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NORGES BANK RESEARCH

6 | 2016

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ISSN 1502-8143 (online)
ISBN 978-82-7553-628-8 (online)

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ISSN 1502-819-0 (online)
ISBN 978-82-7553-907-4 (online)

Testing for micro efficiency in the housing market*

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April 15, 2016

Abstract

While aggregate house price indices display time persistence, less is known about micro persistence. This article proposes that absence of micro persistence implies that an excessively high or low sell price in one transaction is not repeated in the next transaction. We exploit a unique Norwegian data set of publically registered housing transactions between 2002 and 2014 and follow housing units over time to see if excessive prices persist or revert. In a regression with time- and unit-fixed effects of sell-price-to-predicted-price ratios on previous sell-price-to-predicted-price ratios, we reject persistence and find substantial reversion. We also test for possible arbitrage opportunities in the form of excess returns. Once we control for price increases that are due to home improvements, we document that there is little scope for profitable arbitrage in excess of the market return. The overall impression is that the Norwegian housing market is relatively micro efficient.

Keywords: ***Arbitrage; Housing Market; Micro Efficiency; Persistence; Repeat Sales.***

JEL classification: ***R31; D12; D44; C21.***

*This paper should not be reported as representing the views of Norges Bank. The views expressed are those of the authors and do not necessarily reflect those of Norges Bank. The paper was presented at the 2016 annual AEA Meeting, the 2016 NBRE Spring meeting, the 2015 ENHR workshop, and the 2015 annual WEAI conference. We thank participants at research seminars at the University of Stavanger, Statistics Norway, and Norges Bank. We are grateful to Farooq Akram, Lasse Eika, Solveig Erlandsen, Joe Gyourko, Steffen Grønneberg, Mathias Hoffmann, Steinar Holden, Andreas Kostøl, Spencer Norman, Are Oust, Asbjørn Rødseth, Bernt Stigum, Kjetil Storesletten, Genaro Succarat, Paloma Taltavull de La Paz, and Robert Wassmer for stimulating comments and feedback that helped improve this manuscript.

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1 Introduction

House price indices display time persistence. This has led several researchers to the position that returns contain predictable components. However, evidence based on aggregate indices is only part of the story because the development of an index between two time periods reflects movements in the aggregate, i.e. between two scalars that each summarizes thousands of individual transaction prices. An index reveals little about relative prices, which are interesting because economists believe markets coordinate and assimilate information through them, so that people may differentiate between bargains and rip-offs. When people search for bargains and seek to avoid rip-offs, the resulting prices incorporate these efforts, which in turn are reflected in partial prices for housing attributes. This price-correcting capacity lies at the heart of an efficient market. We are interested in how the housing market handles relative prices and this article asks one main question: When a house is sold at an excessively high or low price, what happens to the price the next time the house is transacted?

If there is persistence, a high first sell price relative to an expected price tends to be followed by a high second price relative to an expected price. If there is no persistence but reversion in the spread between sell and expected prices, an investor who paid more than the expected price, whatever the reason, cannot expect to collect a similar premium upon selling the unit. He bought at a high price and experiences a return lower than the market return. Conversely, a buyer who purchases at a price lower than the expected price can reasonably expect to sell at a price that is closer to the expected price. Thus, absence of persistence and presence of reversion imply that the market punishes over-payments and rewards under-payments. At the same time, if under-payments are rewarded, it could be possible to detect units that are under-priced *ex ante* and make an *ex post* gain by investing in these units. For this reason, we investigate the profit possibilities in purchases of *ex ante* undervalued housing units.

Our exploration of housing market efficiency starts by documenting that Norwegian data follow the international pattern of time persistence in aggregate house price indices. Exploiting data on 472,378 transactions on owner-occupier units between 2002 and 2014, we do, however, find that the housing market does not display evidence of micro persistence. To reach this conclusion, we follow units in repeated transactions. We detect a clear pattern. When the first sell price is higher than the price prediction of a standard hedonic model, the price is much closer to the model-predicted price when the unit is sold the next time. The only exception is when the third sell price is higher than the hedonic model's price prediction. Then, the second sell price is also high. The presence of such persistence demonstrates that the market simply discovers what the hedonic model does not, namely key omitted variables. In fact, using the ask price, which reflects the seller's knowledge of the unit (Benitez-Silva et al. (2015), Windsor et al. (2015)), we find the same phenomenon. Moreover, there is little sign of persistence when we consider a repeated cross-section model in which we control for unit-fixed effects. Taking the analysis one step further, we follow an approach similar to Linnemann (1986) and test whether profitable arbitrage opportunities can be made by investing in units that are under-priced relative to the hedonic model *ex ante*. Once we control for home improvements, there is little evidence for an arbitrage opportunity. Thus, our findings suggest that the housing market is micro efficient.

Our contribution is two-fold. First, we propose a simple framework to test for micro persistence in housing markets. Our framework builds on the persistence idea from macro tests. In contrast to macro tests, our results show little micro persistence. Moreover, we find that it is difficult to beat the market systematically by investing in houses that are under-priced relative to the price implied by a hedonic model. Thus, our findings support the notion of a micro efficient housing market. Second, we bring results from a comprehensive data set. The data allow ultra-fine time grids, since all transaction observations are supplemented through real-time, same-day entries by realtors. Thus, we have access to the actual sale date, i.e. the date on which a bid is accepted, not the contract signature date or the publicly registered date of title transfer. The data set also contains information on ask prices, in addition to a long list of attributes. Institutionally, Norway is a well-suited country for studying micro versus macro persistence, since Norwegian households transact houses through speedy and transparent ascending-bid auctions after public showings on one or two pre-announced dates. In these auctions, the realtor mediates bids electronically after potential buyers have volunteered their names, phone numbers, and e-mail addresses upon visiting the showing of the unit. This institutional arrangement makes the transaction process fast and transparent, almost a laboratory of housing auctions.

Our findings of little micro persistence add nuance to the literature following the seminal article by Case and Shiller (1989) that has documented macro persistence in the housing market (Røed Larsen and Weum (2008), Miles (2011), Elder and Villupuram (2012)). Macro predictability has been accepted as a feature of the housing market and Glaeser et al. (2014) list predictability of house price index changes as one of three stylized facts about the housing market. Supporting evidence for this claim is found by e.g. Caplin and Leahy (2011) and Head et al. (2014).

The findings in this paper suggest that the housing market is an example of what Jung and Shiller (2005) dubbed "Samuelson's Dictum", which ventures that the stock market is micro efficient, but macro inefficient. The underlying idea is that the stock market produces accurate and unexploitable relative prices, but price levels that, to a certain extent, contain forecastable and exploitable components. Our results indicate that the housing market involves a similar mechanism that makes it produce relative prices in micro that reflect all available information and are time consistent, even if the absolute levels themselves contain forecastable components.

The rest of our paper is structured as follows. Section 2 presents our conceptual framework and discusses related literature. The data are introduced in Section 3, while our econometric approach is laid out in Section 4. Section 5 shows results for tests for micro persistence in the ratio of sell to predicted prices, and we explore whether an *ex post* artibtrage can be made by exploiting *ex ante* information in Section 6. The final section concludes the paper.

2 Conceptual framework and literature

We build on Fama (1973, 1991) in our thinking on how information is assimilated into prices efficiently and Case and Shiller (1989) on the role played by persistence in assessing the efficiency of housing markets. The starting point of our idea of differentiation between market characterizations based on aggregates and individual micro observations can be traced to Jung and Shiller (2005), who describe Samuelson's Dictum as the hypothesis that the stock market could be micro efficient but macro inefficient. The hypothesis involves the possibility that a market accurately prices object A relative to object B at the same time as the ratio of price A relative to price B moves in forecastable ways. This notion is less straightforward for housing units than for stock prices. Stock auctions are common value, whereas housing auctions are both common value and private value. To see this, keep in mind that objective *ex post* relative values of stock A and B at time t can be assessed at time $t + s$ by computing the sums of discounted income streams of the two stocks during the period s at time $t + s$. Such computations are less straight forward for owner-occupied units, since they comprise both a potential income stream (the imputed rent) arising from the rental opportunity and an unobservable utility stream arising from the consumption of attributes for which a particular individual household has a unique willingness-to-pay.

To see the challenge from private value auctions among owner-occupiers, consider Fama's (1991, p. 1575) definition that market efficiency entails that "*security prices fully reflect all available information*". Since private value objects auctioned at time t do not have income streams in the periods that follows from t, there exists a non-zero subjective component which cannot be assessed on the basis of external information. This challenge is reflected in the paucity of tests of micro efficiency in the housing market. In contrast, for common value auctions of securities, micro efficiency, in Samuelson's sense, means that the market is able to identify the appropriate relative prices between objects A and B. Case and Shiller (1989) tested for time persistence in an index and returns and the subsequent literature has used the notion of a particular stochastic process, the random walk, governing the house price indices and returns as the primary macro test of housing markets. However, it has not been fully clarified how the aggregation of non-zero individual private value components could obfuscate a random walk test of indices even given attempts at employing opportunity costs of housing in the form of imputed rents as the price for and measure of utility extraction.

This article suggests how to identify the common value component of a sell price, separate it from a residual component that contains a private value part, and exploit this separation to test for persistence. Consistent with the house buyer model in Glaeser and Nathanson (2015), let $WTP_{i,t,h}$ be household h's willingness-to-pay for unit i at time t. Let the willingness-to-pay contain a common value price level component, CVPL, for market m_i that unit i belongs to, as assessed by household h at time t and a residual component $R_{i,h,t}$ that comprises the match-utility, $U_{i,h,t}$, originating in the pairing of preferences of household h and attributes of unit i and a stochastic element, $\rho_{i,h,t}$, that originates from a multi-factorial process. This can be summarized by the following equations:

$$WTP_{i,t,h} = CVPL^{m_i}_{h,t} + R_{i,h,t} \tag{1}$$

$$R_{i,h,t} = U_{i,h,t} + \rho_{i,h,t} \tag{2}$$

The first step is to estimate the common value component CVPL. This article uses two sources: a hedonic model and the seller's ask price. By construction, the hedonic model allows us to compute a price prediction from inverting an estimated hedonic function. The hedonic function is estimated by regressing sell prices onto the space spanned by the attributes of the units, which leaves us with estimated coefficients that may be interpreted as implicit partial market prices for attributes (Rosen (1974)). The ask price is the seller's own market assessment of the unit combined with the seller's market knowledge.

The second step is to compute two ratios: sell price relative to predicted price (SPPP) and sell price relative to ask price (SPAP). The difference between sell price and predicted price is the residual deviation. Using the ratios SPPP and SPAP, instead of residual deviation on prices, makes the analysis more transparent, easier to interpret, and also joins the literature on sell price-appraisal value ratios (Bourassa, Hoesli, and Sun (2006), de Vries et al. (2009), and Shi, Young, and Hargreaves (2009)). We measure persistence by following units over time and examining whether a high SPPP or SPAP ratio in one transaction is repeated in a future transaction. If a high SPPP or SPAP ratio is non-repeatable, we say that there is no persistence. Instead, there is reversion. This set-up is inspired by Malkiel (2003) in that we evaluate a housing market as efficient if the price-index-adjusted common value part of the sell price, CVPL, not the price-index-adjusted sell price itself, at time t is the best predictor of the sell price at time $t + s$. In an efficient market, there is no time persistence in residuals for a given unit. At time t, the expected residual deviation at time $t + s$ is zero.

From this idea, we may in a few simple steps construct a test for micro persistence. First, estimate a hedonic time dummy model to obtain a predicted price $\hat{P}_{i,t}$ for each unit i transacted at time t. This hedonic model encompasses the aggregate knowledge of the market. It represents the market expectation, i.e. $E_{i,t}P_{i,t} = \hat{P}_{i,t}$. Second, construct a measure for the ratio of observed sell price to predicted price, which is given by $SPPP_{i,t} = \frac{P_{i,t}}{\hat{P}_{i,t}}$.

Third, estimate an equation of the following form:

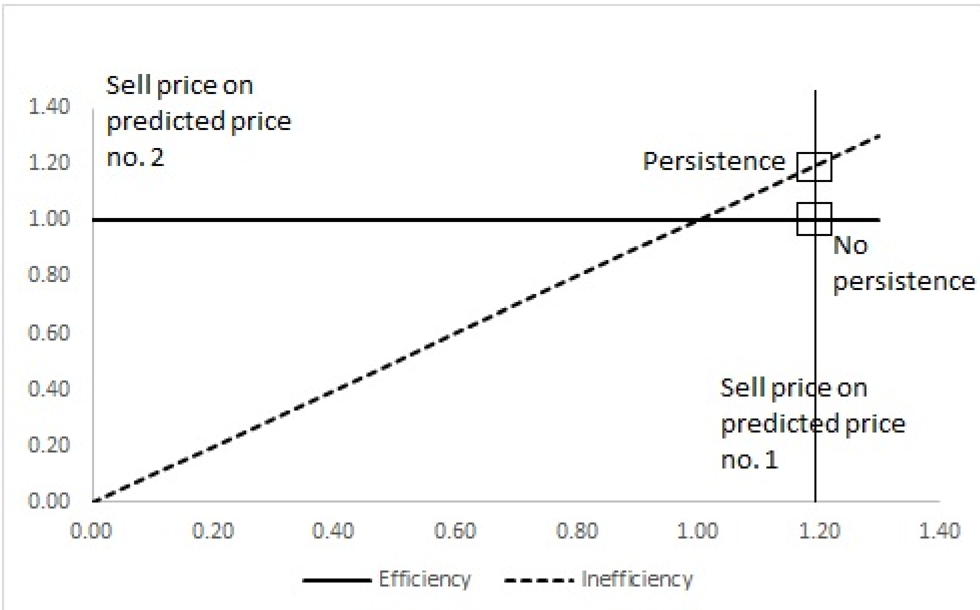
$$SPPP_{i,T2_i} = \alpha + \beta SPPP_{i,T1_i} + \varphi_{i,T2_i}, T2_i > T1_i \tag{3}$$

where the notation $T1_i$ and $T2_i$ makes clear that the dates of the first and second transactions may differ from unit to unit.

Perfect persistence implies that the regression line is identical to the 45-degree line, i.e., $(\alpha, \beta) =$

$(0, 1)$. If so, $SPPP_{i,T1_i}$ is the best predictor for $SPPP_{i,T2_i}$. This implies that residual deviations may be exploited to forecast future residual deviations. Persistence also means $SPAP_{i,T1_i}$ can be used to predict $SPPP_{i,T2_i}$ and $SPAP_{i,T2_i}$. Given the findings from the macro tests, persistence is our null and we reject full persistence if $(\hat{\alpha}, \hat{\beta}) \neq (0, 1)$.

Figure 1. Persistence vs. no persistence. sell price on predicted price, 1st and 2nd sale



Consider a simple example. A hedonic model has been estimated, and it predicts a sell price of NOK 5 million for a given unit i. The observed sell price at time $T1_i$ is NOK 6 million. Thus, $SPPP_{i,T1_i} = 6/5 = 1.2$. What is the best predictor of the next sell price of unit i? Full residual persistence means that the residual deviation in the next round would be expected to be 20 percent. No residual persistence means the expected residual is zero. Thus, if the house price level increases and the hedonic model predicts NOK 7 million for these attributes at time $T2_i$, the best predictor for the next sell price of this particular unit would be $1.2\times$NOK 7 million = NOK 8.4 million under full persistence. Under no persistence, the best predictor is NOK 7 million. In Figure 1, full persistence is indicated where $SPPP_{i,T1_i} = 1.2$ intersects the dotted 45-degree line. No persistence is represented by the horizontal line at $SPPP_{i,T2_i} = 1.00$. This example underlines the importance of constructing a fully specified hedonic model. If not, omitted variables may cause residual persistence. We deal with this challenge in several ways below.

This simple framework invites an interpretative sketch of the residual component R in (2). Housing units are vertically and horizontally differentiated and buyers detect the attributes through a search and matching process (see Nenov, Røed Larsen, and Sommervoll (2015)). We let vertical differentiation refer to the phenomenon that there exist factors in which buyers have consistent, monotonic, and aggregateable preferences, e.g. size. Horizontal differentiation refers to the phenomenon that there exists factors over which buyers have idiosyncratic preferences, e.g. the interior lay out of the unit, or the proximity to an amenity. Nenov, Røed Larsen, and Sommervoll (2015) explain how a search and matching process generate a match utility, which affects the bidder's bid. Consider a transaction of unit i that generated a match utility $U_{i,h,t}$ for household h at time t. If an identical household $k = h$ searches and finds this unit in the subsequent transaction process at time s, a similar match utility is obtained, $U_{i,k,s} = U_{i,h,t}$. The search and matching process is multi-factorial, non-deterministic process. Thus, the residual component R includes bidder- and bidding-specific factors related to the match utility and arrive from processes that comprise stochastic elements from non-specified distributions. Essentially, an efficient market that generates consistent relative prices in micro means that the residual R is not unit-specific and for that reason not persistent nor forecastable because it cannot be linked to information on the unit. Alternatively, persistence indicates that the market is not efficient in that it generates relative prices that may be exploited for profit since the residual R contains forecastable elements. In the numerical example above, persistence implies that an agent may realize that the best predictor for the next transaction price is the model price plus some portion of the earlier 20 percent residual. As long as his bid is lower, he stands to experience a higher appreciation rate on the unit than the general housing market.

2.1 Exploring the scope for arbitrage: Modus operandi

Finding that SPPP is reverting to unity in repeated transactions is a necessary, but not sufficient condition for housing market efficiency. It implies that high sell prices relative to the hedonic model are not repeated, but it does not imply that profitable arbitrage does not exist. No persistence in SPPP suggests that excessively high sell prices are non-repeatable. It also implies that buying at a price below what is predicted by the hedonic model is followed in the next transaction by a price closer to the hedonic prediction, i.e. a return that is higher than the market return. This opens the possibility that one may exploit the reversion on the downside and make a profitable arbitrage by targetted buying of units that sell for prices below the hedonic model's predicted price.

Using survey data for the Philadelphian housing market for the years 1975 and 1978, Linnemann (1986) tested whether the deviation between a self-assessed sell price in 1975 and a predicted price based on the attributes information from the survey could be used to forecast the self-assessed gross return on the unit between 1975 and 1978. His results did indeed suggest that there were possibilities for a gross arbitrage, but that once costs were taken into account, the arbitrage opportunity ceased. We will consider a similar framework, but with the advantage of observing repeated transactions over a 12-year period, and using observed returns based on repeated sales of the same unit instead of the seller's own assessment.

Let β denote the coeffcent obtained by regressing actual return between t_i and s_i ($s_i > t_i$) for unit i on the spread between the sell price, P_{i,t_i}, and the expected price, P^*_{i,t_i}, at t_i. Expected gross percentage return in period t_i is then given by:

$$E_{i,t_i}(R_{i,s_i}) = \left(\frac{E_{i,t_i}(P^*_{i,s_i}) - P^*_{i,t_i}}{P^*_{i,t_i}} + \beta \left(\frac{P_{i,t_i} - P^*_{i,t_i}}{P^*_{i,t_i}} \right) \right) \tag{4}$$

The expected return consists of two terms: (i) the expected market return, as represented by the expected percentage increase in $P^*_{i,}$from t_i to s_i and (ii) the expected excess return from buying units priced below the expected price, which is represented by the difference between P_{i,t_i} and $P^*_{i,t_i,}$. The parameter β measures how buying at a price different from the expected price affects the expected returns. Buying at a price equal to the expected price entails that the expected return on unit i between t_i and s_i is given by the expected market return:

$$E_{i,t_i}(R_{i,s_i} | P_{i,t_i} = P^*_{i,t_i}) = \left(\frac{E_{i,t_i}(P^*_{i,s_i}) - P^*_{i,t_i}}{P^*_{i,t_i}} \right) \tag{5}$$

It follows that the expected excess return from investing in unit i is given by:

$$E_{i,t_i}(R_{i,s_i} | P_{i,t_i} \neq P^*_{i,t_i}) - E_{i,t_i}(R_{i,s_i} | P_{i,t_i} = P^*_{i,t_i}) = \beta \left(\frac{P_{i,t_i} - P^*_{i,t_i}}{P^*_{i,t_i}} \right) \tag{6}$$

When letting the price expectation be measured by the price predicted by a hedonic model, $\hat{P}_{i,t_i}$, we have:

$$E_{i,t_i}(R_{i,s_i} | P_{i,t_i} \neq \hat{P}_{i,t_i}) - E_{i,t_i}(R_{i,s_i} | P_{i,t_i} = \hat{P}_{i,t_i}) = \beta \left(\frac{P_{i,t_i} - \hat{P}_{i,t_i}}{\hat{P}_{i,t_i}} \right) \tag{7}$$

Thus, in expectation, an investor makes an excess gross profit from investing in unit i if and only if:

1. $P_{i,t_i} - \hat{P}_{i,t_i} > 0$ and $\beta > 0$, i.e. buying the unit at a price exceeding the hedonic model price, and at the same time expecting this action to result in a higher return in the future, or

2. $P_{i,t_i} - \hat{P}_{i,t_i} < 0$ and $\beta < 0$, i.e. buying the unit at a price below the hedonic model price and at the same time expecting this action to result in a higher return in the future.

Finding support for 1. or 2. would suggest that there are potential arbitrage opportunities. To get an estimate of β, we estimate an equation of the following form:

$$R_{i,s_i} = \alpha_i + \eta_{t_i} + \eta_{s_i} + \beta \left(\frac{P_{i,t_i} - \hat{P}_{i,t_i}}{\hat{P}_{i,t_i}} \right) + \gamma Years\ elaspsed + \varepsilon_{i,s_i} \tag{8}$$

in which R_{i,s_i} is the actual percentrage return on unit i between t_i and s_i, the variable $Years\ elapsed$ measures the number of days that have elapsed between the two transactions (tranformed to years by dividing by 365). Since we are considering a period of steadily increasing house prices in the Norwegian housing market, this variable controls for the general tendency that the return has been greater for units with a longer holding time. The two time dummies, η_{t_i} and η_{s_i}, control for the year and quarter in which the two transactions took place. These dummies are included to control for business cycle effects that may affect observed excess returns. We also include unit specific intercepts, α_i, to control for permanently omitted variables that are not captured by the hedonic model, e.g. view.

3 Data and institutional background

3.1 The transaction data set

We have acquired data from the firm Eiendomsverdi AS, a private firm that collects data from realtors, official records, and Finn.no (a Norwegian online advertisement firm) and specializes in constructing automated valuation methods that deliver price assessments for commercial banks and realtors in real-time. Commercial data are merged with official records and the resulting data set is a comprehensive register of publicly registered housing transactions in Norway between January 1st, 2002, and February 1st, 2014, and contains information on both the transaction and the unit. Transaction data comprise date of accepted bid, date of announcement of unit for sale, ask price, sell price, and appraisal value made by independent assessor. Unit data include unique ID, address, seven-digit GPS coordinates, size, number of rooms, number of bedrooms, floor, and other attributes.

In order to remove errors, not-arms-length transactions, and invalid entries, we trim the data by truncation at percentile points. Repeat-sales analysis can only be performed on owner-occupier units, so we exclude co-ops. In order to estimate the hedonic model without imputation, we exclude any observation with any missing variable. We are left with 487,468 observations, which we employ in the estimation of the hedonic model, but we truncate on the ratio of sell price to predicted price (SPPP) at the 1^{st} (0.40) and 99^{th} (2.66) percentiles to delete suspicious outliers. 472,378 observations remain. We observe that 73,216 units are sold exactly twice.

The unique unit ID is constructed by the firm Eiendomsverdi on the basis of the official Norwegian register of housing units. As a matter of routine control, we examine the uniqueness of this ID by inspecting latitudes and longitudes using the seven-digit GPS coordinates for each unit. Upon inspection, all first and second transactions have identical GPS coordinates. However, the ground area of houses (footprints) may be altered during reconstruction. In order to ensure that we consider comparable units over time, our study of repeat sales only samples units that have unaltered size. Table 1 summarizes the data.

Table 1. Summary statistics

	Percentiles, median and mean					
	10th	25th	Median	Mean	75th	90th
No. of observations			472,378			
Size	56	77	114	121.1	155	196
Sell price	1,190,000	1,550,000	2,100,000	2,450,947	2,977,244	4,100,000
Percentage Detached			46.9			
Percentage Semi-detached			12.3			
Percentage Rowhouse			7.5			
Percentage Apartment			33.3			
Transactions per unit	Frequency	Share	Accum. sh.			
Sold once	354,007	74.94	74.94			
Sold twice	93,765	19.85	94.79			
Sold three times	20,549	4.35	99.14			

A subset of the transaction data set contains information on year of renovation. In order to control for omitted renovation as a potential confounding factor, we include the variable as a control. To that end, we set the completion of renovation on December 31st in the year of renovation in order to avoid confusion for the cases where year of renovation is equal to year of sale. In those cases, we cannot know whether the renovation took place before or after the transaction. Thus, we only study the transactions where the sell date occurs in the year after renovation or later. In the repeat-sales sample of three sales in the period 2002 - 2014, we found 1,722 observations with renovation after January 1st, 2002, and before the year of the second transaction.Did we control for flipping, i.e. short holding periods and many sales. Multiple sales partially controlled by only studying two transactions, but what about holding duration? Check that. I seem to remember requiring at least a 6 months holding period, but I am not sure.

3.2 Institutional background

The Norwegian housing market is both liquid and transparent. Typically, a unit is announced for sale about a week before a weekend showing on a Saturday or Sunday. Announcements are most frequently posted on the nationwide online service Finn.no and in national and local newspapers. The auction commences on the first workday that follows the last showing. It is an ascending bid auction in which the bids take place by telephone, fax, or electronic submission, and the realtor informs the participants of developments in the auction. Each and every bid is legally binding, and when a bidder makes his first bid, he submits a statement of financing that documents proof of access to funding. About four out of five Norwegians are owner-occupiers, depending on unit of analysis (households, individuals, addresses).

4 Empirical strategy and technique

4.1 The hedonic time dummy model

We construct a hedonic model that, when inverted, may function as a price predictor for the expected price, conditional on attributes. We use a lin-log specification of the following form (Rosen (1974), Cropper, Deck, McConnell (1988), Pope (2008), Kuminoff, Parmeter, and Pope (2010), von Graevenitz and Panduro (2015)):[1]

$$P_{i,t} = a + b_1 log(S_i) + b_2(log(S_i))^2 + \boldsymbol{c}'\boldsymbol{A}_i + \boldsymbol{d}'\boldsymbol{M}_t + \varepsilon_{i,t}, \tag{9}$$

in which $P_{i,t}$ denotes observed sell price for unit i at time t. The size of the unit is denoted S_i, and $\boldsymbol{A}_i$ a vector of attributes, such as type (detached, row house, apartment), , city and geographical dummies, a dummy for lot size above 1,000 square meters and construction period dummies (4 periods). Finally, we include a vector of monthly dummies $\boldsymbol{M}_t$ (146 months). For each sale, we compute a predicted price $\hat{P}_{i,t}$ and calculate the ratio of sell price on predicted price, $SPPP_{i,t} = \frac{P_{i,t}}{\hat{P}_{i,t}}$. All the variables included in $\boldsymbol{A}_i$, along with estimated coefficients of our hedonic model are reported in the Appendix. We achieve an adjusted R-square of 0.661 in the hedonic model.

4.2 Repeat-sales analysis

We identify units that are sold exactly two and three times. For each unit, we compute the ratio of sell price to predicted price for each of the transactions ($SPPP_{i,T1_i}$, $SPPP_{i,T2_i}$, $SPPP_{i,T3_i}$, with

[1] Another specification that offers good fit, reduces the influence of outliers, and allows easy computations of index development is the log-log form. We use this in the hedonic time dummy set-up in order to verify macro persistence. However, we employ the lin-log specification when we predict house prices since the inversion of the log-log form does not yield an unbiased price predictor due to the non-linearity of the log-transformation of the dependent variable.

$T1_i < T2_i < T3_i \; \forall \; i$). We also compute ratios of sell price to ask price (SPAP) and ask price to predicted price (APPP).

The empirical strategy is to run a regression of $SPPP_{i,T2_i}$ onto $SPPP_{i,T1_i}$:

$$SPPP_{i,T2_i} = \alpha + \beta SPPP_{i,T1_i} + \gamma Q_i + u_i, \tag{10}$$

where Q is a unit-specific time-invariant quality indicator not captured by the hedonic model. In order to deal with the challenge of omitted variables, we use additional information from the third transaction, $SPPP_{i,T3_i}$ or $APPP_{i,T3_i}$, as proxies for Q.[2]

We also estimate a fixed-effect, repeated cross-section model, in which unobserved, permanent unit-specific effects are captured by individual unit intercepts, i.e.:

$$SPPP_{i,s_i} = \alpha_i + \beta SPPP_{i,t_i} + u_{h,s_i}, s_i = T2_i,\ T3_i; t_i = T1_i, T2_i \tag{11}$$

5 Empirical results on micro persistence

5.1 Testing for persistence in SPPP

Persistence in deviations from predicted price implies that a high SPPP ratio in the first sale is repeated in the second sale. Reversion implies that a high SPPP in one transaction is followed by a low SPPP in the next transation. Table 3 tabulates results from estimating the baseline specification in (3) using the sample of units for which we have information on exactlytwo transactions.

The coefficient on $SPPP_{i,T1_i}$ is statistically significant and economically important. The explanatory power is high, with an adjusted R^2 of 0.40. The main pattern is a reversion to unit SPPP. The interpretation of the estimated regression coefficients is clear: When the sell price is 30 percent above the predicted price in the first round, it is associated with a sell price that is 14 percent higher than the predicted price in the second round, a substantial reversion towards unit SPPP. When the sell price is 30 percent below the predicted price in the first round, it is associated with a sell price that is 16 percent lower than the predicted price in the second round, a reversion towards unit SPPP. When the sell price is equal to the predicted price in the first round, it is associated with a sell price that is roughly 1 percent lower than the predicted price in the second round.

The regression results in Table 2 supports the notion of reversion to unit SPPP and we reject full persistence of zero intercept and unit slope. This is evidence indicative of the relative pricing ability consistent with the lack of micro persistence, since price deviations are corrected upon the second sale. However, the parsimonious regression specification does not control for omitted variables. Below, we

[2] We compute both classical and White (1980) heteroskedasticity-consistent standard errors, but report the latter. The properties of the $SPPP_{i,T1_i}$-coefficient, β, is thoroughly examined, including the challenge from omitted variables such as view and exterior quality.

turn to the challenge of setting up regressions that take such factors into account.

Table 2. Regressing $SPPP_{i,T2_i}$ on $SPPP_{i,T1_i}$ ($T2_i > T1_i \; \forall \; i$).

Units sold exactly two times. Norway, 2002-2014

Intercept	0.493 (0.004)
$SPPP_{i,T1_i}$	0.495 (0.004)
No. obs.	73,216
Adj. R2	0.400
$SPPP_{i,T1_i} \rightarrow SPPP_{i,T2_i}(SE)$	1.3 $\rightarrow$ 1.136
$SPPP_{i,T1_i} \rightarrow SPPP_{i,T2_i}(SE)$	1.0 $\rightarrow$ 0.988
$SPPP_{i,T1_i} \rightarrow SPPP_{i,T2_i}(SE)$	0.7 $\rightarrow$ 0.839

Note: The table report results when we regress the second SPPP on the first SPPP for units transacted exactly two times. SPPP is an abbreviation for sell price divided by predicted price. Clustered (on ID) standard errors are reported in parentheses.

5.2 Unit-specfic factors and the third sale

Results presented above demonstrate a return to unity when $SPPP_{i,T1_i}$ is high. Omitted variables may bias the results. They can be permanent (e.g. view) or transitory (e.g. renovation) or bidder- or bidding-specific (e.g. high utility matches). Unit-specific latent quality factors (e.g. view) represent a challenge to hedonic models (von Graevenitz and Panduro (2015)). We deal with this challenge in four ways by:

1. Exploiting information from a third transaction
2. Utilizing information on the ask price set by the seller
3. Estimating a fixed-effects model
4. Studying a subset with information on renovation

The first approach is to study units that are sold three times, not two times. The third transaction may function as a control for unobserved quality and we use $SPPP_{i,T3_i}$ as a gauge. If both the first and the third sell price are high relative to the predictions of the hedonic model, it is plausibly caused by a permanent, omitted variable, and it is therefore likely that also $SPPP_{i,T2_i}$ is high. Conversely, if $SPPP_{i,T1_i}$ is high but $SPPP_{i,T3_i}$ is unity, we interpret this as the outcome of bidder- or bidding-specific factors in the first round, and we are especially keen to find the associated $SPPP_{i,T2_i}$. Case

1 and 2 in Table 4 show the fitted $SPPP_{i,T2_i}$ based on estimated regression coefficients for the two pairs of ($SPPP_{i,T1_i}$,$SPPP_{i,T3_i}$), i.e. (1.3,1.3) and (1.3,1.0).

Our second approach uses the knowledge from the most knowledgeable agent, the seller. The seller sets an ask price, in collaboration with the realtor, that reflects attributes included in the hedonic model but also omitted variables. We differentiate between two cases: a) when all three $SPPP_{i,T1_i}$, $APPP_{i,T1_i}$, and $APPP_{i,T2_i}$ are high and b) when $SPPP_{i,T1_i}$ is high, but $APPP_{i,T1_i}$ and $APPP_{i,T2_i}$ are low. The natural interpretation is that case a) occurs when a unit-specific variable is omitted from the hedonic model and b) when $SPPP_{i,T1_i}$ is caused by bidder- or bidding-specific factors (e.g. high utility match). The fitted $SPPP_{i,T2_i}$ based on these specifications are reported as case 3 and 4 in Table 4.[3]

Table 3. Fitted $SPPP_{i,T2_i}$ based on on information on third sale and ask prices.

	Fitted dep. variable is		when independent variables are			
Case		Interpretation	$SPPP_{i,T1_i}$	$SPPP_{i,T3_i}$	$APPP_{i,T1_i}$	$APPP_{i,T2_i}$
1	$SPPP_{i,T2_i}$ = 1.28 (0.002)	unit-specific	1.3	1.3		
2	$SPPP_{i,T2_i}$ = 1.09 (0.002)	bidder or bidding	1.3	1.0		
3	$SPPP_{i,T2_i}$= 1.31 (0.001)	unit-specific	1.3		1.3	1.3
4	$SPPP_{i,T2_i}$ = 1.05 (0.003)	bidder or bidding	1.3		1.0	1.0

Note: The table report fitted values of second SPPP for different values of the explanatory variables. The fitted values are obtained from four separate regressions. Cases 1 and 2 are constructed by regressing second SPPP on first and third SPPP, while Cases 3 and 4 are constructed by regressing second SPPP on first and third APPP. SPPP is an abbreviation for sell price divided by predicted price and APPP stands for appraisal price relative to predicted price. Standard errrors are reported in parentheses next to the fitted values in column 2.

Our main findings are two-fold: The fitted $SPPP_{i,T2_i}$ is high when the associated high $SPPP_{i,T1_i}$ appears to be caused by unit-specific high-quality omitted variables. In contrast, the fitted $SPPP_{i,T2_i}$ is low when the associated high $SPPP_{i,T1_i}$ appears to be related to bidder- or bidding-specific factors. In other words, when persistence is expected, there is persistence. A level of $SPPP_{i,T1_i}$ equal to 1.3, when quality gauges are equal to 1.3, is associated with a fitted level of $SPPP_{i,T2_i}$ in the range 1.28-1.31. When no persistence is expected, there is little persistence. A level of $SPPP_{i,T1_i}$ equal to 1.3, when quality gauges are equal to 1.0, is associated with a fitted level of $SPPP_{i,T2_i}$ in the range 1.05-1.09.

[3]In Table 4, we focus attention on the interpretation of the computed SPPPs, and do not report the underlying estimated coefficients. The underlying estimation results are available upon request.

5.3 A fixed-effect model

Using ask prices in transaction 1 and 2 as controls for unobservable variables omitted by the hedonic model alleviates the confounding effect from unit-specific factors in the persistence test. We also construct and estimate a fixed effect model of the type described by equation (11). As a robustness check, we also consider a specification where SPPP is replaced by SPAP. Results from all these specifications are reported in Table 4.

The rejection of full micro persistence is strengthened when we control for unit-fixed effects. When we control for the business cycle by including year-quarter specific dummies (Column III and Column IV), the results become stronger. There is clear evidence of reversion to unit SPPP. In particular, for $SPPP_{i,t_i} = 0.7/1/1.3$, we reject the null of full persistence and results are closer to suggesting full reversion, i.e., $\hat{\hat{\alpha}} + \hat{\beta} SPPP_{i,t_i} = 1$. This suggest that, with the exception of very high or very low values of $SPPP_{i,t_i}$, the absence of micro persistence is a robust finding.

Table 4. Fixed-effects regression

Indep. var.	Dependent variable is $SPPP_{i,t_i}$			
	I	II	III	IV
Interc.	0.879 (0.007)	0.991 (0.133)	1.046 (0.015)	1.154 (0.134)
$SPPP_{i,s_i}$	0.105 (0.006)	0.090 (0.006)		
$SPAP_{i,s_i}$			-0.057 (0.015)	-0.067 (0.015)
No. obs.	34,094 (17,047 units sold 3 times yield 17,047*2 pairs)			
Within R-sq.	0.025	0.085	0.001	0.069
Between R-sq.	0.672	0.419	0.024	0.003
Overall R-sq	0.514	0.303	0.010	0.011
Time-fixed effects	NO	YES	NO	YES
Unit-fixed effects	YES	YES	YES	YES
$SPPP_{i,t_i} = 0.7 \rightarrow SPPP_{i,s_i}$	0.953 (0.002)	1.054 (0.133)		
$SPAP_{i,t_i} = 0.7 \rightarrow SPAP_{i,s_i}$			1.006 (0.005)	1.108 (0.134)
$SPPP_{i,t_i} = 1.0 \rightarrow SPPP_{i,s_i}$	0.984 (0.002)	1.081 (0.133)		
$SPAP_{i,t_i} = 1.0 \rightarrow SPAP_{i,s_i}$			0.989 (0.003)	1.088 (0.133)
$SPPP_{i,t_i} = 1.3 \rightarrow SPPP_{i,s_i}$	1.016 (0.002)	1.109 (0.133)		
$SPAP_{i,t_i} = 1.3 \rightarrow SPAP_{i,s_i}$			0.972 (0.004)	1.068 (0.134)

Note: The table reports results when we regress SPPP in one transaction on the SPPP in the previous transaction. The regression model utilizes units that are sold exactly three times (N = 17,047) and we use both transaction pairs (1,2) and (2,3). SPPP abbreviates sell price relative to predicted price. Standard errors are reported in parentheses.

5.4 Home improvements

A final confounder could be home improvements. We extract 501 units with three transactions in the period 2002-2014 that comprise information on observed renovation before the second transaction. We repeat the regression of $SPPP_{i,T2_i}$ on $SPPP_{i,T1_i}$ and $SPPP_{i,T3_i}$, while including time between renovation and the second sale. Table 5 demonstrates that the effect of a transitory unit-specific omitted factor, such as renovation, appears to be minimal. Including the variable "Years since renovation" improves the explanatory power slightly and changes the estimated coefficients of $SPPP_{i,T1_i}$ and $SPPP_{i,T2_i}$ only in the second and third decimal. The left column shows that for a unit with a first sell price 30 percent above predicted price ($SPPP_{i,T1_i}= 1.3$) and a third sell price equal to predicted ($SPPP_{i,T3_i}= 1.0$), the fitted $SPPP_{i,T2_i}$ is 1.105. Using the right column and inputting the mean of the variable "years since renovation" (2.1 years), i.e. the mean time between renovation and sale 2, the fitted $SPPP_{i,T2_i}$ becomes 1.104. Since the coefficient of time since renovation is negative, the difference in the first and second column SPPP increases with time since renovation. The obvious interpretation is that the value of renovation depreciates over time. Table 5 shows that the reversion pattern is intact when we include observed renovation year.

Table 5. $SPPP_{i,T2_i}$ **regressed on** $SPPP_{i,T1_i} + SPPP_{i,T3_i}$ **+ renovation**

Independent variables	Dependent variable	
	$SPPP_{i,T2_i}$	$SPPP_{i,T2_i}$
Intercept	0.033 (0.027)	0.048 (0.029)
$SPPP_{i,T1_i}$	0.239 (0.022)	0.241 (0.022)
$SPPP_{i,T3_i}$	0.761 (0.031)	0.762 (0.032)
Years since renovation		-0.009 (0.004)
No. obs.	501 units are observed sold exactly 3 times and has renovation information	
Adj. R-square	0.753	0.757

Note: The table reports results when we regress the second SPPP on the first and third SPPP. SPPP is an abbreviation for sell price relative to predicted price. The first column reports the same regression as we study above, but for the sub-sample for which data on renovation are available. The second column also controls for renovation bv including the variable time since renovation, which measures the period between renovation and second sale. We only have information on renovation year, not date. Thus, to ensure that we study units with renovation between sale 1 and sale 2, we extract transactions in which the first sale is before January 1st of the renovation year and the second sale is after December 31st of the renovation year. We then count number of days since renovation, and set the renovation date at July 1st of the renovation year. Years since renovation are days since renovation divided by 365.

6 Testing for arbitrage opportunities

6.1 Return predictability

Our results suggest that the SPPP reverts to unity in repeated transactions. This implies that a necessary, but not sufficient condition of micro efficiency is satisfied. For sufficiency, we need to rule out profitable arbitrage. Since our results imply that high sell prices (relative to the hedonic model) are not repeated, it does not seem possible to buy over-priced objects and expect to resell them at a higher, profitable price. However, our results also imply that buying at a price below what is predicted by the hedonic model is followed in the next transaction by a price closer to the hedonic prediction. This reversion opens up the possibility that it might be profitable to buy at or above the hedonic model's predicted price when the predicted price is associated with an SPPP substantially below unity.

To explore this possibility, we estimate equation (8). Results are given in Table 6.

Table 6. Test of gross return predictability

Variable	Coefficient	SE	Coefficient	SE
Intercept	0.024	0.003	-0.102	0.081
Spread_t	-0.667	0.019	-0.871	0.016
Years elasped	0.074	0.001	0.103	0.012
No. obs.	34, 094 (17,047 units sold 3 times yield 17,047*2 pairs)			
Within R-sq	0.379		0.638	
Between R-sq	0.121		0.160	
Overall-Sq	0.200		0.303	
Time fixed-effects	NO		YES	
unit-fixed-effects	YES		YES	

Note: The table reports results when we regress the observed percentage increase in the sell price for a given unit between two transactions on the spread between the sell price and the price predicted by the hedonic model in the first transaction, i.e we follow equation (8). We exploit data only for units that are transacted exactly three times. This enables use to use a fixed-effects estimator to control for unit-specific omitted variables that may generate a spurious correlation. Years elapsed are days elapsed divided by 365. Time fixed-effects are estimated by a set-up that entails quarter dummies for transaction pairs, i.e. the quarter and year for transaction two and transaction three.

Two observations are key. First, the estimate of β is negative, suggesting that there may be arbitrage opportunities from investing in units that can be bought below the price predicted by the hedonic model. Second, R^2 is high. Judged by these results, a possible investment strategy is:

1. Estimate the hedonic model to obtain $\hat{P}_{i,t_i}$

2. Estimate (8) to obtain an estimate of β

3. Buy the unit if $E_{i,t_i}(R_{i,s_i}|P_{i,t_i} \neq \hat{P}_{i,t_i}) - E_{i,t_i}(R_{i,s_i}|P_{i,t_i} = \hat{P}_{i,t_i})$ is sufficiently high

Looking at the average return for the units in our sample satisfying this investment strategy, where we control for the time elapsed between the transaction pairs (the trend in the market return), as well as the year and quarter in which the transactions took place, we find the average return to be 6 percent, while the return on the market portfolio is only 1 percent. Thus, results suggest that there might be opportunities for arbitrage by investing in *ex ante* underpriced housing units.

6.2 Time-varying omitted variables

The specification above may suffer from a time-varying omitted variables problem, e.g. due to depreciation of the housing capital or appreciation from renovation. If a unit has great need for renovation at time t_i, we could easily have that $P_{i,t_i} < \hat{P}_{i,t_i}$, just because the hedonic model does not capture the need for renovation. If the same unit is renovated between t_i and s_i, the sell price would be expected to increase. Hence, we could have that $P_{i,s_i} > E_{i,t_i}(\hat{P}_{i,s_i})$ just because the quality improvement is not captured by the hedonic model. Thus, without properly controlling for renovation, the correlation between the spread at t_i and the return between t_i and s_i may be spurious. In this section, we suggest a way of controlling for renovation by exploiting information on the appraisal and ask price.

In the absence of strategic behavior, the ask price should reflect the underlying value of a house, i.e. the reservation price, which is a function of sellers' market beliefs (Genesove and Mayer (2001), Windsor, La Cava, and Hansen (2015)). In ascending bid auctions, the seller may decide to set a price different from the ask price for strategic reasons. For example, a seller could set an ask price lower than the expected value of the house to attract more potential buyers to the viewing in a hope that this will enable her to extract a larger fraction of the consumer surplus in a bidding contest. Alternatively, the seller may set an ask price that is higher than the expected value to signal that the unit is special (a luxury good) or to hope to achieve an anchoring effect. In any case, the ask price of a unit i at time t_i could be expressed as:

$$P^{Ask}_{i,t_i} = P^{*}_{i,t_i} + S_{i,t_i}, \tag{12}$$

in which P^{*}_{i,t_i} is the expected value of the house and S_{i,t_i} represents strategic price setting that makes the ask price deviate from the expected value. In a market without any strategic behavior, we would have $S_{i,t} = 0$, i.e. the ask price is equal to the expected value of the house. The fair market price is unobservable to the econometrician, but what one may observe or estimate is:

1. An appraisal price for a sub-sample of units, $P^{Appraisal}_{i,t_i}$

2. The price implied by an estimated hedonic model, $\hat{P}_{i,t_i}$

Replacing the unobserved underlying housing value by the observable appraisal price in (12), we have:

$$P_{i,t_i}^{Ask} = P_{i,t_i}^{Appraisal} + S_{i,t_i}. \tag{13}$$

Thus, a rough estimate of the contribution of the change in strategic pricing to the change in the ask price is therefore given by $\Delta\hat{S}_{i,t_i} = \Delta P_{i,t_i}^{Ask} - \Delta P_{i,t_i}^{Appraisal}$. Our data contain information on the appraisal price for 28,897 transactions of units with exact three transactions and at least one appraisal price. A regression of the ask price on the appraisal price yields an $R^2$of 0.99 and we find that $\Delta\hat{S}_{i,t_i}$ is close to zero on average.

The question now is how we could construct a measure of time-varying omitted variables for a given unit. The unobserved underlying housing value may be represented as:

$$P_{i,t_i}^{*} = \gamma_1 P_{i,t_i}^{Hedonic} + \gamma_2 Z_i + \gamma_3 W_{i,t_i}, \tag{14}$$

in which Z_i represents unobservable variables that are permanently omitted from the hedonic model, e.g., view, while W_{i,t_i} measures unobservable and time-varying omitted variables, such as renovation. Thus, the underlying house price is a function of what is captured by the hedonic model along with both permanently and time-varying omitted variables. Using the appraisal price as a proxy for the value of the house in (12), we have:

$$P_{i,t_i}^{Appraisal} = \gamma_1 P_{i,t_i}^{Hedonic} + \gamma_2 Z_i + \gamma_3 W_{i,t_i} \tag{15}$$

Thus, estimating (15), we could construct an estimate of the contribution of renovation to the change in the housing value, i.e.:

$$\Delta\hat{v}_{i,t_i} = \Delta P_{i,t_i}^{Appraisal} - \gamma_1 \Delta P_{i,t_i}^{Hedonic} = \gamma_3 \hat{\Delta W}_{i,t_i}, \tag{16}$$

since Z vanishes when differencing, as they are permanent omitted variables. An alternative way of constructing a measure of renovation, where we can calculate this measure for all units (since we have data on the ask price for all units) can be obtained by first combining (12) and (14), which gives:

$$P^{Ask}_{i,t_i} = \gamma_1 P^{Hedonic}_{i,t_i} + \gamma_2 Z_i + \gamma_3 W_{i,t_i} + S_{i,t_i} \quad = \quad \gamma_1 P^{Hedonic}_{i,t_i} + u_{i,t_i} \tag{17}$$

Thus, we have that:

$$\Delta\hat{u}_{i,t_i} = \hat{\gamma_3}\Delta W_{i,t_i} + \Delta S_{i,t_i}, \tag{18}$$

again since Z vanishes in differences. Hence, the change in the residual would yield a measure of the deviation between the price implied by the hedonic model and the ask price that is either due to changes in strategic pricing or changes in the time-varying omitted variables. To the extent that the strategic pricing does not change much (as we argue above), we would therefore have a way of quantifying the time-varying omitted variables, i.e., as long as $\Delta S_{i,t} \approx 0$, we have that $\Delta\hat{u}_{i,t} \approx \gamma_3 \hat{\Delta W}_{i,t}$. Thus, we have an avenue to estimate the part of the change in the ask price from one period to the other that may be attributed to a change in time-varying fundamentals. The intuition is that a seller lets the renovation he undertakes be reflected in an increase of the ask price.

Table 7 summarizes the results obtained from estimating (15) and (17), among which (17) is estimated both for the full sample and for the sample for which we have data on appraisal prices.

Table 7. Tests for presence of time-varying omitted variables

	$Log(P^{Appraisal}_{i,t})$	$Log(P^{Ask}_{i,t})$	$Log(P^{Ask}_{i,t})$
Intercept	2.769 (0.058)	2.753 (0.058)	3.339 (0.003)
$Log(P^{Hedonic}_{i,t})$	0.807 (0.004)	0.808 (0.004)	0.7637 (0.041)
$Adj.R^2$	0.687	0.689	0.677
Mean($\Delta u_{i,t}$)	0.015		
Mean($\Delta v_{i,t}$)		0.020	0.028
No. obs.	28,897	28,897	34,094
Requirement Appraisal	YES	YES	NO

Note: Units with exactly three transactions, with or without the requirement that we have information on appraisal price. A unit is involved in three transactions, i.e. three observations are generated. The table report results from a regression of the logarithm of appraisal and the logarithm of ask price on the logarithm of hedonic price in order to construct a measure of time-varying omitted variables.

We observe that the mean of the change in the time-varying omitted variable is different from zero. We also see that the two alternative measures yield very similar estimates of the mean value of this variable, which again suggests that the change in strategic behavior has relatively little effect on prices. For this reason, we continue our analysis using the measure constructed based on (17) and (18), since this gives us an estimate of the time-varying omitted variable for all observations in our sample. As a simple "eyeball" test of our measure of renovation, we also looked at the correlation between this measure and the sample for which we do have information on renovation. We find that the two measures are correlated. We take this as evidence that this measure is indeed picking up renovation.

Consider the time-varying omitted variable augmented version of equation (8):

$$R_{i,s_i} = \alpha_i + \eta_{t_i} + \eta_{s_i} + \beta \left(\frac{P_{i,t_i} - \hat{P}_{i,t_i}}{\hat{P}_{i,t_i}} \right) + \gamma Years\ elaspsed + \psi \Delta \hat{u}_{i,t_i} + \omega_{i,s_i} \tag{19}$$

Estimating this equation, we get an estimate of β that is constructed not to suffer from omitted variable bias caused by renovation. In addition, and as a by-product, the parameter ψ yields an estimate of by how many percentage points the return between t_i and s_i will increase in face of renovation worth 1 percent of the period t_i housing value. Results from estimating this equation are displayed in Table 8.

Table 8. Gross return predictability when controlling for renovation

Return$_{t+1}$ on Spread$_t$				
Variable	Coefficient	SE	Coefficient	SE
Intercept	0.025	0.003	-0.062	0.066
Spread$_t$	-0.249	0.018	-0.415	0.015
Years elasped	0.070	0.001	0.107	0.010
Renovation	0.638	0.016	0.679	0.014
No. obs.	34,094			
Within R-sq	0.465		0.726	
Between R-sq	0.404		0.414	
Overall-Sq	0.431		0.551	
Time fixed effects	NO		YES	
Unit-fixed effects	YES		YES	

Note: Exactly three transactions. The table reports results when we regress the return on a unit between two periods on the spread between the sell price and the predicted price in the first transaction, controlling for time-varying omitted variables.

We find that the effect of renovation on gross return is positive, as would be expected. Further, we find the effect to be less than one, i.e. if a house is renovated for 1 percent, the seller cannot expect to be repaid the full amount upon selling. The intuition is that this is caused by horizontal differentiation, i.e. heterogeneity in preferences over renovation styles. Third, R^2 increases substantially relative to the specifications without renovation (see Table 7). This suggests that renovation explains quite a bit of variation in gross returns.

Can a profitable arbitrage be made once we control for renovation? We follow the same strategy as previously and say that a unit is deemed as a possible arbitrage object whenever $log(P_{i,t_i}) - log(\hat{P}_{i,t_i}) < 0$. This information is available *ex ante* and does not require us to take any stand on whether a unit is likely to be subject to renovation. *Ex post*, however, we know that part of the return may be due to renovation. Hence, *ex post*, we ask whether the renovation-adjusted return is greater for these units than for the market portfolio. We calculate the average *ex post* renovation-adjusted return to be 1.5 percent for units with a negative sell-predicted spread. For the market portfolio, it is 0.5 percent. Hence, while the difference is still positive, it is far less profitable to invest in under-priced units. The conclusion is that there is little scope for arbitrage in the housing market once renovation is taken into account and that the Norwegian housing market therefore appears to be micro efficient.

7 Concluding remarks and policy implications

We document that a housing unit's sell price that deviates from its expected price in one transaction tends to deviate much less when the same unit is sold the next time. There is little persistence and substantial reversion in price deviations. This is the result of a micro persistence test of the Norwegian housing market. It appears that the housing market is good at ranking houses by value. When a sell price deviates much from the predicted price, it appears to bes due to non-repeatable bidder- or bidding-specific factors, not repeatable unit-specific factors. Since the bidder- or bidding-specific factors are non-repeateable they are also non-exploitable for profit-seeking arbitrageurs. The implication is that it is difficult to buy low and sell high in the housing market on a single unit basis.

This adds nuance to the conventional finding that housing markets are inefficient. While the conventional finding builds on macro tests of persistence in price indices, our results are based on a micro test of persistence in deviations from a model of single units followed over time. In our framework, sell prices that deviate may do so because of high match utility from a search process where unique preferences match with unique attributes. Such outcomes have low probability of being repeated for the same unit.

We use two sources of information to gauge what constitutes a high or low sell price: the price prediction from a standard hedonic model and the seller's ask price. The former builds on the co-variation between attributes and sell prices in the market and the latter employs the information possessed by the most knowledgeable agent, the seller. In a subset, we also draw upon knowledge from assessors when we exploit appraisal values. We summarize the common value of preferences in the market in a hedonic model.

We draw our inference on micro efficiency from regression results. We regresssed the ratio of sell price to predicted price (SPPP) in one transaction on the ratio of sell price to predicted price of the same unit in the previous transaction, while controlling for changes to the unit using information from the third transaction. In addition, we complemented by estimating a fixed-effect model. The former regression estimates imply that when we take into account plausible quality changes, sell prices display reversion to market expectations. The latter regressions corroborate these findings and demonstrate that deviations from hedonic model predictions are short-lived, not unit-specific, and tend not to be repeated.

In a final exercise, which allows us to draw the conclusion that the Norwegian housing market is micro efficient, we test whether a profitable arbitrage in excess of the market return can be made by investing in units that appear underpriced relative to what is implied by a hedonic model. Once we take into account home improvements, we find that no profitable arbitrage can be made. The conclusion is that the conventional finding that the housing market is macro inefficient does not spill over into micro inefficiency. In fact, we document that there appears to be little empirical support for stating that the housing market as micro inefficient.

The policy implications may be considerable since the evidence suggests that, contrary to popular and professional belief, the housing market appears to be quite efficient. The housing market prices units well and so it is very difficult to buy low and sell high. This leaves less room for arguments supporting regulation. In particular, in Norway policymakers have voiced the opinion that housing auctions need strict monitoring and regulation. This article presents the somewhat sobering counter-evidence that housing auctions tend to produce informative and consistent prices that reflect the implicit partial value of attributes.

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Appendix

A1. Additional analyses and tables

Table A1. Hedonic linear-log model with monthly dummies, Norway, 2002-2014

Coefficient	Estimate	Classical	HC
		SE	SE
Intercept	14,020,935	214,181	274,998
Logsize	-7,125,407	87,152	115,395
Sq(logsize)	907,057	8,890	12,088
Type dummies		YES	
Type*Logsize		YES	
Large plot dummy		YES	
Construction year FE		YES	
City FE		YES	
County FE		YES	
Month FE		YES	
DF		487,283	
No. month dummies		145 (1st month default)	
Adj. R2		0.661	

Notes: Classical SE denotes classical standard errors while HC SE denotes heteroskedasticity-consistent ones, computed using the “Sandwich”-package in R and the vcovHC-function.

Note: Semi-detached is default type for type dummies. The notation e7 is short for “times 10^7”.

Macro persistence

Following the seminal contributions of Case and Shiller (1989), there is a copious literature that tests the efficiency of housing markets using aggregate macro data. The standard approach is to consider an equation of the following type:

$$\Delta ph_t = \alpha + \sum_{i=1}^{p} \beta_i \Delta ph_{t-i} + \varepsilon_t,$$

where $\Delta$is a difference operator and ph is the logarithm of some house price index. If housing markets are fully efficient, $\beta_i = 0 \forall i$. Thus, a simple test for efficiency is to test this hypothesis using a standard Wald type test. Looking at our aggregate time series for Norway, we conducted this test using $p = 24$, after having constructed the price index from the hedonic time dummy model. We employed parameterization presented in Table A1 above, with the slight modification that we took the logarithm of the dependent variable. This operation makes the computation of the index very simple, e.g. $P2/P1 = \frac{e^{a+b_1 log(S)+\ldots+d_2 M_2}}{e^{a+b_1 log(S)+\ldots+0}} = e^{d_2}$. The p-value from the test is 0.0000, leading to strong rejection of the null of macro efficiency. In line with the seminal paper of Case and Shiller (1989), we find strong and positive first order autocorrelation (the first lag is highly significant). While coefficients at some longer lags are negative, the sum of the lags is highly positive, suggesting little evidence of mean reversion.

Testing for micro efficiency in the housing market*

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May 6, 2016

Abstract

While aggregate house price indices display time persistence, less is known about micro persistence. This article proposes that absence of micro persistence implies that an excessively high or low sell price in one transaction is not repeated in the next transaction. We exploit a unique Norwegian data set of publically registered housing transactions between 2002 and 2014 and follow housing units over time to see if excessive prices persist or revert. In a regression with time- and unit-fixed effects of sell-price-to-predicted-price ratios on previous sell-price-to-predicted-price ratios, we reject persistence and find substantial reversion. We also test for possible arbitrage opportunities in the form of excess returns. Once we control for price increases that are due to home improvements, we document that there is little scope for profitable arbitrage in excess of the market return. The overall findings suggest that the Norwegian housing market is relatively micro efficient.

Keywords: ***Arbitrage; Housing Market; Micro Efficiency; Persistence; Repeat Sales.***

JEL classification: ***R31; D12; D44; C21.***

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*This paper should not be reported as representing the views of Norges Bank. The views expressed are those of the authors and do not necessarily reflect those of Norges Bank. The paper was presented at the 2016 annual AEA Meeting, the 2016 NBRE Spring meeting, the 2015 ENHR workshop, and the 2015 annual WEAI conference. We thank participants at research seminars at the University of Stavanger, Statistics Norway, and Norges Bank. We are grateful to Farooq Akram, Benjamin Beckers, Lasse Eika, Solveig Erlandsen, Joe Gyourko, Steffen Grønneberg, Mathias Hoffmann, Steinar Holden, Andreas Kostøl, Spencer Norman, Are Oust, Asbjørn Rødseth, Bernt Stigum, Kjetil Storesletten, Genaro Succarat, Paloma Taltavull de La Paz, and Robert Wassmer for stimulating comments and feedback that helped improve this manuscript.

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1 Introduction

House price indices display time persistence. This has led several researchers to the position that returns contain predictable components. However, evidence based on aggregate indices is only part of the story because the development of an index between two time periods reflects movements in the aggregate, i.e. between two scalars that each summarizes thousands of individual transaction prices. An index reveals little about relative prices, which are interesting because economists believe markets coordinate and assimilate information through them, so that people may differentiate between bargains and rip-offs. When people search for bargains and seek to avoid rip-offs, the resulting prices incorporate these efforts, which in turn are reflected in partial prices for housing attributes. This price-correcting capacity lies at the heart of an efficient market. We are interested in how the housing market handles relative prices and this article asks one main question: When a house is sold at an excessively high or low price, what happens to the price the next time the house is transacted?

If there is persistence, a high first sell price relative to an expected price tends to be followed by a high second price relative to an expected price. If there is no persistence but reversion in the spread between sell and expected prices, an investor who paid more than the expected price, whatever the reason, cannot expect to collect a similar premium upon selling the unit. He bought at a high price and experiences a return lower than the market return. Conversely, a buyer who purchases at a price lower than the expected price can reasonably expect to sell at a price that is closer to the expected price. Thus, absence of persistence and presence of reversion imply that the market punishes over-payments and rewards under-payments. At the same time, if under-payments are rewarded, it could be possible to detect units that are under-priced *ex ante* and make an *ex post* gain by investing in these units. For this reason, we investigate the profit possibilities in purchases of *ex ante* undervalued housing units.

Our exploration of housing market efficiency starts by documenting that Norwegian data follow the international pattern of time persistence in aggregate house price indices. Exploiting data on 472,378 transactions on owner-occupier units between 2002 and 2014, we do, however, find that the housing market does not display evidence of micro persistence. To reach this conclusion, we follow units in repeated transactions. We detect a clear pattern. When the first sell price is higher than the price prediction of a standard hedonic model, the price is much closer to the model-predicted price when the unit is sold the next time. The only exception is when the third sell price is higher than the hedonic model's price prediction. Then, the second sell price is also high. The presence of such persistence demonstrates that the market simply discovers what the hedonic model does not, namely key omitted variables. In fact, using the ask price, which reflects the seller's knowledge of the unit (Benitez-Silva et al. (2015), Windsor et al. (2015)), we find the same phenomenon. Moreover, there is little sign of persistence when we consider a repeated cross-section model in which we control for unit-fixed effects. Taking the analysis one step further, we follow an approach similar to Linnemann (1986) and test whether profitable arbitrage opportunities can be made by investing in units that are under-priced relative to the hedonic model *ex ante*. Once we control for home improvements, there is little evidence for an arbitrage opportunity. Thus, our findings suggest that the housing market is micro efficient.

Our contribution is two-fold. First, we propose a simple framework to test for micro persistence in housing markets. Our framework builds on the persistence idea from macro tests. In contrast to macro tests, our results show little micro persistence. Moreover, we find that it is difficult to beat the market systematically by investing in houses that are under-priced relative to the price implied by a hedonic model. Thus, our findings support the notion of a micro efficient housing market. Second, we bring results from a comprehensive data set. The data allow ultra-fine time grids, since all transaction observations are supplemented through real-time, same-day entries by realtors. Thus, we have access to the actual sale date, i.e. the date on which a bid is accepted, not the contract signature date or the publicly registered date of title transfer. The data set also contains information on ask prices, in addition to a long list of attributes. Institutionally, Norway is a well-suited country for studying micro versus macro persistence, since Norwegian households transact houses through speedy and transparent ascending-bid auctions after public showings on one or two pre-announced dates. In these auctions, the realtor mediates bids electronically after potential buyers have volunteered their names, phone numbers, and e-mail addresses upon visiting the showing of the unit. This institutional arrangement makes the transaction process fast and transparent, almost a laboratory of housing auctions.

Our findings of little micro persistence add nuance to the literature following the seminal article by Case and Shiller (1989) that has documented macro persistence in the housing market (Røed Larsen and Weum (2008), Miles (2011), Elder and Villupuram (2012)). Macro predictability has been accepted as a feature of the housing market and Glaeser et al. (2014) list predictability of house price index changes as one of three stylized facts about the housing market. Supporting evidence for this claim is found by e.g. Caplin and Leahy (2011) and Head et al. (2014).

The findings in this paper suggest that the housing market is an example of what Jung and Shiller (2005) dubbed "Samuelson's Dictum", which ventures that the stock market is micro efficient, but macro inefficient. The underlying idea is that the stock market produces accurate and unexploitable relative prices, but price levels that, to a certain extent, contain forecastable and exploitable components. Our results indicate that the housing market involves a similar mechanism that makes it produce relative prices in micro that reflect all available information and are time consistent, even if the absolute levels themselves contain forecastable components.

The rest of our paper is structured as follows. Section 2 presents our conceptual framework and discusses related literature. The data are introduced in Section 3, while our econometric approach is laid out in Section 4. Section 5 shows results for tests for micro persistence in the ratio of sell to predicted prices, and we explore whether an *ex post* artibtrage can be made by exploiting *ex ante* information in Section 6. The final section concludes the paper.

2 Conceptual framework and literature

We build on Fama (1973, 1991) in our thinking on how information is assimilated into prices efficiently and Case and Shiller (1989) on the role played by persistence in assessing the efficiency of housing markets. The starting point of our idea of differentiating between market characterizations based on aggregates and individual micro observations can be traced to Jung and Shiller (2005), who describe Samuelson's Dictum as the hypothesis that the stock market could be micro efficient but macro inefficient. The hypothesis involves the possibility that a market accurately prices object A relative to object B at the same time as the ratio of price A relative to price B moves in forecastable ways. This notion is less straightforward for housing units than for stock prices. Stock auctions are common value, whereas housing auctions are both common value and private value. To see this, keep in mind that objective *ex post* relative values of stock A and B at time t can be assessed at time $t+s$ by computing the sums of discounted income streams of the two stocks during the period s at time $t+s$. Such computations are less straight forward for owner-occupied units, since they comprise both a potential income stream (the imputed rent) arising from the rental opportunity and an unobservable utility stream arising from the consumption of attributes for which a particular individual household has a unique willingness-to-pay.

To see the challenge from private value auctions among owner-occupiers, consider Fama's (1991, p. 1575) definition that market efficiency entails that "*security prices fully reflect all available information*". Since private value objects auctioned at time t do not have income streams in the periods that follows from t, there exists a non-zero subjective component which cannot be assessed on the basis of external information. This challenge is reflected in the paucity of tests of micro efficiency in the housing market. In contrast, for common value auctions of securities, micro efficiency, in Samuelson's sense, means that the market is able to identify the appropriate relative prices between objects A and B. Case and Shiller (1989) tested for time persistence in an index and returns and the subsequent literature has used the notion of a particular stochastic process, the random walk, governing the house price indices and returns as the primary macro test of housing markets. However, it has not been fully clarified how the aggregation of non-zero individual private value components could obfuscate a random walk test of indices even given attempts at employing opportunity costs of housing in the form of imputed rents as the price for and measure of utility extraction.

This article suggests how to identify the common value component of a sell price, separate it from a residual component that contains a private value part, and exploit this separation to test for persistence. Consistent with the house buyer model in Glaeser and Nathanson (2015), let $WTP_{i,t,h}$ be household h's willingness-to-pay for unit i at time t. Let the willingness-to-pay contain a common value price level component, CVPL, for market m_i that unit i belongs to, as assessed by household h at time t and a residual component $R_{i,h,t}$ that comprises the match-utility, $U_{i,h,t}$, originating in the pairing of preferences of household h and attributes of unit i and a stochastic element, $\rho_{i,h,t}$, that originates from a multi-factorial process. This can be summarized by the following equations:

$$WTP_{i,t,h} = CVPL_{h,t}^{m_i} + R_{i,h,t} \tag{1}$$

$$R_{i,h,t} = U_{i,h,t} + \rho_{i,h,t} \tag{2}$$

The first step is to estimate the common value component CVPL. This article uses two sources: a hedonic model and the seller's ask price. By construction, the hedonic model allows us to compute a price prediction from inverting an estimated hedonic function. The hedonic function is estimated by regressing sell prices onto the space spanned by the attributes of the units, which leaves us with estimated coefficients that may be interpreted as implicit partial market prices for attributes (Rosen (1974)). The ask price is the seller's own market assessment of the unit combined with the seller's market knowledge.

The second step is to compute two ratios: sell price relative to predicted price (SPPP) and sell price relative to ask price (SPAP). The difference between sell price and predicted price is the residual deviation. Using the ratios SPPP and SPAP, instead of residual deviation on prices, makes the analysis more transparent, easier to interpret, and also joins the literature on sell price-appraisal value ratios (Bourassa, Hoesli, and Sun (2006), de Vries et al. (2009), and Shi, Young, and Hargreaves (2009)). We measure persistence by following units over time and examining whether a high SPPP or SPAP ratio in one transaction is repeated in a future transaction. If a high SPPP or SPAP ratio is non-repeatable, we say that there is no persistence. Instead, there is reversion. This set-up is inspired by Malkiel (2003) in that we evaluate a housing market as efficient if the price-index-adjusted common value part of the sell price, CVPL, not the price-index-adjusted sell price itself, at time t is the best predictor of the sell price at time $t + s$. In an efficient market, there is no time persistence in residuals for a given unit. At time t, the expected residual deviation at time $t + s$ is zero.

From this idea, we may in a few simple steps construct a test for micro persistence. First, estimate a hedonic time dummy model to obtain a predicted price $\hat{P}_{i,t}$ for each unit i transacted at time t. This hedonic model encompasses the aggregate knowledge of the market. It represents the market expectation, i.e. $E_{i,t}P_{i,t} = \hat{P}_{i,t}$. Second, construct a measure for the ratio of observed sell price to predicted price, which is given by $SPPP_{i,t} = \frac{P_{i,t}}{\hat{P}_{i,t}}$.

Third, estimate an equation of the following form:

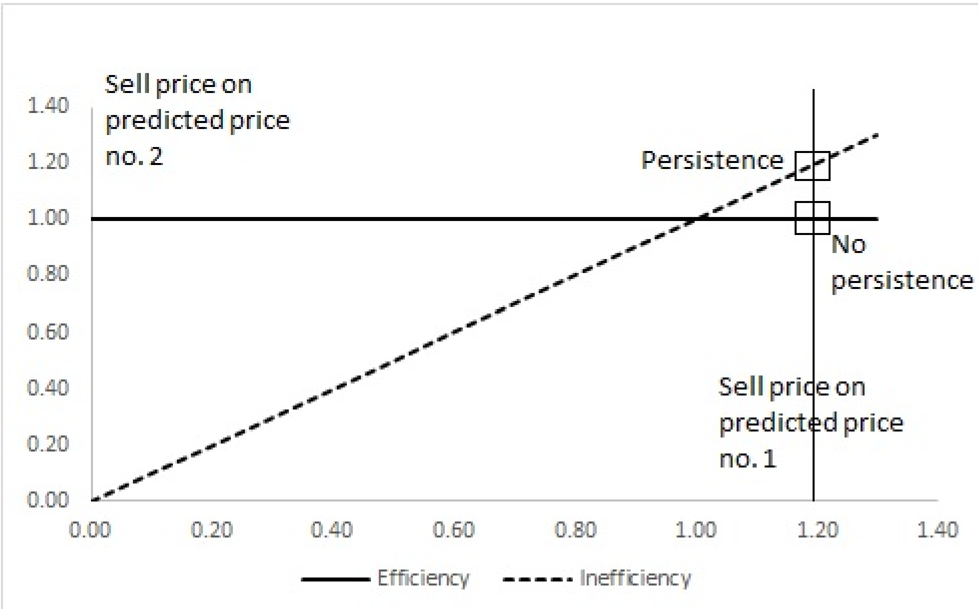
$$SPPP_{i,T2_i} = \alpha + \beta SPPP_{i,T1_i} + \varphi_{i,T2_i}, T2_i > T1_i \tag{3}$$

where the notation $T1_i$ and $T2_i$ makes clear that the dates of the first and second transactions may differ from unit to unit.

Perfect persistence implies that the regression line is identical to the 45-degree line, i.e., $(\alpha, \beta) =$

$(0,1)$. If so, $SPPP_{i,T1_i}$ is the best predictor for $SPPP_{i,T2_i}$. This implies that residual deviations may be exploited to forecast future residual deviations. Persistence also means $SPAP_{i,T1_i}$ can be used to predict $SPPP_{i,T2_i}$ and $SPAP_{i,T2_i}$. Given the findings from the macro tests, persistence is our null and we reject full persistence if $(\hat{\alpha}, \hat{\beta}) \neq (0,1)$.

Figure 1. Persistence vs. no persistence. sell price on predicted price, 1st and 2nd sale



Consider a simple example. A hedonic model has been estimated, and it predicts a sell price of NOK 5 million for a given unit i. The observed sell price at time $T1_i$ is NOK 6 million. Thus, $SPPP_{i,T1_i} = 6/5 = 1.2$. What is the best predictor of the next sell price of unit i? Full residual persistence means that the residual deviation in the next round would be expected to be 20 percent. No residual persistence means the expected residual is zero. Thus, if the house price level increases and the hedonic model predicts NOK 7 million for these attributes at time $T2_i$, the best predictor for the next sell price of this particular unit would be 1.2×NOK 7 million = NOK 8.4 million under full persistence. Under no persistence, the best predictor is NOK 7 million. In Figure 1, full persistence is indicated where $SPPP_{i,T1_i} = 1.2$ intersects the dotted 45-degree line. No persistence is represented by the horizontal line at $SPPP_{i,T2_i} = 1.00$. This example underlines the importance of constructing a fully specified hedonic model. If not, omitted variables may cause residual persistence. We deal with this challenge in several ways below.

This simple framework invites an interpretative sketch of the residual component R in (2). Housing units are vertically and horizontally differentiated and buyers detect the attributes through a search and matching process (see Nenov, Røed Larsen, and Sommervoll (2015)). We let vertical differentiation refer to the phenomenon that there exist factors in which buyers have consistent, monotonic, and aggregateable preferences, e.g. size. Horizontal differentiation refers to the phenomenon that there exist factors over which buyers have idiosyncratic preferences, e.g. the interior lay out of the unit, or the proximity to an amenity. Nenov, Røed Larsen, and Sommervoll (2015) explain how a search and matching process generate a match utility, which affects the bidder's bid. Consider a transaction of unit i that generated a match utility $U_{i,h,t}$ for household h at time t. If an identical household $k = h$ searches and finds this unit in the subsequent transaction process at time s, a similar match utility is obtained, $U_{i,k,s} = U_{i,h,t}$. The search and matching process is multi-factorial, non-deterministic process. Thus, the residual component R includes bidder- and bidding-specific factors related to the match utility and arrive from processes that comprise stochastic elements from non-specified distributions. Essentially, an efficient market that generates consistent relative prices in micro means that the residual R is not unit-specific and for that reason not persistent nor forecastable because it cannot be linked to information on the unit. Alternatively, persistence indicates that the market is not efficient in that it generates relative prices that may be exploited for profit since the residual R contains forecastable elements. In the numerical example above, persistence implies that an agent may realize that the best predictor for the next transaction price is the model price plus some portion of the earlier 20 percent residual. As long as his bid is lower, he stands to experience a higher appreciation rate on the unit than the general housing market.

2.1 Exploring the scope for arbitrage: Modus operandi

Finding that SPPP is reverting to unity in repeated transactions is a necessary, but not sufficient condition for housing market efficiency. It implies that high sell prices relative to the hedonic model are not repeated, but it does not imply that profitable arbitrage does not exist. No persistence in SPPP suggests that excessively high sell prices are non-repeatable. It also implies that buying at a price below what is predicted by the hedonic model is followed in the next transaction by a price closer to the hedonic prediction, i.e. a return that is higher than the market return. This opens the possibility that one may exploit the reversion on the downside and make a profitable arbitrage by targetted buying of units that sell for prices below the hedonic model's predicted price.

Using survey data for the Philadelphian housing market for the years 1975 and 1978, Linnemann (1986) tested whether the deviation between a self-assessed sell price in 1975 and a predicted price based on the attributes information from the survey could be used to forecast the self-assessed gross return on the unit between 1975 and 1978. His results did indeed suggest that there were possibilities for a gross arbitrage, but that once costs were taken into account, the arbitrage opportunity ceased. We will consider a similar framework, but with the advantage of observing repeated transactions over a 12-year period, and using observed returns based on repeated sales of the same unit instead of the seller's own assessment.

Let β denote the coefficent obtained by regressing actual return between t_i and s_i ($s_i > t_i$) for unit i on the spread between the sell price, P_{i,t_i}, and the expected price, P^*_{i,t_i}, at t_i. Expected gross percentage return in period t_i is then given by:

$$E_{i,t_i}(R_{i,s_i}) = \left(\frac{E_{i,t_i}(P^*_{i,s_i}) - P^*_{i,t_i}}{P^*_{i,t_i}} + \beta\left(\frac{P_{i,t_i} - P^*_{i,t_i}}{P^*_{i,t_i}}\right)\right) \tag{4}$$

The expected return consists of two terms: (i) the expected market return, as represented by the expected percentage increase in $P^*_{i,}$from t_i to s_i and (ii) the expected excess return from buying units priced below the expected price, which is represented by the difference between P_{i,t_i} and $P^*_{i,t_i,}$. The parameter β measures how buying at a price different from the expected price affects the expected returns. Buying at a price equal to the expected price entails that the expected return on unit i between t_i and s_i is given by the expected market return:

$$E_{i,t_i}(R_{i,s_i}|P_{i,t_i} = P^*_{i,t_i}) = \left(\frac{E_{i,t_i}(P^*_{i,s_i}) - P^*_{i,t_i}}{P^*_{i,t_i}}\right) \tag{5}$$

It follows that the expected excess return from investing in unit i is given by:

$$E_{i,t_i}(R_{i,s_i}|P_{i,t_i} \neq P^*_{i,t_i}) - E_{i,t_i}(R_{i,s_i}|P_{i,t_i} = P^*_{i,t_i}) = \beta\left(\frac{P_{i,t_i} - P^*_{i,t_i}}{P^*_{i,t_i}}\right) \tag{6}$$

When letting the price expectation be measured by the price predicted by a hedonic model, $\hat{P}_{i,t_i}$, we have:

$$E_{i,t_i}(R_{i,s_i}|P_{i,t_i} \neq \hat{P}_{i,t_i}) - E_{i,t_i}(R_{i,s_i}|P_{i,t_i} = \hat{P}_{i,t_i}) = \beta\left(\frac{P_{i,t_i} - \hat{P}_{i,t_i}}{\hat{P}_{i,t_i}}\right) \tag{7}$$

Thus, in expectation, an investor makes an excess gross profit from investing in unit i if and only if:

1. $P_{i,t_i} - \hat{P}_{i,t_i} > 0$ and $\beta > 0$, i.e. buying the unit at a price exceeding the hedonic model price, and at the same time expecting this action to result in a higher return in the future, or

2. $P_{i,t_i} - \hat{P}_{i,t_i} < 0$ and $\beta < 0$, i.e. buying the unit at a price below the hedonic model price and at the same time expecting this action to result in a higher return in the future.

Finding support for 1. or 2. would suggest that there are potential arbitrage opportunities. To get an estimate of β, we estimate an equation of the following form:

$$R_{i,s_i} = \alpha_i + \eta_{t_i} + \eta_{s_i} + \beta \left(\frac{P_{i,t_i} - \hat{P}_{i,t_i}}{\hat{P}_{i,t_i}} \right) + \gamma Years\ elaspsed + \varepsilon_{i,s_i} \tag{8}$$

in which R_{i,s_i} is the actual percentrage return on unit i between t_i and s_i, the variable $Years\ elapsed$ measures the number of days that have elapsed between the two transactions (transformed to years by dividing by 365). Since we are considering a period of steadily increasing house prices in the Norwegian housing market, this variable controls for the general tendency that the return has been greater for units with a longer holding time. The two time dummies, η_{t_i} and η_{s_i}, control for the year and quarter in which the two transactions took place. These dummies are included to control for business cycle effects that may affect observed excess returns. We also include unit specific intercepts, α_i, to control for permanently omitted variables that are not captured by the hedonic model, e.g. view.

3 Data and institutional background

3.1 The transaction data set

We have acquired data from the firm Eiendomsverdi AS, a private firm that collects data from realtors, official records, and Finn.no (a Norwegian online advertisement firm) and specializes in constructing automated valuation methods that deliver price assessments for commercial banks and realtors in real-time. Commercial data are merged with official records and the resulting data set is a comprehensive register of publicly registered housing transactions in Norway between January 1st, 2002, and February 1st, 2014, and contains information on both the transaction and the unit. Transaction data comprise date of accepted bid, date of announcement of unit for sale, ask price, sell price, and appraisal value made by independent assessor. Unit data include unique ID, address, seven-digit GPS coordinates, size, number of rooms, number of bedrooms, floor, and other attributes.

In order to remove errors, not-arms-length transactions, and invalid entries, we trim the data by truncation at percentile points. Repeat-sales analysis can only be performed on owner-occupier units, so we exclude co-ops. In order to estimate the hedonic model without imputation, we exclude any observation with any missing variable. We are left with 487,468 observations, which we employ in the estimation of the hedonic model, but we truncate on the ratio of sell price to predicted price (SPPP) at the 1^{st} (0.40) and 99^{th} (2.66) percentiles to delete suspicious outliers. 472,378 observations remain. We observe that 73,216 units are sold exactly twice.

The unique unit ID is constructed by the firm Eiendomsverdi on the basis of the official Norwegian register of housing units. As a matter of routine control, we examine the uniqueness of this ID by inspecting latitudes and longitudes using the seven-digit GPS coordinates for each unit. Upon inspection, all first and second transactions have identical GPS coordinates. However, the ground area of houses (footprints) may be altered during reconstruction. In order to ensure that we consider comparable units over time, our study of repeat sales only samples units that have unaltered size. Table 1 summarizes the data.

Table 1. Summary statistics

	Percentiles, median and mean					
	10th	25th	Median	Mean	75th	90th
No. of observations			472,378			
Size	56	77	114	121.1	155	196
Sell price	1,190,000	1,550,000	2,100,000	2,450,947	2,977,244	4,100,000
Percentage Detached			46.9			
Percentage Semi-detached			12.3			
Percentage Rowhouse			7.5			
Percentage Apartment			33.3			
Transactions per unit	Frequency	Share	Accum. sh.			
Sold once	354,007	74.94	74.94			
Sold twice	93,765	19.85	94.79			
Sold three times	20,549	4.35	99.14			

A subset of the transaction data set contains information on year of renovation. In order to control for omitted renovation as a potential confounding factor, we include the variable as a control. To that end, we set the completion of renovation on December 31st in the year of renovation in order to avoid confusion for the cases where year of renovation is equal to year of sale. In those cases, we cannot know whether the renovation took place before or after the transaction. Thus, we only study the transactions where the sell date occurs in the year after renovation or later. In the repeat-sales sample of three sales in the period 2002 - 2014, we found 1,722 observations with renovation after January 1st, 2002, and before the year of the second transaction.

3.2 Institutional background

The Norwegian housing market is both liquid and transparent. Typically, a unit is announced for sale about a week before a weekend showing on a Saturday or Sunday. Announcements are most frequently posted on the nationwide online service Finn.no and in national and local newspapers. The auction commences on the first workday that follows the last showing. It is an ascending bid auction in which the bids take place by telephone, fax, or electronic submission, and the realtor informs the participants of developments in the auction. Each and every bid is legally binding, and when a bidder makes his first bid, he submits a statement of financing that documents proof of access to funding. About four out of five Norwegians are owner-occupiers, depending on unit of analysis (households, individuals, addresses).

4 Empirical strategy and technique

4.1 The hedonic time dummy model

We construct a hedonic model that, when inverted, may function as a price predictor for the expected price, conditional on attributes. We use a lin-log specification of the following form (Rosen (1974), Cropper, Deck, McConnell (1988), Pope (2008), Kuminoff, Parmeter, and Pope (2010), von Graevenitz and Panduro (2015)):[1]

$$P_{i,t} = a + b_1 log(S_i) + b_2(log(S_i))^2 + \boldsymbol{c}'\boldsymbol{A}_i + \boldsymbol{d}'\boldsymbol{M}_t + \varepsilon_{i,t}, \tag{9}$$

in which $P_{i,t}$ denotes observed sell price for unit i at time t. The size of the unit is denoted S_i, and $\boldsymbol{A}_i$ a vector of attributes, such as type (detached, row house, apartment), city and geographical dummies, a dummy for lot size above 1,000 square meters and construction period dummies (4 periods). Finally, we include a vector of monthly dummies $\boldsymbol{M}_t$ (146 months). For each sale, we compute a predicted price $\hat{P}_{i,t}$ and calculate the ratio of sell price on predicted price, $SPPP_{i,t} = \frac{P_{i,t}}{\hat{P}_{i,t}}$. All the variables included in $\boldsymbol{A}_i$, along with estimated coefficients of our hedonic model are reported in the Appendix. We achieve an adjusted R-square of 0.661 in the hedonic model.

4.2 Repeat-sales analysis

We identify units that are sold exactly two and three times. For each unit, we compute the ratio of sell price to predicted price for each of the transactions ($SPPP_{i,T1_i}$, $SPPP_{i,T2_i}$, $SPPP_{i,T3_i}$, with $T1_i < T2_i < T3_i \; \forall \; i$). We also compute ratios of sell price to ask price (SPAP) and ask price to predicted price (APPP).

The empirical strategy is to run a regression of $SPPP_{i,T2_i}$ onto $SPPP_{i,T1_i}$:

[1] Another specification that offers good fit, reduces the influence of outliers, and allows easy computations of index development is the log-log form. We use this in the hedonic time dummy set-up in order to verify macro persistence. However, we employ the lin-log specification when we predict house prices since the inversion of the log-log form does not yield an unbiased price predictor due to the non-linearity of the log-transformation of the dependent variable.

$$SPPP_{i,T2_i} = \alpha + \beta SPPP_{i,T1_i} + \gamma Q_i + u_i, \tag{10}$$

where Q is a unit-specific time-invariant quality indicator not captured by the hedonic model. In order to deal with the challenge of omitted variables, we use additional information from the third transaction, $SPPP_{i,T3_i}$ or $APPP_{i,T3_i}$, as proxies for Q.[2]

We also estimate a fixed-effect, repeated cross-section model, in which unobserved, permanent unit-specific effects are captured by individual unit intercepts, i.e.:

$$SPPP_{i,s_i} = \alpha_i + \beta SPPP_{i,t_i} + u_{h,s_i}, s_i = T2_i,\ T3_i; t_i = T1_i, T2_i \tag{11}$$

5 Empirical results on micro persistence

5.1 Testing for persistence in SPPP

Persistence in deviations from predicted price implies that a high SPPP ratio in the first sale is repeated in the second sale. Reversion implies that a high SPPP in one transaction is followed by a low SPPP in the next transation. Table 2 tabulates results from estimating the baseline specification in (3) using the sample of units for which we have information on exactlytwo transactions.

The coefficient on $SPPP_{i,T1_i}$ is statistically significant and economically important. The explanatory power is high, with an adjusted R^2 of 0.40. The main pattern is a reversion to unit SPPP. The interpretation of the estimated regression coefficients is clear: When the sell price is 30 percent above the predicted price in the first round, it is associated with a sell price that is 14 percent higher than the predicted price in the second round, a substantial reversion towards unit SPPP. When the sell price is 30 percent below the predicted price in the first round, it is associated with a sell price that is 16 percent lower than the predicted price in the second round, a reversion towards unit SPPP. When the sell price is equal to the predicted price in the first round, it is associated with a sell price that is roughly 1 percent lower than the predicted price in the second round.

The regression results in Table 2 supports the notion of reversion to unit SPPP and we reject full persistence of zero intercept and unit slope. This is evidence indicative of the relative pricing ability consistent with the lack of micro persistence, since price deviations are corrected upon the second sale. However, the parsimonious regression specification does not control for omitted variables. Below, we turn to the challenge of setting up regressions that take such factors into account.

Table 2. Regressing $SPPP_{i,T2_i}$ on $SPPP_{i,T1_i}$ ($T2_i > T1_i\ \forall\ i$).

[2] We compute both classical and White (1980) heteroskedasticity-consistent standard errors, but report the latter. The properties of the $SPPP_{i,T1_i}$-coefficient, β, is thoroughly examined, including the challenge from omitted variables such as view and exterior quality.

Units sold exactly two times. Norway, 2002-2014

Intercept	0.493 (0.004)
$SPPP_{i,T1_i}$	0.495 (0.004)
No. obs.	73,216
Adj. R2	0.400
$SPPP_{i,T1_i} \rightarrow SPPP_{i,T2_i}(SE)$	1.3 $\rightarrow$ 1.136
$SPPP_{i,T1_i} \rightarrow SPPP_{i,T2_i}(SE)$	1.0 $\rightarrow$ 0.988
$SPPP_{i,T1_i} \rightarrow SPPP_{i,T2_i}(SE)$	0.7 $\rightarrow$ 0.839

Note: The table report results when we regress the second SPPP on the first SPPP for units transacted exactly two times. SPPP is an abbreviation for sell price divided by predicted price. Clustered (on ID) standard errors are reported in parentheses.

5.2 Unit-specfic factors and the third sale

Results presented above demonstrate a return to unity when $SPPP_{i,T1_i}$ is high. Omitted variables may bias the results. They can be permanent (e.g. view) or transitory (e.g. renovation) or bidder- or bidding-specific (e.g. high utility matches). Unit-specific latent quality factors (e.g. view) represent a challenge to hedonic models (von Graevenitz and Panduro (2015)). We deal with this challenge in four ways by:

1. Exploiting information from a third transaction
2. Utilizing information on the ask price set by the seller
3. Estimating a fixed-effects model
4. Studying a subset with information on renovation

The first approach is to study units that are sold three times, not two times. The third transaction may function as a control for unobserved quality and we use $SPPP_{i,T3_i}$ as a gauge. If both the first and the third sell price are high relative to the predictions of the hedonic model, it is plausibly caused by a permanent, omitted variable, and it is therefore likely that also $SPPP_{i,T2_i}$ is high. Conversely, if $SPPP_{i,T1_i}$ is high but $SPPP_{i,T3_i}$ is unity, we interpret this as the outcome of bidder- or bidding-specific factors in the first round, and we are especially keen to find the associated $SPPP_{i,T2_i}$. Case 1 and 2 in Table 4 show the fitted $SPPP_{i,T2_i}$ based on estimated regression coefficients for the two pairs of ($SPPP_{i,T1_i}$,$SPPP_{i,T3_i}$), i.e. (1.3,1.3) and (1.3,1.0).

Our second approach uses the knowledge from the most knowledgeable agent, the seller. The seller sets an ask price, in collaboration with the realtor, that reflects attributes included in the hedonic model but also omitted variables. We differentiate between two cases: a) when all three $SPPP_{i,T1_i}$,

$APPP_{i,T1_i}$, and $APPP_{i,T2_i}$ are high and b) when $SPPP_{i,T1_i}$ is high, but $APPP_{i,T1_i}$ and $APPP_{i,T2_i}$ are low. The natural interpretation is that case a) occurs when a unit-specific variable is omitted from the hedonic model and b) when $SPPP_{i,T1_i}$ is caused by bidder- or bidding-specific factors (e.g. high utility match). The fitted $SPPP_{i,T2_i}$ based on these specifications are reported as case 3 and 4 in Table 4.[3]

Table 3. Fitted $SPPP_{i,T2_i}$ based on on information on third sale and ask prices.

Case	Fitted dep. variable is	Interpretation	when independent variables are $SPPP_{i,T1_i}$	$SPPP_{i,T3_i}$	$APPP_{i,T1_i}$	$APPP_{i,T2_i}$
1	$SPPP_{i,T2_i}$ = 1.28 (0.002)	unit-specific	1.3	1.3		
2	$SPPP_{i,T2_i}$ = 1.09 (0.002)	bidder or bidding	1.3	1.0		
3	$SPPP_{i,T2_i}$= 1.31 (0.001)	unit-specific	1.3		1.3	1.3
4	$SPPP_{i,T2_i}$ = 1.05 (0.003)	bidder or bidding	1.3		1.0	1.0

Note: The table report fitted values of second SPPP for different values of the explanatory variables. The fitted values are obtained from four separate regressions. Cases 1 and 2 are constructed by regressing second SPPP on first and third SPPP, while Cases 3 and 4 are constructed by regressing second SPPP on first and third APPP. SPPP is an abbreviation for sell price divided by predicted price and APPP stands for appraisal price relative to predicted price. Standard errrors are reported in parentheses next to the fitted values in column 2.

Our main findings are two-fold: The fitted $SPPP_{i,T2_i}$ is high when the associated high $SPPP_{i,T1_i}$ appears to be caused by unit-specific high-quality omitted variables. In contrast, the fitted $SPPP_{i,T2_i}$ is low when the associated high $SPPP_{i,T1_i}$ appears to be related to bidder- or bidding-specific factors. In other words, when persistence is expected, there is persistence. A level of $SPPP_{i,T1_i}$ equal to 1.3, when quality gauges are equal to 1.3, is associated with a fitted level of $SPPP_{i,T2_i}$ in the range 1.28-1.31. When no persistence is expected, there is little persistence. A level of $SPPP_{i,T1_i}$ equal to 1.3, when quality gauges are equal to 1.0, is associated with a fitted level of $SPPP_{i,T2_i}$ in the range 1.05-1.09.

5.3 A fixed-effect model

Using ask prices in transaction 1 and 2 as controls for unobservable variables omitted by the hedonic model alleviates the confounding effect from unit-specific factors in the persistence test. We also construct and estimate a fixed effect model of the type described by equation (11). As a robustness check, we also consider a specification where SPPP is replaced by SPAP. Results from all these specifications are reported in Table 4.

[3]In Table 4, we focus attention on the interpretation of the computed SPPPs, and do not report the underlying estimated coefficients. The underlying estimation results are available upon request.

The rejection of full micro persistence is strengthened when we control for unit-fixed effects. When we control for the business cycle by including year-quarter specific dummies (Column III and Column IV), the results become stronger. There is clear evidence of reversion to unit SPPP. In particular, for $SPPP_{i,t_i} = 0.7/1/1.3$, we reject the null of full persistence and results are closer to suggesting full reversion, i.e., $\hat{\alpha} + \hat{\beta} SPPP_{i,t_i} = 1$. This suggest that, with the exception of very high or very low values of $SPPP_{i,t_i}$, the absence of micro persistence is a robust finding.

Table 4. Fixed-effects regression

Indep. var.	Dependent variable is $SPPP_{i,t_i}$			
	I	II	III	IV
Interc.	0.879 (0.007)	0.991 (0.133)	1.046 (0.015)	1.154 (0.134)
$SPPP_{i,s_i}$	0.105 (0.006)	0.090 (0.006)		
$SPAP_{i,s_i}$			-0.057 (0.015)	-0.067 (0.015)
No. obs.	34,094 (17,047 units sold 3 times yield 17,047*2 pairs)			
Within R-sq.	0.025	0.085	0.001	0.069
Between R-sq.	0.672	0.419	0.024	0.003
Overall R-sq	0.514	0.303	0.010	0.011
Time-fixed effects	NO	YES	NO	YES
Unit-fixed effects	YES	YES	YES	YES
$SPPP_{i,t_i} = 0.7 \rightarrow SPPP_{i,s_i}$	0.953 (0.002)	1.054 (0.133)		
$SPAP_{i,t_i} = 0.7 \rightarrow SPAP_{i,s_i}$			1.006 (0.005)	1.108 (0.134)
$SPPP_{i,t_i} = 1.0 \rightarrow SPPP_{i,s_i}$	0.984 (0.002)	1.081 (0.133)		
$SPAP_{i,t_i} = 1.0 \rightarrow SPAP_{i,s_i}$			0.989 (0.003)	1.088 (0.133)
$SPPP_{i,t_i} = 1.3 \rightarrow SPPP_{i,s_i}$	1.016 (0.002)	1.109 (0.133)		
$SPAP_{i,t_i} = 1.3 \rightarrow SPAP_{i,s_i}$			0.972 (0.004)	1.068 (0.134)

Note: The table reports results when we regress SPPP in one transaction on the SPPP in the previous transaction. The regression model utilizes units that are sold exactly three times (N = 17,047) and we use both transaction pairs (1,2) and (2,3). SPPP abbreviates sell price relative to predicted price. Standard errors are reported in parentheses.

5.4 Home improvements

A final confounder could be home improvements. We extract 501 units with three transactions in the period 2002-2014 that comprise information on observed renovation before the second transaction. We repeat the regression of $SPPP_{i,T2_i}$ on $SPPP_{i,T1_i}$ and $SPPP_{i,T3_i}$, while including time between renovation and the second sale. Table 5 demonstrates that the effect of a transitory unit-specific omitted factor, such as renovation, appears to be minimal. Including the variable "Years since renovation" improves the explanatory power slightly and changes the estimated coefficients of $SPPP_{i,T1_i}$ and $SPPP_{i,T2_i}$ only in the second and third decimal. The left column shows that for a unit with a first sell price 30 percent above predicted price ($SPPP_{i,T1_i}$= 1.3) and a third sell price equal to predicted ($SPPP_{i,T3_i}$= 1.0), the fitted $SPPP_{i,T2_i}$ is 1.105. Using the right column and inputting the mean of the variable "years since renovation" (2.1 years), i.e. the mean time between renovation and sale 2, the fitted $SPPP_{i,T2_i}$ becomes 1.104. Since the coefficient of time since renovation is negative, the difference in the first and second column SPPP increases with time since renovation. The obvious interpretation is that the value of renovation depreciates over time. Table 5 shows that the reversion pattern is intact when we include observed renovation year.

Table 5. $SPPP_{i,T2_i}$ **regressed on** $SPPP_{i,T1_i}$ + $SPPP_{i,T3_i}$ + **renovation**

Independent variables	Dependent variable	
	$SPPP_{i,T2_i}$	$SPPP_{i,T2_i}$
Intercept	0.033 (0.027)	0.048 (0.029)
$SPPP_{i,T1_i}$	0.239 (0.022)	0.241 (0.022)
$SPPP_{i,T3_i}$	0.761 (0.031)	0.762 (0.032)
Years since renovation		-0.009 (0.004)
No. obs.	501 units are observed sold exactly 3 times and has renovation information	
Adj. R-square	0.753	0.757

Note: The table reports results when we regress the second SPPP on the first and third SPPP. SPPP is an abbreviation for sell price relative to predicted price. The first column reports the same regression as we study above, but for the sub-sample for which data on renovation are available. The second column also controls for renovation bv including the variable time since renovation, which measures the period between renovation and second sale. We only have information on renovation year, not date. Thus, to ensure that we study units with renovation between sale 1 and sale 2, we extract transactions in which the first sale is before January 1st of the renovation year and the second sale is after December 31st of the renovation year. We then count number of days since renovation, and set the renovation date at July 1st of the renovation year. Years since renovation are days since renovation divided by 365.

6 Testing for arbitrage opportunities

6.1 Return predictability

Our results suggest that the SPPP reverts to unity in repeated transactions. This implies that a necessary, but not sufficient condition of micro efficiency is satisfied. For sufficiency, we need to rule out profitable arbitrage. Since our results imply that high sell prices (relative to the hedonic model) are not repeated, it does not seem possible to buy over-priced objects and expect to resell them at a higher, profitable price. However, our results also imply that buying at a price below what is predicted by the hedonic model is followed in the next transaction by a price closer to the hedonic prediction. This reversion opens up the possibility that it might be profitable to buy at or above the hedonic model's predicted price when the predicted price is associated with an SPPP substantially below unity.

To explore this possibility, we estimate equation (8). Results are given in Table 6.

Table 6. Test of gross return predictability

Variable	Coefficient	SE	Coefficient	SE
Intercept	0.024	0.003	-0.102	0.081
Spread_t	-0.667	0.019	-0.871	0.016
Years elapsed	0.074	0.001	0.103	0.012
No. obs.	34, 094 (17,047 units sold 3 times yield 17,047*2 pairs)			
Within R-sq	0.379		0.638	
Between R-sq	0.121		0.160	
Overall-Sq	0.200		0.303	
Time fixed-effects	NO		YES	
unit-fixed-effects	YES		YES	

Note: The table reports results when we regress the observed percentage increase in the sell price for a given unit between two transactions on the spread between the sell price and the price predicted by the hedonic model in the first transaction, i.e we follow equation (8). We exploit data only for units that are transacted exactly three times. This enables use to use a fixed-effects estimator to control for unit-specific omitted variables that may generate a spurious correlation. Years elapsed are days elapsed divided by 365. Time fixed-effects are estimated by a set-up that entails quarter dummies for transaction pairs, i.e. the quarter and year for transaction two and transaction three.

Two observations are key. First, the estimate of β is negative, suggesting that there may be arbitrage opportunities from investing in units that can be bought below the price predicted by the hedonic model. Second, R^2 is high. Judged by these results, a possible investment strategy is:

1. Estimate the hedonic model to obtain $\hat{P}_{i,t_i}$

2. Estimate (8) to obtain an estimate of β

3. Buy the unit if $E_{i,t_i}(R_{i,s_i}|P_{i,t_i} \neq \hat{P}_{i,t_i}) - E_{i,t_i}(R_{i,s_i}|P_{i,t_i} = \hat{P}_{i,t_i})$ is sufficiently high

Looking at the average return for the units in our sample satisfying this investment strategy, where we control for the time elapsed between the transaction pairs (the trend in the market return), as well as the year and quarter in which the transactions took place, we find the average return to be 6 percent, while the return on the market portfolio is only 1 percent. Thus, results suggest that there might be opportunities for arbitrage by investing in *ex ante* underpriced housing units.

6.2 Time-varying omitted variables

The specification above may suffer from a time-varying omitted variables problem, e.g. due to depreciation of the housing capital or appreciation from renovation. If a unit has great need for renovation at time t_i, we could easily have that $P_{i,t_i} < \hat{P}_{i,t_i}$, just because the hedonic model does not capture the need for renovation. If the same unit is renovated between t_i and s_i, the sell price would be expected to increase. Hence, we could have that $P_{i,s_i} > E_{i,t_i}(\hat{P}_{i,s_i})$ just because the quality improvement is not captured by the hedonic model. Thus, without properly controlling for renovation, the correlation between the spread at t_i and the return between t_i and s_i may be spurious. In this section, we suggest a way of controlling for renovation by exploiting information on the appraisal and ask price.

In the absence of strategic behavior, the ask price should reflect the underlying value of a house, i.e. the reservation price, which is a function of sellers' market beliefs (Genesove and Mayer (2001), Windsor, La Cava, and Hansen (2015)). In ascending bid auctions, the seller may decide to set a price different from the ask price for strategic reasons. For example, a seller could set an ask price lower than the expected value of the house to attract more potential buyers to the viewing in a hope that this will enable her to extract a larger fraction of the consumer surplus in a bidding contest. Alternatively, the seller may set an ask price that is higher than the expected value to signal that the unit is special (a luxury good) or to hope to achieve an anchoring effect. In any case, the ask price of a unit i at time t_i could be expressed as:

$$P^{Ask}_{i,t_i} = P^{*}_{i,t_i} + S_{i,t_i}, \tag{12}$$

in which P^{*}_{i,t_i} is the expected value of the house and S_{i,t_i} represents strategic price setting that makes the ask price deviate from the expected value. In a market without any strategic behavior, we would have $S_{i,t} = 0$, i.e. the ask price is equal to the expected value of the house. The fair market price is unobservable to the econometrician, but what one may observe or estimate is:

1. An appraisal price for a sub-sample of units, $P^{Appraisal}_{i,t_i}$

2. The price implied by an estimated hedonic model, $\hat{P}_{i,t_i}$

Replacing the unobserved underlying housing value by the observable appraisal price in (12), we have:

$$P^{Ask}_{i,t_i} = P^{Appraisal}_{i,t_i} + S_{i,t_i}. \tag{13}$$

Thus, a rough estimate of the contribution of the change in strategic pricing to the change in the ask price is therefore given by $\Delta\hat{S}_{i,t_i} = \Delta P^{Ask}_{i,t_i} - \Delta P^{Appraisal}_{i,t_i}$. Our data contain information on the appraisal price for 28,897 transactions of units with exact three transactions and at least one appraisal price. A regression of the ask price on the appraisal price yields an $R^2$of 0.99 and we find that $\Delta\hat{S}_{i,t_i}$ is close to zero on average.

The question now is how we could construct a measure of time-varying omitted variables for a given unit. The unobserved underlying housing value may be represented as:

$$P^*_{i,t_i} = \gamma_1 P^{Hedonic}_{i,t_i} + \gamma_2 Z_i + \gamma_3 W_{i,t_i}, \tag{14}$$

in which Z_i represents unobservable variables that are permanently omitted from the hedonic model, e.g., view, while W_{i,t_i} measures unobservable and time-varying omitted variables, such as renovation. Thus, the underlying house price is a function of what is captured by the hedonic model along with both permanently and time-varying omitted variables. Using the appraisal price as a proxy for the value of the house in (12), we have:

$$P^{Appraisal}_{i,t_i} = \gamma_1 P^{Hedonic}_{i,t_i} + \gamma_2 Z_i + \gamma_3 W_{i,t_i} \tag{15}$$

Thus, estimating (15), we could construct an estimate of the contribution of renovation to the change in the housing value, i.e.:

$$\Delta\hat{v}_{i,t_i} = \Delta P^{Appraisal}_{i,t_i} - \gamma_1 \Delta P^{Hedonic}_{i,t_i} = \gamma_3 \hat{\Delta} W_{i,t_i}, \tag{16}$$

since Z vanishes when differencing, as they are permanent omitted variables. An alternative way of constructing a measure of renovation, where we can calculate this measure for all units (since we have data on the ask price for all units) can be obtained by first combining (12) and (14), which gives:

$$P^{Ask}_{i,t_i} = \gamma_1 P^{Hedonic}_{i,t_i} + \gamma_2 Z_i + \gamma_3 W_{i,t_i} + S_{i,t_i} \quad = \quad \gamma_1 P^{Hedonic}_{i,t_i} + u_{i,t_i} \tag{17}$$

Thus, we have that:

$$\Delta\hat{u}_{i,t_i} = \hat{\gamma}_3 \Delta W_{i,t_i} + \Delta S_{i,t_i}, \tag{18}$$

again since Z vanishes in differences. Hence, the change in the residual would yield a measure of the deviation between the price implied by the hedonic model and the ask price that is either due to changes in strategic pricing or changes in the time-varying omitted variables. To the extent that the strategic pricing does not change much (as we argue above), we would therefore have a way of quantifying the time-varying omitted variables, i.e., as long as $\Delta S_{i,t} \approx 0$, we have that $\Delta \hat{u}_{i,t} \approx \gamma_3 \hat{\Delta W}_{i,t}$. Thus, we have an avenue to estimate the part of the change in the ask price from one period to the other that may be attributed to a change in time-varying fundamentals. The intuition is that a seller lets the renovation he undertakes be reflected in an increase of the ask price.

Table 7 summarizes the results obtained from estimating (15) and (17), among which (17) is estimated both for the full sample and for the sample for which we have data on appraisal prices.

Table 7. Tests for presence of time-varying omitted variables

	$Log(P_{i,t}^{Appraisal})$	$Log(P_{i,t}^{Ask})$	$Log(P_{i,t}^{Ask})$
Intercept	2.769 (0.058)	2.753 (0.058)	3.339 (0.003)
$Log(P_{i,t}^{Hedonic})$	0.807 (0.004)	0.808 (0.004)	0.7637 (0.041)
$Adj.R^2$	0.687	0.689	0.677
Mean($\Delta u_{i,t}$)	0.015		
Mean($\Delta v_{i,t}$)		0.020	0.028
No. obs.	28,897	28,897	34,094
Requirement Appraisal	YES	YES	NO

Note: Units with exactly three transactions, with or without the requirement that we have information on appraisal price. A unit is involved in three transactions, i.e. three observations are generated. The table report results from a regression of the logarithm of appraisal and the logarithm of ask price on the logarithm of hedonic price in order to construct a measure of time-varying omitted variables.

We observe that the mean of the change in the time-varying omitted variable is different from zero. We also see that the two alternative measures yield very similar estimates of the mean value of this variable, which again suggests that the change in strategic behavior has relatively little effect on prices. For this reason, we continue our analysis using the measure constructed based on (17) and (18), since this gives us an estimate of the time-varying omitted variable for all observations in our sample. As a simple "eyeball" test of our measure of renovation, we also looked at the correlation between this measure and the sample for which we do have information on renovation. We find that the two measures are correlated. We take this as evidence that this measure is indeed picking up renovation.

Consider the time-varying omitted variable augmented version of equation (8):

$$R_{i,s_i} \quad = \quad \alpha_i + \eta_{t_i} + \eta_{s_i} + \beta \left(\frac{P_{i,t_i} - \hat{P}_{i,t_i}}{\hat{P}_{i,t_i}} \right) + \gamma Years\ elapsed + \psi \Delta \hat{u}_{i,t_i} + \omega_{i,s_i} \tag{19}$$

Estimating this equation, we get an estimate of β that is constructed not to suffer from omitted variable bias caused by renovation. In addition, and as a by-product, the parameter ψ yields an estimate of by how many percentage points the return between t_i and s_i will increase in face of renovation worth 1 percent of the period t_i housing value. Results from estimating this equation are displayed in Table 8.

Table 8. Gross return predictability when controlling for renovation

Return$_{t+1}$ on Spread$_t$				
Variable	Coefficient	SE	Coefficient	SE
Intercept	0.025	0.003	-0.062	0.066
Spread$_t$	-0.249	0.018	-0.415	0.015
Years elapsed	0.070	0.001	0.107	0.010
Renovation	0.638	0.016	0.679	0.014
No. obs.		34,094		
Within R-sq	0.465		0.726	
Between R-sq	0.404		0.414	
Overall-Sq	0.431		0.551	
Time fixed effects	NO		YES	
Unit-fixed effects	YES		YES	

Note: Exactly three transactions. The table reports results when we regress the return on a unit between two periods on the spread between the sell price and the predicted price in the first transaction, controlling for time-varying omitted variables.

We find that the effect of renovation on gross return is positive, as would be expected. Further, we find the effect to be less than one, i.e. if a house is renovated for 1 percent, the seller cannot expect to be repaid the full amount upon selling. The intuition is that this is caused by horizontal differentiation, i.e. heterogeneity in preferences over renovation styles. Third, R^2 increases substantially relative to the specifications without renovation (see Table 7). This suggests that renovation explains quite a bit of variation in gross returns.

Can a profitable arbitrage be made once we control for renovation? We follow the same strategy as previously and say that a unit is deemed as a possible arbitrage object whenever $log(P_{i,t_i})-log(\hat{P}_{i,t_i})<0$. This information is available *ex ante* and does not require us to take any stand on whether a unit is likely to be subject to renovation. *Ex post*, however, we know that part of the return may be due to renovation. Hence, *ex post*, we ask whether the renovation-adjusted return is greater for these units than for the market portfolio. We calculate the average *ex post* renovation-adjusted return to be 1.5 percent for units with a negative sell-predicted spread. For the market portfolio, it is 0.5 percent. Hence, while the difference is still positive, it is far less profitable to invest in under-priced units. The conclusion is that there is little scope for arbitrage in the housing market once renovation is taken into account and that the Norwegian housing market therefore appears to be micro efficient.

7 Concluding remarks and policy implications

We document that a housing unit's sell price that deviates from its expected price in one transaction tends to deviate much less when the same unit is sold the next time. There is little persistence and substantial reversion in price deviations. This is the result of a micro persistence test of the Norwegian housing market. It appears that the housing market is good at ranking houses by value. When a sell price deviates much from the predicted price, it appears to bes due to non-repeatable bidder- or bidding-specific factors, not repeatable unit-specific factors. Since the bidder- or bidding-specific factors are non-repeateable they are also non-exploitable for profit-seeking arbitrageurs. The implication is that it is difficult to buy low and sell high in the housing market on a single unit basis.

This adds nuance to the conventional finding that housing markets are inefficient. While the conventional finding builds on macro tests of persistence in price indices, our results are based on a micro test of persistence in deviations from a model of single units followed over time. In our framework, sell prices that deviate may do so because of high match utility from a search process where unique preferences match with unique attributes. Such outcomes have low probability of being repeated for the same unit.

We use two sources of information to gauge what constitutes a high or low sell price: the price prediction from a standard hedonic model and the seller's ask price. The former builds on the co-variation between attributes and sell prices in the market and the latter employs the information possessed by the most knowledgeable agent, the seller. In a subset, we also draw upon knowledge from assessors when we exploit appraisal values. We summarize the common value of preferences in the market in a hedonic model.

We draw our inference on micro efficiency from regression results. We regresssed the ratio of sell price to predicted price (SPPP) in one transaction on the ratio of sell price to predicted price of the same unit in the previous transaction, while controlling for changes to the unit using information from the third transaction. In addition, we complemented by estimating a fixed-effect model. The former regression estimates imply that when we take into account plausible quality changes, sell prices display reversion to market expectations. The latter regressions corroborate these findings and demonstrate that deviations from hedonic model predictions are short-lived, not unit-specific, and tend not to be repeated.

In a final exercise, which allows us to draw the conclusion that the Norwegian housing market is micro efficient, we test whether a profitable arbitrage in excess of the market return can be made by investing in units that appear underpriced relative to what is implied by a hedonic model. Once we take into account home improvements, we find that no profitable arbitrage can be made. The conclusion is that the conventional finding that the housing market is macro inefficient does not spill over into micro inefficiency. In fact, we document that there appears to be little empirical support for stating that the housing market as micro inefficient.

The policy implications may be considerable since the evidence suggests that, contrary to popular and professional belief, the housing market appears to be quite efficient. The housing market prices units well and so it is very difficult to buy low and sell high. This leaves less room for arguments supporting regulation. In particular, in Norway policymakers have voiced the opinion that housing auctions need strict monitoring and regulation. This article presents the somewhat sobering counter-evidence that housing auctions tend to produce informative and consistent prices that reflect the implicit partial value of attributes.

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Appendix

A1. Additional analyses and tables

Table A1. Hedonic linear-log model with monthly dummies, Norway, 2002-2014

Coefficient	Estimate	Classical	HC
		SE	SE
Intercept	14,020,935	214,181	274,998
Logsize	-7,125,407	87,152	115,395
Sq(logsize)	907,057	8,890	12,088
Type dummies		YES	
Type*Logsize		YES	
Large plot dummy		YES	
Construction year FE		YES	
City FE		YES	
County FE		YES	
Month FE		YES	
DF		487,283	
No. month dummies		145 (1st month default)	
Adj. R2		0.661	

Notes: Classical SE denotes classical standard errors while HC SE denotes heteroskedasticity-consistent ones, computed using the "Sandwich"-package in R and the vcovHC-function.

Note: Semi-detached is default type for type dummies. The notation e7 is short for "times 10^7".

Macro persistence

Following the seminal contributions of Case and Shiller (1989), there is a copious literature that tests the efficiency of housing markets using aggregate macro data. The standard approach is to consider an equation of the following type:

$$\Delta ph_t = \alpha + \sum_{i=1}^{p} \beta_i \Delta ph_{t-i} + \varepsilon_t,$$

where $\Delta$is a difference operator and ph is the logarithm of some house price index. If housing markets are fully efficient, $\beta_i = 0 \forall i$. Thus, a simple test for efficiency is to test this hypothesis using a standard Wald type test. Looking at our aggregate time series for Norway, we conducted this test using $p = 24$, after having constructed the price index from the hedonic time dummy model. We employed parameterization presented in Table A1 above, with the slight modification that we took the logarithm of the dependent variable. This operation makes the computation of the index very simple, e.g. $P2/P1 = \frac{e^{a+b_1 log(S)+...+d_2 M_2}}{e^{a+b_1 log(S)+...+0}} = e^{d_2}$. The p-value from the test is 0.0000, leading to strong rejection of the null of macro efficiency. In line with the seminal paper of Case and Shiller (1989), we find strong and positive first order autocorrelation (the first lag is highly significant). While coefficients at some longer lags are negative, the sum of the lags is highly positive, suggesting little evidence of mean reversion.