255^{***}$
	(72,312)
Type:Apartment	7,886,147
	(5,187,265)
Type:ApartmentXLogSize	$-4{,}792{,}719^{**}$
	(2,132,936)
Type:ApartmentXLogSizeSQ	$678{,}370^{***}$
	(219,414)
PlotAbove1000sqm	1,751
	(26,285)
Epoch:1950-1980	$-544{,}786^{***}$
	(33,090)
Epoch:1980-2000	$-366{,}015^{***}$
	(36,122)
Epoch: $>$ 2000	$276{,}288^{***}$
	(32,205)
Constant	$19{,}370{,}027^{***}$
	(5,079,075)
Observations	7,881
R^2	0.756
Adjusted R^2	0.756
Residual Std. Error	1,031,183.000 (df = 7869)
F Statistic	$2{,}222.129^{***}$ (df = 11; 7869)
Note:	*p<0.1; **p<0.05; ***p<0.01
	Base year 2014

number of quarters ΔP is leading on UR, and the vertical axis the corresponding Adjusted R^2. We observe that the highest Adjusted R^2 of 0.76 is achieved when house price changes lead UR by one quarter.

Figure 2: House price changes and unsold rates. Oslo, 2011-2017. Panel A: Quarterly house price changes and UR (inverted). Panel B: Correlation of house price changes and UR (inverted) at different lags of UR. A positive figure indicates house price changes lead on UR



Notes: The house price index is constructed using a SPAR-approach (Sell Price on Appraisal Ratio) while using a hedonic model in stead of the appraisal value. The unsold rate (UR) is the number of unsold units as a share of units for sale in the housing market, which is the sum of unsold and sold units in the same period.

As described in subsection 5.3, we perform a two-directional test of Granger causality for the unsold rate and changes in the price index. We estimate both equations 7 and 8 with 1-5 lags, e. g. we test the respective null hypotheses, see Table 2. The F-statistics reported in brackets are the Wald statistics for the joint hypothesis $\beta_1 = \beta_2 ... = \beta_N = 0$ for equation 7 and 8, respectively.

For 1-3 lags we cannot reject the hypothesis that UR does not Granger cause ΔP, but we do reject the hypothesis that ΔP does not Granger cause UR. Thus, our evidence suggest that Granger causality runs one way from ΔP to UR and not the other way around. The estimate with one lag provides the best fit.

Table 2: Granger causality. Price change and unsold rate. Oslo, 2011(1)-2017(3)

H_0: $\beta_1 = \beta_2 \, ... = \beta_N = 0$	P-value (F-statistic) No. of lags. N=5				
	1	2	3	4	5
$H_0 : \Delta P$ does not Granger cause UR	0.0010***	0.0112*	0.0112*	0.0059**	0.0378*
(ΔP coefficients are zero)	(14.42)	(5.74)	(5.13)	(5.98)	(3.68)
$H_0 : UR$ does not Granger cause ΔP	0.5940	0.5108	0.3300	0.0245*	0.1074
(UR coefficients are zero)	(0.29)	(0.69)	(1.23)	(4.02)	(2.44)

Notes: We use the software package EViews to test for Granger causality. *** Indicates significance level 0.001,** = 0.01 and * = 0.05.

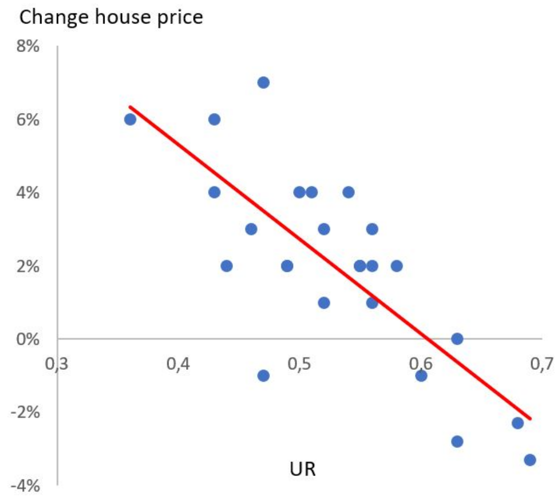
6.3 The housing Phillips curve

Based on the results above, we estimate the Phillips curve by regressing UR_t on ΔP_{t-1} and an intercept. The highly significant estimates of the regression line is presented in Table 3. Figure 3 displays the housing Phillips curve by plotting the lagged quarterly change in the price index versus the level of UR and the regression line, i. e. the price changes for quarter q-1 are plotted against the UR for quarter q. Large price increases are followed by low levels of UR and vice versa. We also estimate the Phillips curve with up to 3 lags and 3 leads. In line with the Granger test, the best fit is achieved with one lag.

Table 3: The housing Phillips curve. UR on lagged ΔP. Oslo, 2011(1)-2017(3)

	Dependent variable UR (st.err.) Oslo
ΔP_{t-1}	-2.322^{**}
	(0.389)
Intercept	0.575^{***}
	(0.013)
Adj. R^2	0.591
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 3: The Phillips housing curve. Oslo, 2011(1)-2017(3)



Notes: The house price index is constructed using a SPAR-approach (Sell Price on Appraisal Ratio) while using a hedonic model in stead of the appraisal value. The unsold rate (UR) is the number of unsold units as a share of units for sale in the housing market, which is the sum of unsold and sold units in the same period. The Phillips curve is estimated by regressing UR_t on ΔP_{t-1} and an intercept

6.4 Other cities

In subsections 6.2 and 6.3, we find clear evidence of a housing Phillips curve in Oslo, and that ΔP Granger causes UR.

However, there is not one single, homogeneous housing market in Norway, but rather many local markets. Norway is a geographically large and sparsely populated country, with a population about 5.5 million people. The air distance from Vadsø in the north of Norway to Kristiansand in the south of Norway is longer than the distance from Kristiansand to Florence, Italy.[9] Sub-markets emerge from geographical heterogeneity in regulations and other institutional conditions and the size of and developments in local labor markets. Oslo with its 680,000 inhabitants is the only truly large housing market in Norway, interacting with a large and diverse labor market. Therefore, the main focus of attention in this paper is on Oslo. For the sake of comparison, we repeat the same exercise for three other Norwegian cities, Trondheim (180,000 inhabitants), Bergen (270,000) and Stavanger (130,000).

[9]Both distances are just over 1,000 miles.

Table 4: The housing Phillips curve. Trondheim, Bergen, and Stavanger, 2011(1)-2017(3)

	Dependent variable (st. err.) = UR		
	Trondheim	Bergen	Stavanger
ΔP_{t-1}	-1.53**	-1.44**	-2.22**
	(0.47)	(0.36)	(0.75)
Intercept	0.57***	0.58***	0.68***
	(0.013)	(0.01)	(0.02)
Adj. R^2	0.28	0.37	0.24

Note:*p<0.1; **p<0.05; ***p<0.01. n=1 for Trondheim and 0 for Bergen and Stavanger

Table 5: Granger causality. Price change and unsold rate. Trondheim, Bergen, Stavanger, 2011(1)-2017(3)

H_0: $\beta_1 = \beta_2 ... = \beta_N = 0$	P-value (F-statistic) No. of lags. N=5				
	1	2	3	4	5
Trondheim					
$H_0 : \Delta P$ does not Granger cause UR	0.0053**	0.0016**	0.0009***	0.0014**	0.0046**
$H_0 : UR$ does not Granger cause ΔP	0.0415*	0.1188	0.2007	0.0773	0.0491*
Bergen					
$H_0 : \Delta P$ does not Granger cause UR	0.3315	0.2131	0.6574	0.8483	0.0378*
$H_0 : UR$ does not Granger cause ΔP	0.7099	0.0999	0.3434	0.5065	0.2179
Stavanger					
$H_0 : \Delta P$ does not Granger cause UR	0.1975	0.6426	2566	0.9721	0.1922
$H_0 : UR$ does not Granger cause ΔP	0.2282	0.7713	0.1352	0.2130	1732

Notes: We use the software package EViews to test for Granger causality. *** indicates significance level 0.001,** = 0.01 and * = 0.05.

We find clear evidence for housing Phillips curves in all three cities, as shown in Table 4. Like the case of Oslo, data for Trondheim also show clear evidence of reverse causality, see Table 5. However, that is not the case for Stavanger and Bergen, where we find no clear indication of the direction of causality. The differing results may be attributable to several factors affecting market dynamics. Stavanger and Bergen are smaller cities with less diverse labor markets. The Stavanger market in particular, is unique and behaves differently than other Norwegian markets. Stavanger is located on the west coast and is the petroleum capital of Norway. It serves as host for oil companies and off-shore activities and is home to a visiting international audience. Stavanger is also a twin city with neighbouring Sandnes, and both markets are sensitive to the cycle in the oil market. Bergen is also located on the west coast and sensitive to the petroleum sector, although at a smaller scale than Stavanger. Hosting two large universities brings a significant population of students to Bergen with a large share of the population on short term rental contracts and large fluctuations in supply and demand in the periods between university semesters.

7 Micro foundations

Our prior is that causality goes from scarcity to price, as in the standard Phillips curve literature. However, in the housing market causality, or at least the timing of events, appears to be reversed since our empirical evidence suggests that price changes Granger cause unsold rates in Oslo. In this section we present a skeleton model consistent with such reversed causality. A related approach, which includes a more elaborate model, is found in Moen et al. (2019). They argue that moving home-owners prefer to buy first whenever there are more buyers than sellers in the market, and that this leads to multiple steady state equilibria and large fluctuations. See also Head et al. (2014) and Guren (2018) for supplementary explanations of search and match dynamics and house price momentum respectively.

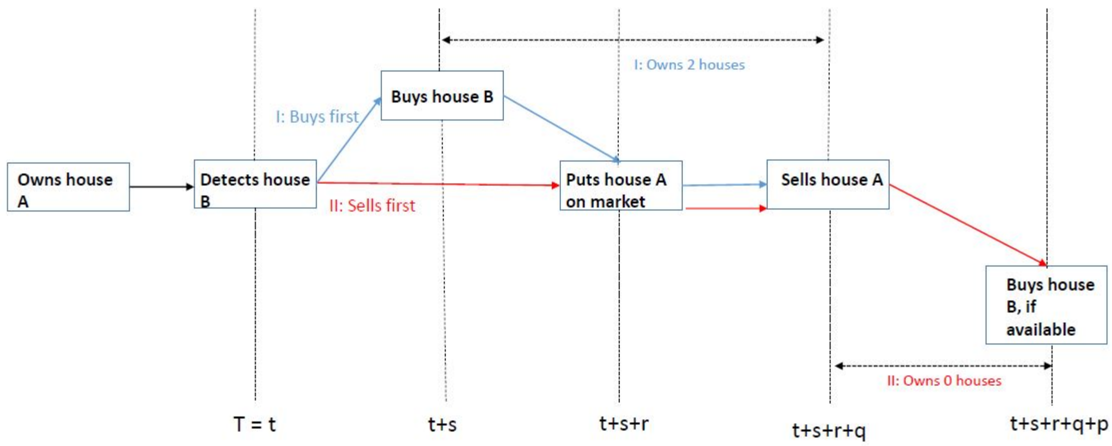
7.1 Reversed causality explained by searching and matching in the housing market

The housing market is characterized by a simultaneous search-and-match activity in which a moving owner-occupier attempts to locate two matches: a buyer of his old house and a seller of his new house. This dual search-and-match activity comes with financial implications most easily understood by keeping in mind that a moving owner-occupier needs to choose between owning two houses or no houses in the transition period.

Consider first a simple timeline of a moving owner-occupier, as illustrated in Figure 4.

While moving and transfer of ownership might occur on different dates, we simplify here in order to illustrate the main point of holding zero or two units. We let a sell date imply that the seller transfers ownership and moves out of his old house.

Figure 4: Timeline buy-first vs sell-first



If a moving owner-occupier of house A first buys a house B, this household will hold two houses, A and B, in a transition period. In Figure 4, the path of a buy-first household is illustrated by the blue line and that of a sell-first household by the red line. If house prices increase in that period, the buy-first household enjoys price appreciation of two assets during the holding time. At the same time, the buy-first household services two mortgages. Finally, by buying the house B when the household detects it, the household locks in a utility gain since it obtains a good match between household preferences and the house attributes of house B.

If the household sells first, the household foregoes the appreciation of two houses, but also avoids interest on two mortgages. Moreover, the household locks in utility from equity certainty, which means that the household avoids risking buying a more expensive house than they would have had they known the magnitude of the realized home equity. However, the sell-first household must rent a house in the transition period. Additionally, there is a probability that some other buyer buys house B and the household must settle for another,

Table 6: Benefits and costs of holding two or zero houses in the transition period

No. houses owned	Benefits	Costs
2	Price appreciation of two assets (given rising prices)	Service of two mortgages
	Locks in utility gain of good match	Equity uncertainty
0	Locks in equity certainty	Cost of renting a house
		Risk of losing preferred house

potentially sub-optimal, house C. The probability of losing out on house B increases as the time in transition increases. This may imply a loss of match-utility since house C may yield less utility than house B. Table 6 contains a sketch of the pros and cons of holding two or zero houses in the transition period.

The decision of owning zero or two houses is affected by the price development in the transition period if the moving owner-occupier has extra-polative expectations[10]. Thus, we sketch an idea about a link from observed prices to households' decisions about selling or buying first that contains the following elements:

- A change in prices leads to a change in expected prices and thus the expected value of holding two houses,
- which leads to a change in the relative values of holding two houses vs holding zero,
- which with preference heterogeneity implies that some, but not all, moving owner-occupiers change their decisions from sell-first to buy-first or vice versa,
- which leads to an observable change in the frequency of moving occupiers buying first,
- which leads to a change in the number of unsold units as a share of the sum of unsold units and sold units, i.e. a change in the unsold rate.

[10]Based on US survey data Armona et al. (2017) find that house price expectations are revised consistently with short-term price momentum

7.2 A permanent shift in the buy-first rate can result in a permanent change in the unsold rate

The dynamics of a shift in the buy first rate (BFR) are not completely straight forward. First, if increasing prices result in more homeowners wanting to buy first, then in the next period the very same homeowners will have to sell their old home, all else equal reversing the surplus demand from the previous period. However, new cohorts of sellers/buyers enter the market in each period. The net outcome depends on their behaviour. In table 7, we illustrate in a stylized example how a permanent shift in the BFR may lead to a new steady state with a lower unsold rate.

Table 7: The unsold rate and the buy-first rate. An illustrative example.

Period	Cohort	BFR^c	Buy First			Sell First			$Sold_t^c$	$\Delta Unsold_t^c$	$Unsold_t$	UR_t
			Sell= SBF_t^c	Buy= BBF_t^c	Net supply= NBF_t^c	Sell= SSF_t^c	Buy= BSF_t^c	Net supply= NSF_t^c				
1	0	0.5	500	0	500	0	500	-500	500	0		
	1	0.5	0	500	-500	500	0	500	500	0	2,000	0.67
2	1	0.5	500	0	500	0	500	-500	500	0		
	2	0.7	0	700	-700	300	0	300	700	-400	1,600	0.57
3	2	0.7	700	0	700	0	300	-300	300	400		
	3	0.7	0	700	-700	300	0	300	700	-400	1,600	0.62

Note: The table shows the BFR, the supply and demand of units of housing from people buying and selling first, respectively, the resulting change in unsold units from the previous period, the number of sold and unsold units and the unsold rate for succeeding cohorts and periods.

Each cohort entering the market consists of a number of home buyers, either buying first or selling first. Among those buying first, SBF_t^c is the number of properties put up for *sale* by cohort c in period t, BBF_t^c is the number of properties *bought* by cohort c in period t and their net supply is given by NBF_t^c=SBF_t^c-BBF_t^c. Correspondingly, net supply by those selling first is given by NSF_t^c. Accordingly, the change in net supply in period t is given by:

$$\Delta Unsold_t = NBF_t^{c-1} + NSF_t^c + NBF_t^c + NSF_t^{c-1} \tag{9}$$

in which $NBF_t^{c-1} + NSF_t^c$ represents new supply in period t and $NBF_t^c + NSF_t^{c-1}$ represents new demand in the same period.

In this example, we only consider those who are already in the housing market and move from one self-owned home to another (and not new entries like first-time buyers and investors or exits by transition to rent, death, investors offloading property etc., which would cause a net increase or a net reduction in demand, respectively). New buyers can buy from new sellers or from a stock of unsold units.[11] Buyers always get to buy; thus if they have special preferences they buy first.[12] New sellers may sell to new buyers or their home enters the inventory, i.e. the unsold category.

We assume that in each period a new cohort of 1,000 owners/homes enters the market, and the owners intend to buy a new home and sell the old. Initially, the market is in a steady state, with a 50/50 split between those who buy and sell first, and a stock of 2,000 unsold homes from previous cohorts.

To see this, consider the process outlined in Table 7. In period 1, those who buy first in cohort 1 sell 0 homes (SBF_1^1) and buy 500 (BBF_1^1), which implies a net supply of new homes to the market of -500 (NBF_1^1). This is offset by those in cohort 1 who sell first, which implies a net supply of 500 homes (NSF_1^1). Thus, there is no change in the number of unsold units (inventory), i.e. $\Delta Unsold_1^1 = 0$, which leaves the stock of unsold homes ($Unsold_1$) unchanged at 2,000 units. The unsold rate UR_t is unchanged at 0.67.[13]

In period 2, the 500 owners who sold first in period 1 buy a house from the 500 owners who bought first in period 1 or from the inventory.[14] A steady state would occur if the behavior of cohort 1 (and previous cohorts) is repeated by the following cohorts.

However, let us assume that from cohort 2 and onward, there is a permanent shift in the buy-first share from 50 to 70 percent. The change in net supply in period 2 is found by inserting from Table 7 in equation 9:

[11] To the extent that new buyers buy from the stock of unsold units, new sellers' properties replace these in the stock of unsold homes.

[12] This implies that the number of buyers = the number of sold = turnover.

[13] $UR = Unsold/(Sold + Unsold) = 2,000/(1,000 + 2,000) = 0.67$

[14] The two extremes are: All 500 sell-first buyers buy from the 500 buy-first sellers or all 500 sell-first buyers buy from the inventory (and not at all from the 500 buy-first sellers).

$$\Delta Unsold_2 = NBF_2^1 + NSF_2^2 + NBF_2^2 + NSF_2^1 = 500 + 300 - 700 - 500 = -400, \quad (10)$$

in which $NBF_2^1 + NSF_2^2 = 500 + 300 = 800$ represents the aggregate new supply in period 2 and $NBF_2^2 + NSF_2^1 = -700 - 500 = -1,200$ represents the aggregate new demand (i.e. negative supply).

This means that new units put up for sale falls to 800 while aggregate demand increases to 1,200 units. As a result of this excess demand the stock of unsold units falls by 400 ($\Delta Unsold_2$), to 1,600 ($Unsold_2$). Thus, UR falls to 0.57 in period 2.[15] However, in period 3 UR increases to 0.62, as the number of sold units falls to 1000 while the number of unsold stays at 1,600. After one period of overshooting, a new steady state with a higher BFR is reached: the stock of unsold is lower (1600), while the number of sold has returned to the level of the initial steady state (1000). Thus, UR is permanently lower.

In this example our pressure gauge UR will decrease following a permanent increase in BFR, resulting in fiercer competition for available homes and a lasting increase in the price pressure.[16].

There has been a substantial amount of work studying the relationship between price and turnover in housing markets, see e.g. Stein (1995), Clayton et al. (2010) and Dröes and Francke (2018). Housing market cycles are typically featured by a positive correlation of prices and trading volume. It is easy to see the parallel to the negative relationship we establish between housing prices and the unsold rate in the present paper.

However, the unsold rate has some different features. This is illustrated in table 7 in which a permanent shift in the BFR implies a *temporary* shift in turnover but a *permanent* shift in UR. Thus, in this case, turnover does not reflect the shift in the market pressure, which suggests that UR could be a better gauge.

[15] $UR = Unsold/(Sold + Unsold) = 1600/(1600 + 1200) = 0.57$.

[16] Note that in the illustrative example with 1,000 new sellers each period, the initial stock of unsold must be at least 400 to avoid a negative UR after the shift in BFR

Table 8: Granger causality. Price change and buy first rate. Oslo, 2011(1)-2017(3)

H_0: $\beta_1 = \beta_2 ... = \beta_N = 0$	P-value (F-statistic) No. of lags. N=5				
	1	2	3	4	5
H_0 : ΔP does not Granger cause BFR	0.0009***	0.0032**	0.0355*	0.1111	0.1755
(ΔP coefficients are zero)	(15.35)	(8.43)	(3.86)	(2.48)	(2.13)
H_0 : BFR does not Granger cause ΔP	0.91	0.2678	0.5706	0.1849	0.2459
(BFR coefficients are zero)	(0.013)	(1.43)	(0.70)	(1.91)	(1.73)

Notes: We use the software package EViews to test for Granger causality. *** indicates significance level 0.001,** = 0.01 and * = 0.05.

7.3 Historical correlation

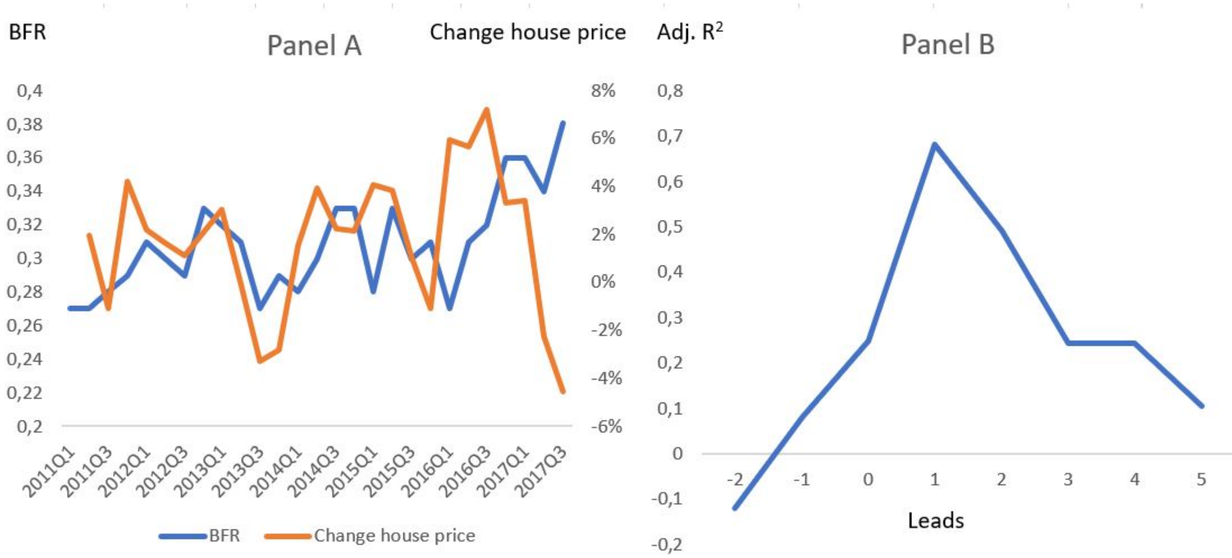
In support of the reasoning in this simple framework, Panel A in Figure 5 indicates a close relationship between changes in the house price index and the buy-first rate, BFR, i.e. the share of households that want to buy before selling, which implies that they hold two dwellings in the transition period.[17] Periods of moderate house price increases are associated with around-average values of the buy-first rate. Rapidly increasing house prices are associated with a larger share of moving owner-occupiers who buy first, and vice versa. Thus, our results are consistent with Anenberg and Bayer (2020), who find empirical evidence that indicates that the dual search and match problem is a substantial driver of fluctuations in transaction volumes and price volatility in the housing market.

Panel B of Figure 5 shows that the highest correlation between house price changes, ΔP, and the buy-first rate, BFR, occurs when ΔP leads on BFR by one period, with an estimated Adjusted R^2 of 0.68.

We perform a two-directional test of Granger causality for the buy first rate and changes in the price index, as described in subsection 6.2. Our results are tabulated in Table 8. For 1-3 lags we cannot reject the hypothesis that BFR does not Granger cause ΔP but we

[17]Extremely high house price growth in Oslo in 2016 (24 per cent from 2015 Q4 to 2016 Q4) was followed by a sharp downturn in 2017. These extreme amplitudes may explain the seemingly weakened relationship between the ΔP in Oslo and BFR for Norway in this period.

Figure 5: House price changes and buy first rates (BFR). Oslo, 2011(1) - 2017(3). Panel A: Quarterly house price changes and BFR. Panel B: Correlation of house price changes and BFR at different lags of BFR. A positive figure indicates house price changes lead on BFR



Notes: The house price index is constructed using a SPAR-approach (Sell Price on Appraisal Ratio) while using a hedonic model in stead of the appraisal value. The BFR reflects the proportion of households who reports that if they were to move, they would buy a new dwelling before selling their existing one.

do reject the hypothesis that ΔP does not Granger cause BFR. Thus, Granger causality appears to run one way from ΔP to BFR and not the other way around. Again, the estimate with one lag provides the best fit.

Thus, these results are consistent with the notion that price changes have momentum and lead to feedback loops, and that such feedback loops initially are triggered by price changes. If a price change induces a shift in the relative values of the decisions to buy or sell first, this could in turn reinforce the price change that triggered it: Rising house price inflation could initiate an increase in buy-first propensities among moving owner-occupiers, which increases relative demand, which in turns induces price increases.

8 Concluding remarks

We find clear evidence of a Phillips curve relationship in the Oslo housing market. While the classical Phillips curve in the labor market represents a scarcity impulse that yields a price response, the housing Phillips curve appears to involve a reverse causality. We propose a simple framework within which we can interpret this finding. It involves sketching the costs and benefits of holding 0 (sell-first) or 2 (buy-first) units in the transition period and explaining how price changes affect the relative values of holding 0 or 2 houses.

This is purely an empirical paper, and it makes several contributions to the literature on the functioning of the housing market. First, although there exist several studies of the link between scarcity and prices in the housing market, we have not found an explicit estimation of a housing Phillips curve. To the best of our knowledge, we are the first to do this. Second, we propose using the unsold rate as a pressure gauge of the housing market, corresponding to the unemployment rate of the labor market. We also acquire data that allow us to estimate this rate. Third, we find empirical evidence of reversed causality, or at least reversed timing of events, in the housing Phillips curve. The Granger causality goes from price changes to the unsold rate, and not the other way around. Fourth, this reversal is explained within the proposed framework, which incorporates the specific characteristic of the housing market of a dual search and match problem, in which moving owner-occupiers are sellers and buyers in the same market. Fifth, we bring empirical evidence on a new indicator, the buy-first rate, study how this variable co-varies with price changes and show how a permanent shift in the buy-first rate may lead to a permanently lower unsold rate. Our example also suggests that the unsold rate may be a better pressure gauge than turnover.

References

Akerlof, G. A. and Yellen, J. L. (1985). A near-rational model of the business cycle, with wage and price inertia. *The Quarterly Journal of Economics*, 100(Supplement):823–838.

Anenberg, E. and Bayer, P. (2020). Endogenous sources of volatility in housing markets: the joint buyer-seller problem. *International Economic Review*.

Antoine, B. and Boldea, O. (2018). Efficient estimation with time-varying information and the new keynesian phillips curve. *Journal of Econometrics*, 204(2):268–300.

Anundsen, A. K. and Røed Larsen, E. (2014). Strategic sequencing behavior among owner-occupiers: The role played by sell-first movers in a housing recovery. *Journal of European Real Estate Research*, 7(3):295–306.

Anundsen, A. K. and Røed Larsen, E. (2018). Testing for micro efficiency in the housing market. *International Economic Review*, 59(4):2133–2162.

Armona, L., Fuster, A., and Zafar, B. (2017). Home price expectations and behavior: Evidence from a randomized information experiment. *Review of Economic Studies, forthcoming*.

Benedictow, A., Kostøl, F. B., and Røtnes, R. (2020). Boligskatt i den norske boligmodellen (housing tax in the norwegian housing model). *Rapport*, 4.

Bhattarai, K. (2016). Unemployment–inflation trade-offs in oecd countries. *Economic modelling*, 58:93–103.

Blanchard, O. and Galí, J. (2007). Real wage rigidities and the new keynesian model. *Journal of money, credit and banking*, 39:35–65.

Bourassa, S. C., Hoesli, M., and Sun, J. (2006). A simple alternative house price method. *Journal of Housing Economics*, 15:80–97.

Clarida, R., Galí, J., and Gertler, M. (1999). The science of monetary policy: a new keynesian perspective. *Journal of economic literature*, 37(4):1661–1707.

Clayton, J., Miller, N., and Peng, L. (2010). Price-volume correlation in the housing market: causality and co-movements. *The Journal of Real Estate Finance and Economics*, 40(1):14–40.

Coibion, O. and Gorodnichenko, Y. (2015). Is the phillips curve alive and well after all? inflation expectations and the missing disinflation. *American Economic Journal: Macroeconomics*, 7(1):197–232.

de Haan, J., van der Wal, E., and de Vries, P. (2009). The measurement of house prices: A review of the sale price appraisal ratio method. *Journal of Economic and Social Measurement*, 34(2-3):51–86.

Dröes, M. I. and Francke, M. K. (2018). What causes the positive price-turnover correlation in european housing markets? *The Journal of Real Estate Finance and Economics*, 57(4):618–646.

Fischer, S. (1977). Long-term contracts, rational expectations, and the optimal money supply rule. *Journal of Political Economy*, 85(1):191–205.

Friedman, M. (1968). The role of monetary policy. *American Economic Review*, 58(1):1–17.

Friedman, M. (1977). Nobel lecture: Inflation and unemployment. *Journal of Political Economy*, 85(3):451–472.

Friedman, M. (1995). The role of monetary policy. In *Essential Readings in Economics*, pages 215–231. Springer.

Gabriel, S. A. and Nothaft, F. E. (2001). Rental housing markets, the incidence and duration of vacancy, and the natural vacancy rate. *Journal of Urban Economics*, 49(1):121–149.

Galbács, P. (2015). *The Theory of New Classical Macroeconomics*. Springer.

Gordon, R. J. (2018). Friedman and phelps on the phillips curve viewed from a half century's perspective. *Review of Keynesian Economics*, 6(4):425–436.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: journal of the Econometric Society*, pages 424–438.

Guren, A. M. (2018). House price momentum and strategic complementarity. *Journal of Political Economy*, 126(3):1172–1218.

Head, A., Lloyd-Ellis, H., and Sun, H. (2014). Search, liquidity, and the dynamics of house prices and construction. *American Economic Review*, 104(4):1172–1210.

Herbener, J. (1992). The fallacy of the phillips curve. *Dissent on Keynes: A Critical Appraisal of Keynesian Economics, New York, NY: Prager*, pages 51–71.

Kumar, A. and Orrenius, P. M. (2016). A closer look at the phillips curve using state-level data. *Journal of Macroeconomics*, 47:84–102.

Leamer, E. E. (2015). Housing really is the business cycle: what survives the lessons of 2008–09? *Journal of Money, Credit and Banking*, 47(S1):43–50.

Lerbs, O. and Teske, M. (2016). The house price-vacancy curve. *ZEW-Centre for European Economic Research Discussion Paper*, 1(16-082).

Lucas, R. E. (1973). Some international evidence on output-inflation tradeoffs. *The American Economic Review*, 63(3):326–334.

Lucas Jr, R. E. (1972). Expectations and the neutrality of money. *Journal of economic theory*, 4(2):103–124.

Mankiw, N. G. (1985). Small menu costs and large business cycles: A macroeconomic model of monopoly. *The Quarterly Journal of Economics*, 100(2):529–537.

Moen, E. R., Nenov, P. T., and Sniekers, F. (2019). Buying first or selling first in housing markets. *Journal of the European Economic Association*.

Phelps, E. S. (1967). Phillips curves, expectations of inflation and optimal unemployment over time. *Economica*, pages 254–281.

Phelps, E. S. (1968). Money-wage dynamics and labor-market equilibrium. *Journal of political economy*, 76(4, Part 2):678–711.

Phillips, A. W. (1958). The relation between unemployment and the rate of change of money wage rates in the united kingdom, 1861–1957 1. *Economica*, 25(100):283–299.

Røed Larsen, E. and Sommervoll, D. E. (2009). The impact on rent from tenant and landlord characteristics and interaction. *Regional Science and Urban Economics*, 39(3):316–322.

Rosen, K. T. and Smith, L. B. (1983). The price-adjustment process for rental housing and the natural vacancy rate. *The American Economic Review*, 73(4):779–786.

Rosen, S. (1974). Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of political economy*, 82(1):34–55.

Rotemberg, J. J. (1982). Monopolistic price adjustment and aggregate output. *The Review of Economic Studies*, 49(4):517–531.

Samuelson, P. A. and Solow, R. M. (1960). Analytical aspects of anti-inflation policy. *The American Economic Review*, 50(2):177–194.

Sargent, T. J. and Wallace, N. (1975). " rational" expectations, the optimal monetary instrument, and the optimal money supply rule. *Journal of political economy*, 83(2):241–254.

Sørlie, K., Aure, M., and Langset, B. (2012). Hvorfor flytte? hvorfor bli boende? bo-og flyttemotiver de første årene på 2000-tallet (why move? why stay? motifs in the early 2000's). *NIBR-rapport 2012:22*.

Stein, J. C. (1995). Prices and trading volume in the housing market: A model with down-payment effects. *The Quarterly Journal of Economics*, 110(2):379–406.

Zabel, J. (2016). A dynamic model of the housing market: The role of vacancies. *The Journal of Real Estate Finance and Economics*, 53(3):368–391.